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Measuring financial markets' expectations of economic downturns in real time

In an economic environment marked by heightened uncertainty and rapid economic turnarounds, macroeconomic analysis relies heavily on econometric models designed to track and forecast changes in activity. These models, which rely primarily on indicators and surveys available on a monthly or quarterly basis, are not designed to incorporate shifts in the economic cycle in real time. Analysts therefore use financial variables that, in principle, continuously reflect market expectations. For example, an inverted yield curve (where long-term rates are lower than short-term rates) generally signals that markets expect an economic slowdown.

This article introduces a new indicator that uses machine learning techniques and aims to measure markets' expectations regarding the risk of an economic downturn in the United States and Europe, based on a vast set of financial variables.

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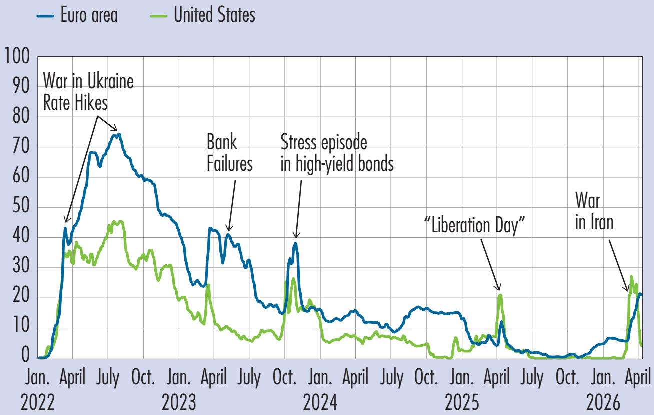
JEL codes
C55, E32,
E37

21%
market-implied probability of a recession in the United States in two quarters from the time of Donald Trump's tariff announcements in April 2025

13%
proportion of quarters in recession in the United States since 1970

21%
market-implied probability of a recession in the euro area in two quarters as of 14 April 2026, against the backdrop of the war in Iran

Market-implied probability of a recession in two quarters
(%)



Sources: Bloomberg; PICON model (market-implied probability of economic contraction) as of 14 April 2026; authors' calculations.
Note: See Chart 2 for a detailed presentation.

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Economic recessions are among the most difficult macroeconomic phenomena to forecast. Public institutions, in particular central banks, traditionally rely on macroeconomic models designed to analyse the transmission mechanisms of economic policy and produce medium-term scenarios. These tools play a central role in the formulation of monetary policy decisions and rely to a large extent on low-frequency aggregate data. Despite advances in forecasting methods and the growing wealth of available data, economic downturns can generally only be identified as and when they are reflected in short-term economic indicators. This difficulty in detecting slowdowns at an early stage has led the literature to explore alternative data sources that are likely to reflect a deterioration in expectations regarding the future state of the economy at an earlier stage.

Financial markets are a valuable source of information for macro-financial analysis. Thanks to the real-time, high-frequency availability of asset prices, economists and analysts are able to derive composite indicators that capture expectations, risk aversion and financial conditions. Indeed, **investors' expectations regarding the economy's trajectory are a key determinant of financial market dynamics**.

Over the 2022–25 period, Russia's invasion of Ukraine, the tightening of monetary conditions in the United States and Europe, episodes of banking stress, and Donald Trump's announcements of tariff increases **led analysts and investors to reassess several times the risk of recession**, both in the United States and in Europe. In both regions, the integration of the risk of an economic downturn was reflected in an adjustment of interest rates on their sovereign debt, a fall in share prices, and an appreciation in safe-haven assets.

These recent episodes illustrate how valuations across different asset classes (equities, bonds, derivatives and commodities) adjust in tandem to geopolitical tensions, measures taken by monetary and fiscal authorities, and, more broadly, financial shocks that may lead market participants to revise their expectations regarding economic activity, inflation and interest rates. The dynamics of these valuations are rarely isolated, and the intensity of their interactions may vary over time depending on the macroeconomic and financial context. **Analysing these joint dynamics is therefore key to understanding financial conditions and their transmission to the real economy.**

1 Perceptions of the risk of economic recession based on financial markets

Random forests as a complement to models based on yield curve inversion

The first formalised models for estimating the risk of recession using market data were developed in the late 1980s and are based primarily on the slope of the yield curve, which is defined as the spread between short-term and long-term yields on the sovereign bond market (Estrella and Hardouvelis, 1991, and more recently for the euro area, Sabes and Sahuc, 2023). A narrowing of this spread, or even its inversion, theoretically reflects expectations of an impending economic slowdown, as investors switch to long-term bonds in anticipation of a future fall in interest rates and the resulting rise in the price of these securities. Historically, this type of behaviour has often preceded recessions, making it a widely used leading indicator for assessing the risk of an economic downturn, even though it is more a measure of market expectations than a true forecast. These models are generally based on parametric econometric approaches, such as probit or logit models; they offer the advantage of simplicity and can be enhanced by the inclusion of additional financial and macroeconomic variables (Bussière and Lhuissier, 2024, for the euro area).

