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Macrofinancial information on the post-COVID-19 economic recovery: Will it be V, U or L-shaped? [☆]

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ABSTRACT

We use standard macrofinancial no-arbitrage term structure models to forecast key macroeconomic variables such as GDP. Simple adaptations to the models are proposed in order to generate plausible forecasts in the context of the COVID-19 crisis. The financial market variables included in the models are shown to improve GDP forecasts. Forecasts of real GDP conditioned on macrofinancial information up to August 2020 suggest that the shape of the recovery will most likely be between a U and an L in most euro area countries considered, with substantial persistent losses.

1. Introduction

The announcement of lockdown measures to contain the COVID-19 virus made it clear that economic activity would be immediately and severely impacted, as was soon confirmed by timely indicators such as purchasing managers' indices and sentiment indicators. However, significant uncertainty remains regarding the longer-term impact of the pandemic, which gives rise to the on-going debate on the potential shapes of the recovery. Analysts typically forecast one of three shapes: V, U or L. Although the origins of this nomenclature is unclear, there is widespread agreement on its meaning. As schematised in Fig. 1, a V-shaped recovery means that GDP swiftly recovers after a short (but potentially deep) recession; a U-shaped recovery means a (slightly) slower recovery; and an L-shaped recovery implies that GDP never (even partly) recovers from the losses incurred during the recession.

The on-going debate (and uncertainty) on the shape of the recovery is also reflected in the uncertainty around real GDP growth forecasts from the ECB's Survey of Professional Forecasters. The survey vintage of the third quarter of 2020 indicates year-on-year real GDP growth expectations of 5.7% for 2021 in the euro area, with a significant probability that growth might be as low as 2% or greater than 10%. Such a large range for GDP growth expectations is unprecedented and reflects the challenge of using standard macroeconomic models in the context of the post-COVID-19 recovery as well as tremendous uncertainty regarding the shape of the

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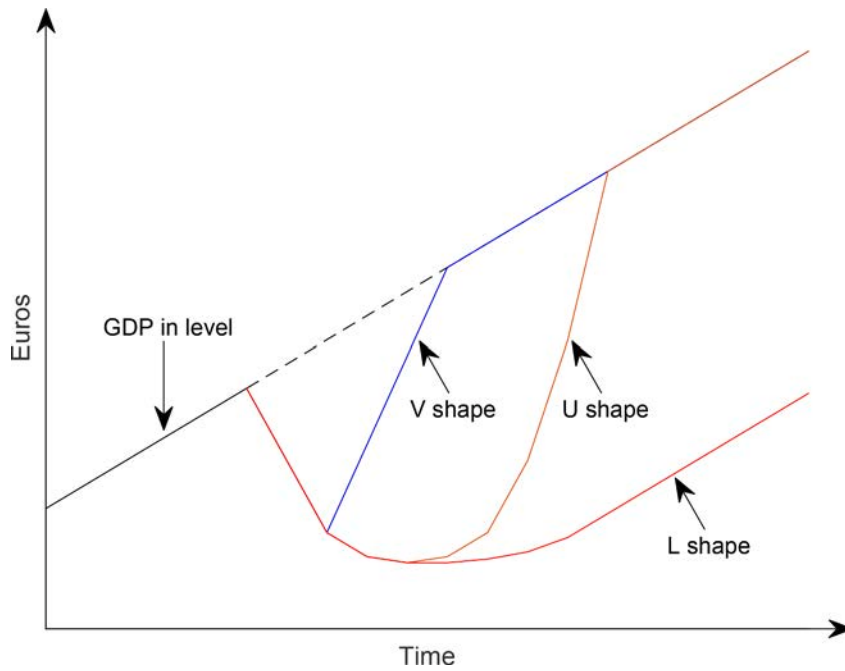


Fig. 1. Potential shapes of the recovery.

Table 1

Granger causality test statistics for GDP growth. Notes: The statistics are computed as $T^* (\log(|\tilde{\Omega}(0)|) - \log(|\tilde{\Omega}|))$, where T is the sample size and $\tilde{\Omega}(0)$ and $\tilde{\Omega}$ are the variances of the residuals from the GDP growth regression with and without zero restrictions. Significance in the upper panel indicates rejection of the null hypothesis of the vector of OIS and spread PCs [PC_1^{OIS} , PC_2^{OIS} , PC_1^{Spr} , PC_2^{Spr}] not Granger causing GDP growth. The same tests are carried out in other panels for financial market variables and the EA economic activity indicators. The tests rely on estimates of model 2 (see Section 4.1); results are similar when based on estimates of model 1 and identical when based on estimates of model 3. Significance at the 10%, 5% and 1% thresholds is indicated by *, ** and ***, respectively.

Austria	Belgium	France	Germany	Italy	Netherlands	Portugal	Spain
OIS and spread PCs							
10.0**	32.5***	10.7**	7.9*	22.5***	11.3**	2.7	27.8***
Financial market variables							
16.0**	62.9***	61.0***	30.5***	45.1***	33.0***	50.2***	78.3***
EA economic activity indicators							
51.9***	34.2***	21.3***	65.1***	44.7***	32.5***	9.6**	12.9***

recovery. A growth rate above 10% for 2021 suggests a V-shaped recovery, whereas a growth rate of 2% suggests an L shape.

2. Data and preliminary analysis

Our dataset consists of global, euro area (EA) and country-specific variables for Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. As EA variables, we use: zero-coupon equivalents to overnight indexed swap (OIS) rates with maturities of 1 to 5 years and 7 and 10 years (proxying for the risk-free rates in the EA); three variables measuring economic activity, namely the Purchasing Managers' Index (PMI), the Economic Sentiment Indicator (ESI) and Industrial Production (IP); the year-on-year growth rate of the EuroStoxx index; the spread between the yield on the German-government-guaranteed bank bonds (such as those issued by KfW) and Bund yields measuring flight-to-safety (F2S); and the European economic policy uncertainty index of Baker et al. (2016) (POL). The country-specific variables are: zero-coupon sovereign yields with maturities of 1 to 5 years and 7 and 10 years; the year-on-year growth rate of real GDP; the year-on-year growth rate of the harmonised index of consumer prices (π); and the year-on-year change in public debt over GDP ($\Delta(D/GDP)$). Finally, our only global variable is the Chicago Board Options Exchange Volatility Index, or VIX, serving as a proxy for global risk aversion. Time series figures and further information on data sources can be found in Appendix A.

Table 2
Zero restrictions in VAR feedback matrix Φ . Notes: model 1 is unrestricted; model 2 entails the zero restrictions shown in the table; model 3 does not entail the bold zero restrictions. For Belgium and the Netherlands, model 3 resulted in non-stationary VAR dynamics. In order to recover stationarity, we imposed an additional zero restriction in the equation of the first Belgian spread PC on the coefficient of the first euro area spread PC. For the Netherlands, we imposed zero restrictions in the equation of $\Delta(D/GDP)$ on the coefficients of Dutch spread PCs.

