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Abstract

Market operators monitor a massive flow of macroeconomic news every day and react to the unexpected component of the releases. Can we replicate automatically the market's pricing of macroeconomic news? In this paper I show that a "Nowcasting Surprise Index", constructed by 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 survey-based forecast errors weighted by using the average effect of news on asset prices. This suggests that market operators and a nowcasting model filter the macroeconomic data flow similarly and confirms the link between news about macroeconomic indicators and asset prices. Moreover, the paper shows that recent cumulated news in macroeconomic data, which carry information about the underlying state of the economy, accounts for a non-negligible part of asset price behaviour.

JEL Classification: E44; E47; G14

Keywords: Macroeconomic News; Macroeconomic forecasting; Nowcasting; Dynamic Factor Model; Asset prices.

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1 Introduction

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

In this strand of the 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 daily flow of heterogeneous information, is to assign weights to the news and to construct "surprise indexes" that synthesize the unexpected information released in a certain window of time. Surprise indexes are a cumulated weighted sum of the news, in which the weights are based either on the effect of macroeconomic news on specific markets or on the predictive content of the variable for economic activity. Being standard practice among practitioners, the relevance of a meaningful surprise index has recently been acknowledged in the economic literature.[2] For example, Scotti (2016) constructs both a surprise and an uncertainty index weighting market-based news by using the contributions of the variables to common factors; Grover et al. (2016) relate GDP forecast errors to market-based news and from 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 explains a relevant share of yield behaviour. These studies show that market operators filter and price new macroeconomic information. However, a market-based index cannot be constructed for any country of interest as it needs survey expectations, which in some cases may be unavailable. Moreover, survey expectations can be costly, prone to sentiment or herding behaviour, and could be affected by respondents giving strategic responses.

Another strand of literature which looks at the flow of macroeconomic releases, the "nowcasting" approach, studies methods to filter the new macroeconomic information in order to produce real-time forecasts for a target variable which is usually released with a time lag (e.g. GDP). This literature has its grounds in Giannone et al. (2008) and has been surveyed in Banbura et al. (2011, 2013).[3] The latest

[1] Among 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 Citigroup Economic Surprise Index or the SIREN Index constructed by Deutsche Bank.

[3] The nowcasting methodology has been applied to many countries, and has been proven to be effective in many applications. Among others Rünstler et al. (2009) and Giannone et al. (2009) for the Euro Area, Lahiri and Monokroussos (2013) and Grant et al. (2016) for the US, Barhoumi et al. (2010) for France, D'Agostino et al. (2008) and Liebermann (2012) for Ireland, Matheson (2010) for New Zealand, Marcellino and Schumacher (2010) for Germany, Aastveit and Trovik (2012) and Luciani and Ricci (2014)

nowcasting techniques permit us to produce forecasts for every macroeconomic variable used in the model, and therefore to construct model-based news as the difference between the forecast of the model and the actual value.

In this paper, I set up a framework to understand the relation between these two literatures that analyse the macroeconomic data flow: despite being very related, the two lines of research have generally been pursued separately. Recent exceptions can be found in Gilbert et al. (2017), in which the authors explain the heterogeneity in the responses in asset prices using the informativeness of a macroeconomic variable in forecasting GDP, inflation and federal funds rate, and in Grover et al. (2016), in which the authors construct a nowcast using market-based news. However, there is as yet no systematic study to connect these two literatures. In order to understand the relation between them, I construct a real-time, model-based, surprise index (a Nowcasting Surprise Index) that summarizes how a short-term forecasting model was surprised by macroeconomic developments in a rolling window of time, and which is capable of replicating automatically the market pricing of 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 suffer from the problems, stated above, of a market-based index. The construction of news and weights is based on a nowcasting model, processing the releases and aggregating macroeconomic news, examining its impact on model updates of the assessment of the current state of the economy. The index is daily and can be updated at any macroeconomic news release: it is a weighted average of the forecast errors of the macroeconomic variables that enters a nowcasting model, and it represents a rolling measure, flexible and judgment free, of the surprise component of the macroeconomic data flow. It is important to take into account the timeliness and quality of the variables which are included in the analysis, and the nowcasting approach permits us to do that using many macroeconomic variables. The weights represent the importance assigned by a nowcasting model to a macroeconomic news release in updating the assessment of the business cycle at each point in time. In particular, I use the weights assigned to macroeconomic news 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 according to the position of the index in the quarter. It is essential to note 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, and I test the properties of bias and efficiency of model-based and market-based forecasts, showing that they have similar properties and that the model is at least as efficient as market participants in forecasting individual macroeconomic variables.

