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An Empirical Analysis of the Predictive Power of European Yield Curves*

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For various reasons, the yield curve of government bonds serves as a reliable predictor of recessions in the US. This study provides an empirical analysis of whether there is such a relationship in European countries. The methodological framework employed in this study encompasses the utilisation of the Hodrick–Prescott filter in conjunction with a probit model. The modelling procedure in the literature is extended by optimally combining government bond maturity spreads and examining whether the results are also robust for European yield curves. The main finding of the paper is that in the US the spreads calculated from the yield of 7-year and 1-year government bonds are the best predictors, and they are similarly suitable for predicting economic crises in half of the European countries as well.

Journal of Economic Literature (JEL) codes: G17, O11, O47

Keywords: yield curve, recession, probit model

1. Introduction

For all economic actors, predictions about business cycles are crucial, and such projections have been offered for hundreds of years. Of the leading variables that can be used to forecast fluctuations in business cycles, the development of interest rates was already studied after the First World War in Hungary (*Máténé Bella et al. 2019*). Analysis of the recession-predicting capacity of the slope of the yield curve started in the late 1980s (for example, *Keen 1989*; *Stevens 1989*), and by the end of the 1990s this topic had generated numerous studies. These studies look at the dynamics of the difference between the yields on government bonds with different maturities over time, and at the relationship between this difference and real economic output. Empirically, downturns have been preceded by an inversion of the yield curve, when yields on short-term government bonds are higher than on

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long-term ones, meaning that the yield spread is negative. This is because investors' risk perception about a country's economy affects the country's yield curve (*Matolcsy – Palotai 2016*). In such a scenario, investors' expectations reflect a potential recession for the period between the two maturities, along with a corresponding drop in inflation and an expansionary monetary response. There are two typical methods of analysis for predicting recessions based on this information: (1) forecasting the GDP growth rate in a quantitative manner with continuous models, and (2) predicting the probability of recessions with binary models. *Estrella et al.* (*2003*) find that the latter approach is better.

Estrella – Mishkin (*1996*) argue that yield spreads are useful indicators, partly because they are strongly influenced by monetary policy, and may therefore be able to sway the real economy. Moreover, they contain the expectations about inflation and interest rates, which the authors also consider to be crucial. The same authors published another paper on the predictive capacity of financial indicators, such as interest rates, share prices, monetary aggregates and the yield spread, using probit models (*Estrella – Mishkin 1998*). They showed that on a time horizon of 1–3 quarters, share prices and monetary aggregates are equally good out-of-sample predictors, but for forecasts longer than that the yield spread clearly dominates, typically alone, without the inclusion of any other variable.

By contrast, *Wright* (*2006*) concludes that yield spreads in themselves are not quite as good predictors of recession as when the model contains yields as separate variables. Interestingly though, the models supplemented with yields on the basis of the model did not predict a recession in 2006, while the yield spreads in themselves did. Wright believed the multivariate model, but it turned out that he was wrong. Prior to the 2008 crisis, another group of analysts from the Federal Reserve, *Haubrich et al.* (*2006*), also found that falling yield spreads are not likely to predict a recession.

After the Great Recession, several studies were published on this topic (*Chinn – Kucko 2015; Rudebusch – Williams 2009*), and in 2017 the American yield curve started to flatten once again. *Bauer – Mertens* (*2018a*) showed that the critical threshold of the yield spread is 0, and thus a positive value close to 0 is no cause for concern, but a negative yield curve spells trouble. The authors argued that since the period after the financial crisis was characterised by a low interest rate and yield environment, a peculiar phenomenon by historical standards, no definitive conclusions can be drawn from the dynamics of yield spreads.

In early 2019, various media outlets, including *Forbes*, *The Economist* and *Bloomberg*, wrote about the flattening of the American yield curve and argued that it was only a question of time before an inverted yield curve became reality and that this suggested an impending recession to economists. In August 2019, the difference between long-term and short-term US Treasury yields became negative, but instead of the projected financial crisis, the coronavirus pandemic ushered in a major downturn. Many analysts wondered whether this was simply a coincidence.

