Macroeconomic news and market reaction: Surprise indexes meet nowcasting

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Abstract

Market operators monitor a massive flow of macroeconomic information every day, and react to the unexpected component of the releases. Can we replicate in an automatic way market's pricing of macroeconomic news? In this paper I show that a "Nowcasting Surprise Index", constructed aggregating forecast errors from a nowcasting model using model-based weights, resembles surprise indexes proposed in the recent literature or constructed by practitioners, which cumulate market's forecast errors weighting them using the average news effects on asset prices. This comparison suggests that market operators and a nowcasting model filter the relevant macroeconomic data in a similar way, and confirms the connection between asset prices and news about macroeconomic fundamentals. Moreover, I show that a non-negligible part of asset prices behaviour can be associated to the recent cumulated news in macroeconomic data which carry information about the underlying state of the economy. These results also open a new route for algorithmic trading based on macroeconomic conditions.

Keywords: Dynamic Factor Model, Macroeconomic News, Nowcasting, Asset Prices, Survey Expectations.

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1 Introduction

Macroeconomic data are released every day, and are closely monitored by market participants: they need to filter the new information updating their view of the current state of the economy, given that the most comprehensive measures of economic activity have low frequencies and are released only with a lag. If markets are efficient, market operators react when the actual releases are different from their expectations: macroeconomic "news" move the markets (for a survey see Gürkaynak and Wright, 2013). This fact has been extensively documented in the literature looking at different asset classes (yields, stock prices, exchange rates) and frequencies (from tick-by-tick data to quarterly frequency).[1] To have an idea of the economic relevance of the phenomenon, news explain more than one third of bond yields fluctuations at low frequency, and their effect is statistically significant and persistent (Altavilla et al., 2017).

In this strand of literature the "market-based" news is constructed as the difference between the actual macroeconomic release and market expectations, available through surveys among market participants. One way to aggregate the news, in order to interpret this massive flow of heterogeneous information coming every day, is to assign some weights to the news and to construct "surprise indexes" that synthesize the unexpected information released in a certain window of time. They are a cumulated weighted sum of these news, in which the weights are based on the effect of macroeconomic news on specific markets or on their predictive content for economics activity. Being a standard practice among practitioners, the relevance of a meaningful surprise index has been recently acknowledged in the economic literature.[2] For example, Scotti (2016) construct a surprise and an uncertainty index weighting market-based news using the contributions of the variables to common factors;[3] Grover et al. (2016) relate GDP forecast errors to market-based news and from

[1] Among the others, for studies on yields and stocks see Hardouvelis (1988); Balduzzi et al. (2001); Andersen et al. (2003); Gürkaynak et al. (2005); Simpson et al. (2005); Pearce and Solakoglu (2007); Andersen et al. (2007); Faust et al. (2007); Kilian and Vega (2011); Goldberg and Grisse (2013); Swanson and Williams (2013); Gilbert et al. (2017); and for studies on exchange rates see Almeida et al. (1998); Galati and Ho (2003); Ehrmann and Fratzscher (2005); Caruso (2016).

[2] For examples among practitioners, see the Citi Economic Surprise Index or the SIREN Index constructed by Deutsche Bank.

[3] However, the paper use a dataset which is limited in size and not fully real time, not mimicking the information set available to market participants

this build a nowcasting model; Altavilla et al. (2017) aggregate and cumulate macroeconomic news using a measure of their high frequency impact on bonds, and show that their surprise index explain a relevant share of yields behaviour.

These studies show that market operators filter and price the new macroeconomic information: is it possible to use an automatic machine and replicate the market pricing of macroeconomic news? A positive answer would provide us with another perspective to try to understand the importance of fundamentals in driving asset prices. Moreover, it can inform whether there is scope to invest further in studying algorithmic trading strategies based on macroeconomic news. A model-based index is more flexible than a market-based one, since it can be constructed for any country of interest as it does not need survey expectations, which in some cases can be not available; moreover, survey expectations can be costly, prone to sentiment or herding behaviour, and could be affected by respondents giving strategic responses.

