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Evidence from the Euro Area

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Radu Gabriel Cristea[†‡]

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Contents

List of Abbreviations

ACI	Augmented credit impulse
AR	Auto-regressive
BEM	Bridge Equation Model
BGR (2010)	Bańbura, Giannone & Reichlin (2010)
cca.	circa
DFM	Dynamic Factor Model
DM	Diebold & Mariano (2002)
EA	Euro area
EABCN	Euro area Business Cycle Network
EC	European Commission
ECB	European Central Bank
ENTSOE	European Network of Transmission System Operators for Electricity
EM	Expectation Maximisation
ESTAT	Eurostat
EU	European Union
Fed	Federal Reserve Bank
GRS (2008)	Giannone, Reichlin & Small (2008)
GT	Google Trends
HLN	Harvey, Leybourne & Newbold (1997)
KF	Kalman filter
KS	Kuiper's Score
lhs	Left hand side
MIDAS	Mixed-frequency data sampling
MKS	Modified Kuiper's Score
NY	New York
OLS	Ordinary least squares
PMI	Purchasing Managers' Index
pp.	percentage point(s)
(Q)ML	(Quasi) Maximum Likelihood
(R)GDP	(Real) Gross Domestic Product
rhs	Right hand side
RMSE	Root Mean Squared Error
SSF	State space form
SWDA	Seasonally and weekday adjusted
US	United States
w.r.t.	with respect to

1 Introduction and Motivation

The tenuous, yet vital, task of predicting the present, the near future and the recent past[1] is paramount to conducting sound macroeconomic policies and professional investing. The need for systematically tracking big datasets characterising the economy in real time has fuelled the pursuit of methodical forecasting approaches. Now part of the suite of real-time forecasting tools at leading institutions[2], the 'dynamic factor model (DFM)' *nowcasting* has been elevated as the new norm by Giannone, Reichlin & Small (2008). Notwithstanding the success of nowcasting among policy-makers or financial market participants, the model may not fully capture the effect of 'black-swan' shocks, the COVID-19 crisis being a case in point.

As most recently proposed by Bank of England's Chief Economist Andy Haldane (2020), calling for a V-shaped recovery in the UK based on evidence from alternative data, these sources of information could potentially address the shortcomings of nowcasting with standard data. While such high-frequency indicators have already been the subject of debates at other institutions[3], their proliferation has been precipitated by recent events. Google search and mobility data, restaurant bookings, physical stores footfall and energy consumption, to name a few, have all become popular proxies for economic activity in real time, used by private and public sector analysts to gauge the extent of the ongoing recession and the potential recovery. However, the lack of structure and quality controls specific to these data may bring noise to traditional models, warranting, thus, cautious interpretations. Nevertheless, with their nearly real-time availability and much higher frequency, alternative data may provide timely information about turning points and, although forecasting with such data has already been conducted in other settings, these ought to be considered in the nowcasting framework too.

Drawing on work from Bańbura, Giannone & Reichlin (2010), our approach to nowcasting euro area activity is novel on several dimensions. First, we introduce alternative high-frequency data, i.e. electricity consumption, Google Trends internet search query data and the German truck toll mileage index, previously unexploited in the nowcast literature. Second, we adjust the factors structure to better account for the salient features of the macroeconomy. To this end, we go beyond standard euro area models' global, nominal and real factors and introduce separate factors for soft data, labour and financial markets, real-time indicators and supply side shocks. Third, albeit to a lesser extent innovative yet useful, revisiting how some of the traditional data are used, we introduce the augmented credit impulse for measuring monetary developments and change how business surveys are considered. Traditionally, lending and money supply data have been exploited through their sheer stock size, but flows might matter more for economic growth; we address this issue with the inclusion of our comprehensive measure of monetary developments, the augmented credit impulse. Furthermore, we change the focus of business survey data from headline to output indices, which have a higher correlation with economic growth, and introduce a measure of purely new demand, namely the excess of new orders relative to inventories. We hypothesise these novelties should increase out-of-sample forecasting precision and test this hypothesis empirically.

We examine the performance of our proposed dynamic factor nowcasting model against the industry standard for the euro area presented in Bańbura, Giannone & Reichlin (2010).

[1]In Bańbura, Giannone & Reichlin (2010) parlance.

[2]Bok, Caratelli, Giannone, Sbordone & Tambalotti (2018) detail Fed's approach, Bańbura, Giannone & Reichlin (2010) ECB's one, both drawing on Giannone, Reichlin & Small (2008).

[3]E.g. the ECB has long been investigating how digitalisation can be exploited to better understand the macroeconomy; former Member of the Executive Board Benoît Cœuré (2017) gave an earlier account of these efforts.

We use quantitative and qualitative assessment criteria in pseudo out-of-sample forecasting exercises, thus simulating the real-time availability of data at the time of nowcasting. As a result of our enhancements, out-of-sample forecasting exercises indicate non-negligible reductions in uncertainty around our point forecast (lower RMSE) and increases in directional forecasting accuracy (higher Kuiper's score). While these gains are meaningful at first sight, gains in nowcasting precision are rather modest when discarding 'black-swan' observations pertaining to the 'Great Lockdown' – suggesting our proposed approach is particularly useful during times of severe stress. With our assessment also taking into account the shock induced by the COVID-19 pandemic, we find that our nowcast timely indicates the severity of the downturn in Q1-2020 based on alternative data, also correctly indicating further contraction in Q2-2020. Interpreting these results, our enriched dataset and the jointly significant factors structure allow for a better and more timely signal extraction, as the *news*-based analysis of the data flow throughout the quarters also reveals. Our findings may imply that forecasting, as we know it, could undergo significant changes in the near future, embracing alternative data as a beacon of light for investing and policy making, particularly during times of heightened stress. Concluding on our findings, empirical evidence seems to support our conjecture that alternative data carry an important informational content which can be exploited using our enhanced methodology.

The remainder of the paper is structured as following. The second section goes through the literature on forecasting and nowcasting, from inception to its frontiers. The third section explains our methodology, while section four details the dataset. Section five illustrates the empirical evidence supporting our claims, while section six concludes and draws further directions of research. Technical details are provided in the appendices.

2 A Survey of Academic and Industry Practice

Predicting the present, the near future and the recent past has long been central to policy-makers and financial market participants alike. Be it central bankers, the fiscal authority or investment professionals, in order to make well informed decisions, they all need to regularly gauge the state of the economy. Due to the nature of hard economic data, released with a lag and in a staggered fashion, practitioners need tools to address the lack of real-time information. In such a context, any data points preceding official statistics such as GDP embed a signal value about the unobserved state of the economy, warranting, thus, close monitoring (Burns & Mitchell 1946). Against this background, the advancements in economics and statistics through the last decades have lead to a remarkable proliferation of forecasting models.

2.1 Forecasting before Nowcasting

Literature predating present nowcasting tools has developed on several strands. Based on earlier work of Friedman (1962), Chow & Lin (1971) have introduced an interpolation method relating monthly data to quarterly GDP figures, later generalised by Mitchell, Smith, Weale, Wright & Salazar (2005) and implemented to estimate monthly GDP in the UK. Other aggregation schemes, also assuming monthly output to be an unobserved process, have been used alongside state space models (e.g. Mariano & Murasawa 2003, Liu & Hall 2001). In a similar vein, Evans (2005) has developed a technique relating daily data to quarterly GDP. Somewhat differently, structural time series models explicitly model stochastic trends, cycles and seasonal components using the state space form and the Kalman filter (Harvey 1990).

Without relying on big datasets, these have also proven to be precise, outperforming autoregressive integrated moving averages (ARIMAs) (Harvey, Koopman & Penzer 1998). On the other hand, without *a priori* imposing much structure, the multivariate vector autoregression (VAR) proposed by Sims (1980) has also rapidly entered the standard macroeconometrics toolbox. Furthermore, Bayesian and mixed-frequency VARs represent important modelling extensions that improved macroeconomic forecasting (e.g. Sims & Zha 1998, Anderson & Vahid-Araghi 2011 for a survey). More recently, advancements in the estimation of microfounded dynamic stochastic general equilibrium (DSGE) models have enabled DSGEs to compete with the more standard VARs in terms of data coherence (Christoffel, Coenen & Warne 2010). Furthermore, quoting evidence from Smets & Wouters (2004), Edge, Kiley & Laforte (2010) and Rubaszek & Skrzypczyński (2008), Christoffel et al. (2010) advocate forecasting with DSGEs, their new generation showing similar forecasting performance to the one of conventional tools. Although popular and effective, these previous approaches are not suitable for nowcasting with high-dimensional datasets.

Forecasting with big information sets characterised by ragged-edges and mixed release frequency has been popular even before factor models. Financial markets and hard data together with business survey indicators have been routinely followed by practitioners for judgment-based forecasting, well before the advent of more systematic tools. The ragged-edge at the end of the sample comes as a byproduct of the staggered release pattern of hard data and the more timely availability of survey and financial data. However, this more systematic mixed-frequency data sampling (MIDAS) approach, whereby lower-frequency variables are 'bridged' by higher-frequency ones in parsimonious regressions, quickly became both powerful and popular (Bridge Equation Models, BEMs). A survey of the large literature on BEMs in the MIDAS setting is beyond the scope of this study[4].

Turning to the geographic focus of our study, Diron (2008) found the inclusion of survey and financial data can improve forecasting performance in the euro area, even in a real-time forecast evaluation. Similarly, Rünstler & Sédillot (2003) advocate the use of MIDAS and BEMs instead of forecasting with lower frequency data. Bridge equations with MIDAS have even been proven to outperform univariate time series models (Baffigi, Golinelli & Parigi 2004; Golinelli & Parigi 2007). Overall, previous studies support the inclusion of mixed-frequency ragged-edge data to help improve the performance of euro area nowcasting.

2.2 'Bridging' with Factors

While previous work has demonstrated the advantages of MIDAS-based nowcasting, the 'curse of dimensionality' began to arise as the number of relevant variables grew over time. The literature has adopted dynamic factor models (DFMs) as the standard solution to this problem. The temptation of over-fitting regressions to maximise in-sample performance is usually followed by poor out-of-sample forecasting accuracy. Early evidence favouring dimensionality reduction and modelling with few factors and limited *a priori* restrictions can be ascribed to Geweke (1977) or Sargent & Sims (1977). When high dimensionality in the cross section of long data panels is the case, it is possible to consistently estimate factors (Stock & Watson 1998; Forni, Hallin, Lippi & Reichlin 1999) and use them for efficient forecasting (Stock & Watson 1999; Marcellino, Stock & Watson 2003). These pioneering ideas are essentially bridge equations with principal components as covariates, to exploit common movements in the data, while avoiding the over-fitting problem.

Although traditional DFMs address the 'curse of dimensionality', they do not solve the

[4]We leave the interested reader with Ghysels, Sinko & Valkanov (2007) and Andreou, Ghysels & Kourtellos (2010) for an extensive exposition.

ragged-edge problem and cannot fully exploit the timeliness of data releases for real-time nowcasting purposes. The characteristic of MIDAS is that, due to asynchronous data releases, the end of the sample contains missing observations, making it difficult for traditional models, including DFMs, to properly account for all available information and produce accurate nowcasts. Addressing this issue, the seminal work of Giannone, Reichlin & Small (2008) – hereafter GRS (2008) – combine the DFM approach with Kalman filtering (KF) and effectively develop a real-time tracker of the US business cycle. Their refinement of earlier methodologies consists of seamlessly casting a monthly data factor model in the state space form (SSF), using KF techniques to fill in missing values; the KF is also used to forecast at desired horizons. While the approach resembles Harvey & Chung (2000) work on forecasting UK quarterly unemployment with monthly claimant accounts data, it had not been used before in conjunction with DFMs to produce nowcasts. GRS (2008) extract principal components, in a first step, from a balanced data panel and use OLS to estimate factor loadings. In the second step, the Kalman smoother refines the factor estimates, addressing the ragged-edge issue. The approach of GRS (2008) has become very popular in policy and investment institutions, with various applications for the euro area and extensive studies on its econometric properties.

The consistency property of GRS's (2008) methodology, later enhanced by others, has been extensively explored. Doz, Giannone & Reichlin (2011) prove the asymptotic convergence of estimators following the two-step procedure of GRS (2008). Furthermore, Doz, Giannone & Reichlin (2012) go beyond convergence and present an efficiency-based ranking. The latter asserts the superior nature of Quasi Maximum Likelihood (QML) estimation, whereby initialisation with principal components coupled with ML estimation of factor loadings and the machine learning expectation maximisation (EM) algorithm leads to the convergence of factors and loadings estimators. The properties of the techniques are evaluated both empirically and in Monte Carlo simulations. Evidence is strongly supporting QML over the two-step estimation; the one-step principal components option[5] fares worse than both, but remains an essential initialisation in the iterative EM algorithm.

The seminal paper on euro area nowcasting is Bańbura, Giannone & Reichlin (2010), which refined GRS (2008) with more efficient QML estimation and the introduction of the *news* concept. As per Doz et al. (2012), Bańbura & Modugno (2014) reiterate the advantages of QML in DFMs and is the core of estimation in Bańbura et al. (2010) (BGR (2010), hereafter). Although availability of higher-frequency data would warrant the estimation of a daily model, BGR (2010) use an unbalanced monthly panel of data; evidence from Bańbura, Giannone & Reichlin (2011) suggests the inclusion of daily financial data increases the uncertainty surrounding the nowcast[6]. Not only does BGR (2010) effectively implement the nowcast for the euro area, but also provide the means for an automatic and judgement free analysis of the data flow and its impact on growth projections throughout the quarter, through the *news* concept. 'Patented' by Harvey (1990; 2006) in the KF setting, *news*, in the DFM context, relate data surprises, given conditional expectations formed on the basis of the factor model and the Kalman smoother, to the resulting revisions in the nowcast. The *news* concept is, thus, preferred to the forecasting weights of Bańbura & Rünstler (2011),

[5]The approach consists of extracting the first (or several) principal components from the balanced dataset, considering these the true factors, while the associated eigenvectors would be their loadings. The n^{th} principal component, given n series (n vectors) of data, is the product of their first n eigenvectors, ordered by eigenvalues, and the original vectors of data. Principal components, ordered descending by their eigenvalue, are orthogonal; the first component explains most of the dataset's variation, the contribution of the subsequent ones being incrementally smaller.

