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COFACE ECONOMIC PUBLICATIONS

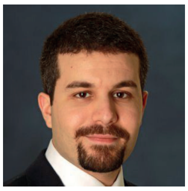
Eurozone economic slowdown: Evidence from Coface's activity indicators

Since the start of 2019, the signals warning of a slowdown in world growth have multiplied. While all economists agree on this downward trend, following the cyclical peak reached in 2017, there is now a question mark as to the scale of this slowdown, especially in the eurozone. While some commentators are suggesting the likelihood of a recession in 2020, most economists are predicting "only" a slight downturn.

In this period of high uncertainty, forecasting growth is even more difficult and important, which is why Coface has decided to develop its own forecasting tool: the CRAFT (Coface Research Activity Forecasting Tool), which we present in this publication.

This activity indicator is constructed using the statistical method known as Principal Component Analysis (PCA), which enables Coface to extract common signals transmitted by a large number of variables by reducing them to "common factors" or principal components. The variables most likely to affect economic activity are selected *via machine learning* models. The variables retained - between thirty and fifty for each country - can be grouped into four distinct categories: hard data, survey data, monetary and financial variables, and international indicators. To these four types of variable commonly used for the construction of activity indicators, Coface has added the company default rate on trade receivables insured by Coface aggregated by country. Due to the way it is constructed, CRAFT is strongly correlated with the quarterly GDP growth rate and allows GDP to be correctly projected for the current quarter (*nowcasting*) and for the next quarter (*forecasting*).

According to the results of this model, Germany will enter recession in the 3rd quarter (-0.1% after -0.1% already in the previous quarter), before stagnating in the last three months of the year. The French economy will continue to show resilience, but will also slow in the 3rd quarter (+0.2%) before rebounding at the end of the year (+0.3%). Conversely, growth will pick up again in Spain in the 3rd quarter (+0.6%) before slowing slightly (+0.5%), while nonetheless remaining solid. Finally, activity will remain sluggish in Italy: after a modest rebound in the 3rd quarter at 0.1%, it will again stagnate in the 4th quarter.



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1 METHODOLOGY FOR ESTABLISHING THE LEADING INDICATORS

Indicators enabling the tracking of changes in real activity

The methodology for establishing the activity indicators developed by Coface relies, in part, on econometric and statistical techniques commonly used in the business services of international organisations (**Box 1**). Nevertheless, given the dual purpose of our approach, namely to both create an activity indicator and use it to make forecasts of the quarterly change in GDP, a step enabling the selection of only the most relevant variables to be integrated in the analysis was introduced. This involved compiling an initial database for each country in which the indicators most likely to have an impact on economic activity are recorded. These indicators are grouped into four distinct categories (**Part 2**):

- Hard data
- Survey data
- Monetary and financial variables
- International indicators

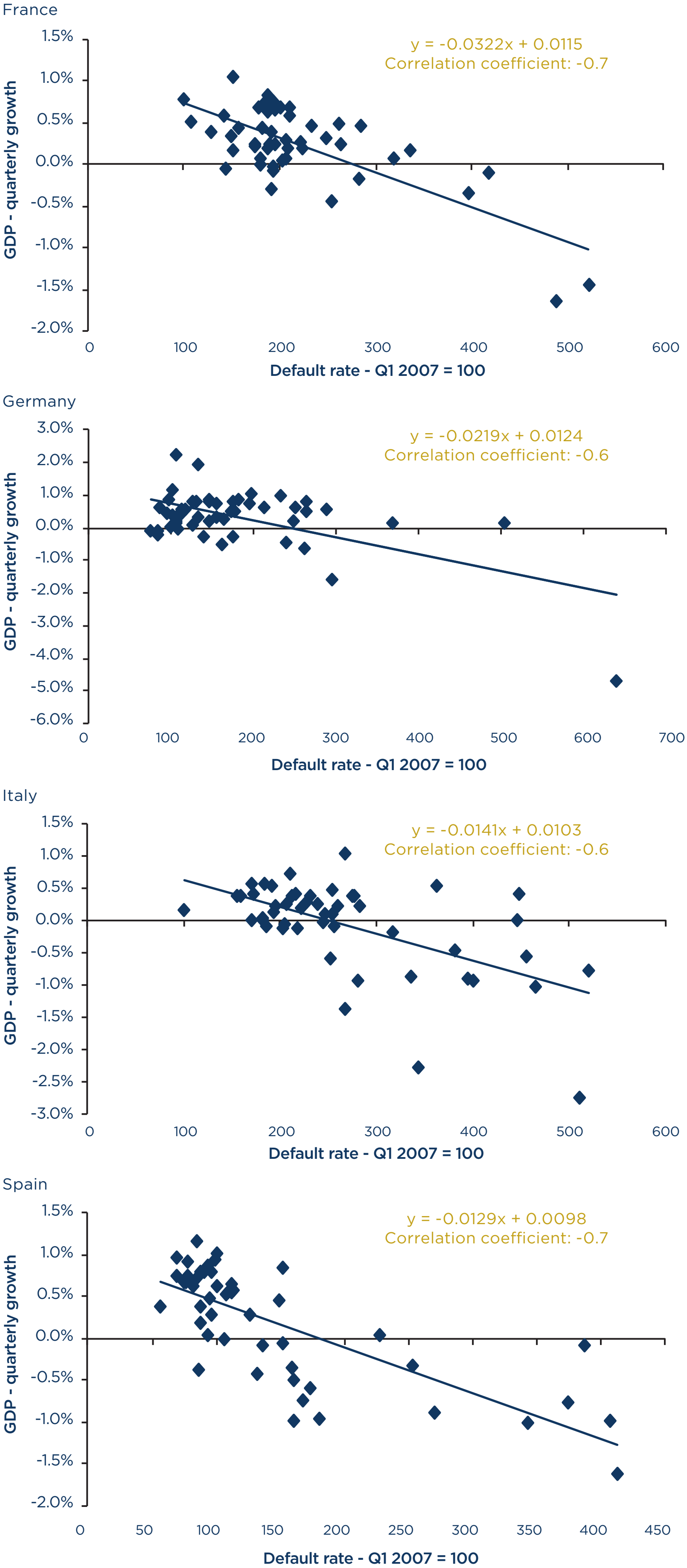
A total of around hundred variables were obtained for each of the countries in the sample. Since these are usually observed at a monthly frequency, a conversion step was necessary to create quarterly data sets so that the frequency was the same as that for calculating the GDP growth rate. A three-month average was applied to each indicator. However, the delay in releasing certain data (especially those related to industrial production and its components) can result in missing values for certain months of the current quarter. To counter this problem, the value of the current quarter is given by the average of the last three observations. *Machine learning* models (*Random Forest*, *Gradient Boosting Machine – GBM* and *Least Absolute Shrinkage and Selection Operator - LASSO*) were then used so as to keep only those variables[1] most closely correlated with GDP growth rate. Continuing the study with all the variables, including those that were relatively insignificant for explaining growth, could have blurred the signs of what was actually happening in the economy during the construction of our composite indicator. This step allows us, then, to keep between only thirty and fifty variables for each country.

