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Back to the present: Learning about the euro area through a now-casting model[☆]

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ABSTRACT

We build a multi-country model for simultaneously nowcasting economic conditions in the euro area and its three largest member countries—Germany, France, and Italy. The model formalizes how market participants and policymakers monitor in real time both euro-area and country-specific market-moving indicators. The out-of-sample evaluation corroborates the usefulness of a multi-country approach to monitor the euro area. Indeed, the model provides accurate real-time predictions of economic conditions both on average and in the past three recessions, while finding that soft data are timely and intrinsically informative.

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1. Introduction

The most comprehensive indicator of economic activity—gross domestic product (GDP)—is typically measured at a quarterly frequency and released with a substantial delay.¹ However, economists are still left with the arduous task of monitoring the economy accurately and in a timely manner. In the euro area, this task is particularly challenging for two reasons documented in this paper. First, economists follow a multi-country approach: not only do market participants track macroeconomic indicators about both the euro-area aggregate and its largest countries, but also policymakers build euro-area forecasts from projections for individual countries.² Second, hard

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¹ For example, in the euro area and the United States, GDP is currently first released about 30 days after the end of the reference quarter. However, until 2015, the euro-area GDP was first released about 45 days after the end of the reference quarter.

² For instance, see “A guide to the Eurosystem/ECB staff macroeconomic projection exercises” (2016). The monitoring of regional

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data are released with a substantial delay compared to other economies. Thus, market participants closely track soft data, such as confidence surveys, that provide timely snapshots about economic activity.

We propose a multi-country econometric framework to nowcast economic activity and use it to formalize how market participants and policymakers simultaneously monitor economic conditions of the euro-area aggregate and its three largest member countries—Germany, France, and Italy. We find three main results. First, the model improves the nowcasting performance relative to single-economy models, and captures real-time cross-country spillovers and co-movements. Model predictions are informative about not only whether each economy is slowing down or accelerating, but also whether this is happening simultaneously. Second, data releases from a specific country lead to sizable GDP nowcasting revisions not only for that country, but also for other euro-area countries and the region aggregate. Similarly, data releases from the region aggregate lead to sizable GDP nowcasting revisions for the countries. Third, soft data releases lead to sizable GDP nowcasting revisions, especially in the weeks leading to the start of the quarter.

To illustrate our three main results, we relive the eve of the European sovereign debt crisis using our nowcasting model (Fig. 1). Specifically, we focus on nowcasting the euro-area 2011Q3 GDP growth, as the start of the recession that followed.³ Starting in June 2011, the model estimates a sharp decline in GDP growth in the euro area that was also pervasive across member countries (top panel). Fig. 1 also illustrates how country-specific data are important for nowcasting the euro-area aggregate GDP, and vice versa (middle panel). When we decompose the weekly nowcasting revisions of euro-area GDP growth between those from aggregate (blue bars) and country-specific data, the latter lead to sizable revisions to GDP growth. It should not be surprising that economists simultaneously monitor data of the euro area and its major countries. Business cycle fluctuations of these economies are well synchronized (see, e.g., Giannone, Lenza, & Reichlin, 2010), and hence news about individual economies may carry important signals about other economies and the whole euro area. Angelini, Lalik, Lenza, and Paredes (2019), Dieppe, González Pandiella, and Willman (2012), Marcellino, Stock, and Watson (2003), and Albonico et al. (2019) showed the importance of a multi-country approach for forecasting and scenario analysis in the euro area. However, in the context of *real-time* nowcasting of economic activity, scholars and policy institutions have focused on single-economy models and thus overlooked multi-country frameworks.⁴

information has also been given less attention in other monetary unions. The Bureau of Economic Analysis only started publishing quarterly GDP for U.S. states in December 2015, with a longer delay than the aggregate figures, and Bloomberg relevance indexes are not available for these statewide releases.

³ We use the classification from the Centre for Economic Policy Research (CEPR).

⁴ Section 3 lists several papers on nowcasting the euro area economy and its member countries.

Turning to the importance of soft data for nowcasting the euro area, we find that this result arises because these data are both timely and intrinsically informative about GDP growth. Using our model, we decompose weekly nowcasting revisions of GDP growth originating from either soft or hard data. We estimate that releases of soft data typically lead to much larger nowcasting revisions than those from hard data. However, the importance of soft data may depend not only on their intrinsic relationship with GDP growth, but also on the timeliness of their release (see, e.g., Giannone, Reichlin, & Small, 2006 and Gilbert, Scotti, Strasser, & Vega, 2017). Thus, we build a counterfactual dataset in which the release of hard data is anticipated for a schedule similar to the United States. Still, we continue to find that soft data lead to the majority of nowcasting revisions of GDP in this counterfactual calendar schedule. While the importance of soft data for monitoring euro-area aggregate activity has been highlighted before (e.g., Giannone, Reichlin, & Simonelli, 2009 and Bańbura & Rünstler, 2011b), our multi-country framework and the weekly frequency of our results provide a comprehensive accounting of the relevance of soft data across countries and time. The lower panel of Fig. 1 exemplifies these results on the eve of the European sovereign debt crisis: using our model, the timely soft data releases from June to August 2011 lead to sizable downward revisions (blue bars) in the estimates for 2011Q3 GDP growth, while hard data lead to small revisions (pink bars) that mostly reinforce the previously conveyed economic deterioration.

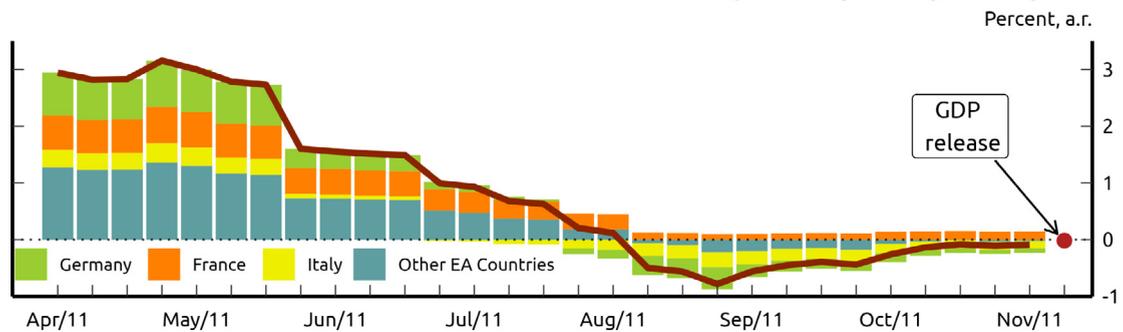
Finally, we show that our multi-country nowcasting model produces accurate predictions for the euro area and its three major countries during their past three recessions. These results come from three key features of our framework. First, it uses a large set of market-moving indicators for the euro area and its three largest economies, totaling 58 data series. We can then interpret the importance of these releases in real time for nowcasting all four economies, showing a sizable dynamic interaction between these economies and corroborating the view from practitioners that it is efficient to monitor the euro area and its major countries simultaneously. Second, our model explicitly accounts for the lead-lag relationship in the economic activity of the euro area and its main countries. This feature allows us to capture the dynamic heterogeneity of business-cycle fluctuation across countries. Third, the model handles non-synchronous data releases, exploiting the tradeoff between timeliness and data quality.

The remainder of our paper is organized as follows. In Section 2, we document which euro-area data releases are tracked by market participants. In Section 3, we describe our nowcasting model. In Section 4, we discuss the main nowcasting results of the paper. In Section 5, we relive the past three recessions of the euro area, showing that our model performs well at anticipating economic conditions in these periods. Section 6 concludes.

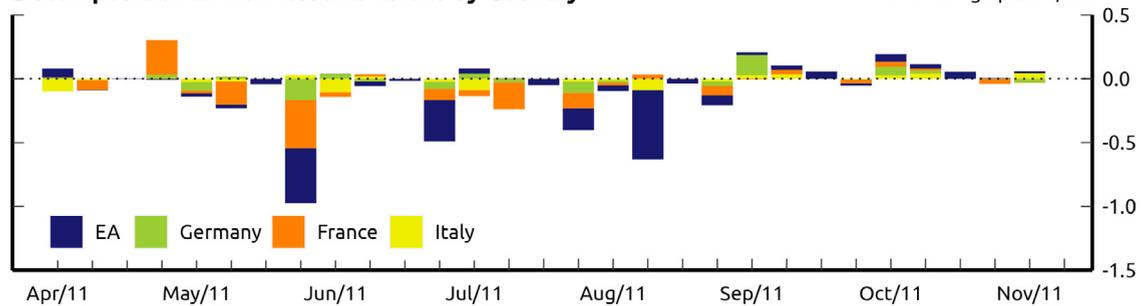
2. Data flow of the euro area

In this section, we document which euro-area macroeconomic indicators economists closely monitor on a daily basis, and discuss the timeliness of these indicators.

Evolution of Estimates of Euro-Area Real GDP Growth in 2011Q3 Decomposed by Country



Decomposition of Now-cast Revisions by Country



Decomposition of Now-cast Revisions by Data

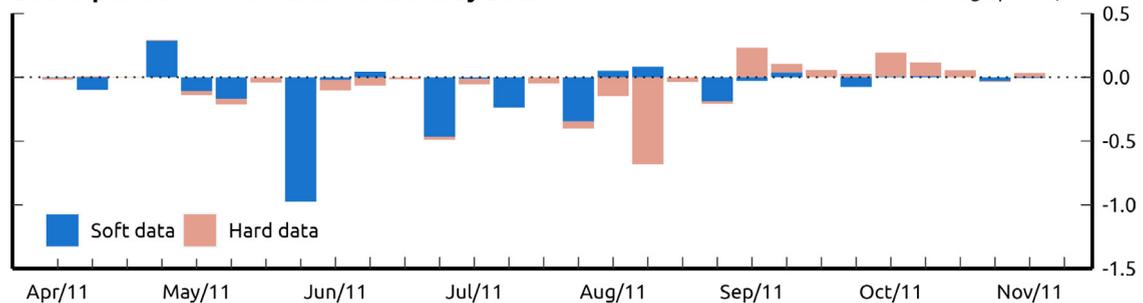


Fig. 1. Euro-area GDP growth on the eve of its sovereign debt crisis.

Note: The top panel presents weekly out-of-sample forecasts from our nowcasting model. The red dot in the top panel represents the euro-area quarterly GDP growth of 2011Q3. The middle panel presents the decomposition of the model forecast revisions by the country of origin of the data, whereas the bottom panel presents revisions by hard/soft data. Revisions due to estimation updates are not shown. More details are given in Sections 3 and 4.

2.1. What euro-area data do economists monitor?

In the euro area, similar to the United States, there is a large daily flow of data releases revealing information about the state of the macroeconomy, and these releases receive major attention from economists in business, the media, and policy institutions. These economists aim at disentangling movements that are idiosyncratic to particular data releases from those signaling broad-based fluctuations in economic activity. For instance, policymakers try to anticipate economic downturns because their policy responses either take time to be negotiated (e.g., fiscal policy) or have long delays in their economic effects (e.g., monetary policy, as shown in [Christiano, Eichenbaum, & Evans, 1999](#)), while market participants build

portfolios of financial assets whose performance depends on the state of the macroeconomy. Economists then carefully monitor the economy using a longstanding iterative approach: (i) using all available information, they form expectations about incoming GDP growth and soon-to-be-released key economic indicators; (ii) once a key indicator is released, they evaluate whether it was better or worse than expected and then return to step (i). Indeed, when data releases differ from market participants' expectations, asset prices move in a statistically and economically significant way (e.g., [Altavilla, Giannone, & Modugno, 2017](#)).

What are the macroeconomic data releases that keep economists monitoring their computer screens during workdays? We answer this question using the Bloomberg

relevance index, which calculates the percentage of Bloomberg users that set an automatic alert notifying them of a specific data release. We focus on variables with a Bloomberg relevance index above 50%, with most of these variables also marked on the Bloomberg website as “Market Moving Indicators”.⁵ Table 1 reports the economic indicators collected, with the corresponding Bloomberg relevance index from November 2019 in column (7).⁶ For instance, the GDP release has an index of 90% for the euro-area aggregate, 89% for France, 80% for Germany, and 86% for Italy.⁷ The great majority of the variables are monthly, with the only quarterly data being real GDP growth. Moreover, most variables are “headline” series, indicating that economists’ data expertise leads them to view disaggregated data as not routinely important to monitor the economy, which is also consistent with the econometric evidence.⁸ Additionally, statistical offices and private survey owners release most of their series under a format that is stationary, and we apply additional transformations only in a few cases.

Our selection criterion shows that economists track a large number of economic indicators, about both the euro-area aggregate and its major countries. In fact, our dataset has 58 indicators: 15 for Germany, 16 for France, 14 for Italy, and 13 for the euro-area aggregate; and the relevance index for many variables, such as GDP and retail sales, has similar magnitudes for the euro area and its major countries.⁹ This multi-country aspect of our dataset signals that economists internalize that key euro-area aggregate economic variables are constructed from country-specific data, and policymakers build their forecasts by aggregating those for euro-area economies. For example, Eurostat builds the flash estimate of the euro-area GDP by aggregating its members’ GDP data, instead of collecting data directly at the aggregate level, while the ECB and the European Commission follow procedures under which their forecasts for the eurozone are aggregates of those from individual countries.¹⁰ These methodologies point to the importance of simultaneously tracking data from both the euro area and its major countries not only to understand regional developments, but also to forecast them.

⁵ We allow for some exceptions to this rule, to include similar indicators across the different economies. For example, while euro-area and German imports are below 50%, Italian and French imports are above.

⁶ McCoy, Modugno, Palazzo, and Sharpe (2020) use the relevance index to weight macroeconomic surprises in an index that explains a large portion of stock return variation over the FOMC cycle.

⁷ The relevance index has changed only a handful of times over our sample, and only by a few basis points. Accordingly, we use the last available figures.

⁸ For more details, see Bańbura, Giannone, and Reichlin (2010, 2011), Bańbura and Modugno (2010), and Bańbura and Modugno (2014).

⁹ For variables about the whole euro-area economy, we use variables aggregating the 19 countries that adopted the euro as their single currency. In a few exceptions, euro-area variables are not available, so we use those defined for the European Union.

¹⁰ For details about Eurostat’s flash estimate, see [PreliminaryGDPflashestimatein30daysforEurope](#). For details about the ECB’s forecast, see [“AguidetotheEurosystem/ECBstaffmacroeconomicprojectionexercis”\(2016\)](#). The European Commission provides additional information [here](#).

Importantly, the multi-country approach for the euro area stands in stark contrast to the one used by economists monitoring U.S. data, where state-specific counterparts of market-moving aggregate data, such as GDP, consumption, and employment, are not closely followed by market participants and are published with either long delays, short historical series, or annual frequency.¹¹

Our dataset also shows that economists track variables representing many different sectors of the euro-area economy, as well as different types of data, such as hard and soft data. For instance, economists closely monitor variables about labor markets (e.g., the unemployment rate), the industrial sector (e.g., the index of industrial production, and industrial turnover), the construction sector (e.g., the index of production in construction), private consumption (e.g., retail sales and car registrations), and the external sector (e.g., exports and imports of goods). However, economists look beyond these *hard data*—that is, data collected by statistical agencies based on measurable quantities. They also closely monitor *soft data*—survey indexes that portray the feelings and perceptions of economic agents about current and future economic prospects. Among the many monitored soft data sources are the purchasing managers’ index (PMI) on large companies’ economic perspectives, and the European Commission’s indexes on consumer confidence and business climate.¹²

It is important to point out that we intentionally left out daily and weekly indicators, such as financial variables. As shown in Bańbura, Giannone, Modugno, and Reichlin (2013), such data do not improve the performance of a nowcasting model either during normal times or during the Great Recession, due to their noisy nature and their detachment from the real economy, if not for their low frequencies. We also left out some alternative types of data, such as from web searches, electronic transactions, and textual analyses. The ability of these alternative sources to improve timely estimates of economic activity is still subject to debate. For example, Larson and Sinclair (2020) showed that Google Trends do not improve the accuracy of unemployment insurance claims nowcasts in normal times or in the time of Covid-19. However, we leave these avenues for future research. In this paper, we focus on formalizing how market participants monitor the euro-area data, and especially on the roles of the multi-country dimension and of soft data in a traditional nowcasting setting.

