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Nowcasting and the Use of Big Data in Short-Term Macroeconomic Forecasting: A Critical Review

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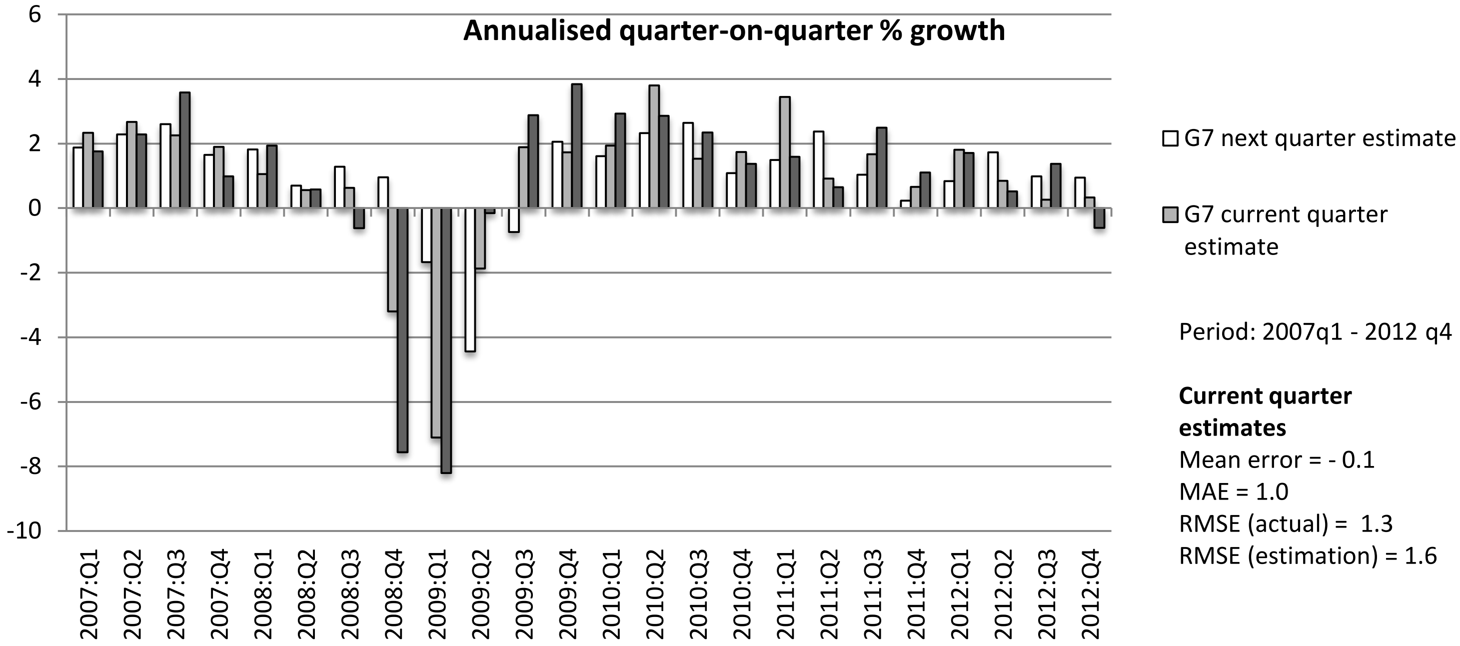
Presentation outline

- Background and Motivation
- The relevance of Big Data to Economic Forecasting?
- Background to Internet Search-based studies
- Review of Internet Search-based studies
- The limitations of the general approach
- Social Media based studies and their limitations
- Other Big Data sources and related studies
- Some broad conclusions
- Key references