We use a **random forest** model (see Box 1) **to estimate an implied probability of economic downturn (PICON)** based on a broad set of variables drawn exclusively from financial markets and available on a daily basis, **and to incorporate the complex, non-linear interactions between these variables, which are of interest for analysis beyond mere predictive performance**.

Indeed, studies that rely on machine learning algorithms such as random forests to predict economic events tend to show that **this family of models does not systematically offer better out-of-sample predictive performance than**

more traditional methods.[1] This is due in particular to the fact that recessions are relatively rare events, with a limited historical record and frequency of observation, and a temporal dependence of observations with potential structural breaks.[2]

Thus, from the perspective of market sentiment analysis, it is more prudent to interpret our results as the **perception** of the risk of recession by the markets rather than as a forecast of that risk.

Comparison of the PICON model's results with a benchmark model

We compare the results of the PICON model over a four quarter horizon, with those of the benchmark model for predicting a recession in the United States in twelve months – that of the Federal Reserve Bank of New York[3] (NY Fed) – and relate them to the recessions actually identified by the National Bureau of Economic Research (NBER). Of the four recessionary episodes since 1990, the PICON model

BOX 1

Modelling the probability of recession risk using random forests

Our model infers amarket-implied probability of recession at a given horizon T from real-time financial asset valuations:

$$Probability(Recession_{t+T}) = RandomForests(FinancialVariables_t)$$

where $Recession_{t+T}$ is a 0/1 indicator variable, equal to 1 if a recession is observed within T quarters based on the financial observations available at time t.

For the United States, we use the benchmark definition of the National Bureau of Economic Research (NBER), which is based on a broader assessment of economic activity than simply two consecutive quarters of negative GDP growth. For the euro area, we define a technical recession as two consecutive quarters of negative growth, as well as any period of cumulative negative growth over three quarters.

The random forests model (Breiman, 2001) combines the predictions of a large number of decision trees, each of which identifies relationships between our financial variables (see Appendix, *Definition of the model's predictor variables*) and the occurrence of a recession. Each tree "votes" and provides its prediction: the proportion of trees signalling a recession is a continuous value between 0 and 1, which can be interpreted as an implied probability of recession at the horizon under consideration.

A value close to 0 indicates that, given the observed market conditions, the majority of the trees in the model associate these conditions with a scenario of economic expansion at the horizon under consideration, whilst a value close to 1 reflects a strong convergence of financial signals towards a recessionary scenario.

The model has been trained since 1990 for the United States and since 2000 for the euro area, depending on the period for which financial data are available for each region. In this article, we present the results of the model trained up to and including 2021, with the forecast period beginning in early 2022 (see Appendix, *Model training methodology*).

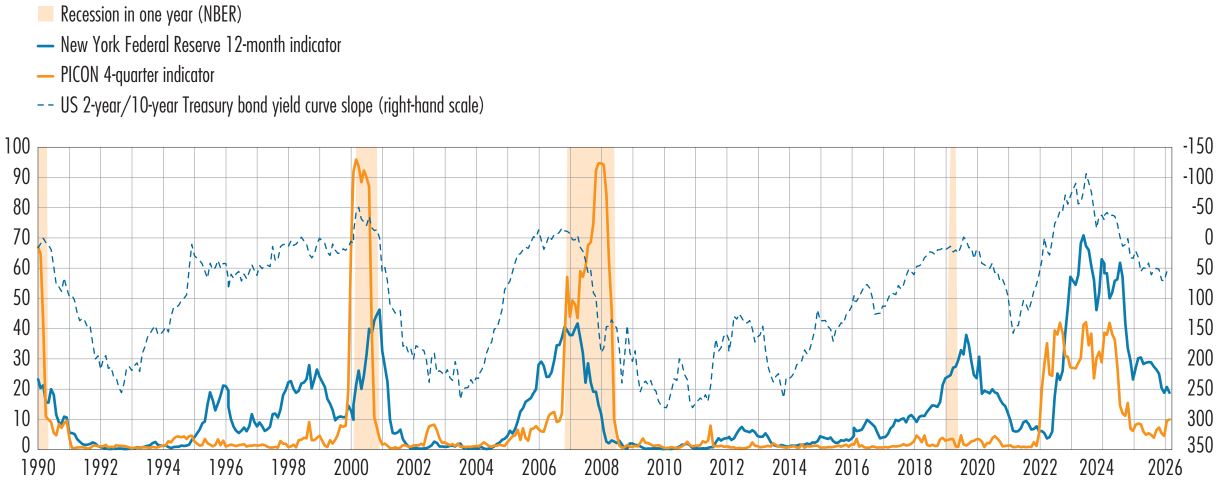
1 See Beutel, List and von Schweinit, 2019, for a review of performance in predicting banking crises; Puglia and Tucker, 2020, for the prediction of recessions in the United States using financial variables and economic indicators since 1972.

