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Nowcasting French GDP Growth During Exceptional Periods

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- Nowcasting, or very short-term forecasting, is a crucial tool for understanding major changes in the economy and detecting turning points in the business cycle. Nowcasting is the first stage in the economic forecasts at the two-year horizon established by the Directorate General of the Treasury to prepare France's budget acts and stability programmes.

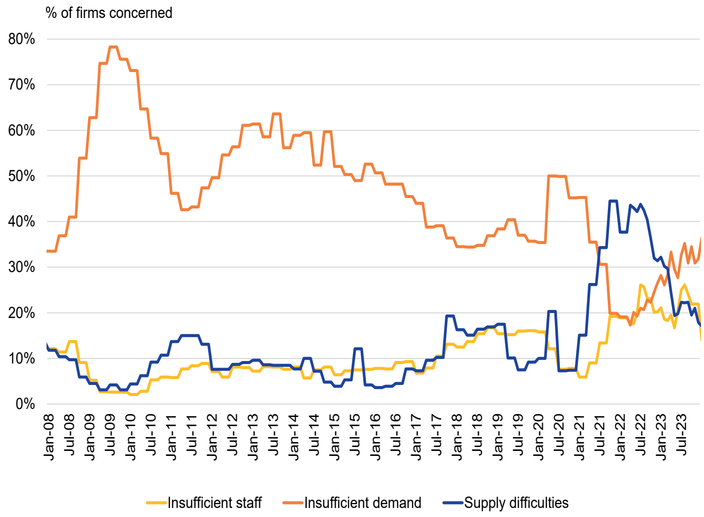
- In the period from 2020 to 2023, supply difficulties arising from the COVID-19 health crisis and Russia's war of aggression in Ukraine played a greater role in restricting economic activity than demand for firms' output (see Chart). France's economic trajectory during this exceptional period was thus influenced more by supply factors than by demand factors that typically dominate.

- The predictive performance of economic models based explicitly or implicitly on demand variables thus worsened during the crisis period, notably in the case of the nowcasting models that rely on composite business climate indicators to predict GDP growth.

- Alternative models incorporating automatic input variable selection can be used to identify, from a vast array of data sources, those items that make the greatest contribution to improving predictive performance. Such models are simple to interpret and econometrically similar to conventional models.

- For the recent period, an *ex post* estimation shows that variables such as supply constraints in manufacturing, which are typically absent from conventional models, would have made the greatest contribution to improving short-term GDP forecasting for France.

Supply and demand constraints in manufacturing



Source: French National Statistics Institute (INSEE).

1. The health crisis and energy crisis have substantially changed the analysis and use of business climate surveys

The COVID-19 health crisis caused unprecedented disruptions in the French economy. The economic indicators conventionally used in forecasting models failed to capture the magnitude of the shock, and the shortcomings persisted in the wake of Russia's invasion of Ukraine and other geopolitical conflicts. The survey-based composite business climate indicators[1] have thus shown their limitations since 2020. Outlook surveys have been distorted by three factors: (i) the qualitative nature of the surveys has prevented them from capturing the full extent of shocks; (ii) shifts in respondent behaviour have made it more difficult to compare "business climates" over time; and (iii) the economic interpretation of certain variables has changed, leading to bias in the composite indicators, e.g. the balance of opinion on speed of supplier deliveries in the S&P Global Purchasing Managers' Index (PMI) surveys (see below).

1.1 The COVID-19 health crisis: exceptional magnitude not captured by business outlook surveys

During the Great Recession, the INSEE business climate indicator fell 22 points, from an average 95 in Q3 2008 to an average 73 in Q1 2009. Later, during the first COVID-19 lockdown in France (March 17 to May 11, 2020), the INSEE surveys recorded a 42-point drop, from 106 in Q4 2019 to 64 in Q2 2020. The decline was thus 1.9 times greater in the second episode than in the first. The corresponding decline between the same two periods was 1.2 times for the Banque de France business sentiment indicator, and 2.6 times for the S&P Global indicator. Yet the actual decline in GDP was nearly 6 times greater during the second episode, with a drop of 17.7% in 12-month-to-date values, from Q4 2019 to Q2 2020, compared to the 3.2% decline from Q3 2008 to Q1 2009.