[6]Giannone, Reichlin & Simonelli (2009) and Girardi, Gayer & Reuter (2016), *inter alia*, claim that industrial production and survey data are already powerful nowcast ingredients, financial series potentially adding volatility, yet being promising at the onset of the quarter, when data are scarce.

providing a transparent way of tracking the business cycle in real time.

DFM-based nowcasting applications vary across geographies in terms of data and factors structure, but, in spite of employing a wide range of forecast evaluation approaches, DFMs' forecasting outperforms most other previous tools. Angelini, Bańbura & Rünstler (2008) and Angelini, Camba-Mendez, Giannone, Reichlin & Rünstler (2011) indicate DFM-based nowcasts clearly outperform quarterly time series models or traditional BEMs in pseudo real-time assessments. Both studies also present a stylised bi-monthly release calendar that mimics the data availability pattern at the aggregate euro area level. Consistent with findings of Bańbura & Rünstler (2011), evaluation results stress out the importance of differences in publication lags. Results from the dense literature on nowcasting are still somewhat inconclusive on whether country specific nowcasts pooled together would always be better than forecasting at the aggregate currency union. However, the studies we explored, particularly the European focused ones, are predominantly consensual on MIDAS DFMs nowcasting outperformance, even in genuine real time, sometimes even against surveys of professional forecasters[7].

2.3 Alternative Data: Back to the Future

While the literature exploring DFM-based nowcasting is large, a salient feature of it is the absence of (quasi) real-time alternative data – from electricity consumption to internet search activity, air quality or even satellite imaging. Digitalisation and the pervasiveness of internet has precipitated the exponential growth of data sources, particularly for alternative ones. We refer to alternative data as being non-traditional information, not necessarily subject to the same quality standards and scrutiny as official statistics, but nevertheless informative of economic activity in approximately real time. Electricity consumption, proxied by real-time power load data, is routinely followed by professional forecasters. Similarly, internet search activity, in particular from Google, is increasingly more followed by marketing professionals and economists. While forecasting with Google data has been documented, alternative sources of data have not been exploited and, if anything, are absent in the context of DFM-based nowcasting.

Seminal work of Choi & Varian (2009; 2012) illustrates the power of internet search data in the context of unemployment and private consumption growth forecasting in the US. Google collects internet search activity data and reports anonymised statistics using its Trends platform. Given Google's virtual monopoly on the web search market, one may claim such data is representative for the internet user population. Choi & Varian (2009; 2012) show how, using simple time series models, the timeliness of Trends data can be exploited to demonstrate informational content of internet search patterns in forecasting. Ever since, Trends data have been successfully used in a wide rage of applications even outside the US.

Google Trends classifies search terms in categories and subcategories, thus allowing for various ways of forecasting with its data. Fundamentally, prior to any purchase, consumers in fairly digitalised economies with strong internet usage habits, are likely to engage in search activity. Fluctuations in the popularity of keywords or categories may indicate the underlying state of the economy, changes in consumers preferences or simply suggest unexpected shocks (natural disasters, terrorism, geopolitical events). Model pooling, dynamic model averaging or dimensionality reduction have all been successfully applied to various forecasting models

[7] Details in Jansen, Jin & de Winter (2016); Kuzin, Marcellino & Schumacher (2013); Marcellino, Stock & Watson (2003); Marcellino & Schumacher (2010); Liebermann (2010); Rünstler, Barhoumi, Benk, Cristadoro, Den Reijer, Jakaitiene, Jelonek, Rua, Ruth & Van Nieuwenhuyze (2009); Schumacher & Breitung (2008); Camacho & Perez-Quiros (2010).

of private consumption based on (sub)categories or keywords search data in the US, the euro area and Germany – all solid testimonials of the forecasting potential of such data[8]. To our knowledge at the time of writing this paper, none are, however, implemented in the DFM setup.

Internet search data from Google have also been successfully used in forecasting labour market developments. As for purchases of goods and services, matters relating to (un)employability are very likely to prompt individuals 'to google' relevant terms. In the UK, McLaren & Shanbhogue (2011) demonstrate the power of Trends in nowcasting unemployment. Askitas & Zimmermann (2009) forecast Kurzarbeit and unemployment in Germany using year-on-year changes in Trends indices, while work of D'Amuri (2009) and D'Amuri & Marcucci (2017) confirms the leading properties of internet search data and demonstrates the out-performance of forecasting models based on it, for the US and Italy; the recent work of Simionescu (2020) does the same for Romania. Fondeur & Karamé (2013) reiterates the findings for French unemployment using the KF and the SSF. The more formal treatment from the Research Institute of the Finnish Economy, where euro area, EU-wide and country specific unemployment nowcasts (ETLAnow) are maintained, uses Bayesian methods on uni- and multivariate time series models with Google Trends data (Tuhkuri 2016; Lehmus, Widgrén & Tuhkuri 2016; Anttonen 2018). Not only encouraging, these applications also justify the use of Google Trends and alternative real-time data in nowcasting problems.

3 Methodology

Our methodological approach relies mainly on BGR (2010), drawing on GRS (2008), with the Matlab implementation of Bok et al. (2018) from the NY Fed. The theoretical underpinnings we start from are detailed in BGR (2010); we proceed by expanding the information set and, subsequently, the factors structure – our most impactful contribution to the literature. The estimation of the obtained model is conducted *à la* Bańbura & Modugno (2014) using QML and the EM algorithm. Expressions for the QML estimators of the model parameters are derived from the first order conditions for maximising the joint likelihood function. Please see Bańbura, Giannone, Modugno & Reichlin (2013) for more details.

3.1 The Problem and the *News* Concept

For brevity purposes, we only summarise the exposition of the nowcasting problem introduced in BGR (2010). BGR (2010) illustrate the problem of nowcasting euro area GDP growth, but the approach can be extrapolated to any other variable. Formally, denoting Ω_ν the vintage of data at time ν and y_t^Q real GDP growth at time t, we define the nowcast as an orthogonal projection of y_t^Q on the available information set Ω_ν. The nowcast is the expectation of the variable conditional on the information set, $\mathbb{E}[y_t^Q|\Omega_\nu]$. Forming expectations is a feature specific to the modelling strategy adopted, as we shall see later.

Characterised by ragged-edges and MIDAS, the information set can be formally described as $\Omega_\nu = \{x_{i,t}, t_i = 1, 2, ..., T, i = 1, 2, ..., n; y_{3k}^Q, 3k = 3, 6, ..., T_{Q,\nu}\}$. The first block is comprised of monthly data, while the second represents quarterly data observed in the last month of the quarter. $T_{i,\nu}$, the last instance of time when series i is available/published at vintage time ν, varies across series indexed by i, given the asynchronous pattern of data availability. The challenge of nowcasting is to exploit the large cross-section of monthly series to form

[8]See Götz & Knetsch (2019), Vosen & Schmidt (2011), Vosen & Schmidt (2012), Nymand-Andersen & Pantelidis (2018), Kholodilin, Podstawski & Siliverstovs (2010), Kohns & Bhattacharjee (2019), Koop & Onorante (2019).

accurate (conditional) expectations of the target variable. These features of the dataset, where subsequent vintages for the same reference period become available and provide more information with each additional data release, are central to tracking developments in the business cycle.

Given the high-frequency and irregular release pattern of data, nowcasting involves computing several projections. The nature of the data implies an irregular and high-frequency updating of the information set. Two consecutive vintages, Ω_ν and $\Omega_{\nu+1}$, can be related through the following, if, for simplicity and without loss of generality, we abstract from data revisions:

$$\Omega_{\nu+1} - \Omega_\nu = \{x_{j,T_{j,\nu+1}} | j \in \mathbb{J}_{\nu+1}\} \tag{1}$$

$$T_{j,\nu+1} = T_{j,\nu} + 1, \forall j \in \mathbb{J}_{\nu+1} \tag{2}$$

meaning, thus, the information set is expanding by one observation for each j-indexed series in the set of indices $\mathbb{J}$ corresponding to variables x with upcoming releases. The nowcasts, given the consecutive vintages, are the conditional expectations: $\mathbb{E}[y_t^Q|\Omega_\nu]$ and $\mathbb{E}[y_t^Q|\Omega_{\nu+1}]$.

Central to tracking business cycle developments is the possibility of relating revisions in the sequence of nowcasts to releases of new data, revisions and their difference from model-based expectations, through the *news* concept. The *news* concept in DFMs has been introduced by BGR (2010), defining the new forecast as a sum of the old nowcast and its revision

$$\mathbb{E}[y_t^Q|\Omega_{\nu+1}] = \mathbb{E}[y_t^Q|\Omega_\nu] + \mathbb{E}[y_t^Q|I_{\nu+1}] \tag{3}$$

where $I_{\nu+1}$, the *news*, is the subset of $\Omega_{\nu+1}$ orthogonal to Ω_ν. $I_{\nu+1}$, comprised of $J_{\nu+1}$ elements, with $J_{\nu+1}$ the number of elements in $\mathbb{J}_{\nu+1}$, is the unexpected part of the new vintage, given expectations conditional on the prior information set:

$$I_{\nu+1} = x_{j,T_{j,\nu+1}} - \mathbb{E}[x_{j,T_{j,\nu+1}}|\Omega_\nu] \tag{4}$$

A more elegant, intuitive and useful for application purposes expression for the *news*-induced nowcast revision in (3) can be easily derived.

We apply the Lemma on Conditional Expectations[9] to derive a more useful expression for nowcast revisions, $\mathbb{E}[y_t^Q|I_{\nu+1}]$. Applying the Lemma and recalling series are standardised when entering the KF, i.e. $\sim N(0,1)$ (Gaussian by assumption), we obtain the expression from BGR (2010):

$$\mathbb{E}[y_t^Q|I_{\nu+1}] = \mathbb{E}[y_t^Q I'_{\nu+1}]\,\mathbb{E}[I_{\nu+1}I'_{\nu+1}]^{-1}I_{\nu+1} \tag{5}$$

and rearranging (3) yields:

$$\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu] = \mathbb{E}[y_t^Q I'_{\nu+1}]\,\mathbb{E}[I_{\nu+1}I'_{\nu+1}]^{-1}I_{\nu+1} \tag{6}$$

While the left hand side of (6) represents the nowcast revision given updates and noting the aforementioned standardisation of data, the right hand side contains the expression of an OLS regression coefficient estimator, since, through the Law of Iterated Expectations, $\mathbb{E}[y_t^Q I'_{\nu+1}] = \mathrm{cov}(\mathbb{E}(y_t^Q|\Omega_{\nu+1}), I_{\nu+1})$ and $\mathbb{E}[I_{\nu+1}I'_{\nu+1}] = \mathrm{var}(I_{\nu+1})$. Rewriting the multiplication of terms in expectations as an $J_{\nu+1}\times J_{\nu+1}$ matrix $B_{t,\nu+1}$ with generic elements $b_{j,t,\nu+1}$ and, recalling $I_{\nu+1}$

[9] $\mathbb{E}[Y|X] = \mathbb{E}[Y] + \mathrm{cov}(X,Y)\,\mathrm{var}(X,Y)^{-1}[X - \mathbb{E}(X)]$; $X, Y \sim N(0,1)$.

is a $J_{\nu+1}$-dimensional column vector, we obtain the familiar BGR (2010) expression:

$$\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu] = \sum_{j\in\mathbb{J}_{\nu+1}} b_{j,t,\nu+1} I_{j,\nu+1} = \sum_{j\in\mathbb{J}_{\nu+1}} b_{j,t,\nu+1}(x_{j,T_{j,\nu+1}} - \mathbb{E}[x_{j,T_{j,\nu+1}}|\Omega_\nu]) \quad (7)$$

Intuitively, expression (7) indicates the nowcast revisions are weighted sums of *news*, depending on both the size of the *news* and their relevance to the target variable, captured by $b_{j,t,\nu+1}$. This *news*-based decomposition of forecasts revisions can illustrate how the data flow through the reference quarter impacts the nowcast for the target variable.

3.2 The Monthly Factor Model and the Aggregation Scheme

To fully exploit the presence of alternative data in our model, we add a number of factors to the standard structure of previous DFMs. As we explain in the data section, we expand the panel with real-time alternative data (electricity consumption, internet search intensities, truck toll mileage index) and bring other changes pertaining to how survey and monetary data are considered (we replace headline with output indices, introduce the new orders less inventories index and the augmented credit impulse). In order to fully benefit from the added informational content, we augmented the factors structure introduced by BGR (2010) [10]. Our enriched specification includes, beyond standard global, real and nominal factors from BGR (2010), additional factors for soft data, real activity, labour and financial markets and two new others for real-time data and supply side shocks. Descriptions of blocks and loadings follow in the data sections and appendices; it is worth mentioning we have modified loadings of all blocks[11], but the latter two are genuinely new, containing electricity consumption, internet search data and survey-based indicators of capacity utilisation and production constraints. Pseudo real-time forecast evaluation results confirm it is the specific data and the blocks structure that lead to our model's gains in prediction accuracy.

