A new composite climate indicator to forecast price changes

The inflationary surge observed in 2021-2023 has brought the challenges of the short-term forecasting of inflation back to the forefront. While the macroeconomic determinants of inflation are relatively well known (oil, expectations, wage costs, competition, etc.), month-to-month price formation mainly reflects decisions taken at company level. Thus agents' opinions on prices collected during INSEE's monthly business tendency surveys can clearly provide some valuable information for understanding these short-term price decisions.

This *Focus study* proposes a new composite indicator for "price climate", constructed from questions relating to sales prices in the business tendency surveys and perceptions collected through the household consumer surveys. This "price climate" correlates very well with observed changes in the Consumer Price Index (CPI), significantly improving its forecast relative to standard models. This predictive power is at its maximum at a three-month forecast horizon but quickly disappears for longer time horizons.

Bruno Bjaï, Marie-Cécile Cazenave-Lacrouts and Juan-Pablo Ugarte

Business tendency surveys provide relevant forward-looking information on price changes

Several methods for forecasting inflation are proposed in the literature: one series is based on structural methods that match price trends with variables of tensions in the labour market (unemployment, job vacancies) and commodity price data (►**Banerjee et Marcellino, 2002** or ►**Garner, 1995**). Other analyses highlight the role of expectations (►**Mankiw, 2004**), measured either by professional forecasters (Survey of Professional Forecasters at the European Central Bank), or from indexed financial products, or from households (Surveys of Consumers by the University of Michigan). However, few studies use business tendency studies directly even though, as highlighted by ►**Bernanke (2007)**, they constitute a prime source, as corporate decisions are at the heart of price formation.

In fact, studies using survey variables to forecast inflation suggest that they provide additional information to standard inflation models. ►**Stockhammar and Osterholm (2016)** show that using Swedish outlook surveys (businesses and households) can significantly improve inflation forecasting, especially in the short term, although this improvement appears to come mainly from households' expectations. Using a factor model, ►**Basselier and al. (2018)** show that using qualitative price expectations from outlook surveys significantly improves inflation forecasting for Belgium and the Eurozone as a whole: in their study, the improvement in predictive power comes this time rather from the addition of corporate data. More recently, by mobilising a very large number of series selected from big data analysis methods, ►**Huber and al. (2024)** show the specific predictive power of business surveys from the European Commission's harmonised programme,[1] and in particular of forward-looking balances on activity, to estimate inflation in the Eurozone.

In France, INSEE publishes a provisional estimate of the Consumer Price Index (CPI) on the last day of the month for the current month. The definitive estimate is available less than two weeks after the end of the month under consideration.

Every month, INSEE also carries out business tendency surveys on companies in different sectors of activity. These surveys are used to collect recent information on changes in many economic variables, such as activity or recruitment. In particular, INSEE questions business leaders on changes observed in their selling prices over the last three months, as well as changes they expect over the next three months. There is also a monthly consumer confidence survey of households, and they are questioned mainly on their perceptions of price changes over the last twelve months and their expectations for the momentum of prices over the next twelve months. This information helps to improve the economic analysis of inflation.

A composite price climate indicator appears to be well correlated with change in consumer prices

To summarise the information collected in the business tendency surveys, INSEE has constructed composite indicators called "climate" indicators, for the business climate or the employment climate, for example. These indicators are well correlated with changes in economic aggregates: GDP and payroll employment. They were built using factor analysis methods, which extract the information common to several balances of opinion in the form of a single indicator.

