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Short-term real-time forecasting during turbulent times. A model for the Spanish GDP after the pandemic

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Abstract

Following the outbreak of the COVID-19 pandemic, most economic indicators experienced an increase in observed volatility, reducing the accuracy of nowcasting econometric models. In this paper, we propose a new specification for a mixed-frequency dynamic factor model used to nowcast the quarterly GDP growth rate of the Spanish economy –the Spain-STING–. With the aim of improving the predictive capacity of the model, we consider three proposals: (i) the relationship between the indicators and the estimated common factor is now contemporaneous, and not leading for some of the indicators; (ii) the variance of the common component is estimated by a stochastic process to allow it to vary over time; (iii) the set of variables is revised with the aim of including only those that add the most relevant information to the nowcast of the quarterly GDP growth rate. All these three modifications imply a notable improvement in the nowcasting performance during the period after the COVID-19 pandemic, while maintaining the accuracy obtained before it. These proposals could be also useful to revise other forecasting models.

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1. Introduction

The Spain-STING model[1] is one of the tools used by the Bank of Spain to forecast short-term quarter-on-quarter GDP growth. Spain-STING is a dynamic factor model that uses a set of (monthly and quarterly) economic indicators and breaks down their time series into a common factor and an idiosyncratic component. The common factor captures the common dynamics of the different indicators, while the idiosyncratic component reflects the part of the change in each indicator that cannot be attributed to the common component.

Up until December 2019, Spain-STING displayed a notable capacity to predict Spanish GDP growth. However, with the inclusion of the COVID-19 pandemic period, forecasting errors have increased in the tools used to model non-observable components, and also in this model. This is essentially due to the sharp changes observed in the dynamics of the variables and the greater volatility of such variables, which appear to have distorted the long-term correlation between the indicators and the common factor estimated by the model.

In this sense, recent literature has focused on adapting models to address the COVID-19 shock. For instance, in the context of BVAR models, **?** suggested excluding the COVID period from the model estimation. Lenza and Primiceri (2022) introduced a specific form of heteroscedasticity to account for this period. Carriero et al. (2024) proposed an outlier-augmented stochastic volatility model, inspired by Stock and Watson (2016).[2] In the framework of dynamic factor models, several proposals have been made. For instance, Maroz et al. (2021) included an additional factor specifically for the COVID period, and Antolín-Díaz et al. (2024) suggested that innovations to both factor and idiosyncratic components should be modeled using stochastic volatility, while also accounting for the possibility of student-t distributed outliers.[3]

Following this literature, we modify the Spain-STING model by assuming that the model's volatility is time-dependent to account for the increased variability of the variables during the pandemic period. Our procedure contributes to the stream of literature that does not need to specify exactly what is considered the "COVID period" in economic terms, which can be controversial, and it implements a straightforward methodology that would simplify the use of the tool in real time. Additionally, we revise two other key aspects of the model. Firstly, we reassess the time correlation assumed between the variables included in the model and the estimated common factor, which could potentially be coincident (i.e., indicator and common factor relate at time t), lagging (i.e., at time $t-l$) or leading (i.e., at time $t+l$). Secondly, we revise and modify the set of quantitative and qualitative indicators included in the model.

Each of the modifications made is assessed with a view to enhancing the predictive power (in the current quarter) of the Spain-STING model during the period following the worst phase of the pandemic, without, in turn, impairing such power in the period leading up to the pandemic.

[1]The first version of the Spain-STING model is detailed in Camacho and Pérez Quirós (2011). Arencibia Pareja et al. (2020) later expanded the model to jointly predict both GDP and its demand components.

[2]Focusing on an inflation forecasting BVAR model, Bobeica and Hartwig (2023) incorporated a fat-tailed distribution for the model residuals.

[3]Pescatori and Zaman (2011) provide a concise overview of different macroeconomic model classes (structural, non-structural, and large-scale) and their strengths and limitations for forecasting and policy design, which helps frame the evolution of these methods.

In other words, the revision of the model aims to reduce nowcasting errors during the whole period. Forecasting models must be monitored and revised to ensure that the forecasts on which economic agents base their decisions are reliable, particularly in the aftermath of crises or extreme events.

Following this introduction, the paper is structured as follows. The second section describes the theoretical and methodological framework of the model used until December 2019, as well as its pre- and post-pandemic predictive performance. The third section looks at the three changes (detailed above) made to the model with a view to enhancing its predictive power. Lastly, the overall effectiveness of such changes is analyzed in terms of the predictive power of the revised model as compared with its predecessor. The last section includes some closing observations.

2. The pre-pandemic Spain-STING model

2.1 Description of the model

The Spain-STING model originally proposed by Camacho and Pérez Quirós (2011), and updated by Arencibia Pareja et al. (2020), is a small-scale dynamic factor model that allows for the use of mixed frequencies (in particular, a combination of monthly and quarterly economic indicators) and which is essentially used to forecast, in real time, quarter-on-quarter Spanish GDP growth.

The course of the time series is depicted as the sum of two orthogonal components. Specifically, the growth rate (z_t^j) of a monthly variable – or the growth rate (x_t^j) of a quarterly variable – is expressed as the sum of a common factor (f_t), which captures the common dynamics of the different indicators included in the model, and an idiosyncratic component (ε_t^j), which reflects the part of the dynamics of each indicator that cannot be attributed to the common component, where $t = 1, \ldots, T$ represents the period expressed in months and $j = 1, \ldots, J$ represents the variables included in the model. The model is adapted to combine variables expressed in both month-on-month and quarter-on-quarter growth rates, thus enabling the integration of data with monthly and quarterly frequencies—this approach is typically known as a mixed-frequency model. Such adaptation is crucial for extracting information from variables published at the quarterly level (such as GDP) alongside those reported monthly (for example, industrial production). To this end, the methodology proposed by Mariano and Murasawa (2003) is used, whereby the quarter-on-quarter growth rate of a variable can be estimated as the weighted average of its month-on-month growth rates.[4] Thus, for a specification that contains only one quarterly and

[4]The quarter-on-quarter growth rate of a variable (x_t) can be estimated as the sum of the month-on-month growth rates (z_t) of the same variable, using the following formula: $x_t = \frac{1}{3}z_t + \frac{2}{3}z_{t-1} + z_{t-2} + \frac{2}{3}z_{t-3} + \frac{1}{3}z_{t-4}$

one monthly variable ($j = 1, 2$), the model is described as follows:

$$\begin{aligned} x_t^1 &= \frac{1}{3}\beta_1 f_t + \frac{2}{3}\beta_1 f_{t-1} + \beta_1 f_{t-2} + \frac{2}{3}\beta_1 f_{t-3} + \frac{1}{3}\beta_1 f_{t-4} + \\ &\qquad + \frac{1}{3}u_t^1 + \frac{2}{3}u_{t-1}^1 + u_{t-2}^1 + \frac{2}{3}u_{t-3}^1 + \frac{1}{3}u_{t-4}^1 && (1) \\ z_t^2 &= \beta_2 f_t + u_t^2 && (2) \\ \phi_f(L) f_t &= \varepsilon_{f_t} && (3) \\ \phi_j(L) u_t^j &= \varepsilon_t^j && (4) \end{aligned}$$

where $\phi_j(L)$ and $\phi_f(L)$ are lag polynomials of order p_j and q, respectively, and it is assumed that the errors are distributed as $\varepsilon_t^j \sim N(0, \sigma_j)$ and $\varepsilon_{f_t} \sim N(0, \sigma_f)$ and are independent of one another. The β_j parameters are known as factor loadings and capture the correlation between the common factor and the variables.