I find that the Nowcasting Surprise Index behaves similarly to indexes constructed using market-based weights and news, showing good correlation with asset prices and good in-sample predictive power, especially at quarterly frequency. The fact that a model-based index can replicate market-based indexes is a remarkable result. Firstly, it means that market news and model forecast errors are similar, and thus that a computer-based model fed with a large data set is capable of replicating market expectations. Secondly, and in line with Gilbert et al. (2017), this result shows empirically, within a coherent

for Norway, Bragoli et al. (2014) for Brazil, Luciani et al. (2015) for Indonesia, Bragoli and Modugno (2016) for Canada, Bragoli (2017) for Japan, Caruso (2018) for Mexico, Matheson (2013) for 32 economies, Bragoli and Fosten (2016) for India, Yazgan et al. (2016) for Turkey.

statistical framework, that financial market operators react because a series of news events triggers an update about the current state of the economy. Finally, this result would warrant pursuing algorithmic trading based on macroeconomic conditions.

The paper is structured in the following way: section 2 explains the difference between market-based and model-based surprise indexes. Section 3 describes the data and the nowcasting model behind the construction of the Nowcasting Surprise Index. Section 4 presents 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" as the difference between the actual release and the median survey forecast among 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 from a few days before the announcements and can be updated by the respondents up to one hour before the release. In line with Altavilla et al. (2017) I define "market-based weights" W_i^{mkt} as 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 yield and $X_{i,t}$ are the market-based news releases.[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 releases and the median of the Bloomberg survey expectations among practitioners given their information set at vintage ν.

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

2.2 Model-based news and weights

In order to extract model-based news, I use a nowcasting model to predict the quarterly GDP growth rate of the United States. 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

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

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 deal 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 by 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 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 interpreted as the importance assigned by the model to that specific release in the updating process 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" of the state of the economy after having incorporated a new piece of information represented by the unexpected component 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:

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

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

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

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 assigned by the model to news in updating the projection about a specific quarter: the current one (nowcasting), the previous one (backcasting) or the following one (forecasting). Using the nowcast and only the weights relative to the nowcast update would also not be correct, as the weights refer to a fixed time frame whereas the surprise index is a rolling concept. For example, at the beginning of the quarter, the weights referring to the nowcast represent the importance given by the model to the news giving 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 referring to the nowcast represent the importance given to the news in the update about the assessment of 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 to the backcast, the nowcast and the 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 weight them temporally in order to have coherent rolling model weights $W_{i,t}^{mdl}$. Define d as the distance from the beginning of the reference quarter.

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

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

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, not on the variables themselves (as in Scotti, 2016), since what matters to market participants is the unexpected component of the releases. Third, it has a rolling reference period, not being based on a fixed event forecast (as the standard nowcast or as in Grover et al., 2016), making nowcasting completely 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" (higher than 50%), 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 in order to have exactly the same values of the real-time data base of St. Louis Fed (ALFRED), which is the source of the real-time news extracted by a nowcasting model (for example, I have excluded some variables with a slightly different definition or that were not available in some periods during the sample.)