These pre-selected indicators are supplemented by the company default rate[2] on trade receivables insured by Coface aggregated by country. These data, which are exclusively related to credit insurance activity, make it possible to record the number of claims and are strongly correlated with real activity, moving in the opposite direction of the economic cycle (**Chart 1**).

1 Each of the variables was previously made stationary after applying the difference operator and unit root presence tests (ADF and KPSS).

2 This monthly variable collected by Coface is calculated as the ratio between reserves and registered exposures. Reserves correspond to the amount reimbursed by Coface to its policyholders following a claim, while exposures represent the total amount of trade credits that Coface has agreed to cover between a customer and a given supplier.

Chart 1:
Relationship between quarterly GDP growth and the default rate



Box 1:

Methods used in the literature

Driven by the work of Stock and Watson (1989[3], 1999[4]), Principal Component Analysis (PCA) has become a mainstay for the construction of activity indicators. This method enables the extraction of common signals transmitted by a large number of variables by reducing them to "common factors" or principal components. So, an activity indicator generally corresponds to the first principal component resulting from PCA. The Chicago Fed National Activity Index (CFNAI), an activity index developed by the Chicago Federal Reserve, follows this methodology: PCA is applied to 85 indicators (relating to production, retail sales, consumption, wages and incomes) where only the first component is retained. The CFNAI identifies with 95% accuracy the periods of recession and expansion of economic activity in the United States. European equivalents of CFNAI were then developed by the Bank of Italy following the work of Altissimo et al. (2010)[5] and Aprigliano and Bencivelli (2013)[6], which gave rise to the Euro-coin and Ita-Coin activity indices. Factor models, in their static or dynamic form, beyond being used for the creation of indicators, can also be used directly to forecast the GDP growth rate, which needs a different approach: the number of main components retained is higher and is determined according to strategic criteria. This type of approach has notably gained popularity within the European Central Bank thanks to the work of Doz, Giannone, and Reichlin (2006)[7].

The methodology developed by Coface is thus a combination of these different approaches of which the purpose is both to create an activity indicator and to use it to forecast the quarterly change in GDP. To achieve this, our approach differs from the techniques referred to above thanks to the integration of *machine learning* models that are efficient in the presence of a high number of variables, which allowed us to preselect only those variables essential to include in the analysis.

3 Stock, J.H. and Watson, M.H. (1989) "New Indexes of Coincident and Leading Economic Indicators", NBER Macroeconomic Annual 1989, 351-94.

4 Stock, J.H. and Watson, M.H. (1999) "Diffusion indexes", NBER Working Paper N.6702.

5 Altissimo F., Cristadoro R., Forni M., Lippi M., Veronese G. (2010). «New Eurocoin: Tracking Economic Growth in Real Time», The Review of Economics and Statistics, 92 (4), pp. 1024-1034.

6 Aprigliano,V. and Bencivelli, L. (2013)."Ita-coin: a new coincident indicator for the Italian Economy". Bank of Italy Temi di Discussione (Working Paper) No, 935.

7 Doz C., Giannone D., Reichlin L. (2006). "A quasi maximum likelihood approach for large approximate dynamic factor models", CEPR Discussion Paper, No. 5724.

Static factor models are then applied to all variables to create our activity indicators. This form of modelling has the advantage of enabling a large amount of data to be studied by reducing the information they contain to a limited number of latent variables, called common factors. This is made possible by the underlying assumption that each explanatory variable is obtained as the sum of two separate unobservable components: a "common" component (χ_{it}) present in each of the variables, generated by common factors, and an idiosyncratic component (ξ_{it}) which is exclusively related to a shock specific to the variable considered and which thus represents the part of the variable that is not explained by the common component. Considering a vector of *p* explanatory variables *i* (denoted by X_i), previously standardised, the static factor model is expressed as follows:

$$X_{it}=\chi_{it}+\xi_{it}$$

Where the common component (χ_{it}) is given by the sum of *r* common factors *j* (F_{jt}):

$$\chi_{it}=\lambda_{i1}F_{1t}+\cdots+\lambda_{ir}F_{rt}$$

So, each of the explanatory variables can be rewritten as follows:

$$X_{it}=\lambda_{i1}F_{1t}+\cdots+\lambda_{ir}F_{rt}+\xi_{it}$$

λ_{ij} represents the contribution of the explanatory variable X_i to the common factor F_j and makes it possible to measure the correlation between the variable and the factor. The common factors, as well as the weights λ_{ij}, are estimated using Principal Component Analysis (PCA). Each activity indicator thus corresponds to the first common factor (i.e. the first principal component), which is the most important factor capturing the majority of the information (i.e. most of the explained data variance). For each country, the activity indicator can be interpreted as a weighted average of all the explanatory variables introduced in the analysis, where the weight[8] assigned to each of them is inversely proportional to λ_{ij}. Therefore, the indicator can serve as a proxy to plot real activity.