The explanation lies in the use of composite indicators formed by combining the qualitative responses by the business leaders surveyed (Phung, 2023).[2] Individual responses are weighted by the relative size of firms in the sector to yield a total percentage of responses reporting conditions to be the same, better or worse, and to calculate balances of opinion.[3] For example, in the Banque de France monthly survey, the question on past manufacturing production asks for "the change in your output last month, compared with the previous month". Because the survey choices are "increase", "decrease" and "remain unchanged", this item fails to capture the magnitude of any rise or fall; even if 90% of firms report lower output, the response provides no information on the extent of the decline. During crisis periods, this characteristic of business outlook surveys weighs on the performance of forecasting models that rely on surveys as a principal source of data.

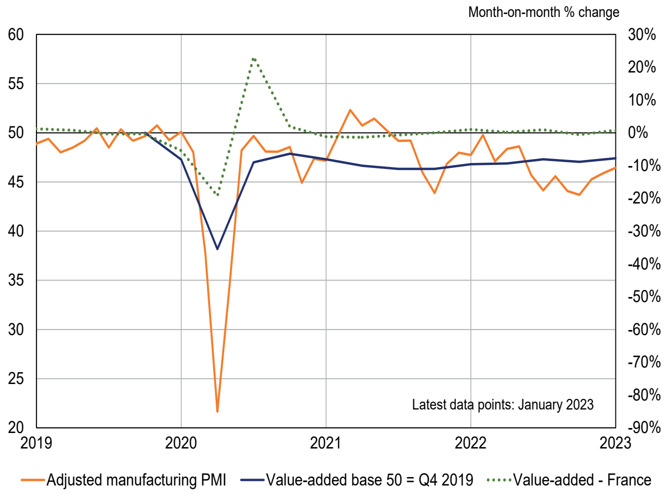
1.2 A shift in business survey respondent behaviour

Another factor limiting the ability of business outlook surveys to capture economic shocks comes from a shift in how businesses now respond to surveys – a phenomenon first identified in the 2010s.[4] Since the eurozone crises in 2008-2009 and 2011-2013 and the ensuing slow recoveries, consumers and business leaders appear to have adjusted their economic expectations to a lower "new normal". This involved a clear shift in the relationship between qualitative survey data and quantitative data before and after the crisis. The change was even greater during the 2020 crisis, when responses to survey questions on trends relative to the previous period tended to be based on an implicit comparison with much earlier (pre-crisis) levels (i.e. higher or lower than pre-crisis) rather than a comparison with the immediately preceding period.

The dissonance between questions asked and firms' responses has been most conspicuous in the area of manufacturing output. In France, while actual output rebounded sharply in 2020, survey indicator levels remained below the level reported at the end of 2019; the PMI failed to break the 50 threshold that would have signalled an increase in production, as firms' responses focused on their still-degraded situation rather than the actual rebound.

(1) There are three major monthly business surveys for France, the INSEE monthly business tendency surveys in various sectors (in services, in industry, etc.), the Banque de France monthly business survey and the S&P Global PMI survey.
(2) See L. Phung (2023), "Guide pratique des enquêtes de conjoncture & protocole de prévision en temps reel", DG Trésor *Working Paper* 2023/2 (in French only).
(3) Responses to each business survey question are tracked over time in a single series, the balance-of-opinion series (Phung, 2023, pp. 8-10).
(4) See C. Gayer and B. Marc (2018), "A 'New Modesty'? Level Shifts in Survey Data and the Decreasing Trend of 'Normal' Growth", European Commission, *European Economy Discussion Paper* 083.

Chart 1: PMI manufacturing index and manufacturing value-added



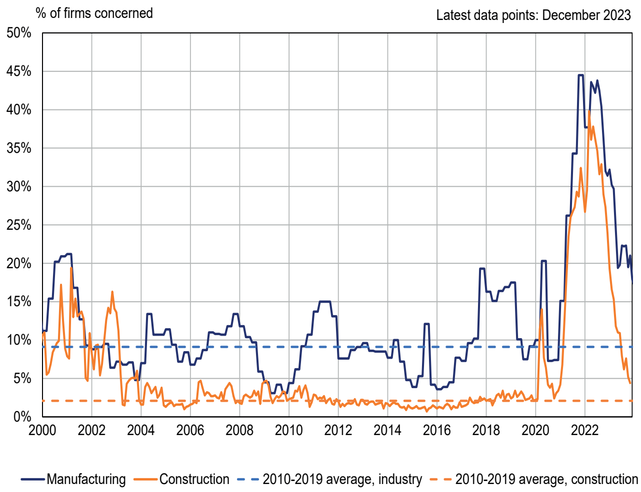
Sources: INSEE and S&P Global.