In line with findings from the literature, we refrain from further complicating the factors lag structure or their number per block. ECB's nowcast documented in BGR (2010) and NY Fed's one from Bok et al. (2018) rely on single-factor AR(1) blocks initialised by first principal components with AR(1) processes for idiosyncratic components. Although beyond the scope of our paper, we briefly inspect how alterations of these model choices affect the result. We find our specification is broadly robust to changes in the number of factors per block and their lag structure. This is in line with evidence from Bańbura & Modugno (2014) and Doz et al. (2012), who find no material gains[12] from such deviations. We, therefore, do not depart from this baseline either.

Before diving into the mathematical apparatus, an intuitive exposition of the model is useful. Our DFM assumes variation in the data is driven by a few unobserved common factors. Thus, we resort to an unobserved components model, assuming a few driving factors are behind the observed data. We also impose that an autoregressive process generates the latent factors – not entirely unrealistic, given, barring 'black swan' events, macroeconomic data exhibit a certain degree of inertia. Kalman filtering is particularly useful for separating a latent component from the observed noisy data. Due to this feature, the KF is also helpful

[10] The Bok et al. (2018) NY Fed US nowcast is already modifying BGR (2010), using blocks for global, real, nominal, soft data and labour markets.

[11] Subjectively, based on judgement and economic intuition, we have changed data blocks; details of the new distribution of series across factors are present in table 5.

[12] The literature argues that, based on Monte Carlo simulations, factor estimates converge to true factors in long and dense enough panels of data, this feature being robust to altering the number of factors or the order of their AR process. Empirical evidence using data up to the financial crisis indicates very modest gains in increasing factors numbers and lag orders at the expense of computational complexity.

for dealing with missing values and asynchronous data releases, given the ragged-edge and the mixed frequency of the data. Casting the model in the SSF and using the KF facilitates filling in missing past values and forecasting, exploiting information, in a timely manner, contained in our alternative data.

Against this backdrop, we formally define dynamics of monthly data as in BGR (2010). Monthly series enter the KF standardised and transformed[13]. Denoting x_t the $n \times 1$ vector of transformed monthly data, we impose the factor representation:

$$x_t = \Lambda f_t + \epsilon_t \tag{8}$$

where f_t is the $r \times 1$ vector of latent common factors with loadings Λ. ϵ_t stores the idiosyncratic components. To exploit inertial dynamics and increase factor estimates precision, factors are modelled as AR(1) processes, given later restrictions on Q:

$$f_t = Af_{t-1} + u_t \qquad u_t \sim NID(0, Q) \tag{9}$$

With the rationale of increasing accuracy, albeit with limited value added (Bańbura & Modugno 2014), idiosyncratic components are also modelled as AR(1) processes, with cross-sectionally uncorrelated residuals, $\mathbb{E}[e_{i,t}e_{j,t}] = 0$ for $i \neq j$:

$$\epsilon_{i,t} = \alpha_i \epsilon_{i,t-1} + e_{i,t} \qquad e_{i,t} \sim NID(0, \sigma_i^2) \tag{10}$$

Given our blocks structure and the partitioning of f_t into mutually independent global (G), soft data (S), real activity (R), labour (L) and financial markets (F), real-time data (RT) and supply side shocks (SS) requires additional restrictions[14]. We illustrate restrictions on the AR coefficients, covariance matrices and the partitioning for the factors vector in appendix A. This specific structure, whereby a global factor is loaded by all variables, exploits the cross-correlation among series, before extracting common components from the more specific and locally fine-tuned blocks.

As far as modelling of quarterly series is concerned, we employ the same aggregation scheme as BGR (2010). Alternative techniques extract latent monthly observations for the quarterly series, but the aim of this paper is not to produce smoothers. Consequently, we rely on Mariano & Murasawa (2003), but we leave the interested reader to consult the original paper or BGR (2010) for details. Accordingly, the quarterly data are included in the framework through the modelling of partially observed monthly series and can be recovered through the following aggregation scheme:

$$y_{3k}^Q = y_{3k} + 2y_{3k-1} + 3y_{3k-2} + 2y_{3k-3} + y_{3k-4} \tag{11}$$

The latent monthly data used above is modelled in the same fashion as the observed monthly series:

$$y_t = \Lambda_Q f_t + \epsilon_t^Q \tag{12}$$

$$\epsilon_{i,t}^Q = \alpha_{Q,i} \epsilon_{i,t-1}^Q + e_{i,t}^Q \qquad e_{i,t}^Q \sim NID(0, \sigma_{Q,i}^2) \tag{13}$$

[13]More details in the data section and appendix C.

[14]BGR (2010) and most of the work for the euro area nowcasts rely on nominal and G, R factors, while NY Fed's uses G, S, R, L factors.

3.3 Estimation and Forecasting

Having laid out the modelling framework in equations (8)-(13), we can resort to the SSF and the KF. Letting $\overline{x}_t = (x_t', y_t^{Q'})'$ we can also cast the model in the SSF as in BGR (2010):

$$\overline{x}_t = Z(\theta)\alpha_t + \gamma_t$$

$$\alpha_t = T(\theta)\alpha_{t-1} + \eta_t, \qquad \eta_t \sim NID(0, \Sigma_\eta(\theta)) \tag{14}$$

where the first and second equations are the observation and, respectively, the transition equations, with α_t the unobserved states containing the common factors and the idiosyncratic components. θ is a column vector storing the parameters of the model, $\Lambda, \Lambda_Q, A, Q, \alpha_1, ..., \alpha_n, \alpha_Q, \sigma_1, ..., \sigma_n, \sigma_Q$. $\gamma_t' = \begin{pmatrix} \epsilon_t & \epsilon_t^Q \end{pmatrix}$ stores the residuals. We rely on a very in-depth exploration of the KF mechanics from Harvey (2006), but we do briefly present some details in appendix B. Further details on the SSF are also available in the appendix.

As in BGR (2010), the estimation of parameters in θ is conducted using QML and implemented with the EM algorithm. Proposed by Doz et al. (2012) and further explored by Bańbura & Modugno (2014), the recursive algorithm ensures convergence of factors and estimates to a fixed point with proven consistency properties of the estimators. In the implementation we worked on, the initialisation step consists estimating the common factors, $f_t(0)$, by means of principal components from monthly data; we OLS regress series on these to obtain preliminary estimates of the factor loadings, $\Lambda(0)$; OLS regressions are used for estimating AR(1) coefficients for $f_t(0)$, after which estimates of the covariance matrices for factors and idiosyncratic components are also computed, all stored in $\theta(0)$. The next step, the expectation step (E-step), uses estimates $\theta(j)$ from the previous step j, the SSF and KF to fill in missing factors and observations through the Kalman smoother and, based on this artificially augmented dataset, updates the likelihood function. The maximisation step (M-step) uses the maximum likelihood approach and the likelihood function updated in the E-step to re-estimate θ, storing it in $\theta(j+1)$. We iterate E-M steps until convergence; the method ensures consistency of the factor and coefficients estimators.

Provided the model is estimated on sufficiently long and dense cross-sections, Kalman filtering can be reliably employed to fill in missing values, smooth the data or produce forecasts (analysing them through the *news*), exploiting the timeliness of MIDAS for more accurate predictions. For a correct extraction of factors, we estimate the model on truncated datasets, excluding incomplete quarters at the end of the sample. We then run the data through the filter, using the updating and prediction recursions to exploit the timeliness of the additional data beyond the estimation sample. Readily available in this framework, the Kalman smoother seamlessly fills in missing observations (backcast). After accounting for all available data in one running quarter and updating the factors estimates, the filter provides, through the observation equation which converts factors to observations, the nowcast for the target variable. It is this feature of the model that ensures factors are more accurately estimated, making use of timely data and increasing forecasting accuracy. Beyond backcasting and nowcasting, this framework can produce further ahead forecasts by simply applying the prediction recursion for factors and switching from factors to observations representation via the observation equation[15]. The KF framework is so rich, it even makes readily available the calculations for the impact on nowcasts, due to revisions and new releases, in the *news*-based analysis (BGR 2010, Bańbura & Modugno 2014).

[15]Without updating factors' estimates, given data are missing beyond the running quarter.

An important caveat of our current approach is the assumption of Gaussian states and disturbances. Tail-event shocks, such as the ongoing COVID-19 pandemic recession, are clearly not normally distributed. One way of circumventing this important issue is to discard the extreme observations from March-2020 onwards as proposed by Lenza & Primiceri (2020). Given these discarded observations would be essential in updating the states optimal estimates during the pandemic shock, such an approach would defeat the initial purpose of forecasting during times of extreme stress. As further indicated by Lenza & Primiceri (2020), modelling the volatility to capture the non-linearities is another option. Beyond the scope of our paper, non-Gaussian KF models with disturbances explicitly modelled to reflect dynamic volatility and heavy tails could be more fruitful (e.g. Antolin-Diaz, Drechsel & Petrella 2020 drawing on earlier work of Harvey 2013, Durbin & Koopman 2012). Furthermore, a different strand of the literature combines well-established DFMs with machine learning and deep neural networks to model factor nonlinearities and produce more accurate predictions (e.g. Andreini, Izzo & Ricco 2020). However, our choice for leaving these more sophisticated modelling strategies for further research is rooted in the current practice from the euro area nowcasting literature; ultimately, our aim is to investigate how the addition of alternative data and new factors to standard DFMs improves nowcasting accuracy.

4 Data

In terms of data, the standard macroeconomic and financial time series are retrieved using Haver Analytics and their Microsoft Excel API, while IHS Markit and Google proprietary data are obtained directly from source. ENTSOE electricity data and Germany's truck toll mileage index are available on a daily basis in Haver and are monthly aggregated. We use the Bloomberg Terminal to set up the stylised calendar of releases. While all data is standardised prior to being processed by the algorithm, we follow BGR (2010) and Bok et al. (2018) in terms of additional transformations of the data to ensure stationarity. Details for model specifications, the data and factor loadings are available in appendix C.

For genuine real-time data vintages, we rely on the euro area Business Cycle Network's (EABCN) repository, available through the ECB's Statistical Data Warehouse (SDW). The EABCN's efforts for building the real-time database (RTDB) are documented in Giannone, Henry, Lalik & Modugno (2012). The RTDB contains 230 mixed-frequency series from 1999 onwards. The database uses a 'snapshot' approach, freezing databases available as of one day prior to the ECB's Governing Council, thus providing us with only a limited number of vintages for Q1/Q2-2020; where vintages for particular series are not available in SDW, we use the data as of 30-June-2020, which we further restrict by applying the release calendar to simulate the real-time data availability pattern. Applying transformations and seasonal adjustments where necessary, we use the SDW and set up four relevant vintages: 11-March-2020, 29-April-2020, 3-June-2020 from RTDB and 30-June-2020 from our own dataset. The availability of the series we used in the RTDB is documented in appendix C. We use the vintages and the *news*-based decomposition to illustrate how our nowcast reacted to the data-flow throughout the quarter, as the pandemic hit the economy.

4.1 Revisiting the Standard Dataset

The standard monthly panel and the specification from BGR (2010) are used for the benchmark DFM-based nowcast. Data are retrieved using Haver. Euro area Purchasing Managers Indices (PMIs) are obtained directly from Markit. Quarterly series are reported in the third month of the quarter, hence recording missing values in the remaining months, while financial data coming at a higher frequency are reported as the end of the month print.

In terms of business survey data, we analyse methodologies of the PMIs and European Commission's Business Survey (EC Survey hereafter) and conclude that PMIs are more accurate indicators for the running month's activity. Different collection and calculation methodologies are justifying why PMI-based GDP growth indicators are popular and powerful, faring better than other business surveys, particularly against the EC Survey. Somewhat different than what has been done so far is also how we chose to include PMIs. Instead of using the headline figure which aggregates across several subindices of output, employment or delivery times, we go straight to the GDP-related components, namely to output indices for a higher correlation with economic activity. We choose to include output indices for both manufacturing and services, without resorting to averaging by value added weights. Our other addition to the standard procedure is the inclusion of the difference between new orders and inventories, capturing, thus, the potential building of momentum for genuine new demand, beyond built-up producers' stocks. Using this composite index, which can turn negative, would also partially solve the censoring issue inherent to the standard PMI series – bounded in [0, 100], unable to fall below 0 in the event of an extremely severe shock. Given the extensive and more accurate information in the PMIs, we limit the usage of EC Survey data to its quarterly capacity utilisation and supply constraints series. While PMIs output and new orders less inventories data are featured in the soft data factor, surveys on capacity utilisation from Markit and EC's one on supply constraints are considered separately in the supply side factor.