Background and Motivation

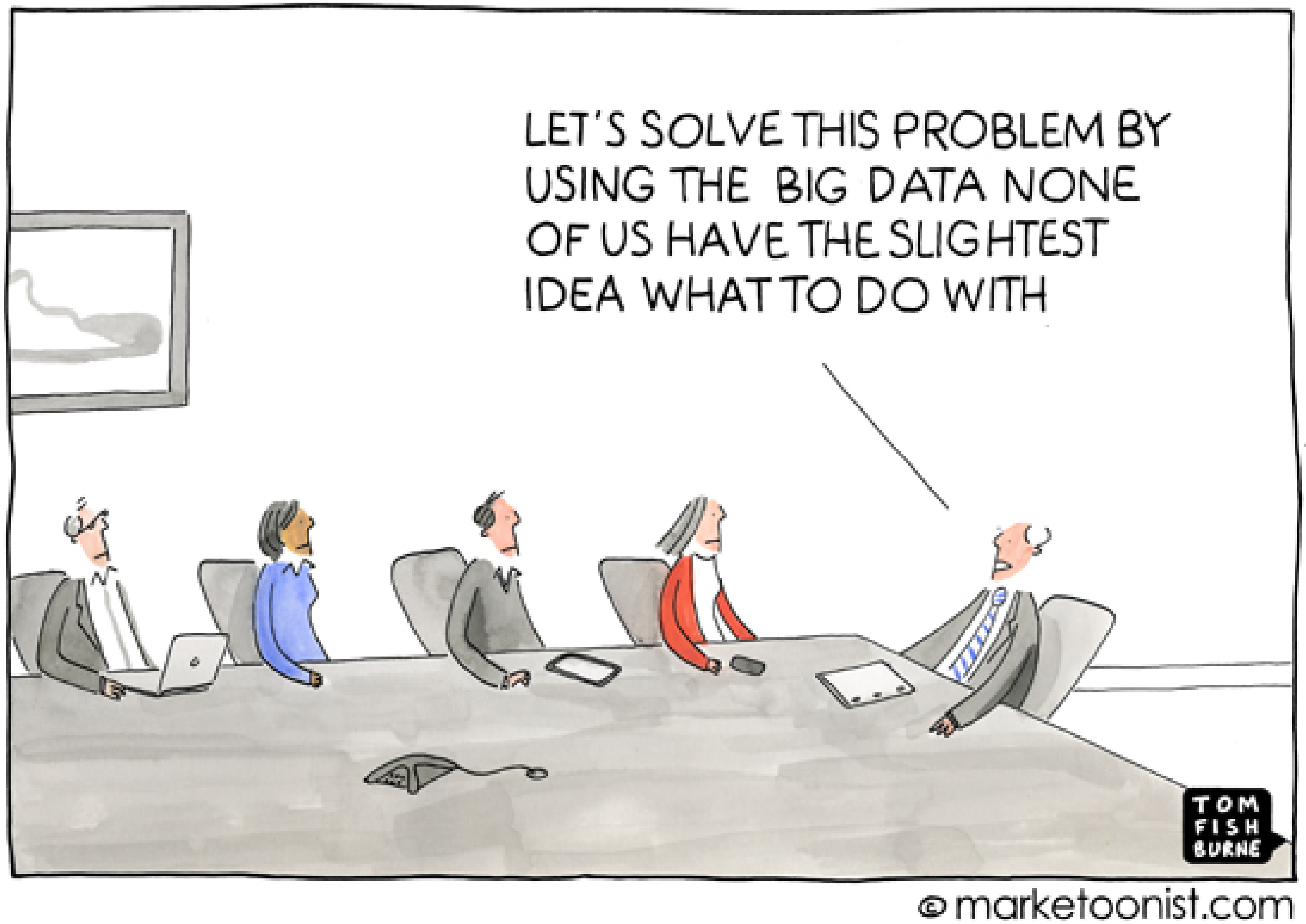
OECD Indicator model-based current and next quarter GDP projections G7 economies



Source: Pain, Lewis, Dang, Jin and Richardson (2014) OECD Forecasts during and after the Financial Crisis: A Post Mortem

- A key limitation of indicator and now-cast models is the lag in availability of hard statistical information.
- Typically goodness-of-fit and out-of-sample predictive performance improve significantly the more information is available for monthly hard indicators during the quarter in question
- Would more timely data from new and unconventional sources assist short-term assessment?

The relevance of Big Data to economic forecasting?



The relevance of Big Data to economic forecasting

- **Big Data** – a broad term originating in the 1990's computing industry, describing data sets so large or complex that traditional data processing applications are (or were) inadequate, such as transactions based electronic data.

- In economics, **Diebold (2000)** was first to refer to the **Big Data** phenomenon thus:
  - "the explosion in the quantity (and sometimes quality) of available and potentially relevant data, largely the result of recent and unprecedented advancements in data recording and storage techniques"

- **Big Data** present some major challenges to analysis, capture, preparation, search, sharing, storage, transfer, visualization, and information privacy.

- But many of these existed before e.g. the early work by Burns and Mitchell, Kuznets and others in developing measures of business cycles and National Accounts systems and in the later development and computerisation of statistical and modelling techniques.