A similar dilemma was faced with respect to the forecasts observed at the time of the 11 September 2001 terrorist attacks in New York. *Chauvet – Potter* (*2005*) compared the forecasting capacity of the standard probit model with more sophisticated and extended probit models. The latter typically fared better in out-of-sample scenarios, but only the standard model predicted a recession for the end of 2001 on the basis of the information available until March 2001. The authors argue that based on this it would be wrong to conclude that the standard model performs better, since the information available to it did not include the events of 9/11, which had a marked effect on the downturn. Therefore, it can be said that predictive capacity of yield spreads should generally be tested on recessions that are primarily attributable to endogenous reasons rather than exogenous shocks. Accordingly, this analysis uses time series ending in 2019, thereby excluding the shocks caused by the coronavirus and the Russia–Ukraine war.

In connection with the war, one might contend that the pricing in the capital markets could have been used to predict a downturn. *Granát et al.* (*2023*) found that investor expectations only incorporated the threat of war 50 days before it started on 24 February 2022, and the literature on forecasting with the yield curve contains predictions for a much longer horizon (4 quarters), so the war period should also be excluded.

1.1. European yield curves

Examination of the yield curve's recession-predicting capacity was inspired by US Treasury bonds, but many studies devote special attention to the yield difference between European government bonds of different maturities. *Estrella – Mishkin* (*1997*) and *Chinn – Kucko* (*2015*) find that German and UK yield spreads are fairly good in predicting the probability of a recession, although the UK yield spread often predicts a high probability for an economic downturn in times without a recession. The French and Italian yield curves were also examined, but did not prove to be accurate indicators of recession. *Duarte et al.* (*2005*) used aggregate euro area data and probit models to successfully forecast the recessions in the European Economic and Monetary Union. *Hasse – Lajaunie* (*2022*) analysed the forecasting capacity of the yield spread of 10-year and 3-month bonds in 13 OECD countries, including 8 from Europe, using a panel logit model. The yield spread proved to be significant even when various control variables, such as housing market yields, economic uncertainty or the central bank base rate, were included.

The present study analyses the case of the United States and looks at European countries[1] to see the recession-predicting capacity of yield spreads in the past 25 years.

2. Data and methodology

The daily and monthly data for government securities with different maturities were accessed from investing.com and the FRED database.[2] Some problems were caused by incomplete data and the fact that the length of the time series varied across countries. Since the yield spread used in the model was defined as the difference of two yields, the analysis could only utilise the observations where data was available for government securities of both maturities. The seasonally adjusted quarterly real GDP data were taken from Eurostat[3] and the FRED database. In the case of yield spreads, the quarterly values were defined as the geometric mean of daily observations.

Economists use different yield spreads in the literature. Some suggest maximising the difference between the maturities of the government bonds under review (*Ang et al. 2006*), others have a preference for the yield spreads of short-term and medium-term bonds (e.g. *Estrella et al. 2003*), while others examine the difference between the yields of the standard 10-year and 3-month bonds. The results of the latest paper by *Estrella* (*2022*) show that the 10-year/3-month yield spread has the best predictive capacity, and that the combined use of 10-year/2-year and 18-month/3-month spreads gives a more accurate prediction of recessions than when only one of these is included in the model. However, yield spreads usually follow very similar paths (*Bauer – Mertens 2018b*). The present paper looks at various potential combinations for the different countries.

[1] The countries under review: Belgium, Bulgaria, Czechia, France, Germany, Ireland, Italy, Poland, Portugal, Romania, Spain, Switzerland and the United Kingdom. Other European countries could not be included due to a lack of data.

[2] https://fred.stlouisfed.org/

[3] https://ec.europa.eu/eurostat/data/database

A probit model is used to predict the forecasting capacity. The models containing a binary dependent variable basically differ from OLS regression in that the dependent variable is binary, which implies that the estimated Y, the prediction, actually classifies the given observation into one of two groups. Such dependent variables are mostly modelled with linear probability models (LPM), logit models and probit models. Out of these, the LPM is the easiest to manage, but a major drawback is that the predicted probabilities can fall outside the range of [0,1], and the partial effects calculated in this modelling framework are sometimes logically impossible (*Wooldridge 2012*). The basic idea behind a logit and probit regression is that while keeping the linear combination, its result is transformed in such a way that the dependent variable interpreted in the (–∞, ∞) range is translated into a range of [0,1].