		Variables															
		PC_1^{OIS}	PC_2^{OIS}	PC_1^{Eurspr}	PC_2^{Eurspr}	PMI	IP	ESI	VIX	EuroStoxx	F2S	POL	PC_1^{Spr}	PC_2^{Spr}	GDP growth	π	$\Delta(D/GDP)$
Equations	PC_1^{OIS}			0	0	0	0	0	0	0	0	0	0	0	0	0	0
	PC_2^{OIS}			0	0	0	0	0	0	0	0	0	0	0	0	0	0
	PC_1^{Eurspr}					0	0	0	0	0	0	0	0	0	0	0	0
	PC_2^{Eurspr}					0	0	0	0	0	0	0	0	0	0	0	0
	PMI												0	0	0	0	0
	IP												0	0	0	0	0
	ESI												0	0	0	0	0
	VIX												0	0	0	0	0
	EuroStoxx												0	0	0	0	0
	F2S												0	0	0	0	0
	POL												0	0	0	0	0
	PC_1^{Spr}			0	0	0	0	0	0	0	0	0			0	0	0
	PC_2^{Spr}			0	0	0	0	0	0	0	0	0			0	0	0
	GDP growth														0		
	π					0	0	0									0
	$\Delta(D/GDP)$					0	0	0								0	

We carry out Granger causality tests to assess whether yield curves, financial market variables and EA economic activity indicators help to predict country-specific GDP growth. The set of financial market variables tested entails: the VIX; the EuroStoxx growth rate; the F2S index; the first two principal components (PCs) of country-specific yield spreads with respect to OIS yields, PC_1^{Spr} and PC_2^{Spr} ; and the first two principal components of EA yield spreads, PC_1^{Eurspr} and PC_2^{Eurspr} . The first two principal components of OIS rates, PC_1^{OIS} and PC_2^{OIS} , are left out of the set of financial market variables as OIS rates would likely be included in macroeconomic models to account for monetary policy. The set of EA economic activity indicators includes the PMI, the ESI, and IP.

Table 1 reports the outcome of the Granger causality tests for the three groups of variables. The results indicate that the information embedded in yield curves, financial market variables and EA economic activity indicators helps to predict GDP growth in almost all of the countries in our panel. The only exception to this general finding is Portugal (and partially Germany), where yield curves are not found to Granger cause GDP growth. Overall, the results highlight the importance of accounting for the information embedded in forward-looking variables and EA economic activity indicators in predicting GDP growth. More detailed results on Granger causality tests can be found in Table B.1 (in Appendix B).

In the next section, we present a macrofinance modelling framework capable of incorporating yield curves, financial and macroeconomic information in a consistent (no-arbitrage) setting.

3. Modelling framework

Following Dewachter et al. (2015, 2019), we propose two-country term structure models relating OIS rates and country-specific sovereign yields to a set of macrofinancial variables. The models consist of three ingredients. First, the short-term OIS rate and country j 's short-term sovereign yield, respectively r_t^{OIS} and r_t^j , are affine in a set of PCs:

$$r_t = \rho_0 + \rho_1 \mathcal{P}_t, \quad (1)$$

where $r_t = [r_t^{OIS}, r_t^j]'$, $\mathcal{P}_t = [\mathcal{P}_t^{OIS'}, \mathcal{P}_t^{Sprj'}]'$ is a column vector of the first two PCs of OIS rates and the first two PCs of country j 's sovereign spreads, ρ_0 is a 2-by-1 vector and $\rho_1 = [1 \ 1 \ 0 \ 0; 1 \ 1 \ 1 \ 1]$ is a 2-by-4 matrix so that r_t^{OIS} does not load on $\mathcal{P}_t^{Sprj}$ and r_t^j is the sum of OIS and spread PCs (Dai and Singleton, 2000).

Second, $\mathcal{P}_t$ evolves under the risk-neutral probability measure $\mathbb{Q}$ as a one-lag vector autoregressive process (VAR(1)) with $K = 4$ variables:

$$\mathcal{P}_t = C^{\mathbb{Q}} + \Phi^{\mathbb{Q}} \mathcal{P}_{t-1} + \nu, \quad \nu \sim N(0, \Psi). \quad (2)$$

Finally, the last ingredient of our models relates $\mathcal{P}_t$ to the column vector of $N = 12$ macrofinancial factors ($\mathcal{M}_t$) via a VAR(1) under the physical probability measure $\mathbb{P}$:

$$Z_t = C + \Phi Z_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Omega), \quad (3)$$

where, $Z_t = [\mathcal{M}_t, \mathcal{P}_t]'$.

Given Eqs. (1)–(3), the OIS rates and country j 's sovereign yields are linearly related to $\mathcal{P}_t$:

$$Y_t = A + B \mathcal{P}_t + \eta_t, \quad \eta_t \sim N(0, \Sigma), \quad (4)$$

where, $Y_t = [Y_t^{OIS'}, Y_t^j]'$ and A and B are derived from no-arbitrage conditions. We model Σ as a diagonal matrix with identical entries.

Given Eqs. (1) and (4), the macrofinancial factors $\mathcal{M}_t$ are said to be unspanned by the yield curves (Joslin et al., 2014). The parameters in C and Φ in Eq. (3) are estimated by ordinary least squares and the rest of the parameters in Eqs. (1)–(4) is estimated by maximum likelihood (Joslin et al., 2011).

4. Conditional forecasts

4.1. Set-up

Because of the major disruptions due to the COVID-19 outbreak, we adapt standard VAR practice along two dimensions: (i) the VAR feedback matrix Φ is restricted mainly to limit the endogenous propagation of the significant shocks observed in some variables in 2020 to the forecasts of variables that were less affected by the COVID-19 outbreak (and hence to obtain more reasonable forecasts for those variables that were less affected); and (ii) the models are estimated using data up to December 2019 only, i.e. the latest and extreme data points observed in 2020 are not taken into account in the estimation as they would garble parameter estimates and in fact often result in non-stationary VAR dynamics.

Regarding the first adaptation, we impose zero restrictions in the matrix Φ as shown in Table 2 according to two principles: (i) the PCs of risk-free rates and sovereign spreads are made “block exogenous” (in the time series sense), ensuring that COVID-19 shocks do

not drive yield curve dynamics with a lag;¹ and (ii) zero restrictions are imposed in the equations of country-specific macroeconomic variables to streamline the forecasts of these variables, so that inflation forecasts do not show excessive variation given the relatively limited impact of the COVID-19 outbreak on inflation so far (see the zero restrictions in the π equation on the coefficients of real economic activity indicators), GDP growth forecasts are not directly related to lagged inflation so that a strong link between GDP growth and EA economic activity indicators is preserved (see the zero restriction in the GDP growth equation on the π coefficient) and $\Delta(D/GDP)$ forecasts are closely linked to GDP growth forecasts (see the zero restrictions in the $\Delta(D/GDP)$ equation). Besides, country-specific variables are excluded from the equations of EA variables, ensuring that forecasts of EA variables remain the same across country models.

In addition to an unrestricted model and a model with the zero restrictions detailed above, we also consider a model with less zero restrictions, namely relaxing the restrictions based on the first principle (block exogeneity of yield and spread PCs). To sum up, we focus on three macrofinancial models:

- Model 1: unrestricted model;
- Model 2: model with zero restrictions in Φ according to the principles above;
- Model 3: same as model 2 but without block exogeneity of yield and spread PCs.