Indicators that can be used to forecast the GDP growth rate

Due to the way it is constructed, CRAFT is strongly correlated with the quarterly GDP growth rate and should allow this rate to be correctly modelled. We note Y_t as the growth rate of a given country, and F_t as the associated activity indicator, the forecast of Y_t is based on a regression estimated by the Ordinary Least Squares (OLS) method where F_t is introduced as an explanatory variable. The model then takes the following form:

$$Y_{t+h}=\theta+\delta F_t+\varepsilon_{t+h} \qquad t=1,\ldots,T\text{-}h$$

The objective being to make forecasts for the current quarter (h = 0), as well as for the following quarter (h = 1), two different equations are used according to the horizon considered.

For *nowcasting* (current quarter forecast), the model takes into account the information available in real time and is expressed as follows:

$$Y_t=\theta_1+\delta_1 F_t+\varepsilon_t^1 \qquad (1)$$

On the other hand, for the following quarter forecast, as the horizon is further away, no data are available and consequently no contemporaneous F_t is retained. The growth rate is then regressed on the delayed indicator of a period as follows:

$$Y_{t+1}=\theta_2+\delta_2 F_t+\varepsilon_{t+1}^2 \qquad (2)$$

It is possible to check the fit quality of models (1) and (2), i.e. their explanatory power and capacity to model the growth rate, by carrying out a full information estimate, namely on the entire sample of data we have for each country. The results obtained are presented in **Table 1**.

Table1:
Regression of the GDP growth rate on the leading indicator, 2007 Q1 - 2019 Q2

	France			Germany			Italy			Spain		
	i	ii	iii	iv	v	vi	vii	viii	ix	x	xi	xii
Constant	0.1 (0.07)	0.23*** (0.03)	0.22*** 0.06)	0.17 (0.13)	0.31*** (0.06)	0.29* (0.11)	-0.02 (0.08)	-0.09* (0.05)	-0.09 (0.07)	0.01*** (0.04)	0.51 *** (0.04)	0.47 *** (0.05)
Lagged GDP	0.52*** (0.12)			0.41** (0.13)			0.69*** (0.11)			0.9*** (0.06)		
Activity indicator		0.12*** (0.01)			0.2*** (0.02)			0.23*** (0.02)			0.13 *** (0.01)	
Lagged activity indicator			0.07*** (0.02)			0.12*** (0.03)			0.18*** (0.02)			0.13 *** (0.01)
Excl. sovereign debt crisis	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-sq	0.26	0.83	0.28	0.15	0.78	0.31	0.45	0.79	0.55	0.81	0.86	0.84
Std. Error	0.42	0.20	0.41	0.86	0.43	0.79	0.54	0.34	0.50	0.30	0.26	0.27

Note: The values in brackets below the estimated coefficients correspond to the standard deviations. The codes *, **, *** indicate a significativity of 0.01; 0.001 and 0.0 respectively. For the models indicated, the exclusion of the sovereign debt crisis corresponds to the introduction of a dichotomous variable taking the value 1 for the period Q1 2011 - Q1 2013. Spain is the only country concerned: having been all the more affected by the crisis than its European peers, the associated models were unable to capture the entire contraction in growth.

8 The weights given by type of variable within the indicators are presented for each country in Charts 3, 4, 5 and 6, on page 9.

Nowcasting models based on the contemporaneous value of the indicators appear as powerful monitors of activity: for each of the countries in the sample, they manage to capture between 78% and 86% of the variations in the growth rate (**Table 1** - models ii, v, viii and xi). In particular, these models fitted perfectly and were able to measure the contraction in the growth rate during the financial crisis of 2008, which justified keeping this period in our sample - not introducing any dichotomous ("dummy") variables. The forecasting models (**Table 1** - models iii, vi, ix, xii) fit less accurately and react with a slight delay, being based on the indicators' past dynamics. Nevertheless, the two types of specification (*nowcasting* and *forecasting*) are still more efficient than traditional models where the growth rate is regressed on its own lagged value of one period (**Table 1** - model i, iv, vii and x). Standard deviations of adjustment errors are higher and the coefficients of determination[9] lower in the case of autoregressive processes.

However, since the forecast made previously, with all available data - called an "in-sample" estimation - does not allow us to fully account for the predictive ability of the models, as, by definition, when forecasting some of the information is unknown. Thus, it is not guaranteed that a model that performs well across the entire sample also provides good forecasts. It is advisable, then, to make a so-called "out of sample" forecast in order to complete this analysis (**Table 2**), which is closer to what the forecaster needs to do.

Box 2:

