SHORT-TERM REAL-TIME FORECASTING MODEL FOR SPANISH GDP (SPAIN-STING): NEW SPECIFICATION AND REASSESSMENT OF ITS PREDICTIVE POWER

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Abstract

The predictive power of short-term forecasting models was impaired by the increased volatility observed in most economic indicators following the outbreak of COVID-19. This paper sets out a revision of the Spain-STING model (one of the tools used by the Banco de España for short-term forecasts of quarter-on-quarter GDP growth) with a view to improving its predictive power in the wake of the pandemic. In particular, the revision entails three main changes: (i) the correlation between the indicators included in the model and the estimated common component is now coincident for all of the indicators, rather than leading in the case of some of them; (ii) by using a stochastic process to model the variance in the estimated common component, such variance may now vary over time; (iii) the set of indicators has been revised in order to include only those that provide the most relevant information when it comes to predicting post-pandemic GDP growth. These modifications yield a substantial improvement in the predictive power of Spain-STING in the post-pandemic period, and maintain such predictive power for the pre-pandemic period.

Keywords: business cycles, Spanish economy, dynamic factor models, COVID-19.

JEL classification: C22, E27, E32.

Resumen

El incremento de la volatilidad observada en la mayoría de los indicadores económicos tras la irrupción del COVID-19 redujo la capacidad predictiva de los modelos de previsión a corto plazo. En este documento se presenta una revisión del modelo Spain-STING —una de las herramientas que utiliza el Banco de España para la predicción a corto plazo del crecimiento intertrimestral del PIB— al objeto de mejorar su capacidad predictiva tras la pandemia. En particular, la revisión comporta tres cambios principales: i) la relación entre los indicadores incluidos en el modelo y el componente común estimado pasa a ser contemporánea para todos los indicadores, en lugar de adelantada en el tiempo para alguno de ellos; ii) se permite que la varianza del componente común estimado pueda sufrir cambios en el tiempo, al modelarse a través de un proceso estocástico; iii) se revisa el conjunto de indicadores con el fin de incluir solo aquellos que aportan la información más relevante a la hora de predecir el crecimiento del PIB tras la pandemia. Estas modificaciones redundan en una mejora sustancial de la capacidad predictiva de Spain-STING en el período posterior a la pandemia y mantienen la correspondiente al período anterior a ella.

Palabras clave: ciclos económicos, economía española, modelos de factores dinámicos, COVID-19.

Códigos JEL: C22, E27, E32.

Content

1 Introduction

The Spain-STING model[1] is one of the tools used by the Banco de España to forecast short-term quarter-on-quarter GDP growth. Spain-STING 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 in this model in particular. 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.

This paper sets out a revision of three key aspects of the model to accommodate the changes observed in the dynamics of the variables as a result of the pandemic. The first is a reassessment of the time correlation assumed between the variables included in the model and the estimated common factor, which could potentially be coincident, lagging or leading. The second is the incorporation of stochastic volatility to account for the greater variability of the variables during periods such as the pandemic period. The third is the revision and modification of 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 (predictive power is not assessed in situations of considerable uncertainty associated with highly volatile scenarios, such as that observed at the height of the pandemic in 2020). In other words, the revision of the model aims to reduce nowcasting errors during the period running from 2021 Q1 to 2023 Q2. 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

1 The first version of the Spain-STING model is detailed in Camacho and Pérez-Quirós (2011). Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020) later expanded the model to jointly predict both GDP and its demand components.

predictive power. Lastly, the overall effectiveness of such changes is analysed 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, Gómez Loscos, De Luis López and Pérez-Quirós (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 of a monthly variable (z_t^j) – or of a quarterly variable (x_t^j) – 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,..,T represents the period expressed in months and j = 1,..,J represents the variables included in the model. Given that a mix of frequencies is used, the model must be adjusted to enable the combination of variables expressed in month-on-month and quarter-on-quarter growth rates. 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.[2] Thus, for a specification that contains only one quarterly and one monthly variable (j = 1,2), the model is described as follows::

$$\begin{pmatrix} x_t^1 \\ z_t^2 \end{pmatrix} = \begin{bmatrix} 1/3\beta_1 & 2/3\beta_1 & \beta_1 & 2/3\beta_1 & 1/3\beta_1 \\ \beta_2 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \end{bmatrix} + \begin{bmatrix} 1/3 & 2/3 & 1 & 2/3 & 1/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_t^1 \\ u_{t-1}^1 \\ u_{t-2}^1 \\ u_{t-3}^1 \\ u_{t-4}^1 \\ u_t^2 \end{bmatrix} \quad (1)$$

$$\phi_f (L)\, f_\tau = \varepsilon_{f_t} \quad (2)$$

$$\phi_j (L)\, u_t^j = \varepsilon_t^j \quad (3)$$

where ϕ_j (L) and ϕ_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

2 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: $x_t = (1/3)z_t + (2/3)z_{t-1} + z_{t-2} + (2/3)z_{t-3} + (1/3)z_{t-4}$

Table 1

INDICATORS USED IN THE MODEL IN ARENCIBIA PAREJA, GÓMEZ LOSCOS, DE LUIS LÓPEZ AND PÉREZ-QUIRÓS (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		Monthly	Coincident	1991-02	+ 50 days

SOURCE: Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020).

a The variable "Apparent consumption of cement" was used in the model of Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (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.

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. For a more detailed explanation of the model and its estimation, see Camacho and Pérez-Quirós (2011) and Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020).