This model can be represented in state-space form and, using the Kalman filter (see, for example, Hamilton (1994)), can be estimated using a maximum likelihood estimator. Following the methodology proposed by Mariano and Murasawa (2003), the estimation can be adjusted to include missing observations, which is particularly useful given that, first, it means that there is no need to have a balanced sample at the end of the period and, second, the fact that the quarter-on-quarter variables are observed only once a quarter can be addressed.[5]

The set of indicators included, following the update to the model by Arencibia Pareja et al. (2020), comprises 11 variables: 1 quarterly variable (GDP) and 10 monthly variables (see Table 1). The monthly variables can, in turn, be divided into activity indicators (commonly referred to as hard) and survey-based indicators (generally referred to as soft). It is worth noting that the hard indicators are included in the model as month-on-month growth rates in the manner described in equation (1). The soft indicators, meanwhile, are included in levels per the following specification:

$$x_t^j = \sum_{i=0}^{11} \beta_j f_{t-i} + u_t^j \qquad (5)$$

where u_t^j follows the dynamics described in equation (4).[6]

Moreover, the correlation modeling the dynamics of the variables with that of the common factor is particularly important. The variables may act as coincident indicators (correlated in the manner described in equation(1), leading indicators (x_{jt} is correlated with f_{t+l}) or lagging indicators (x_{jt} is correlated with f_{t-l}). Arencibia Pareja et al. (2020) found that the specification that best predicted the quarter-on-quarter rate of growth of Spanish GDP (on data up to 2016 Q3)

[5] For a more detailed explanation of the model and its estimation, see Camacho and Pérez Quirós (2011) and Arencibia Pareja et al. (2020).

[6] As noted in Arencibia Pareja et al. (2020) including the indicators in levels may create a potential modeling problem as stationary and integrated variables are considered simultaneously. This issue is solved by following the indications of the European Commision (2006), according to which soft indicators are correlated with the year-on-year growth rate of the variable of interest. Therefore, the level of the soft indicators depends on a 12-month moving average of the common factor, and this is the source of its unit root.

was the one that included three of the monthly indicators with a one quarter lead.[7] Specifically, the two soft indicators and the construction Industrial Production Index (IPI).

Table 1 specifies, first, the indicators included in the model – GDP, the Economic Sentiment Indicator (ESI) excluding consumers, the composite Purchasing Managers' Index (PMI), electricity consumption, social security registrations, sales of large firms, the non-energy IPI, the construction IPI, credit to non-financial corporations, real imports of goods and real exports of goods – and, second, the frequency of each indicator, its type (hard or soft), the sample start month, the lag in publication and the time correlation assumed between the variables included in the model and the estimated common factor (coincident, lagging or leading).

Table 1

Indicators used in the Spain-STING model in Arencibia Pareja et al. (2020)

Indicator	Type of indicator	Source	Frequency	Correlation	Starting date	Lag in publication
GDP growth	Activity	INE	Quarterly	Coincident	1990-03	+ 30 days
Economic Sentiment Indicator (ESI) excluding consumers	Survey-based	European Commission	Monthly	Leading (3 months)	1990-01	0 days
Composite Purchasing Managers' Index (PMI)	Survey-based	IHS Markit	Monthly	Leading (3 months)	1990-08	+ 5 days
Electricity consumption	Activity	Red Eléctrica de España	Monthly	Coincident	1990-02	+ 1 day
Social security registrations	Activity	Social Security	Monthly	Coincident	1990-01	+ 3 days
Sales of large firms	Activity	Spanish Tax Agency	Monthly	Coincident	1996-02	+ 10 days
Non-energy Industrial Production Index (IPI)	Activity	INE	Monthly	Coincident	1992-02	+ 36 days
Construction Industrial Production Index (IPI) (a)	Activity	INE	Monthly	Leading (3 months)	1992-02	+ 36 days
Credit to non-financial corporations	Activity	Banco de España	Monthly	Coincident	1995-02	+ 30 days
Real exports of goods	Activity	Customs Department and MINECO	Monthly	Coincident	1991-02	+ 50 days
Real imports of goods	Activity	Customs Department and MINECO	Monthly	Coincident	1991-02	+ 50 days

- Source: Arencibia Pareja et al. (2020)

(a) The variable "Apparent consumption of cement" was used in the model of Arencibia Pareja et al. (2020). However, in late 2019, given an issue with the frequency with which this series is published, it was replaced with the Construction IPI, which offers information comparable to that of the "Apparent consumption of cement" series.

[7] This means that if the monthly indicator was a hard indicator, the correlation established in equation (1) would be written as $x_t^j = \beta_j f_{t+3} + u_t^j$, whereas if the variable was a soft variable, the correlation would be described as $x_t^j = \sum_{i=0}^{11} \beta_j f_{t+3-i} + u_t^j$

2.2 Predictive power of the model up until 2019 and impairment of such power following the inclusion of the pandemic period

Up until December 2019, the model specified in the manner described in equations (1) to (5) (the "Previous model") displayed a notable capacity to nowcast GDP. Figure 1a shows how the GDP nowcasts – obtained using the information available midway through the third month of each of the quarters for which a nowcast was made – compared with both the first (flash) and second estimates of quarter-on-quarter GDP growth published by the National Statistics Institute (INE) for every quarter from 2015 to 2019. Meanwhile, Figure 1c shows the absolute nowcasting errors in respect of Figure 1a. As can be seen, the predictive power of the projections remains stable, with errors at low levels throughout those years, the mean absolute error (MAE) for the period standing at around 0.1 pp. These findings suggest that the Previous model had considerable predictive power up until end-2019.

However, as in the case of most nowcasting models based on non-observable factors, the inclusion of the post COVID-19 period[8] saw a notable rise in the Spain-STING model's nowcasting errors, due to the difficulties in dealing with the variations seen in the economic variables, which increased significantly during the pandemic. Thus, Figures 1b and 1c show a major deterioration in the model's projections, as borne out by a notable rise in errors, up to around 0.5 pp, during the post-COVID-19 period (2021 Q1-2023 Q2).

One possible reason behind the impairment of the model's predictive power can be found in the significant variability displayed by the variables from 2020 onwards. Table 2 shows the variance of each of the variables included in Spain-STING during the period before and after COVID-19, as well as for the sample overall. As can be seen, in general the indicators have become significantly more volatile in the post-pandemic period.

Table 2

Variance observed by period

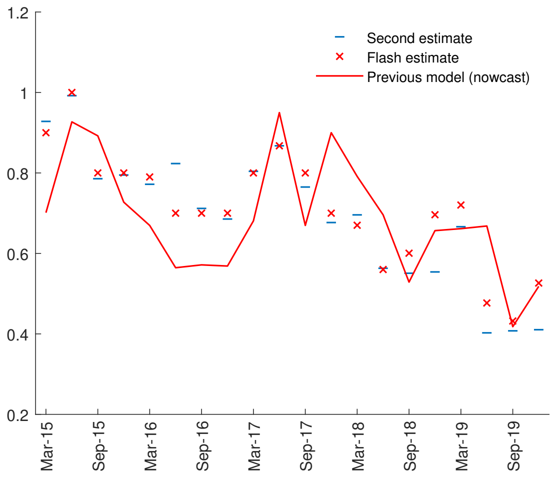
Indicator	Total (2015–2023)	Pre-COVID-19 (2015–2019)	Post-COVID-19 (2021–2023)
GDP growth	20.93	0.07	1.63
Economic Sentiment Indicator (ESI) excluding consumers	48.45	5.12	19.96
Composite Purchasing Managers' Index (PMI)	47.12	3.53	24.36
Electricity consumption	4.86	3.18	1.81
Social security registrations	4.64	0.02	0.18
Sales of large firms	12.83	0.52	4.78
Non-energy Industrial Production Index (IPI)	18.45	2.45	1.27
Construction Industrial Production Index (IPI) (a)	82.47	2.11	11.42
Credit to non-financial corporations	1.36	0.65	1.73
Real exports of goods	18.96	7.15	7.29
Real imports of goods	26.24	6.48	11.68

Furthermore, the effect of the pandemic on the dynamics of the variables and, in particular, their greater volatility, appear to have directly affected the existing long-term correlation between the different indicators and, by extension, the dynamics of the common component extracted

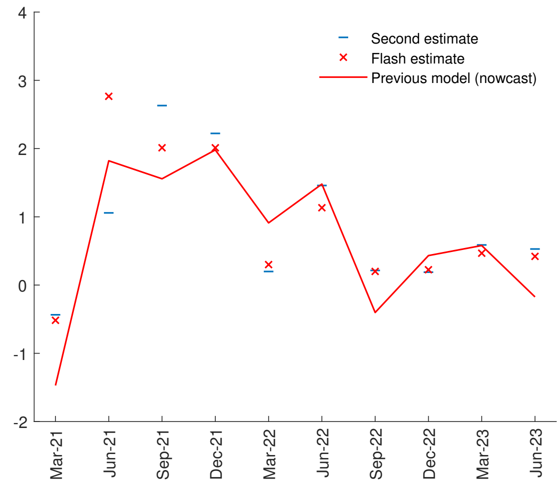
[8] This analysis does not take into account the most acute phase of COVID-19, which would have to be dealt with using a different methodological approach that has little to do with the aims of this paper.