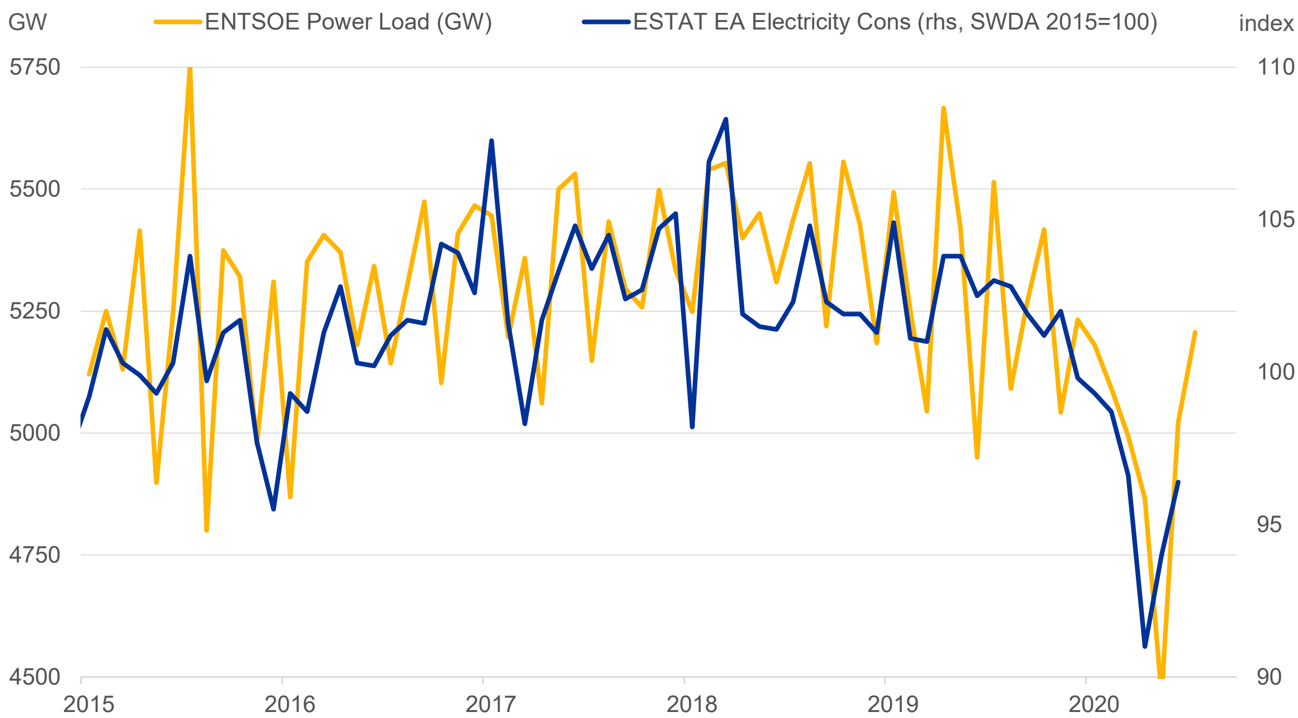
Another potential area of improvement identified in the literature is the treatment of monetary data. The inclusion of monetary aggregates and lending data is limited to (notional) stocks and does not extend to flows. Intuition, but also more elaborate studies such as Biggs, Mayer & Pick (2009), suggests flows matter too; in fact, we believe it is flows of lending that push businesses to invest/produce more and consumers to spend more, acting as an impetus for economic growth (with GDP a flow measure itself). Biggs et al. (2009) advocate the usage of a credit impulse measure to easily quantify the impetus of lending to GDP growth. We follow Cristea & Cabau (2019) and claim that the full picture in terms of crediting the economic activity is given by an augmented credit impulse (ACI), which also accounts for corporates' market net issuance of debt and equity. Evidence suggests the euro area ACI leads domestic demand and we believe its inclusion would provide more accurate accounting of bank and market based lending developments. Our ACI data is featured in the financial markets data block.

4.2 Alternative Data

Much of nowadays economic activity is conditioned by the usage of electricity, its consumption being, thus, a real-time proxy for the underlying momentum. We rely on ENTSOE power load data which comes in real time and is available on a country-by-country basis, instead of using only Eurostat data, available with a significant lag; we reconcile the two sources of data, ENTSOE aggregating up to Eurostat series. Without using the more refined temperature-adjustment approach of McWilliams & Zachmann (2020), we rely on original series aggregated for the euro area. Nevertheless, the data in figure 1 illustrates the expected dynamics: a severe downturn starting in March-2020, bottoming out in May, as the 'Great Lockdown' reaches its full swing, gradually bouncing back thereafter.

As a reliable alternative proxy for euro area industrial activity, we consider the truck toll

Figure 1: Euro Area Electricity Consumption



Source: Haver Analytics, Author's Calculations. Notes: More figures in appendix C.
Latest Observation: July-2020.

mileage index, in spite of it being confined to Germany only. With the increased integration of global value chains, Germany has consolidated its central industrial hub position and we expected data for industrial activity to be a reliable proxy for the sector's health at the euro area level. Indeed, the dynamics of the German toll index are closely following euro area manufacturing PMIs. As a consequence to its high correlation with surveys, we chose to include the toll index in the soft data factor.

In terms of internet search queries, we obtain data from Google Trends platform, using both keywords and categories search frequencies, from 2004 to present on a monthly and country-by-country basis[16]. Nymand-Andersen & Pantelidis (2018) and Anttonen (2018) provide a detailed presentation of the Google dataset. We use results from the former to apply national weights, based on population and internet access, for the euro area aggregation of our Google Trends indices. Trends data on search terms popularity is available for keywords, but also for 26 categories and even more numerous subcategories classified by Google's natural language processing software; the data is anonymised, reported as an index[17] and with an added white noise component[18]. We develop euro area indices for unemployment, short time work and economic activity/private consumption exploiting both categories and keywords search data.

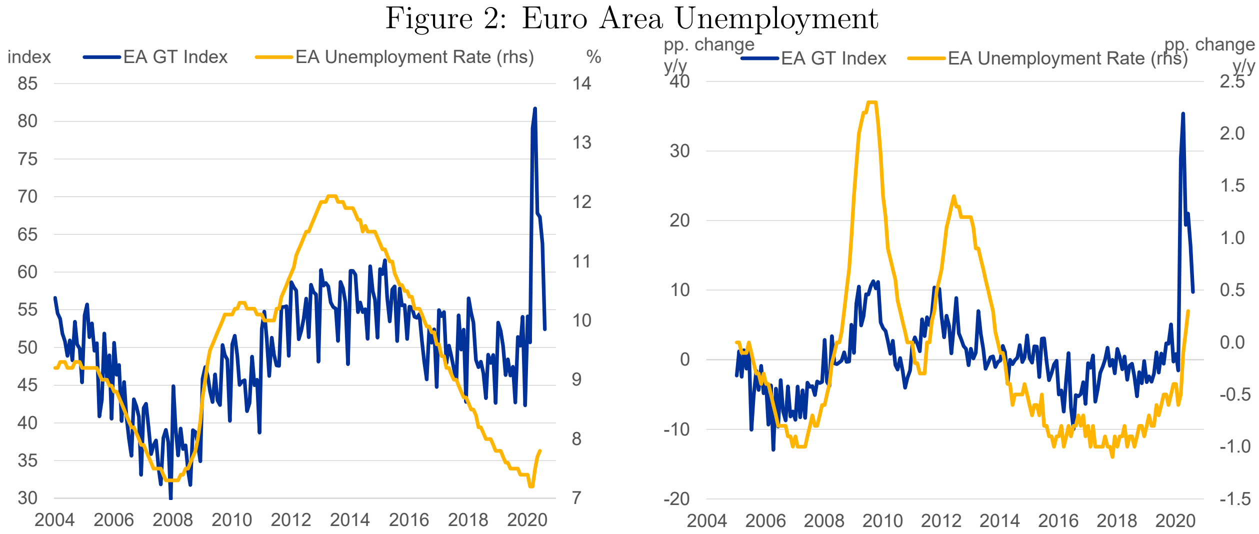
We construct unemployment and short-time work Google indices for the euro area using

[16]Given the large number of queries a full aggregation would entail, we rely on the law of large numbers and on data from the biggest six economies of the euro area (Germany, France, Italy, Spain, the Netherlands and Belgium – Big6 hereafter), cumulatively accounting for more than 85% of euro area's population and GDP.

[17]Between 0 and 100, where 100 is reported when a keyword/category has registered its highest historical interest. According to Anttonen (2018) and also to our own understanding, the reported search intensity index of a term/category is calculated as $I_{t,i} = \frac{K_{t,i}/G_{t,i}}{\max_t[K_{t,i}/G_{t,i}]} \times 100$, with $K_{t,i}$ the search volume of term 'K' at time t in geography i, with $G_{t,i}$ the volume of total searches at t in i. Through this normalisation, $I_{t,i}$ is, effectively, the proportion/probability that one searches for 'K' at time t in geography i.

[18]Querying the database on different days results in slightly different results, but the noise can be filtered out through sequential querying and averaging.

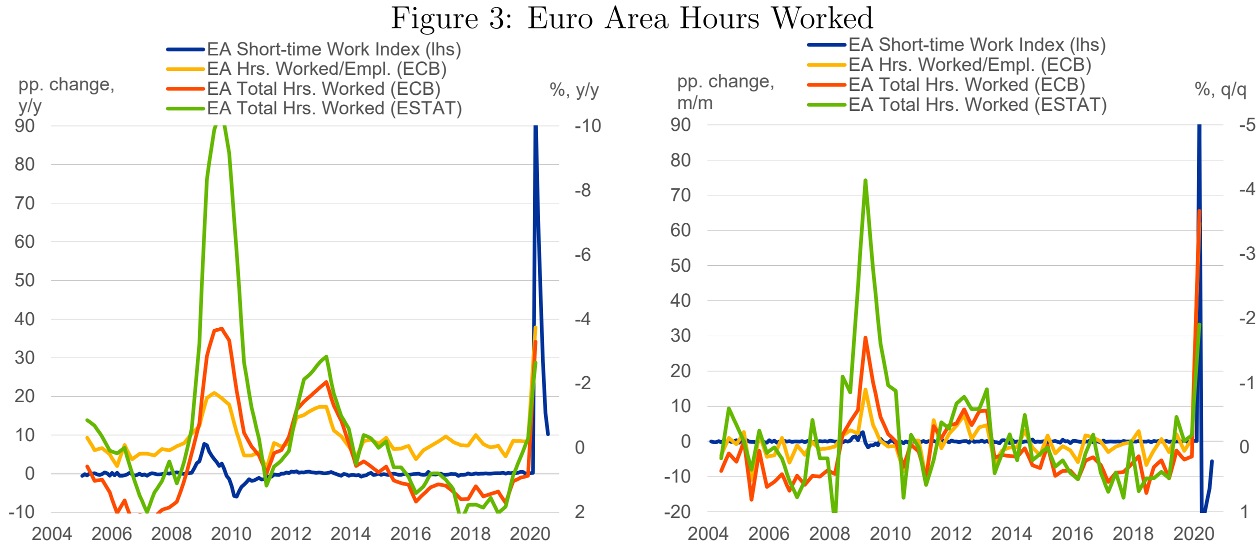
Figure 2: Euro Area Unemployment



Source: Haver Analytics, Google Trends, Author's Calculations. Notes: More figures in appendix C. Latest Observation: June-2020 for unemployment and August-2020 for Google Trends.

keywords search data. Our euro area unemployment index is built upon aggregated Big6 data, using the methodology and the list of search terms from the Research Institute of the Finnish Economy on their ETLAnow project. We extrapolate ETLAnow's approach for unemployment to the short-time work index, by retrieving search intensity data on a list of terms related to short-time work arrangements, widely employed under European Commission's SURE relief package but also used before, during the great recession[19]. We report compelling evidence in figures 2 and 3 (more in appendix C) suggesting first differences in our constructed indices are leading, or at least coincident (yet available very timely, well before official data), with the changes in unemployment rate, total hours worked or the number of applications for short-time work. Our findings strongly recommend the inclusion of our labour market search indices in our euro area nowcast. Facilitating a more timely and accurate update of the labour factor estimate, unemployment and short-time work indices are included in the labour block, alongside euro area unemployment rate, employment and hours worked indices.

Figure 3: Euro Area Hours Worked



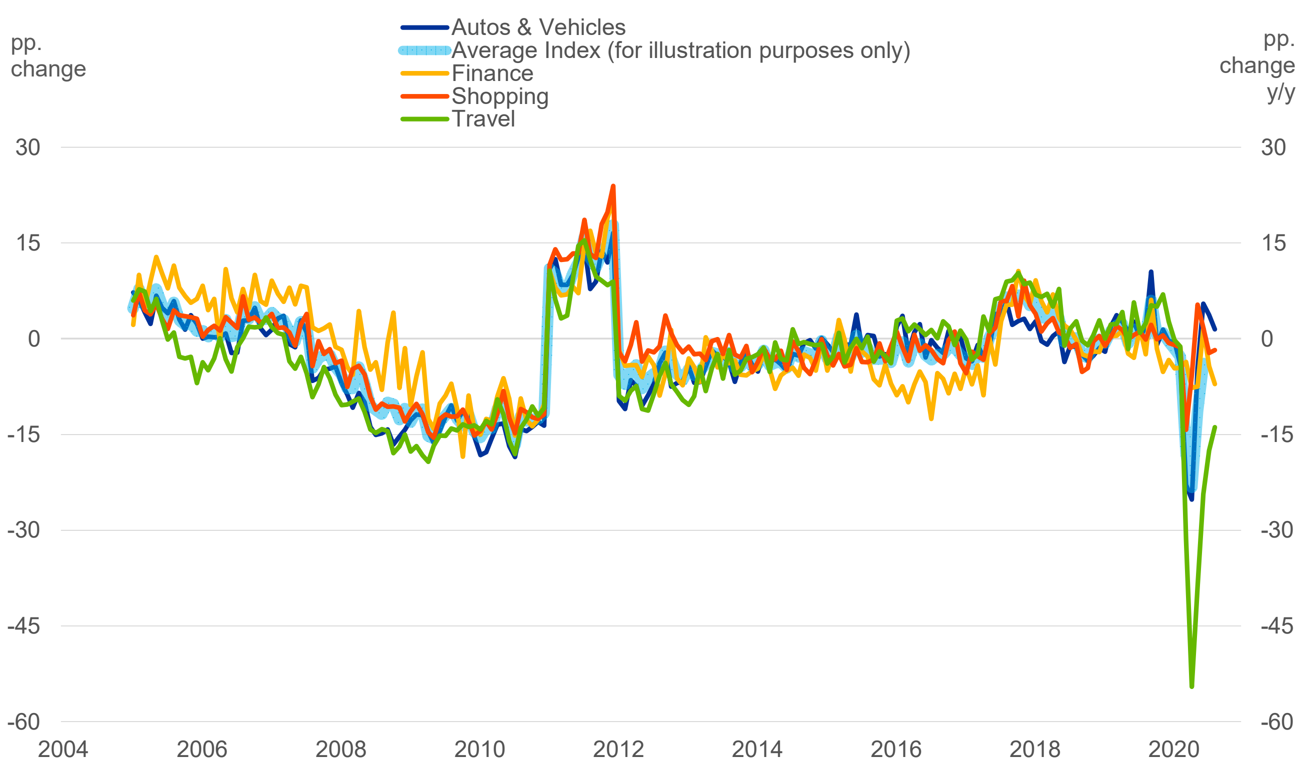
Source: Haver Analytics, Google Trends, Author's Calculations. Notes: More figures in appendix C. Latest Observation: Q1-2020 for hours worked, August-2020 for Google Trends.