Related to the second adaptation, models are estimated based on data going from August 2005 (start of the long-term OIS rates time series) to December 2019 (to avoid the extreme data points observed in 2020 which would otherwise garble parameter estimates). Accordingly, we generate three types of forecasts:

- **Unconditional forecasts** (in the sense of Doan et al., 1986; Waggoner and Zha, 1999; Jarociński, 2010): as of December 2019, h -month ahead unconditional forecasts of the macrofinancial factors, $E_{Dec.2019}(Z_{Dec.2019+h}) \forall h \geq 1$, are generated by iterating forward the VAR dynamics in Eq. (3):

$$E_{Dec.2019}(Z_{Dec.2019+h}) = \left(\sum_{j=0}^{h-1} \Phi^j \right) C + \Phi^h Z_{Dec.2019}, \quad (5)$$

and unconditional yield forecasts $E_{Dec.2019}(Y_{Dec.2019+h})$ are obtained by mapping the PCs' forecasts into yield space using Eq. (4):

$$E_{Dec.2019}(Y_{Dec.2019+h}) = A + B E_{Dec.2019}(\mathcal{P}_{Dec.2019+h}). \quad (6)$$

In the next subsection, figures display unconditional forecasts from model 2 only since unconditional forecasts obtained from the three macrofinancial models are broadly similar although those from model 2 are somewhat smoother than those from models 1 and 3.

- **Forecasts conditional on data observed in 2020:** These forecasts reconcile the models' forecasts with data points observed in 2020. More specifically, forecasts conditional on data observed in 2020 are generated according to (5) and (6), with the restriction that the forecasts match any value taken in 2020 by any of the 16 variables included in the VAR systems. Forecasts conditional on 2020 observations are computed from model 1 - to illustrate that an unrestricted model, even if estimated with data up to December 2019, generates exuberant forecasts - and 2, while model 3 is devoted to the third type of forecasts (see below). Besides, forecasts conditional on 2020 observations are computed from a macroeconomic model without financial market variables to serve as benchmark.
- **Path-dependent conditional forecasts:** This type of forecasts not only takes into account the data points observed in 2020, but also complies with any specific (long-run) paths imposed on any of the 16 variables included in the VAR systems. We use this type of forecasts for model 3 in conjunction with specific paths up to the end of 2025 for the OIS rates PCs and the sovereign spreads PCs. If no specific paths were imposed on these PCs, model 3 would generate exuberant forecasts for OIS rates and sovereign spreads as the PCs' forecasts would be allowed to endogenously integrate the large shocks observed in other variables in 2020. Regarding the specific paths taken by the PCs, we impose the values of conditional forecasts obtained from model 2 as those values seem plausible and help to compare conditional forecasts across models.²

Conditional forecasts are generated as in Doan et al. (1986) and Waggoner and Zha (1999). Finally, note that we impose that inflation forecasts converge to 1.9% in the long run, anchoring inflation expectations in line with the ECB's price stability mandate.

4.2. Forecasts

Fig. 2 shows forecasts of real GDP growth up to the end of 2025. Unconditional forecasts remain broadly flat at end-of-2019 growth

¹ The core of the term structure model therefore essentially becomes a "yield-only" specification similar to many classic term structure models (Adrian et al., 2013; Kim and Wright, 2005; Lemke and Vladu, 2017). However, unlike classic yield-only models, the set of zero restrictions does not exclude the macrofinancial variables from being contemporaneously related to yields and spreads, i.e. the model entails an implicit Taylor rule.

² Conditional forecasts for other variables may differ between models 2 and 3 because the pseudo residuals computed in 2020 and the estimates of the covariance matrix Ω may differ between models.

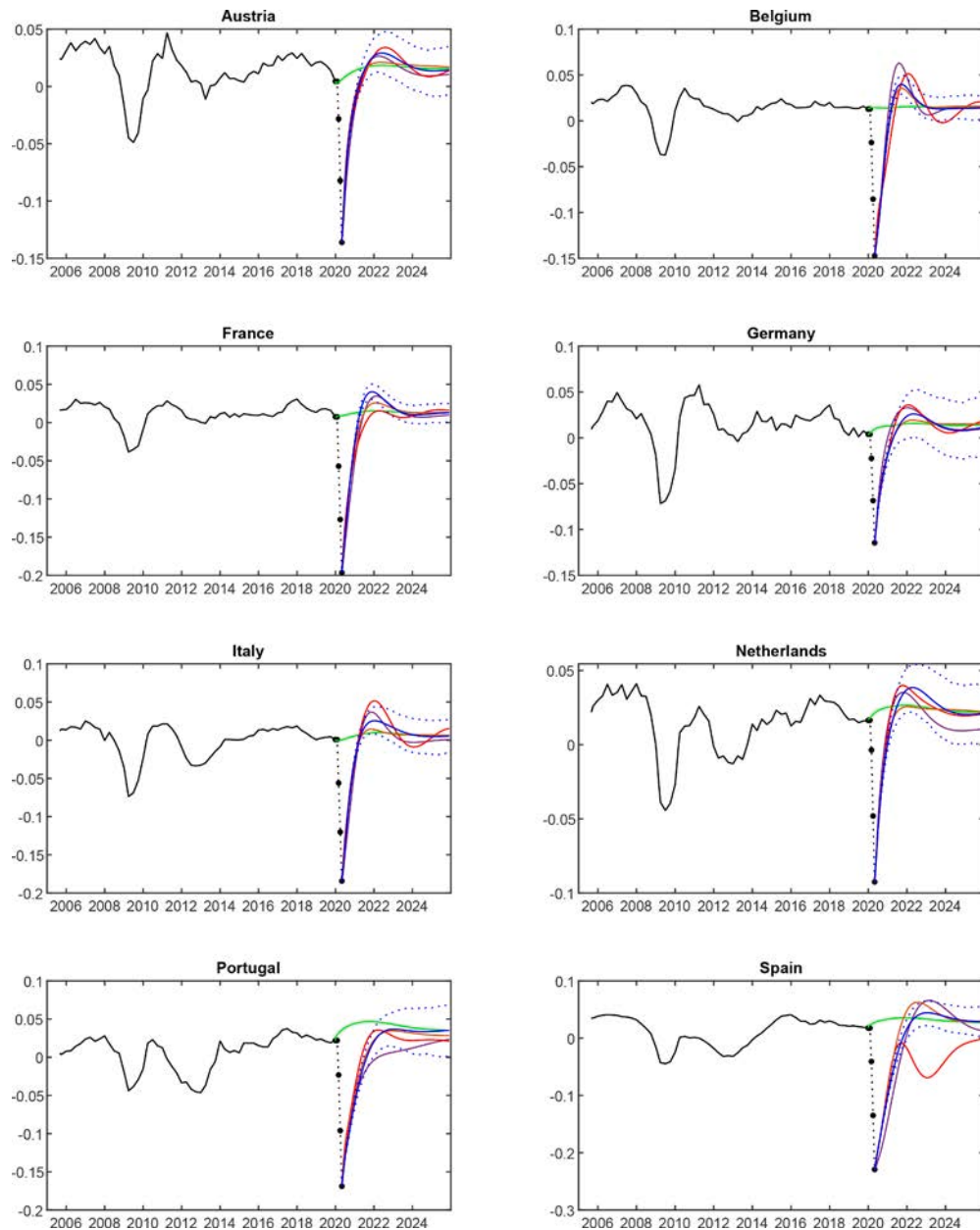


Fig. 2. GDP growth. Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red, blue, orange and purple lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1, 2, 3 and from a macroeconomic model without financial market variables. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