In this paper I construct a real time, model-based, surprise index that summarizes how a short term forecasting model has been surprised by macroeconomic developments in a rolling window of time. The construction of news and weights is based on the "nowcasting" approach, processing the releases and aggregating macroeconomic news looking at their impact on model updates of the assessment of the current state of the economy (Giannone et al., 2008; Banbura et al., 2013). The index is daily and can be updated at any macroeconomic release, and it is a weighted average of the forecast errors of the macroeconomic variables that enters a nowcasting model. The index represents a rolling measure of the surprise component of the macroeconomic data flow, flexible and judgement free. It is important to take into account the timeliness and quality of the variables which are part of the analysis: the nowcasting approach permits us to do that using many macroeconomic variables. The weights represent the importance assigned by the model to a macroeconomic release in updating the assessment of the business cycle at each point in time. In particular, I use the weights assigned to macroeconomic news by a nowcasting model in order to calculate its updates of the nowcast, forecast, or backcast of GDP; then, to have a consistent rolling index, I weight these weights depending on the position of the index in the quarter. It is essential to remark that the weights refer to the macroeconomic news, which is what matters for market participants, and not to the variables. I analyse the properties of the model-based forecasts, showing that they replicate well market expectations. Moreover, I test the properties of bias and efficiency of model-based and market-based forecast, showing that they have similar properties and that the model is at least as efficient as market participants in forecasting individual macroeconomic variables.

The Nowcasting Surprise Index has a similar behaviour to indexes constructed using market-based weights and/or news, showing good correlation with asset prices and in-sample predictive power, especially at quarterly frequency. The fact that a model-based index can replicate market-based indexes is a remarkable result: on the one hand, that means that market news and the model forecast errors are similar, and that a model is able to replicate market expectations; on the other hand, it is useful to understand, in a coherent statistical framework, whether financial market operators react because a series of news events triggers an update about the current state of the economy.

The paper is structured in the following way: section 2 explains the difference between market-based and model-based surprise indexes. Section 3 shows the data and the nowcasting model behind the construction of the Nowcasting Surprise Index. Section 4 I present the relationship with asset prices and other indexes. Section 5 concludes.

2 Methodology and surprise indexes

2.1 Market-based news and weights

I define "market-based news" the difference between the actual releases and the median of the forecast of surveys of leading practitioners, as the standard practice in the literature (see for example Balduzzi et al., 2001). I use the surveys collected by Bloomberg, considered a good benchmark for market expectations also in the recent related works constructing news indexes (Scotti, 2016; Altavilla et al., 2017). These surveys are available since a few days from announcements and can be updated by the respondents up to one hour before the actual release. In line with Altavilla et al. (2017) I define "market-based weights" W_i^{mkt} the estimated β_i of the following regression:

$$y_t = \alpha + \sum_{i=k}^{K} \beta_i X_{i,t} + \epsilon_t \tag{1}$$

Where y_t is the daily difference of the 10-year government bond and $X_{i,t}$ are the market-based news.[4] The news about variable i at time t is defined as $X_{i,t} \equiv x_{i,t} - \mathbb{E}[(x_{i,t}|Info_\nu)]$, where $x_{i,t}$ and $\mathbb{E}[(x_{i,t}|Info_\nu)]$ are the actual release and the median of the Bloomberg survey expectations among practitioners given their information set.

Then we can define the market based surprise index as:

$$SI_t^{mkt} \equiv \sum_{s=t-win}^{t} \sum_{i \in I} W_i^{mkt} X_{i,s}, \tag{2}$$

where the lenght of the window win in the present work is 66 working days (approximately one quarter).

2.2 Model-based news and weights

I order to extract model-based news I use a nowcasting model to predict the quarterly GDP growth rate of the United States. The nowcasting approach has its grounds in Giannone et al. (2008) and has been surveyed in Banbura et al. (2011, 2013). A nowcasting model extracts the relevant information about the state of the economy contained in indicators that are more timely than GDP, taking into account the characteristics of the macroeconomic data flow: a (potentially) large data set, the non-synchronicity of data releases and their mixed frequency. The information is funnelled into an estimate that can be updated at every data release. The solution adopted to dealing with a large number of variables is to use a dynamic factor model, which compresses the information into a few unobserved factors that drive the co-movement of the macroeconomic variables in the model (see Forni et al., 2000; Stock and Watson, 2002). The issues of the mixed frequency and the non non-synchronicity of the data releases is solved casting the model in state space form and using Kalman filters and smoothers.