2 Not all recessions are alike, nor do they have the same causes. The relationship between the predicted variable and the explanatory variables may change over time.

3 A probit regression model, which estimates the risk of recession in the United States based on the yield curve.

C1 Market perceptions of the risk of a recession in the United States in one year
PICON model vs New York Federal Reserve model

(left-hand scale: percentages; right-hand [inverted] scale: basis points)



Sources: National Bureau of Economic Research (NBER), Federal Reserve Bank of New York, Bloomberg; authors' calculations.
Key: In July 2023, the 10-year bond yield was 106 basis points lower than the 2-year bond yield, a level not seen since the 1980s; the yield curve is therefore said to be "inverted".
Notes: Last data point at 31 March 2026. The Treasury bond yield curve slope refers to the difference between 10-year and 2-year yields.

detects three with amarket- implied probability of over 50%: the US recessions of the early 1990s, 2000 and 2008, in line with the Federal Reserve's model (see Chart 1).[4]

By contrast, the model is less sensitive to the yield curve inversion in autumn 2019, as the probability of a recession is just over 15%. While the Covid pandemic did indeed trigger a recession at the start of the following year, the event was exogenous and it could hardly have been forecast by the markets one year ahead.

Furthermore, both models signal an increased risk of recession with the inversion of the yield curves between 2022 and 2024, a period during which, according to the NBER, there was no recession in the United States; however, PICON reacts less strongly than the Federal Reserve's model and has only very occasionally produced a false positive when using a 50% trigger threshold.

2 An analysis of the market-implied probability of a recession in the United States and the euro area since 1 January 2022

Results for the 2022–25 period: four episodes of heightened risk

Using the methodology described above, we apply the model to a shorter prediction horizon[5] (recession within two quarters) and extend it to market data for the euro area. We thus compare the predictions for the two regions since the cycle of monetary tightening that began in 2022 (see Chart 2). The market-implied probabilities of recession derived from the PICON model highlight how financial markets, in both Europe and the United States, have adjusted their perception of economic risk in response to a series of clearly identifiable events. This period provides a use case that illustrates the value of the PICON model as a complementary tool for real-time macro-financial analysis.

4 A certain degree of "overfitting" of PICON to the data is evident over our training period between 1990 and 2019; this does not preclude a higher out-of-sample performance (i.e. using data distinct from the training data).

5 In line with the economic literature (see Estrella and Mishkin, 1998) and our own analyses (see Chart 5), we use PICON over a shorter time horizon, where other asset classes such as equities and credit are more likely to make a significant contribution to the model's prediction.

Thus, **following the outbreak of the war in Ukraine and the ensuing energy crisis**, the indicator reflects the prevailing perception of a risk of recession, which intensified during the summer of 2022, at a time when the first interest rate rises had been implemented in response to persistent inflation and post-Covid supply shocks. This high level of perceived risk persisted for several months during the summer of 2022 and only gradually subsided, with the probability of a recession remaining lastingly higher in the euro area than in the United States**.**

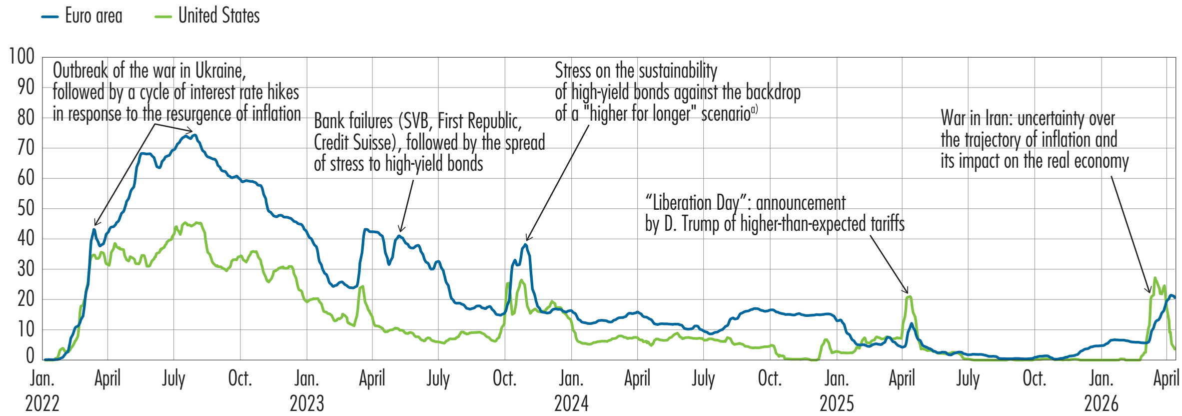
The collapse of Silicon Valley Bank (SVB) on 10 March 2023 **and that of Credit Suisse** also reignited fears of a financial crisis that could spread to the real economy. Recession fears were more persistent in the euro area than in the United States, which had a lasting impact on European bank shares and high-yield bond indices.[6]