Figure 1

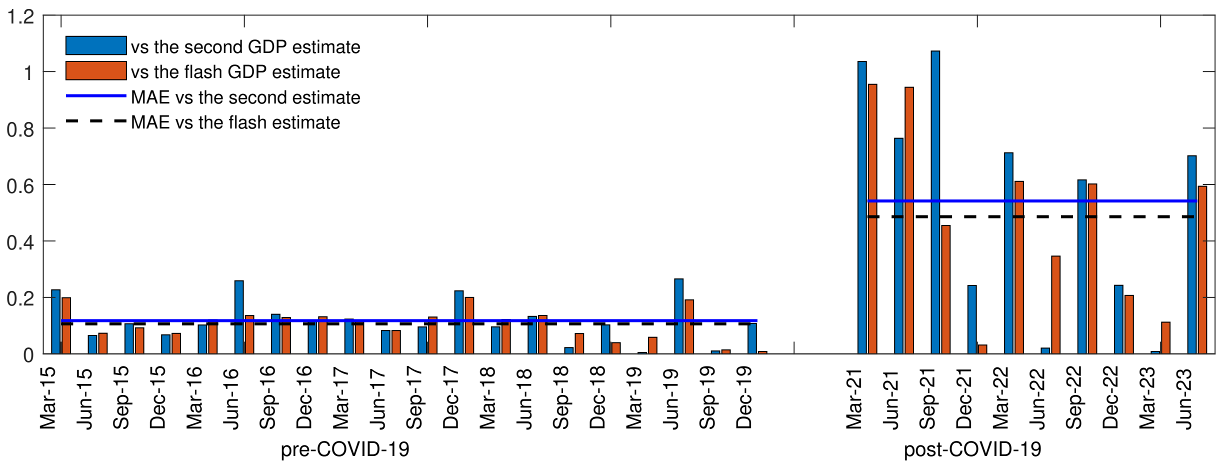
(a) GDP: Observed and nowcast. 2015-2019



(b) GDP: Observed and nowcast. 2021-2023



(c) Absolute errors by quarter. Previous model. Pre-COVID-19 period (2015 Q1 - 2019Q4) and post-COVID-19 period (2021 Q1-2023 Q2)

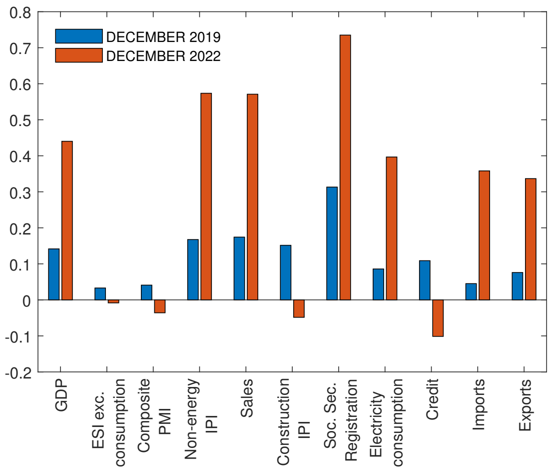


Note: The horizontal lines represent the mean absolute errors (MAE) in the pre- and post-COVID-19 periods, separately, vs the second and flash GDP estimates.

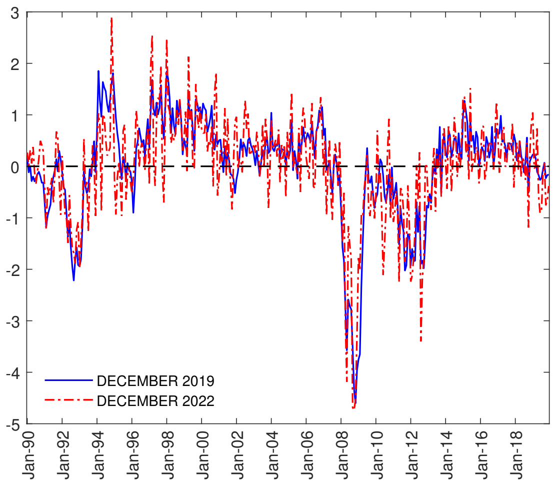
using the Spain-STING model (see equation (1)). By way of example, the two metrics below reveal how the model's estimations were affected by the COVID-19 period. First, Figure 2a shows, for different indicators, a substantial change in the factor loadings (β_j) estimated by the Previous model on the data available up until December 2022 (including the COVID-19 period) versus those obtained on data until December 2019 (the pre-COVID-19 period). In certain cases, such as the ESI excluding consumers, the composite PMI, the construction IPI and credit to non-financial corporations, there is a change in sign of the factor loadings, indicating a reversal of the correlation between such variables and the common component. Second, Figure 2b shows the common component estimated by the Previous model, again on the data available until December 2019 and December 2022, and weighted by the respective standard deviation of each component in the period running from 1990 to 2019. As can be seen, the month-on-month variation rate of the common factor increases significantly once the COVID-19 period has been included (red line). In terms of the absolute month-on-month rate of variation of the common factor, on average the rate estimated including the pandemic period triples the rate estimated without including this period. This increase in the month-on-month variability of the factor estimated reflects the fact that the long-term correlations of the variables are no longer captured in the same way once the COVID-19 period has been included in the estimation.

Figure 2

(a) Factor loadings estimated on information up
to December 2019 and December 2022



(b) Common factor estimated on information up
to December 2019 and December 2022



Note: The two Figures show the results of the estimations resulting from the "Previous model" including the information available up to December 2019 or December 2022. The factor loadings refer to the β parameters of equation (1). Each common factor in Figure 2b is divided by the standard deviation of the factor itself during the period 1990-2019.

3. The new Spain-STING model

3.1 Reassessing temporal specification in the dynamic factor model

The COVID-19 pandemic fundamentally altered the dynamics of several key economic indicators in Spain. Before the pandemic, variables such as the ESI excluding consumers, the composite PMI, and the Construction IPI were considered leading indicators of GDP as regards of the model, meaning they anticipated changes in economic activity (see Arencibia Pareja et al., 2020). However, the unprecedented shock of the pandemic raised the question of whether these relationships had changed, potentially undermining the model's predictive power.

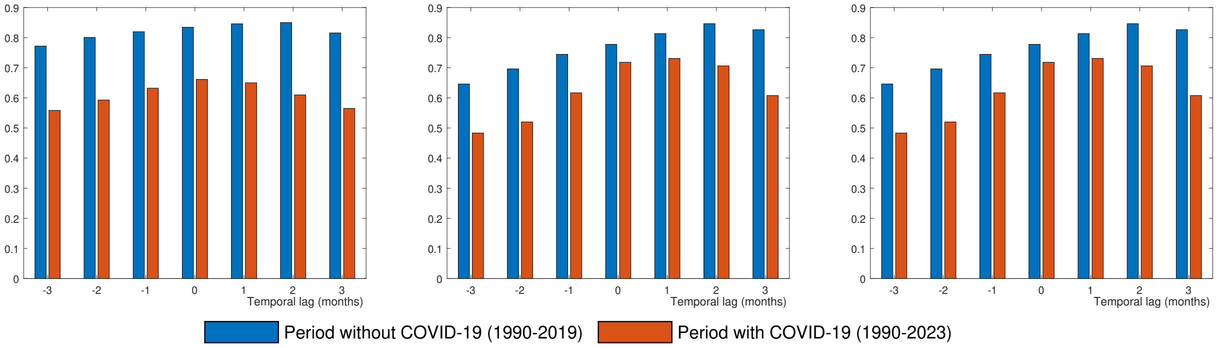
To address this, we conducted a detailed analysis of the cross-correlations between these indicators and GDP, comparing the pre-pandemic period (1990–2019) with the period including the pandemic (1990–2023). Figure 3 shows the correlation between the year-on-year GDP growth

Figure 3

(a) Cross-correlation of the ESI exc. consumers and GDP

(b) Cross-correlation of the composite PMI and GDP.