Importantly, since the variables are jointly modelled, the technique allows us to have forecasts

[4] I standardize them to have mean zero and variance equal to 1.

for any indicator of interest, and to calculate the "model-based news" as the difference between the forecast of the model at the moment of the release and the actual value. Banbura et al. (2011) explain how to extract model based news as the difference between the prediction of the model and the actual realization of the macroeconomic data. A nowcasting model also permits us to calculate a weight for each release of interest, which can be seen as the importance assigned by the model to that specific release in the process of the update of the nowcast (estimate of the GDP of the current quarter), the backcast (previous quarter) and the forecast (following quarter). In other words, the weights express how much the model changes its "view" about the state of the economy after having incorporated a new piece of information represented by the unexpected part of a macroeconomic release. In our case, following Banbura et al. (2011), let y_t^Q be the GDP at time t, and Ω_ν the information set at time ν, where ν is a vintage of data. The nowcast is the projection of y_t^Q using the available data, $\mathbb{E}[y_t^Q|\Omega_\nu]$. At any release, ignoring revisions, the information set expands: $\Omega_\nu \subset \Omega_{\nu+1}$, and it is possible to decompose the new forecast in:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}]}_{\text{new forecast}} = \underbrace{\mathbb{E}[y_t^Q|\Omega_\nu]}_{\text{old forecast}} + \underbrace{\mathbb{E}[y_t^Q|I_{\nu+1}]}_{revision} \tag{3}$$

Where $I_{\nu+1}$ is the information in $\Omega_{\nu+1}$ orthogonal to Ω_ν. Therefore, it is possible to express the revision as a weighted sum of news from the released variables, where $b_{j,t,\nu+1}$ are the weights:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu]}_{revision} = \sum_{j\in J_{\nu+1}} w_{j,t,\nu+1} \underbrace{(x_{i_j,t_j} - \mathbb{E}[(x_{i_j,t_j}|\Omega_\nu)]}_{news} \tag{4}$$

It would be wrong to use the GDP nowcast as a "Nowcasting Surprise Index", as it is a fixed event forecast and refers to GDP in a specific quarter. Moreover, also the weights represent the importance given by the model to a news in updating the projection about a specific quarter: the current one (nowcasting exercise), the previous one (backcasting) or the following one (forecasting). Using the nowcast and just the weights relative to the nowcast period would not be correct, as the surprise index is a rolling concept while the weights are referred to a fixed time frame. For example, at the beginning of the quarter, the weights referring to the nowcast represent the importance given by the model to the news given the update of the assessment about the GDP in the near future (the next 3 months quarter). In the last day of the quarter, instead, the weights referred to the nowcast represent the importance given to the update about the assessment about the GDP in the near past (the last three months). In order to have an index which evolves in a rolling fashion, I use a consistent weighting scheme weighting the weights relative ot the the backcast, nowcast and forecast depending on the position in the quarter.

Let $w_{i,t}^{BC}$, $w_{i,t}^{NC}$, $w_{i,t}^{FC}$ be the weights corresponding to the updates in the Backcast, Nowcast and Forecast. I temporally weight them in order to have coherent rolling centered model weights $W_{i,t}^{mdl}$. Define d as the distance from the beginning of the reference quarter.

$$\text{If } 0 \leq d \leq 33, \text{ then } W_{i,t}^{mdl} = \tfrac{33+d}{66} * w_{i,t}^{NC} + \tfrac{33-d}{66} * w_{i,t}^{BC}$$

$$\text{If } 33 \leq d \leq 66, \text{ then } W_{i,t}^{mdl} = \tfrac{99-d}{66} * w_{i,t}^{NC} + \tfrac{d-33}{66} * w_{i,t}^{FC}$$

Then I construct a market-based and a model-based "Nowcasting Surprise Index" from a nowcasting model using these news and weights:

$$SI_t^{mdl} \equiv \sum_{s=t-win}^{t} \sum_{i \in I} W_{i,s}^{mdl} X_{i,s}. \tag{5}$$

A "Nowcasting Surprise Index" has some key features. First, it can potentially include a large number of indicators, as the dynamic factor model assures dimensionality reduction, without needing survey expectations for each variable. Second, the weights are based on macroeconomic news, since what matters to market participants is the unexpected component of the releases, and not on the variables themselves (as in Scotti, 2016). Third, it has a rolling reference period, not being based on a fixed event forecast (as the nowcast or as in Grover et al., 2016), making nowcasting totally compatible with surprise indexes.