As far as activity is concerned, following the technique in Nymand-Andersen & Pantelidis

[19] We construct our list based on the March- 2020 briefing note on short-time work measures across EU member states following COVID-19.

(2018), we retrieve country-by-country categories level search intensity data from Trends on a subjectively selected list and construct euro area indices. We rely on a few search categories encompassing a wide range of potential search terms related to private consumption and credit demand: 'Autos & Vehicles', 'Finance', 'Shopping' and 'Travel'. Our choice is motivated by Boivin & Ng (2006), claiming that factors extracted from smaller numbers of series may have higher forecasting potential, and empirically confirmed by Götz & Knetsch (2019), Vosen & Schmidt (2011) and Vosen & Schmidt (2012) (subcategories or too big of a keywords/categories selection distorts the signal). Visual inspection of year-on-year percentage changes in these categories search intensity, as reported in figure 4, reveals an unsurprising pattern to analysts accustomed to economic developments throughout the last 15 years – yet a 'temporary structural break' during the sovereign debt crisis remains a mystery to us (absent in month-on-month changes). Given our results, Google search intensity indices for activity enter the DFM as monthly month-on-month changes of underlying levels through the real-time data factor, together with ENTSOE and Eurostat electricity consumption.

Figure 4: Euro Area Activity Indices



Source: Google Trends, Author's Calculations.
Latest Observation: August-2020.

Although we restrict ourselves to using a monthly enriched factor model with alternative data, numerous exciting extensions to our approach are left for future research. While our alternative data sources are limited to electricity, internet search data and the toll index, efforts on building more timely, easily accessible and more granular data are gaining momentum, if anything, the pandemic only accelerating these trends. Due to short sample sizes, limited country coverage or lacking quality, which prevented proper training and back-testing of our DFM, we chose not to include in our dataset mobility indices, restaurant bookings, pollution or satellite imaging data, to name a few. However, alongside even more novel sources of data, such as web scraping, these are ideal candidates for leading/coincident activity indicators, with great potential in DFM-based nowcasting. A different avenue for research is also exploring daily-factor models, which have been studied in the past, but not with alternative data. Bańbura et al. (2011) investigated the role of daily financial data in DFM-based nowcasting, but found their volatility and potential disconnect from economic fundamentals do not lead to improvements in out-of-sample forecasting precision. Alternative daily data, such as most of the sources mentioned here, could potentially address the issue. One aspect is certain: the ever ongoing digitalisation will only spur the interest in alternative data and open more avenues for time series research.

5 Empirical Evidence and Discussion

In this section, we compare the nowcast performance of our proposed rich DFM model against several competing approaches from previous work. We replicate BGR's (2010) best performing euro area nowcast[20] and consider it one contender. Going beyond academic literature and relying on industry practices, we also consider the PMI-based GDP growth tracker. Following previous academic studies, we report results relative to the benchmark model of a naïve autoregressive process of order 1 (AR(1)) fitted on quarterly euro area real GDP growth. Various out-of-sample forecast evaluation approaches confirm that our rich DFM, due to its additional data and factors, tends to produce more accurate nowcasts relative to models proposed in previous academic work and the PMI-based GDP growth tracker. We report the forecast evaluation findings and explore, using the *news* concept, our nowcasts for Q1/Q2-2020 based on pseudo and genuine real-time data vintages.

Although not the focus of academic research, business survey data, particularly PMIs, have become increasingly important for professional forecasters. As previously discussed in the data section, PMIs tend to be preferred over EC Survey data due to their methodology, shorter publication lag, high data quality and a resulting higher correlation with real GDP growth in the euro area and worldwide. Due to these features, simple models based on composite output PMIs have rapidly become reliable tools for real-time forecasting in practice. Recent Markit Economic Research reports[21] propose parsimonious OLS regression models for GDP growth explained by composite output PMIs (in logs to account for non-linearities), with rather impressive out-of-sample forecasting precision, competing with standard nowcasts or traditional time series models. Results from testing our own specifications are in line with evidence from the aforementioned reports[22]. We consider this PMI-based tracker as a separate contender in our models comparison exercise.

5.1 The Pseudo Real Time Forecast Evaluation

We follow the literature and conduct a pseudo real-time assessment, whereby we simulate the data availability pattern at the time of computing the forecast. To this end, we use the stylised calendar set up in the appendix, which accounts for publication lags of included series[23]. Accounting for data revisions and performing a genuine real time exercise for all generated nowcasts is computationally burdensome and earlier evidence indicated negligible differences (Bernanke & Boivin 2003, Schumacher & Breitung 2008).

[20] We do acknowledge BGR (2010) is not necessarily the official tool used by the ECB in its suite of models; it is surely a starting framework which has been systematically reviewed over the years.

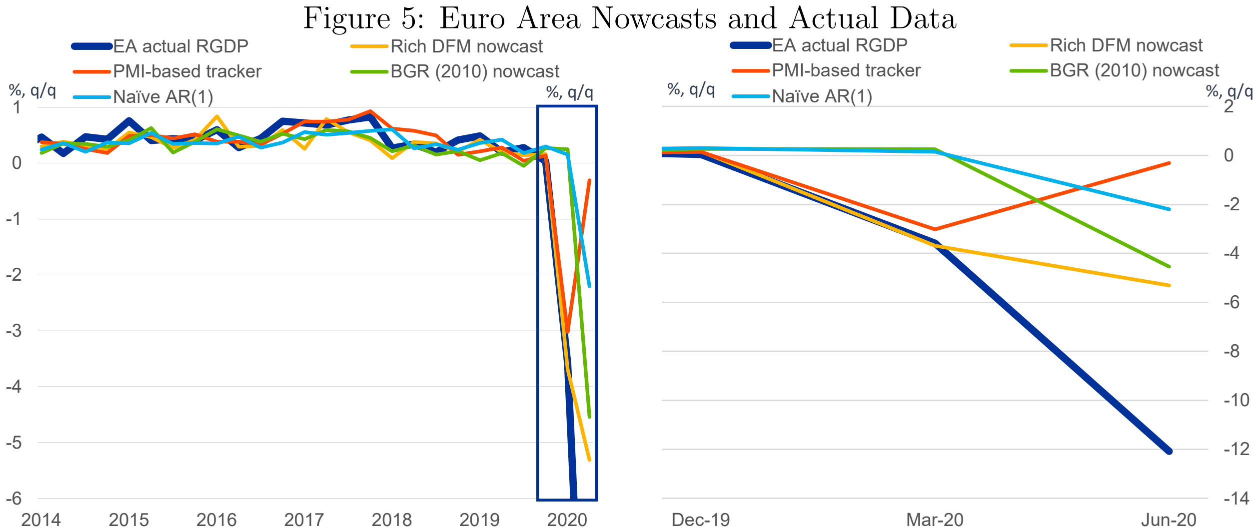
[21] Smith (2018), Smith & Hayes (2019) and Smith & Hayes (2020)

[22] We test several specifications for an euro area GDP growth tracker based on PMI composite output, using level and log terms, squared and cubics in our OLS regressions. Regressing linearly interpolated GDP growth on monthly natural logs of PMI composite output is the best performing model. Using the OLS estimates, we fit, recursively and with fixed estimation, growth using the PMI data from the last month of the quarter (alternative methods, such as averaging monthly PMIs over the quarter are inferior). We evaluate the forecasts using the RMSE criterion on the basis of quarterly fitted and realised growth.

[23] The literature and the cyclical pattern of data releases suggest considering data updates in the middle and at the end of the month. Generally, many hard data points are released with various lags in the first half, others, such as monetary, prices and survey data, at the end of the month.

We consider the end of the quarter nowcast as the most relevant one for the purposes of this exercise. While properties of nowcasts as they are computed throughout the quarter have been already extensively explored, for this part we only consider nowcasts derived from data available when the reference quarter ends. We first estimate the DFM on a fully balanced dataset truncated before the target quarter and then, exploiting KF techniques and the estimated model, we compute pseudo out-of-sample nowcasts, employing this procedure recursively[24]. For a robustness check, we also restrict ourselves to nowcasting after a fixed sample estimation of the DFM[25]. We follow the same pseudo real-time approach for computing BGR's (2010) nowcast, the PMI-based tracker and the naïve AR(1) forecast.

Figure 5: Euro Area Nowcasts and Actual Data



Source: Haver Analytics, IHS Markit, Author's Calculations. Notes: Models are trained on a 2000-2013 sample of data and nowcasts are computed recursively thereafter. For a target quarter, the nowcast is computed after estimating the underlying model on the panel of data up to the previous quarter, simulating the real-time data availability pattern at each point, but abstracting from data revisions (pseudo real-time forecasting). We use the data vintage available as of 30-June-2020.
Latest Observation: 30-June-2020.

Employing qualitative and quantitative metrics, we assess the forecasting performance of our best nowcast (referred to as 'rich DFM') against the other contenders[26]. Visual inspection of nowcasts in figure 5 indicates that, during normal times, the models tend to perform somewhat similarly. However, our model manages to timely detect the turning point in Q1-2020, due to the COVID-19 shock, and correctly points at further contraction in Q2, albeit wrongly predicting the order of magnitude. In terms of quantitative assessment criteria, we use the Root Mean Squared Error (RMSE) and the Diebold-Mariano (DM) test (2002), together with its modification from Harvey, Leybourne & Newbold (1997) (HLN test). We also calculate Kuiper's Score (KS) to assess qualitative properties of the forecasts, namely how accurate the nowcasts are in calling for quarter-on-quarter contractions/expansions; we propose a modified version of the score (MKS) for checking accuracy in terms of predicting accelerations/decelerations in economic growth. The comparison of RMSEs in table 1 shows that, regardless of the estimation approach (recursive or fixed) and training sample (2000-2011 or 2000-2014), our rich DFM nowcast is cca. 75% more accurate than the AR(1)

[24] We firstly estimate the DFM on a balanced panel of 2000-2013 data, accounting for two recessions and construct a forecast for Q1-2014. We then extend the estimation sample by a quarter and nowcast Q2-2014. We iterate until Q2-2020.

[25] We no longer expand the DFM estimation sample. Once the DFM is estimated on the 2000-2013 data, we fix estimates and use them for nowcasting

[26] It would be tempting to directly compare results to evidence from BGR (2010), Bańbura & Modugno (2014). We caution this would not be adequate. The two papers forecast evaluation uses data prior to the global financial crisis, not accounting, hence, for extreme shocks to growth. This naturally leads to lower RMSE, even if the models were able to pick up non-linearities.

prediction and BGR's (2010) nowcast. However, forecasting accuracy gains over the PMI-based tracker are modest. At the same time, evidence from the KS and MKS for directionality accuracy are consistent with the RMSE comparisons, favouring the usage of alternative data, modified factors structure and the other small, yet relevant, fine-tunings in the dataset.

Table 1: Pseudo Out-of-sample Performance Relative to the Naïve AR(1) Forecast

	Recursive 2000-2011			**Recursive 2000-2013**			**Fixed 2000-2013**		
	RMSE	**KS**	**MKS**	**RMSE**	**KS**	**MKS**	**RMSE**	**KS**	**MKS**
PMI-based tracker	0.35	1.53	2.18	0.28	90.01	2.73	0.28	90.01	4.32
BGR (2010) nowcast	1.02	0.74	1.18	1.02	-3.75	1.73	1.05	-4.17	2.16
Rich DFM nowcast	0.29	0.79	2.64	0.23	90.01	3.67	0.24	90.01	5.21

Headers indicate the type of estimation and the time span of the used sample for the training of underlying models and parameters estimation. Results are reported relative to the metrics obtained from the same exercise applied for predictions made with a naïve AR(1) model. Formulae for the Root Mean Squared Error (RMSE), the Kuiper Score (KS) and our proposed modification of it (MKS) are presented in the appendix, where raw statistics for all models are also included. Forecast evaluation metrics are calculated on windows starting after the endpoint of the estimation sample, also simulating the real-time data availability pattern at each point in time where a nowcast is computed, but abstracting from data revisions (pseudo real-time forecasting). Results of the pseudo out-of-sample exercise are based on a vintage of data available at the end of June 2020.