The set of indicators included, following the update to the model by Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (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:

$$x_t^j = \sum_{i=0}^{11} \beta_j f_{t-i} + u_t^j \tag{4}$$

where u_t^j follows the dynamics described in equation (3).[3]

Moreover, the correlation modelling 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, Gómez Loscos, De Luis López and Pérez-Quirós (2020) found that the specification that best predicted the quarter-on-quarter rate of growth of Spanish GDP (on data up to 2016 Q3) was the one that included three of the monthly indicators with a one quarter lead.[4] Specifically, the two soft indicators and the construction 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 Industrial Production Index (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 correlation with the common factor assumed in the model (coincident or leading).

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 (4) (the "Previous model") displayed a notable capacity to nowcast GDP. Chart 1.1 shows how the GDP nowcasts – obtained using the information available midway through the third month of each of the quarters for which a forecast 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, Chart 1.3 shows the absolute nowcasting errors in respect of Chart 1.1. 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[5] saw a notable rise in the Spain-STING model's nowcasting errors, due to the difficulties in dealing with the variations seen in the

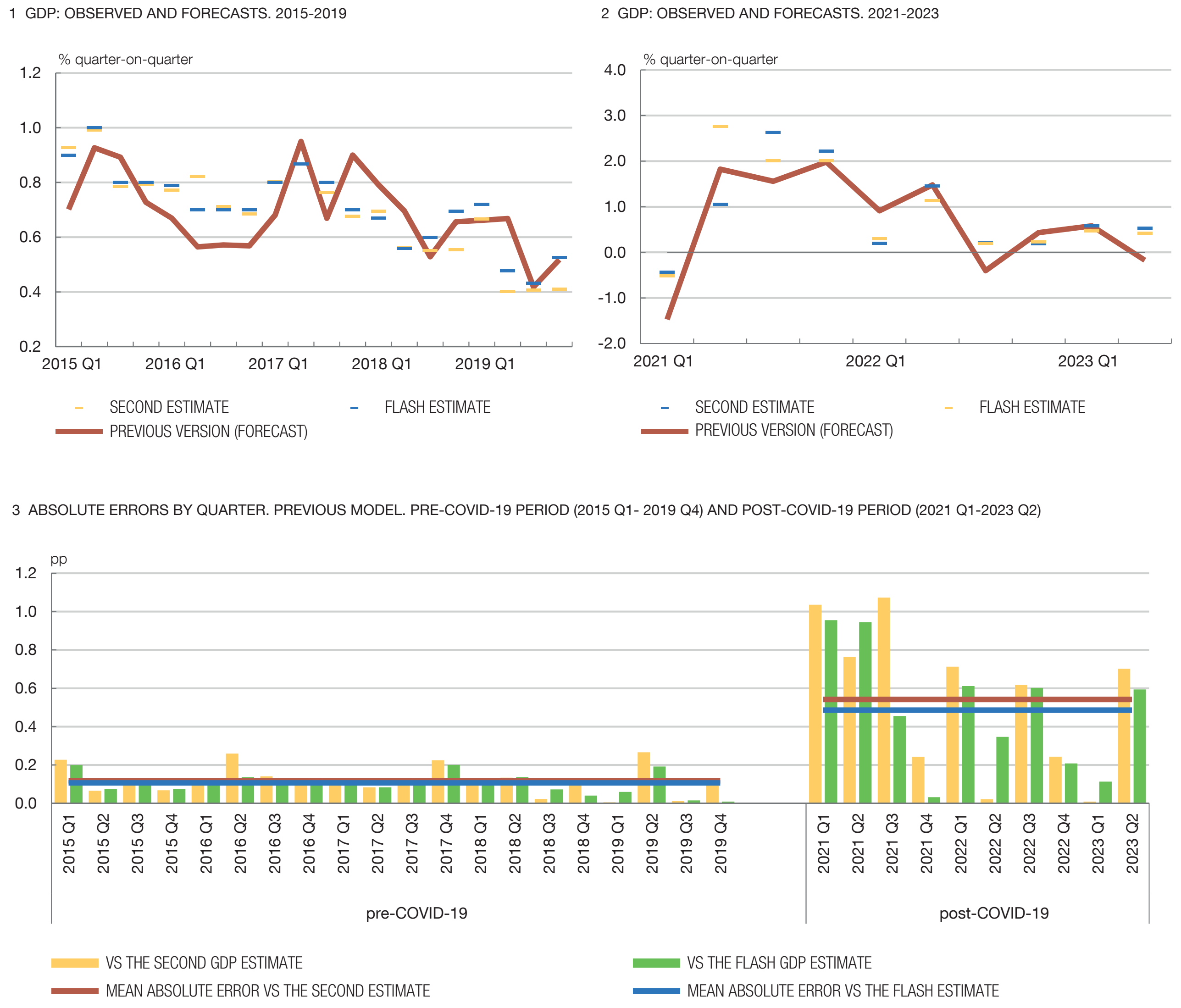
3 As noted in Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020), including the indicators in levels may create a potential modelling problem as stationary and integrated variables are considered simultaneously. This issue is resolved by following the indications of the European Commission (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.

4 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 $x_t^j = \sum_{i=0}^{11} \beta_j f_{t+3-i} + u_t^j$

5 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.