¹¹ For instance, Bloomberg relevance indexes are not available for U.S. states’ GDPs. Additionally, when the Bureau of Economic Analysis started publishing U.S. states’ quarterly GDPs in 2015, the data were released, on average, five months after the end of the quarter. Currently, statewide GDPs are released after three months, and unemployment rates after 20 days (compared to five days for the national figure). State-specific personal consumption expenditure is published at an annual frequency.

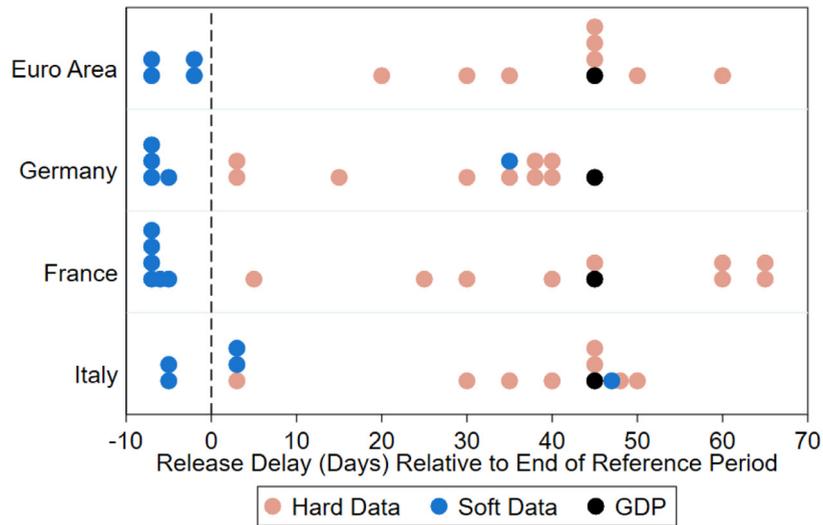
¹² In the surveys underlying these indexes, respondents generally answer questions on whether a particular economic condition improved, remained stable, or worsened. Final indexes are then weighted averages of responses, indicating the improvement or worsening of sectoral conditions.

Table 1
Macroeconomic variables, release delays, and relevance indexes.

Country	Series name	Units	Freq.	Transf.	Delay	Relevance	Category
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EA	Gross Domestic Product	SWDA, Mil.Ch.2010.EUR	q	pca	45	92.5	Hard
EA	Unemployment Rate	SA, %	m	lin	30	67.5	Hard
EA	Industrial Turnover: Manufacturing	SWDA, 2015=100	m	pch	60	75	Hard
EA	IP: Industry excl Construction	SA/WDA, 2015=100	m	pch	45	62.5	Hard
EA	Industrial Production: Construction	SA/WDA, 2015=100	m	pch	50	15	Hard
EA	PMI: Manufacturing Flash	SA, 50+=Expansion	m	lin	-7	90	Soft
EA	PMI: Services Business Activity Flash	SA, 50+=Expansion	m	lin	-7	70	Soft
EA	Retail Sales Volume Index	SA/WDA, 2015=100	m	pch	35	50	Hard
EA	Consumer Confidence Indicator, % Balance	SA, %	m	lin	-2	75	Soft
EA	Business Climate Indicator	SA, std-dev pts	m	lin	-2	30	Soft
EA	Exports of Goods	SA/WDA,Thous.EUR	m	pch	45	82	Hard
EA	Imports of Goods	SA/WDA, Thous.Euros	m	pch	45	25	Hard
EA	EU 28 excl Malta: New Passenger Car Registrations	NSA, Units	q	pc1	20	45	Hard
FR	Gross Domestic Product	SWDA Mil.Chn.2014.Euros	q	pca	45	89	Hard
FR	Registered Unemployed: Act. Seeking, Not Working	SWDA, EOP, Thous	m	pch	25	37	Hard
FR	New Passenger Car Registrations	NSA, Units	m	pc1	5	90	Hard
FR	Industrial Production: Manufacturing	SA/WDA, 2005=100	m	pch	40	60	Hard
FR	Industrial Production: Construction	SA/WDA, 2005=100	m	pch	45	60	Hard
FR	HH Consumption Exp: Total Manufactured Goods	SA/WDA, Bil.chn.2005.Euros	m	pch	30	17	Hard
FR	Business Survey: Order Books & Demand, Manuf.	SA, % Balance	m	lin	-7	11	Soft
FR	Turnover: Manufacturing	SWDA, 2005=100	m	pch	60	11	Hard
FR	PMI: Manufacturing Flash	SA, 50+=Expansion	m	lin	-7	97	Soft
FR	PMI: Services Flash	SA, 50+=Expansion	m	lin	-7	77	Soft
FR	Retail Sales Vol. excl Motor Vehic. & Motorcyc.	SWDA, 2005=100	m	pch	60	55	Hard
FR	Household Survey: Overall Household Conf. Ind.	SA, LT Avg=100	m	lin	-5	80	Soft
FR	BdF Mo Bus Survey: Business Sentiment Indicator	SA, Long-term Avg=100	m	lin	-6	51	Soft
FR	Composite Business Climate Indicator	NSA, LT Avg=100	m	lin	-7	11	Soft
FR	Total Imports including Military Equipment	SA, Mil.Euros	m	pch	65	54	Hard
FR	Total Exports including Military Equipment	SA, Mil.Euros	m	pch	65	51	Hard
GE	Gross Domestic Product	SWDA Bil.Chn.2015.Euros	q	pca	45	80	Hard
GE	Registered Civilian Unemployment Rate	SA, %	m	lin	3	68	Hard
GE	Job Vacancies [Unsubsidized]	SA, Thous	m	pch	3	68	Hard
GE	Industrial Production including Construction	SA/WDA, 2005=100	m	pch	38	92	Hard
GE	Industrial Production: Construction	SA/WDA, 2005=100	m	pch	38	92	Hard
GE	Manufacturing Orders [Volume]	SA/WDA, 2005=100	m	pch	35	91	Soft
GE	Industry Sales [Volume]: Manufacturing	SA/WDA, 2005=100	m	pch	35	91	Hard
GE	New Passenger Car Registrations	NSA, Number	m	pc1	15	48	Hard
GE	PMI: Manufacturing Flash	SA, 50+=Expansion	m	lin	-7	90	Soft
GE	PMI: Services Flash	SA, 50+=Expansion	m	lin	-7	73	Soft
GE	Retail Sales Volume excl Motor Vehicles	SWDA, 2005=100	m	pch	30	62	Hard
GE	Ifo Business Climate Index: All Sectors	SA, 2005=100	m	lin	-7	98	Soft
GE	GfK Consumer Climate	SA, %	m	lin	-5	92	Soft
GE	Exports of Goods	SA, Bil.Euros	m	pch	40	98	Hard
GE	Imports of Goods	SA, Bil.Euros	m	pch	40	44	Hard
IT	Gross Domestic Product	SA/WDA, Mil.Chn.2010.EUR	q	pca	45	86	Hard
IT	Harmonized Unemployment Rate	SA, %	m	lin	30	56	Hard
IT	Production in Construction	SA, 2005=100	m	pch	48	97	Hard
IT	IP: Total Industry excl Construction	SA/WDA, 2005=100	m	pch	40	94	Hard
IT	Manufacturing Orders	SA, 2005=100	m	pch	47	62	Soft
IT	Industrial Turnover	SA, 2005=100	m	pch	50	62	Hard
IT	Passenger Car Registrations	NSA, Units	m	pc1	3	37	Hard
IT	PMI: Manufacturing	SA, 50+=Expansion	m	lin	3	90	Soft
IT	PMI: Services: Business Activity	SA, 50+=Expansion	m	lin	3	70	Soft
IT	Retail Sales excl Motor Vehicles & Motorcyc. Value	SA, 2005=100	m	pch	35	72	Hard
IT	ISAE Consumer Confidence Indicator	SA, 1980=100	m	lin	-5	90	Soft
IT	ISAE Business Confidence Indicator	SA, 2005=100	m	lin	-5	55	Soft
IT	Merchandise Exports, fob	SA, Mil.Euros	m	pch	45	93	Hard
IT	Merchandise Imports, cif	SA, Mil.Euros	m	pch	45	74	Hard

Note: This table provides the list of variables in our dataset. Moreover, for each variable, it provides the following details: the economy to which the variable belongs; unit of measurement; observation frequency; transformation applied to the data; release delay, measured by the average days elapsed from the end of the reference period (month/quarter) to the date of the data release; Bloomberg relevance index; and category to which the variable belongs (soft/hard data). For most of our sample, GDP was released with an average delay of 45 days. After October 2015, the publication delay for GDP diminished to an average of 30 days.

(a) Release Delay of Variables by Country and Data Type



(b) Release Delay of Hard Data Variables: Euro Area and United States

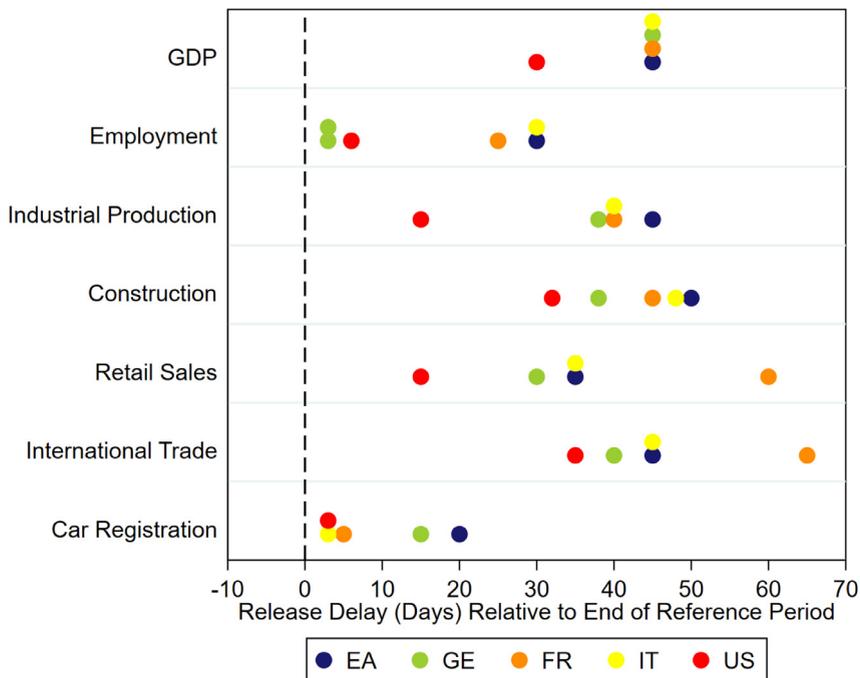


Fig. 2. Timeliness of euro-area data.

Note: The figures above present the release delay of the variables included in our dataset. In both figures, we measure the release delay by the average days that elapse from the end of the reference period (month/quarter) to the date of the data release. For monthly data, the end of the period is the last day of the month, while for quarterly data it is the last day of the quarter. Fig. 2(a) includes all variables in our dataset sorted by the economy to which they refer (rows). Fig. 2(b) focuses on major hard data variables, including the release delay for United States variables.

2.2. Timeliness of the euro-area data

One feature of our dataset is that soft data for the euro area are available in a timely manner, while hard data are often released with a delay that is not only long but also longer than their U.S. counterparts. Fig. 2(a) shows the release delay of each variable in our dataset, sorted by the economy to which it refers (rows). We measure the

release delay by the average days that elapse from the end of the reference period (month/quarter) to the date of the data release. For monthly data, the end of the period is the last day of the month, while for quarterly data it is the last day of the quarter. Fig. 2(a) shows that 31 out of 38 hard data variables (pink and black dots) are released with a delay of at least 30 days, with these dots clustered on the right-hand side of the figure. In contrast, 16 out of

20 soft data variables (blue dots) are released before the end of the month (dots clustered in the left-hand side of the figure), consistent with the release delays of the soft data of other advanced economies.¹³ Fig. 2(b) compares the release delay of major hard data variables (rows) across euro-area economies and the United States. The figure shows that U.S. variables (red dots) are most often released much earlier than their euro-area counterparts. Graphically, we see that most U.S. variables (red dots) are to the left of the euro-area variables (blue, green, orange, and yellow dots).

Finally, we learn from our dataset that country-specific and euro-area aggregate hard data are released asynchronously. Fig. 2(b) shows that, for most variables, the data of at least one major euro-area country are released before the data for the euro-area aggregate. This feature points to a potential gain in nowcasting euro-area aggregate GDP using country-specific information. There are also euro-area aggregate variables that are released before their country counterparts, such as retail sales and international trade. This property also points to possible gains in using euro-area aggregate data to nowcast countries' GDP.¹⁴

3. Econometric framework

In this section, we propose a multi-country nowcasting model for the euro-area aggregate and its major countries—Germany, France, and Italy—in contrast to other scholars who have generally focused on single-economy nowcasting models, including for the euro-area aggregate and its member countries.¹⁵

¹³ For instance, flash PMIs are released for many advanced countries, such as Canada and United Kingdom, between 10 days before and a couple days after the end of the reference month.

¹⁴ The release of soft data is relatively synchronous across euro-area economies, leading us to focus on hard data in Fig. 2(b).

¹⁵ This class of models has been successfully employed for nowcasting economic conditions in many economies: the United States (Antolin-Diaz, Drechsel, & Petrella, 2020; Bańbura et al., 2013; Bok, Caratelli, Giannone, Sbordone, & Tambalotti, 2018; Giannone, Reichlin, & Small, 2008; Lahiri & Monokroussos, 2013), Brazil (Bragoli, Metelli, & Modugno, 2015), Canada (Bragoli & Modugno, 2017), China (Yiu & Chow, 2010; Giannone, Agrippino, & Modugno, 2013), the Czech Republic (Arnostova, Havrlant, Růžička, & Tóth, 2011), Japan (Bragoli, 2017; Hayashi & Tachi, 2020), New Zealand (Matheson, 2010), Norway (Aastveit & Trovik, 2012; Luciani & Ricci, 2014), Switzerland (Siliverstovs, 2012), Turkey (Modugno, Soybilgen, & Yazgan, 2016), and the United Kingdom (Anesti, ao, & Miranda-Agrippino, 2018). For the euro area, researchers have developed separate models for the euro area and individual countries, ignoring cross-country information. In particular, nowcasting models for the aggregate euro area have been proposed by Angelini, Bańbura, and Rünstler (2010), Angelini, Camba-Mendez, Giannone, Reichlin, and Rünstler (2011), Bańbura et al. (2011), Bańbura and Modugno (2014), Bańbura and Rünstler (2011a), Camacho and Perez-Quiros (2010), and Carriero, Galvão, and Kapetanios (2019). Barhoumi, Darné, and Ferrara (2010) and Bessec and Doz (2014) applied the same framework for France. Andreini, Senftleben-König, Hasenzagl, Reichlin, and Strohsal (2020), Marcellino and Schumacher (2010) developed a model for Germany, de Antonio Liedo (2015) for Belgium, and D'Agostino, McQuinn, and O'Brien (2012) for Ireland. Rünstler et al., 2009 and Jansen, Jin, & de Winter, 2016 consider several European countries. Bańbura et al. (2013, 2011), Bok et al. (2018), Luciani (2017), Stock and Watson (2017) provide surveys of the literature on nowcasting.

3.1. Multi-country nowcasting model

Our nowcasting model is a dynamic factor model (DFM) that decomposes every economic indicator into three parts: (i) an euro-area component driven by a factor that affects all euro-area aggregate variables, (ii) a country-specific component driven by a factor that affects all variables from the specific country, and (iii) an idiosyncratic component driven by indicator-specific shocks.