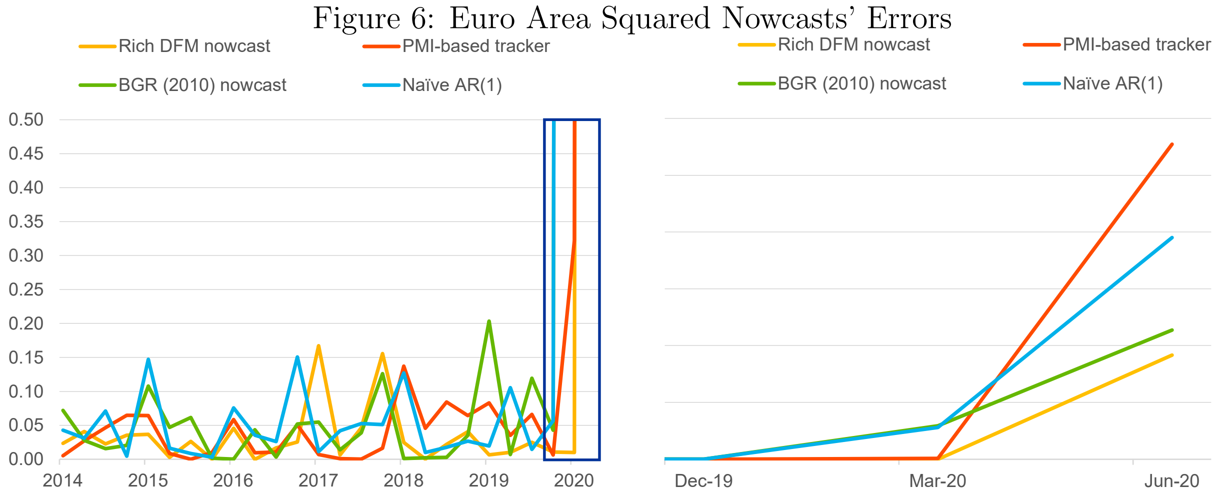
Table 2: Diebold-Mariano Tests for Differences between Squared Nowcasts' Errors

	Recursive 2000-2011			**Recursive 2000-2013**			**Fixed 2000-2013**		
	RMSE	**DM**	**HLN**	**RMSE**	**DM**	**HLN**	**RMSE**	**DM**	**HLN**
Rich DFM nowcast	0.20	1.05	1.03	0.18	1.03	1.01	0.19	1.02	1.00
		(0.30)	(0.31)		(0.32)	(0.32)		(0.32)	(0.33)
Naïve AR(1) Forecast	0.70			0.78			0.77		

Headers indicate the type of estimation and the time span of the used sample for the training of underlying models and parameters estimation. Formulae for the Root Mean Squared Error (RMSE), the Diebold-Mariano (DM) test and its modified version (HLN) are presented in the appendix, where raw statistics for all models are also included. Forecast evaluation metrics are calculated on windows starting after the endpoint of the estimation sample, also simulating the real-time data availability pattern at each point in time where a nowcast is computed, but abstracting from data revisions (pseudo real-time forecasting). Results of the pseudo out-of-sample exercise are based on a vintage of data available at the end of June 2020. The Diebold-Mariano (DM) and its modified version (HLN) use the calculated statistic to test for H_0: 'No significant difference in the squared error' against the alternative. A high statistic is evidence against the null hypothesis and indicates our rich DFM nowcast is more accurate, in a statistically significant manner, provided P-values reported in parentheses are commensurately small with the desired significance level. Testing is concerned with differences in squared nowcasts' errors between the rich DFM and the AR(1) models.

Several results and aspects inherent to the considered sample and frequency of data prompt us to qualify our argument. Although some marked differences in RMSE exist, the DM test seems to fail to reject the null of no significant difference in the squared errors between our nowcast and the AR(1) prediction, at confidence levels beyond 70% (table 2). While this may, indeed, be the case between our nowcast and the PMI-based tracker, it can hardly be true when it comes to BGR's (2010) or the AR(1)'s performance, where the RMSE differences are notably higher. However, the confluence of several factors may distort results from the DM and HLN tests, also true for KS and MKS scores. Firstly, actual GDP data comes in with quarterly frequency and, in spite of having a long panel of monthly data, there are only 80 quarterly observations. Secondly, estimating the model on already cca. 70% of the data leaves us with a small number of out-of-sample quarterly data points for evaluation (25), this being problematic, particularly for the DM test. Among the first attempting to address some of the DM test's issues, Harvey, Leybourne & Newbold (1997) highlight its potential small sample bias. Furthermore, as illustrated in Enders (2008) and appendix D, the DM and HLN tests rely on the Central Limit Theorem to establish the loss differential is normally distributed and use its asymptotic variance in the calculations of test statistics. Consequently, our very limited sample size implies the results from the DM and HLN tests may not be valid. Nevertheless, the RMSE is still indicating sizeable gains in nowcasting with alternative data and richer factors structure.

Figure 6: Euro Area Squared Nowcasts' Errors



Source: Haver Analytics, IHS Markit, Author's Calculations. Notes: Models are trained on a 2000-2013 sample of data and nowcasts are computed recursively thereafter. For a target quarter, the nowcast is computed after estimating the underlying model on the panel of data up to the previous quarter, simulating the real-time data availability pattern at each point, but abstracting from data revisions (pseudo real-time forecasting). We use the data vintage available as of 30-June-2020 and, for the purposes of calculating the squared error in Q2 only, we artificially add the GDP figure for Q2-2020, unavailable, otherwise in the considered sample.
Latest Observation: 30-June-2020.

Turning to another angle in comparing the forecasting accuracy of our models, we inspect directly the out-of-sample squared forecast errors (figure 6). As it was already evident with the nowcasts in figure 5, we ascribe the higher RMSE of nowcasts based on BGR (2010) and AR(1) models mainly to their inability of picking up the downturn in Q1-2020, squared errors remaining somewhat similar before 2020. While the BGR (2010) nowcasts are fairly similar to those of our proposed rich DFM prior to 2020, the BGR (2010) nowcast for Q1-2020 indicated a positive 0.2% quarter-on-quarter growth, significantly different from the actual outcome. BGR's (2010) specification relies on a traditional dataset, where most timely sources of data are business survey series, a large fraction of which had already been collected by the time COVID-19 has affected activity in mid-March. It should, therefore, perhaps not be surprising that more timely alternative data helped the rich DFM model indicate the turning point better. Furthermore, as we show in table 3, while differences in RMSE remain in favour of the rich DFM, they become modest when excluding the 'black swan' shock of Q1-2020. Artificially including the real GDP growth outcome of Q2-2020[27] in the vintage of data we used (end of June 2020) further increases the disparities in RMSE. These findings support our view that while in normal times the rich DFM does not add much to nowcasting accuracy, abnormal times illustrate the usefulness of its expanded dataset and factors structure.

To further support our proposed model extensions, we illustrate how the sequential addition of factors impacts the RMSE of our nowcasts. We depart from nowcasting with a DFM specification strongly resembling that of BGR's (2010), which uses global, nominal and real factors. Starting from a dual-factor model comprising global and real blocks, we sequentially add specific data and factors and report the pseudo out-of-sample nowcasting RMSE in table

[27]For RMSE calculation purposes only and not DFM estimation or Kalman filtering, since the observation was not available as of 30-June-2020, our used vintage.

Table 3: Pseudo Out-of-sample Forecast Evaluation on Different Data Samples

	Naïve AR(1) forecast	**PMI-based tracker**	**BGR (2010) nowcast**	**Rich DFM nowcast**
Including Q4-19	0.22	0.19	0.21	0.18
Including Q1-20	0.78	0.22	0.80	0.18
Including Q2-20	2.08	2.32	1.67	1.34

The table reports nowcasting RMSE, for models mentioned in the headers, where nowcasts are considered up to Q4-2019, Q1-2020 and Q2-2020. Estimation of the underlying models is conducted on the 2000-2013 sample of data, available as of 30-June-2020, also simulating the real-time data availability pattern at each point in time where a nowcast is computed, but abstracting from data revisions (pseudo real-time forecasting). Nowcasts are computed recursively, thereafter. Q2-2020 real GDP growth outcome has been artificially added to the vintage for RMSE calculation purposes only.

4. Except for the addition of the labour factor, the real-time data factor and the ACI series in the financial data factor, enriching the factors structure has resulted in outright reductions of RMSE. We then test the jointly restricted DFM-based nowcast, where factors and data previously increasing the RMSE have been excluded. Results indicate that excluding these data and factors from the model leads to significant deterioration in nowcasting accuracy, i.e. these discarded factors are seemingly jointly significant. We believe these findings suggest a DFM without the rich factors structure may be misspecified, the omission of these factors and variables biasing the nowcasts and leading to higher RMSE.

Table 4: Pseudo Out-of-Sample Forecast Evaluation with Sequential Factors Addition

	Model Specification		
	BGR (2010)	**Rich DFM (restricted)**	**Rich DFM**
	0.80		
G R		0.80	
G R S (ex. Trucks Toll Index and PMI New Orders-Inventories)		0.72	
G R S		0.70	
G R S L		0.71	
G R S L F (ex. ACI)		0.35	
G R S L F		0.54	
G R S L F RT		0.54	
G R S L F RT SS		0.18	
Joint Restriction: G R S F (ex. ACI) SS without L RT factors		0.73	
			0.18

The table reports the RMSE for various nowcasts based on restricted and unrestricted DFM specifications. Global (G), Real (R), Soft Data (S), Labour (L), Financial Data (F), Real-time Data (RT) and Supply Side Shocks (SS) factors are sequentially considered in the DFMs trained on 2000-2013 data, with nowcasts computed recursively thereafter, based on the vintage of data from the end of June 2020. BGR (2010) original specification encompasses G, R and nominal factors, but, given our proposed approach, we start with the closest specification, namely a dual G, R factors structure. We sequentially add restricted and unrestricted factors to assess their contribution to the reduction of uncertainty around the point forecast. The table reports RMSE for each specification, including a jointly restricted model where factors and data that were increasing the RMSE with their addition have been jointly excluded. RMSE for BGR's (2010) and our full specification Rich DFM are reported for comparison. The lhs column indicates which specification is used in the Restricted Rich DFM nowcast.

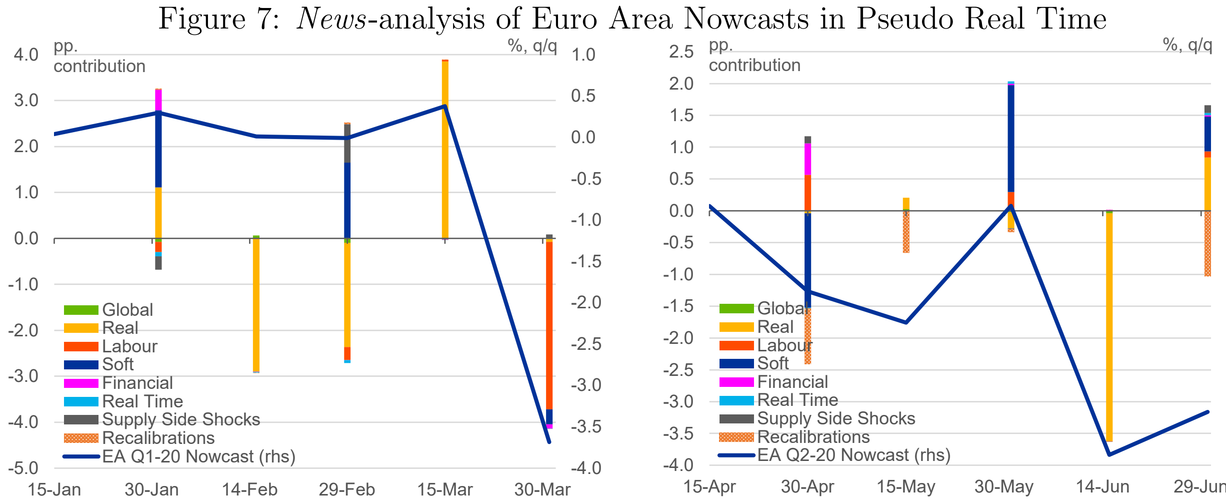
5.2 The COVID-19 Shock

This section makes use of the *news*-based decomposition of the nowcast revisions, introduced in DFMs by BGR (2010), to illustrate the contribution of specific blocks to the changes in our rich DFM-based predictions for Q1/Q2-2020. We present results from two exercises. In the first one, we use the pseudo real-time environment and the stylised calendar to generate and analyse the series of nowcasts for Q1/Q2-2020 in the middle and at the end of each month of the quarter, roughly corresponding to the release dates of major data points. Our second exercise looks into the evolution of our Q2-2020 nowcast using two EABCN vintages of data alongside our dataset as available at the end of June-2020[28]; given the availability of data in the RTDB, the exercise is not feasible in the case of Q1-2020. Forecasts are computed recursively, in the sense that, at each moment in the quarter, we train the rich DFM and

[28]We use the RTDB vintages from 29-April-2020 and 03-June-2020 alongside our own 30-June-2020 vintage. Wherever the needed series were unavailable in the RTDB, these have been sourced from the 30-June-2020, in this respect the exercise remaining a pseudo real-time simulation, and not a genuine one.

re-run the data through the KF using the panel of data ending prior to the running quarter, with the real-time data availability pattern simulated according to the same stylised calendar at each point of the projection; unavoidably, the retraining and refiltering leads to model recalibrations[29]. Results indicate three important aspects: for one, alternative data sources and the rich factors structure seem to have been driving the nowcasts towards detecting the turning point; secondly, the impact from revisions seems to be rather muted, in line with findings from earlier literature; last but not least, the volatile and non-Gaussian nature of the datapoints reflecting the pandemic-induced shock leads to non-negligible model recalibrations with marked effects on how the nowcasts are revised.

Figure 7: *News*-analysis of Euro Area Nowcasts in Pseudo Real Time



Source: Haver Analytics, IHS Markit, Author's Calculations. Notes: Models are trained on a 2000-2013 sample, with nowcasts computed recursively thereafter, based on a 30-June-2020 vintage. Nowcasts are computed after estimating the model on the sample up to the previous quarter. Charts illustrate, using the news, how data surprises from various factors impact the nowcast throughout the quarter. Factors contributions to the nowcast revision are multiplied by 10 up to and including 15-March in order to be visible when compared to the pandemic-shock.