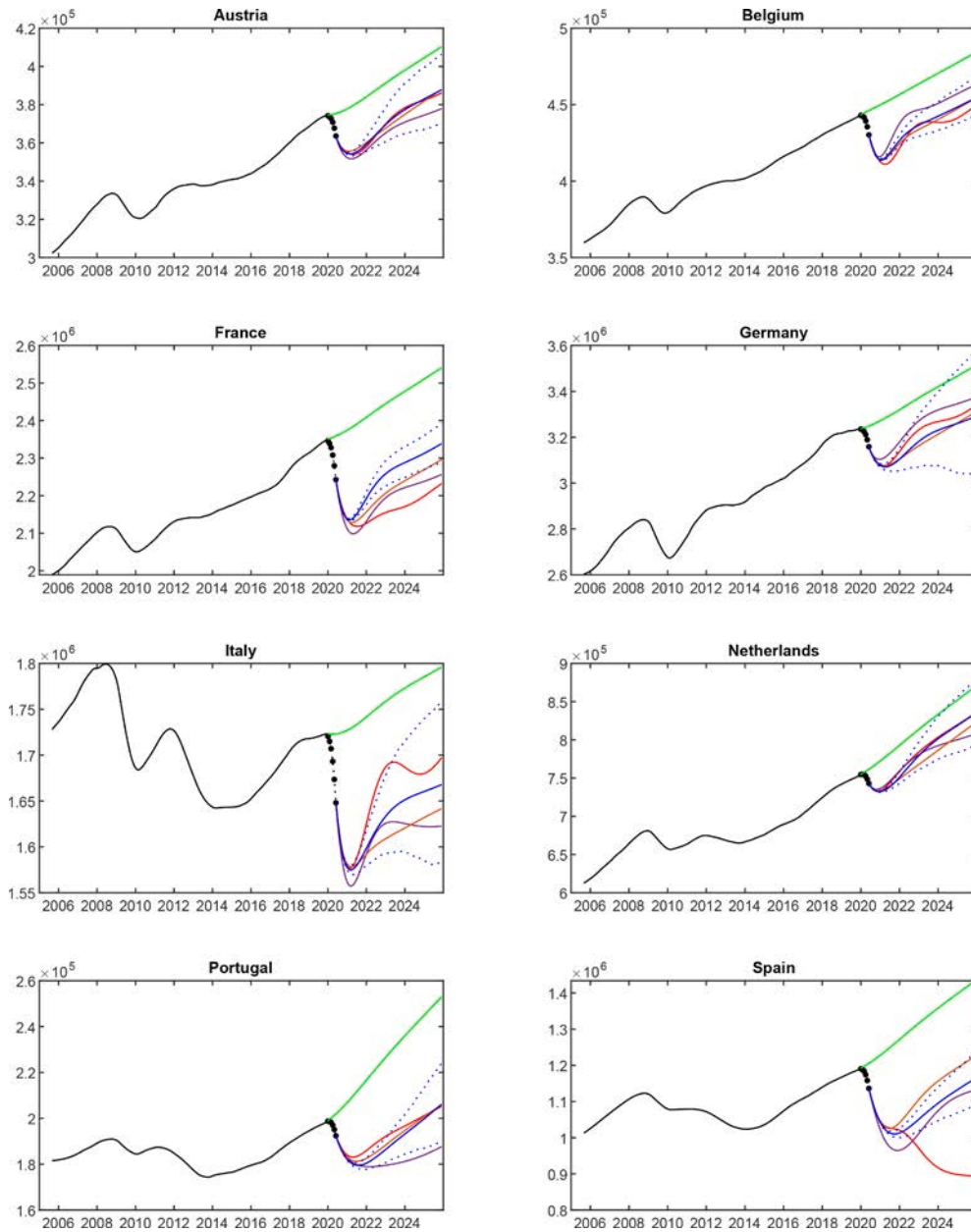


Fig. 3. Yearly cumulated GDP. Notes: Million euros. Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red, blue, orange and purple lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1, 2, 3 and from a macroeconomic model without financial market variables. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3

RMSE ratios. Notes: The table shows RMSEs for GDP growth forecasts obtained from model 2 when accounting for the timely information in some variables over the RMSEs obtained when not accounting for timely information. Financial market variables and EA economic activity indicators comprise respectively [VIX, EuroStoxx, F2S, PC_1^{Spr} , PC_2^{Spr} , PC_1^{Eurspr} , PC_2^{Eurspr}] and [PMI, ESI, IP]. RMSE ratios significantly smaller than one at the 10%, 5% and 1% thresholds are indicated by *, ** and ***, respectively (one-sided tests). Significance results are based on Diebold-Mariano tests which consist in testing the significance of the intercept with heteroskedasticity-and-autocorrelation-consistent standard errors in intercept-only regressions of the difference in squared forecast errors between models with and without timely information (Diebold and Mariano, 2002; Diebold, 2015).

	Austria	Belgium	France	Germany	Italy	Netherlands	Portugal	Spain
α	OIS and spread PCs							
	1-month	0.95*	0.93**	0.98	0.99	0.97*	0.99	0.98
	3-month	0.88**	0.79*	0.93	0.97	0.93**	0.95	0.92
	6-month	0.85*	0.77*	0.76*	0.88**	0.86**	0.84	0.83
	1-year	0.98	0.94	0.92*	0.99	0.91**	0.98	0.95
	2-year	0.98	0.99	0.99	0.95	0.97	1.00	0.97
	3-year	0.98	0.98	0.97	0.97	0.98*	0.99	0.98
	Financial market variables							
	1-month	0.97*	0.96**	0.97*	1.00	0.95**	0.98	0.89***
	3-month	0.90**	0.86**	0.85**	0.96	0.88**	0.92**	0.72***
	6-month	0.84*	0.78*	0.71*	0.81**	0.79**	0.75**	0.65**
	1-year	0.92*	0.89**	0.85**	0.97	0.92	0.87	0.81***
	2-year	1.00	0.98**	0.98**	1.01	0.98	0.97	0.98
	3-year	0.98**	0.99	0.96**	0.98*	0.98***	0.99	1.00
	EA economic activity indicators							
	1-month	0.94**	0.95**	0.96	0.90**	0.88***	0.96**	0.95**
	3-month	0.79***	0.88*	0.89*	0.84**	0.80***	0.89**	0.91*
	6-month	0.69***	0.81*	0.73*	0.83*	0.66**	0.72**	0.79*
	1-year	0.85***	0.92**	0.85**	0.79**	0.82**	0.82**	0.87**
	2-year	0.99	0.99	0.98**	1.02	1.01	0.99*	1.00
	3-year	0.99	0.99	0.97**	1.00	0.99	0.97*	0.98
	All variables							
	1-month	0.89***	0.88***	0.95*	0.87***	0.82***	0.92**	0.84***
	3-month	0.72***	0.72**	0.79**	0.77***	0.70***	0.82***	0.70***
	6-month	0.62***	0.64**	0.58**	0.72**	0.61***	0.61**	0.58***
	1-year	0.84***	0.85**	0.79***	0.79**	0.80**	0.84*	0.78***
	2-year	0.94***	0.96**	0.97*	0.93*	0.92**	0.96*	0.94*
	3-year	0.97*	0.98	0.95*	0.97	0.97**	0.95	0.98

levels in all countries. By contrast, conditional forecasts start from the low points reached in the second quarter of 2020.³ The various models generate broadly consistent conditional forecasts of GDP growth in the sense that GDP growth is forecasted to return to more normal levels relatively quickly, with in general some overshooting above unconditional forecasts in 2021 and 2022. Nevertheless, some differences appear across models. First, for some countries the forecasts generated from the benchmark macroeconomic model without financial market variables and from model 1 appear less plausible. For example, the benchmark macroeconomic model forecasts for Portugal that GDP growth will return to normality only after 2024, and model 1 forecasts negative growth rates in Spain up to 2025. Second, forecasts from model 2 are smoother, homogeneous across countries and often close to the average forecasts from the other models, and hence seem more intuitive (in particular looking at the forecasts of sovereign spreads in Fig. A.3).⁴