More precisely, we specify our model as follows:

$$\mathbf{y}_t = \mathbf{A} \cdot \mathbf{F}_t + \mathbf{e}_t, \quad (1)$$

$$\mathbf{F}_t = \mathbf{A} \cdot \mathbf{F}_{t-1} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \text{i.i.d. } N(\mathbf{0}, \mathbf{Q}), \quad (2)$$

$$\mathbf{e}_t = \mathbf{D} \cdot \mathbf{e}_{t-1} + \mathbf{v}_t, \quad \mathbf{v}_t \sim \text{i.i.d. } N(\mathbf{0}, \mathbf{R}), \quad (3)$$

where \mathbf{y}_t denotes all monthly and quarterly standardized economic indicators; \mathbf{F}_t comprises the euro-area and country-specific factors; \mathbf{A} represents the loadings of economic indicators on the factors; \mathbf{A} represents the autoregressive matrix of the factors (in companion form); and \mathbf{D} and \mathbf{R} are diagonal matrices. We then assume a block structure in which each economic indicator loads only on its economy-specific factor:

$$\begin{bmatrix} \mathbf{y}_t^{ea} \\ \mathbf{y}_t^{fr} \\ \mathbf{y}_t^{ge} \\ \mathbf{y}_t^{it} \end{bmatrix} = \begin{bmatrix} \mathbf{A}^{ea} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{fr} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}^{ge} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{A}^{it} \end{bmatrix} \begin{bmatrix} \mathbf{f}_t^{ea} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{it} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_t^{ea} \\ \mathbf{e}_t^{fr} \\ \mathbf{e}_t^{ge} \\ \mathbf{e}_t^{it} \end{bmatrix}, \quad (4)$$

where we partition the data \mathbf{y}_t into indicators from the euro-area aggregate (\mathbf{y}_t^{ea}), Germany (\mathbf{y}_t^{ge}), France (\mathbf{y}_t^{fr}), and Italy (\mathbf{y}_t^{it}). We assume one factor per economy: euro-area aggregate (\mathbf{f}_t^{ea}), Germany (\mathbf{f}_t^{ge}), France (\mathbf{f}_t^{fr}), and Italy (\mathbf{f}_t^{it}). And we partition the idiosyncratic shocks \mathbf{e}_t and factor loadings \mathbf{A} on a per “country” basis, analogous to Eq. (4). This specification also assumes that all observable variables are coincident indicators for the common factors, and that the euro-area and country-specific common factors, Eq. (2), evolve as a vector auto regression with one lag, VAR(1).¹⁶

We devise our multi-country nowcasting model to capture the rich data dynamics and cross-country spillovers of the euro area, with the following intuition for our main assumptions. First, via a block structure, we stipulate that the data of each one of the four economies depend only on its own economy-specific factor, thus preserving the relationship between the economy's underlying data and its economy-specific factor. Second, we model the economy-specific factors with a VAR(1), which then allows euro-area economies leading in the business cycle to improve the nowcasting of lagging economies. Specifically, the euro-area aggregate factor can affect country-specific variables, while a country-specific factor can spill over to other country-specific variables, as well

¹⁶ This assumption amounts to restricting monthly observable variables to load only on the contemporaneous value of the common factors, and quarterly variables to load on the contemporaneous value and the first four lags of the common factors. Additionally, the loadings of quarterly variables are subject to the restriction that coefficients are proportional and satisfy the monthly to quarterly growth rate aggregation of Mariano and Murasawa (2003).

as to euro-area aggregate variables. The model also implies dynamic heterogeneity, as it does not stipulate that the effect of shocks is homogeneous across countries.¹⁷

Our model is intentionally simple in many aspects. For instance, the framework is linear, parameters are time-invariant, and errors are homoskedastic. Moreover, we refrained from fine-tuning many modeling choices through pretesting, instead focusing on simplicity and the information reported by market participants: the number of factors is set to one per economy; the selection of economic indicators and their transformations mirrors those continually monitored by economists in business, the media, and policy institutions; and the number of lags for the common and idiosyncratic factors, Eqs. (2)–(3), is set to one. Despite the simplicity of our model, its forecasts provide automated and judgment-free predictions that compare well to the best practices and expert judgments of professional private-sector forecasters (Consensus Economics) and the ECB, as we show in Section 5.¹⁸ The reason why, despite its simplicity, the proposed model performs well is the robustness of factor models to misspecification (e.g., Doz, Giannone, & Reichlin, 2012) and structural changes (e.g., Bates, Plagborg-Møller, Stock, & Watson, 2013), as well as its ability to parsimoniously capture business cycle co-movements (first discovered by Burns & Mitchell, 1946).

3.2. Estimation

We estimate the model by quasi-maximum likelihood. Doz et al. (2012) showed that when the number of economic indicators is large and the factor structure is strong, likelihood-based inference for DFMs is viable and robust to non-Gaussianity and to the presence of weak correlation among idiosyncratic components. For the computation of the estimates, we follow Bańbura and Modugno (2014), who modified the expectation–maximization algorithm of Dempster, Laird, and Rubin (1977) to estimate the parameters of a state-space model on datasets with arbitrary patterns of missing data.

As shown in Fig. 3, the common factors for the euro area aggregate and its major countries tend to co-move strongly over time. This result is in line with Giannone et al. (2010), who documented a strong commonality in euro-area business cycles. This suggests that economic signals from any country are likely to carry relevant information for the rest of the euro area, a feature that we exploit by modeling all economies simultaneously.

¹⁷ Other papers have proposed different solutions to address dynamic heterogeneity. For instance, D’Agostino, Giannone, Lenza, and Modugno (2016) include 12 lags of the observable variables and common factors, maintaining parsimony via shrinkage methods. However, their model has only six observable variables.

¹⁸ In Appendix B, we also show that the accuracy of our model compares well with those from two less parametrized models: (i) DFMs applied to the data of each economy separately, and (ii) a DFM that uses all the economic indicators and has only one euro-area factor. Despite the large number of parameters needed to model all countries jointly and allow for not perfectly synchronized business cycles, our multi-country model achieves a nowcasting accuracy similar to (if not better than) those from the alternative models.

Fig. 3(b) also shows the presence of some dynamic heterogeneity in the economic activity of euro-area economies, with lead–lag relationships between the common factor in different economies. Our model then takes these leads and lags into account using the dynamic interaction of the factors in the VAR of Eq. (2).

3.3. Country spillovers in the model

In this section, we show how our model captures cross-country spillovers and lead–lag relationships present in the euro-area data, which are fundamental ingredients of our multi-country forecasts. Specifically, we investigate how shocks to area-wide economic activity disseminate over time through the GDP growth of Germany, France, and Italy, as well as the rest of the euro area.

To achieve this rich evaluation of economic effects, we implement three procedures with the sole purpose of aiding the interpretation of the results. First, we rewrite the VAR Eq. (2) so that \mathbf{F}_t^* includes the factors collected by \mathbf{F}_t , and also a factor for the euro-area activity happening outside the three major economies ($\mathbf{f}_t^{r,ea}$), implied by the estimated factors and the country weights.¹⁹

$$\mathbf{F}_t^* = \mathbf{G} \cdot \mathbf{F}_{t-1}^* + \mathbf{s}_t, \quad (5)$$

where $\mathbf{G} = \mathbf{W} \cdot \mathbf{A} \cdot \mathbf{W}^{-1}$, $\mathbf{s}_t \sim \text{i.i.d. } \mathbf{N}(\mathbf{0}, \mathbf{W} \cdot \mathbf{Q} \cdot \mathbf{W}')$, and \mathbf{W} is a matrix based on euro-area country GDP weights. Second, we identify the propagation of area-wide shocks with the Stock and Watson (2005) factor-structural VAR model. The intuition for this identification is that movements across interconnected economies may be driven by a common shock, which in our application is equivalent to the following orthogonalization of \mathbf{s}_t :

$$\mathbf{s}_t = \mathbf{\Gamma} \mathbf{g}_t + \boldsymbol{\xi}_t, \quad (6)$$

where $\mathbf{\Gamma}$ is a loading matrix, \mathbf{g}_t is the common area-wide shock, and $\boldsymbol{\xi}_t$ is a vector of country-specific shocks to economic activity. Third, we recover the effect of the common area-wide shock in terms of GDP growth, instead of focusing on the country-specific factors of Eqs. (2) and (5). We provide the details of these procedures in Appendix A.

The impulse response functions (IRFs) of GDP growth to an area-wide shock provide an accurate quantification of the lead–lag relationships within the euro-area economy (Fig. 4). First, IRFs share a high degree of comovement, with all of them increasing for five to eight months after the shock, and decreasing thereafter. However, larger economies, such as Germany and France, have lower peak responses relative to smaller economies, consistent with the larger economies being more diversified and facing less volatile business cycles. Additionally, the IRF for Italy shows an earlier peak relative to the others, exemplified by its early softening of economic activity in both the 2008 and 2011 recessions. Lastly, the IRF for France exhibits a much more delayed effect, possibly because of rigidities in product and labor markets that dampen cyclical fluctuations.

¹⁹ The full expanded matrix description is detailed in Appendix A.1.

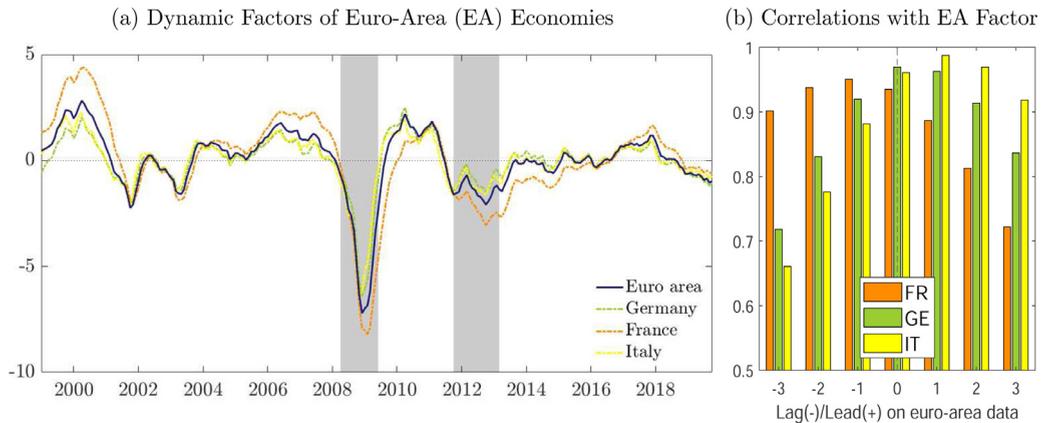


Fig. 3. Estimated factors and euro-area business cycles.

Note: Fig. 3(a) displays the dynamic factors of each economy (euro-area aggregate, Germany, France, and Italy) estimated by our model. Shaded areas are euro-area recession periods, as dated by the Center for Economic and Policy Research. Fig. 3(b) shows the cross-correlations among the dynamic factors by leading (positive x-axis) or lagging (negative x-axis) the factor of the euro-area aggregate.

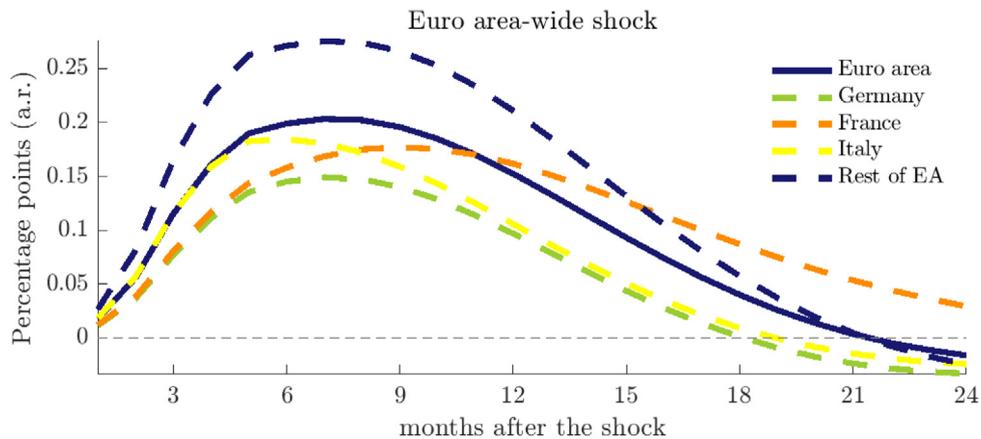


Fig. 4. Euro area-wide economic activity shock and GDP growth responses.

Note: Impulse response functions to GDP growth after an euro area-wide shock, as described in Section 3.3. Time periods are measured in months.

3.4. Pseudo-out-of-sample forecasts

In Sections 4 and 5, we evaluate the performance of our multi-country nowcasting model through out-of-sample exercises that give our model an information set similar to the one faced by market participants. These exercises have the following features in common. First, we assume that the data availability at each point in time of our sample is similar to the average release delay documented in Fig. 2(a).²⁰ Second, for every month, we produce forecasts with the information set available on four different dates: the 7th, 14th, 21st, and 28th day of the month. Third, for each of these dates, we forecast

the previous quarter (backcast), the current quarter (nowcast), and the next quarter (forecast). We then number each week of a reference quarter to indicate the timeline: weeks 0 to 12 for nowcasts, negative weeks for forecasts, and weeks 13 onward for backcasts. Finally, we use an expanding estimation window that starts in January 1999 and generates its first forecast for January 2006.

Our pseudo-out-of-sample exercises also take into account the change in the release calendar of GDP. Until 2015, euro-area statistical agencies released their GDP estimates, on average, 45 days after the end of the reference quarter.²¹ For example, the GDP reading of 2014Q1 was released in mid-May 2014 for all the countries studied in this paper. Starting in 2016, the release calendar became timelier for the euro-area aggregate and France, with their GDP being released 30 days after the end of the quarter. Italy followed suit in May 2018 for its 2018Q1 GDP, and Germany did so in July 2020 for its 2020Q2 GDP. Because

²⁰ For Sections Section 4, 5.1, and 5.2, we use the data vintage available in August 2019 due to the lack of real-time data for Germany, France, and Italy. For Section 5.3, we collect and use real-time data, showing that our results are robust to this data feature. Moreover, as argued by Giannone, Henry, Lalik, and Modugno (2012), revisions for the euro-area real-side data are limited in comparison with the United States and Japan. This higher accuracy of euro-area data may be related to its longer release delay.

²¹ For more details, see Box 4 of the ECB's Economic Bulletin, Issue No. 4/2016.

of these changes in the GDP release calendar, we only calculate four backcasts for the GDP of each evaluated quarter, against 12 forecasts and 12 nowcasts.²²

4. Nowcasting results

In this section, we show that our multi-country nowcasting model rationalizes three properties of market participants' forecasts for the euro area. First, monitoring data releases for *many countries* and in *real time*, as market participants do, increases the accuracy of GDP forecasts (Section 4.1). Second, country-specific data contribute significantly to nowcasting the euro-area aggregate GDP, and vice versa, consistent with the simultaneous attention given by economists to both country-specific and aggregate euro-area data (Section 4.2). Third, soft data are important for nowcasting the euro area because of both their timeliness and their intrinsic relationship with GDP growth (Section 4.3), consistent with economists' focus on soft data.

4.1. Multi-country modeling improves nowcasting

In order to evaluate the relative accuracy of the forecasts produced with our multi-country model for the euro area and its major countries when compared with the forecasts produced using single-country data, we rely on two separate metrics. The first metric is the root mean square forecast errors (RMSFEs), with which we compare the accuracy of the forecasts produced by each competing model on each single variable separately. However, comparing the accuracy of two competing models for one single variable, averaging over a long time span, can conceal the large gains that a multidimensional approach can generate when being jointly accurate on several variables at the same time. For this reason, we also compare the out-of-sample log-likelihood of the competing models.