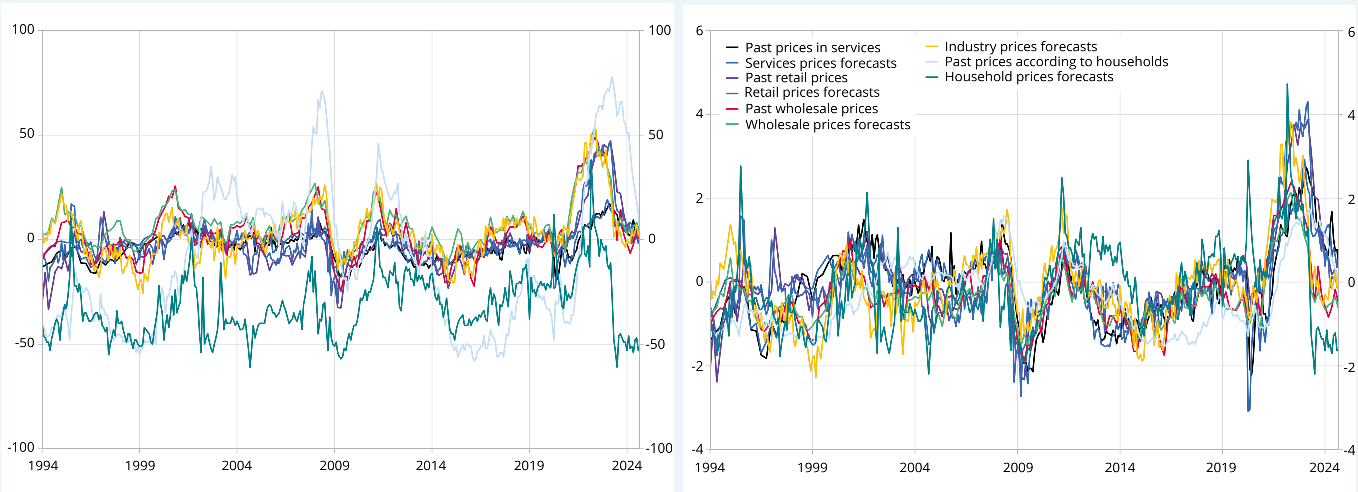
1 INSEE produces the DGECFIN business and consumer surveys (blog post, in French) for France.

Using an identical method (►**Method box**), a "price climate" indicator can be constructed, bringing together information from the balances of opinion on prices in the outlook surveys. This indicator is constructed from nine balances of opinion: past and expected changes in selling prices in services, retail trade and wholesale trade, change forecast in selling prices in the manufacturing industry[2] and past inflation and that forecast by households.[3] These balances appear to be well correlated with each other (►**Figure 1**): a common trend can therefore be extracted.

2 Price balances from the survey of the construction industry are not included as they do not improve the correlation of the indicator with the CPI.
3 In the household survey, the forward-looking question concerns the acceleration (or deceleration) of inflation and not the level, unlike the question on perceived infla-tion over the last 12 months.

►1. Balances of opinion selected to calculate price climate

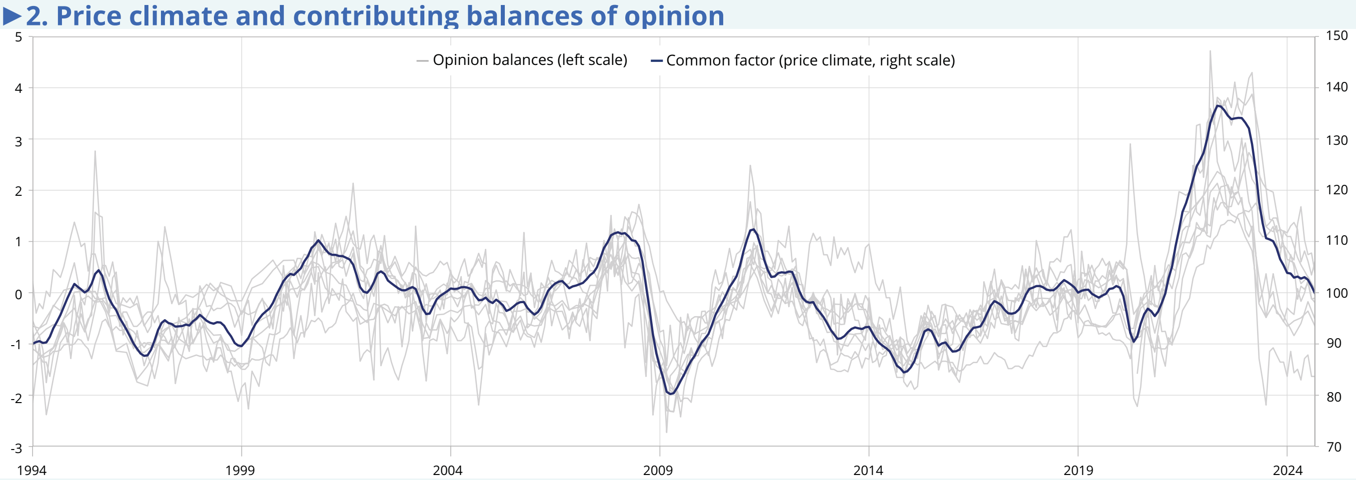
Original balances | **Standardized and scaled balances**