An extended dataset for a more comprehensive nowcasting model, used as a robustness check, consists of 26 variables, and includes indicators that are widely followed by practitioners or are often used in the forecasting literature, but with a limited availability or history of Bloomberg expectations; the results using the larger model are very similar to those using the model with 13 variables, and are reported in the Appendix. 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

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 analysis. The first 13 variables show an exact correspondence between ALFRED and Bloomberg. In the "Transformation" column, "Diff" stands for "monthly differences" and "MoM" for "month-on-month growth rate".

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 indicators 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. Data on government bond yields (10-Year Treasury Constant Maturity Rate) and on stock prices (S&P 500 index) were downloaded from the Federal Reserve Economic Data (FRED) website maintained by the St. Louis Fed.

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 rxr 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 follows a $AR(2)$ process.[6]

4 Results

In Figure 1, I plot the market-based surprise index against the model-based "Nowcasting Surprise Index". The indexes show a good correlation, indicating that the market participants and the model were surprised in a similar way by the macroeconomic data flow. Moreover, that means that the impact that macroeconomic news had on 10-year bonds resembles that assigned to the same news by the nowcasting model. That could shed some light on why market participants reacted to macroeconomic news: their reaction, at least in part, is due to the news that could change their assessment of the current state of the economy.

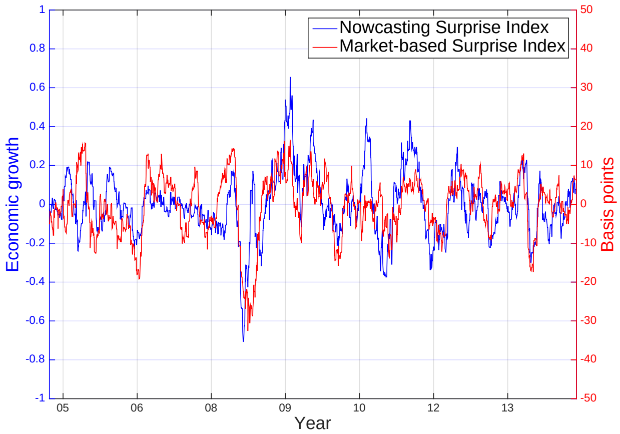

Figure 1: Standardized market-based and model-based surprise indexes (13 variables). Window=66 working days.

In Figure 2, I plot the Nowcasting Surprise Index against the S&P 500 and the Citigroup Economic Surprise Index, 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. The correlation with the USD/EUR exchange rate is much lower, confirming the difficulty in tracking the exchange rate using macroeconomic fundamentals. The market-based index shows similar properties: the correlation with the asset prices considered is around 40% at quarterly frequency. The Citigroup Index is correlated with the model-based index, although it looks more volatile until 2008.[7] In the Appendix, I also report the results using as weights the daily effects on the

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

[6] Results, especially at lower frequency, are robust to changes in the specification, regarding the number of factors being 1, 2 or in blocks (following Banbura et al. (2011)), assigning the variables to a "real" and a "nominal" block from which I have extracted specific factors.

[7] At quarterly frequency, the correlation of the Citigroup index is 0.40 with the 10-year bond yield and 0.23 with the S&P 500 returns.

USD/EUR exchange rate (in line with the construction of the Citigroup Index) and on stock prices; the correlations are lower but still increasing at lower frequency and around 30% at quarterly frequency.

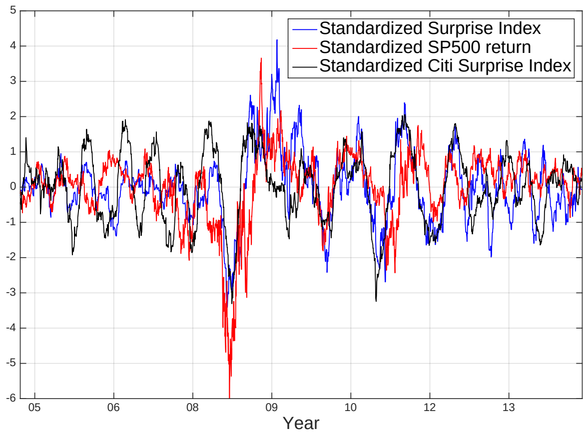

Figure 2: Standardized model-based surprise index (13 variables, window=66 working days), quarterly returns of S&P 500 and Citigroup Economic Surprise Index.