Chart 1

FORECASTING ERRORS IN THE PREVIOUS MODEL BEFORE AND AFTER INCLUDING THE POST-COVID PERIOD



SOURCE: Devised by authors.
NOTE: The horizontal lines represent the mean absolute errors in the pre- and post-COVID-19 periods, separately, vs the second and flash GDP estimates.

economic variables, which increased significantly during the pandemic. Thus, Charts 1.2 and 1.3 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

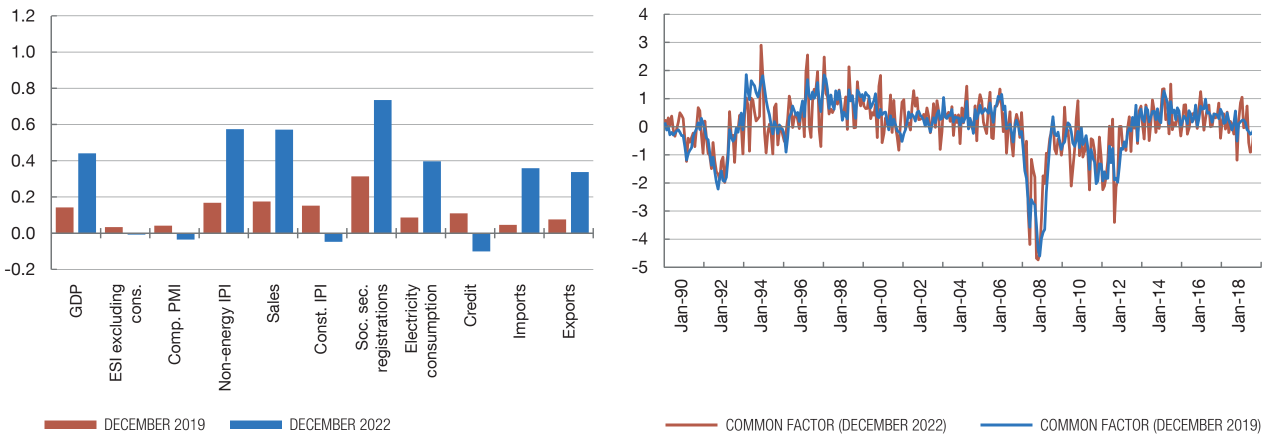
	Total (2015-2023)	Pre-COVID-19 (2015-2019)	Post-COVID-19 (2021-2023)
GDP growth	20.93	0.07	1.63
Economic Sentiment Indicator (ESI) excluding consumers	48.45	5.12	19.96
Composite Purchasing Managers Index (PMI)	47.12	3.53	24.36
Electricity consumption in industry	4.86	3.18	1.81
Social security registrations	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 IPI	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

SOURCE: Devised by author

Chart 2
EFFECT OF INCLUDING THE POST-COVID PERIOD IN THE ESTIMATIONS OF THE PREVIOUS MODEL

1 FACTOR LOADINGS ESTIMATED ON INFORMATION UP TO DECEMBER 2019 AND DECEMBER 2022

2 COMMON FACTOR ESTIMATED ON INFORMATION UP TO DECEMBER 2019 AND DECEMBER 2022



SOURCE: Devised by authors.
NOTE: The two charts 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 Chart 2.2 is divided by the standard deviation of the factor itself during the period 1990-2019.

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 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, Chart 2.1 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 specific 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, Chart 2.2 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.

3 The new Spain-STING model

3.1 Modification of the time correlation between the variables and the common component

As noted in section 2, in the model proposed by Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020), the composite PMI, the ESI excluding consumers and the construction IPI are included in the model with a three-month lead on the other variables. These variables were considered leading indicators since the first two refer to surveys that capture expectations (the surveys address how agents expect to perform over a three-month time horizon), while the construction IPI, by its very idiosyncrasy, potentially anticipates how construction (and, by extension, GDP) will perform. However, based on the findings in section 2, the correlation between the above variables and GDP may have changed after the pandemic.

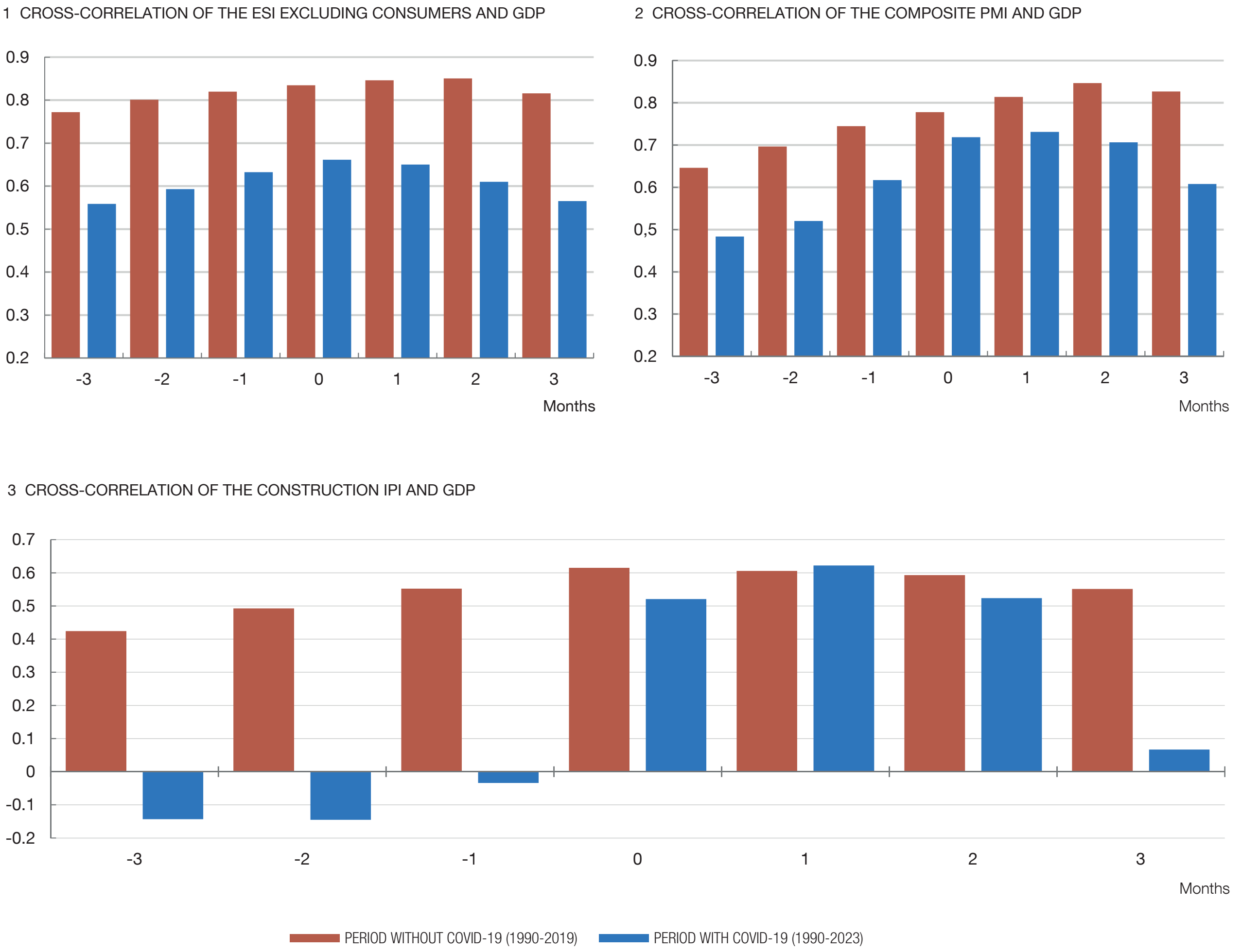
To analyse this hypothesis, for the periods before and including the pandemic (1990-2019 and 1990-2023, respectively), Chart 3 shows the correlation between the year-on-year GDP growth rate and the levels[6] of the composite PMI and the ESI excluding consumers, with different time lags. In other words, different correlations (coincident or with a lag or a lead of some months) between the indicators and GDP are estimated. By way of example, in the x-axis, the value "t+1" (correlation with a one-month lead) shows the correlation between the quarterly average of the indicator in the months of February, May, August and November and the year-on-year GDP growth rate in March, June, September and December, respectively.