How to read this chart: Value-added in manufacturing fell by close to 20% in Q2 2020 and then rebounded by 22% in Q3 2020. By contrast, the adjusted PMI manufacturing index, i.e. adjusted for speed of supplier deliveries (see Box 2), remained below 50 until March 2021, indicating that firms responded according to relative levels, rather than the trend from the previous period.

1.3 Supply bottlenecks distort the interpretation of business climate indicators

Following the initial lockdowns across the globe in 2020, the resumption of economic activity saw supply bottlenecks of an exceptional magnitude. For example, as early as January 2021, business leaders in the French automotive sector reported in INSEE business surveys that they were facing severe supply difficulties, particularly owing to the shortage of semiconductors; those difficulties severely limited automotive production and hampered the sector's recovery (Chart 2). Supply difficulties were compounded by hiring difficulties, which were now more acute than before the crisis, exacerbating pre-existing labour market tensions in France (Grobon, Ramajo, & Roucher, 2021; Zuber & Himpens, 2023). This supply chain shock was exacerbated by Russia's invasion of Ukraine in February 2022, as higher energy prices impacted energy-intensive sectors such as chemicals, metals and metal products, wood and paper products, and rubber and plastic products, as well as petrochemical-dependent sectors including agriculture.

Chart 2: Supply difficulties in manufacturing and in construction



Source: INSEE.

The shock disrupted the interpretation of business outlook surveys. Many economic variables, e.g. speed of supplier deliveries, raw materials prices and selling prices, which traditionally reflected strong demand and therefore growth in economic activity, now came to reflect supply difficulties which constrained production and reduced growth. These circumstances were reflected in the poorer performance of models whose coefficients were based on the traditional interpretation of those variables (Box 2).

Box 1: Trade-off between simplicity and performance

Nowcasting models have varying degrees of sophistication. Those constructed using composite indicators from business outlook surveys (INSEE and Banque de France business climate surveys or the S&P Global PMI manufacturing index) have the advantage of being very simple, in that they use a linear regression on a single series and exhibit highly satisfactory performance in normal periods (Phung, 2023, p. 36). These "conventional" models have been used since 2015; when estimated for the 1990-2015 period, they showed a correlation coefficient of 90% between the business-outlook surveys' composite indicators and the year-on-year change in French GDP.[a]

Other, more sophisticated, models such as neural networks and dynamic factor models may potentially exhibit better performance or allow earlier detection of turning points, but are more complicated to develop, demand far more computing power, and deliver results that are harder to interpret than those based on a simple linear regression model because changes to forecasts are dependent on changes in a very large number of variables.[b]

a. See T. Rioust De Largentaye and D. Roucher (2015), "How Closely Do Business Confidence Indicators Correlate With Actual Growth?", *Trésor-Economics*, No. 151.

b. See M. Blanchet and M. Coueffe (2020), "Improved GDP Nowcasting Using Large Datasets", *Trésor-Economics*, No. 254.

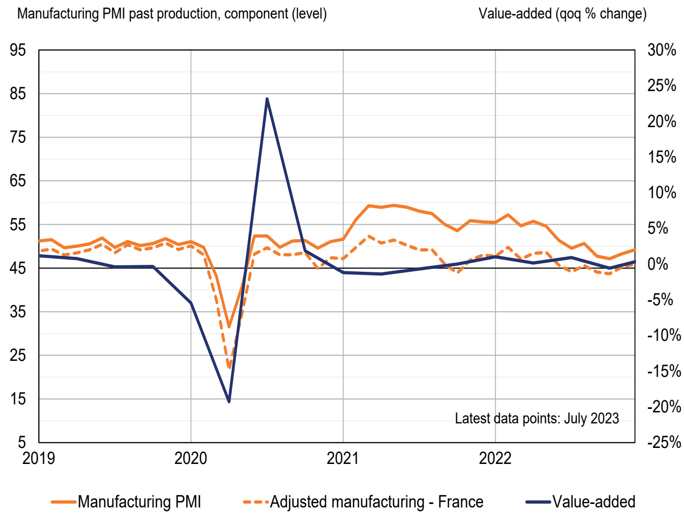
Box 2: Supply shocks had a peculiar impact on composite indicators