Since October 2023, a number of concurrent factors have contributed to increasing the perceived risk of recession in Europe and the United States. On the one hand, the outbreak of the conflict in the Middle East has heightened geopolitical uncertainties and weighed on investor confidence. On the other hand, financial conditions have tightened significantly in both regions. The rise in long-term interest rates to their highest levels in a decade, together with investors' expectations of persistently high rates driven by very cautious communication from central banks (the so-called higher for longer scenario), have heightened the risk of a significant delayed impact of the monetary tightening initiated in 2022 on investment and consumption in both the United States and Europe.

The announcement made by the United States in April 2025 of significant and widespread tariffs, together with the onset of a new phase of trade tensions, led investors to consider it more likely that a recession would emerge from the third quarter of 2025, particularly in the United States. However, the level of risk perceived by the markets, as measured by our indicators, did not reach the alert thresholds recorded in 2022, at the peak of inflation, of geopolitical tensions in Europe and monetary tightening. As trade negotiations progressed, this risk gradually subsided, until it disappeared from markets' prevailing perception.

C2 Market perceptions of the risk of a recession in two quarters in the euro area and the United States

(%)



a) Higher for longer scenario: investors expect persistently high interest rates.
Sources: Bloomberg; PICON model (market-implied probability of an economic recession) at 14 April 2026, authors' calculations.
Key: On 16 March 2022, in the wake of the outbreak of the war in Ukraine, the market-implied probability (derived from financial asset prices) of being in a recession in two quarters later stood at 43% in the euro area and 35% in the United States.

6 High-yield bonds refers to bonds that offer a potentially high yield in return for what is perceived as higher issuer credit risk.

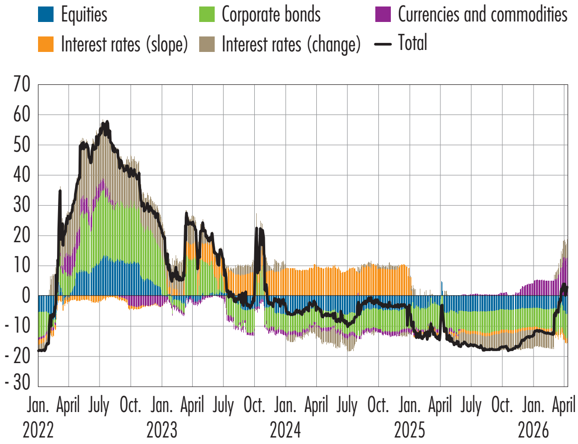
In the euro area: an estimate of each asset class' contribution to episodes of economic stress

Thanks to a simple aggregation, it is possible to estimate the contribution of each variable to each prediction (see Box 2), and thus to identify the variables explaining the peaks in the risk of an economic downturn.

For the four episodes of heightened recession risk identified by the model, this analysis provides an interpretation of the factors that exacerbated this risk (see Chart 3):

- **In early 2022, the sharp rise in perceived risk** reflected the rapid fluctuations in interest rates on sovereign and corporate debt in the euro area and the fall in share prices. The inversion of the German sovereign yield curve in 2022 (i.e. the yield on 10-year government bonds fell below the 3-month yield) did not play a key role during this period;
- **The peaks in market anxiety in March and October 2023** were linked to the corporate bond asset class. The marked inversion of the German yield curve contributed to increasing the market-implied probability of a recession between April 2023 and January 2025, but was offset by other asset classes over the same period (see the section "PICON model provides a comprehensive analysis […]" in part 3);
- **The peak in market anxiety in April 2025** was driven primarily by equity valuations.

C3 Contributions by asset class to the model's predictions of a recession in two quarters for the euro area
Deviation from the historical average prediction
(percentage points)



Sources: Bloomberg; PICON model, authors' calculations.
Key: Real-time deviation from the historical average prediction (17%), and the contribution of each asset class to this deviation. The perception of recession risk is all the more pronounced as it exceeds this average threshold, represented by 0 on the y-axis.

BOX 2

Interpreting models using SHAP values

As with other machine learning algorithms, the flexibility offered by random forests (see Box 1) comes at the cost of reduced interpretability. However, there are recognised approaches for opening these "black boxes", such as SHAP (Shapley additive explanations), which stems from the work of Shapley (1958) and was subsequently applied to random forests by Lundberg (2018).

This method involves isolating the contribution of each variable by comparing predictions with and without that variable, whilst taking into account all possible configurations of the other variables. In other words, the same value for a variable will not necessarily have the same impact (and therefore the same 'SHAP value') depending on the prediction date considered, due to different interactions with the other variables.