Fig. 3 translates the GDP growth forecasts into forecasts of GDP in level (yearly cumulated). Virtually none of the models forecasts a complete V-shaped recovery in any country. Furthermore, even if short-term forecasts are in general in line with a V or U-shaped recovery, longer-term forecasts show substantial persistent losses resulting from the COVID-19 crisis. In particular, model 2 forecasts GDP to partially recover from the crisis in most countries but not to converge back to the trend path prevailing before the pandemic. Instead, GDP forecasts settle on a parallel trend path, lower than the one forecasted before the COVID-19 outbreak. As a result, the shape of the recovery is forecasted to be something between a U and an L, with significant persistent losses. These results are in line with those of [Primiceri and Tambalotti, 2020](#), [Lenza and Primiceri, 2020](#), [Foroni et al., 2020](#), and [Schorfheide and Song, 2020](#) who also predict persistent losses from the COVID-19 crisis in various jurisdictions.

5. Impact of short-term conditions on forecasts

Conditioning forecasts on data observed in 2020 gives a helping hand to forecast GDP given that GDP suffers from significant publication lags. At the time of writing, GDP is available only up to the second quarter of 2020, whereas financial market variables are already available up to August 2020 as they are released in real time. Similarly, the EA economic activity indicators included in the model are timely published (e.g. the PMI and the ESI are published at the end of the month they refer to).

We study the impact of the timely information available in financial market variables and EA economic activity indicators on GDP growth forecasts in an in-sample conditional forecasting exercise. Table 3 shows the results of the exercise in the form of RMSE ratios: RMSE of GDP growth forecasts incorporating timely information from some variables over the RMSE of GDP growth forecasts disregarding timely information (forecasts are based on model 2).⁵ The results complement the Granger causality tests carried out in Section 2. They show that accounting for the timely information in yield curves, financial market variables, and EA economic activity indicators helps to improve GDP growth forecasts (RMSE ratios are significantly smaller than 1). Improvements are most important at short horizons (three and six months) but remain substantial up to the three-year horizon in some cases.

Given these results, it is clear that short-term conditions play an important role in shaping GDP growth forecasts. In particular, the model would have predicted a V-shaped recovery would the information in timely variables have been more upbeat. Such a counterfactual would typically entail stronger bounce-back effects in PMI, ESI and IP, and lower sovereign spreads, F2S and VIX.

6. Conclusion

In this paper, we forecast the shape of the post-COVID-19 recovery in several EA countries using a macroeconomic model without financial market variables and several versions of a macrofinancial model. Most of the models indicate that the shape of the recovery will most likely be between a U and an L, with substantial persistent losses. Given the contrasting relatively good shape of financial markets, the results suggest that a low-for-long interest rate environment is priced in.

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³ The low points are reached in May 2020 (middle of the second quarter). Besides, GDP growth in January and February 2020 is assumed to remain the same as in December 2019 so that the decline in GDP growth registered in the first quarter is attributed to March 2020, i.e. when lockdown measures were implemented in Europe.

⁴ Two technical remarks are in order. First, the distribution around sovereign spread forecasts from model 2 is symmetric around the baseline forecasts and hence cover a significant area in negative territory, which is an issue for some countries whose spreads have never been negative and can hardly be expected to be significantly negative in the coming years (see also [Fujiwara et al., 2013](#)). Second, confidence bands around the forecasts generated by model 2 - computed as in [Jarociński \(2010\)](#) - are somewhat narrow for short-term forecasts. One could therefore use the proposition of [Lenza and Primiceri, 2020](#) to widen confidence bands so as to reflect increased forecast uncertainty after the COVID-19 outbreak.

⁵ In this exercise, financial market variables, PMI, ESI and inflation are assumed to be observable for three more months than GDP and IP is assumed to be observable for one more month, as is the case at the time of writing.

Appendix A. Data

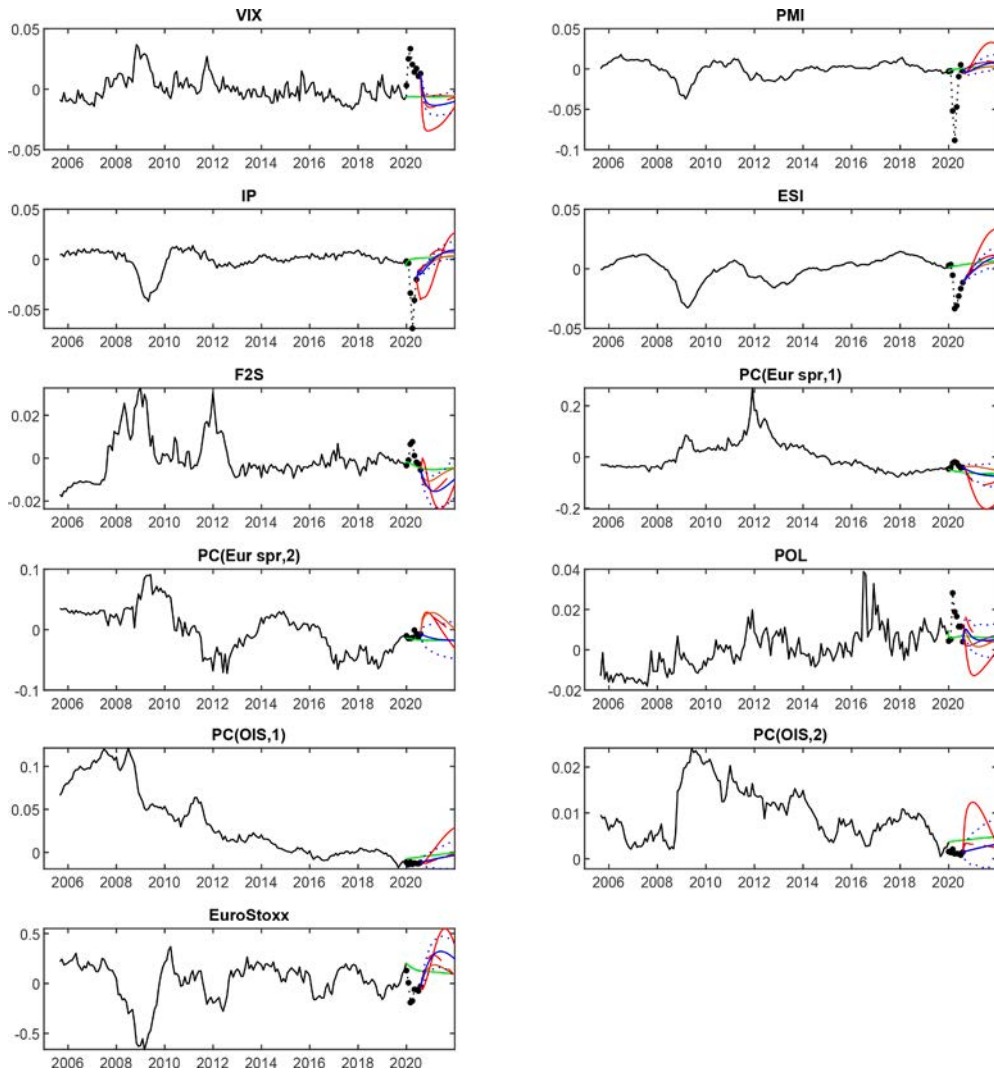


Fig. A.1. Unspanned and spanned common factors. Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, blue, orange and purple lines denote respectively unconditional forecasts (from model 2), conditional forecasts from models 2, 3 and from a macroeconomic model without financial market variables. Continuous and dashed red lines represent conditional forecasts from model 1 with respectively Belgium and the Netherlands appended to the model. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