The probit model differs from logistic analysis in one central point. In contrast to the logit, the probit does not assume that the distribution of the probability *P* is logistic, instead a normal distribution is assumed. But this distribution function does not have a closed shape, so using a logit model is much simpler and more widespread. The probit model can be stated as equation (1):

$$E(Y \mid X) = P(Y = 1 \mid X) = \phi\left(\beta_0 + \beta_{spread}\right), \tag{1}$$

where $\phi(z) = P(Z < z), Z \sim N(0,1)$.

Recessions were defined with the Hodrick–Prescott filtering of real GDP data for European countries, while in the case of the US the NBER (2021) database[4] was used. The formal definition of the HP filter is shown in equation (2).

$$\min_{\tau}\left(\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda\sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2\right), \tag{2}$$

where the first term expresses how closely the time series is followed by the trend, while the second denotes how smoothly the latter reflects the former. The λ coefficient determines the trade-off between the two terms, which was chosen to be 1600 due to the quarterly data, in line with the literature. After the HP filtering, the cyclical components of real GDP were derived, which show the deviation from the trend. Based on empirical results, a recession is defined in the study as a period characterised by a cyclical component of real GDP that is lower than –1 per cent, because this was the value where the periods defined as recession by the NBER could be reproduced on US data. The same definition of recession was employed for European countries, which was justified as the European results were to be compared to US results. It must be noted though that the HP estimate does not

[4] https://www.nber.org/research/business-cycle-dating

always approximate actual European recessions, which should be taken into account when interpreting the results.

The study starts by examining US data to see whether the conclusions of *Estrella – Mishkin* (*1996*) can be extended for the 25 years that have elapsed since then. Unlike the authors mentioned above, who used 10-year and 3-month government bonds, the present models used the difference between the 10-year and 1-year government securities yields available to us, on two different horizons, with a 4-quarter lag. By reproducing the above study, the earlier period is from 1962 Q1 to 1995 Q1, while the second period is from 1995 Q2 to 2019 Q4. The predictive capacity in the two periods is used to draw conclusions about the present-day applicability of the findings from 1996.

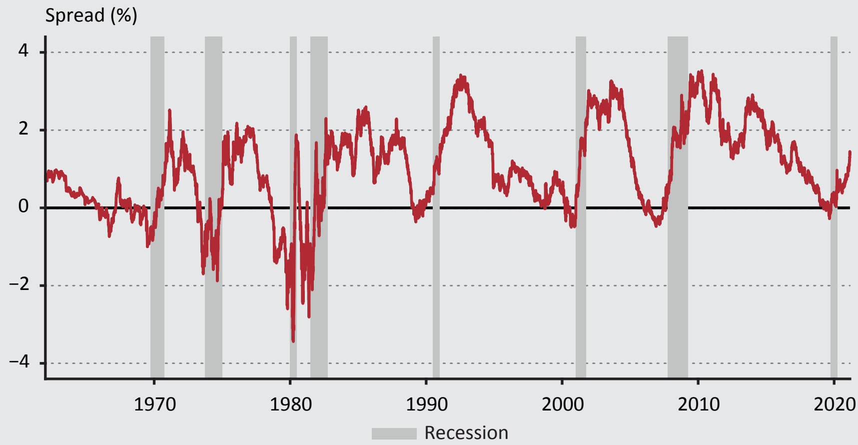
After this, it is examined whether the 10-year and 1-year maturities used are the best maturity combination from the perspective of predictive capacity. The scope of the analysis is then expanded to include various European countries, where the maturity combinations with the greatest predictive capacity are used.

3. Results

3.1. Results based on US data

In the case of the US, the difference between the 10-year and 1-year government securities yields was compared to the business cycle fluctuations defined by NBER. *Figure 1* shows the monthly and daily yield spreads, on a horizon starting in April 1953 and January 1962, respectively, and ending in March 2021 in both cases. It must be underlined that the study deducted shorter maturities from longer ones, although there are rare cases in the literature when the difference is defined in a "short-long" form. The procedure used here implies that the points in the figure that indicate an inversion of the yield curves are the ones where the yield spread enters negative territory.