	Correlations		
	1-month	2-months	3-months
Nowcasting Surprise Index			
10y yields	0.23	0.33	0.36
S&P 500	0.24	0.37	0.42
USD/EUR	0.13	0.17	0.14
Market-based Surprise Index			
10y yields	0.33	0.40	0.45
S&P 500	0.19	0.32	0.44
USD/EUR	-0.06	0.02	0.13

Table 2: Correlation of the Nowcasting Surprise Index (NSI) with 13 variables and the market-based Index with differences of 10-year bond yield, S&P 500 returns and change of the USD/EUR exchange rate at different frequencies.

Then I estimate the following model 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. As reported in Table 3, the 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 combinations of market-based and model-based news and weights. For example, the number in the left-bottom cell is the correlation of the index constructed using model-based weights and market-based (Bloomberg) news, similar to Scotti (2016). In order not to obtain a lower correlation with stock prices, it seems important to use model-

	Regressions - R^2		
	1-month	2-months	3-months
Nowcasting Surprise Index			
10y yields	0.05	0.11	0.17
S&P 500	0.06	0.14	0.18
USD/EUR	0.02	0.03	0.02
Market-based Surprise Index			
10y yields	0.11	0.16	0.21
S&P 500	0.04	0.10	0.19
USD/EUR	0.00	0.00	0.02

Table 3: R^2 of the regression in equation (7).

based weights only associated with model-based news, given the link of the model-based weight with a specific (model-based) news release. It is worth noting 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 0.30.

		News	
		Market	*Model*
Weights	*Market*	0.44	0.17
	Model	0.40	0.42 / 0.30*

Table 4: Correlation at quarterly frequency with S&P 500 returns 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, plotted in Figure 3. 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 (which can be the median of Bloomberg surveys or 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 forecasts are not efficient. Table 5 and Table 6 report the results of such tests. As can be seen from the tables, there are some macroeconomic variables for which either market-based forecasts or model-based forecasts are not efficient. However, for some important variables (notably, Non-Farm Payrolls, Unemployment rate, CPI), model-based news shows better properties than market-based news.

The model-based news can also 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.

In Table 7, I report the results of a forecast exercise of the median of the surveys conducted by

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	-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	0.090	-0.140		0.146		0.705

Table 6: Efficiency test for model-based news.

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.