Note: a balance of opinion corresponds to the difference between the weighted percentage of responses trending "upwards" and the weighted percentage of responses trending "downwards"..
Source: INSEE, business surveys.

Like other climate indicators, this one is standardised so as to present a long-term average equal to 100 and a standard deviation of 10, which allows an intuitive interpretation of the value of the indicator. It can be seen that this price indicator reached a low point of 80 in the spring of 2009, in the middle of a recession, and that conversely, its maximum is observed in the spring of 2022, at 136, at the height of the inflationary surge (►**Figure 2**). This last value reflects the exceptional nature of the period: the indicator is more than three standard deviations above its long-term average (conventionally set at 100). It has gradually decreased since then, reaching its long-term average in September 2024 (100).

►2. Price climate and contributing balances of opinion



Source: INSEE, business surveys.

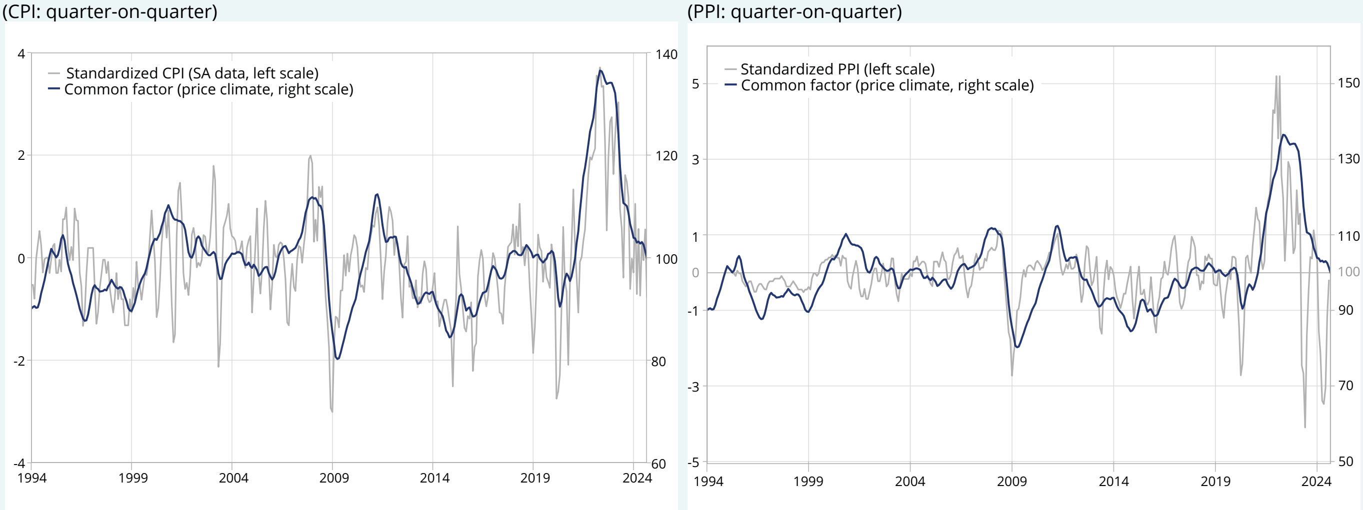
A price climate constructed in this way has an excellent correlation with inflation. More precisely, its correlation is 0.73 with the quarterly shift observed in consumer prices[4] (►**Figure 3.a**), consistent with the horizon considered in the business tendency survey questions, and reached 0.82 with the year-on-year variation in the CPI. The indicator also shows much less volatility than the shifts in CPI. Finally, the price climate is also well correlated with the quarterly shift in producer prices (►**Figure 3.b**), although less markedly (0.55).