(c) Cross-correlation of the construction IPI and GDP



Note: In the case of the ESI excluding consumers and the composite PMI, the cross-correlation is shown with respect to the year-on-year GDP growth rate. For the construction IPI, it is calculated with respect to the quarter-on-quarter GDP growth rate. The horizontal axis depicts the number of months' difference in terms of correlation. Negative values indicate the indicator lags GDP by the specified months; positive values indicate the indicator leads GDP by the specified months; zero represents contemporaneous correlation

rate and the levels[9] of the composite PMI and the ESI not including consumers, with different time lags. In other words, we estimate various correlations (contemporaneous or with a lag or a lead of several months) between the indicators and GDP. For example, on the x-axis, the value "$t+1$" (correlation with a one-month lead) represents the correlation between the quarterly average of the indicator in February, May, August, and November and the year-on-year GDP growth rate in March, June, September, and December, respectively. The figure illustrate that, while the strongest correlations were previously observed when these indicators led GDP by two to three months, the post-pandemic data show a shift. One potential explanation for these changes is the sharp decline in the values of these indicators during periods of strict mobility restrictions, which also coincided with the steepest falls in economic activity.

Regarding the construction IPI, the correlation between the quarter-on-quarter growth rates of this variable and of GDP is analysed.[10] As observed in Figure 3c, the correlation with a three-month lead weakens once the post-pandemic period is included, with the closest correlation now when the construction IPI leads GDP by a single month; the coincident correlation is also similar.

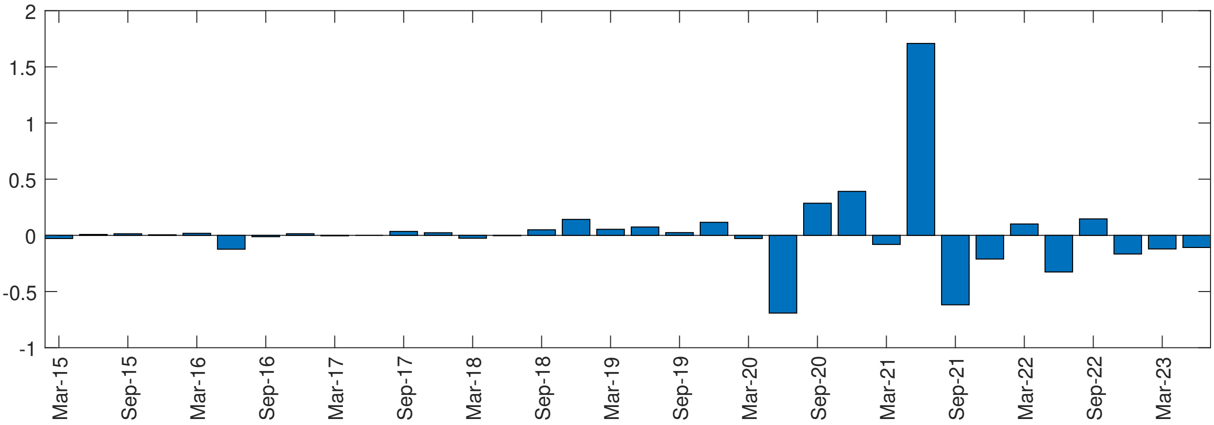
These findings suggest that the three variables may no longer serve as leading indicators of economic activity, and thus an alternative is considered in which their correlation with the common factor is coincident.[11] For the other variables, which were already included coincidentally

[9]Using a three-month moving average.

[10]To calculate the quarter-on-quarter growth rate of the construction IPI, a three-month moving average of the variable is first estimated, and then the growth rate is computed for each month.

[11]The decision to use a coincident correlation for the composite PMI and the construction IPI—rather than a one-month lead, as might be indicated by the correlation analysis—is motivated by the goal of a parsimonious model. Since the other variables are included on a coincident basis, advancing these variables by just one month

Figure 4. Difference between the flash and second GDP estimates



Source: INE and devised by authors.

in the model by Arencibia Pareja et al. (2020), no changes in the time correlations are observed following the inclusion of the COVID-19 period.

To assess the potential benefits of revising the time correlation among variables, we evaluate the forecasting errors obtained with and without the changes to the model specification —specifically, these adjustments involve treating the indicators as coincident variables relative to the common factor. For this purpose, during the third month of each quarter—from January 2015 to June 2023—quarter-on-quarter GDP growth is forecasted using both specifications described above. Specifically, both one-quarter-ahead and two-quarters-ahead forecasts are produced based on the information available on the 23rd day of each month. In other words, the estimates are generated in "real time".[12] The accuracy of these forecasts is then assessed by comparing predictions to both the flash and the second GDP releases. This is crucial, as substantial revisions can occur between the flash and second estimates, and these revisions may significantly affect the evaluation of the model's performance. In fact, such revisions were especially notable between 2020 Q1 and 2022 Q2 (see Figure 4), implying that results may change depending on which GDP release is used as the basis for comparison.

Although the modification does not significantly reduce nowcasting errors in the post-pandemic period, it is essential for preventing counterintuitive results, such as the emergence of negative correlations between activity indicators and GDP, which arose when the previous specification was maintained. As detailed in Section 2.2, before COVID-19, historical correlations (reflected in the signs of the factor loadings) between the common component—which can be interpreted as a measure of economic activity—and the ESI excluding consumers, the composite PMI, and the construction IPI were positive. However, this relationship turned negative after the pandemic, meaning that these variables became inversely correlated with economic activity—an outcome that defies economic intuition. The change in the time correlation specification, by treating the-

does not result in any meaningful improvement in forecast accuracy.

[12]"Real-time" forecasting refers to producing estimations using only the data available to the analyst at each specific point in time.

se indicators as coincident with the common factor, reverses this problem and restores positive correlations (and, consequently, appropriately signed factor loadings), in line with economic expectations, thereby improving the interpretability and robustness of the model in the current economic context.

3.2 Incorporating Stochastic Volatility in the Common Factor

To address the sharp increase in the volatility of the indicators used in the model (see Table 2), especially in the wake of the COVID-19 pandemic, which posed a significant challenge for the Spain-STING model, we reconsider the assumption regarding the common factor's variance. The original specification assumed that the variance of the common factor remained constant over time, a constraint that proved too rigid during periods of crisis or extreme events, when the volatility of the indicators surged and the model struggled to accurately capture the dynamics of the Spanish economy in the post-pandemic period.

To overcome this limitation, we introduce stochastic volatility into the dynamics of the common factor. Specifically, the variance associated with the common factor is now allowed to evolve over time, following a random walk process. This approach enables the model to better accommodate periods of heightened volatility, such as those experienced during the pandemic, and to downweight their influence when estimating the common component. In this way, when the indicators become more volatile, the increase in the volatility of the factor—rather than the level of the factor itself—explains most of the common dynamics of the variables.

In order to incorporate stochastic volatility into the common factor, equation (3) from the previous version of the model is replaced with the following specification:

$$\phi_f(L) f_t \quad = \quad \sigma_{f_t} \epsilon_{f_t} \tag{6}$$

where $\epsilon_{f_t} \sim N(0,1)$ and the factor variance logarithm (σ_{f_t}) follow a random walk, as described below

$$log\sigma_{f_t} \quad = \quad log\sigma_{f_{t-1}} + \nu_{f_t} \qquad \nu_{f_t} \sim N(0, \omega_{f_t}) \tag{7}$$

Allowing for time-varying volatility enhances the flexibility and robustness of mixed-frequency dynamic factor models, especially when confronted with sudden economic shocks. Rather than attributing all movements in economic indicators to shifts in underlying economic activity, the model is now capable of distinguishing between genuine structural changes in the common factor and temporary surges in volatility. This distinction is vital for generating reliable forecasts during periods of heightened uncertainty.