Out-of-Sample Analysis Approach with Rolling Range Estimate

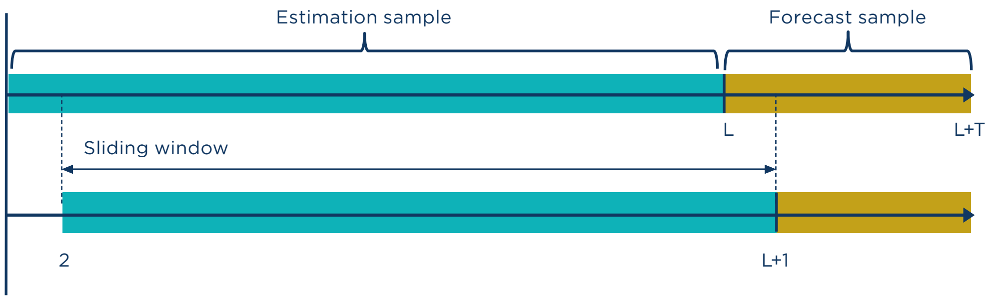
An out-of-sample estimation is a process that can be performed using a "rolling range", which is tantamount to testing the model for the past, estimating it over a portion of the sample and then making forecasts for the other part of the sample based on the information that was available on that date. The forecasts are then compared with the observed values in order to assess whether the model was able to correctly predict the target variable or to measure the forecast error obtained. More specifically, a rolling range estimation is carried out as follows: historical data are divided into two sub-sets, the first being the sliding window (corresponding to 80% of the total sample data), ranging from observation 1 to L, on which the models are estimated. A forecast of the growth rate value in L+1 is then performed and stored in the second subset (the forecast sample - corresponding to 20% of the total historical data). Subsequently, the true value observed in L+1 is introduced into the rolling range, which shifts a notch starting at the date L = 2 up to L+1, such that the size of the rolling range remains the same (**Chart 2**). The estimate is made again and a forecast of the L+2 value is calculated. The process repeats itself until the end of the sample in L+T, such that the forecasts are calculated in a rolling process. The forecasts are then compared to the actual observed values. For this, the forecast error is defined as the difference between the actual observed value of the growth rate and the value forecast by the model:

$$e_{T+h}=Y_{T+h}-\hat{Y}_{T+h|T}$$

The performance of the forecasting models is then analysed using deviation criteria such as the Mean Absolute Forecast Error (*MAFE*) and the square root of the Root Mean Squared Forecast Error (*RMSFE*), given as follows:

$$MAFE=E[|e_{T+h}|] \qquad RMSFE=\sqrt{(E\,[e_{T+h}]^2)}$$

Chart 2:
Functioning of a Rolling Range Estimation



9 The coefficient of determination is a measure of the fit quality of a model. It is between 0 and 1 the closer it is to 1, the better is the model.

Based on a rolling range out-of-sample estimation, we obtain the deviation criteria presented in **Table 2**. Knowing that the higher the predictive performance of a model, the weaker the criteria, it appears that the forecasts obtained at the very beginning of the quarter – i.e. the forecasts from model (2) when data for the current quarter are not yet available - are not as good as those obtained from the *nowcasting* model (1), except for Spain. So, as soon as the information for the current quarter is integrated in the indicator, the forecasts become more precise and the errors made are lessened. As the MAFE and RMSFE criteria allow us to measure the average size of the forecast errors as well as their dispersion, during our forecasting exercise using model (1) the values of the quarterly growth rate predicted by the model were, on average, further from the actual value observed by ± 0.13%, 0.21%, 0.07% and 0.08% for France, Germany, Italy and Spain, respectively. The use of CRAFT in forecasting the growth rate therefore allows us to capture the trend of real activity in the very short term, which was our primary objective. Although the forecasts for the following quarter seem less reliable, they provide a first glimpse of how activity might evolve, and are estimations that are intended to be updated and corrected with the release of data for the current quarter.

Table 2:
Forecast errors after an out-of-sample estimation

	France		Germany		Italy		Spain	
	ii	iii	v	vi	viii	ix	xi	xii
MAFE	0.13	0.19	0.21	0.21	0.07	0.13	0.08	0.07
RMSFE	0.17	0.23	0.23	0.29	0.09	0.16	0.1	0.09

Note: The models are numbered as for Table 1.

2 VARIABLES RETAINED

A base set of variables common to all countries

Not surprisingly, we find a significant number of variables in common for the leading indicator of our four countries. Among the **hard data**, **industrial production**, which measures the evolution of industrial activity, is a statistically significant variable in France, Germany, Italy and Spain. Although industry has a very different weight in the GDP of the main eurozone economies (12% in France, 16% in Spain, 17% in Italy and 22% in Germany), it has a significant ripple effect in terms of business services and consumption of intermediate goods. **Foreign trade data**, for both exports and imports, also appear to be significant for the four countries. Foreign trade is one of the main growth drivers, with net exports being one of the sources of added value. **Labour market** variables, such as the unemployment rate, job creation or wage developments, are important data for predicting activity, since their evolution largely determines the purchasing power of households and, ultimately, household consumption. Only Italy is an exception among our four economies. **Sector variables** such as car registrations are also significant for France and Italy. Finally, **producer price** movements have a significant influence in France and Germany.

Opinion surveys make it possible to anticipate changes in activity, insofar as they make it possible to take the "pulse" of economic agents. Thus, the results of **business confidence surveys** - or business climate surveys - based in particular on the status of domestic or export order books, hiring intentions or inventory levels, are significant in the four countries. The **production capacity utilisation rate**, which gives an overview of the supply constraints on the production base and allows an understanding of the potential obstacles to economic growth, is evident in the indicators for France and Germany. Lastly, **household confidence surveys** are also significant in most countries, as they enable anticipation of consumption behaviour - the main growth driver.