3 Data and nowcasting model

I consider a set of 13 variables relative to the US economy which are reported on Bloomberg with a high "relevance index", which is the ratio of alerts requested for new releases of that variable over the total number of alerts, and could be seen as a measure of the importance assigned by financial market operators to that indicator. They are also chosen to have an exact correspondence in the real-time data base of St. Louis Fed (ALFRED), which is the source of the real-time news extracted by a nowcasting model.

Name	**Bloomberg**	**Transformation**
Building Permits	✓	MoM
Capacity Utilization	✓	Diff
Civilian Unemployment Rate	✓	Diff
Conference Board: Consumer Confidence	✓	Level
Consumer Price Index	✓	MoM
Housing Starts	✓	MoM
Industrial Production	✓	MoM
ISM Mfg: PMI Composite Index	✓	Level
Producer Price Index	✓	MoM
Real Gross Domestic Product	✓	MoM
Total Nonfarm Employment	✓	Diff
Trade balance	✓	MoM
University of Michigan: Consumer Sentiment	✓	Level
All Employees: Total Private Industries		MoM
Average Weekly Hours Mfg		MoM
Commercial and Industrial Loans		MoM
Disposable Personal Income		MoM
Inventories to Sales Ratio		Diff
M2 Money Stock		MoM
Mfg New Orders: Durable Goods		MoM
Mfg' New Orders: Nondefense Capital Goods Excl.Aircraft		MoM
Personal Consumption Expenditures		MoM
Personal Consumption Expenditures: Chain-type Price Index		MoM
Producer Price Index of Interm. Materials: Supplies and Components		MoM
Retail Sales		MoM
Total Business Inventories		MoM

Table 1: Data used in the anaysis. The first 13 variables show an exact correspodence between ALFRED and Bloomberg. In the "Transformation" column, "Diff" stands for "monthly differences" and "MoM" for "month-on-month growth rate".

An extended dataset for a more comprehensive nowcasting model consist of 26 variables, and includes indicators that are widely followed or used in the forecasting literature but with a limited availability or history of Bloomberg expectations, and I use it showing that the result are robust to a use of a wider dataset. In order to have a fully real-time News Index, it is essential to reconstruct exactly the information set available at each point. I use all the real-time vintages of the releases since 2005 for any single indicator, and I use them reproducing the exact calendar of the releases. The variables are listed in Table 1. Starting from the 1st January 2005, the model updates its forecasts at any macroeconomic release. At each point in time, I use the real-time vintage for all the macroeconomic indicator available in that moment. This is the only way to exactly reconstruct the availability of the indicators included in the model to a market participant who is assessing the current economic conditions.

The dynamic factor model used in this work can be described as follows. The variables are assumed to have a factor structure:

$$x_t = \Lambda f_t + \epsilon_t \tag{6}$$

Where x_t is a vector of standardized stationary monthly variables, f_t are unobserved common factors with zero mean and unit variance, Λ are the factor loadings, ϵ_t a vector of idiosyncratic components of dimension N which follow an $AR(1)$ process uncorrelated with f_t at any leads and lags.

The dynamics of the factors is modelled as a stationary Vector Autoregressive process with p lags, in which $A_1, ..., A_p$ are $r \times r$ matrices of autoregressive coefficients. I follow the approximation of Mariano and Murasawa (2003), including the quarterly variable in the model as a monthly partially-unobserved variable, in order to accommodate the mixed frequency nature of the dataset. Following Doz et al. (2012), the model is estimated using Maximum Likelihood within an Expectation-Maximization algorithm.[5]

The estimation sample starts in 1991, and the evaluation period is 2005-2014. The specification of the factor model is with 1 factor which follow a $AR(2)$ process (results are robust to changes in the specification).