The relevance of Big Data to economic forecasting

- A number of recent, mostly post-crisis, studies have focussed on the possible usefulness for forecasting of three such new sets of information:
  - Internet search statistics (principally Google Trends)
  - Social Media data (principally Twitter)
  - Micro-level transactions data available mostly from economic and financial systems
- In principle, main advantages of these source:
  - Coverage and detail
    - very large samples (at least as source material)
    - available at micro transactions level
    - scope of economic and social transactions
  - Timeliness
    - Near real-time snapshots of current transactions and trends
    - before they are recorded in official statistics

Internet Search based studies

- A growing body of studies has evolved on the use Internet Search statistics in forecasting models, following Ettredge et al (2005), Choi and Varian (2009a and 2009b) and Wu and Brynjolsson (2009)
- Rationale:
  - Growth of internet search as a widespread means for economic agents to obtain information relevant to their immediate economic activities and decisions, ultimately reflected in their behaviour and the wider set of official economic statistics.
  - embodies relevant additional information which is available quickly, at high frequency and possibly with a significant lead time on transactions being recorded.
- Typically involve the construction of weekly, monthly and quarterly indicators of “frequency” of Internet searches for specific keywords/phrases relevant to a specific category of economic activity by country.
  - e.g. searches for terms such as “welfare” or “unemployment” or “benefits” or “mortgage foreclosure” or “car loans”, “car scrapping schemes” etc. for specific countries.
- The relevant indicator is then typically added to and tested for significance within a baseline forecasting model on within- and out-of-sample bases.

Internet Search and the Google Trends Search Tool

- Earliest studies by Ettredge et al (2005) used fairly raw internet search statistics from diverse search engines and sources (WordTracker, Top 500 etc.)
- In 2009, Choi and Varian at Google Labs launch a series of studies and fairly refined facilities on Google Trends/Google Insights website. See Choi and Varian (2009 and 20011) also Varian (2014).
- Google Trends enables researchers to recover tailor-made sample statistics on the **frequency** of searches for specific keywords by location and on a near real-time basis, starting from around 2004. Essentially mining Google's **Big Data** search archives.
- Sample sizes for time-series pose a specific limitation on their general usefulness for modelling, as is the sampling method which is inevitably variable over time.
- A wide range of studies: originally focussing on unemployment indicators, but then widened to include housing, tourism, retail sales and consumption, housing markets, inflation expectations and stock and financial markets, and for a variety of countries.

Internet Search-based studies: Labour markets (1)

- The early work of Ettredge et al (2005), looks at US monthly unemployment 2001-2004, uses Internet search indicator of job-search within a simple autoregressive forecasting model. Finds a significant relationship with published unemployment data for adult males, and superior to the official weekly claims data.

- Broadly similar results are reported for monthly total unemployment for:
  - Germany by Askitas and Zimmermann (2009) using Google Insights Search 2004-2008,
  - Choi and Varian (2009b) for the United States,
  - D'Amuri and Marcuccio (2009) for the United States at aggregate and state level
  - Suhow (2009) for Israel,
  - D'Amuri (2009) for Italy,
  - Anvik and Gelstad (2010) for Norway
  - McLaren and Shanbhogur (2011) for the United Kingdom
  - Tuhkuri (2015) United States and Finland

Internet Search-based studies: Labour markets (2)

- Most of these studies use similar methods - adding the search indicator to fairly naïve time series models in level or first-differenced terms (AR1)
- D'Amuri and Marcuccio (2009), use more sophisticated models which include other economic variables and leading indicators relevant to unemployment.
- Most studies find the relevant search indicator to be significant and to provide superior out-of-sample performance compared with naïve baseline models and in some cases other relevant indicators, for example the US Survey of Professional Forecasters.
- The recent US study by Tuhkuri (2015) is extremely thorough in the choice and sophistication of models and estimation techniques finds that :
  - improvements in predictive accuracy from using Google data appear robust to different model specifications and search terms
  - but are more modest and limited to short-term predictions
  - and the informational value of search data tends to be quite time specific.

Internet Search-based studies: Consumption (1)

- Studies of consumption, retail sales and car sales include:
  - US: Choi and Varian (2009a and 2011) and Kholodilin et al (2010) and Schmidt and Vosen (2011)
  - UK: Chamberlin (2010)
  - Chile: Carriere-Swallow and Labbe (2010)
  - Hungary: Toth and Hadju (2012)
  - France: Bortoli and Combes (2015)
- Some follow a similar strategy to those used for unemployment by adding relevant internet search indicators to relatively naïve time series forecasting models
- Others include search indicators in combination with other measures of consumer sentiment or, more fully specified reduced form economic models which include lagged income, interest rates and stock market price variables , Schmidt and Vosen (2011), .
- In most cases internet search variables are found to be significant either in their own right or in combination with other variables, though sometimes the gains are found to be relatively small.