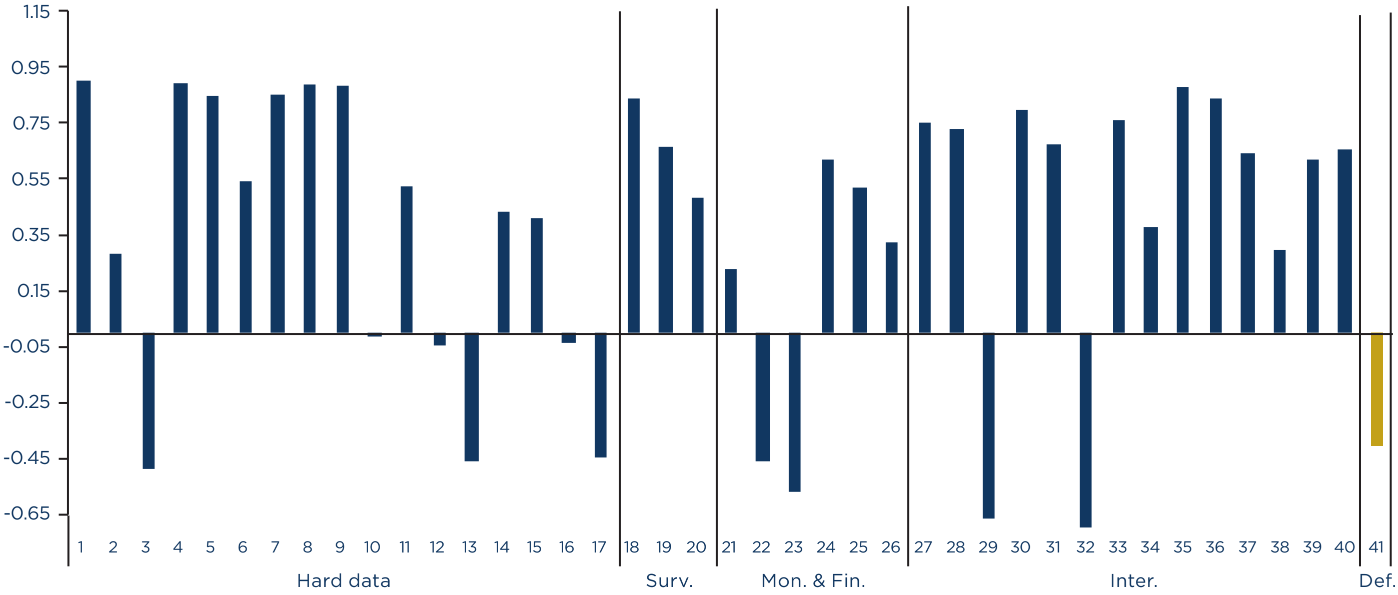
Several **monetary and financial variables** are also statistically significant in all countries. These include **interest rates on government bonds**, which determine the cost of government financing on the markets and which condition the margin for manoeuvre. **Bank loans to the private sector**, and, in particular, to businesses, influence the evolution of economic activity based on consumption and the investment they facilitate. It is therefore logical that the **supply of money in circulation** index also appears in the majority of countries, like the ECB refinancing rate or the interbank interest rate.

Finally, while the **euro exchange rate** is significant for all countries, because of its influence on trade, the relevant reference currency varies by country: while the importance of the euro's parity against the dollar or sterling is due to the fact that the United States and the United Kingdom are among the main partners of the major eurozone economies, the influence of parity against the Polish zloty on activity in Germany can be explained by the weight of Poland in its trade (6th largest partner in 2018).

International variables are also retained. **Membership of the single European market and a common currency area** has helped to deepen the economic and financial ties of each of the four economies with its neighbours. Unsurprisingly, the evolution of activity indicators in Germany, such as industrial production, or the value of the main index of the Frankfurt Stock Exchange (Dax30), is significant in estimating activity in the other three countries. At the same time, activity indicators in Italy and, especially, in France appear in our forecasting tool for Germany. Similarly, Spanish activity is dependent on the variables of its three main trading partners (one-third of Spain's combined trade in 2018).

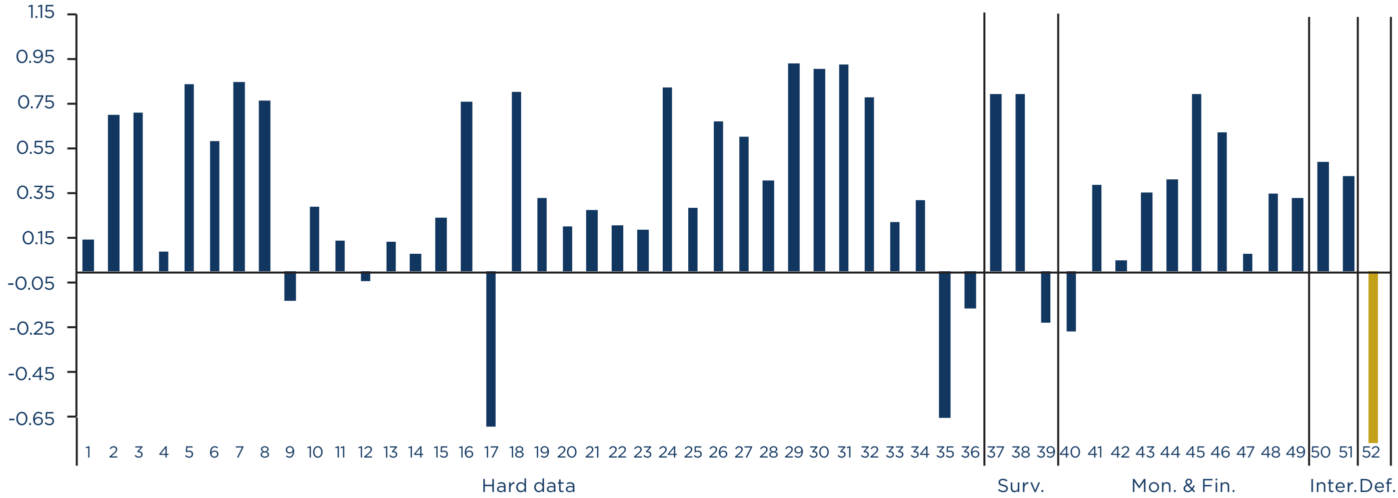
Finally, the **Coface default rate** is included in the model. This variable has a significant negative effect on activity in the four countries studied. Also, unsurprisingly, an increase in the default rate in a country is synonymous with a slowdown in activity (**Chart 1**).