[5]Bańbura and Modugno (2014) adapt the algorithm to an arbitrary pattern of missing data.

4 Results

In Figure 1 I plot the market-based surprise index against the model-based "Nowcasting Surprise Index". The indexes are indeed very correlated, meaning that the market participants and the model have been surprised in a similar way by the macroeconomic data flow. Moreover, that means that the impact that macroeconomic news had on 10-year bonds resemble the weights they have been assigned to the same news by the nowcasting model. That could shed some light on why market participants reacted to macroeconomic news: their reaction is associated to the news that could change their assessment of the current state of the economy.

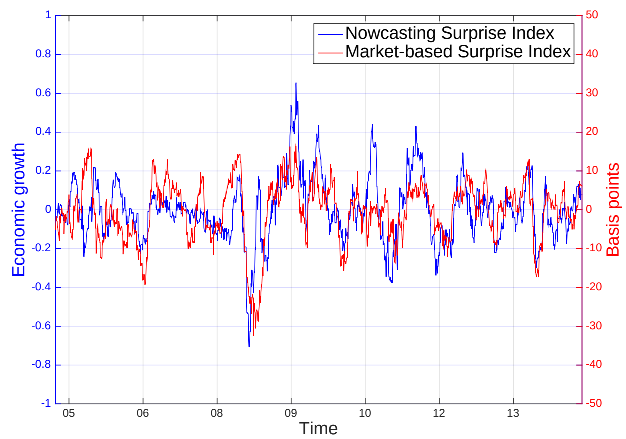

Figure 1: Standardized market-based and model-based surprise indexes (13 variables). Window=66 working days.

In Figure 2 I plot the Nowcasting Surprise Index against the S&P500, and in Table 2 I show the correlation of the indexes with it at different frequency. As reported in Table 2, the correlation is notable and increases with the length of the window considered, confirming the result of Altavilla et al. (2017) that the effect of macroeconomic news is permanent and amplified at lower frequency.[6] The market based index shows similar properties: the correlation with the asset prices considered is around 40% at quarterly frequency.

[6]Correlation of other benchmarks, the Citi Economic Surprise Index and the index constructed in Scotti (2016) are in the appendix.

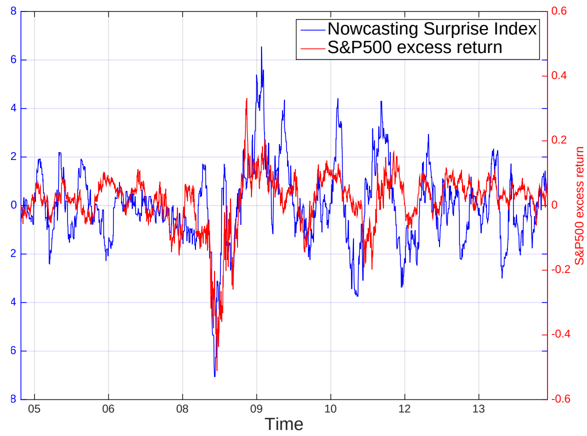

Figure 2: Standardized model-based surprise index (13 variables, window=66 working days) and quarterly excess returns of S&P500.

	Nowcasting Surprise Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.23 / 0.19*	0.33 / 0.30*	0.36 / 0.41*
S&P 500 excess returns	0.23 / 0.23*	0.37 / 0.36*	0.42 / 0.45*

	Market Surprise Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.33	0.40	0.45
S&P 500 excess returns	0.19	0.33	0.46

Table 2: Correlation of the market-based and the model-based indexes (13 variables) with S&P500 at different frequencies. *Larger model with 26 variables

Then I estimate the following models using OLS with Newey-West s.e.:

$$\Delta^w AssetReturn_{i,t} = \alpha + \beta_i(Index_t^w) + \epsilon_{i,t} \tag{7}$$

Where w can be 22, 44 or 66 working days. For example, if $w = 22$ $AssetReturn_{i,t}^w$ is the monthly return of asset i. Also here, as reported in Table 3the R^2 of the regressions using the model-based indexes are similar to the R^2 obtained using the market-based indexes. Table 4 reports different correlations with S&P 500 using different combinations of market-based and model-based news and weights. If is worth noticing that if we simply use the nowcast as a surprise index, not using the temporal rolling weighting scheme proposed in this paper, the correlation with S&P 500 drops dramatically from 0.42 to 0.25.