3 Is the PICON model an indicator of financial or economic stress?

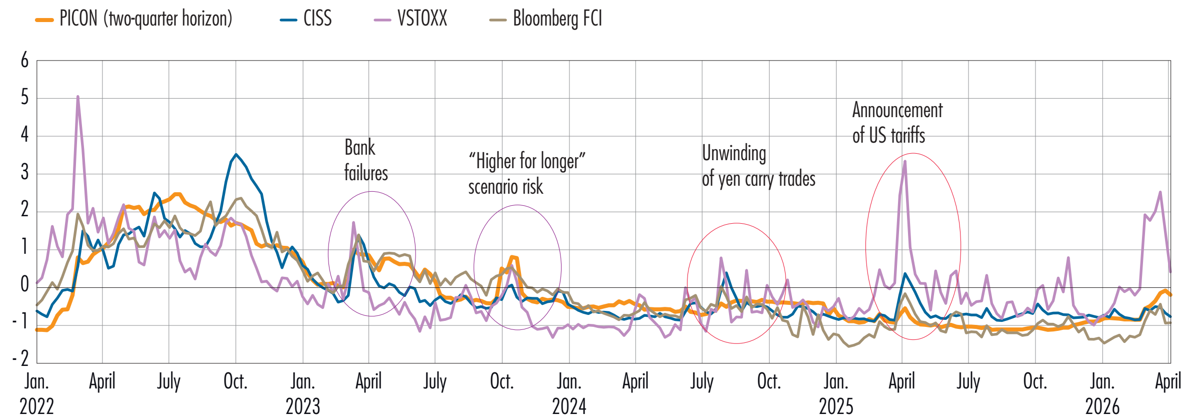
Among episodes of financial stress, the PICON model identifies those associated with a risk of an economic downturn

An analysis of the PICON model's market-implied probabilities of a recession highlights its **ability to identify periods in which market turbulence is primarily linked to expectations of an economic downturn. These measures complement other indices** of financial stress or implied volatility in equity markets (VIX for the S&P 500 in the United States, VSTOXX for the STOXX 600 in Europe),[7] which are not necessarily linked to macroeconomic trends. While trends may sometimes be similar, not all episodes of market stress are necessarily linked to a significant increase in the risk of recession, according to the PICON model.

In the euro area, two episodes of financial—but not economic—stress can be identified (see Chart 4, red circles): the brief episode of unwinding of carry trade[8] positions on the yen in August 2024, and the announcements of US tariffs in April 2025, which, according to the PICON model, did not result in an increase in the risk of recession over the following two quarters. By contrast, certain episodes, such as the collapse of the US bank SVB in March 2023 and the risk of a higher for longer scenario in October 2023 (see mauve circles), show a simultaneous rise in both financial stress indicators and PICON.

When considered from January 2022 onwards, the correlation between PICON and the euro area financial stress indicators is positive, but falls as the prediction horizon increases, particularly beyond three quarters in the United States. Thus, PICON bears a closer resemblance to the family of financial conditions indices (FCI) designed

C4 Comparison of PICON predictions for the euro area with other benchmark composite indicators
(number of standard deviations)



Sources: Bloomberg; authors' calculations.
Key: Certain events, such as the collapse of the US bank SVB in March 2023 and the risk of a "higher for longer" scenario in October 2023, were accompanied by a concurrent rise in both financial stress indicators and PICON. By contrast, the brief episode of unwinding of yen carry trades in August 2024 and the announcements of US tariffs in April 2025 did not result in a rise in the risk of recession over a two-quarter horizon, according to PICON.
Notes: All indicators have been centered and standardised to be plotted on the same scale.
CISS, composite indicator of systemic stress; VSTOXX, Euro Stoxx 50 Volatility; FCI, financial conditions index.
Higher for longer scenario: investors expect persistently high interest rates.

7 These volatility indicators, calculated using equity market options, are generally interpreted as indicators of financial stress.
8 A carry trade, which in this context involves borrowing in a currency with a low interest rate and then investing the funds raised in a currency with a high interest rate.

to summarise information on the future state of the economy. The correlation between PICON and these indices remains high, even when the prediction horizon extends to four quarters ahead (see table). Furthermore, compared with these financial conditions models, one of its strengths lies in the combination of market price series using a random forest rather than other aggregation techniques.[9]

The PICON model provides a comprehensive analysis of all asset classes, particularly in the short term

In the model's prediction, the contribution of the inversion of the German yield curve from 2023 to early 2025 proves to be significant. It contributes up to 10 percentage points to the probability of recession over this period (see the "Interest rates (slope)" item in Chart 3 above), but according to PICON, **this is not sufficient on its own to signal a high risk of recession given the valuations of other asset classes**. Furthermore, while the model does identify a marked threshold effect at the point of yield curve inversion, it is able to differentiate its impact depending on the trend in other financial variables. For example, a yield curve inversion will be all the more closely linked to a risk of recession if it is accompanied by expectations of a decline in long-term inflation or stable or falling short-term interest rates (see Appendix, Illustrating the interactions between variables).