We start by defining the RMSFEs and then we discuss the results obtained under this metric. Specifically,

$$RMSFE_w = \sqrt{\frac{\sum_{t=T_0}^T (\hat{\mu}_{gdp,t,w} - y_{gdp,t}^c)^2}{T - T_0 + 1}}, \quad (7)$$

where T_0 and T are the quarters in which we start and end the out-of-sample evaluation, respectively; $y_{gdp,t}^c$ is the realized value of the quarterly GDP growth of economy c at an annualized rate in quarter t for each of the four economies; and $\hat{\mu}_{gdp,t,w}^c = \mathbb{E}[y_{gdp,t}^c | \Omega_w]$ is the prediction for $y_{gdp,t}^c$ conditional on the information set, Ω_w , which was available in each week w within the quarter. The expected value is computed using the real-time estimates of the model parameters.

²² For each of the four weeks of the month, we produce three predictions: a backcast, the prediction of GDP growth for the previous quarter (unless it has already been released); a nowcast, the prediction of GDP growth for the current quarter; and a forecast, the prediction of GDP growth for the following quarter. For example, on February 7, 2014, we compute the backcast of 2013Q4, the nowcast of 2014Q1, and the forecast of 2014Q2. With a total of four vintages per month, three months per quarter, and three estimations per vintage, we compute a total of 12 forecasts, 12 nowcasts, and four backcasts for each evaluated quarter, from 2006Q2 to 2019Q1.

The accuracy of our model's GDP forecasts steadily increases over time (orange lines in Fig. 5) as the release of an ever-larger number of economic indicators is incorporated by our model. More precisely, the RMSFEs from our nowcasting model for all economies consistently decrease throughout the forecasting horizon.²³ These results mirror the ability of market participants to increase the accuracy of their forecasts as they increase their information set (e.g., Loungani, 2001).

To show that the nowcasting gains of our model originate from its multi-country approach, we compare its performance with alternative models that only account for data from their associated economies. Specifically, these models apply the general DFM structure to the data of each economy separately and are equivalent to restricted versions of the multi-country model, Eqs. (1)–(4), in which \mathbf{A} is diagonal. We call these DFMs the Single Factor Euro Area, Single Factor Germany, Single Factor France, and Single Factor Italy.

Fig. 5 shows that our multi-country model (orange lines) nowcasts are more accurate than the single-factor models (blue lines), as the RMSFEs of the latter lie above those from our multi-country model. The advantage of using the multi-country model is evident until week 8/9 of the current quarter. This result can be understood by looking at the timeliness of the releases in Fig. 2. By week 8/9, most of the hard data and the previous-quarter GDP are available, such that information from other countries is not very informative after that period. Only for the euro-area aggregate is there an advantage in using the multi-country model beyond the 9th week.

In addition to the point forecast precision, we also aim at understanding whether exploiting multi-country data can produce *joint* predictions of each GDP that are contemporaneously and consistently superior to the predictions produced using only country-specific information. To do so, we evaluate out-of-sample log-likelihoods of our multi-country model, and we compare them with the sum of the out-of-sample log-likelihoods of the single-factor models. Specifically, we calculate the log-likelihood as

$$LSCORE_{t,w} = -\frac{1}{2}(\log |\hat{\Sigma}_{gdp,t}| + (\hat{\mu}_{gdp,t,w} - \mathbf{y}_{gdp,t})' \times \hat{\Sigma}_{gdp,t}^{-1} (\mu_{gdp,t,w} - \mathbf{y}_{gdp,t})), \quad (8)$$

where $\mathbf{y}_{gdp,t}$ and $\hat{\mu}_{gdp,t,w}$ respectively denote the vectors of actual and predicted GDP growth in the four economies. The matrix $\hat{\Sigma}_{gdp,t} = \mathbb{E}[(\mathbf{y}_{gdp,t} - \mu_{gdp,t})(\mathbf{y}_{gdp,t} - \mu_{gdp,t})' | \Omega_w]$ is the covariance of the errors. Expectations are computed using the real-time estimates of the model's parameters. For the single-country models, the matrix $\hat{\Sigma}_{gdp,t}$ is diagonal, with entries equal to the variance implied by each model.

The results are reported in Fig. 6, where we plot the relative average log scores of the two models over the entire evaluation sample and over a sample that covers only the recession periods. Two main results emerge. First, the

²³ In the Appendix, we also document that forecast errors from our nowcasting model are larger during recessions. For details, see Fig. E.1.

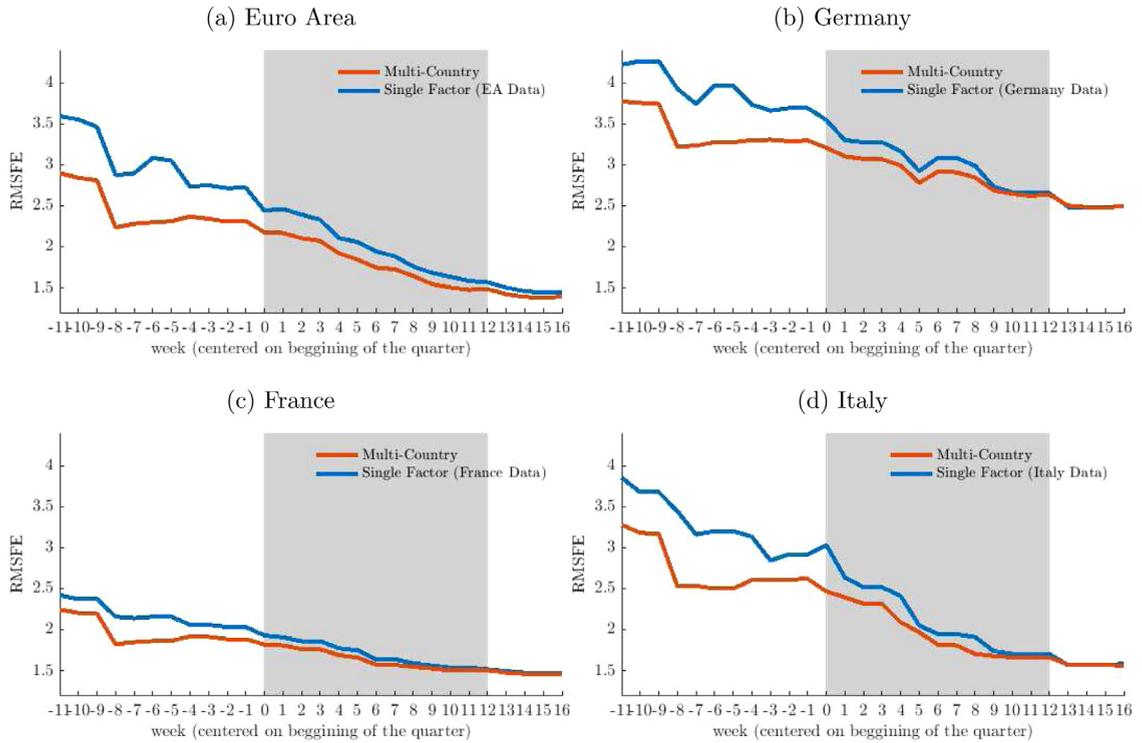


Fig. 5. Out-of-Sample nowcasting performance.

Note: Root mean square forecast errors (RMSFEs), Eq. (7), are calculated under the out-of-sample exercise described in Section 3.4. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. Shaded areas represent nowcast weeks (current-quarter forecasts). Orange lines represent the RMSFEs of the multi-country model (Section 3.1) and blue lines represent the RMSFEs of the single-factor models (Section 4.1). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

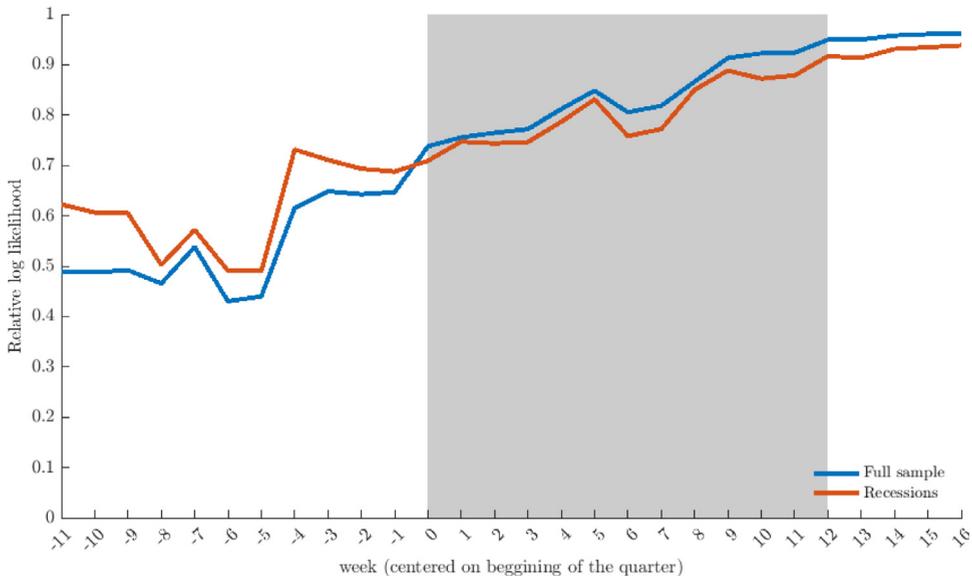


Fig. 6. Relative out-of-sample joint nowcasting log-likelihood.

Note: The log-likelihood is calculated in the out-of-sample exercise described in Section 4.1. The blue line shows the relative log-likelihood between our joint multi-country nowcasting model (Section 3.1) and the countries' joint log-likelihood for a factor model where each country and the euro area only take signals from their individually associated data. The orange line show the same relation, but only considering a sub-sample of forecasts performed for periods classified by the NBER as a recession. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. The shaded area represents nowcast weeks (current-quarter forecasts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

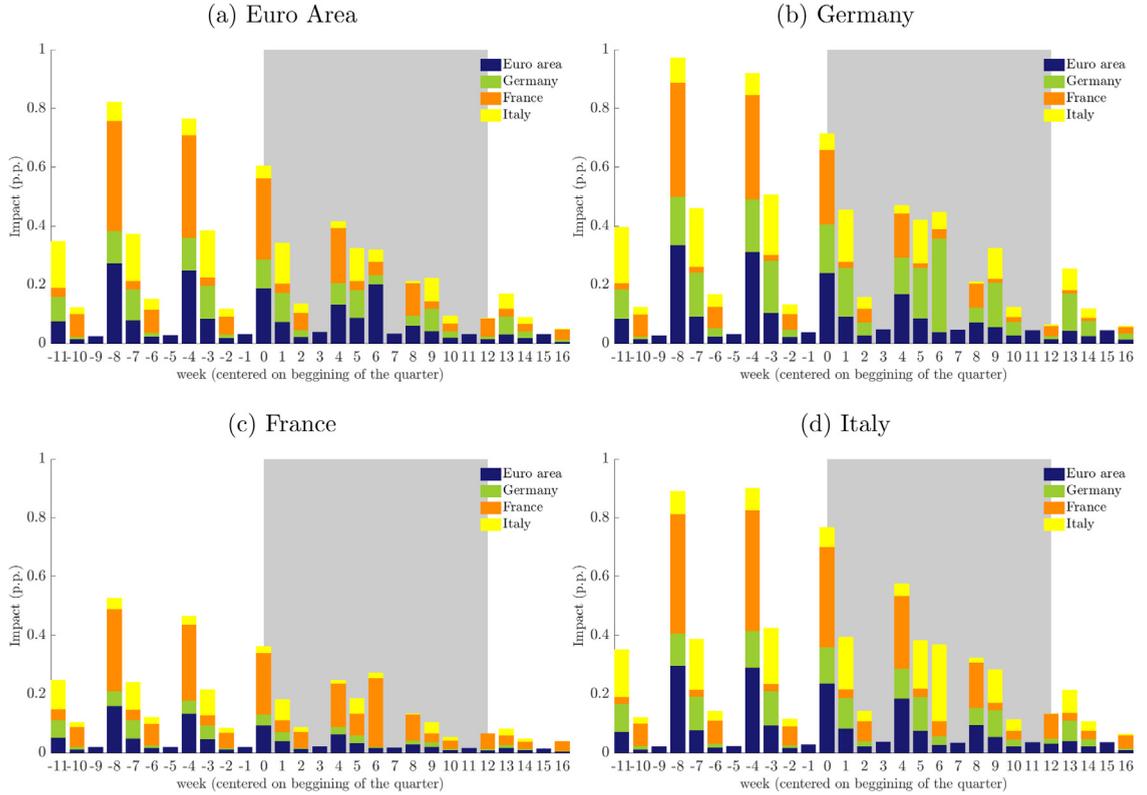


Fig. 7. News decomposition of GDP growth: Origin of the data.

Note: News is calculated as the average of the (absolute) forecast revisions led by a particular data release, Eq. (9). For the GDP growth of each economy (Figs. 7(a)–7(d)), we group news from data releases about the euro area (blue bars), Germany (green bars), France (orange bars), and Italy (yellow bars). The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. The shaded areas represent nowcast weeks (current-quarter forecasts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

likelihoods of the multi-country model are higher than those from the single-factor models, both on all the sample and on the only-recession sample, where the ratio is always below one. Second, confirming the RMSFE results shown in Fig. 5, the multi-country model performs particularly better than the single-factor models from week –11 through weeks 8/9.

4.2. Country data to nowcast the euro area (and vice versa)

By jointly modeling the euro-area aggregate and its major countries, we show that data releases from one economy typically lead to important nowcasting revisions of the others. Following Bańbura and Modugno (2010), we calculate the average news of nowcasting the GDP growth of economy c from variable i at week w as follows:

$$News_{gdp,w}^{i,c} = \frac{\sum_{t=T_0}^T (|\hat{\mathbb{E}}[y_{gdp,t}^c | \Omega_{w(i)}] - \hat{\mathbb{E}}[y_{gdp,t}^c | \Omega_{w-1}]|)}{T - T_0 + 1}, \quad (9)$$

where y_t^c is the GDP growth to be estimated, w is the week of the reference quarter, $\hat{\mathbb{E}}[y_{gdp,t}^c | \Omega_{w-1}]$ is the estimate of $y_{gdp,t}^c$ using the information set of all variables available at week $w - 1$, and $\hat{\mathbb{E}}[y_{gdp,t}^c | \Omega_{w(i)}]$ is the estimate of $y_{gdp,t}^c$

using the information set that includes variable i released at week w in addition to all the variables available at week $w - 1$. For instance, if we focus on the contribution of the euro-area aggregate PMI released in the week before the start of the reference quarter (week –1) to forecast German GDP, $News_{-1}^{EA-PMI,ge}$ measures the average revision to the German GDP forecast arising from the release of the euro-area aggregate PMI.

To measure how data releases from one economy influence the nowcast revisions of other economies, we group news led by the indicators of each of the euro-area economies. Thus, for every week in the forecasting, nowcasting, and backcasting periods, Fig. 7 shows the sizes of typical forecast revisions for GDP growth led by data from the euro area (blue), Germany (green), France (orange), and Italy (yellow). The figure also reports the news decomposition for the GDP growth of each one of these economies (Figs. 7(a)–7(d)). Importantly, the overall size of nowcast revisions consistently decreases as we approach the GDP release date, in line with the results from Section 4.1.

Not only are country-specific data important for predicting euro-area aggregate GDP growth (Fig. 7(a)), but the reverse is also true: euro-area data are important for predicting country-specific GDP growth (Figs. 7(b)–7(d)).