Chart 3:
Weight of each variable (standardised) in the construction of CRAFT for Germany



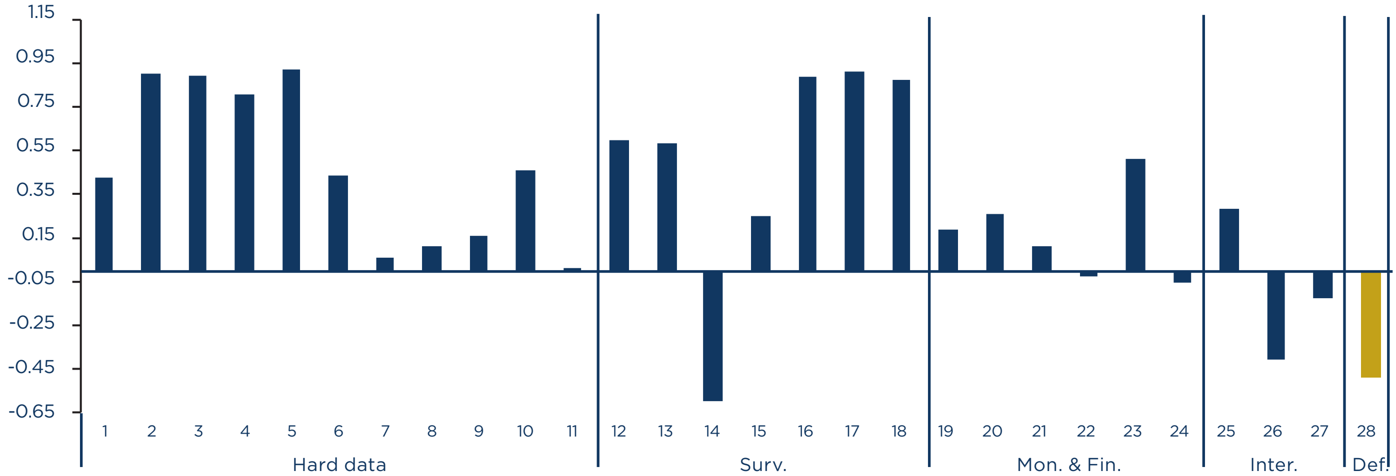
Source: Coface

Chart 4:
Weight of each variable (standardised) in the construction of CRAFT for France



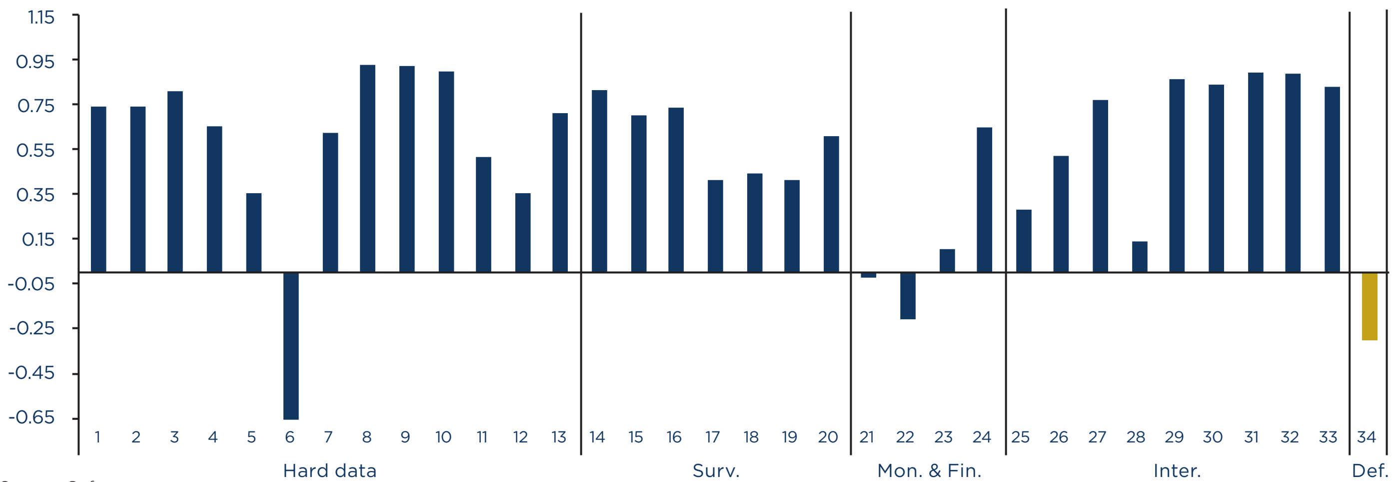
Source: Coface

Chart 5:
Weight of each variable (standardised) in the construction of CRAFT for Italy



Source: Coface

Chart 6:
Weight of each variable (standardised) in the construction of CRAFT for Spain



Source: Coface

Specific factors according to the importance of certain partners or sectors in the economy

While the activity indicators of the other three countries are composed of international variables from several countries (mainly the eurozone, as well as Poland for Germany), that of France contains only German international variables (Dax30 and 10-year interest rates on German government bonds). This specific factor is attributable **to the preponderance of Germany in French trade: at 15% of trade,** its weight represents the twice that of Italy, France's second largest partner.