The S&P Global PMI that is used to track activity in manufacturing is a weighted average of the balances of opinion regarding a past output (25%), new orders (30%), employment (20%), suppliers' delivery times (15%) and stocks of purchases (10%). Before the COVID-19 crisis, an increase in suppliers' delivery times was interpreted as pointing to strong economic activity to meet high consumer demand that was evidenced in companies' high demand for intermediate goods. This logic explains why longer delivery times make a "positive" contribution in the PMI formula.

During the recent period, however, the uncharacteristic increase in delivery times actually pointed to a restriction in economic activity. As the formula for the PMI manufacturing index is fixed, the longer lead times raise the index while actual output is hampered. In other words, the index no longer adequately reflects the economic trend. This effect can be corrected by assigning a "negative" contribution to delivery times in the adjusted index (Chart 3).

Similar issues can arise with the INSEE and Banque de France business climate values, which are also based on composite models incorporating survey data (Phung, 2023, pp. 11-12). For instance, the unusually high business climate in construction reported by INSEE in 2021 and 2022 could be explained in part by higher prices, which make a "positive" contribution to the composite indicator.

Chart 3: PMI manufacturing and manufacturing value-added



Sources: INSEE and S&P Global.

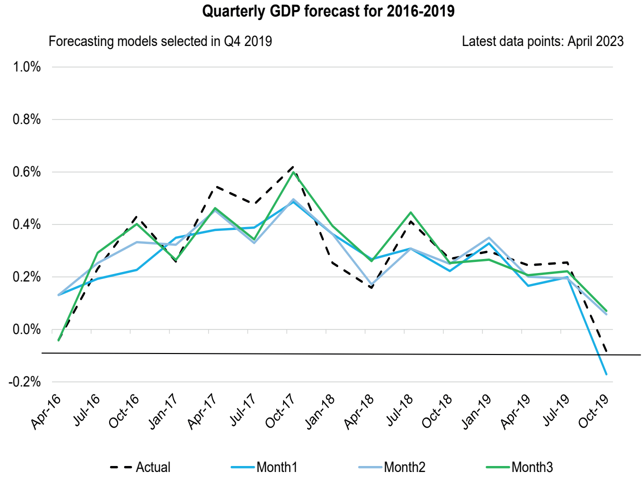
These supply constraints have affected the performance of the conventional models used to nowcast French GDP based on business climates or PMI manufacturing index values (Chart 4);[5] these models (even when estimated *ex post*) performed much better over the 2016-2019 period than for 2021-2023. The decreased performance is seen in higher forecast errors as measured by the root mean square error, RMSE[6] (Table 1, below). For example, for the Month1 (M1) alternative model, the RMSE value of 0.17 was much lower (i.e. better) for the 2016-2019 period than for the 2021-2023 period (0.34). While the decreased performance may be attributable partly to greater economic volatility, it also reflects the diminished capacity of conventional models to account for supply constraints.

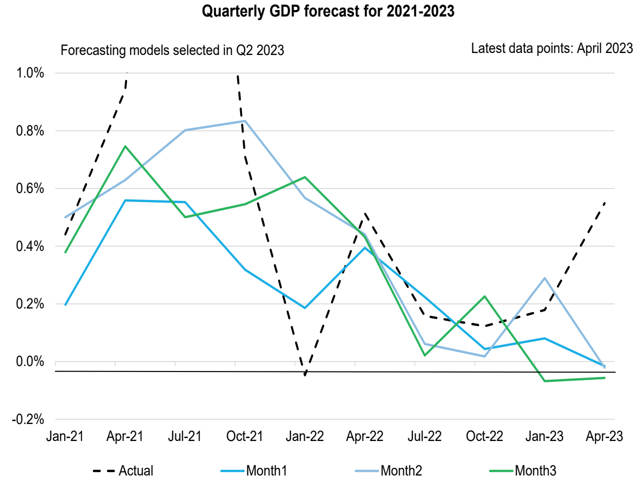
Given the sharply diminished performance of conventional models, an exercise to rebuild nowcasting models was launched at the end of 2022. The alternative models are similar in that both use linear regressions, but differ in that they use an automated procedure for selecting the input variables from a large number of candidate variables.