	Nowcasting Surprise Index		
OLS - R^2	1-month	2-months	Quarterly
Change in 10y yields	0.05 / 0.04*	0.11 / 0.09*	0.17 / 0.17*
S&P 500 excess return	0.04 / 0.05*	0.08 / 0.13*	0.18 / 0.21*

	Market Surprise Index		
OLS - R^2	1-month	2-months	Quarterly
Change in 10y yields	0.11	0.16	0.21
S&P 500 excess return	0.04	0.10	0.19

Table 3: Results of regression in equation (6). *Larger model with 26 variables

Weights	**News** *Market*	**News** *Model*
Market	0.46	0.17
Model	0.40	0.42 / 0.25*

Table 4: Correlation at quarterly frequency with S&P500 excess return of indexes constructed using model or market weights. *Correlation using the nowcast.

4.1 News analysis

It is important to study the properties of the market based and of the model-based forecast. Regarding the market-based forecast, some studies (Balduzzi et al., 2001; Andersen et al., 2003; Scotti, 2016) show that they are not always efficient. I test the efficiency of forecasts for variable i, F_i (Bloomberg survey as well of the model-based forecasts), testing for $\alpha_i = \beta_i = 0$ in the following regression:

$$News_{i,t} = \alpha_i + \beta_i F_{i,t} + \epsilon_{i,t} \tag{8}$$

In the spirit of Mincer and Zarnowitz (1969), if the coefficients are jointly significant, we can say that the forecast are not efficient. Table 5 reports the results of such tests.

Efficiency test - Bloomberg news

	α		β		F		F-pvalue
Industrial Production	-0.300	***	0.781	***	13.849	***	0.000
Capacity Utilization	-0.182	**	0.846	***	15.943	***	0.000
Housing Starts	0.019		0.058	***	8.047	***	0.005
Building Permits	0.022		0.042		1.482		0.226
Trade Balance	0.067		0.000		1.384		0.242
Change in Nonfarm Payrolls	-0.118		-0.001		1.403		0.239
U. of Mich. Sentiment	2.189	***	-0.024	***	8.369	***	0.005
Unemployment Rate	-0.207	**	2.581	***	7.884	***	0.006
CPI	-0.313	***	1.583	***	32.469	***	0.000
PPI	-0.119		0.862	***	34.695	***	0.000
Consumer Confidence Index	-0.072		0.001		0.088		0.767
ISM Manufacturing	1.276		-0.022		1.575		0.212
GDP Annualized	-0.041		-0.024		0.095		0.759

Table 5: Efficiency test for market-based news.

Efficiency test - Nowcasting news

	α	β		F		F-pvalue
Industrial Production	0.086	-0.610	***	17.067	***	0.000
Capacity Utilization	-0.067	-0.839	***	15.679	***	0.000
Housing Starts	0.020	-0.035		2.376		0.126
Building Permits	0.018	-0.102	*	3.228	*	0.075
Trade Balance	0.009	0.000		0.187		0.666
Change in Nonfarm Payrolls	-0.052	0.001		1.562		0.214
U. of Mich. Sentiment	0.837	-0.011		1.331		0.251
Unemployment Rate	-0.018	1.294		1.736		0.190
CPI	0.085	-0.442		0.532		0.467
PPI	0.099	-0.670	**	3.998	**	0.048
Consumer Confidence Index	0.321	-0.004		1.071		0.303
ISM Manufacturing	0.732	-0.014		0.590		0.444
GDP Annualized	0.090	-0.140		0.146		0.705

Table 6: Efficiency test for model-based news.

As it can be seen from the tables, there are some macroeconomic variables for which either market-based and model-based forecast are not efficient. However, for some important variables (notably, Non-Farm Payrolls, Unemployment rate, CPI), model-based news show better properties than market-based news.

The model-based news are also to replicate the forecasts of the markets in real time. The exercise is particularly relevant and has been done using financial data by Ghysels and Wright (2009). The nowcasting framework permits us to do that even with macroeconomic variables, taking into account all the relevant information, the quality and the timeliness of macroeconomic releases.