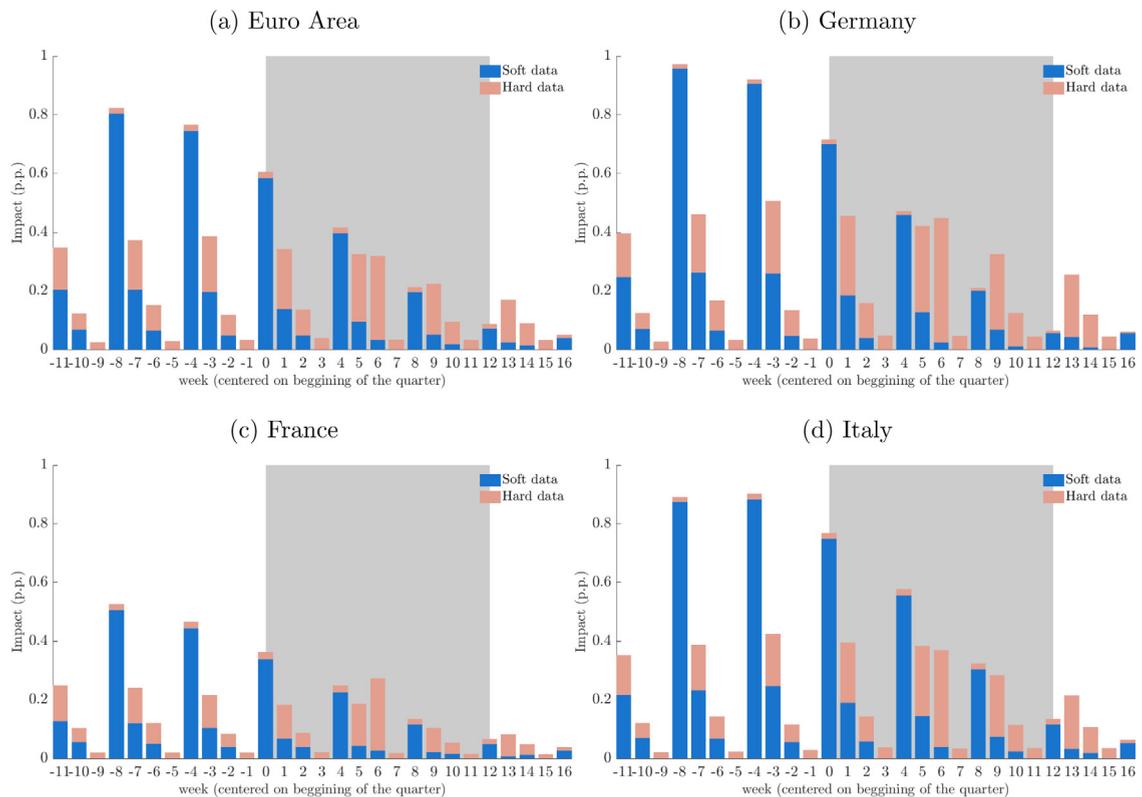


Fig. 8. News decomposition of GDP growth: Hard vs. soft data.

Note: News is calculated as the average of the (absolute) forecast revisions led by a particular data release, Eq. (9). For the GDP growth of each economy (Figs. 8(a)–8(d)), we group news from releases of hard (pink bars) and soft (blue bars) data. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. The shaded areas represent nowcast weeks (current-quarter forecasts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For instance, during weeks -8 through 4 , French data (orange bars) generally lead to large revisions to the forecasts of euro-area GDP. In some weeks during this early forecasting period, French data lead to revisions that are typically even larger than those from the euro-area data. This result is due to the fact that, as we can see in Fig. 2, there are six soft data releases for France in that period, more than any of the other economies. Moreover, in the next section, Fig. 8 corroborates this result, showing that most of the information in the early forecasting period is conveyed by surveys. Conversely, data releases from the euro-area aggregate and France generally lead to sizable forecast revisions to the German and Italian GDPs in the early weeks of the forecast.

These results rationalize the simultaneous monitoring of the euro-area aggregate and its major economies by market participants and policymakers, as documented in Section 2.1. Economists do so not only to ensure consistency in their cross-country forecasts, but also because the cross-country data are informative from a forecasting perspective.

4.3. Soft data are important for nowcasting the euro area

Releases of soft data typically lead to much larger nowcasting revisions than those from hard data in all studied

euro-area economies. To show this result, we group the news (Eq. (9)) led by hard (pink bars) and soft (blue bars) indicators from all economies (Fig. 8).²⁴ Releases of soft indicators have large implications for GDP forecasts as early as two months before start of the quarter, with average revisions still sizable in week 4 of the forecasted quarter. In contrast, releases of hard indicators generally lead to smaller forecast revisions than those from soft indicators until week 5. Thereafter, forecast revisions led by hard data are relatively larger, but the overall size of all revisions quickly shrinks.

As emphasized by Giannone et al. (2006) and Gilbert et al. (2017), the information content of an economic indicator depends not only on its intrinsic relationship with the nowcasted variable, but also on the timeliness of its release. To shed light on these two potential explanations for the nowcasting performance of soft data, we build a counterfactual dataset in which the release of hard data is anticipated to follow a calendar similar to the United States (as illustrated by Fig. 2(b)).

Our counterfactual exercise shows that the importance of soft data to nowcasting euro-area economies originates

²⁴ Table 1 describes the classification of hard and soft data for each of the variables in our dataset.

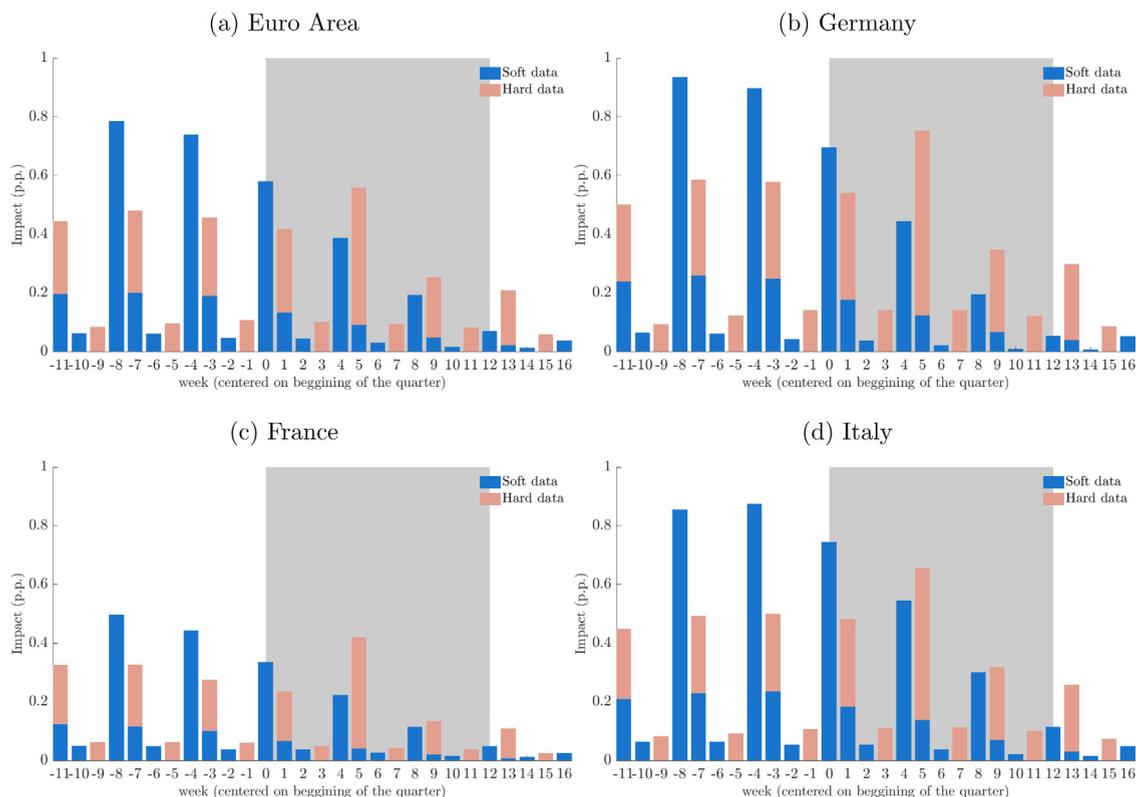


Fig. 9. News decomposition of GDP growth: Anticipating hard data releases.

Note: News is calculated as the average of the (absolute) forecast revisions led by a particular data release, Eq. (9). For the GDP growth of each economy (Figs. 9(a)–9(d)), we group news from releases of hard (pink bars) and soft (blue bars) data. Counterfactual news assumes that releases of hard data are anticipated to follow a calendar similar to the United States. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. Shaded areas represent nowcast weeks (current-quarter forecasts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

from both the timeliness of their releases and their intrinsic information content about economic conditions. Fig. 9 shows that, under the counterfactual dataset, nowcasting revisions from soft data (blue bars) remain sizable and essentially unchanged (relative to Fig. 8) during weeks in which important soft indicators, such as PMIs, are released (e.g., weeks -8 , -4 , 0 , and 4). Hard indicators, in turn, increase their importance (pink bars) to revisions of GDP, although they remain far from overturning the role of soft indicators. This result points to the informativeness of soft indicators about the GDP of euro-area economies even under a calendar that has timely hard data. If we, alternatively, delay soft data releases to match the calendar of hard data, soft data remain the predominant force in nowcasting revisions (Appendix C).

We offer the following interpretation for the results of this section. Given the timely release calendar of soft indicators (Fig. 2(a)), our multi-country nowcasting model readily and heavily loads on them to produce its forecasts. Then, when the bulk of hard data for the quarter is released (near the end of the second month), a large share of the relevant forecasting information had already been conveyed by the soft data released earlier. Finally, the fact that soft data are both available in a timely manner and informative about the nowcasted GDP leads to relatively

small nowcast revisions in the last month of the quarter (weeks 9 through 12 in Fig. 8).

The results from this section also indicate that the timeliness of soft data compensates for the long delay in the release of hard data in the euro area. While there is typically a tradeoff between the timeliness of soft data and the precision of hard data, our results show that the euro-area soft data are both timely and relatively precise, consistent with the results of Giannone et al. (2009) and Basselier, de Antonio Liedo, and Langenus (2018). Moreover, these results indicate that an effort to reduce the delay of releases of hard data could bring timely and accurate information to market participants and policymakers, but would likely add little from a nowcasting perspective.

5. Model performance in historical episodes

In this section, we show that our model performs well at anticipating euro-area GDP growth in its previous three recessions.²⁵

²⁵ Recession periods are those defined by the Center for Economic and Policy Research (CEPR).

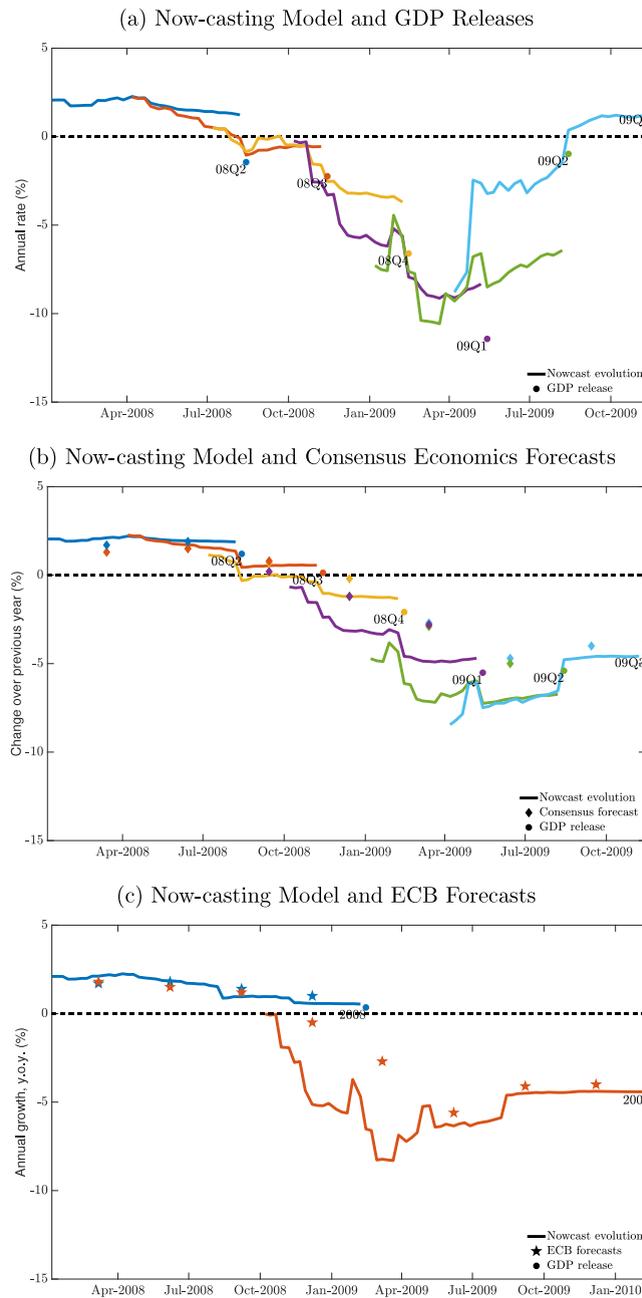


Fig. 10. Nowcasting evolution of euro-area GDP growth in 2008–09. Note: Solid lines show the evolution of GDP growth nowcasts for different quarters using our model (Section 3). Dates of GDP releases are from the release calendar schedule (Fig. 2(a)). GDP growth in Fig. 10(a) is measured as quarter-on-quarter change at an annualized rate. GDP growth in Fig. 10(b) is measured as four-quarter change. GDP growth in Fig. 10(c) is measured as year-over-year change.

5.1. The great recession

Fig. 10 shows our forecasts closely tracking the economic activity during the 2008–2009 period. Solid lines represent our model forecasts and dots represent GDP releases. Looking closer, we observe this tracking performance in two ways. First, for a given forecasted quarterly GDP growth value, such as 2009Q3 in Fig. 10(a), the continuous flow of data consistently pushes the model

prediction (light blue line) toward the GDP growth number released later. Second, the model is able to anticipate important short-term trends in economic activity because it continually forecasts previous-, current-, and next-quarter GDP growth. We see this ability in periods such as July 2008, when estimates of moderate growth for 2008Q2 are accompanied by estimates of contraction for 2008Q3 and 2008Q4. For April 2009, the model behaves similarly but points to an improvement in activity.

Comparing our model forecasts with those from professional forecasters, we find that ours are more accurate for the deeper part of the recession. Fig. 10(b) shows the Consensus Economics forecasts and those from our model, with the former underestimating the drop in GDP growth by more than what our model would have done during the 2008Q3–2009Q1 period. The comparison between our forecasts and those from the ECB (Fig. 10(c)) paints a similar picture, with the important caveat that the ECB's forecasts were available only for GDP growth in year-over-year changes. At the start and end of the Great Recession, our forecasts were reasonably similar to those from Consensus and the ECB.

5.2. The European sovereign debt crisis

The beginning of the euro-area recession led by the European sovereign debt crisis was marked by a rapid reversal of economic conditions. Indeed, professional forecasters and the ECB took several months to recognize these deteriorating conditions. In contrast, our model would have quickly signaled these adverse economic conditions, as illustrated by Fig. 11(a).

The comparison between our model's forecasts and those of professional forecasters points to how timely our model could have been in signaling the 2011 economic reversal. Fig. 11(b) compares our forecasts with the ones from Consensus Economics. It shows that in early September 2011, our model was already forecasting GDP growth at about 0.4% for 2011Q4, while Consensus still had it at 1.3%. The comparison with ECB forecasts (Fig. 11(c)) is more difficult, as the ECB previously reported only forecasts for year-over-year growth rates. Even so, by October 2011, our model would have forecasted a significant drop in GDP growth from 2011 to 2012, relative to a smoother pattern followed by the ECB forecasts. From mid-2012 onward, our model would have performed broadly in line with the ECB and Consensus forecasts.

5.3. The great lockdown

The Great Lockdown in 2020 imposed a collapse in global economic activity with unprecedented speed and magnitude. These circumstances present a particularly stringent challenge to evaluate the performance of our model. Even so, our model was able to quickly signal the historic drop in economic activity in the euro area.

To highlight the abrupt deterioration in economic activity in the euro area and the lack of timely hard data for professional forecasters, we focus on the period from January 7 to July 31, 2020. During this period, governments imposed sudden shutdowns of large parts of the euro-area economy. For instance, Italy (the first major euro-area country affected by the pandemic) went from mild restrictions on social mobility at the end of February to an almost complete countrywide lockdown on March 10.²⁶ Moreover, with lockdown measures in the rest of

the euro area becoming more stringent at the end of March, the hard data showing the economic repercussions of the pandemic only became available in mid-May, more than two months after the start of the lockdowns.