Figure 1
Covariance between the 10-year and 1-year yield spread and recessions in the US



Source: Calculated from FRED data

Figure 1 clearly shows that yield curves were typically inverted 1–2 years prior to recessions, which can be explained by investors fearing an impending recession in these periods, and the figure indicates that these expectations usually proved to be correct. The figure also demonstrates that yield spreads sometimes start to increase even before the recession starts.

The probit model used was first run on US data, explaining the probability of recession with the yield spread defined as the difference between the 10-year and 1-year yields, with a 4-quarter lag. *Table 1* shows the probability of recession based on the model with different yield spreads before 1995, after 1995 and the period as a whole. As the yield spread declines, the probability of recession clearly increases over a 4-quarter horizon.

Table 1
Probability of recession with different yield spreads based on a probit model with a 4-quarter lag

Spread (percentage point)	Probability of recession (%)		
	Before 1995	After 1995	Total
1.21	0.08	6.66	5.32
0.76	0.97	11.11	9.81
0.46	3.74	15.06	14.06
0.22	9.03	18.82	18.25
0.02	16.62	22.37	22.29
–0.17	26.81	26.06	26.55
–0.50	49.64	33.15	34.82
–0.82	71.97	40.66	43.60
–1.13	87.58	48.28	52.42
–1.46	96.11	56.45	61.68
–1.85	99.35	65.74	71.78
–2.40	99.98	77.28	83.40
AUC (%)	**88.79**	**84.14**	**84.77**

Note: AUC is defined in the section 3.1.1.
Source: Calculated from FRED data

When comparing the results for the period before 1995 to the results of *Estrella – Mishkin* (*1996*), it was seen that the probabilities of a given yield spread were lower for spreads of over –0.5 per cent and higher for spreads of –0.5 per cent and below in our calculations. The comparison of these to the results of the period after 1995 shows that the present model predicts a recession with a lower probability with negative yield spreads than the model estimated based on the pre-1995 period. Based on *Bauer – Mertens* (*2018a*), namely that the development of the yield spreads is only a cause for concern if they enter negative territory, it was concluded that the predictive capacity of the yield spreads slightly diminished after 1995 relative to the period before that, although the yield spread was statistically significant in the model run for the period after 1995. The corresponding regression coefficients are summarised in *Table 3 of the Appendix*. The results for the whole period also attest that negative yield spreads are less likely to predict a recession in the model than based solely on the observations prior to 1995.

3.1.1. The model's classification capacity

When it comes to the classification task of binary models, the basic measures for assessing the goodness of the model's predictive capacity are sensitivity and specificity as well as the AUC (area under the curve), which can be defined as the size of the area under the ROC (receiver operating characteristics) curve. The model's sensitivity (equation (3)) is the ratio of the correctly classified 1 values (the occurrence of a recession in the present case) to all 1 values.

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \tag{3}$$

where *TP* (true positive) means the number of classifications when the model predicted a recession that actually occurred, and *FN* (false negative) denotes the cases when the model was wrong not to predict a recession.

By contrast, specificity is the ratio of the correctly classified recession-free periods to all recession-free periods (equation (4)).

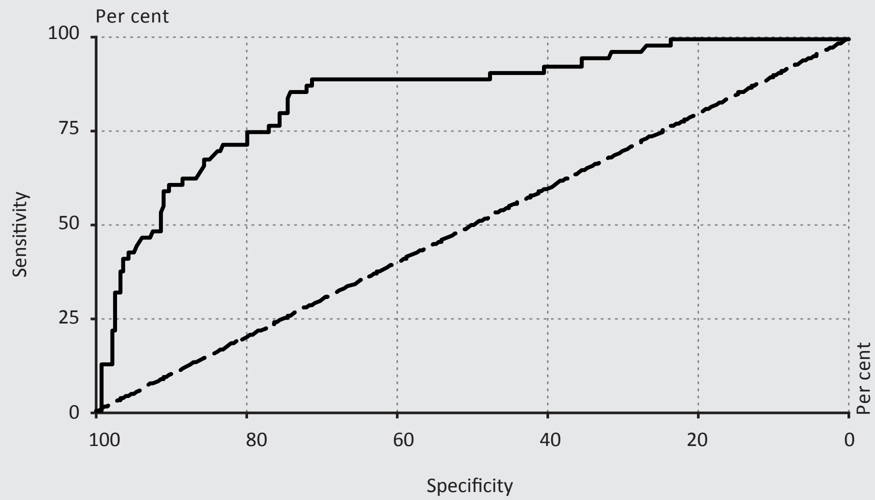
$$\text{Specificity} = \frac{TN}{TN + FP}, \tag{4}$$