4 The quarterly shift is the ratio of the monthly price level to its level three months before.

►3. Correlation between price climate and inflation

a. Consumer prices **b. Producer prices**

(CPI: quarter-on-quarter) (PPI: quarter-on-quarter)



Note: changes in consumer prices and producer prices are standardized for comparison with the price climate.
Source: INSEE, business surveys and price indices.

Price climate significantly improves the short-term inflation forecast

The good correlation between the price climate and changes in the CPI suggests its usefulness for forecasting inflation. Here, we are interested in forecasting the quarterly shift in the CPI. To assess the contribution of the indicator to the forecast, our reference model is based on the lags in the observed variable. More precisely, we take as a benchmark an autoregressive model of order 7 (AR(7)), estimated over the period 1994 to 2010.

$$\pi_m = a + \sum_{i=1}^{7} b_i \pi_{m-i} + u_m,$$ where π_m is the price shift between month m and month m-3

If we first consider a test period from 2010 to 2019, before the health crisis and the inflationary surge, we see that this model already has some predictive power. For a one-month forecast horizon, the square root of its root mean squared error (RMSE) estimated in real pseudo-time is 0.17, compared to a standard deviation of the variable of interest of 0.28 over the period[5] (►**Figure 4**). By adding the price climate to this model, we obtain a lower error of 0.15.

$$\pi_m = a + \sum_{i=1}^{7} b_i \pi_{m-i} + \sum_{i=1}^{7} c_i \, Climate_{price_{m-i}} + u_m$$

If we consider a three-month forecast horizon, the contribution of the price climate variable is a little more significant: the AR model of reference gives an error of 0.29, compared to only 0.24 when the price climate is included, i.e. a reduction in the forecast error of around 20%. For longer forecast horizons, the predictive power of the two models becomes very weak, or even negligible. Price climate therefore makes a modest but positive contribution to forecast quality for horizons of one to three months.

If the analysis is extended to the period 2010-2024, which includes the health crisis and the inflationary surge, the predictive power of the price climate appears to be slightly more pronounced. The indicator therefore seems effective, both in periods of normality, and in periods of more volatile prices.

5 The standard deviation of the variable of interest represents a useful reference to put the RMSE of the different models into perspective. A naive model giving the mean of the variable of interest as a forecast would obtain an RMSE equal to the standard deviation of the variable.

►4. Mean squared error of price shifts at different forecast horizons for the two test periods

RMSE	2010-2019		2010-2024	
Horizon (in months)	Benchmark model (auto-regressive, AR)	AR + climate	Benchmark model (auto-regressive, AR)	AR + climate
h=1	0.17	0.15	0.24	0.20
h=2	0.23	0.18	0.33	0.25
h=3	0.29	0.24	0.41	0.32
h=4	0.29	0.28	0.42	0.37
h=5	0.29	0.29	0.43	0.37
h=6	0.30	0.28	0.43	0.39
standard deviation	**0.28**		**0.48**	

How to read it: (for the period 2010-2024, the RMSE of the forecasting model including the price climate (AR + climate) is worth 0.20 in a 1-month forecasting horizon, against 0.24 for the reference model *benchmark*).