Our model was able to quantify the dramatic economic deterioration that happened in a matter of weeks. Highlighting both the precision and the timeliness of soft data for nowcasting the euro area, our model made its first large downward revision once it incorporated the release of flash PMIs at the end of March. For the euro-area aggregate (Fig. 12), the forecasted GDP growth dropped from 1% in March 21 to -3.7% in March 28, only two weeks after the lockdown in Italy. The drop in GDP was broad, with negative contributions from Germany, France, Italy, and from the (implied) aggregate of the other euro-area countries (vertical bars in the top panel). Additional soft data indicators continued to push down the GDP forecast in the following weeks (blue bars in the lower panel), with the April PMIs reducing the GDP forecast to about -12% . In mid-May, hard data indicators for March, such as industrial production, were finally released and only consolidated the abysmal forecast for the period. The results for the major euro-area countries are similar to those for the aggregate region, and presented in Appendix D.

One additional consideration is that the extreme fluctuations in macro-data due to the pandemic may induce some instability in the estimation algorithm, due to the violation of basic statistical assumptions. Indeed, some recent papers tried to formalize how to deal with this problem directly in the context of VARs (e.g., Cascaldi-Garcia, 2022 and Lenza & Primiceri, 2020). In our experience, the best way to proceed is to consider these extreme values as missing data in the estimation of the model parameters, given that these are one-off events that are not informative about the historical auto- and cross-correlation among macro-variables.

6. Conclusion

In this paper, we proposed an econometric framework that formalizes how market participants and policymakers monitor the euro-area economic conditions. We simultaneously nowcasted the economic activity of the euro-area aggregate and its three largest member countries—Germany, France, and Italy. The model delivered accurate predictions during the last two decades by providing effective solutions to the challenges of the big-data problem at hand. Specifically, our model (i) processes a large *volume* of data, as it includes almost 60 time series covering the euro area and its three largest countries; (ii) has *velocity* in continually updating GDP nowcasts every time new data become available; and (iii) handles a large *variety* of data, such as time series from different sectors of the economy, available at different frequencies, and from different types of sources, such as hard data (measurable quantities) and soft data (perceptions about economic conditions).

Consistent with market participants' monitoring practices, our model shows that area-wide and country-specific data provide informative signals to nowcast the economic

²⁶ For instance, see the stringency index of lockdown measures compiled by Hale, Webster, Petherick, Phillips, and Kira (2020).

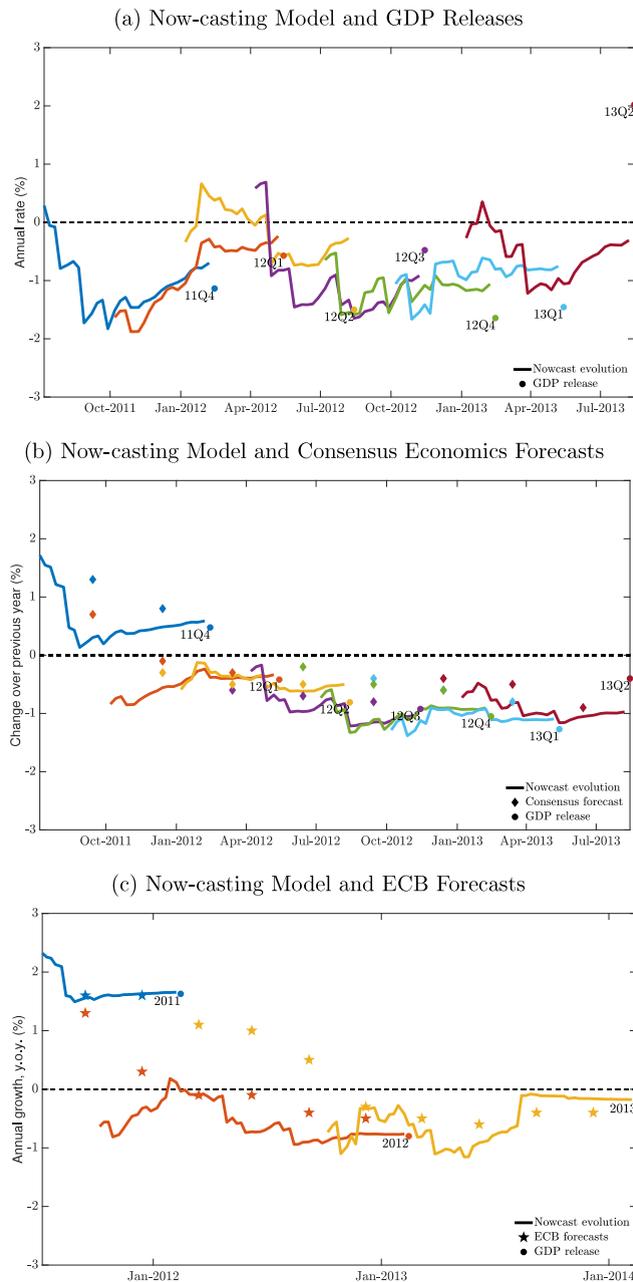


Fig. 11. Nowcasting evolution of euro-area GDP growth in 2011–13.

Note: Solid lines show the evolution of GDP growth nowcasts for different quarters using our model (Section 3). Dates of GDP releases are from the release calendar schedule (Fig. 2(a)). GDP growth in Fig. 10(a) is measured as quarter-on-quarter change at an annualized rate. GDP growth in Fig. 10(b) is measured as four-quarter change. GDP growth in Fig. 10(c) is measured as year-over-year change.

conditions in the euro area and member countries. We also found that soft data, such as opinion surveys, are particularly important for nowcasting the euro area, since hard data are released with a substantial delay.

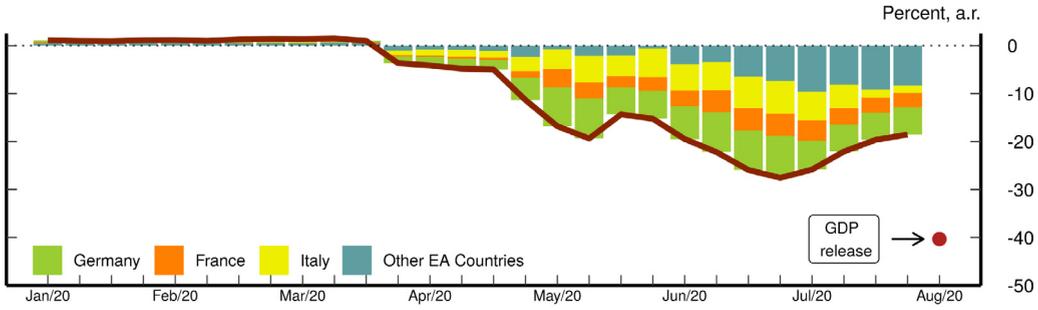
With economies around the world becoming more economically and financially integrated, market participants and policymakers have gradually monitored an increasing number of economies in a simultaneous fashion. Our paper provides directions upon which researchers may follow to design models that help economists

nowcast multi-country economic conditions, such as building world nowcasting models.

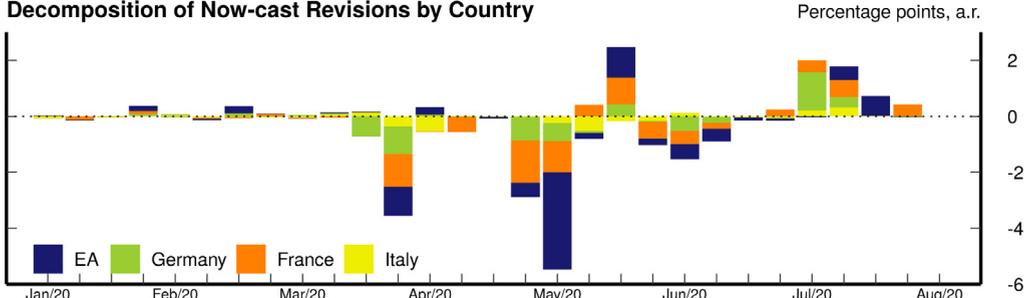
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Evolution of Estimates of Euro-Area GDP Growth in 2020Q2



Decomposition of Now-cast Revisions by Country



Decomposition of Now-cast Revisions by Data

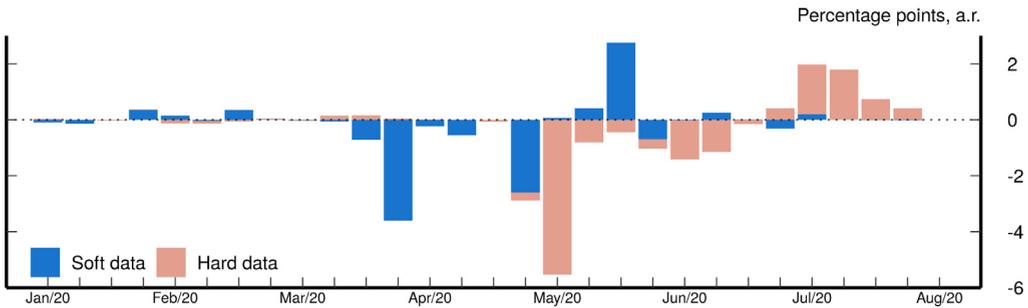


Fig. 12. Euro-area GDP growth during the 2020 Covid-19 crisis.

Note: The top panel presents weekly out-of-sample forecasts from our nowcasting model. Vertical bars in top panel represent the contributions from Germany, France, Italy, and the other euro-area countries to the euro-area GDP growth. The red dot in the top panel represents the euro-area quarterly GDP growth of 2020Q2. The middle panel presents the decomposition of the model forecast revisions by the country of origin of the data, whereas the bottom panel presents revisions by hard/soft data. More details are given in Sections 3 and 4.

Appendix A. Country spillovers in the model: Details

In this appendix, we provide more details about how we shed light on cross-country spillovers and lead-lag relationships present in the euro-area data. Specifically, we describe the three procedures briefly discussed in Section 3.3.

In the first procedure, we recover the (implied) rest of the euro area from our system plus the factors of Germany, France, and Italy through the transformation

$$\mathbf{F}_t^* = \mathbf{W} \cdot \mathbf{F}_t, \tag{A.1}$$

$$\mathbf{F}_t = \mathbf{W}^{-1} \cdot \mathbf{F}_t^*, \tag{A.2}$$

where \mathbf{W} is a weight matrix based on the contributions of Germany, France, and Italy to the euro area's aggregate GDP growth. The full expanded matrix description is

detailed in Appendix A.1. From Eq. (A.2), it is possible to rewrite the VAR in Eq. (2) as

$$\mathbf{W}^{-1} \cdot \mathbf{F}_t^* = \mathbf{A} \cdot \mathbf{W}^{-1} \cdot \mathbf{F}_{t-1}^* + \mathbf{u}_t, \tag{A.3}$$

$$\mathbf{F}_t^* = \mathbf{W} \cdot \mathbf{A} \cdot \mathbf{W}^{-1} \cdot \mathbf{F}_{t-1}^* + \mathbf{W} \cdot \mathbf{u}_t, \tag{A.4}$$

$$\mathbf{F}_t^* = \mathbf{G} \cdot \mathbf{F}_{t-1}^* + \mathbf{s}_t, \tag{A.5}$$

where $\mathbf{G} = \mathbf{W} \cdot \mathbf{A} \cdot \mathbf{W}^{-1}$ and $\mathbf{s}_t \sim \text{i.i.d. N}(\mathbf{0}, \mathbf{W} \cdot \mathbf{Q} \cdot \mathbf{W}')$.

In the second procedure, we identify the propagation of euro area-wide and country-specific shocks with the Stock and Watson (2005) factor-structural VAR model. The idea of the procedure is that movements across interconnected economies are driven by a common shock and idiosyncratic shocks originating in each economy. It follows that each economy's business cycle can be explained by the common shock, by its own shock, or

by spillovers. In our application, the decomposition is equivalent to the orthogonalization of \mathbf{s}_t under the form

$$\mathbf{s}_t = \mathbf{\Gamma} \mathbf{g}_t + \boldsymbol{\xi}_t \quad (\text{A.6})$$

$$\mathbb{E}(\mathbf{g}_t \mathbf{g}'_t) = \sigma_g \quad (\text{A.7})$$

$$\mathbb{E}(\boldsymbol{\xi}_t \boldsymbol{\xi}'_t) = \begin{bmatrix} \sigma_{r,ea} & 0 & 0 & 0 \\ 0 & \sigma_{ge} & 0 & 0 \\ 0 & 0 & \sigma_{fr} & 0 \\ 0 & 0 & 0 & \sigma_{it} \end{bmatrix}, \quad (\text{A.8})$$

where $\mathbf{\Gamma}$ is a loading matrix, \mathbf{g}_t is a common euro area-wide shock, and $\boldsymbol{\xi}_t$ has the country-specific idiosyncratic shocks for Germany, France, Italy, and the rest of the euro area.

In the third procedure, we recover the effect of these shocks in terms of GDP growth, instead of the factors of Eqs. (2) and (5). We do so for the aggregate euro area, Germany, France, Italy, and the rest of the euro area using the following transformation of Eq. (1):

$$\mathbf{y}_{gdp,t} = \mathbf{y}_{gdp,t}^* + \mathbf{H} \cdot \mathbf{e}_t, \quad (\text{A.9})$$

$$\mathbf{y}_{gdp,t}^* = \mathbf{H} \cdot \boldsymbol{\Lambda}_{gdp} \cdot \mathbf{F}_t, \quad (\text{A.10})$$

$$\mathbf{y}_{gdp,t}^* = \mathbf{H} \cdot \boldsymbol{\Lambda}_{gdp} \cdot \mathbf{W}^{-1} \cdot \mathbf{F}_t^*, \quad (\text{A.11})$$

where $\mathbf{y}_{gdp,t}^*$ is the GDP common component of the euro area aggregate, Germany, France, Italy, and the rest of the euro area; \mathbf{H} is a transformation matrix based on GDP weights; and $\boldsymbol{\Lambda}_{gdp}$ is a matrix that collects the GDP loadings for the euro area, Germany, France and Italy. Finally, the GDP impulse responses can be recovered as

$$\frac{\partial \mathbf{y}_{gdp,t+h}^*}{\partial \mathbf{g}_t} = \frac{\partial \mathbf{y}_{gdp,t+h}^*}{\partial \mathbf{F}_t^*} \cdot \frac{\partial \mathbf{F}_t^*}{\partial \mathbf{g}_t} = \mathbf{H} \cdot \boldsymbol{\Lambda}_{gdp} \cdot \mathbf{W}^{-1} \cdot \mathbf{G}^h \cdot \mathbf{\Gamma} \cdot \mathbf{e}_t^g \quad (\text{A.12})$$

$$\frac{\partial \mathbf{y}_{gdp,t+h}^*}{\partial \boldsymbol{\xi}_{i,t}} = \frac{\partial \mathbf{y}_{gdp,t+h}^*}{\partial \mathbf{F}_t^*} \cdot \frac{\partial \mathbf{F}_t^*}{\partial \boldsymbol{\xi}_{i,t}} = \mathbf{H} \cdot \boldsymbol{\Lambda}_{gdp} \cdot \mathbf{W}^{-1} \cdot \mathbf{G}^h \cdot \mathbf{e}_t^{\boldsymbol{\xi},i} \quad (\text{A.13})$$