The incorporation of stochastic volatility, as outlined by Marcellino et al. (2016) and further developed by Pacce and Pérez Quirós (2019) in the context of the Euro-STING model (Camacho and Pérez-Quirós, 2010), provides the methodological foundation for this approach. This paper adopts the second methodological framework, requiring the specifications in equations (1),(2), (4), (6), and (7) to be reformulated using a stacked vector representation.[13] This formulation

[13]For Bayesian estimation of mixed-frequency dynamic factor models, we employ the stacked vectors approach proposed by Koopman and Pacce (2016). Appendix A details the model specifications in equations (1), (4), (6), and (7) following this approach.

facilitates straightforward Bayesian estimation once stochastic volatility is incorporated. Appendix B provides a thorough explanation of the Bayesian estimation procedure, which utilizes a Metropolis-Hastings algorithm within a Gibbs sampling framework.[14]

It is important to emphasize that the main goal of introducing time-varying volatility is not only to improve forecasts in the post-pandemic period, but also to ensure that the model does not underperform in the pre-pandemic context. In other words, the objective is to identify model specifications that deliver consistent results even under extraordinary uncertainty—as witnessed in 2020. However, achieving accurate forecasts specifically during episodes of high volatility is not the aim; rather, obtaining reliable predictions in such exceptional periods would require alternative tools, such as econometric approaches that incorporate higher-frequency economic information.

As an alternative to modeling stochastic volatility in the common factor, one might consider treating observations during the most critical phase of the COVID-19 pandemic—when variable dynamics changed most dramatically—as missing data. This approach would effectively regard the economic information from indicators during this time as incomplete. However, while this option was assessed among various modeling alternatives, it was ultimately rejected because it produced less satisfactory results than the stochastic volatility specification. Appendix C presents a detailed explanation of this alternative and offers a comparative analysis of the results.

To assess whether it is worthwhile to introduce stochastic volatility into the model, we present a selected set of relevant tests designed to evaluate the predictive power of the modeling alternatives—specifically, the "Previous model" and the specification with stochastic volatility (the "SV model").[15] Based on the variables included in the Arencibia Pareja et al. (2020) model (see Table 1),[16] our analysis focuses on comparing the predictive power of the "Previous model" against the specification that incorporates stochastic volatility into the common component. To isolate the improvements from adding stochastic volatility from changes in the time correlations described in the preceding section, the composite PMI, the ESI excluding consumers, and the construction IPI are included with a coincident correlation to the common factor in both specifications.

Table 3 reports the nowcasting errors of the two models across different sample periods, presenting root mean squared errors and mean absolute errors calculated using the real-time procedure described in Section 3.1. These errors correspond to forecasts produced in the third month of each quarter, when information is available for one or two months of the quarter in

[14] The methodology introduced by Kim et al. (1998) is used to estimate the stochastic component of the factor's volatility.

[15] A broader set of specifications than those shown in this section has been designed and evaluated in terms of predictive power. However, these results are not detailed in this paper due to their poor predictive performance. In particular, no results are provided for two alternative specifications: one that adds stochastic volatility to both the factor and the variables, and another that adds such volatility only to the model's variables, while keeping factor volatility constant. The outcomes of these exercises are available from the authors upon request.

[16] Between March 2020 and March 2022, furlough schemes (ERTEs) were activated in Spain, allowing employment contracts to be temporarily suspended without dismissals. The unadjusted series of social security registrations does not exclude furloughed contracts during this period. To ensure the series accurately reflects Spain's economic activity and has greater explanatory power for GDP, furloughed workers have been excluded from the social security registration series since February 2020.

progress (depending on the variable).

The results show that the "SV model" demonstrates superior predictive power compared to the "Previous model". In the post-COVID-19 period (2021–2023), the "SV model" yields a substantial reduction in both root mean squared errors and mean absolute errors, for both the second GDP estimate and, in particular, the flash estimate. During the pre-pandemic period (2015–2019), the "SV model" also achieves marginally lower nowcasting errors, confirming that its added flexibility does not diminish performance in more stable times. Lastly, when the large error in 2021 Q2 is omitted—a quarter in which the difference between the flash and second GDP estimates was nearly 2 pp (see Figure 4)—the predictive advantage of the "SV model" with respect to the second GDP estimate becomes even more pronounced.

In summary, incorporating stochastic volatility into the common factor is a key innovation that enables the Spain-STING model to remain effective in the face of unprecedented economic uncertainty. This modification ensures that the model's forecasts are not unduly influenced by temporary surges in volatility, thereby enhancing its reliability for policymakers and analysts.

Table 3
Nowcasting errors in the pre- and post-COVID-19 periods

	Pre-COVID-19 (2015 Q1–2019 Q4)		**Post-COVID-19** (2021 Q1–2023 Q2)		**Post-COVID-19** (2021 Q1–2023 Q2) Excl. 2021 Q2	
	Flash est.	**2nd est.**	**Flash est.**	**2nd est.**	**Flash est.**	**2nd est.**
Mean absolute error						
Previous model*	0.10	0.12	0.67	0.67	0.61	0.67
SV	0.08	0.10	0.25	0.46	0.25	0.35
Root mean squared error						
Previous model*	0.11	0.14	0.85	0.84	0.82	0.86
SV	0.11	0.13	0.30	0.60	0.30	0.41

Note: The mean squared errors and mean absolute errors shown are related to the forecasts made in the third month of the target quarter. The "previous model*" refers to the model described in section 2, but including the ESI excluding consumers, the composite PMI and the construction IPI with a coincident (as opposed to leading) correlation with the common factor. The SV model refers to the model that adds stochastic volatility to the factor. The error committed in the second quarter of 2021 was excluded when calculating the mean squared error and the root mean squared error in columns seven and eight.

3.3 Modification of the set of variables of the model

The composition of the indicators included in the Spain-STING model is pivotal for its predictive accuracy. In the aftermath of the pandemic, certain variables may have lost their explanatory power, while others—previously not considered—could improve the model's performance. Due to the high collinearity present among macroeconomic indicators, simply increasing the number of variables does not necessarily enhance forecasts and may even reduce interpretability.

To assess whether further improvements can be achieved in GDP nowcasting by modifying the set of variables, we follow a statistical selection procedure. This paper adopts the methodology proposed by Camacho and Pérez-Quirós (2010)[17]. Specifically, we start with a baseline model composed of a parsimonious set of activity indicators. The analysis then explores whether the inclusion of additional variables improves predictive performance in the post-COVID-19 period, while maintaining accuracy in the pre-pandemic period.

The baseline model integrates key activity indicators (GDP, electricity consumption), supply (non-energy IPI), employment (social security registrations), both external and internal demand (real exports and imports of goods), and at least one survey-based indicator published near the end of the reference month (composite PMI). We subsequently evaluate the sequential addition of further variables: the ESI excluding consumers, large firms' sales, and the construction IPI.

At each step, the impact of adding each variable on nowcasting errors is evaluated for both the pre-pandemic and post-pandemic periods. The criterion for retaining a variable is its capacity to reduce prediction errors without negatively affecting performance during stable periods. Table 4 reports the mean absolute error and root mean squared error for each estimated model.[18] The results suggest that, generally, forecasting errors decrease slightly as more variables are included, highlighting the added explanatory power of each. Specifically, the construction IPI delivers the most significant reduction in nowcasting errors during the post-pandemic period (2021 Q1–2023 Q2).

Overall, Table 4 illustrates that this systematic approach ensures that only variables enhancing predictive performance are retained in the final model. Moreover, the final specification produces marginally lower nowcasting errors than the alternative model in Table 3, where credit to non-financial corporations is also included. As discussed in Section 2.2, the sign of the credit variable's factor loading turns negative when the pandemic period is incorporated, complicating its economic interpretation.[19] Consequently, credit to non-financial corporations was ultimately excluded from the final model.