Based on the results obtained, for the period 1990-2019, both in the case of the ESI excluding consumers and the composite PMI, the closest correlation with the year-on-year GDP growth rate is obtained when each of the indicators has a lead of at least two months (see Chart 3). However, for the period 1990-2023 (once the pandemic period has been included), these correlations change: in the case of the ESI excluding consumers, the closest correlation can be seen when the correlation is coincident and, in the case of the composite PMI, when the indicator has a lead of one month, although this value is only slightly higher than that observed in the coincident correlation. One possible explanation for this change in the time correlation between these variables and GDP is the sharp fall in the values of such variables in the months of the tightest mobility restrictions and, therefore, the sharpest decline in activity. In the case of the construction IPI, the correlation between the month-on-month growth rates of this variable and of GDP are analysed.[7] As can be seen in Chart 3, the correlation with a three-month lead becomes weaker once the post-pandemic period has been included in the sample, and the correlation in which the construction IPI leads GDP by one month is the closest, although the coincident correlation is also close. The changes observed in the time correlations analysed raise the prospect that the three variables may have ceased to be leading indicators of activity, and an alternative is therefore analysed in which they have a coincident correlation with the

6 Using a three-month moving average.

7 To calculate the quarter-on-quarter rate of growth of the construction IPI, a three-month moving average of the variable is estimated and the quarter-on-quarter rate is calculated for each month.

Chart 3
CROSS-CORRELATION OF GDP AND CERTAIN SELECTED VARIABLES



SOURCE: Devised by authors.
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

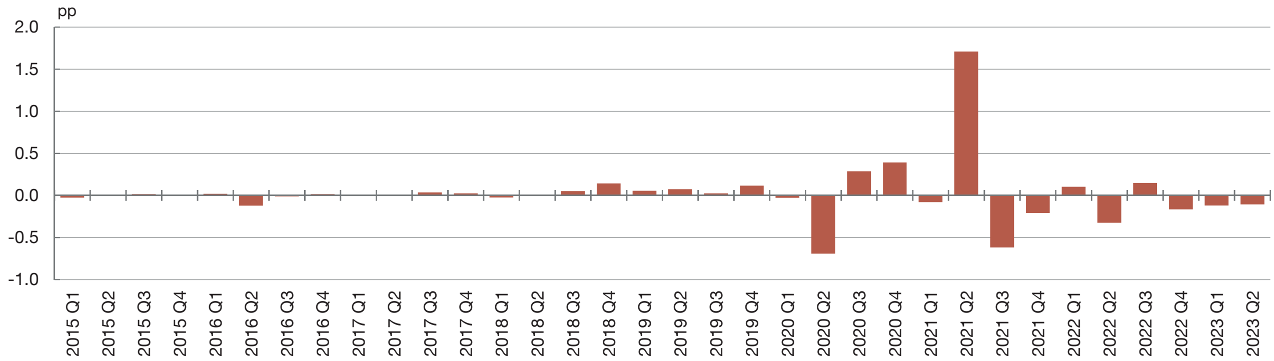
common factor.[8] In the case of the other variables, which were included with a coincident correlation in the model of Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020), no change can be seen in the time correlations analysed following the inclusion of the COVID-19 period.

When assessing the potential gains to be made from revising the time correlation of the variables, it is essential to estimate the nowcasting error obtained with and without the change to the specification of the model. To this end, in the third month of each quarter,

8 The choice of a coincident correlation in the cases of the composite PMI and the construction IPI, as opposed to a correlation with a one-month lead, as would appear to be suggested by the correlation analysis, is based on the desire for a parsimonious model, since the other variables are included on a coincident basis, and bringing these variables forward by only one month does not yield any significant changes in terms of the forecasts obtained.