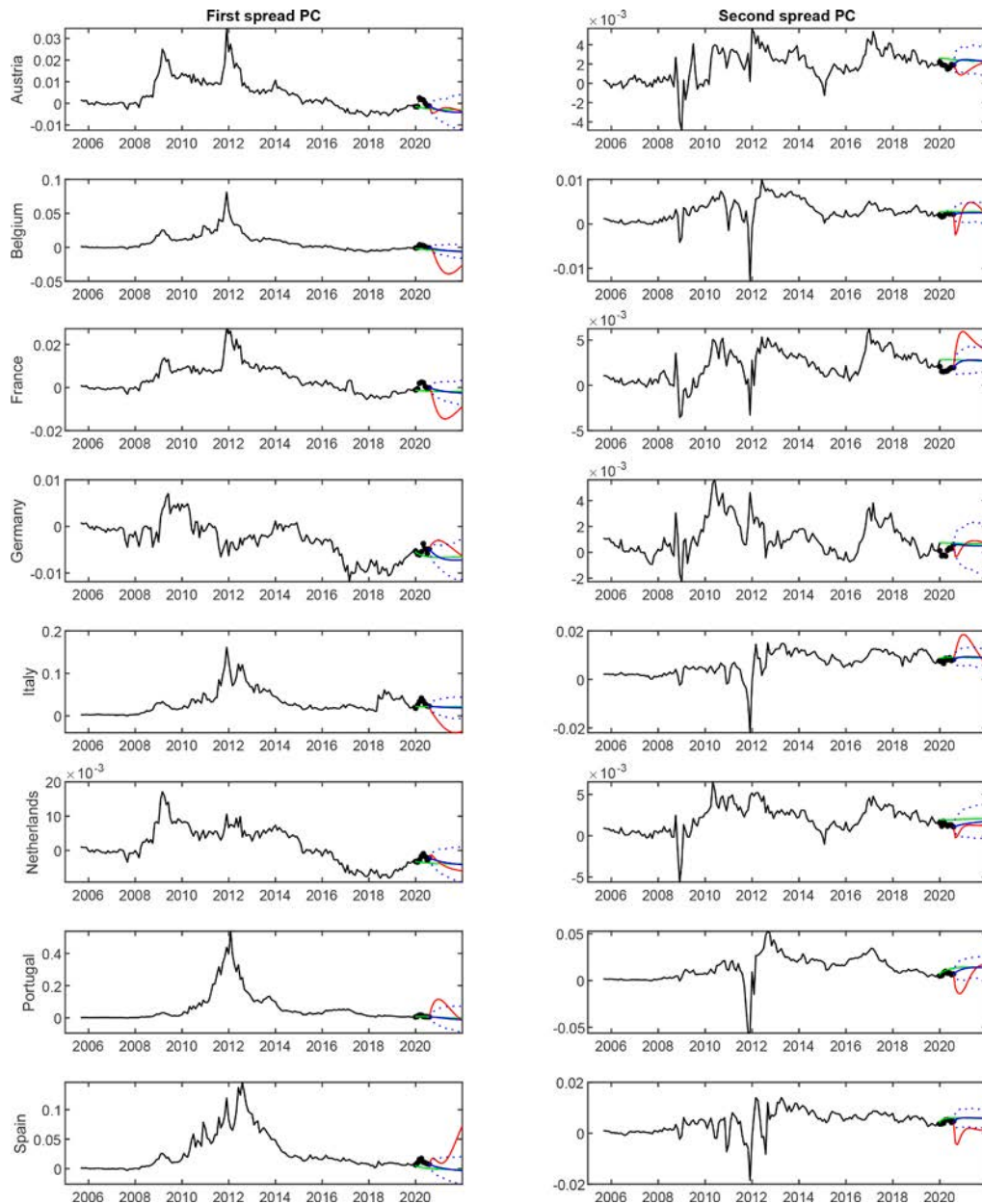


Fig. A.2. Spanned country-specific factors (spread PCs). Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red and blue lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1 and 2. The paths imposed in model 3 match the blue lines. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