Internet Search-based studies: Consumption (2)

- The results of Schmidt and Vosen (2011) are particularly telling:
  - individual significance of such variables to be greatest in simple AR(1) models.
  - For semi-structural consumption function s perform as well as or well in combination with the Conference Board Indicator, though the best one-month-ahead nowcasts are given by models including the Google Indicator.
  - the Michigan Consumer Sentiment indicator is found to have no additional value.
- Schmidt and Vosen (2012) find search indicators useful in modelling and predicting the effects of motor vehicle scrapping schemes (so called “cash for clunkers”) for new car sales for the United States, France, Germany and Italy in the period 2002-2009.
- Hence possibly useful role in detecting and predicting the effects of special events or structural change at times when other timely information are not available.
- However, the authors note that major challenges lie in identifying significant irregular events and constructing an appropriate indicator from Google Insights.
- In Bortoli and Combes (2015) study for modelling French consumption (agg and disagg), results are mixed and suggest that search statistics improve monthly expenditure forecasts in only a limited way for a narrow set of goods and services (clothing, food, household durables and transport).

Internet Search-based studies: Other personal sector variables

- For the US housing market,
  - Webb (2009) finds high correlations between searches for "foreclosure" and recorded foreclosures,
  - Wu and Brynjolfsson (2009, 2013) find a housing search indicator significant/strongly predictive for housing market sales and prices and the sales of home appliances.
  - Hellerstein and Middledorp (2012) find similar improvements for predicting mortgage refinancing, though the gains are found to be insignificant beyond a lead time of one week.
- UK house prices: McLaren and Shanbhogur (2011) -- strong results, internet search indicator outperforming other indicators over the period 2004-2011.
- Tourism:
  - Choi and Varian (2011) report significant results for Hong Kong tourism
  - Artola and Galen (2012) find similar results when adding Google based indicators to ARIMA models of the UK demand for holidays in Spain; but note high sensitivity to the choice of baseline model and search keywords, particularly when used in other languages.
- US Inflation expectations: Guzman (2011) finds that high frequency Google-based indicators generally outperform lower frequency traditional measures.

Internet Search-based studies: Financial sector

- Financial sector studies have not typically been in a forecasting context.
  - Andrade et al (2009) : to identify market volatility in the run up to the 2007 Chinese stock market bubble,
  - Vlastakis and Markellos (2010) : report strong correlations between search volume data by company name and trading volumes and excess stock returns for the 30 largest companies traded on the New York Stock Exchange.
  - Da et al (2010 and 2011) find similar correlations between product search variables and revenue surprises and investor attention for 3000 US companies
  - Preis et al (2012) find strong correlations between name searches and transactions volumes for S&P 500 companies.
  - Dimpf and Jank (2012) report strong co-movements between Google company name searches and US stock market movements and volatility, providing better out of sample forecasts than ARIMA models.
  - Hellerstein and Middledorp (2012) find a Google search indicator to be significant in modelling movements in dollar-Renminbi forward market variables, but with low predictive power.
- The lack of firm evidence or applications on the forecasting side is perhaps of less importance given the availability of high frequency indicators for financial markets.

Internet Search-based studies: Wider Macroeconomic studies (1)

- Koop and Onorante (2013) use a different approach using search-based probability measures into a dynamic model switching (DMS) system, one in which current outcomes are regressed on lagged values of the set of dependent variables and Google indicators.
- The rationale
  - internet search information may indicate which macroeconomic variables are most important to economic agents expectations at given points in time.
  - where the underlying economic structure is not constant
  - particularly suited to deal with unexpected events like financial crises and other shocks.
- Applying this method to models for monthly US data for including inflation, industrial production, unemployment, oil prices, money supply and other financial indicators
  - Find dynamic switching models to be generally superior to others, regardless of whether these models involve search-based probabilities or not.
  - But results are mixed across variables, being most positive for inflation, wage, price and financial variables, inconclusive for industrial production and strongly inferior for unemployment.

Internet Search-based studies: Wider Macroeconomic studies (2)

- Tkacz (2013) :
- Canadian study examining the use of Google search indicator for predicting recent turning points and recessions in key macroeconomic indicators.
- Examines internet recession-related search indicators alongside other financial and payments variables within probit models to predict turning points in GDP and unemployment.
- Finds that the usage of Google searches for “recession” and “jobs” could have predicted the 2008 recession up to three months in advance of its onset. Shortness of sample prevents analysis of other turning points.
- Provides good review of the nature and limitations of search related variables, noting both advantages in their timeliness but also their qualitative nature and sensitivity to specific choices.

Limitations of the Internet Search approach: the data sets (1)

- Results are mixed across topics and subject to specific limitations and biases.
  - Search indicators – not the <u>absolute</u> number of searches but the <u>proportion</u> of searches for a specified keyword at any one time, suitably scaled. Hence the need for data to be "cleaned" for specific or aberrant outliers e.g. major sporting events
  - They draw on variable and non-stratified samples, which evolve on a continuous basis according to changes in internet use and search specifications.
- Both add noise and make the indicators more qualitative than at first sight
- Question the nature of the underlying relationship (scale, linearity and sign)

Limitations of the Internet Search approach: the data sets (2)

- Short sample sizes:
  - limit the scope for the testing within a range of existing models.
  - Most studies rely on relatively short sample, high frequency data which are subject to strong seasonality, with the risk of swamping the underlying relationships.
  - At least visually, this seems to be the case for a number of studies claiming to illustrate close historical relationships between the search indicator and variable in question.