Chart 4

DIFFERENCE BETWEEN THE FLASH AND SECOND GDP ESTIMATES



SOURCE: INE and devised by authors.

between January 2015 and June 2023, quarter-on-quarter GDP growth is forecast using the two specifications described. Thus, a forecast one and two quarters ahead is made based on the data available on the 23rd of each month. In other words, the estimates are obtained in "real-time".[9] The error in the above estimates is then calculated with respect to the flash and the second GDP estimations. It is important to note that significant revisions are occasionally made between the two estimates, and these were particularly significant between 2020 Q1 and 2022 Q2 (see Chart 4).

There is no decline in the nowcasting errors committed in the post-pandemic period following the proposed change to the specification of the time correlation between the above three variables and the common factor, although there is also no increase. Nonetheless, the change introduced does yield a substantial improvement in terms of the economic interpretation of the model. As noted in section 2.2, the historical correlation between the common component (which may be interpreted as a measure of activity) and the ESI excluding consumers, the composite PMI and the construction IPI, which was positive before COVID-19, turned negative (see Chart 2.1). In other words, these variables became inversely correlated with economic activity. This circumstance, which is counter-intuitive from an economic standpoint, is reversed following the changes in the time correlation between these variables and the common component (i.e. the correlation becomes positive). With this in mind, it has been seen fit to include these three variables with a coincident correlation with the common factor, and they have been included in this way in the rest of this paper.

3.2 Incorporation of stochastic volatility associated with the common factor

To address the sharp rise in the volatility of the indicators used in the model (see Table 2), the possibility that the volatility of the common factor estimated by the model might vary over time

9 "Real-time" forecasting refers to the fact that the estimations are made on the data available to the analyst at each point in time.

is considered. In the previous version of the model, described in the preceding section, a key characteristic of the common factor's behaviour was that its associated variance was assumed to remain constant over time. This specification may prove excessively rigid in scenarios of crisis or extreme events, when the volatility of the indicators tends to increase sharply, thus affecting the dynamics of the estimated common component. By allowing the variance associated with the common factor to vary over time, the periods in which the indicators are more volatile become less relevant when estimating the common component, since it is the increase in the volatility of the factor (as opposed to the factor in and of itself) that would explain most of the common dynamics of the variables.

In order to introduce stochastic volatility in the dynamics of the common factor, equation (2) in the previous version of the model is replaced with the following specification:

$$\phi^f(L)\, f_\tau = \sigma_{f_t} \epsilon_{f_t} \tag{5}$$

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

$$\log \sigma_{f_t} = \log \sigma_{f_{t-1}} + \nu_{f_t} \quad ; \quad \nu_{f_t} \sim N(0,\omega_{f_t}) \tag{6}$$

The incorporation of stochastic volatility in mixed-frequency dynamic factor models was proposed by Marcellino, Porqueddu and Vendetti (2016), and later by Pacce and Pérez-Quirós (2019) within the framework of the Euro-STING model (Camacho and Pérez-Quirós, 2010). The second methodological approach is used in this paper, meaning that the specifications described in equations (1), (3), (5) and (6) must be rewritten using a stacked vector representation.[10] This specification enables a Bayesian estimation of the model, making the estimation more straightforward once stochastic volatility has been incorporated into the model. Appendix 2 includes a detailed description of the Bayesian estimation model, which is made using a Metropolis-Hastings algorithm based on Gibbs sampling.[11]

It is important to note that the primary aim of the solution proposed is not only to improve the predictions in the post-pandemic period, but also to ensure that the model does not perform worse in terms of the predictions made in the pre-pandemic period. However, the aim is not to identify the specifications of a model that yields satisfactory results in highly uncertain situations, such as that seen throughout 2020. To do so, it would be necessary to take a different approach or use other econometric tools that consider higher-frequency economic information.

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10 For the Bayesian estimation of mixed-frequency dynamic factor models, the stacked vectors approach proposed by Koopman and Pacce (2015) has been used. Appendix 1 details the form of the model specified in equations (1), (3), (5) and (6) following the above approach.

11 To estimate the stochastic component of the factor's volatility, the methodology described in Kim, Shephard and Chib (1998) is used.

As an alternative to the inclusion of stochastic volatility in the common factor, missing observations could be assigned during the most critical phase of the COVID-19 pandemic, which saw the biggest changes in the dynamics of the variables. In other words, the economic information obtained from the indicators during this period is left incomplete. While this option was considered when assessing the different modelling alternatives, it was ruled out as it yielded less satisfactory results than those obtained from the modelling in which stochastic volatility is incorporated. Appendix 3 contains a detailed explanation of this option and a comparative analysis of the results obtained.

To analyse whether or not it is worth introducing stochastic volatility in the model, a selected set of relevant tests is presented with a view to assessing the predictive power of the modelling alternatives described. Specifically, the Previous model and the model with stochastic volatility (the "SV model").[12] Based on the variables included in the Arencibia Pareja, Gómez Loscos, De Luis López and Pérez-Quirós (2020) model (see Table 1),[13] the analysis focuses on a comparison between the predictive power of the Previous model and the specification adding stochastic volatility to the common component of the model. However, to isolate the potential improvements obtained from adding stochastic volatility from the changes to the time correlations of the variables described in the preceding section, the composite PMI, the ESI excluding consumers and the construction IPI are included with a coincident correlation with the common factor in both specifications.