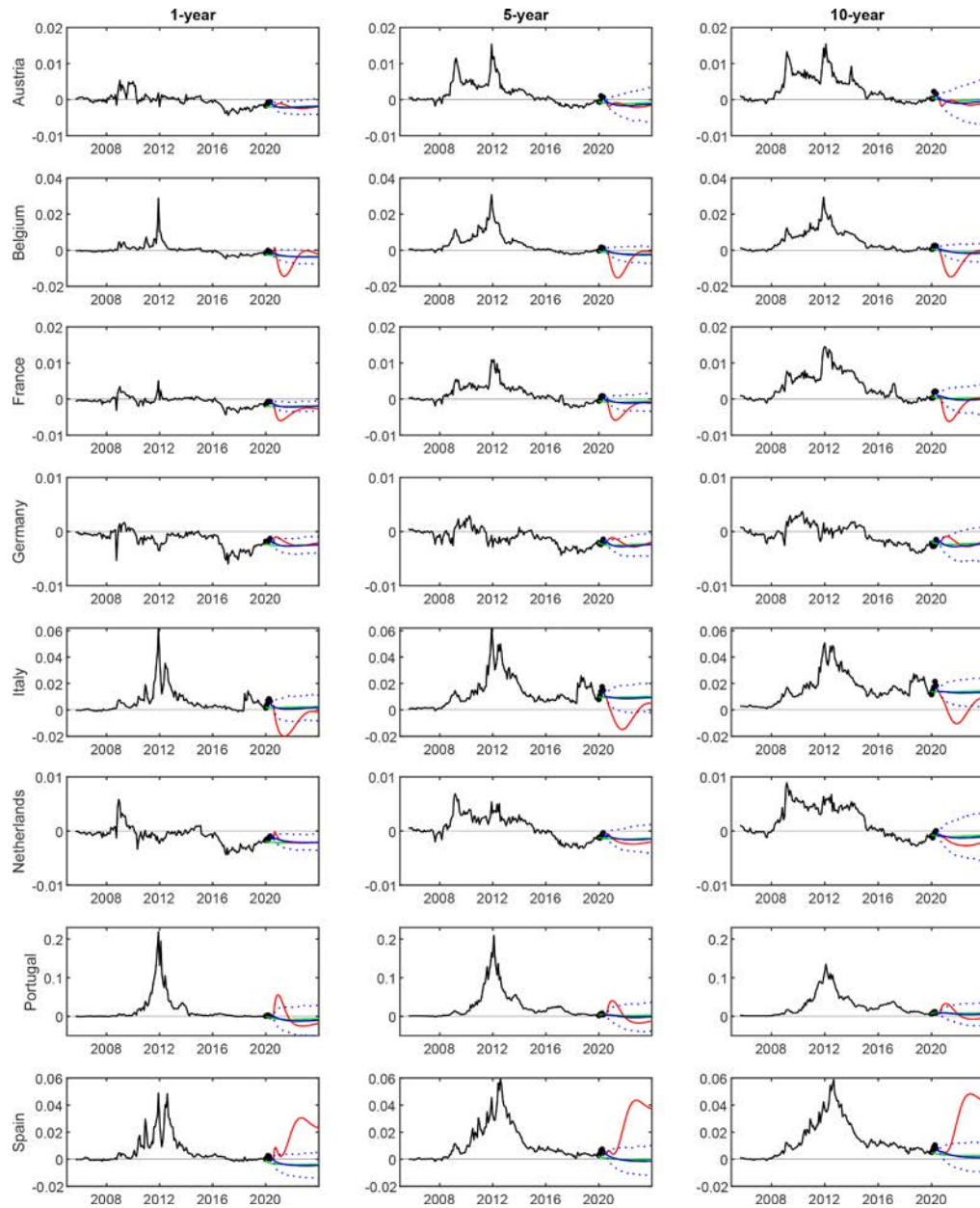


Fig. A.3. Sovereign spreads. Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red and blue lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1 and 2. The paths imposed in model 3 match the blue lines. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

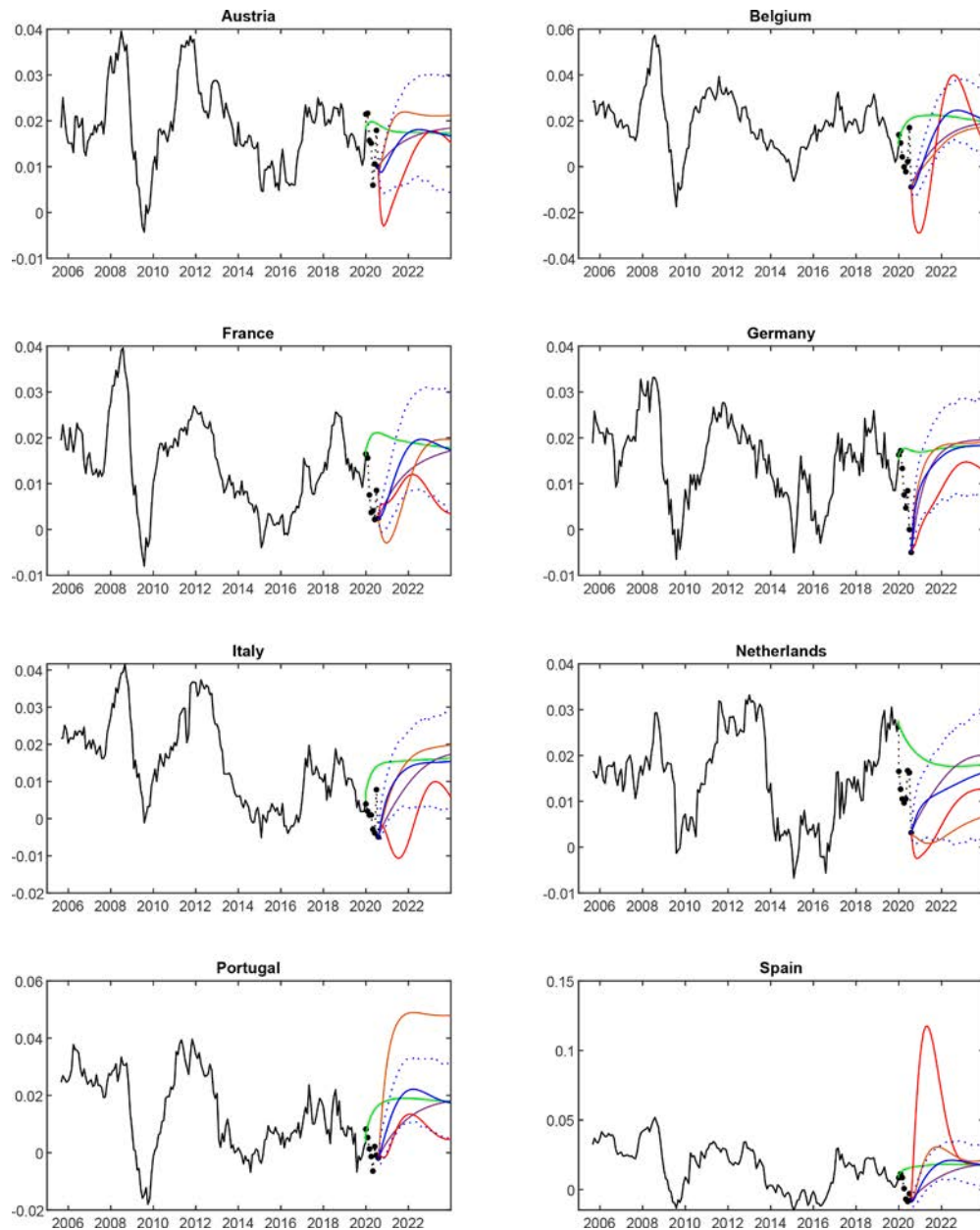


Fig. A.4. Inflation. Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red, blue, orange and purple lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1, 2, 3 and from a macroeconomic model without financial market variables. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