where *TN* (true negative) means the classifications when the model correctly predicted that no recession would occur, and *FP* (false positive) denotes the cases when the model was wrong to predict a recession.

Classification models estimate one probability, whether a given observation has a value of 1 (recession) or not. Here, a threshold should be determined for deciding when to consider something 1 rather than 0. If a crisis is predicted even for very low probabilities, there will be less of a chance to miss recessions (high sensitivity), but of course false predictions will be all the more common (low specificity). In other words, sensitivity and specificity also depend on the threshold of choice.

The ROC curve can be drawn in a coordinate system where the *y* axis shows the different *sensitivity* values, and the *x* axis shows the different 1 – *specificity* values with thresholds of 0 and 1. The ROC curve that can be drawn in the model is shown in *Figure 2*.

Figure 2
ROC curve of the probit model for the whole period based on the 10-year and 1-year US yield spread



Note: The area under the curve (AUC) is 0.78. A ROC curve along the dashed 45-degree line would mean a model with random predictions.

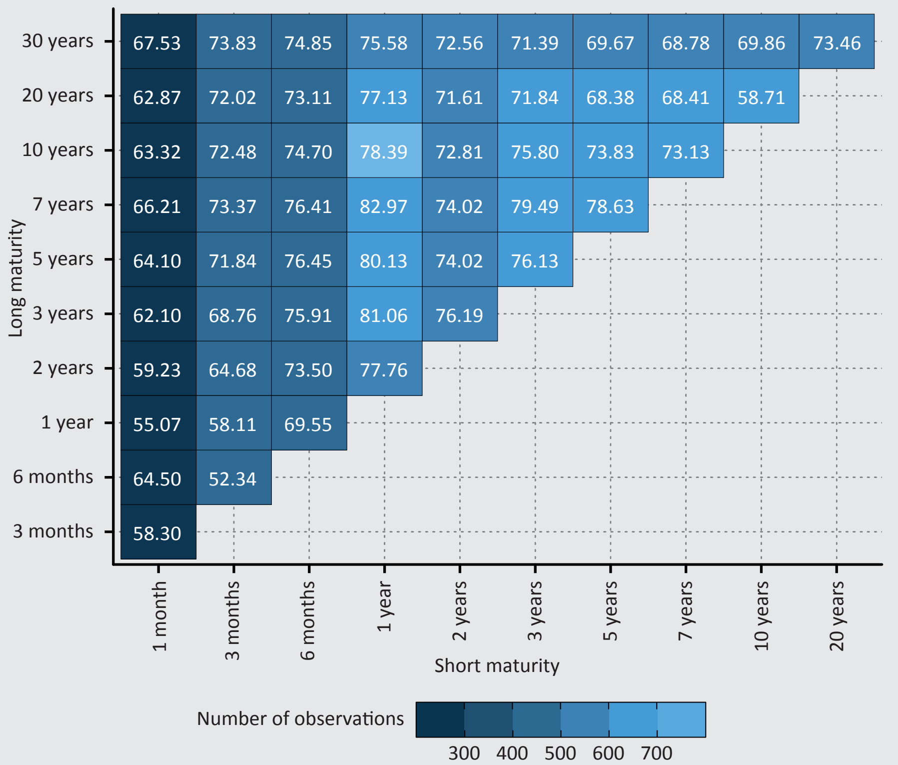
Source: Calculated from FRED data

Based on the area under the ROC curve, the AUC is 0.78. As the closer the AUC to 1 the better the classification capacity of a model (the greater the potential for high sensitivity with high specificity), it can be stated that the model where the yield spread was defined as the difference between the 10-year and 1-year government securities yields mostly predicts accurately.