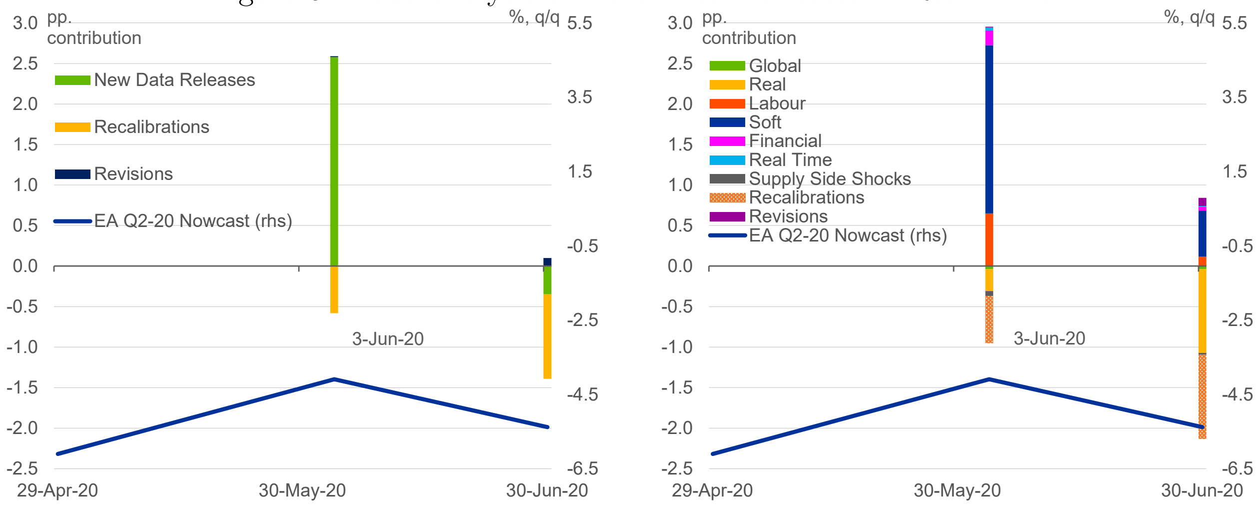
News-based pseudo real-time analysis of the data flow in the first quarter of 2020 reveals how our alternative data and factors detect the turning point. The first panel in figure 7 illustrates the evolution of our Q1 nowcast, using the *news* concept[30]. As the euro area economy was slowly bottoming out of its industrial recession, soft data factors have systematically picked up data surprises, eventually being matched by revisions due to the lagged hard data releases in the real factor in mid-March. As COVID-19 started to ravage Europe, the first relevant data points and nowcast revisions came in through soft data, more precisely business surveys and the toll index with reference to March activity. However, the bulk of the nowcast downward revision came from the labour factor (cca. -3 pp.), where our Google Trends labour and short-time work indices detected pressures on employment and jittery sentiment among employees, surprising to the downside model-based expectations. Without our novel labour factor's contribution, our nowcast would have indicated, *ceteris paribus*, a modest -0.1% quarter-on-quarter growth.

Looking into the most affected quarter at the time of writing, our Q2 nowcast and the *news*-based analysis of the data flow indicates our model has correctly identified the underlying economic trends. In Q2, with synchronised lock-downs in full swing across Europe, April tepid activity has been reflected in downward nowcast revisions stemming from business

[29]These imply both changes in the estimated model parameters but also in the estimated unobserved factors.

[30]Factors contributions are multiplied by 10 up to and including 15-March in order to be visible when compared to the pandemic-shock.

Figure 8: *News*-analysis of Euro Area Nowcasts in Real Time



Source: Haver Analytics, IHS Markit, Author's Calculations. Notes: Models are trained on a 2000-2013 sample, with nowcasts computed recursively thereafter, based on RTDB and our own 30-June-2020 real-time vintages. Nowcasts are computed after estimating the model on the sample up to the previous quarter. Charts illustrate, using the news concept, how data surprises from various factors impact the nowcast throughout the quarter.

survey releases in April and lagged hard data prints coming in mid-June (rhs figure 7). As a result of monetary and fiscal policy pledges and the gradual lifting of lock-down measures, the tentative rebound in confidence and activity from May and June was reflected in soft and real data factors. These have surprised our model to the upside, lifting somewhat our Q2 nowcast too. Evidence from the genuine real-time exercise illustrated in figure 8 is consistent with our observations; it also confirms earlier findings in the literature that data revisions have a limited impact only. However, the striking aspect coming out of Q2's data is the impact of recalibrations and refiltering with each nowcasting iteration, likely reflecting the fact that our DFM model heavily relies on the assumption of Gaussian data, the COVID-19 shock coming in clearly as a tail-event.

6 Concluding Remarks

In this paper, we take the standard approach of nowcasting euro area real GDP growth of Giannone, Reichlin & Small (2008) and explore how several extensions impact the accuracy of the forecasts. More precisely, we look at how nowcasting performance changes after augmenting the standard model with alternative data, expanding the latent factors structure and changing how some of the standard model data is included. We report results from several pseudo and genuine out-of-sample forecast evaluation exercises and illustrate how our nowcasts have performed throughout Q1 and Q2-2020, the height of the COVID-19 induced recession in the euro area.

We present empirical evidence in favour of the hypothesis that our proposed dataset and factors expansion increase nowcasting accuracy in times of severe stress. While gains in forecasting accuracy remain modest over other standard models outside the COVID-19 crisis, improvements in the root mean squared error and Kuiper's score for directionality accuracy, when considering the whole panel of data, are meaningful and non-negligible. In the paradigm of the classical regression model hypothesis testing, we also explore the contribution of each of our model innovations to the improvement in nowcast accuracy. Finally, building on the *news*-based nowcasting revisions decomposition proposed by Bańbura et al. (2010), we show how and owing to what data sources our forecasts have changed throughout the quarters. The *news*-based analysis indicates the alternative data did help detecting the turning point in Q1 and, while it deems data revisions irrelevant, it also shows that model recalibrations, due to recent non-Gaussian observations, lead to significant nowcast revisions.

While our results seem exciting and encouraging for data science enthusiasts, we note several caveats the researcher should bear in mind. The increasingly more rapid expansion of alternative data sources means more opportunities for implementing this new paradigm in traditional models used by policy-makers and investors. At the same time, these novel sources of data should be cautiously embraced, as they are not subject to the same structuring, quality controls and scrutiny specific to traditional official statistics. Relying on tools exploiting such data when making policy or investing decisions seems premature. Furthermore, our proposed methodology is essentially attempting to capture non-linearities using a linear model; given the underlying Kalman filtering techniques we used are grounded in the assumption of normally distributed data, our results, particularly given the severe shock of the 'Great Lockdown', should be read with even more caution. Nevertheless, our study is, we hope, a useful illustration of how alternative data could be effectively employed in real-time nowcasting.

As discussed throughout our paper, there are several avenues of future research. In spite of having been explored in the past, daily factor models have not included yet alternative data sources. As the pandemic has accelerated the use and public dissemination of these data and many other, this approach may be fruitful. Another direction for future research consists of explicit and more sophisticated (than we did) modelling of stochastic volatility and using non-Gaussian Kalman filtering in the nowcasting framework.

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Appendices

A Details of the State Space Form (SSF)

Factors partitioning, AR coefficients, covariance matrix:

$$\Lambda = \begin{pmatrix} \Lambda_{S,G} & \Lambda_S & 0 & 0 & 0 & 0 & 0 \\ \Lambda_{R,G} & 0 & \Lambda_R & 0 & 0 & 0 & 0 \\ \Lambda_{L,G} & 0 & 0 & \Lambda_L & 0 & 0 & 0 \\ \Lambda_{F,G} & 0 & 0 & 0 & \Lambda_F & 0 & 0 \\ \Lambda_{RT,G} & 0 & 0 & 0 & 0 & \Lambda_{RT} & 0 \\ \Lambda_{SS,G} & 0 & 0 & 0 & 0 & 0 & \Lambda_{SS} \end{pmatrix} \qquad f_t = \begin{pmatrix} f_t^G \\ f_t^S \\ f_t^R \\ f_t^L \\ f_t^F \\ f_t^{RT} \\ f_t^{SS} \end{pmatrix}$$

$$A = \begin{pmatrix} A_G & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & A_S & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & A_R & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_L & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & A_F & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & A_{RT} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & A_{SS} \end{pmatrix} \qquad Q = \begin{pmatrix} Q_G & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & Q_S & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & Q_R & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & Q_L & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & Q_F & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & Q_{RT} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & Q_{SS} \end{pmatrix}$$

The SSF:

$$\overline{x}_t = \begin{pmatrix} \Lambda & 0 & 0 & 0 & 0 & I_n & 0 & 0 & 0 & 0 & 0 \\ \Lambda_Q & 2\Lambda_Q & 3\Lambda_Q & 2\Lambda_Q & \Lambda_Q & 0 & 1 & 2 & 3 & 2 & 1 \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \epsilon_t^Q \end{pmatrix}$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} = \begin{pmatrix} A & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_n & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_{n_Q} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 \end{pmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \epsilon_{t-1} \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \\ \epsilon_{t-5}^Q \end{pmatrix} + \begin{pmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{15}$$

n/n_Q: number of monthly/quarterly series; $\alpha_n = diag(\alpha_1, ..., \alpha_n)$; $\alpha_{n_Q} = diag(\alpha_{Q,1}, ..., \alpha_{Q,n_Q})$.

B The Kalman Filter (KF) and Smoother

Given full SSF notation from (14) and Harvey (2006) notes on KF, we have f_{t-1} the latent true states at $t-1$ with their unconditional optimal estimate, the unconditional mean a_{t-1} using information up to and including $t-1$ and covariance matrix $P_{t-1} = \mathbb{E}[(f_{t-1} - a_{t-1})(f_{t-1} - a_{t-1})']$. The prediction equations yielding factors' expectations and the covariance at t conditional on $t-1$ information are:

$$a_{t|t-1} = T(\theta)a_{t-1} \tag{16}$$

$$P_{t|t-1} = T(\theta)P_{t-1}T(\theta)' + \Sigma_\eta(\theta) \tag{17}$$

New observations in $\overline{x}_t$ update the estimate of f_t, $a_{t|t-1}$, and the covariance through the updating equations (yielding unconditional means/variances for factors estimates):

$$a_t = a_{t|t-1} + P_{t|t-1}Z(\theta)'F_t^{-1}[\overline{x}_t - Z(\theta)a_{t|t-1}] \tag{18}$$

$$P_t = P_{t|t-1}T(\theta)' - P_{t|t-1}Z(\theta)'F_t^{-1}Z(\theta)P_{t|t-1} \tag{19}$$

where $F_t = Z(\theta)P_{t|t-1}Z(\theta)' + Q_t$. The innovation term in brackets in the first updating equation is an error between realised and predicted values. One can intuitively read the updating equations as correcting the state estimate given innovations, while the covariance, i.e. uncertainty, around the state estimate shrinks with new information. A key quantity is the Kalman gain, $P_{t|t-1}Z(\theta)'F_t^{-1}$; it provides the means for 'correcting' (updating), the state estimates and covariance when innovations become available.

The SSF, the prediction and updating equations are key in our model and enable us to exploit the timeliness of data. The updating equation helps increasing the accuracy of states estimators given incoming data, while the prediction equation forms expectations about the states in the future. The observation equation in (14) enables us go back from states representation to pure observations and form our nowcasts.

Before KF predicting and smoothing, one has to recover the parameters stored in θ. The estimation of θ is conducted through maximising the joint likelihood of the observed data. This ML estimation, the M-step in the EM algorithm of the QML, is equivalent to minimising the prediction error and variance. The log-likelihood in Harvey (2006) is:

$$LL(\overline{x}_{1,\dots,n}|\theta) = -\frac{NT}{2}\log 2\pi - \frac{1}{2}\sum_{1}^{T}\log|F_t| - \frac{1}{2}\sum_{1}^{T} v_t' F_t^{-1} v_t \tag{20}$$

where $v_t = \overline{x}_t - \mathbb{E}_{t|t-1}[\overline{x}_t]$ are innovations. Missing values in $\overline{x}_t$ are filled in, using the Kalman smoother, with $\mathbb{E}_{t|T}[\overline{x}_t]$; this data augmentation with fabricated observations is crucial in computing the joint likelihood and represents the E-step of the EM algorithm. Taking the first order conditions to maximise $LL(\overline{x}_{1,\dots,n}|\theta)$ w.r.t θ yields the expressions for the QML estimators (BGR (2010), Bańbura & Modugno 2014, Bańbura et al. 2013).

While the KF enables prediction of observed and latent data at t given prior information, the Kalman smoother yields expectations conditional on the whole information set. Filtering relies on information up to and including $t-1$ for predicting the state and, through the observation equation, the observable data in time t, i.e. $\mathbb{E}_{t|t-1}[f_t]$ and $\mathbb{E}_{t|t-1}[\overline{x}_t]$, respectively. The smoother gives the model implied expectation of states and observations at t conditional on the whole data up to T, i.e. $\mathbb{E}_{t|T}[f_t]$ and $\mathbb{E}_{t|T}[\overline{x}_t]$. Since t runs from 1 to T, the smoother is a 'backcasting' tool, crucial in filling in missing values (E-step). Forecasting/nowcasting implies using the KF – e.g. nowcasting the state with $\mathbb{E}_{T|T-1}[f_T]$, i.e. $a_{T|T-1}$, and, through the observation equation, obtaining the nowcast for the target series from the vector $\mathbb{E}_{T|T-1}[\overline{x}_T] = Z(\theta)a_{T|T-1}$.