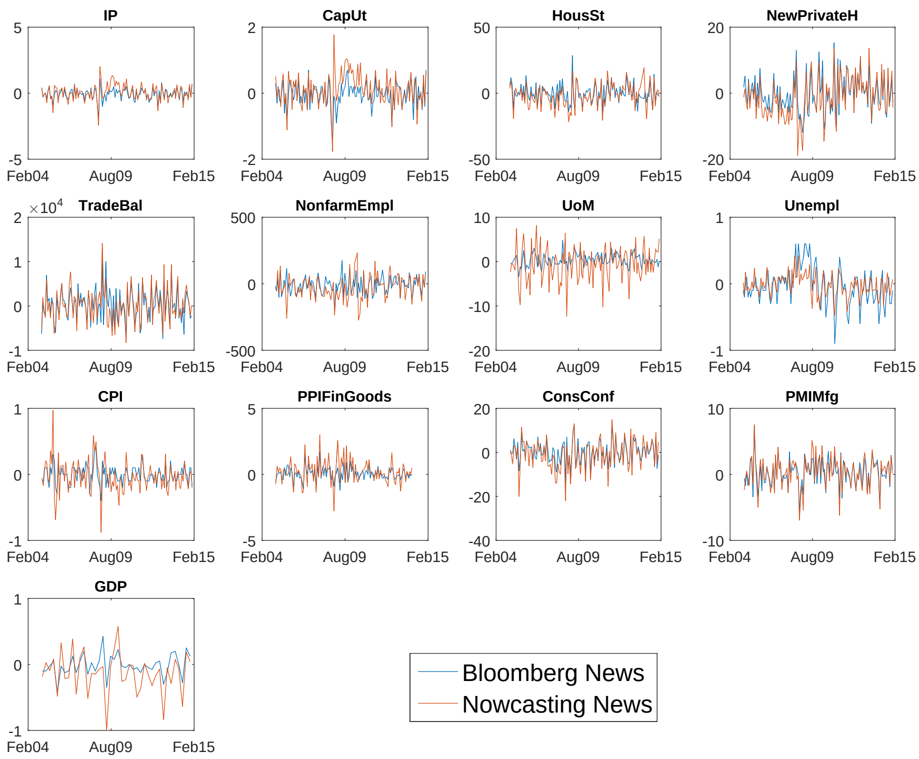

Figure 3: Model-based (13 variables) and market-based news.

In Table 7 I report the results of a forecast exercise of the median of the surveys conducted by Bloomberg at the moment of the release, using the model predictions updated up to the previous macroeconomic release. The table shows that, for the majority of the variables, the nowcasting model is able to replicate survey-based forecasts reported by Bloomberg.

RMSFE relative to previous release	
Capacity Utilization	0.81
Housing Starts	0.67
Building Permits	0.72
Trade Balance	1.21
Change in Nonfarm Payrolls	0.87
U. of Mich. Sentiment	0.75
Unemployment Rate	0.73
CPI	0.63
PPI	1.09
Consumer Confidence Index	0.62
ISM Manufacturing	0.44
GDP	1.27

Real time out of sample, 2005-2014

Table 7: The table reports the RMSFE of the model-based forecast of the median of survey expectations reported by Bloomberg, relative to a forecast equal to the previous release.

5 Conclusions

In this paper I have constructed a real time model-based "Nowcasting Surprise Index", based on weighted forecast errors of macroeconomic variables produced by a nowcasting model for US GDP growth rate. The index behaves in a similar way than market-based news indexes based on survey-based forecast errors weighted using their impact on asset prices: a nowcasting model and market operators filter the flow of macroeconomic data in a similar way. The model-based index has the advantage that it comes from a coherent model that is not prone to judgement or mood and that can be built without collecting surveys expectations. The "Nowcasting Surprise Index" shows a good correlation with asset prices at quarterly frequency, confirming the results of a recent literature that links asset prices behaviour at low frequency to a cumulated weighted stream of macroeconomic surprises: a large part of markets' reaction to macroeconomic news is due to their informational content about the current state of the economy. The results also open a new route to algorithmic trading based on macroeconomic information.