The influence of yield curve slopes increases with the prediction horizon and becomes predominant after three or four quarters. In the United States, the influence of equities on the prediction is less significant and limited to the short term, which is consistent with the work of Estrella and Mishkin (1998). In the euro area, the German government bond yield curve also plays a key role, but the impact of other factors, such as the Italy–Germany yield spread and corporate bond indices, is also significant

Correlation coefficients between the PICON model and other indicators

Comparison across different recession risk prediction horizons

a) Euro area models

	PICON				
	Real time	In 1 Q	In 2 Q	In 3 Q	In 4 Q
Bloomberg FCI	0.92	0.90	0.90	0.88	0.82
ECB CISS (ZE)	0.92	0.88	0.87	0.71	0.65
VSTOXX	0.56	0.49	0.53	0.40	0.33

b) US models

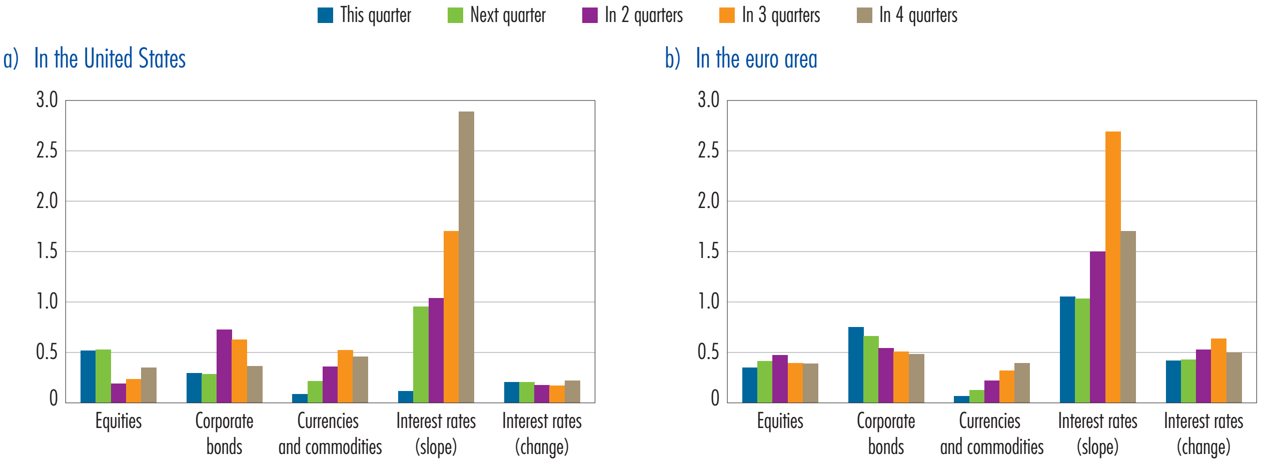
	PICON				
	Real time	In 1 Q	In 2 Q	In 3 Q	In 4 Q
GS FCI	0.28	0.40	0.29	0.46	0.62
Chicago Fed FCI	0.64	0.78	0.70	0.83	0.65
ECB CISS (US)	0.78	0.77	0.76	0.76	0.25
OFR FSI	0.75	0.75	0.80	0.79	0.24
VIX	0.54	0.45	0.59	0.48	-0.15

Sources: Bloomberg; authors' calculations.
Key: For the United States, the correlation between the VIX index and PICON is strong when the latter is used for predicting over a short-term horizon (up to 0.59 in 2 quarters), but becomes slightly negative when the model is trained for a medium-term horizon (–0.15 in 4 quarters).
Notes: Blue indicates a positive correlation, ranging from weak to strong; pink indicates a negative but weak correlation.
PICON: market-implied probability of economic contraction.
GS FCI, Goldman Sachs financial conditions index; ECB CISS, European Central Bank composite indicator of systemic stress; OFR FSI, Office of Financial Research financial stress index; VIX, volatility index.

9 These aggregations are generally carried out by averaging the sub-indicators (after standardisation), sometimes by dynamically adjusting the weights using econometric methods, or through principal component analysis (see Hatzius et al., 2010, for a review of these methods).