A.1. Recovering the rest of the euro area aggregate

In this appendix, we provide the detailed versions of the equations described in Appendix A:

$$\underbrace{\begin{bmatrix} \mathbf{f}_t^{ea} \\ \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{it} \end{bmatrix}}_{\mathbf{F}_t \quad 20 \times 1} = \underbrace{\begin{bmatrix} \mathbf{A}_{1,1} & \mathbf{A}_{1,2} & \mathbf{A}_{1,3} & \mathbf{A}_{1,4} \\ \mathbf{A}_{2,1} & \mathbf{A}_{2,2} & \mathbf{A}_{2,3} & \mathbf{A}_{2,4} \\ \mathbf{A}_{3,1} & \mathbf{A}_{3,2} & \mathbf{A}_{3,3} & \mathbf{A}_{3,4} \\ \mathbf{A}_{4,1} & \mathbf{A}_{4,2} & \mathbf{A}_{4,3} & \mathbf{A}_{4,4} \end{bmatrix}}_{\mathbf{A} \quad 20 \times 20} \underbrace{\begin{bmatrix} \mathbf{f}_{t-1}^{ea} \\ \mathbf{f}_{t-1}^{ge} \\ \mathbf{f}_{t-1}^{fr} \\ \mathbf{f}_{t-1}^{it} \end{bmatrix}}_{\mathbf{F}_{t-1} \quad 20 \times 1} \quad (\text{A.14})$$

$$\mathbf{A}_{i,i5 \times 5} = \begin{bmatrix} a_{i,i} & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}_{5 \times 5} \quad (\text{A.15})$$

$$\mathbf{A}_{i,j5 \times 5} = \begin{bmatrix} a_{i,j} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{5 \times 5} \quad (\text{A.16})$$

$$\underbrace{\begin{bmatrix} \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{it} \\ \mathbf{f}_t^{ea} \end{bmatrix}}_{\mathbf{F}_t^* \quad 20 \times 1} = \underbrace{\begin{bmatrix} \mathbf{0}_{5 \times 5} & \mathbf{I}_{5 \times 5} & \mathbf{0}_{5 \times 5} & \mathbf{0}_{5 \times 5} \\ \mathbf{0}_{5 \times 5} & \mathbf{0}_{5 \times 5} & \mathbf{I}_{5 \times 5} & \mathbf{0}_{5 \times 5} \\ \mathbf{0}_{5 \times 5} & \mathbf{0}_{5 \times 5} & \mathbf{0}_{5 \times 5} & \mathbf{I}_{5 \times 5} \\ \mathbf{I}_{5 \times 5} \cdot \frac{1}{w^{r,ea}} & \mathbf{I}_{5 \times 5} \cdot \frac{-w^{ge}}{w^{r,ea}} & \mathbf{I}_{5 \times 5} \cdot \frac{-w^{fr}}{w^{r,ea}} & \mathbf{I}_{5 \times 5} \cdot \frac{-w^{it}}{w^{r,ea}} \end{bmatrix}}_{\mathbf{W} \quad 20 \times 20} \underbrace{\begin{bmatrix} \mathbf{f}_t^{ea} \\ \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{it} \end{bmatrix}}_{\mathbf{F}_t \quad 20 \times 1} \quad (\text{A.17})$$

$$\underbrace{\begin{bmatrix} y_{t,gdp}^{ea,*} \\ y_{t,gdp}^{ge,*} \\ y_{t,gdp}^{fr,*} \\ y_{t,gdp}^{it,*} \\ y_{t,gdp}^{r,ea,*} \end{bmatrix}}_{\mathbf{y}_{t,gdp}^* \quad 5 \times 1} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ \frac{1}{w^{r,ea}} & \frac{-w^{ge}}{w^{r,ea}} & \frac{-w^{fr}}{w^{r,ea}} & \frac{-w^{it}}{w^{r,ea}} \end{bmatrix}}_{\mathbf{H} \quad 5 \times 4} \quad (\text{A.18})$$

$$\underbrace{\begin{bmatrix} \lambda_{5 \times 1}^{ea} & \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} \\ \mathbf{0}_{5 \times 1} & \lambda_{5 \times 1}^{ge} & \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} \\ \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} & \lambda_{5 \times 1}^{fr} & \mathbf{0}_{5 \times 1} \\ \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} & \mathbf{0}_{5 \times 1} & \lambda_{5 \times 1}^{it} \end{bmatrix}}_{\boldsymbol{\Lambda}_{gdp} \quad 4 \times 20} \times \underbrace{\begin{bmatrix} \mathbf{f}_t^{ea} \\ \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{it} \end{bmatrix}}_{\mathbf{F}_t \quad 20 \times 1}$$

where $w^{r,ea} = 1 - w^{ge} - w^{fr} - w^{it}$ is the sum of the GDP weights of the euro-area countries other than Germany, France, and Italy. \mathbf{f}_t contains the contemporaneous value and four lags of each country factor, with their respective λ_{gdp}^i loadings, following the Mariano and Murasawa (2003) aggregation.

$$\underbrace{\begin{bmatrix} y_{t,gdp}^{ea,*} \\ y_{t,gdp}^{ge,*} \\ y_{t,gdp}^{fr,*} \\ y_{t,gdp}^{it,*} \\ y_{t,gdp}^{r,ea,*} \end{bmatrix}}_{\mathbf{y}_{t,gdp}^* \quad 5 \times 1} = \mathbf{H}_{5 \times 4} \cdot \boldsymbol{\Lambda}_{4 \times 20}^{gdp} \cdot \mathbf{W}_{20 \times 20}^{-1} \cdot \underbrace{\begin{bmatrix} \mathbf{f}_t^{ge} \\ \mathbf{f}_t^{fr} \\ \mathbf{f}_t^{it} \\ \mathbf{f}_t^{ea} \end{bmatrix}}_{\mathbf{F}_t^* \quad 20 \times 1} \quad (\text{A.19})$$

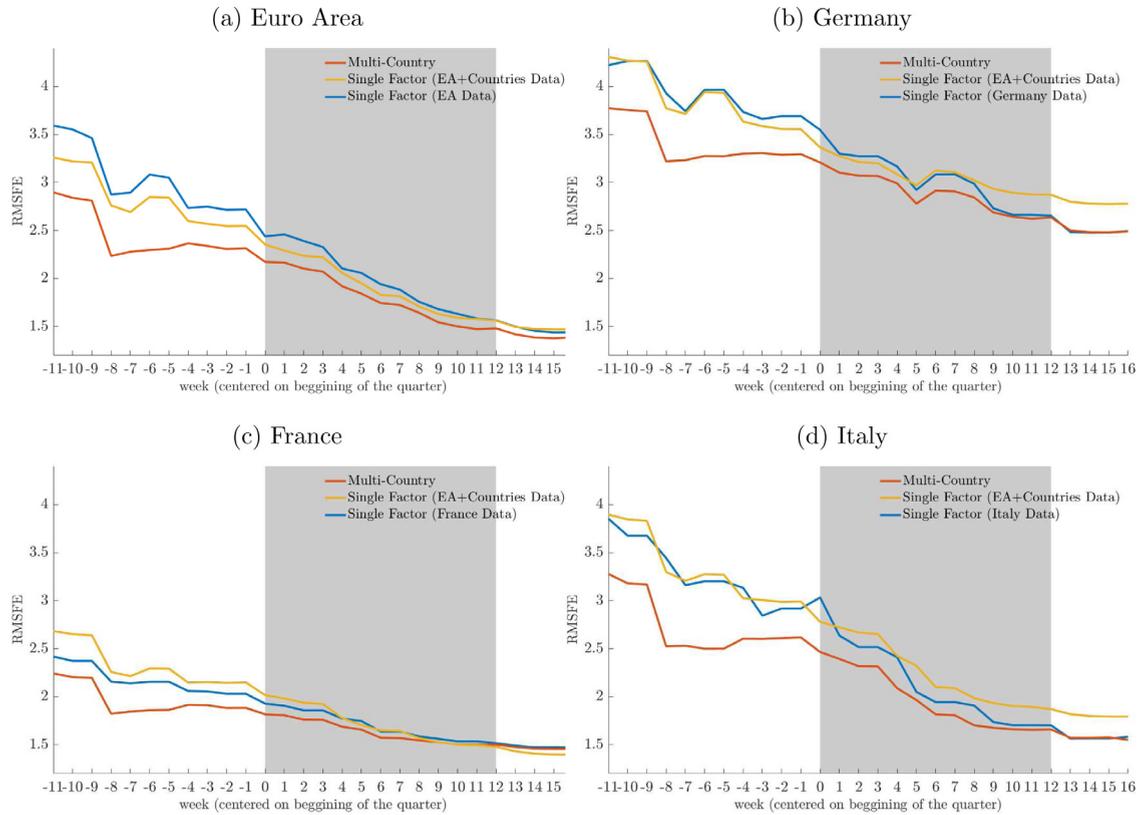


Fig. B.1. Out-of-sample performance of different nowcasting models.

Note: Root mean square forecast errors (RMSFEs), Eq. (7), are calculated under the out-of-sample exercise described in Section 3.4. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. Shaded areas represent nowcast weeks (current-quarter forecasts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix B. Alternative models and performance comparisons

To better understand the nowcasting gains of our multi-country model, we build two alternative models. We choose these models to show that, to produce accurate nowcasts for the euro area and its major economies, it is important to (i) use the data from all these economies, and (ii) take into account the cross-country spillovers of these economies. The first alternative model applies the general DFM structure to the data of each economy separately and is equivalent to a restricted version of the multi-country model, Eqs. (1)–(4), in which \mathbf{A} is diagonal. We call these DFMs the Single Factor Euro Area, Single Factor Germany, Single Factor France, and Single Factor Italy. Importantly, there are no cross-country spillovers in these single-factor DFMs. In our second alternative model, the Single Factor Euro Area and Countries DFM, we jointly nowcast all four economies using one factor, the only one allowed in Eq. (2). The Single Factor Euro

Area and Countries DFM uses the data from all economies, but it allows neither country-specific factors nor cross-country spillovers. Moreover, the Single Factor Euro Area and Countries DFM stipulates that the effect of its common factor is homogeneous. That is, the response of all economic indicators to changes in the factor is the same, up to a constant of proportionality related to the factor loadings.

Fig. B.1 summarizes the out-of-sample performance of all nowcasting models, including the Multi-Country baseline model. In our out-of-sample exercise, the RMSFEs of all models and economies consistently fall as we get closer to the GDP release (Fig. B.1). This finding indicates that incorporating incoming data into the information set of our models, on average, reduces the distance between the forecasted GDP growth and the actual GDP growth later released. There is also a substantial drop in all RMSFEs around eight weeks before the start of the forecasted quarter, which is explained by the release of PMIs and sentiment indicators.

The results for the euro-area aggregate (Fig. B.1(a)) show a clear hierarchy across models, with the Multi-Country DFM performing best. The Single Factor Euro Area DFM displays the highest RMSFEs, with this model using only the data specific to the euro-area aggregate (blue line). When we add the data of the three major euro-area countries while keeping the structure of the DFM unchanged (Single Factor Euro Area and Countries DFM), we improve the nowcasting performance for the euro-area aggregate. In fact, the RMSFEs of the Single Factor Euro Area and Countries DFM (yellow line) are consistently lower than those of the Single Factor Euro Area DFM (blue line). Finally, when we use the data of all four economies *and* model the dynamic relationship of these economies (Multi-Country DFM), we achieve the best performance. The RMSFEs of the Multi-Country DFM (red line) are lower than those of the two previous models. Of note, the difference in performance across models becomes much smaller in the backcast period.

The nowcasting improvement driven by jointly modeling euro-area economies and their dynamic relationship is also compelling for the major euro-area countries.

For Germany (Fig. B.1(b)), France (Fig. B.1(c)), and Italy (Fig. B.1(d)), our Multi-Country DFM performs best across the many different forecast horizons. However, in contrast to the euro-area aggregate, there is not a clear ranking in the performance of the Single Factor Country DFMs and Single Factor Euro Area and Countries DFM across the three euro-area countries. These results emphasize once more the need to model these economies jointly and exploit their lead-lag relationship. If one focuses only on jointly modeling these economies to take advantage of their non-synchronous release schedule, the performance gains might not be significant, as shown by the comparison between the Single Factor Euro Area and Countries DFM and the Single Factor Country DFMs.

Appendix C. Counterfactual: Postponing soft data releases

In this appendix, we build a counterfactual dataset in which the release of soft data matches the calendar of hard data. This exercise shows that the importance of soft data to nowcasting euro-area economies originates from

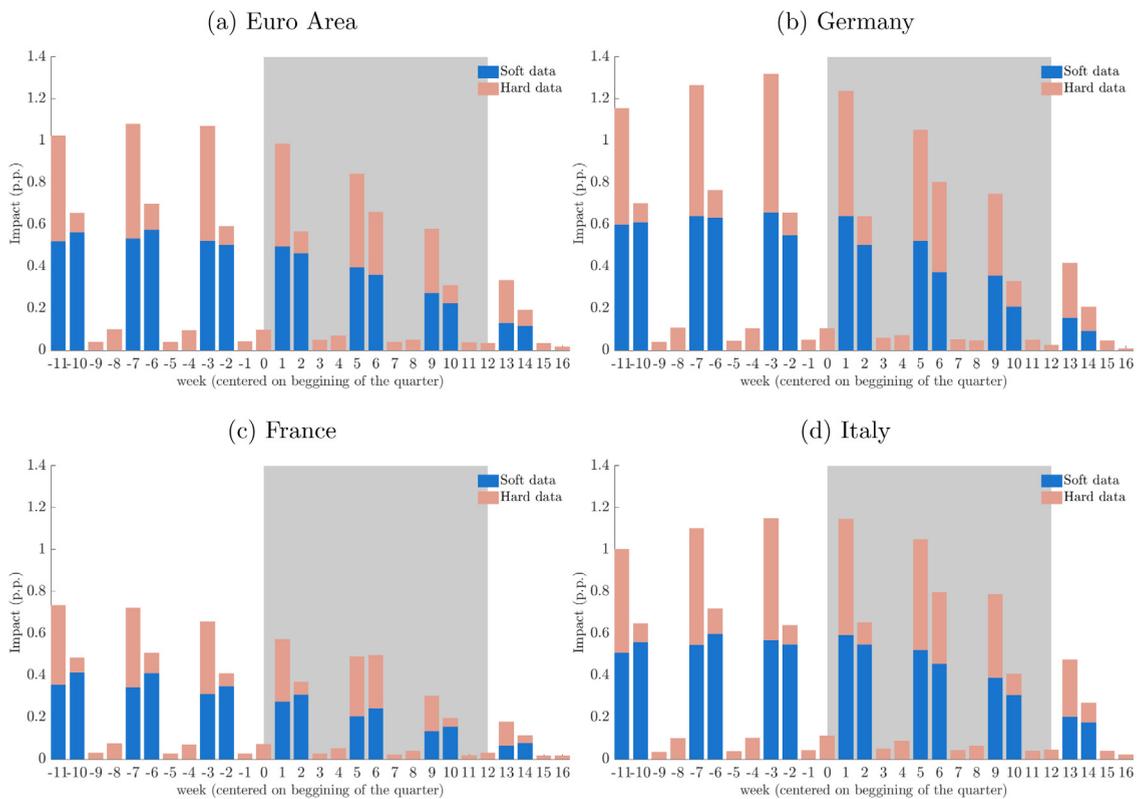


Fig. C.1. News decomposition of GDP growth: Postponing soft data releases.

Note: News is calculated as the average of the (absolute) forecast revisions led by a particular data release, Eq. (9). For the GDP growth of each economy (Figs. C.1(a)–C.1(d)), we group news from releases of hard (pink bars) and soft (blue bars) data. Counterfactual news assumes that releases of soft data are postponed, following a calendar similar to the industrial production of the associated country. The x-axis represents the weeks of the reference quarter, with negative numbers for weeks before the start of the quarter. Shaded areas represent nowcast weeks (current-quarter forecasts).

both the timeliness of their releases and their intrinsic information content about economic conditions. Fig. C.1 shows that, under the counterfactual dataset, the share of nowcasting revisions led by soft data (blue bars) relative to overall revisions decreases in the forecasting horizon (compared to Fig. 8). This result is consistent with the timeliness of soft data releases playing an important role in the real-time monitoring of economic conditions in the euro area. However, nowcasting revisions from soft data remain sizable, accounting for at least half of the revisions during weeks in which soft indicators are (counterfactually) released. This result points to the informativeness of soft indicators about the GDPs of euro-area economies even under this delayed release calendar. Hard indicators increase their importance (pink bars) to revisions of GDP, although they are far from taking over the role of soft indicators.