- Many authors note the sensitivity of results to the choice of keywords and language

- Much is left to the individual researcher, which can be an advantage but:
  - A need for care in the construction of an indicator targeted for a specific use.
  - A lack of standardised measures at national or international levels specific to macroeconomic monitoring.

Limitations of the Internet Search approach: modelling framework

- Studies reporting high significance/superior out-of-sample forecasts do so by comparison with relatively naïve univariate time series models -- AR(1) or low order ARIMA.
  - rarely able to provide more than smooth short-term projections, adjusting recent out-turns to longer term trends
  - fail to pick up erratic short-term movements or major turning points.
- Few studies test or embed Internet search-based variables within a wider set of indicator models for forecasting near-term GDP or trade movements or turning points.
- A relatively small subset (Koop and Onorante (2013) and Tkacz (2013)) successfully use search-based indicators to augment and improve more conventional economic and/or indicator-based models or to allow for special factors in specific relationships at macro and sectoral levels.
- Further work in all the above areas would seem necessary to exploit the key advantages of Internet search-based indicators over other indicators, as the relevant data sets are extended and improved over time.

Big Data and Social Media based indicators

- Social media data sets, e.g. from Twitter, have advantages over indicators based on internet search frequencies:
  - Available sample sizes can be considerable larger and on a near continuous basis
  - data are more varied in scope, with greater general and specific detail of posts
  - permit a more stratified approach, by analysing information coming from selected "representative" samples or well-defined user groups
  - absence of pre-preparation/filtering by data proprietors, as with Google Trends, may be an advantage or disadvantage.
  - Social media blog entries and Tweets can be about any topic, being totally up to the user what they choose to broadcast.
  - often publicly available either directly in raw form or indirectly through social media Application Programming Interfaces (API's).
- Overall - increasingly accessible and popular source of information for constructing general and specific mood/intentions indicators at a given place and time, and particular topics.

Social Media based empirical studies:

- Previous social media applications using so-called mood indicators cover a fairly wide range of topics :
  - book sales [Gruhl et al (2005])
  - cinema box office receipts Mishne and Glance (2005] and Liu et al (2007)
  - influenza pandemics [Ritterman et al (2009)];
  - TV ratings [Wakamiya et al. (2011)]; and election results [O'Connor et al.(2010) and Tumasjan et al. (2010)].

- In Economics the large majority of empirical studies using social media data as input to economic models and forecasting are relatively near-term and in the area of stock market prices and finance.

Social Media based studies: Financial Markets (1)

- Gibert and Karahalios (2010)
  - use dataset of over 20 million LiveJournal posts, to construct a measure of public
  - use panel of 13K contributors, judged to frequently express varying degrees of general anxiety (not specifically economic events) as sub-sample to build Anxiety Index based on their daily blog posts through 2008
  - regression and Granger causality tests for its “influence" on the S&P500 stock market index, with baseline model involving lagged index values and the lagged levels and changes in the volume of transactions.
- broad conclusion -- the Anxiety Index appears to contain statistically significant information not apparent from other market data but.
- weakened by inclusion of Chicago Board Options Exchange VIX fear index, but collinearity seen as support for more broadly based Anxiety Index as a measure of uncertainty.
- Notes: need for work on difficulties in interpreting blog-based information and potential ambiguities, and index volatility associated with non-economic external events and, importantly, that the sample year 2008 was exceptional in many respects.

Social Media based studies: Financial Markets (2)

- A number of parallel studies have looked only at correlations between the social media-based mood indicators and relevant economic variables:
- Zhang et al (2010) - uses large sample of daily Twitter entries March/September 2009 to construct a variety of measures of differing degrees of positive and negative moods, ranging from fear to hope.
- These are then correlated against corresponding values of the Dow Jones, NASDAQ and S&P500 indices, as well as the VIX index.
- Statistically significant correlations are found, consistent with negative impacts of lagged mood indicators on current stock market prices and the VIX.
- But this holds for both positive and negative mood indicators, indicating relative importance of emotional outbursts as opposed to specific mood directions over the sample period.