[17] Álvarez et al. (2012) discuss the empirical trade-offs between large-scale and small-scale factor models, noting that as the number of time series increases, so does the correlation between them, potentially biasing the estimation of the common factor through increased correlation of the idiosyncratic component. Furthermore, Bai and Ng (2008) underscore the necessity of parsimony in model specification to improve predictive power, even when the idiosyncratic component exhibits zero cross-correlation. Lastly, Boivin and Ng (2006) show that the theoretical advantages of large-scale factor models may not always materialize in practice.

[18] Each model is estimated assuming contemporaneous correlations among all variables and the common factor, as well as stochastic volatility in the dynamics of the estimated common component.

[19] This change of sign likely reflects the fact that credit in Spain remained resilient during the steepest contraction, supported by government measures for firms and households.

Table 4

SV model nowcasting errors: base model vs base model plus additional indicators

		Pre-COVID-19 (2015 Q1–2019 Q4)		Post-COVID-19 (2021 Q1–2023 Q2)	
		GDP (Flash est.)	GDP (2nd est.)	GDP (Flash est.)	GDP (2nd est.)
Mean absolute error	(1) Base model	0.10	0.12	0.43	0.65
	(2) Base model + ESI exc. consumers	0.10	0.11	0.42	0.63
	(3) Base model + ESI exc. consumers + Sales of large firms	0.09	0.10	0.40	0.68
	(4) Base model + ESI exc. consumers + Sales of large firms + Construction IPI	0.08	0.10	0.24	0.46
Root mean squared error	(1) Base model	0.14	0.16	0.57	1.01
	(2) Base model + ESI exc. consumers	0.13	0.15	0.54	0.98
	(3) Base model + ESI exc. consumers + Sales of large firms	0.11	0.13	0.49	0.92
	(4) Base model + ESI exc. consumers + Sales of large firms + Construction IPI	0.11	0.13	0.29	0.60

Note: The mean squared errors and mean absolute errors shown are related to the forecasts made in the third months of the target quarter. All of the specifications refer to the model that adds stochastic volatility to the factor. The base model includes the following variables: GDP, social security registrations, electricity consumption, the composite PMI, the non-energy IPI, real exports of goods and real imports of goods. The variable(s) added to the base model for the estimation are specified for the other models.

Two additional exercises were conducted. First, the impact of adding the Services Sector Activity Index (SSAI) was examined. Since the services sector accounts for a substantial share of GDP, including this variable could potentially enhance the model's predictive power. Accordingly, the SSAI was incorporated into the last specification presented in Table 4 (specification 4). While the results suggest that this indicator may slightly improve the model's predictive ability, the sign of the associated factor loading is contrary to what would be expected in the post-COVID-19 period. Therefore, the inclusion of this indicator as an additional variable in the model has been ruled out.

Second, the possibility of replacing the large firms' sales indicator with the Retail Trade Index (RTI) was analyzed. This test was also performed under on specification (4) of Table 4. In this case, the findings indicate that including the RTI significantly diminishes the model's predictive performance.

Finally, after reviewing the relevant tests, the specification that produced the lowest estimated nowcasting errors—both in terms of mean absolute error and root mean squared error—and maintained factor loadings with signs consistent with economic theory, is the one in which all indicators are included with a coincident correlation to the common factor, and which contains the following variables: GDP, social security registrations, large firms' sales, electricity consumption, non-energy IPI, composite PMI, real exports of goods, real imports of goods, the ESI excluding consumers, and construction IPI (see Table 5). This careful selection ensures that the model remains both parsimonious and robust, enhancing its predictive accuracy in both stable and volatile periods.

Table 5
Indicators used in the revised Spain-STING model

Indicator	Type of indicator	Source	Frequency	Correlation	Starting date	Lag in publication
GDP growth	Activity	INE	Quarterly	Coincident	1990–03	+ 30 days
Economic Sentiment Indicator (ESI) excluding consumers	Survey-based	European Commission	Monthly	Coincident	1990–01	0 days
Composite Purchasing Managers' Index (PMI)	Survey-based	IHS Markit	Monthly	Coincident	1990–08	+ 5 days
Electricity consumption	Activity	Red Eléctrica de España	Monthly	Coincident	1990–02	+ 1 day
Social security registrations	Activity	Social Security	Monthly	Coincident	1990–01	+ 3 days
Sales of large firms	Activity	Spanish Tax Agency	Monthly	Coincident	1996–02	+ 10 days
Non-energy Industrial Production Index (IPI)	Activity	INE	Monthly	Coincident	1992–02	+ 36 days
Construction Industrial Production Index (IPI) (a)	Activity	INE	Monthly	Coincident	1992–02	+ 36 days
Real exports of goods	Activity	Customs Department and MINECO	Monthly	Coincident	1991–02	+ 50 days
Real imports of goods	Activity	Customs Department and MINECO	Monthly	Coincident	1991–02	+ 50 days

3.4 Assessment of the predictive power of the Revised model vs the Previous model

After describing the three main modifications—adjusting the timing of correlations, incorporating stochastic volatility, and updating the set of variables—it becomes crucial to assess their overall impact on the predictive performance of the Spain-STING model. To achieve a thorough evaluation, the predictive power of the revised model, which incorporates these changes simultaneously, is compared with that of the previous specification, thus providing a clear perspective for both stable and volatile periods.

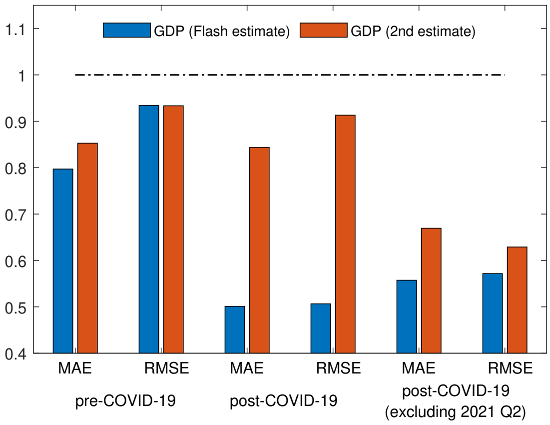
This assessment is based on a real-time comparison of forecasting errors from the revised and previous models, covering two distinct periods: the pre-pandemic era (2015 Q1 to 2019 Q4) and the post-pandemic era (2021 Q1 to 2023 Q2). Forecasting errors are calculated using both mean absolute error (MAE) and root mean squared error (RMSE), with results evaluated against both the GDP flash estimate and the second GDP estimate. Figure 5a illustrates the ratio of forecasting errors for the revised model relative to the previous model. Values below 1 indicate that the revised model outperforms its predecessor with lower errors, while values above 1 suggest the opposite. The analysis distinguishes between the pre- and post-pandemic periods, always considering both the GDP flash and second estimates.

The main finding, consistently observed across all scenarios, is that the revised model delivers lower nowcasting errors than the previous one, as shown in Figure 5a. During the pre-pandemic period, the revised model reduces forecasting errors by 10–20 %, depending on the metric used, thereby not only preserving but modestly exceeding the original target for this period. In the post-pandemic era, the improvements become even more significant: for the GDP flash estimate, forecasting errors fall by up to 50 %; for the second GDP estimate, errors are reduced by around 10 %. Notably, if the highly volatile second quarter of 2021 is excluded—a period marked by a revision exceeding 1.5 pp between the first and second GDP estimates—the improvement climbs to between 25 % and 35 %. These results, supported by Figure 5b, demonstrate that the revised model is capable of adapting to the structural changes brought about by the pandemic, while also maintaining or improving forecast precision in more stable times.