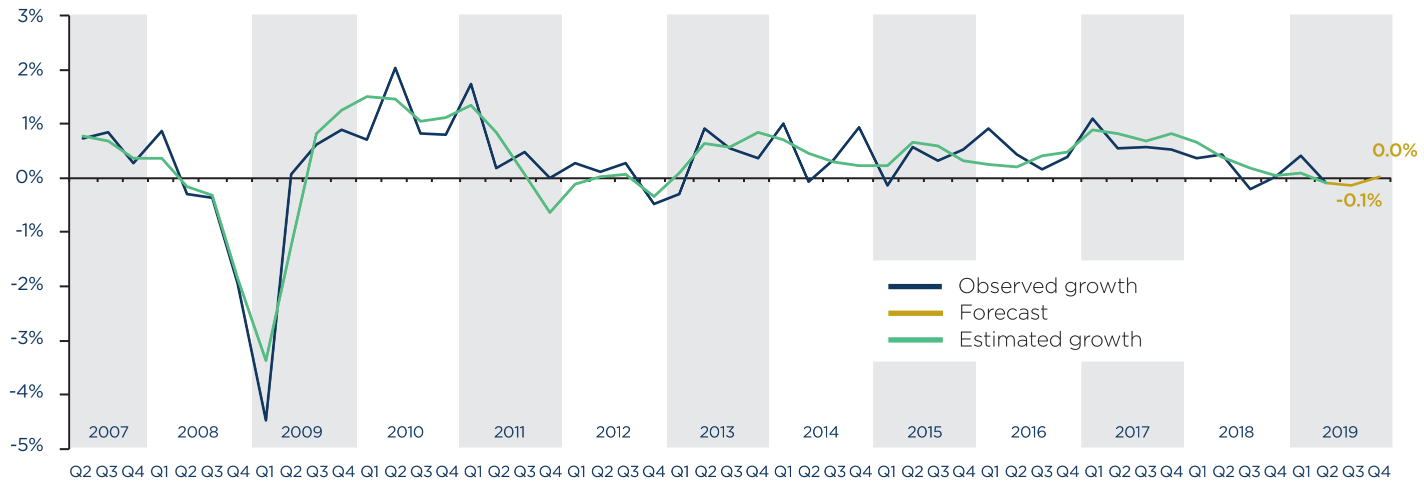
The importance of the **Italian banking sector**, which holds a large part of the public debt and whose companies are particularly dependent on financing, is illustrated by the significance of the share price of some Italian banks in our activity indicator as well as by the non-performing loans ratio in the sector.

3 FORECAST RESULTS

According to the results of CRAFT, Germany will enter into recession in the 3rd quarter (-0.1% after -0.1% already in the previous quarter), **before stagnating** in the last three months of the year (+0.03%; **Chart 7**). The German economy, particularly dependent on the country's industry, itself exposed to external headwinds due to the weight of exports, **has suffered particularly from the worsening international economic environment** since early 2018. The pace of economic growth will remain significantly lower than that recorded since 2013, in a still uncertain environment that is unfavourable to trade. Insofar as the United States, China and the United Kingdom are among Germany's top five export markets, the economic development in these countries will be crucial for the direction of business growth. Finally, the potential introduction of tariffs in the United States on European car imports, which is likely to be decided in mid-November, could prolong the contraction in GDP.

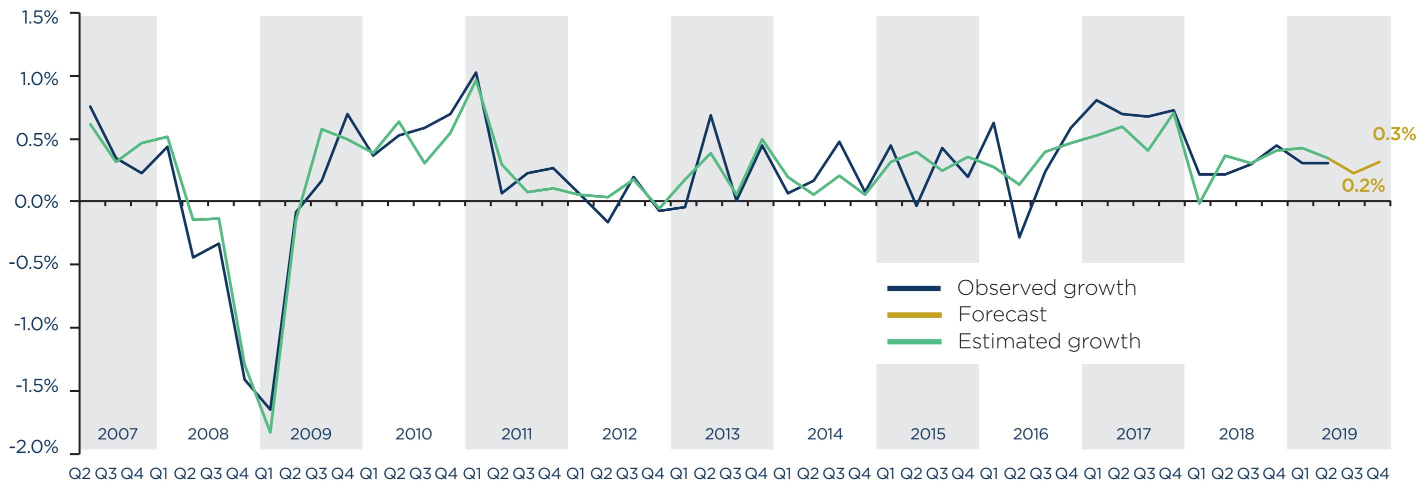
The French economy will also slow in the 3rd quarter (+0.2%) before **rebounding at the end of the year** (+0.3%), showing proof of **resilience** in this difficult context **(Chart 8)**. GDP will accordingly grow by 1.3% over the year. Although activity has been slowing since 2017 (+2.4% then +1.7% in 2018), French growth has remained positive and consistently higher at 0.2% in quarterly terms, far from the ups and downs of most of its neighbours. While the tax measures, decided following the "yellow vests" movement, have increased household purchasing power and ultimately their consumption, this resilience of the French economy is mainly attributable to structural factors. Less open than its neighbours, France is less dependent on external demand but benefits less from global growth when it is dynamic. In addition, the French economy is characterised by significant stabilizers because of its heavy tax burden, generous social security and unemployment benefits, which mitigate the consequences of economic downturns.