Social Media based studies: Financial Markets (3)

- More formally, Bollen et al. (2011), examine the relationship between mood indicators from large-scale Twitter feeds and changes in the Dow Jones index over time.
- Twitter feeds used to derive different measures analysed by two API tools (OpinionFinder and Google-Profile of Mood States)
  - a daily time series for positive vs. negative balance of public mood (OF).
  - a more detailed measure of changes in sentiment for different mood states - Calm, Alert, Sure, Vital, Kind, and Happy (GPOMS).
- then correlate against the Dow Jones index on a daily basis between March to December 2008 using a general autoregressive model and Granger causality testing framework.
- Concludes that predictive accuracy of daily stock market models is significantly improved (by around 6%) when some (Calm and Happy) but not all mood dimensions are included. but not the overall balance of optimism and pessimism as measured by OpinionFinder.
- This "landmark" result is hotly disputed by more recent authors, see Lachanski and Pav (2017) - fail to replicate any of the results and consider the approach to be fundamentally flawed and a "growing deadweight loss to the finance literature".

Social Media based studies: Financial Markets (4)

- Mao et al (2012), look more closely at finance-specific Twitter information as opposed to general positive and negative mood expressions.
- Examine daily tweets mentioning S&P 500 stocks and associated stock prices and traded volumes at the aggregate level, for each of 10 industry sectors and for Apple Inc.
- Correlations between daily stock market measures over 3 month period (February to May 2012) and the Twitter volume indicators.
- Then uses simple linear autoregressive regression models, to predict the stock market indicators with the Twitter data indicator as an exogenous input.
- The overall results are fairly mixed and vary between levels of aggregation. Significant correlations for:
  - levels and changes in prices, though not trading volumes, at the aggregate level
  - for levels of traded volumes but not prices for 8 out of 10 industry and corporate sectors
  - for volumes and prices for financial and Apple, though limited improvements in forecast accuracy.

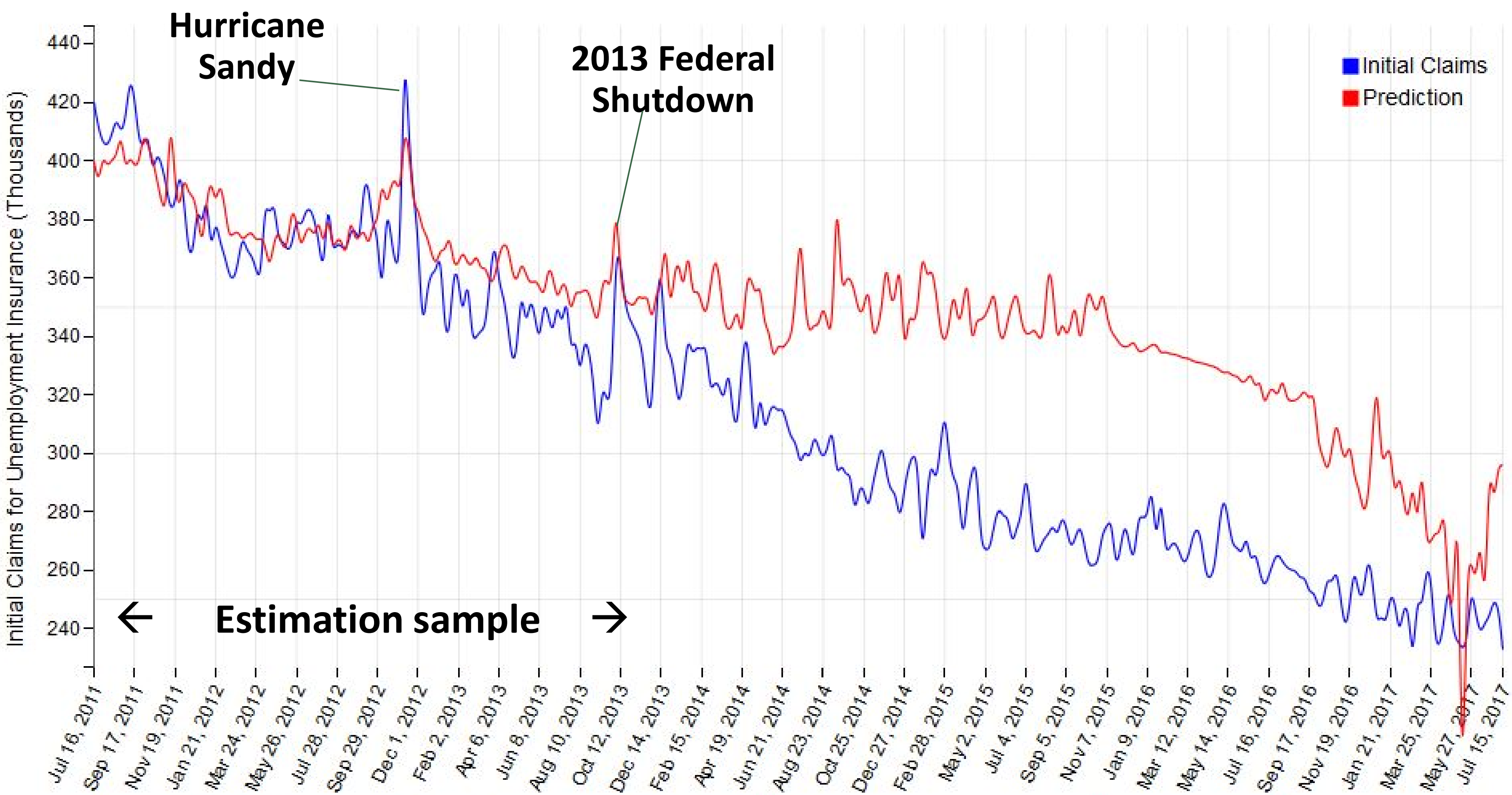
Social Media based studies: Financial Markets (5)