3.1.2. Comparison of various maturity combinations

As noted before, there is no consensus in the literature about the maturity combination that best predicts recessions. The paper analyses the AUC values for the various combinations, and the results are summarised in *Figure 3*.

Figure 3
Analysis of the recession-predicting capacity of various yield spreads in the US



Note: The numbers in the figure show the AUC values corresponding to the individual maturity combinations (in per cent).
Source: Calculated from FRED data

The number of observations depends on the number of times the data for both maturity structures of the combination were available, and thus the number of observations exhibits a relatively large variability.

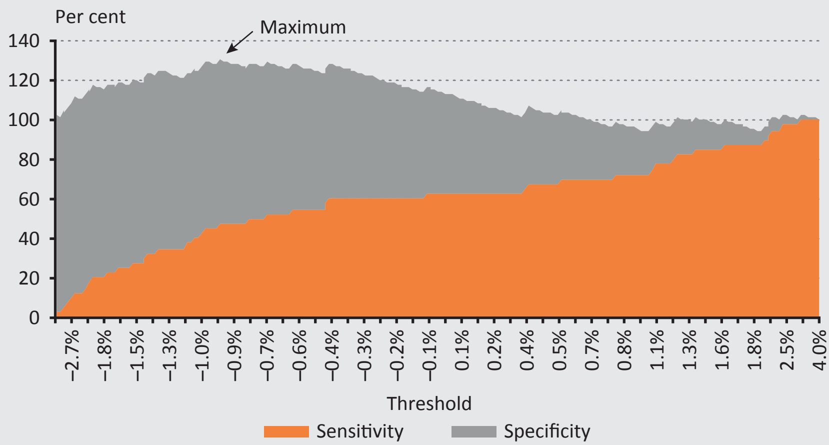
Figure 3 shows that the AUC takes its highest value in the case of 7-year and 1-year government securities, rather than in the original model. This is all the more interesting because this combination is not recommended by any study known to us, although 7-year bonds are more like medium-term paper, in which case the present results tally with the findings of *Estrella et al.* (*2003*). The average AUC values for the different maturities are summarised in *Table 4* of the *Appendix.* The often-used 10-year and 3-month combination is less appropriate according to the present results (although it still produces an AUC of 0.6–0.7), but the good performance of short maturities is in line with the claims that the predictive capacity of yield curves mainly depends on the change in short-term yields. It can also be established that the 1-year maturity performs well when coupled with any of the longer maturities under review, and so this Treasury yield can be key in predicting recessions in the US.

3.1.3. Defining recession periods with the help of the cyclical components of GDP

In order to extend the model to European countries, the threshold of the cyclical component of GDP had to be established where a recession occurs, as no classification similar to that of NBER was available for these countries.

US data was analysed to see how the cyclical component of GDP derived with the Hodrick–Prescott filter can reproduce the recessions defined by NBER. This step in demonstrated in *Figure 4*.