This direct approach offers only an aggregated view of price changes and is therefore a complement to the traditional disaggregated approach to forecasting. For its inflation forecasts, INSEE uses a range of tools: macroeconomic models that model the usual price-formation behaviour based on production costs; detailed modelling of sub-components of the CPI shopping basket that takes extra information into account (price of oil for energy, administered prices such as those of tobacco or health, for example) and models based on the outlook surveys.

For the end of 2024, the price climate suggests a continuing slowdown in prices. In September 2024, it stood at 100, its long-term average, and down sharply from its high point in May 2022 (136). The "direct" forecasting method, using the price climate presented above, suggests that inflation, which fell to +1.2% year on year in September, is likely to stabilise at between 1.1% and 1.2% by December. This estimate corresponds to the forecast retained from the disaggregated method: +1.2% in December. ●

Methodology

The factor models are based on the following model:

$$X_{it} = \lambda_i f_t + \varepsilon_{it}$$

where :

- x_{it} corresponds to the balance of opinion *i* on date *t*, standardized and scaled;
- f_t corresponds to the common factor for date *t*, it is the same for all the balances of opinion. This is a latent, non-observed variable;
- λ_i corresponds to the loading of *i*, which measures the correlation between the balance of opinion *i* and the common factor. For a given balance, it is the same for all the dates;
- ε_{it} corresponds to the idiosyncratic component of balance *i* on date *t*.

Two variants of factor models are used for the composite indicators from INSEE's surveys. The variant described as "static", which is simpler, allows the factor to be reconstructed as a linear combination of balances of opinion (standardized and scaled). The variant described as "dynamic" specifically models the dynamics of the factor and is based in particular on the Kalman filter.

The price climate indicator presented here is based on the dynamic variant, which allows it to include the balances of opinion from the bi-monthly survey in wholesale trade. With the static variant it is not possible to use series of different frequencies.

In this model, the dynamic structure of the factor is modelled explicitly. An AR(2)-type process was chosen for this study:

$$f_t = \alpha_1 f_{t-1} + \alpha_2 f_{t-2} + \varepsilon_t$$

The model is then estimated using the two-step method proposed in ►**Doz and al.** (2011).

The model was implemented with an R package "dfms". ●

Bibliography

Banerjee A. et M. Marcellino (2006), “Are there any reliable leading indicators for US inflation and GDP growth?”, International Journal of Forecasting.

Bardaji J., Minodier C., Clavel L. and Tallet F. (2008), “Two new indicators to help analyse the economic outlook in France”, INSEE *Economic outlook*, December.

Basselier R., De Antonio Liedo D., Jonckheere J. and G. Langenus (2018), “Can inflation expectations in business or consumer surveys improve inflation forecasts ?”, Working paper research, National Bank of Belgium.

Bernanke. B.S. (2007), “Inflation expectations and inflation forecasting. speech given at the Monetary Economics Workshop of the National Bureau of Economic Research Summer Institute”, Cambridge. Massachusetts, July 10, 2007.

Doz. C., Giannone. D., & Reichlin. L. (2011), “A two-step estimator for large approximate dynamic factor models based on Kalman filtering”, Journal of Econometrics, 164 (1).

Doz. C., & Lenglart. F. (1999), “Analyse factorielle dynamique : Test du nombre de facteurs. estimation et application à l’enquête de conjoncture dans l’industrie”, Annales d’Économie et de Statistique.

Garner C.A. (1995), “How Useful Are Leading Indicators of Inflation?”, Federal reserve of Kansas City, Economic Review.

Huber F., Onorante L., Pfarrhofer M. (2024), “Forecasting euro area inflation using a huge panel of survey expectations”, International Journal of Forecasting.

Krantz S., Bagdziunas R. (2023), dfms: Dynamic Factor Models. R package version 0.2.1, https://sebkrantz.github.io/dfms/.

Mankiw. NG., R. Reis et J. Wolfers (2004), “Disagreement about inflation expectations”, NBER Macroeconomics Annual 2003.

Stockhammer. P. and P. Österholm (2016), “Do inflation expectations Granger cause inflation?”, National institute of economic research working paper. ●