- Mao et al (2014) uses a simpler set of indicators, based on the frequency of use of terms related to financial market "bullishness" or "bearishness" in both Twitter posts and Google search queries.
- calculated on daily (for Twitter) over the period 2010 to 2012, and weekly (for Google Trends) bases over the period 2007 to 2012,
- Relative predictive powers are then analysed in the context of small dynamic models of the US, UK Canadian and Chinese stock market prices and returns.
- Using detailed dynamic VAR modelling framework for the United States (including trading volumes and other sentiments indicators as explanatory variables)
  - Twitter-based indicator is found to be both statistically significant and provide better predictions of stock returns on a daily basis.
  - Google-based indicator is also found to be statistically significant but with lower predictive power, attributed to its low frequency and lack of relevant dynamics.
- Similar results for UK, Canada and China – using simpler bi-variate models - but with lower predictive power for China. The Google indicator is also found to be significantly correlated with all four stock market prices but with lower predictive power.

Social Media based studies: US Labour Market

- Relatively few economic studies outside the area of financial markets. An important exception is for US labour markets by Antenucci et al (2014) at the University of Michigan
  - Uses large sample Twitter data to produce job loss/search/posting indices as a means of analyzing high frequency weekly estimates of job flows from 07/2011 to 11/2013.
  - Measures derived from the frequency of use of job loss and search-related phrases in the sample of Tweets, combined into composite measures using their principal components to track initial claims for unemployment insurance at medium and high frequencies.
  - Index found to account for 15 to 20 percent of the variance of the prediction error of the consensus forecast for initial claims.
  - considered useful in providing realtime indicators of events such as Hurricane Sandy and the 2013 government shutdown
  - work under “major revision” as original model “began to deviate in its estimates around mid-2014”

Social Media based studies: US Labour Market



Sources: Initial Claims for Unemployment Insurance (seasonally adjusted), U.S. Department of Labor; Prediction, University of Michigan Social Media Job Loss Index.

The limitations in the use of social media in forecasting studies

- The challenges in the extraction and use of social media based data sets are greater than those involved with internet search material.
  - need to devise methods of searching across large sets of blog entries to identify within a given sample and timeframe the frequency of the use of specific phrases or keywords.
  - richer in content, but more exposed to differences in linguistics, interpretation and nuances in the use of language
  - build on developments in the informatics, machine learning and AI domain, for the design and application of sophisticated automated filters to mine the data
- Much of the literature originates in the study of computational, linguistic and machine learning methods as opposed to economics and finance
  - not always embedded in the sound and familiar theoretical and empirical frameworks more commonly used in other areas of economic research and econometrics.
  - often embody "state of the art" computational machine learning techniques but relatively little evidence of testing to see whether all the "bells and whistles" are superior to simpler frequency balance measures.

The limitations in the use of social media in forecasting studies

- A sense of searching for a "Holy Grail" financial market indicator which is both broadly based and able to explain, predict or, at best, correlate with chosen financial variables.
- the chosen time samples often seem to be idiosyncratic and restrictively short, as noted by Lachanski and Pav (2017).
- the more recent work of Mao et al (2015) focussing on simple balance variables more narrowly defined for financial markets over a longer sample period seems more rewarding.
- often an excessive focus on very (daily) near-term predictive power and in having more detailed and workable model for US stock prices, as opposed to those for other economies.
- as for internet search based studies, the models used in many social media-based studies are almost exclusively statistical and may be too simple to say much about the underlying dynamics or relative predictive values of the different indicators being analysed.
- important omission : financial markets are inherently international and therefore linked to each other and influenced by other global phenomena.