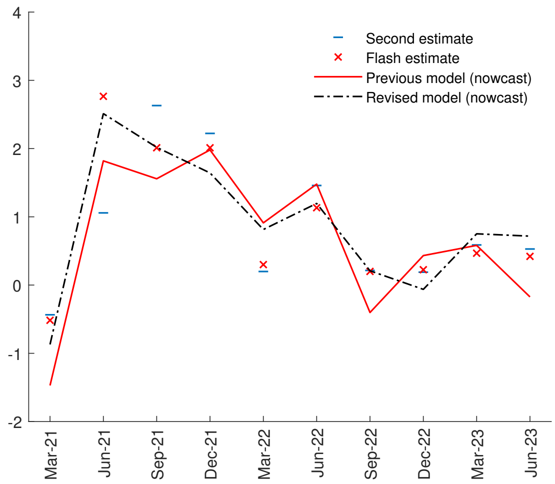
Beyond these error metrics, regression analyses taking the flash and second GDP estimates as dependent variables and the nowcasts as explanatory variables reveal that the revised model's

Figure 5

(a) Relative nowcasting errors. Revised model vs Previous model (nowcasting in real-time)



(b) GDP: observed and nowcast. (2021-2023)



Note: The forecasting errors of the Revised model are depicted in relation to the errors of the model described in Section 2. The errors committed using information up to midway through the third month of each quarter are shown. The “pre-COVID-19” period refers to the quarters running from 2015 Q1 to 2019 Q4. The “Post-COVID-19” period runs from 2021 Q1 to 2023 Q2. In the “Post-COVID-19 (excluding 2021 Q2)” period, the error committed in 2021 Q2 is excluded from the calculation of the “Post-COVID-19” period errors, given the major revision made in that quarter between the flash and second GDP estimates. MAE refers to the estimated mean absolute error and RMSE to the estimated root mean squared error.

projections are less biased and display a better fit, as detailed in Appendix D. The simultaneous adoption of the three improvements substantially corrects the deterioration in predictive power observed between 2021 and 2023. Thanks to these adjustments, the revised Spain-STING model stands as a more robust and reliable tool for generating short-term economic forecasts, which is especially valuable for central banks and public institutions navigating periods of unprecedented uncertainty.

4. Final remarks

Short-term forecasts of the future course of the economy play an essential role in decision-making by central banks and other national and international institutions. The pandemic-related disruptions entailed an unprecedented increase in the volatility of economic indicators, thus impairing the predictive power of short-term forecasting models. In the case of the Spain-STING model, the change in the variables’ dynamics and the rise in volatility have affected the long-term correlation between the indicators and the common component estimated by the model, giving rise to a significant reduction in the model’s predictive power during the post-COVID-19 period.

This paper looks at three key changes to the specification of the Spain-STING model that improve its post-pandemic predictive power. Specifically: (i) all of the variables used in the forecast are considered to have a coincident correlation with the common component identified (rather than including some of them as leading variables), (ii) stochastic volatility is included in the model's common component; and (iii) the set of variables included in the model is re-assessed.

In quantitative terms, compared with the Previous model, the combination of the three changes reduces nowcasting errors during the post-COVID-19 period by between 10 % and 50 %, depending on whether the flash estimate forecast or the second GDP estimate forecast is assessed. The simultaneous inclusion of the changes proposed in this paper yields a model specification that substantially corrects the impairment of predictive power observed between 2021 and 2023. Nonetheless, these results should be interpreted with caution. First, there are few observations for the post-COVID-19 period. Second, it is uncertain whether the changes observed in the variables' dynamics are temporary, owing to the pandemic, or longer lasting. In any event, the results obtained also show some improvement (around 10 %) in the model's predictive power during the pre-pandemic period, when the volatility of the variables was much lower.

Online Appendix

A Stacked vector approach to the representation of the model

Taking a stacked vector approach, equations (1) and (1) may be written as follows:

$$\begin{pmatrix} x_\tau^1 \\ z_{\tau,3}^2 \\ z_{\tau,2}^2 \\ z_{\tau,1}^2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3}\beta_1 & \frac{2}{3}\beta_1 & \beta_1 & \frac{2}{3}\beta_1 & \frac{1}{3}\beta_1 \\ \beta_2 & 0 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 & 0 \\ 0 & 0 & \beta_2 & 0 & 0 \end{pmatrix} \begin{pmatrix} f_{\tau,3} \\ f_{\tau,2} \\ f_{\tau,1} \\ f_{\tau-1,3} \\ f_{\tau-1,2} \end{pmatrix} + \begin{pmatrix} u_\tau^1 \\ u_{\tau,3}^2 \\ u_{\tau,2}^2 \\ u_{\tau,1}^2 \end{pmatrix} \tag{A-1}$$

$$\phi_1(L)u_\tau^1 = \varepsilon_\tau^1 \tag{A-2}$$

$$\phi_2(L)u_{\tau,3}^2 = \varepsilon_{\tau,3}^1 \tag{A-3}$$

where sub-index (τ, k) with $k = 1, 2, 3$ refers to quarter $\tau = 1, \ldots, T/3$ and month $1, 2, 3$ in each quarter (for example, if τ is the first quarter of 2023, then $(\tau, 1)$ is January 2023). Note that this kind of representation allows the error associated with the quarterly variable (u_τ^1) to have a quarterly frequency and the operator L to act on that frequency, while operator L on $u_{\tau,3}^2$ continues to affect the errors on a monthly frequency as in equation (4). This small change is essential when estimating the model under a Bayesian approximation. In particular, the quarterly variable's dynamics can be represented as:

$$\phi_1(L)x_\tau^1 = \phi_1(L)\beta_1^1\left(\frac{1}{3}f_{\tau,3} + \frac{2}{3}f_{\tau,2} + f_{\tau,1} + \frac{2}{3}f_{\tau-1,3} + \frac{1}{3}f_{\tau-1,2}\right) + \varepsilon_\tau^1 \tag{A-4}$$

where the error of the equation is white noise and, therefore, the standard Bayesian specifications can be used to estimate the β_1 and σ_1[20] parameters. For further details on the gains associated with this representation in the estimation of mixed-frequency dynamic factor models, see Koopman and Pacce (2016).

In the case of equation (6), the estimation of autoregressive parameters associated with the common factor error dynamics when stochastic volatility is incorporated can be done simply by solving for ϵ_{f_t}, such that,

$$\frac{\phi_f(L)f_\tau}{\sigma_{f_\tau}} = \epsilon_{f_\tau} \tag{A-5}$$

where ϵ_{f_τ} is white noise.

[20] Note that if the basis is the representation of equation (1), the pre-multiplication of that equation by the corresponding lag polynomial results in:

$$\phi_1(L)x_t^1 = \phi_1(L)\beta_1^1\left(1/3\, f_t + 2/3\, f_{t-1} + f_{t-2} + 2/3\, f_{t-3} + 1/3\, f_{t-4}\right) + \left(1/3\, \varepsilon_t^1 + 2/3\, \varepsilon_{t-1}^1 + \varepsilon_{t-2}^1 + 2/3\, \varepsilon_{t-3}^1 + 1/3\, \varepsilon_{t-4}^1\right)$$

where the error associated with $\phi_1(L)x_t^1$ is MA(4) and is therefore difficult to estimate from a Bayesian standpoint.

B Bayesian estimation

A Metropolis-Hastings algorithm based on Gibbs sampling is used to estimate the model. The authors broadly follow the algorithms described by Kim and Nelson (1999) when the variance of the common component is fixed and by Kim et al. (1998) to introduce stochastic volatility in the common component. In particular, three steps are basically followed:

1. The unobserved common component is estimated $(f_t, \ldots, f_T)$ conditioning on the factor's stochastic volatility $(\sigma_{f_1}, \ldots, \sigma_{f_T})$ and on all the model's parameters $(\beta, \sigma.\phi)$. This procedure is based on the simulation smoother algorithm proposed by Carter and Kohn (1994) and by Durbin and Koopman (2002)

2. The second step consists of estimating the factor's stochastic volatility $(\sigma_{f_1}, \ldots, \sigma_{f_T})$ conditioning the unobserved common component $(f_t, \ldots, f_T)$ and on all the model's parameters $(\beta, \sigma.\phi)$. To this end, the methodology described in Kim et al. (1998) is followed.

3. Lastly, conditioning on the unobserved common component $(f_t, \ldots, f_T)$ and on the factor's stochastic volatility $(\sigma_{f_1}, \ldots, \sigma_{f_T})$ equations (1)-(5) are independent of each other, allowing them to be treated individually, and the Bayesian estimation of each one of the model's parameters can be done in a standard manner (see Kim and Nelson (1999)).