Figure 4
Finding the optimal threshold for classifying recessions in the US



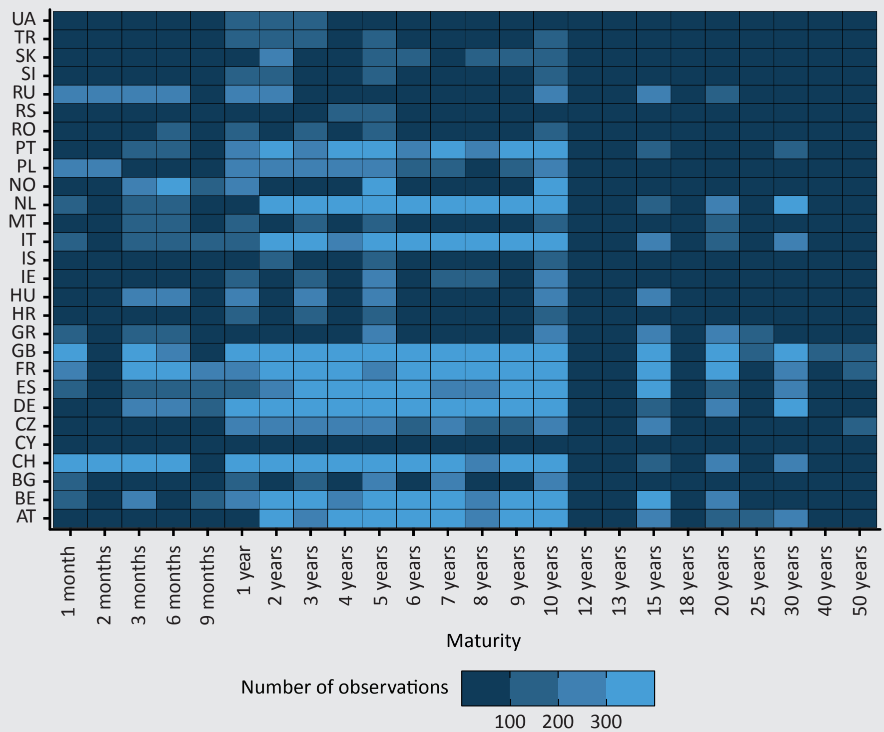
Note: Specificity and sensitivity are capped with a threshold of –1 per cent.
Source: Calculated from NBER and FRED data

The results show that the threshold can be determined as –1 per cent of the cyclical component of GDP. Accordingly, based on the data derived from the HP filtering of real GDP, only those periods can be classified as recessions in European countries when the cyclical component was –1 or lower. With this threshold, 47.5 per cent of the periods reported by NBER as recessions are classified correctly, along with 83.6 per cent of non-recession periods. Although determining the output gap like this is a common method, and only this can be used in European countries to determine recessions with a uniform methodology, it must be admitted that there is a major difference.

3.2. Extending the model to European countries

Based on the results derived from US data, the model was extended to European countries. The difference between the 7-year and 1-year yields was used in the same model as before, and recessions were defined based on the –1 per cent threshold of the cyclical component of GDP. Our initial database contained the yields of various government securities in Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Malta, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Switzerland, Turkey, Ukraine and the United Kingdom. The number of observations per country and maturity are shown in *Figure 5*.

Figure 5
Number of observations per country



Source: Based on investing.com

It can be clearly seen that the lack of data causes problems in several countries, and thus the model was only extended to 13 countries: Belgium, Bulgaria, Czechia, France, Germany, Ireland, Italy, Poland, Portugal, Romania, Spain, Switzerland and the United Kingdom[5]. After the extension was narrowed to the countries listed here, the probit model was run on the data for these countries, where the yield spread used as an explanatory variable was chosen to be the difference between the 7-year and 1-year government securities yields, in line with the earlier results.

Table 2 gives a summary of the AUC values for the different countries, and it can be argued that most of the examined European yield curves have a good recession-predicting capacity. The model run for the Bulgarian and Spanish data performs even better than the US model in this regard.

Table 2
Results of the probit models run for European countries

	Coefficient	Standard error	P-value	AUC[a]/N[b]
Belgium				
Constant	–0.33	0.48	0.49	0.84
Spread	141.22	72.97	0.05	61
Bulgaria				
Constant	–5.54	1.76	0.00	0.95
Spread	–250.99	84.40	0.00	36
Czechia				
Constant	–0.27	0.30	0.37	0.49
Spread	5.75	24.75	0.82	73
France				
Constant	–1.14	0.37	0.00	0.45
Spread	14.03	31.22	0.65	81
Germany				
Constant	–1.20	0.29	0.00	0.63
Spread	–28.25	21.21	0.18	96
Ireland				
Constant	–1.03	0.35	0.00	0.72
Spread	–70.51	26.50	0.01	35
Italy				
Constant	–1.00	0.45	0.03	0.64
Spread	–31.76	23.12	0.17	52

[5] One condition was that at least 20 observations had to be available, with both the lagged values of the 1-year and 7-year yield spreads and the corresponding GDP data.