Table 3 shows the nowcasting errors of the two models for the different periods. Specifically, it shows the root mean squared errors and the mean absolute errors, calculated using a real-time exercise such as the one described in section 3.1. In other words, it includes the errors committed in the estimations made in the third month of each quarter, when information is available for one or two months of the quarter in progress (depending on the variable). Based on the results obtained, the SV model displays better predictive power than the Previous model. First, in the case of the post-COVID-19 period (2021-2023), the SV model yields a significant improvement in terms of the root mean squared errors and the mean absolute errors, in the case of both the second GDP estimate and, in particular, the flash estimate. Second, the SV model has marginally fewer nowcasting errors than the Previous model during the pre-pandemic period (2015-2019). Lastly, it is worth noting that when the error committed in 2021 Q2 is omitted – when the change between the flash and the second GDP estimates stood at almost 2 pp (see Chart 4) – the predictive power of the SV model improves significantly in terms of the errors committed with respect to the second GDP estimate.

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12 It is worth noting that a broader set of specifications than that shown in this section has been designed and assessed in terms of its predictive power. Nonetheless, these results are not set out in detail in this paper given the poor predictive performance displayed. In particular, there is no description of the results obtained using two alternative modelling specifications: the first adds stochastic volatility to both the factor and the variables, and the second adds such volatility only to the model's variables, while holding the volatility associated with the factor constant. The results of these exercises are available from the authors upon request.

13 Between March 2020 and March 2022 furlough schemes (ERTEs) were activated in Spain, whereby employment contracts could be temporarily suspended without the need to dismiss workers. The unadjusted series of social security registrations does not exclude the furloughed employment contracts during the above period. With a view to ensuring that the series reflects the level of economic activity in Spain as accurately as possible and therefore has better explanatory power in terms of GDP, furloughed workers are excluded from the social security registration series from February 2020 onwards.

Table 3

FORECASTING 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) Excluding 2021 Q2	
		GDP (Flash estimate)	GDP (2nd estimate)	GDP (Flash estimate)	GDP (2nd estimate)	GDP (Flash estimate)	GDP (2nd estimate)
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

SOURCES: Devised by authors
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

To analyse whether further improvements can be made to the GDP nowcast, consideration is given to the possibility that some of the indicators included in the model until now may have lost explanatory power, whereas others that were not included in that set of variables could enhance the quarterly GDP forecast. Given the colinearity of the most habitual macroeconomic indicators, it is worth noting that the tentative inclusion of additional variables need not necessarily enhance the model's predictive power. It is therefore worth using a statistical selection procedure to identify which variables are significant, based on particular statistical criteria. The methodology proposed by Camacho and Pérez-Quirós (2010) is followed in this paper.[14] Specifically, a base model that includes a parsimonious set of variables representing changes in activity is used as a starting point, before analysing whether the incorporation of additional variables yields any improvement to the model's predictive power in the post-COVID-19 period, without impairing such power in the pre-pandemic period.

Thus, the base model's set of variables is selected with the aim of using indicators on activity (GDP and electricity consumption), supply (the non-energy IPI), employment (social security registrations), external and internal demand (real exports and imports of goods) and at least one survey-based indicator published close to the end of the reference month (the composite PMI). Meanwhile, the inclusion in this base model of the other indicators that had been included in the previous version of the model is assessed, one

14 Álvarez-Aranda, Camacho and Pérez-Quirós (2012) examine the empirical pros and cons of forecasting using large-scale versus small-scale factor models, finding that the greater the number of time series, the closer the correlation between them, and, consequently, the closer the correlation of the idiosyncratic component (this being the correlation that could skew the results of the estimated common factor). Moreover, Bai and Ng (2008) have demonstrated the importance of using parsimonious specifications to boost the predictive power of factor models, even where a cross-correlation equal to 0 is maintained in the idiosyncratic component. Lastly, Boivin and Ng (2006) show that the asymptotic advantages of large-scale factor models are by no means maintained in empirical applications.

Table 4

SV MODEL FORECASTING ERRRORS: BASE MODEL VS BASE MODEL PLUS ADDITIONAL INDICATORS

		Pre-COVID-19 (2015 Q1-2019 Q4)		Post-COVID-19 (2021 Q1-2023 Q2)	
		GDP (Flash estimate)	GDP (2nd estimate)	GDP (Flash estimate)	GDP (2nd estimate)
Mean absolute error	(1) Base model	0.10	0.12	0.43	0.65
	(2) Base model + ESI excluding consumers	0.10	0.11	0.42	0.63
	(3) Base model + ESI excluding consumers + Sales of large firms	0.09	0.10	0.40	0.68
	(4) Base model + ESI excluding 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 excluding consumers	0.13	0.15	0.54	0.98
	(3) Base model + ESI excluding consumers + Sales of large firms	0.11	0.13	0.49	0.92
	(4) Base model + ESI excluding consumers + Sales of large firms + Construction IPI	0.11	0.13	0.29	0.60

SOURCE: Devised by authors

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.

by one: the ESI excluding consumers, sales of large firms and the construction IPI. The predictive power of the model is analysed at each stage, in real time, for the pre- and post-COVID-19 periods, with regard to the values observed for both the root mean squared error and the mean absolute error. Thus, the criterion for deciding whether or not to add a specific variable is whether this helps to reduce the model's nowcasting errors, i.e. whether it enhances its predictive power.

Table 4 shows the mean absolute error and the root mean squared error of each model estimated, in all cases applying both a coincident correlation between all of the variables and the common factor and stochastic volatility in the dynamics of the estimated common component. It can thus be seen that, in general, in both the pre-and post-COVID-19 periods the forecasting errors decline slightly as and when each of the above variables is added, illustrating the explanatory power of each of the variables added to the model. The inclusion of the construction IPI in the model yields the most significant reduction in nowcasting errors in the post-pandemic period (2021 Q1-2023 Q2).