(5) The conventional nowcasting models use linear regression typically estimated by ordinary least squares.

(6) The RMSE (Root Mean Square Error) is the standard deviation of the residuals (the distance between the regression line and the data points, i.e. the error in prediction). This measures a model's performance over a given period of time.

Chart 4: Comparison of performance of conventional models in predicting French GDP growth in 2016-2019 and 2021-2023





Sources: INSEE, Banque de France, S&P Global; DG Trésor calculations.

How to read this chart: For each quarter, three forecasting moments are defined, based on data availability. The Month1 forecasting moment includes the data available at the end of the first month of the quarter, the Month2 moment includes the data available at the end of the second month, and so on.

2. New nowcasting models

2.1 Presentation of alternative nowcasting models

To improve nowcasting performance in crisis periods, such as 2021-2023, alternative models incorporating automatic input variable selection have been developed. The aim is to better capture the supply constraints discussed above (Box 3). Compared with conventional models, they incorporate additional variables, in particular financial data and more-detailed survey data,[7] in addition to the business climate. In the remainder of this paper, a distinction will be made between the period of supply constraints (covering the years 2020 to 2023) and the normal period (earlier years when supply constraints were not predominant).

Over the evaluation period (Q1 2021 to Q2 2023), the alternative models incorporating automatic input variable selection are found to perform much better than conventional models. Taking the data available at the Month1 forecasting moment (M1), the conventional models have an RMSE value of 0.34 for the 2021-2023 period, compared with 0.13 for the alternative models.

Table 1: RMSE values of conventional and alternative models over 2016-2019 and 2021-2023

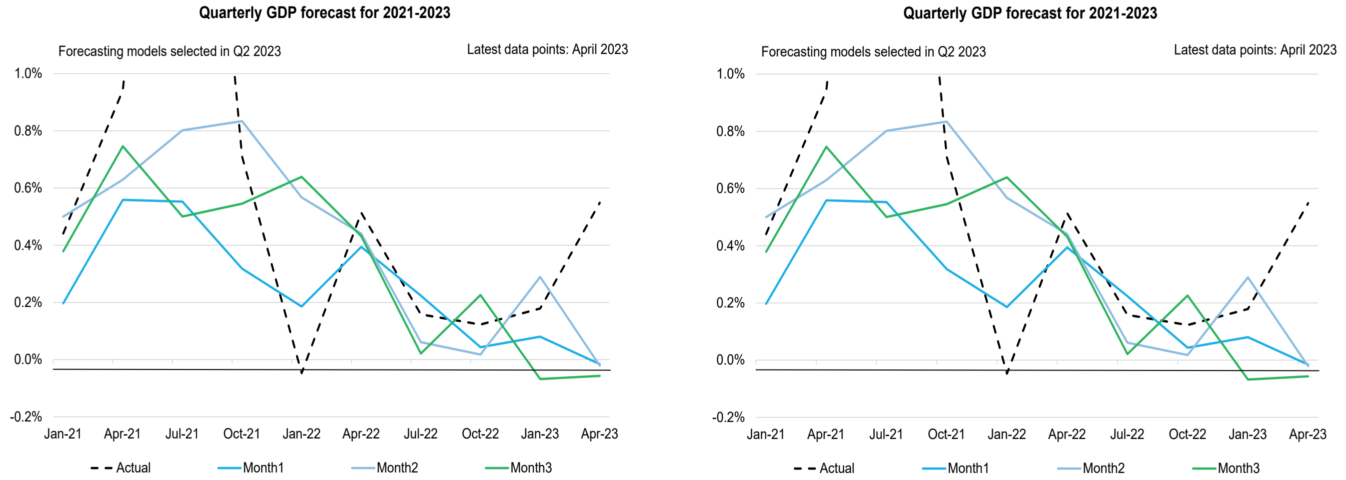
Forecasting moment	Benchmark	RMSE	
		Performance over normal period (Q2 2016-Q4 2019)	Performance over crisis period (Q1 2021-Q2 2023)
Flash M1	Conventional model	-	-
	Alternative model	-	0.170
M1	Conventional model	0.174	0.341
	Alternative model	-	0.128
M2	Conventional model	0.146	0.347
	Alternative model	-	0.175
M3	Conventional model	0.142	0.311
	Alternative model	-	0.123
Lead1	Conventional model	0.135	0.275
	Alternative model	-	0.072

Source: DG Trésor.