C5 Average contributions of predictors by asset class according to the prediction horizon

(percentage points)



Sources: Bloomberg; authors' calculations.
Key: In the United States, each of the yield curve slope variables contributes, on average, 2.9 percentage points to the predicted probability of a recession in four quarters.
Notes: For each asset class, the average of the absolute SHAP values is calculated over the 2022–25 period, regardless of whether their contributions are downward or upward relative to the central prediction. SHAP (Shapley additive explanations) values: values that measure the contribution of each variable to a given model prediction.

in the perception of macroeconomic risk (see Chart 5). Indeed, the price of these bonds contains information on investors' expectations regarding the risk of default by corporate borrowers, and on their risk appetite (Favara et al., 2016).

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The indicator of an market-implied probability of a recession (PICON) is in line with models used by institutions to measure the risk perceived by financial markets. It offers an alternative approach by using a non-parametric estimation method – random forests – which can handle complex and non-linear relationships between classes of financial assets. Its second feature is that it relies solely on daily financial data, going beyond sovereign yield curves alone: PICON estimates the extent to which the risk of an economic turnaround is integrated into market prices on any given day.

In the 2022–25 test sample, the model clearly distinguishes between episodes of stress linked to economic concerns in the United States (the higher for longer scenario, announcements of tariff increases by Donald Trump) and in the euro area (the 2022 energy crisis, the banking crisis in March 2023) from episodes of purely financial stress (August 2024). This is due to the model's multi-asset and non-parametric approach.

The PICON model complements the range of tools used to monitor financial markets on a daily basis. The "black box" effect of non-parametric models is offset by the estimation of each variable's contribution, which enhances the interpretation of the results. By using only daily financial data, the PICON model goes beyond a mere assessment of market sentiment; it can derive from market prices a collective assessment of the economic outlook for the United States and the euro area.

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Appendix
Methodology

Definition of the model's predictor variables

The market valuations used as predictor variables are considered either in terms of levels or changes (see table below). Several types of change are used, with the aim of detecting economic turnarounds or breaks over different time horizons: i) short-term change, namely the spot price minus the 50-day moving average; ii) Golden Cross, the 200-day moving average minus the 50-day moving average; iii) Drawdown, the difference between the current price and its high calculated over a one-year sliding window.

Model training methodology

The model is "trained" over the 1990–2021 period, excluding the Covid period, which is an "exogenous" type of recession that is difficult to forecast, regardless of the valuation of asset classes in 2019. Market data are daily, but the predicted variables (recession) are quarterly, and their daily values are obtained by applying the quarterly value each day. The effective sample size is therefore not as large as it appears since the observations are not independent and identically distributed, but are temporally dependent.

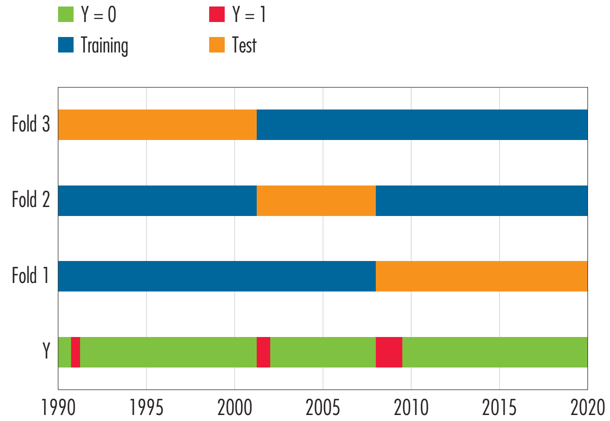
List of indicators used in the PICON models for the United States and the euro area
Comparison across different recession risk prediction horizons

	Asset class	Transformation(s)
Corporate Investment Grade Option Adjusted Spread		Level – Change
Corporate High Yield Option Adjusted Spread	Credit	Level – Change
Relative performance: HY vs IG		Change
US/German 2-year vs 10-year Treasury yield curve		Level
US/German 5-year vs 30-year Treasury yield curve		Level
US/German 3-month vs 10-year Treasury yield curve	Yield curve	Level
US/German 1-year Treasury bill term premium		Level
US/German 10-year Treasury bond term premium		Level
Actuarial yield on US/German 2-year Treasury bills	Trends in sovereign bond yields	Change
Actuarial yield on US/German 5-year Treasury bills		Change
Actuarial yield on US/German 10-year Treasury bills		Change
Actuarial yield on US/German 30-year Treasury bills		Change
5Y5Y inflation swap (EA model only)		Change
1Y10Y inflation spread (EA model only)		Change
BTP and OAT-Bund spread (EA model only)		Level – Change
S&P 500/Eurostoxx 50	Shares	Change (%)
Nasdaq (US model only)		Change (%)
Cyclical vs Defensive Index		Change (%)
Banks (KBW Index) / Eurostoxx Banks		Change (%)
Russell 2000 Index / Eurostoxx Small Caps		Change (%)
Relative performance: IG Credit vs Equity		Change (%)
EUR/USD		Change
AUD/JPY	Currencies	Change
EUR/CHF (EA model only)		Change
Silver	Commodities	Change
Brent		Change

Source: Authors.
Notes: EA, euro area.