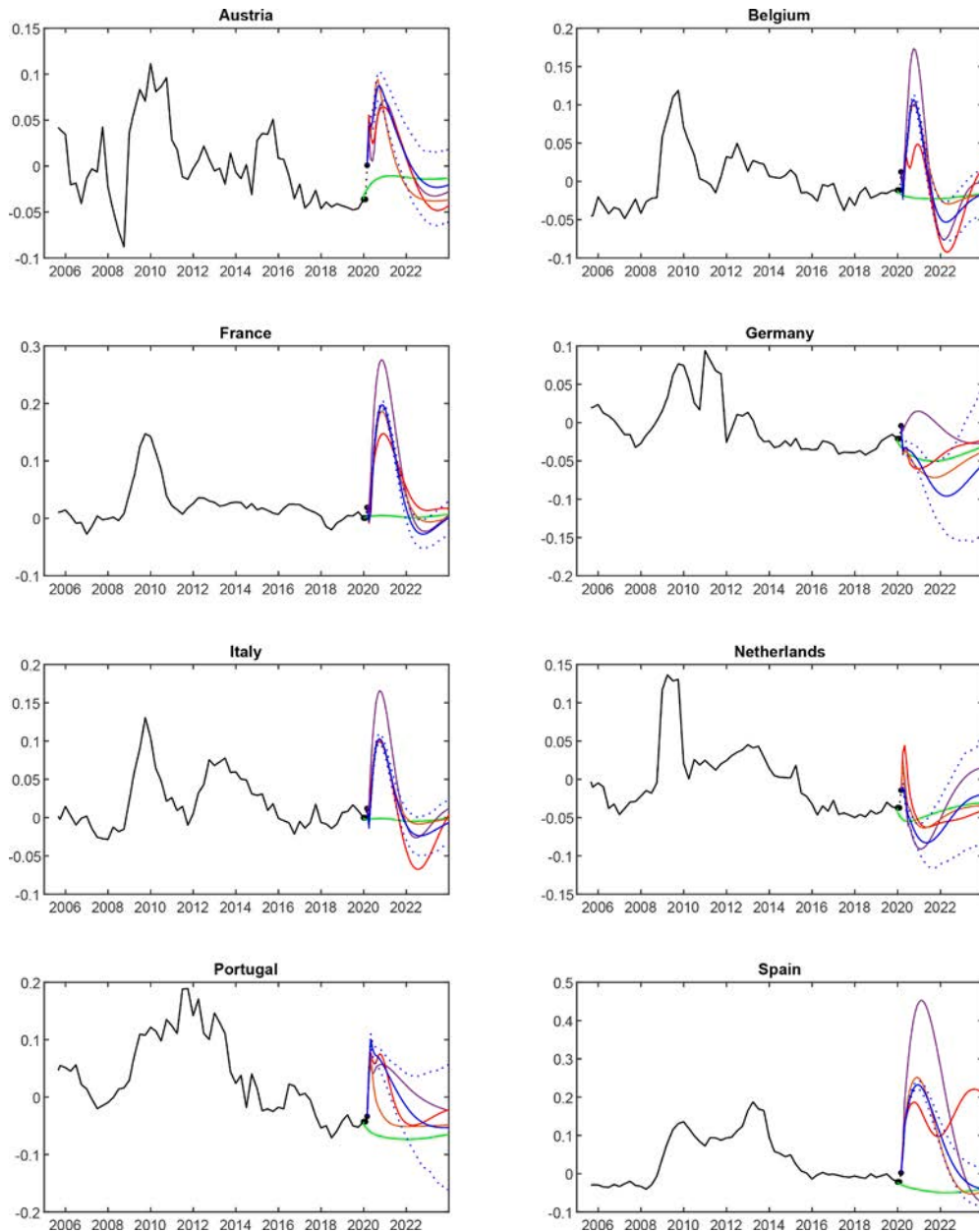


Fig. A.5. Debt/GDP changes. Notes: Black (dotted) lines represent data up to December 2019 (in 2020). Other lines represent forecasts: green, red, blue, orange and purple lines denote respectively unconditional forecasts (from model 2) and conditional forecasts from models 1, 2, 3 and from a macroeconomic model without financial market variables. Blue lines are surrounded by the 16%-84% confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table A.1

Data sources for macrofinancial series in $\mathcal{M}_t$. Notes: The two PC^{Eurspr} are obtained after standardising sovereign spreads (mean 0 and standard deviation 1). F2S is the average spread across maturities. GDP and D/GDP are linearly interpolated. EuroStoxx, GDP, Inflation and IP are transformed into year-on-year growth rates (log changes). Regarding GDP specifically, annual growth rates are obtained by first cumulating interpolated monthly GDP over twelve months and then computing month-on-month log changes multiplied by 12. D/GDP is transformed into year-on-year changes. The series F2S, PMI, ESI, log(VIX) and POL are standardised.

	Source	Mnemonic
PC^{Eurspr}	Reuters and Bloomberg	See Table A.2
F2S	Bloomberg	C3191Y(2Y,5Y,10Y) Index C9101Y(2Y,5Y,10Y) Index
PMI	IHS Markit	Composite output
IP	ECB's statistical data warehouse	STS.M.I8.W.PROD.NS0010.4.000
ESI	Eurostat	ei_bssi_m_r2
VIX	Refinitiv (Reuters Eikon)	CBOEVIX
EuroStoxx	Refinitiv (Reuters Eikon)	STOXXE
POL	www.policyuncertainty.com	European_News_Index
GDP	ECB's statistical data warehouse	MNA.Q.Y.?.W2.S1.S1.B.B1GQ.Z.Z. Z.EUR.LR.N
D/GDP	ECB's statistical data warehouse	GFS.Q.N.?.W0.S13.S1.C.L.LE.GD.T.Z.XDC.R_B1GQ_CY.T.F.V.N.T
Inflation	Eurostat	prc_hicp_midx

Table A.2

OIS rates and sovereign yields data sources. Notes: OIS rates are bootstrapped as in Veronesi (2016) to obtain zero-coupon yield equivalents. Only bootstrapped zero-coupon yields of maturities 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year are used for the estimation of the models.

	Source	Mnemonic
OIS	Refinitiv (Reuters Eikon)	EUREON1Y(2Y,3Y,4Y,5Y,6Y,7Y,8Y,9Y,10Y)
Austria	Bloomberg	F90801Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Belgium	Bloomberg	F90001Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
France	Bloomberg	F91501Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Germany	Bloomberg	F91001Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Italy	Bloomberg	F90501Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Netherlands	Bloomberg	F92001Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Portugal	Bloomberg	F91701Y(2Y,3Y,4Y,5Y,7Y,10Y) Index
Spain	Bloomberg	F90201Y(2Y,3Y,4Y,5Y,7Y,10Y) Index

Appendix B. Additional Granger causality tests

Table B.1

Granger causality test statistics. Notes: The statistics are computed as $T * (\log(|\tilde{\Omega}(0)|) - \log(|\tilde{\Omega}|))$, where T is the sample size and $\tilde{\Omega}(0)$ and $\tilde{\Omega}$ are the covariance matrices of the respective residuals from the VARs with and without zero restrictions. Significance in the upper panel indicates rejection of the null hypothesis of the vector of OIS and spread PCs [PC_1^{OIS} , PC_2^{OIS} , PC_1^{Spr} , PC_2^{Spr}] not Granger causing the vector of other variables included in the VAR (first line) or not Granger causing GDP growth (second line). The same tests are carried out in other panels for the two OIS PCs [PC_1^{OIS} , PC_2^{OIS}], the two country-specific spread PCs [PC_1^{Spr} , PC_2^{Spr}], financial market variables [VIX, EuroStoxx, F2S, PC_1^{Spr} , PC_2^{Spr} , PC_1^{Eurspr} , PC_2^{Eurspr}] and the EA economic activity indicators [PMI, ESI, IP]. The tests rely on estimates of model 2 (see Section 4.1); results are similar when based on estimates of models 1 and 3. Significance at the 10%, 5% and 1% thresholds is indicated by *, ** and ***, respectively.

	Austria	Belgium	France	Germany	Italy	Netherlands	Portugal	Spain
OIS and spread PCs								
Overall test	96.2***	114.2***	114.2***	94.3***	116.0***	102.2***	92.8***	125.1***
Test for GDP	10.0**	32.5***	10.7**	7.9*	22.5***	11.3**	2.7	27.8***
OIS PCs								
Overall test	97.5***	91.4***	89.1***	95.7***	103.1***	94.5***	79.8***	114.9***
Test for GDP	10.0***	22.4***	7.0**	0.8	6.3**	9.4***	1.4	25.4***
Spread PCs								
Overall test	14.7	12.6	26.2	3.48	20.0	18.7	20.9	29.5
Test for GDP	0.1	5.9*	2.7	7.3**	21.2***	0.5	0.9	9.5***
Financial market variables								
Overall test	139.1***	197.2***	190.5***	150.7***	177.0***	158.9***	144.8***	185.9***
Test for GDP	16.0**	62.9***	61.0***	30.5***	45.1***	33.0***	50.2***	78.3***
EA economic activity indicators								
Overall test	64.7***	44.8	32.3	72.9***	53.8*	39.6	14.4	20.1
Test for GDP	51.9***	34.2***	21.3***	65.1***	44.7***	32.5***	9.6**	12.9***

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