The model is identified assuming that both the factor loadings associated with each of the variables (in the case of the model described, GDP is taken as a reference) and ω_{f_t} in equation (7) are equal to 1.

C The COVID-19 period as unobserved

This appendix describes an empirical approach whereby the period in which the variables' dynamics fluctuate the most is excluded when estimating the model (the "Missing model"), as recently suggested in the literature. Maroz et al. (2021) consider a broad set of indicators for the US economy and they define the COVID-19 period as that which spans from March to June 2020. They also suggest that there is evidence indicating that the economic indicators returned to their historical patterns at end-2020. Consequently, they propose that an alternative for the empirical estimation is to exclude the period in which the variables' dynamics fluctuate the most when estimating the model. An example of the application of this methodology in the United States was conducted by Schorfheide and Dongho (2021), who found a significant improvement in their real-time forecasts.

In Spain, the COVID-19 period is defined as that which spans from March to July 2020, since that was when the variability of the economic indicators was greater and when the most severe mobility restrictions were in place. The main advantage of this empirical strategy is that the model can be estimated for periods subsequent to the pandemic considering the information before February 2020 and after July 2020,[21] without the sharp variations observed during this period affecting the long-term correlations of the variables.

[21] The information for GDP in 2020 Q3 is also considered as unobserved.

From a methodological viewpoint, the values observed for each of the indicators during the COVID-19 period are replaced by missing observations. This alternative is viable because, as mentioned earlier, the estimation is made using a Kalman filter. However, in terms of predictive power, the evidence suggests that the Missing option is not better than the alternative of incorporating stochastic volatility in the factor, as described in the main text. This can be seen in Table A-1,[22] which shows the absolute average error and the root squared error for both the Missing model and the stochastic volatility (SV) model.

Table A-1

Nowcasting errors in the pre- and post-COVID-19 periods

		Pre-COVID-19 (2015 Q1–2019 Q4)		**Post-COVID-19** (2021 Q1–2023 Q2)		**Post-COVID-19** (2021 Q1–2023 Q2) Excl. 2021 Q2	
		GDP (Flash est.)	GDP (2nd est.)	GDP (Flash est.)	GDP (2nd est.)	GDP (Flash est.)	GDP (2nd est.)
Mean absolute error	Previous model*	0.10	0.12	0.67	0.67	0.61	0.67
	Missing	–	–	0.59	0.52	0.44	0.54
	SV	0.08	0.10	0.25	0.46	0.25	0.35
Root mean squared error	Previous model*	0.11	0.14	0.85	0.84	0.82	0.86
	Missing	–	–	0.79	0.67	0.50	0.70
	SV	0.11	0.13	0.30	0.60	0.30	0.41

Note: The mean squared errors and mean absolute errors shown are related to the forecasts made in the third month of the target quarter. The "Previous model*" refers to the model described in Section 2, but including the ESI excluding consumers, the composite PMI and the construction IPI with a coincident (as opposed to leading) correlation with the common factor. The SV model refers to the model that adds stochastic volatility to the factor. The error committed in the second quarter of 2021 was excluded when calculating the mean absolute error and the root mean squared error in columns seven and eight.

D Assessment of bias and fit in the proposed models

This appendix analyses the potential biases in the projections yielded by the two models considered by using regressions that take the flash estimate or the second GDP estimate as a dependent variable and the nowcasts of the different models as an explanatory variable (see Table A-2). Once again, the results for the pre-COVID-19 period (upper panel) and the post-COVID-19 period (lower panel) are differentiated.

[22] Note that for the pre-COVID-19 period the Previous model and the Missing model are the same, since the inclusion of missing observations during the pandemic period can only affect the forecasts after that period. For this reason, no results are shown for the pre-COVID-19 period (2015-2019).

Table A-2

Regressions for estimating GDP pre-COVID-19 (2015 Q1–2019 Q4) and post-COVID-19 (2021 Q1–2023 Q2)

	GDP (flash estimate)		GDP (2nd estimate)	
	Previous model	Revised model	Previous model	Revised model
pre-COVID-19 (2015 Q1–2019 Q4)				
Constant	0.22	0.13	0.33**	0.27**
	[0.13]	[0.12]	[0.12]	[0.11]
	(–1.64)	(–1.07)	(–2.99)	(–2.42)
Forecast	0.66*	0.76	0.51**	0.59**
	[0.18]	[0.17]	[0.16]	[0.15]
	(–1.88)	(–1.43)	(–2.99)	(–2.67)
R^2	0.43	0.54	0.36	0.44
R^2 adjusted	0.40	0.51	0.32	0.41
Number of observations	20	20	20	20
post-COVID-19 (2021 Q1–2023 Q2)				
Constant	–0.16	0.06	–0.12	0.18
	[0.25]	[0.13]	[0.30]	[0.28]
	(–0.66)	(0.45)	(–0.40)	(0.65)
Forecast	0.93	0.92	0.92	0.82
	[0.19]	[0.10]	[0.24]	[0.22]
	(–0.40)	(–0.76)	(–0.35)	(–0.81)
R^2	0.76	0.91	0.65	0.64
R^2 adjusted	0.73	0.90	0.61	0.59
Number of observations	10	10	10	10

Note: The pre-COVID-19 period refers to the errors obtained between 2015 Q1 and 2019 Q4. The post-COVID-19 period refers to the quarters running from 2021 Q1 to 2023 Q1. In all cases the forecasts obtained midway through the third month of each of the quarters in the period are considered. The standard error is given in square brackets, and the t-statistic for each of the null hypotheses is given in brackets. In the case of the constant, *, ** and *** indicate that it is significantly different from zero for a confidence level of 90 %, 95 % and 99 %, respectively. Also, *, ** and *** indicate that the coefficient associated with the regressor is significantly different from 1 for a confidence level of 90 %, 95 % and 99 %, respectively. "Previous model*" refers to the model described in Section 2, but in which the ESI excluding consumers, the composite PMI and the construction IPI have a coincident (as opposed to a leading) correlation with the common factor. The Revised model refers to the model that adds stochastic volatility to the factor, excludes the Credit variable and in which all of the variables have a coincident correlation with the factor.

In the pre-pandemic period, when the dependent variable is the GDP flash estimate, no systemic bias is observed in the nowcasts, as the null hypothesis that the coefficient is different from zero cannot be rejected at any level of statistical significance. The same cannot be said when the dependent variable is the second GDP estimate, although the apparent bias is small. Also, the positive and high value of the coefficients associated with the "Nowcast" variable indicate that the projections arising from both the Previous model and the model that includes the changes described in the previous sections are good predictors. In addition, the Revised model seems to behave relatively better insofar as said coefficient is not statistically different from 1 where the dependent variable is the flash estimate. Lastly, the adjusted R-squared is higher than in the Revised model. The following stylised facts are identified in the estimates that include the post-COVID-19 period,[23] regardless of whether the results are analysed for the flash estimate or for the second GDP estimate. First, no systematic bias is observed in the nowcasts, since the constant is not significantly different from 0, in all the specifications analysed. Second, the possibility that the coefficient associated with the nowcast, for both the Previous and the Revised models, is different from 1 cannot be rejected from a statistical viewpoint, once again indicating the good fit of the projections arising from the models.

Lastly, the adjusted R-squared of the model with stochastic volatility has the highest value when the dependent variable is the flash estimate. However, if the dependent variable is the second GDP estimate, the Previous model has the best fit from the standpoint of the afore-mentioned statistic, although the difference is relatively minor.

Consequently, the results of the tests contributed to show that the changes introduced in the model have improved the forecasts of quarter-on-quarter GDP growth since 2021 Q1, while marginally improving those for the pre-pandemic period. Also, the Revised model does not seem to show any bias in the nowcasts and at the same time improves the goodness of fit of the data based on the adjusted R-squared.

[23]It must be noted that the post-COVID-19 period includes a small number of observations and, consequently, these results must be interpreted with caution.

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