We assume the following delays in releases, which are roughly equivalent to postponing the release of soft indicators by about two months:

- Euro area: consumer confidence, business climate, manufacturing PMI and services PMI matching the release of the euro-area industrial production;
- Germany: GfK consumer climate, Ifo business climate, manufacturing PMI and services PMI matching the release of Germany's industrial production;
- France: manufacturing business survey (order books & demand), household confidence, BdF business sentiment, composite business climate, manufacturing PMI and services PMI matching the release of France's industrial production;
- Italy: ISAE consumer confidence, ISAE business confidence, manufacturing PMI and services PMI matching the release of Italy's industrial production.

Appendix D. 2020 Covid-19 crisis

(see Figs. D.1–D.3).

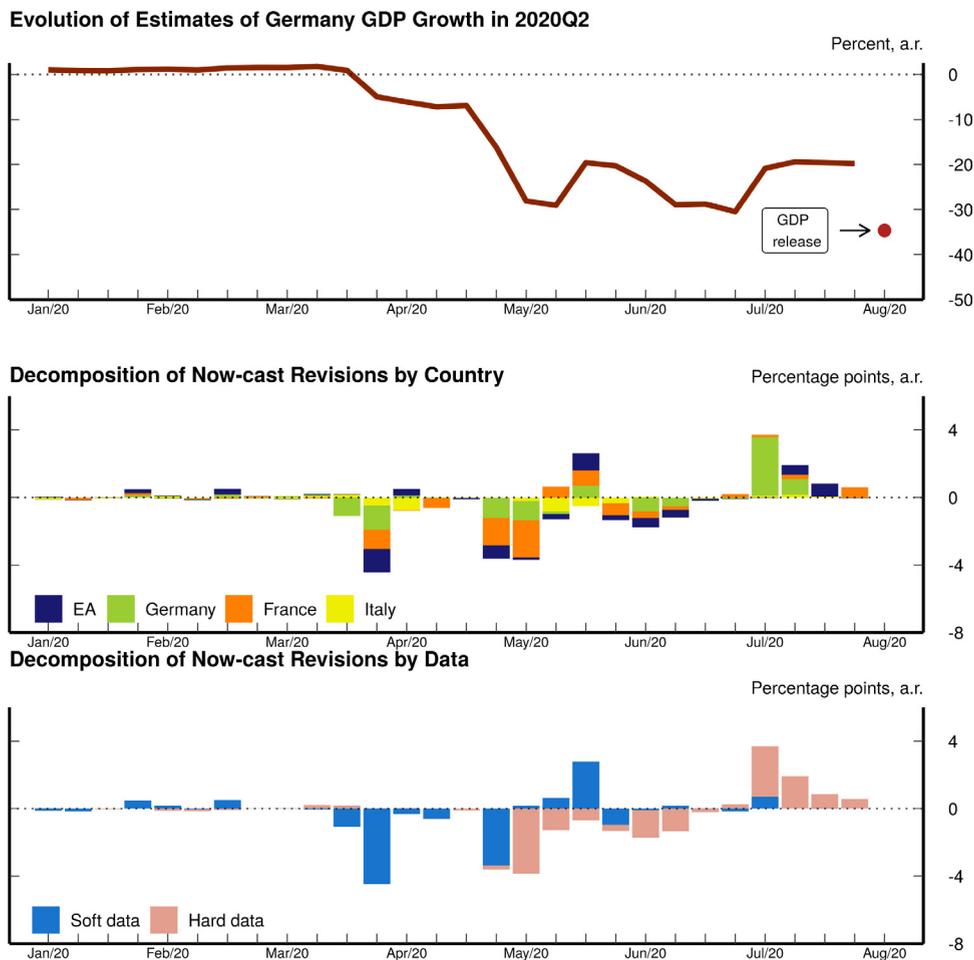


Fig. D.1. Germany GDP growth during the 2020 Covid-19 crisis. Note: The top panel presents weekly out-of-sample forecasts from our nowcasting model. The red dot in the top panel represents Germany quarterly GDP growth of 2020Q2. The middle panel presents the decomposition of the model forecast revisions by the country of origin of the data, whereas the bottom panel presents revisions by hard/soft data. Revisions due to estimation updates are not shown. More details are given in Sections 3 and 4.

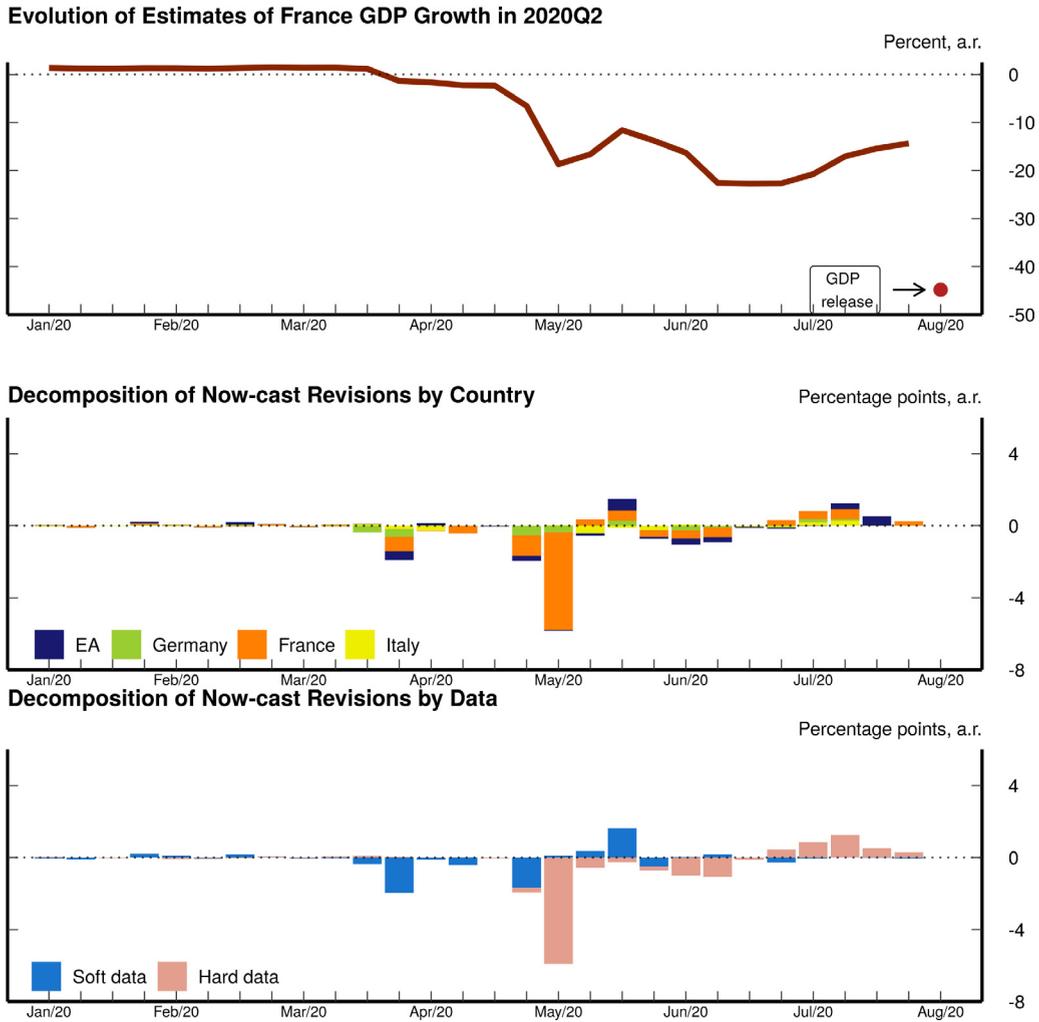
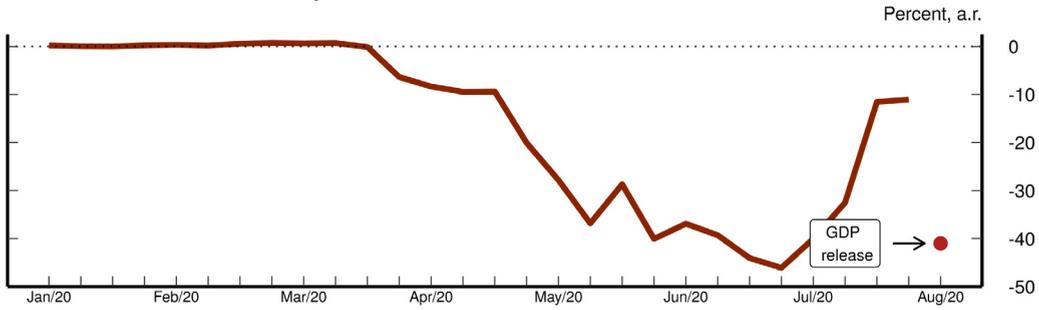
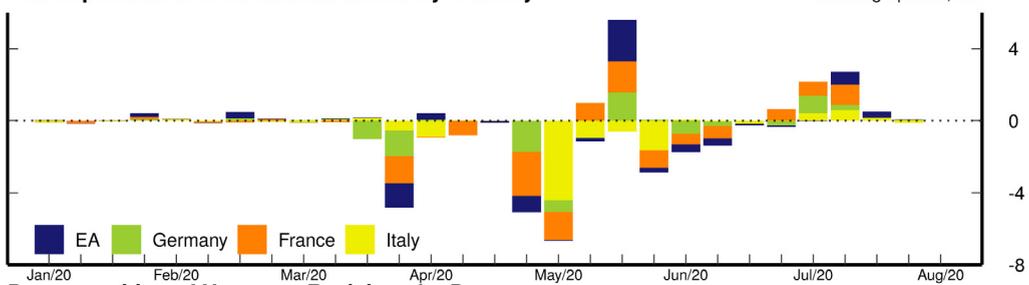


Fig. D.2. France GDP growth during the 2020 Covid-19 crisis.
 Note: The top panel presents weekly out-of-sample forecasts from our nowcasting model. The red dot in the top panel represents France quarterly GDP growth of 2020Q2. The middle panel presents the decomposition of the model forecast revisions by the country of origin of the data, whereas the bottom panel presents revisions by hard/soft data. Revisions due to estimation updates are not shown. More details are given in Sections 3 and 4.

Evolution of Estimates of Italy GDP Growth in 2020Q2



Decomposition of Now-cast Revisions by Country



Decomposition of Now-cast Revisions by Data

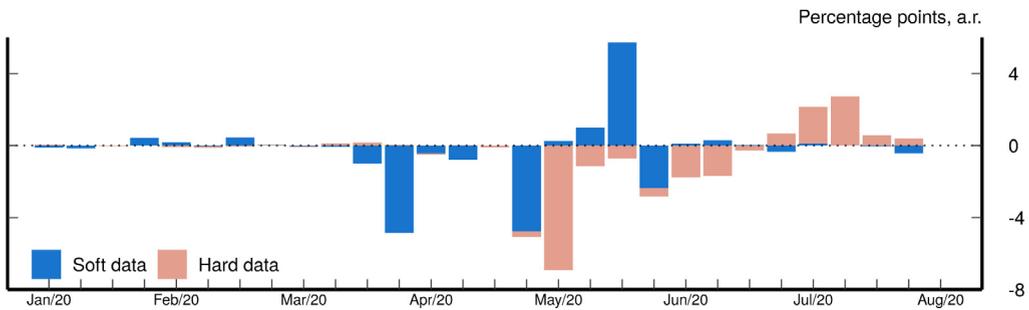


Fig. D.3. Italy GDP growth during the 2020 Covid-19 crisis.
 Note: The top panel presents weekly out-of-sample forecasts from our nowcasting model. The red dot in top panel represents Italy quarterly GDP growth of 2020Q2. The middle panel presents the decomposition of the model forecast revisions by the country of origin of the data, whereas the bottom panel presents revisions by hard/soft data. Revisions due to estimation updates are not shown. More details are given in Sections 3 and 4.

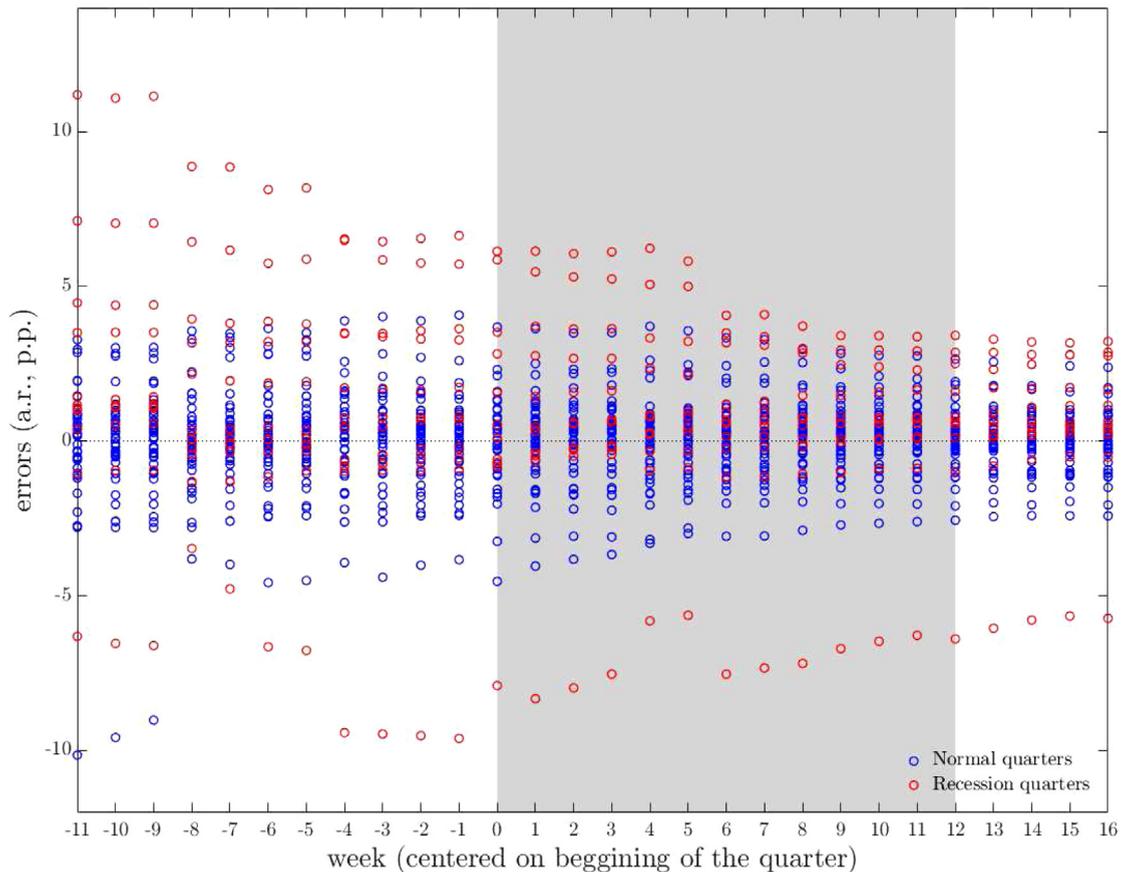


Fig. E.1. Empirical distribution of forecast errors for the euro area.

Note: Forecast errors are calculated in the out-of-sample exercise described in Section 3.4 using our nowcasting model (Section 3.1). Red dots represent the errors when the forecasted quarter is in a recession period (from 2008Q2 to 2009Q2, and from 2011Q4 to 2013Q1), as defined by the Center for Economic and Policy Research (CEPR). Blue dots represent the errors when the forecasted quarter is of non-recession periods. The x-axis represents the weeks of the forecasted quarter, with negative numbers referencing the weeks before the start of the quarter. The shaded area represents the nowcasting period (current-quarter forecasts). The white area before the shaded area represents forecast periods (one-quarter-ahead forecasts). The white area after the shaded area represents backcast periods (previous-quarter forecast).

Appendix E. Supplementary results

(see Fig. E.1).

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