How to read this chart: Taking the data available at Month1 (M1), the conventional linear regression models had an RMSE value of 0.17 for the "normal" period (2016-2019) and 0.34 for the crisis period (2021-2023).

(7) Examples include not only the leading European stock exchanges indices, commodity prices, short-term and long-term interest rates spreads, or the euro-dollar exchange rate, but also survey data, particularly employment survey data. It should be noted that incorporation of data on household consumption and the industrial production index (IPI) for the period from January 2009 to June 2023 failed to yield satisfactory results; these indicators are not included in the dataset used to generate the results set out here.

Chart 5: Comparison of performance of conventional models and alternative models in predicting French GDP growth in 2021-2023



Sources: INSEE, Banque de France, S&P Global; DG Trésor calculations.

How to read this chart: This chart, in the same way as previous charts, illustrates models' performance at various forecasting moments (Month1, Month2, Month3) based on data availability.

Box 3: Methodological framework and modelling

The alternative models presented were selected from a group of candidate models based on an iterative out of sample analysis (see Phung, 2023, p.30 and 33). The sample available for estimating the models begins in Q4 2007[a] and runs through Q4 2019; outliers related to the economic crises are excluded from the samples.[b]

In these alternative models, the coefficients of the variables are estimated using a robust linear regression method, with the iterative (re-)weighted least squares (IWLS) technique. This method is robust to outliers, to errors and to heteroskedasticity. Variable selection is based on forward stepwise selection in which models are built one variable at a time. With a dataset containing *n* predictors, n models each containing one of the *n* predictors are estimated; then one selects the *k* models – at this stage, the *k* predictors – with the best RMSE performance. One then generates (without duplication) all possible combinations with a first predictor from among the *k* selected, and a second from the full set of predictors; from these models one next selects the *k* best performing models with two predictors. The next step, and in this case the final step, is to generate all the possible combinations with three predictors starting from these *k* combinations. This has the primary advantage of reducing the number of combinations tested from several million to approximately 28,000.

Finally, for each forecasting moment, three models each based on three predictors are selected. The main consideration is their performance-weighted average in generating the best quarterly GDP forecast, but the relevance of the variables chosen by the automatic selection method is also taken into account, in order to avoid selecting a model particularly influenced by noise specific to the quarter.

To identify the variables most relevant for forecasting changes in France's economic growth during a period of supply shock (2021-2023), we examine the 100 models with the lowest RMSE for each forecast moment ranked by RMSE from best to worst. We then focus on all the predictive variables that appear in 5 percent or more of the 100 models tested, and define the model in which they first appear as the first rank estimation. This allows us to establish two metrics for measuring the relevance of variables: the first estimation rank and the percentage of occurrence.[c]

Once the most relevant values are selected, the models are then *evaluated* in real time, i.e. with the data available at a given date, and thus excluding any subsequent revisions in the series used, but they are not *selected* in real time. For each quarter Q, we calculate the forecast that the models would have generated using the data then available. The performance of each model is measured based on these out of sample forecasts, and the models are then selected according to their performance. This method allows us to identify *ex post* which models would have performed best in a period of crisis (here, 2021-2023), but does not allow identification *ex ante* of the best models to use at the onset of the crisis.[d]

a. The data for the previous year's quarterly GDP in volume at chained prices is available only from this date.
b. This concerns the following three periods: Q4 2008-Q1 2009, Q1 2020-Q4 2020 and Q3 2021.
c. It should be noted however that this approach to nowcasting does not allow us to infer which determinants cause growth, but only to present the factors, or combinations of factors, whose evolution is most closely aligned with changes in GDP growth.
d. A selection of true real-time models, over the given period, failed to deliver satisfactory results. For example, at one month (M1), so-called adaptive models (selected in real time) had an RMSE value of 0.51, compared with 0.34 for the conventional models. These results evidence the difficulty of rapidly adapting forecasting models to a significant economic shock.