Recursions for fixed interval smoothing from Harvey (2006):

$$a_{t|T} = a_t + P_t^*(a_{t+1|T} - Z(\theta)a_t) \tag{21}$$

$$P_{t|T} = P_t + P_t^*(P_{t+1|T} - P_{t+1|t})P_t^{*\prime} \tag{22}$$

with $P_t^* = P_t Z(\theta)' P_{t+1|t}^{-1}$, while t runs backwards from $T-1$ to 1. 'Initial conditions' starting the smoother are $a_{T|T} = a_T$ and $P_{T|T} = P_T$ stored, together with a_t and P_t, after running the data through the standard KF.

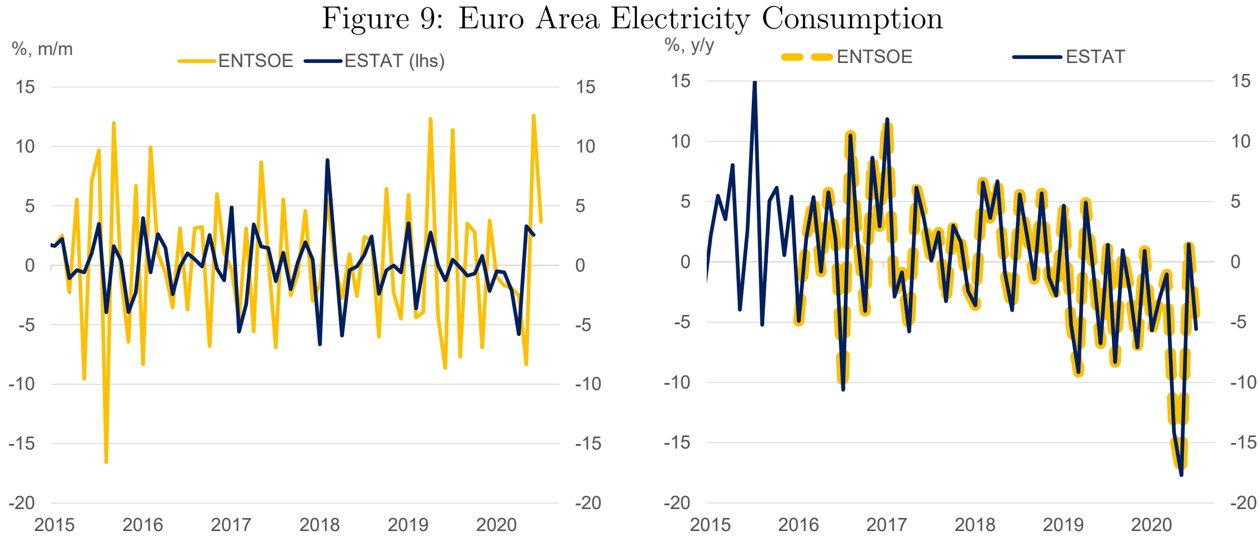
C The Dataset and Model Specifications

Table 5: Data Description and Model Specification

Series	Group	Freq.	Transf.	Pub. Lag	Week	Rich DFM	BGR (2010)	EABCN
IP, Total Industry	Real	Monthly	pch	2	2	x	x	x
IP, Manufacturing	Real	Monthly	pch	2	2	x	x	x
Retail Trade	Real	Monthly	pch	2	1	x	x	x
New Passenger Car Registrations	Real	Monthly	pch	1	3	x	x	x
Manufacturing New Orders	Real	Monthly	pch	2	3	x	x	
Extra EA Exports	Real	Monthly	pch	2	2	x	x	
Unemployment Rate	Labour	Quarterly	chg	3	1	x	x	x
Index of Employment, Total Industry ex Energy	Labour	Quarterly	pch	3	3	x	x	x
PMI Manufacturing Output	Soft	Monthly	chg	0	4	x		
PMI Manufacturing New Ord - Inventories	Soft	Monthly	chg	0	4	x		
PMI Manufacturing Capacity Utilisation	Supply Side Shocks	Monthly	chg	1	4	x		
PMI Manufacturing Headline	Soft	Monthly	chg	0	4		x	
PMI Services Headline	Soft	Monthly	chg	0	4	x		
EC Survey Industrial Confidence	Soft	Monthly	chg	0	4		x	
EC Survey Consumer Confidence	Soft	Monthly	chg	0	4		x	
EC Survey Services Confidence	Soft	Monthly	chg	0	4		x	
EC Survey Retail Confidence	Soft	Monthly	chg	0	4		x	
EC Survey Construction Confidence	Soft	Monthly	chg	0	4		x	
HICP Overall	Global	Monthly	pch	0	4	x	x	x
PPI	Global	Monthly	pch	2	1	x	x	x
EC Survey Industrial Selling Price Exp	Soft	Monthly	chg	0	4		x	
M3 Index of Notional Stocks	Financial	Monthly	pch	1	4		x	x
Lending Index	Financial	Monthly	pch	1	4		x	
DJ Euro Stoxx Broad	Financial	Monthly	pch	0	4	x	x	x
3-month EURIBOR	Financial	Monthly	chg	0	4	x	x	x
Narrow Effective Exchange Rate	Financial	Monthly	pch	0	4		x	
EA RGDP Chained	Real	Quarterly	pch	3	4	x	x	x
Employment	Labour	Quarterly	pch	3	2	x	x	x
EC Survey Industry Expected Constraints	Supply Side Shocks	Quarterly	chg	0	4	x		
EC Survey Capacity Utilisation Index	Supply Side Shocks	Quarterly	chg	0	4	x		x
EC Survey Capacity Utilisation Services	Supply Side Shocks	Quarterly	chg	0	4	x		
US RGDP	Global	Quarterly	pch	2	4		x	
Unit Labor Costs	Labour	Quarterly	pch	3	2		x	
Compensation per Employee	Labour	Quarterly	pch	3	2		x	
Augmented Credit Impulse (levels)	Financial	Monthly	chg	2	2	x		
Real Time Electricity Consumption ENTSOE	Real Time	Monthly	pch	0	4	x		
EUROSTAT Electricity Consumption	Real Time	Monthly	pch	2	2	x		
Google Trends Autos & Vehicles	Real Time	Monthly	chg	0	4	x		
Google Trends Finance	Real Time	Monthly	chg	0	4	x		
Google Trends Shopping	Real Time	Monthly	chg	0	4	x		
Google Trends Travel	Real Time	Monthly	chg	0	4	x		
Google Trends Short-time Work	Labour	Monthly	chg	0	4	x		
Google Trends Unemployment	Labour	Monthly	chg	0	4	x		
ECB Total Hours Worked	Labour	Quarterly	pch	3	2	x		
ECB Hours Worked Per Employee	Labour	Quarterly	pch	3	2	x		
ESTAT Total Hours Worked	Labour	Quarterly	pch	3	4	x		
Germany Trucks Toll Index	Soft	Monthly	pch	0	4	x		

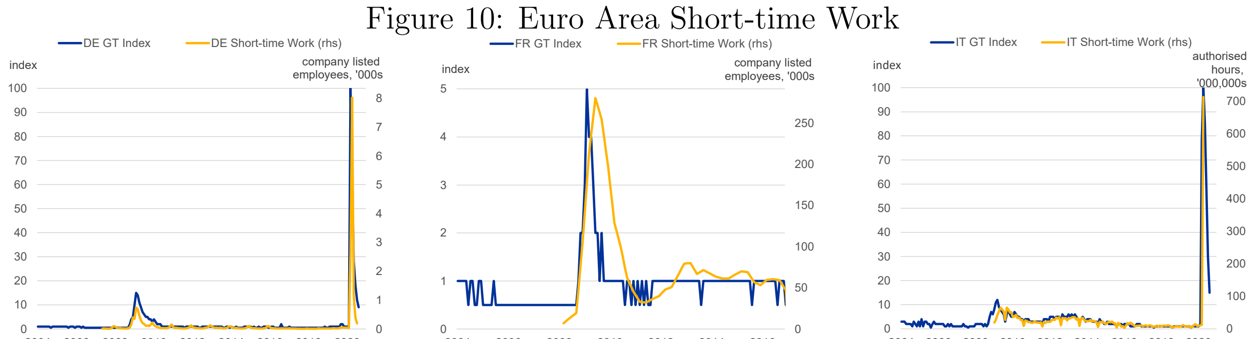
"Group" refers to the factor block which the series is loaded on, by default all variables being loaded on the Global factor, most of them having loadings on other narrow factors, too. The two possible transformations applied to the series are monthly percentage changes ("pch") or monthly changes ("chg"). Publication lags and the specific week indicate the lag, with respect to the running month, and the week of the month when the data are finally published, needed for the stylised calendar. We label our specification "Rich DFM" while the benchmark from the literature "BGR (2010)"; note that our DFM has its specific factors structure and for BGR's (2010) specification we use the structure from the original paper. We start from a panel of 90 series but through systematic trial and error end up with a panel of dimensions $(N, T) = (34, 249)$. EABCN column indicates the availability of series in the EABCN RTDB, or lack thereof.

Figure 9: Euro Area Electricity Consumption



Source: Haver Analytics, Author's Calculations.
Latest Observation: July-2020.

Figure 10: Euro Area Short-time Work



Source: Haver Analytics, Google Trends, DARES, Cassa Integrazzione, Author's Calculations.
Latest Observation: August-2020.

D Details of the Empirical Results

Table 6: Full Results of the Pseudo Out-of-sample Nowcasting Evaluation

	Recursive 2000-2011			**Recursive 2000-2013**			**Fixed 2000-2013**		
	RMSE	**KS**	**MKS**	**RMSE**	**KS**	**MKS**	**RMSE**	**KS**	**MKS**
Naïve AR(1) Forecast	0.70	0.63	0.24	0.78	0.01	0.19	0.77	0.01	0.12
PMI-based tracker	0.24	0.96	0.53	0.22	1.00	0.53	0.21	1.00	0.53
BGR (2010) nowcast	0.71	0.46	0.29	0.80	-0.04	0.34	0.81	-0.04	0.27
Rich DFM nowcast	0.20	0.50	0.64	0.18	1.00	0.71	0.19	1.00	0.64

Headers indicate the type of estimation and the time span of the used sample for the training of underlying models and parameters estimation. Results are raw, not relative to the metrics obtained from the same exercise applied for predictions made with a naïve AR(1) model. Formulae for the Root Mean Squared Error (RMSE), the Kuiper Score (KS) and our proposed modification of it (MKS) are presented in the appendix, where raw statistics for all models are also included. Forecast evaluation metrics are calculated on windows starting after the endpoint of the estimation sample, also simulating the real-time data availability pattern at each point in time where a nowcast is computed, but abstracting from data revisions (pseudo real-time forecasting). Results of the pseudo out-of-sample exercise are based on a vintage of data available at the end of June 2020.

$$RMSE = \sqrt{\frac{\{y_{target} - \mathbb{E}_T[y_{target}]\}^2}{T}}$$

In answering whether the prediction accuracy significantly differs between models, we use the Diebold-Mariano (DM) test, yet remain cautious on its interpretation. Diebold & Mariano (2002) introduced the method which relies on the loss function associated with the exercise – here, the squared error $L(y_{target}, \mathbb{E}_T[y_{target}]) = L(e_{target}) = \{y_{target} - \mathbb{E}_T[y_{target}]\}^2$. It then tests the null of equal expected loss, $\mathbb{E}[L(e^a_{target})] = \mathbb{E}[L(e^b_{target})]$, against the alternative (different accuracy). The DM test is based on the loss differential $d_{target,T} = L(e^a_{target}) - L(e^b_{target})$, testing $H_0 : \mathbb{E}[d_{target}] = 0$ vs. $H_a : \mathbb{E}[d_{target}] \neq 0$. The test is concerned with population quantities, but is conducted using sample counterparts:

$$DM = \frac{\overline{d}}{\sqrt{avar(\overline{d})}} = \frac{\overline{d}}{\sqrt{LRV_{\overline{d}}}} \sim N(0,1)$$

with $\overline{d} = \frac{1}{N}\sum_{i=1}^{N} d^i_{target,T}$, $LRV_{\overline{d}} = \gamma_0 + 2\sum_{k=1}^{\infty}\gamma_k$ and $\gamma_k = \text{cov}(d_{target}, d_{target-k})$; N denotes the number of nowcasts computed. Hence, the test is not ideal for small samples, as it is the case in our analysis.

Harvey, Leybourne & Newbold (1997) suggest modifying the DM, but their HLN test does not fully address small sample issues either. We use it following $HLN = DM \times k$ where $k = \{[N + 1 - 2 \times h + h \times (h-1)/N]/N\}^{1/2}$ and h denotes the horizon for the nowcast computation.

Table 7: Events and Outcomes for the KS (MKS)

		Outcomes	
		Up $y_t \geq 0$ ($y_t \geq y_{t-1}$)	**Down** $y_t < 0$ ($y_t < y_{t-1}$)
Forecasts	**Up** $\mathbb{E}_t[y_t] \geq 0$ ($\mathbb{E}_t[y_t] \geq y_{t-1}$)	Hits N_{uu}	False Alarm N_{ud}
	Down $\mathbb{E}_t[y_t] < 0$ ($\mathbb{E}_t[y_t] < y_{t-1}$)	Misses N_{du}	Correct Rejection N_{dd}

Note the headers indicate in parantheses the definition of events and outcomes for the MKS as well

The qualitative criteria we use are Kuiper's Score (KS) and our proposed modification of it (MKS), aiming to assess the ability of our models to correctly identify economic events from non-events, checking whether the models are correctly distinguishing booms/recessions and accelerations/decelerations. We define events and outcomes below and compute the scores as a differential between the proportion of correct hits, H, and false alarms, F; $H = \frac{N_{uu}}{N_{uu}+N_{du}}$ and $F = \frac{N_{ud}}{N_{ud}+N_{dd}}$.