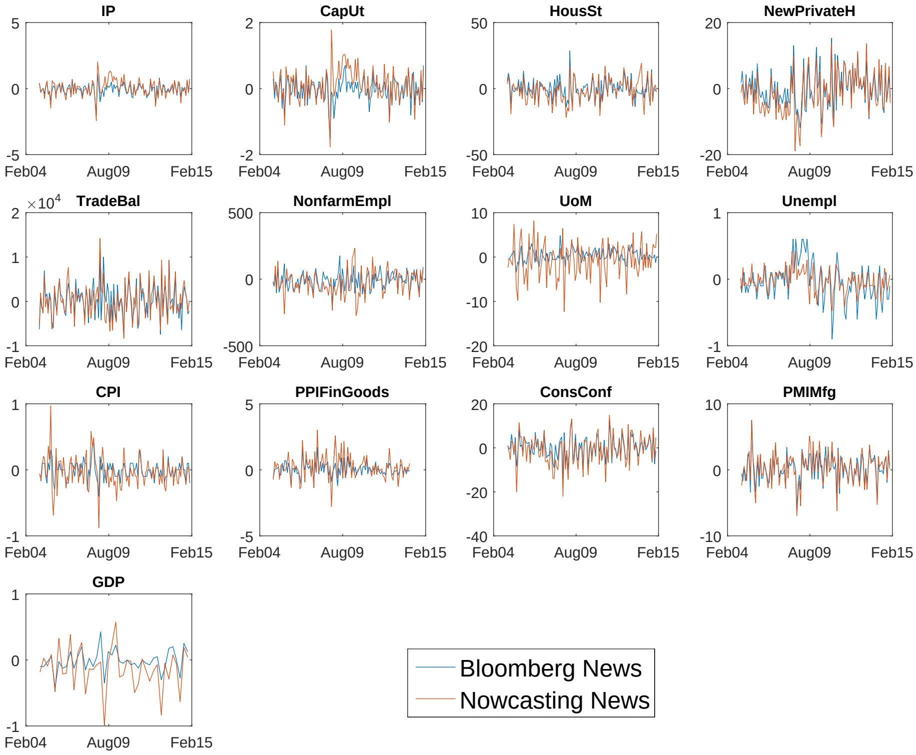

Figure 3: Model-based (13 variables) news and market-based news. Units are different for different variables and correspond to the original units of Bloomberg variables.

RMSFE relative to previous release		
Industrial Production	0.44	***
Capacity Utilization	0.51	***
Housing Starts	0.33	***
Building Permits	0.36	***
Trade Balance	0.31	***
Change in Nonfarm Payrolls	0.98	
U. of Mich. Sentiment	0.90	*
Unemployment Rate	0.24	***
CPI	0.74	***
PPI	0.64	***
Consumer Confidence Index	1.02	
ISM Manufacturing	0.83	***
GDP	0.57	***

Real time out of sample, 2005-2014

Table 7: The table reports the RMSFE of the model-based forecast (model with 26 variables) in forecasting the median of survey expectations reported by Bloomberg, relative to a forecast equal to the previous release. (*) and (***) indicate significance at the 10% and 1%, respectively, using the Diebold and Mariano (1995) test statistic.

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. This framework connects two strands of literature which study and interpret the daily flow of macroeconomic information: one which analyses the impact of macroeconomic news on asset prices, and one which uses the news to construct models to assess current macroeconomic conditions in real-time. A "Nowcasting Surprise Index" behaves in a way similar to market-based news indexes, which are based on survey-based forecast errors weighted by their impact on asset prices. That means that a nowcasting model and market operators filter similarly the flow of macroeconomic data, which provides signals that are not specific to the way they are aggregated. A model-based index has several advantages: it comes from a coherent model that is not prone to judgment, mood or strategic answers; it is cheaper than market-based ones; it can be applied to any country of interest, since it can be built without collecting survey expectations. The "Nowcasting Surprise Index" shows a good correlation with asset prices at quarterly frequency, confirming the results of recent literature that links asset price behaviour at low frequency to a cumulated weighted stream of macroeconomic surprises: a large part of market reaction to macroeconomic news is due to how the news updates the macroeconomic outlook, a process which in turn depends on the quality and timeliness of the news release. The results also open a new route to algorithmic trading based on macroeconomic information.

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Appendix

Table .8 reports the correlation of the index with the 10-year yield, the S&P 500 and the USD/EUR exchange rate using the larger model with 26 variables, and also reports the correlations with the market-based indexes constructed using as weights the betas of the regression on market-based news of the daily change of USD/EUR exchange rate and of the daily S&P 500 returns.

	Correlations		
	1-month	2-months	3-months
Nowcasting Surprise Index, 26 vars			
10y yields	0.19	0.30	0.41
S&P 500	0.24	0.36	0.45
USD/EUR	0.09	0.14	0.18
Market-based Index: weights from USD/EUR			
10y yields	0.23	0.29	0.33
S&P 500	0.09	0.17	0.26
USD/EUR	0.07	0.00	-0.11
Market-based Index: weights from S&P 500			
10y yields	0.25	0.30	0.33
S&P 500	0.07	0.18	0.32
USD/EUR	0.03	0.10	0.18

Table .8: Correlation at different frequencies of differences of the 10-year bond yield, S&P 500 returns and change of the USD/EUR exchange rate with the Nowcasting Surprise Index (26 variables) and the market-based indexes constructed using different weights.