The alternative nowcasting models performed better than the conventional models for the crisis period (2021-2023) but performed worse – with higher RMSE values – for the "normal" period (2016-2019).

This may be due to greater GDP volatility in 2021-2023 and the still-unresolved issue of capturing GDP growth determinants other than supply constraints. Still, much of the deterioration in conventional models' performance can be surmounted by the alternative approach.

However, the limited number of observations – only nine quarters – argues for caution in interpreting these results, including those regarding the models' performance.

Chart 5 shows the superiority of the alternative models incorporating automatic input variable selection during the supply crisis period (2021-2023). The left-hand panel, which reproduces the right-hand panel of Chart 4 above, shows that the deterioration in performance severely limits the relevance of the conventional models in forecasting. The right-hand panel shows that alternative models can substantially improve performance, producing forecasts that are much closer to observed data.

2.2 These alternative models illustrate the influence of supply constraints in 2021-2023

Predictors relating to supply factors play a far greater role in the alternative models than in conventional models, in which demand factors predominate. This can be seen in the two extreme forecasting moments, "Flash M1" and "Lead1". "Flash M1" is the first forecasting moment examined; it corresponds to the mid-point of the first month, which includes the very first short-term data. "Lead1", when almost all the short-term data has been released, is the last forecasting moment examined.

Conventional models are based primarily on demand factors, e.g. order books and expected demand, whereas most alternative models incorporating automatic input variable selection will use supply factors, e.g. the number of firms facing labour shortages, supply chain difficulties, financial difficulties or supply constraints.

Table 2: The most prevalent predictors in alternative models at "Lead1" forecasting moment

2000-2019		2021-2023	
Predictor	**Occurrence**	**Predictor**	**Occurrence**
Speed of supplier deliveries in PMI manufacturing index	87%	*Finished product inventories in industry (INSEE)*	100%
Expected demand in services (INSEE)	43%	Insufficient staff in industry (INSEE)	52%
Past invoiced prices (INSEE)	22%	*Gold spot price*	19%
Past manufacturing production (INSEE)	15%	*Business climate in retail (INSEE)*	10%
Unemployment	14%	Financial constraints in industry (INSEE)	10%
Change in order backlogs (PMI manufacturing index)	12%		
New orders in services (PMI services index)	10%		
Constraints on demand (INSEE)	5%		

In green: demand factors	In orange: supply factors

Source: DG Trésor.

How to read this table: The balance of opinions for speed of supplier deliveries in the PMI manufacturing index is used in 87% of the forecasting models tested for the 2000-2019 period.

Some balance-of-opinion components can be considered to be both supply indicators and demand indicators. Employment tendencies, for instance, can be indicative of employers' expectations of labour required to meet future demand, and of their actual capacity to increase (or not increase) their headcount. Similarly, whereas a rise in finished-product inventories in "normal" times could reflect lower-than-expected demand, on the contrary, in the 2021-2022 period, it could signal anticipatory behaviour to avoid shortages – of electronic components in particular – and thus reflect firms' production strategies in a period of constraint.

These models and the accompanying analysis provide the basis for a strictly econometric selection of variables. Yet this is not the final stage in determining the specifications of the models selected. Forecasters must also consider the economic link between the variables used and the resulting forecast. If the link appears too difficult to interpret, the model in question is not selected. For example, the Ibex 35 index of the Madrid stock exchange is identified as a relevant variable in some of the best-performing models, but while stock valuations can be used to measure a country's economic health, the link with the French economy remains uncertain, given that Spain is an important – but not France's leading – trading partner. Such considerations sometimes result in selection of a somewhat worse-performing model with a more straightforward economic interpretation.

While the search for alternative nowcasting models through automatic input variable selection has refocused attention on the importance of supply factors in certain economic contexts, the supply constraints discussed here have now diminished, and output once again appears to be constrained primarily by demand. This raises the issue of whether conventional models will regain the upper hand in terms of performance, or whether the succession of crises may have given a lasting advantage to new, more open approaches, enabling more effective coverage of periods that depart from conventional economic equilibrium conditions.

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