Chart 7:
Forecast GDP growth in Germany



Sources: Eurostat, Coface, Coface Forecast

Chart 8:
Forecast GDP growth in France

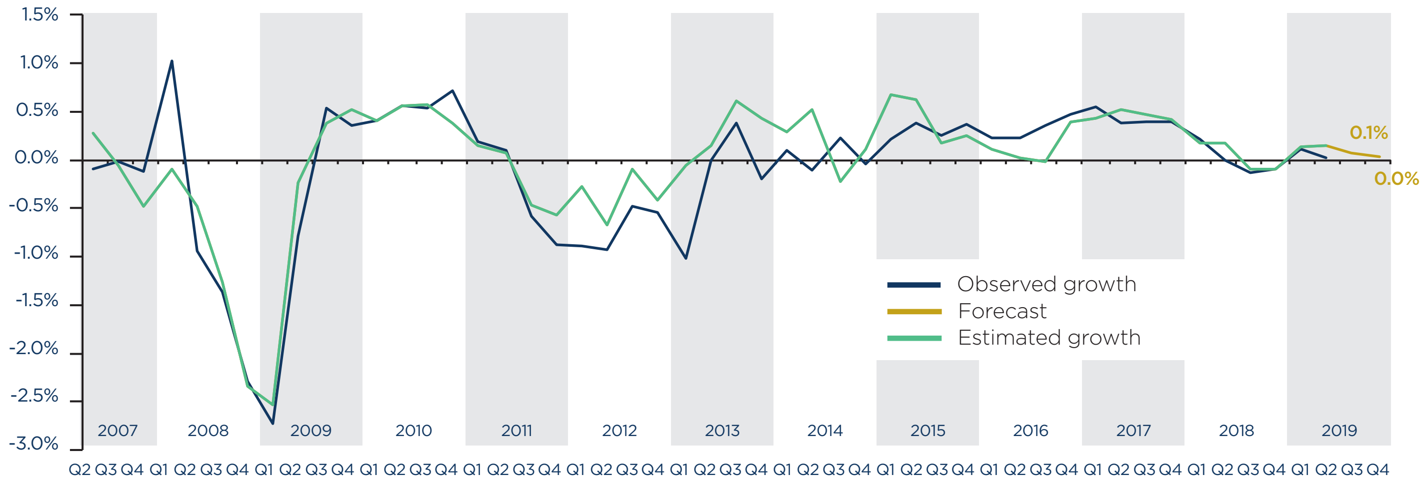


Sources: Eurostat, Coface, Coface Forecast

According to the results of our activity indicator, during the 3rd **quarter in Italy, growth will rebound slightly at 0.1% before stagnating again** in the last quarter of the year (**Chart 9**). Accordingly, Italian GDP will grow by 0.1% over the whole year, just avoiding negative growth in 2019 despite several political twists and turns. However, the Italian economy will have recorded **the worst performance of the eurozone countries in 2019**, for the second year in a row. The possible rebound in Italian economic growth over the coming quarters will depend on the stability of the new government coalition and the reactions of the financial markets.

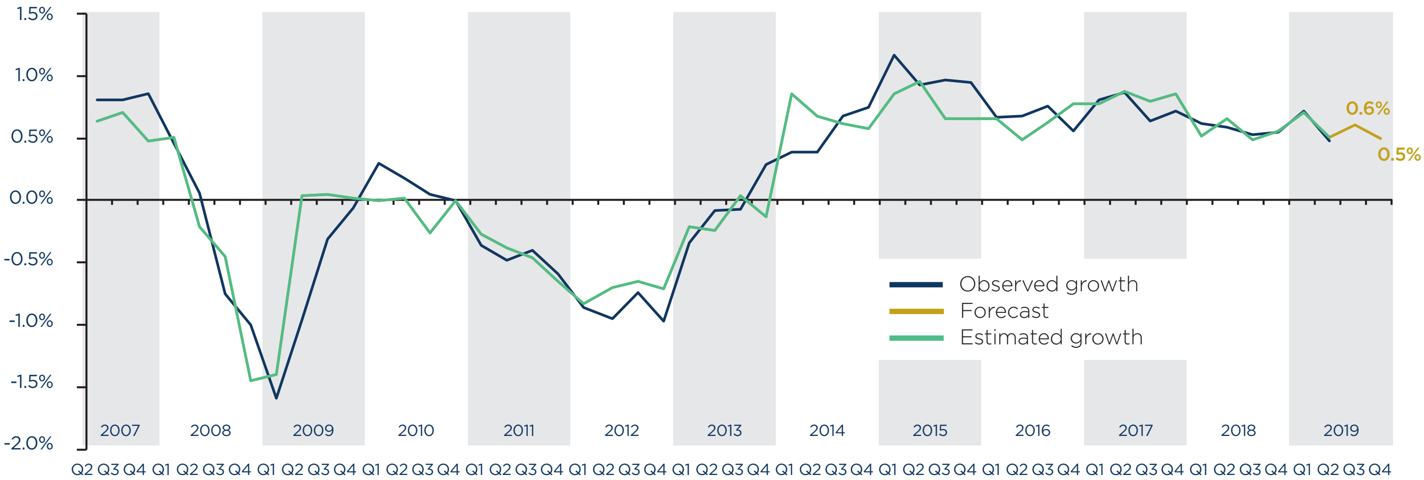
At the same time, GDP growth is also expected **to pick up in Spain in the 3rd quarter** (+0.6%) **before slowing slightly** in the last three months of the year (+0.5% ; **Chart 10**). While activity is less dynamic than in 2017, when it was between 0.8% and 0.9% in each quarter, it remains **strong** and is slowing very gradually. For the year as a whole, GDP growth will settle at 2.3%, having been at 2.6% in 2018. Despite a still very high unemployment rate (14% of the economically active population at the end of June) and the country's political instability, Spain's economy has been remarkably steady since the recovery started in late 2013.

Chart 9:
Forecast GDP growth in Italy



Sources: Eurostat, Coface, Coface Forecast

Chart 10:
Forecast GDP growth in Spain



Sources: Eurostat, Coface, Coface Forecast

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