It is worth highlighting that the above model displays marginally lower nowcasting errors than those shown in Table 3, which come from the same model, though also including credit to non-financial corporations. Moreover, this variable displays a sign in the associated factor loading that makes it hard to interpret in economic terms, since, as noted in section

2.2, the sign turned negative when the pandemic is included in the period analysed. This would therefore appear to suggest that increases in credit are correlated with declines in activity.[15] With this in mind, it was decided to exclude the credit to non-financial corporations variable from the final model.

Two further exercises were conducted. First, the result of adding the Services Sector Activity Index (SSAI) was studied. By measuring activity in the services sector (which has a significant weight in GDP), this variable could prove useful for boosting the model's predictive power. Thus, the SSAI was added to the last specification shown in Table 4 (specification 4). While the results suggest that this indicator could yield a slight improvement in the model's predictive power, the sign of the associated factor loading is opposite to what might be expected in the post-COVID-19 period. The inclusion of this indicator as a potential additional model variable has therefore been ruled out. Second, the possibility of replacing the sales by large firms indicator with the Retail Trade Index (RTI) was analysed. This exercise was also conducted on specification (4) of Table 4. In this case, the results of these tests indicate that the specification including the RTI notably impairs the predictive power of the model.

Lastly, after analysing the set of relevant tests, the specification that displayed the lowest estimated nowcasting errors in the form of mean absolute and root mean squared errors, and which also retains a sign in the factor loadings associated with each of the variables that is consistent with economic theory, is the specification in which all of the indicators are included with a coincident correlation with the common factor and which contains the following variables: GDP, social security registrations, sales of large firms, electricity consumption, the non-energy IPI, the composite PMI, real exports of goods, real imports of goods, the ESI excluding consumers and the construction IPI (see Table 5).

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

After explaining the three changes made in the model and analysing the improved predictive power stemming from each change, it is essential to compare the predictive power of the Revised model (which simultaneously incorporates the three changes described) with the predictive power of the Previous model.[16]

Chart 5.1 shows the forecasting errors, in real time, of the Revised model as compared with the errors of the Previous model. Where the value of the ratio is lower than 1, the Revised model shows better predictive power than the Previous model, as it has smaller forecasting errors. The opposite occurs when the value is greater than 1. Specifically, an analysis is conducted, first, of the errors made between 2015 Q1 and

15 The change in sign of the factor loading may be due to the fact that, at the height of the pandemic (when activity fell most sharply), credit in Spain remained buoyant as a result of the economic policies set in place by the authorities to support firms and households.

16 The model described in Section 2, which contains variables that have a leading correlation with the common factor, does not allow the common factor variance to vary over time, and includes credit to non-financial corporations as an indicator.

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)	Activity	INE	Monthly	Coincident	1992-02	+ 36 days
Real imports of goods	Activity	Customs Department and MINECO	Monthly	Coincident	1991-02	+ 50 days
Real exports of goods	Activity		Monthly	Coincident	1991-02	+ 50 days

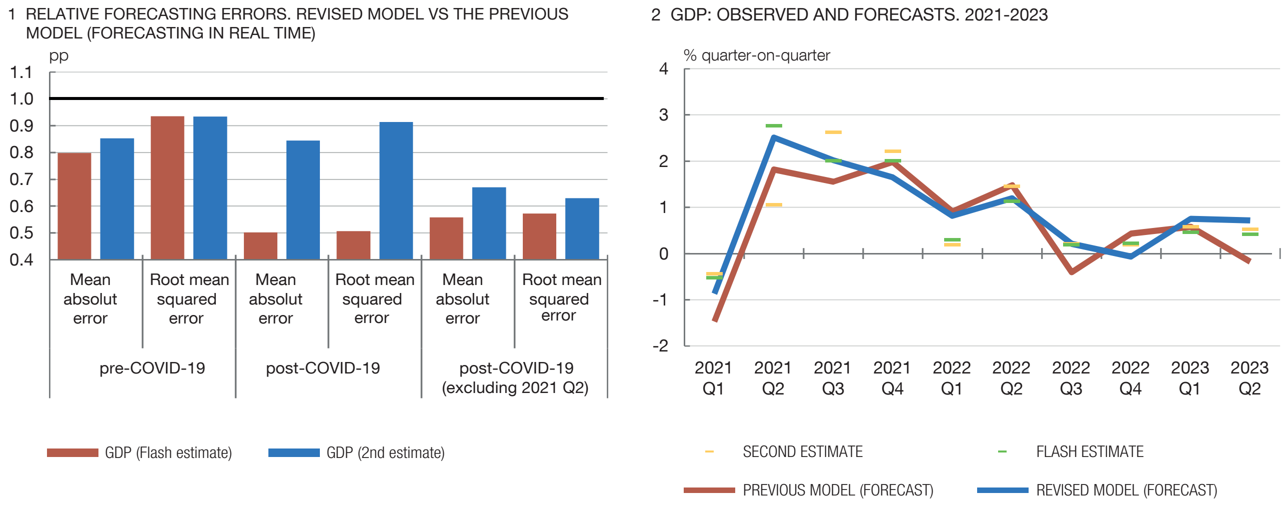
SOURCE: Devised by authors.

2019 Q4 (pre-COVID-19 period) and, second, those made between 2021 Q1 and 2023 Q2 (post-COVID-19 period), as compared with both the GDP flash estimate and the second estimate.