Big Data and other indicators : SWIFT (1)

- **S**ociety of **W**orldwide **I**nternational **F**inancial **T**elecommunications – the messaging system through which the majority of international banking transactions are communicated
- International Chamber of Commerce Global Surveys of Trade and Finance (2010,2011,2012) and the EBRD (2011,2012) draw attention to the use of SWIFT indicators in tracking trade credit and the volume trade transactions.
- Both report sharp year-on-year decline in SWIFT trade-related messages from end-2008 to end-2009 and in early 2011 and hence relationship with related global and regional trends in trade.
- Looking at different electronic indicators of wholesale and retail payments Gill, Perera and Sunner (ABS 2012) find that a SWIFT payments indicator combined with conventional short-term macro indicators, improves short-term predictive performance for GDP relative to naïve autoregressive baseline models. Other retail payments indicators including credit card transactions do less well.

Big Data and other indicators: SWIFT (2)

- SWIFT (2012) with CORE Louvain,
  - use an OECD aggregate index of filtered transactions in a suite of GDP bridge models, showing significant results for quarterly movements in OECD real GDP for the period 2000 to 2011. The underlying baseline model is a relatively simple statistical ARMA model, taking account of no other relevant information.
  - quarterly notes on the nowcasting results based on various SWIFT indicators covering the US, the UK, Germany and the EU27.
- Monthly and daily SWIFT traffic reports are also available directly from the SWIFT site at https://www.swift.com/about-us/swift-fin-traffic-figures
- Overall results to date are generally supportive of the broad approach, and with the advantage of being available for a longer sample period, merit further investigation.
- **Caveat**: SWIFT indicators relate to the **volume of messages** not the **levels of transactions** and need to be filtered for content and coverage, as between trade, financial and other activity-related transactions.

Big data and other indicators: CPA bank transactions and electronic payments data

- The recent Canadian study by Galbraith and Tkacz (2015) reports an interesting approach combining within a set of mixed frequency GDP indicator models:
  - Growth in values and volumes of monthly and quarterly Canadian debit, credit and cheque transactions, aggregating payments that clear through the Canadian Payments Association (CPA) on a daily basis (NB over 12m debit card transactions a day)
  - CLI indicators for Canada and the US
  - Monthly Canadian Unemployment rates
  - Lagged GDP growth
- Key findings:
  - improvement in accuracy for the earliest nowcasts, through the inclusion of debit card payments
  - observed for the first two months of the nowcast period, but not detectable once the previous quarter's GDP value is observed (month 3).
  - Support the need for combining electronic transactions with other data that can be measured with some accuracy at a daily frequency

Other Big Data indicators: ADP and ADS

- Automatic Data Processing Inc's National Employment Report (2012) for the United States takes monthly and bi-weekly payroll data processed by the ADP's system -- covering approximately 20% of U.S. private sector workers – filtered and classified by size and industry to provide pair-wise matches with the sample used in producing BLS monthly employment data.
- A set of adjusted sectoral ADP indicators used, in conjunction with the Philadelphia Fed ADS Business Conditions Index (see Aruoba, Diebold and Scotti, 2009), to estimate a system of VAR equations to predict monthly changes in BLS private employment data by sector, since April 2001.
- Significance of individual variables is not reported but overall in-sample correlations appear to be relatively high (0.83 to 0.95) and the models appear to track overall monthly movements in BLS employment for the total private sector and 5 broad sectors fairly closely.

Other Big Data indicators: Ceridian Pulse

- Ceridian-UCLA Anderson Pulse of Commerce Index (PCI) - based on Ceridian electronic card payment services for US transportation industry, diesel sales for freight haulage.

- The PCI's main advantage over other economic indicators is its basis on real-time, actual fuel consumption data in advance of published monthly statistics.

- To date no published analytical studies appear to be available using the PCI

- UCLA Anderson produce a monthly newsletter 4 to 5 days in advance of the publication of monthly industrial production data and reports that back-testing to 1999 shows the index to closely match growth in real GDP and changes in Industrial Production.

Some broad conclusions

- Internet search and social media based indicators and other Big Data sources provide a novel and possibly useful means of measuring aspects of consumer and business behaviour in an almost a real time basis.

- may embody information which are not captured by other economic indicators or beavailable on such a timely basis.

- The range of studies reviewed provides interesting insights and some evidence of significant correlations and predictive performance across a range of topics.

- However, the results are generally quite mixed, reflecting both the relative simplicity of the models used and important limitations in terms of quality, form, sample sizes and their "qualitative" nature.

Some broad conclusions

- The overall message is that Big Data sets provide new and useful sources of information for economic analysis, but also warrant further refinement, development and monitoring in parallel with other macroeconomic indicators and forecasting techniques.

- More needs to be done to:
  - refine and improve the quality standards of Big Data sets and their accessibility,
  - develop better methods for extracting relevant economic information relevant to specific fields of economic research,
  - improve the means of comparing and testing between alternative measures
  - adapt and improve relevant testing and modelling frameworks, to be more useful to the task of incorporating near-term information in short-term macroeconomic forecasts.

- A welcome addition to the economist's and statistician's toolkit for short-term analysis.

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