Illustration of the method for setting the hyperparameters by k-fold

(in percentage points)



Source: Authors.
Key: In *fold* 1, the model is trained on data from 1990 to 2007 inclusive, and its performance is assessed over the period 2008–19, which contains at least one recession (Y=1).
Note: The 3-*fold* variant presented here respects the temporal dependence of the data, ensures that in each of the three iterations the model is trained on observations covering at least two recessions, and assesses the accuracy of the predictions on a sample containing at least one further recession episode.

The model's hyperparameters (number of trees in the forest, maximum tree height, number of variables sampled for each tree) are selected using a cross-validation procedure[1] that allows predictions to be compared across different specifications; the specification that yields the best performance on a precision-recall curve metric (PR–AUC, where AUC denotes the area under the ROC curve) is selected.[2] Furthermore, the observations are not shuffled randomly but retain the temporal order of the data. This prevents any overestimation of the model's out-of-sample performance.

Illustrating the interactions between variables

As a reminder, random forests are used to link the effect of one variable to the values simultaneously taken by other variables, without imposing any a priori functional structure.

For example, in the PICON model, the role played by an inverted yield curve also depends on the other variables. When the German sovereign yield curve inverts by 100 basis points, the contribution to the market-implied probability of a recession in the euro area in two quarters varies between 3% and 10%, depending on the dynamics of short-term interest rates or inflation expectations (see Chart B/a on the following page, illustrating the link between a sovereign yield curve inversion and changes in short-term sovereign interest rates). Thus, the contribution of an inverted yield curve to the risk of recession is all the greater when the German short-term rate is trending downwards.

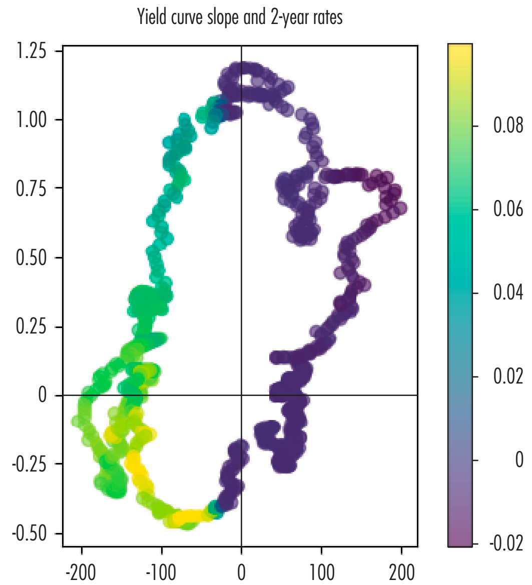
1 k-fold cross-validation involves training and assessing a model on several different data combinations. This provides a more realistic picture of the model's performance outside its training data, allowing for a more robust selection of hyperparameters.

2 This metric assesses the levels of precision and recall based on decision thresholds for classification. In other words, it assesses the extent to which the model succeeds in identifying most recessions while avoiding false positives. It also provides a more accurate picture of the model's performance than the ROC (receiver operating characteristic) curve, particularly when there are only a limited number of recession periods to predict.

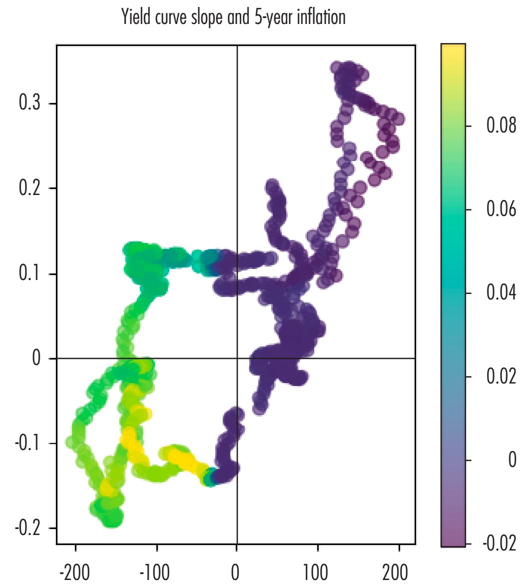
Contribution of the slope of the yield curve to the prediction, depending on the dynamics of short-term interest rates and long-term inflation expectations

(x-axis: value of the slope of the German yield curve [10-year rate – 3-month rate], in basis points;
y-axis: short-term interest rates and long-term inflation expectations, in percentage points)

a) Impact of the yield curve slope depending on the interaction between the dynamics of short-term rates and the value of the slope



b) Impact of the yield curve slope depending on the interaction between the dynamics of long-term inflation and the value of the slope



Sources: Bloomberg; authors' calculations.
Colour scale: contribution of the yield curve slope to PICON's overall prediction over a two-quarter horizon (from 0 to 10%).

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