The first notable finding is that, in all the cases analysed, the nowcasting errors of the Revised model are smaller than those of the Previous model, which confirms that the predictive power of the new model has improved. An analysis of the results by period reveals that the improved performance of the Revised model for the pre-COVID-19 period (between 10% and 20%, depending on whether the mean absolute error or the mean squared error is analysed) not only meets the initial goal of ensuring that the predictive power for that period is not impaired, it even improves it somewhat. As regards the post-COVID-19 period, a significant difference is observed in the results when the aim is to nowcast the GDP flash estimate compared to when the aim is to nowcast the second GDP estimate. Specifically, there is a 50% reduction in the errors associated with the Revised model in the first case, compared with those of the Previous model, while for the second GDP estimate the improvement is close to 10%. However, as seen in Chart 5.2, which shows a comparison of the models' nowcasts with the second estimate and the GDP flash estimate for each of the quarters in the post-pandemic period, this result is heavily influenced by the inclusion in the period under analysis of the second quarter of 2021, when a revision of more than 1.5 pp was observed in the quarter-on-quarter GDP growth rate between the first and the second estimate. If that quarter is excluded from the nowcasting error calculations, the reduction achieved by the Revised model in the second GDP estimate, compared with the Previous model, is between 25% and 35%.

In addition to the analysis of the nowcasting errors, the potential biases in the projections yielded by the two models considered can be analysed using regressions that take the flash estimate or the second GDP estimate as a dependent variable and the

Chart 5
IMPROVEMENTS IN THE FORECAST OF THE REVISED MODEL VS THE PREVIOUS MODEL



SOURCE: Devised by authors.
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.

nowcasts of the different models as an explanatory variable (see Table 6). Once again, the results for the pre-COVID-19 period (upper panel) and the post-COVID-19 period (lower panel) are differentiated.

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,[17] 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.

17 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.

Table 6

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

SOURCE: Devised by authors.

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.

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 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.

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 (2021-2023).

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.

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Annex 1: Stacked vector approach to the representation of the model

Taking a stacked vector approach, equations (1) and (3) may be written as follows:

$$\begin{pmatrix} x^1_\tau \\ z^2_{\tau,3} \\ z^2_{\tau,2} \\ z^2_{\tau,1} \end{pmatrix} = \begin{bmatrix} 1/3\beta_1 & 2/3\beta_1 & \beta_1 & 2/3\beta_1 & 1/3\beta_1 \\ \beta_2 & 0 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 & 0 \\ 0 & 0 & \beta_2 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_{\tau,3} \\ f_{\tau,2} \\ f_{\tau,1} \\ f_{\tau-1,1} \\ f_{\tau-1,2} \end{bmatrix} + \begin{bmatrix} u^1_\tau \\ u^1_{\tau,3} \\ u^1_{\tau,2} \\ u^1_{\tau,1} \end{bmatrix} \tag{7}$$

$$\phi_1 (L)\, u^1_\tau = \varepsilon^1_\tau \tag{8}$$

$$\phi_2 (L)\, u^2_{\tau,3} = \varepsilon^2_{\tau,3} \tag{9}$$

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^1_τ) to have a quarterly frequency and the operator L to act on that frequency, while operator L on $(u^2_{\tau,3})$ continues to affect the errors on a monthly frequency as in equation (3). This small change is essential when estimating the model under a Bayesian approximation. In particular, the quarterly variable's dynamics can be represented as:

$$\phi_1 (L)\, x^1_\tau = \phi_1 (L)\, \beta_1 \left(\tfrac{1}{3} f_{\tau,3} + \tfrac{2}{3} f_{\tau,2} + f_{\tau,1} + \tfrac{2}{3} f_{\tau-1,3} + \tfrac{1}{3} f_{\tau-1,2}\right) + \varepsilon^1_\tau \tag{10}$$

where the error of the equation is white noise and, therefore, the standard Bayesian specifications can be used to estimate the β_1 y σ_1[18] parameters. For further details on the gains associated with this representation in the estimation of mixed-frequency dynamic factor models, see Koopman and Pacce (2015).

In the case of equation (5), 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,

$$\frac{\phi_f (L)\, f_\tau}{\sigma_{f_t}} = \epsilon_{f_t} \tag{11}$$

where ϵ_{f_t} is white noise.

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

$$\phi_1 (L)\, x^1_t = \phi_1 (L)\, \beta_1 (1/3f_t + 2/3f_{t-1} + f_t + 2/3f_{t-2} + 1/3f_{t-3}) + (1/3\varepsilon^1_t + 2/3\varepsilon^1_{t-1} + \varepsilon^1_{t-2} + 2/3\varepsilon^1_{t-3} + 1/3\varepsilon^1_{t-4})$$

where the error is associated with ϕ_1 (L) x^1_t such that MA(4) and is therefore difficult to estimate from a Bayesian standpoint.

Annex 2: 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, Shepard and Chib (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, ..., f_T) conditioning on the factor's stochastic volatility ($\sigma_{f_1}, \ldots, \sigma_{f_T}$) and on all the model's parameters (β, σ, ϕ). 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, ..., f_T) and on all the model's parameters (β, σ, ϕ). To this end, the methodology described in Kim, Shepard and Chib (1998) is followed.

3 Lastly, conditioning on the unobserved common component (f_t, ..., f_T) and on the factor's stochastic volatility ($\sigma_{f_1}, \ldots, \sigma_{f_T}$), equations (1)-(4) 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 (6) are equal to 1.

Annex 3: The COVID-19 period as unobserved

This annex 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, Stock and Watson (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 Song (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,[19] without the sharp variations observed during this period affecting the long-term correlations of the variables.

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.

Table A3.1
FORECASTING 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) Excluding 2021 Q2	
		GDP (Flash estimate)	GDP (2nd estimate)	GDP (Flash estimate)	GDP (2nd estimate)	GDP (Flash estimate)	GDP (2nd estimate)
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

SOURCE: devised by authors.
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.

19 The information for GDP in 2020 Q3 is also considered as unobserved.

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 7,[20] which shows the absolute average error and the root squared error for both the Missing model and the stochastic volatility (SV) model.

20 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).

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