Table 2
Results of the probit models run for European countries

	Coefficient	Standard error	P-value	AUC[a]/N[b]
Poland				
Constant	1.17	0.75	0.12	0.84
Spread	191.87	72.61	0.01	29
Portugal				
Constant	–1.74	0.41	0.00	0.79
Spread	–41.76	13.43	0.00	53
Romania				
Constant	–1.06	0.72	0.14	0.49
Spread	–14.53	37.95	0.70	24
Spain				
Constant	–4.50	1.14	0.00	0.93
Spread	–239.77	62.51	0.00	35
Switzerland				
Constant	–2.00	0.36	0.00	0.81
Spread	–111.52	28.44	0.00	94
United Kingdom				
Constant	–1.43	0.24	0.00	0.67
Spread	–33.71	19.77	0.09	97

Note: [a] AUC: area under the curve (Constant rows). [b] N: number of observations (Spread rows).
Source: Calculated from investing.com data

Table 2 also shows the regression results of the probit models run for various European countries. The results attest that the yield spread only proved to be significant at 5 per cent in Bulgaria, Ireland, Portugal, Spain and Switzerland. In the United Kingdom, the spread's predictive capacity can be considered significant at a significance level of 10 per cent. Moreover, for Bulgaria and Spain the AUC shows that the yield spread of 7-year and 1-year bonds is a more accurate predictor than in the US (where the AUC was 82.79). The estimated coefficient of the yield spread was contrary to expectations in Belgium, Czechia, France and Poland, while in the other countries a drop in the spread (an upward shift of an inverted curve) predicts the closing of the output gap. Based on our results, there is a negative relationship between the yield spread and the probability of recession in nearly 70 per cent of the countries examined. However, this relationship is significant in only 38 (or 46) per cent of the countries. In nearly one third of the European countries, we obtained results that differed from the expectations, and the relationship was significantly positive in one sixth of the countries.

4. Conclusion

The study used a probit model to first examine whether the predictive capacity of the yield spread, defined as the difference between the 10-year and 1-year government securities yields, changed on a 4-quarter horizon in the past 25 years compared to the period before 1995. It was found that the probability of a recession decreased in the case of inverted yield curves, albeit only slightly, but the statistical significance of the spreads was preserved in the model run for the later period.

After this, US data was used to find the maturity combination best predicting recessions. According to the results, the difference between the 7-year and 1-year yields is the best predictor.

Before the model was extended, US data was used to find the –1 per cent threshold for the cyclical component of GDP, under which an economy can be said to be in recession (output gap signalling a recession). These results were used to run the model on European countries where sufficient data was available. According to the findings, out of the 13 countries examined, the yield spread has a significant and negative relationship to the future output gap in only 6 cases. Furthermore, based on the AUC, yield spreads in Bulgaria and Spain are more effective in predicting recessions than in the US.

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Appendix

Table 3
Estimated coefficients of the probit models run for the US

	Coefficient	Standard error	P-value
Probit, before 1995			
Constant	–0.93	0.19	0.00%
Spread	–1.85	0.41	0.00%
Probit, after 1995			
Constant	–0.75	0.12	0.00%
Spread	–0.62	0.10	0.00%
Probit, Total observations			
Constant	–0.75	0.09	0.00%
Spread	–0.72	0.10	0.00%
LPM, Total observations			
Constant	0.25	0.02	0.00%
Spread	–0.12	0.01	0.00%

Source: Calculated from FRED data

Table 4
Average AUC results for the US calculated on the basis of various yield spread combinations, using a probit model

Maturity[a]	Average AUC	Maturity[b]	Average AUC
1 month	0.62	3 month	0.58
3 months	0.67	6 months	0.58
6 months	0.74	1 year	0.61
1 year	0.79*	2 years	0.69
2 years	0.74	3 years	0.73
3 years	0.75	5 years	0.74
5 years	0.73	7 years	0.76*
7 years	0.70	10 years	0.73
10 years	0.64	20 years	0.69
20 years	0.73	30 years	0.72

*Note: [a] Used as short-term in the model. [b] Used as long-term in the model. * Highest value.*
Source: Calculated from FRED data