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	Scotti Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.02	-0.05	0.02
S&P 500 excess returns	0.06	0.16	0.21

	Citi Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.27	0.31	0.4
S&P 500 excess returns	0.15	0.19	0.22

Appendix

5.1 Nowcasting US GDP in real time: historical reconstruction

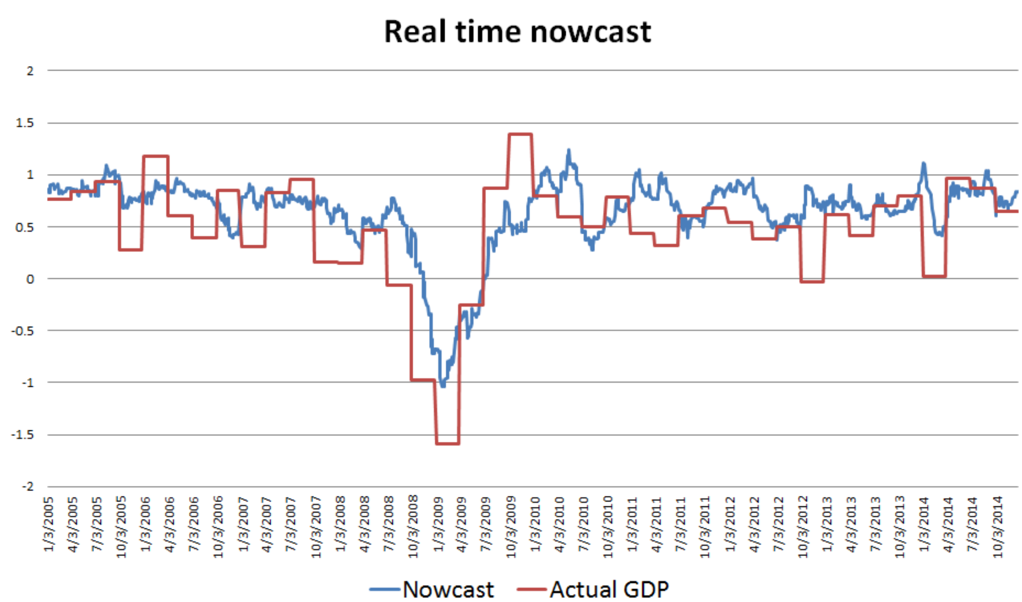
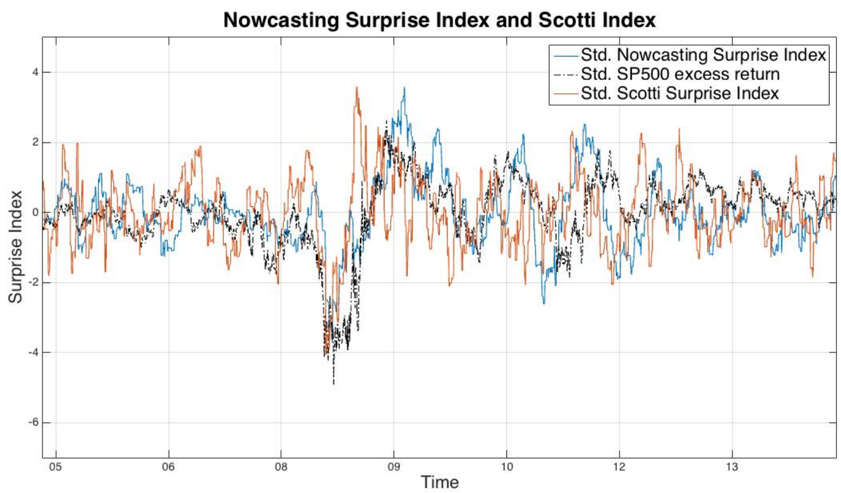


Figure 4: Nowcast...

5.2 Nowcasting Surprise Index and Scotti index


Nowcasting Surprise Index and Scotti Index
Std. Nowcasting Surprise Index
Std. SP500 excess return
Std. Scotti Surprise Index
Surprise Index
Time
4
2
0
-2
-4
-6
05
06
08
09
10
12
13