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Predicting recessions using VIX–yield curve cycles

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ABSTRACT

The VIX index and the spread between long- and short-term Treasury bond yields co-move in counterclockwise cycles that align with the business cycle. Based on this empirical fact, I predict U.S. recessions using an indicator of the economy's location on the VIX–yield curve cycle. The proposed indicator significantly outperforms the yield curve spread in predicting U.S. recessions from 1950–2022 both in- and out-of-sample and using both static and dynamic probit models. VIX–yield curve cycles also contain predictive power above and beyond other leading economic indicators.

1. Introduction

This paper proposes a new predictor of U.S. recessions based on the interaction between equity volatility and the yield curve. As is well known, the spread between long- and short-term bond yields is useful for forecasting recessions (Estrella & Hardouvelis, 1991; Estrella & Mishkin, 1998; Harvey, 1988). Indeed, the yield curve has inverted, with long-term rates below short-term rates, preceding every recession in the post-war period. In addition, recent literature suggests that the equity premium varies over the business cycle, with sharp declines leading up to business cycle peaks (Gómez-Cram, 2022; Moench & Stein, 2021). As a result, equity volatility increases around recessions. This is supported by Danielsson, Valenzuela, and Zer (2016), who find that volatility increases the probability of financial crises.

Motivated by these strands of literature, I show that the combination of the yield curve spread and equity volatility offers tremendous improvements in predicting U.S. recessions compared with the spread alone. My approach is based upon the empirical observation that the VIX index, a measure of implied volatility in S&P 500 index options, and the slope of the yield curve co-move in counterclockwise cycles that are aligned with the business cycle.[2] Recessionary periods are characterized by a combination of high levels of the VIX index and a flat yield curve. This relationship is robust and has repeated itself through all business cycles for which VIX index data are available. In broad terms, VIX–yield curve cycles capture the interplay between financial markets and the stance of monetary policy.

I begin by constructing various indicators that measure the economy's location on the VIX–yield curve cycle in a single variable. Summarizing the VIX–yield curve cycle in a single measure is beneficial for interpreting and monitoring recession signals. These cycle indicators are then used as predictors in a probit model for the probability of a recession within 6, 12, and 18 months. I evaluate the performance of these predictors relative to a probit model using the yield curve spread alone. The models are

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[2] VIX–yield curve cycles are described by Erik Norland in a CME Group report available at https://www.cmegroup.com/education/featured-reports/vix-yield-curve-cycle-at-the-door-of-high-volatility.html (visited March 31, 2021).

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compared based on measures of fit and their ability to correctly classify periods of recession, which can be assessed using the receiver operating characteristics (ROC) curve, as in Liu and Moench (2016). To extend the sample, I proxy the VIX index using realized volatility computed by summing squared daily returns within each month. The VIX index and realized volatility are strongly correlated.

The results unambiguously show that recessions are predicted more precisely when considering equity volatility alongside the yield curve spread. The preferred cycle indicator is given by the slope of the tangent line from the origin to the VIX–yield curve cycle, i.e., the fraction of the spread to volatility. Predicting recessions using this cycle indicator generates performance measures that are statistically indistinguishable from the model which includes the spread and volatility as separate predictors. Recession prediction is thus not improved by letting the probit model determine the coefficients on spread and volatility separately. These results hold both in- and out-of-sample.

Then, I compare the preferred cycle indicator with other predictors which have been found to be successful in the literature. The cycle indicator outperforms these alternative predictors at long forecasting horizons, and the performance is similar at short forecasting horizons. When including the cycle indicator alongside the alternative predictors in multivariate probit models, the cycle indicator remains significant and improves AUROC values over the univariate models without the cycle indicator. Moreover, for the 18-month-ahead forecast, the alternative predictors do not add significant predictive power over the univariate model based on the cycle indicator alone.

The main results are validated through several robustness checks and extensions. First, there also exist circular patterns in the scatter plots of the yield curve spread and other measures of volatility and uncertainty. Specifically, I show that the cycle indicator constructed by replacing equity volatility with the Economic Policy Index (EPU) from (Baker, Bloom, & Davis, 2016) or the Merrill Lynch Option Volatility Estimate (MOVE) index, which measures implied volatility in Treasury bond markets, also contains predictive power for future recessions. The indicator using the MOVE index is not significantly different from the baseline results. In contrast, using the EPU index delivers statistically worse predictive outcomes. These results indicate that the predictive power of the cycle indicator stems from the interaction between monetary policy and financial market volatility, rather than the uncertainty around policy.

Second, I examine whether the yield curve flattening caused by unconventional monetary policy has weakened the predictive power of the cycle indicator, by using the shadow rate from (Wu & Xia, 2016) to construct the yield curve spread. The results indicate that unconventional monetary policy does not impact the predictive power of the cycle indicator. Third, I validate the results using dynamic probit models, as proposed by Kauppi and Saikkonen (2008) and Nyberg (2010). Finally, I evaluate the performance of the cycle indicator in non-U.S. economies. I find promising results for Germany and the U.K., whereas the yield curve spread and the cycle indicator both struggle to predict recessions in Japan.

The literature on predicting recessions is vast. The observation that the yield curve moves with the business cycle dates to Kessel (1965) and Fama (1986). Harvey (1988, 1989, 1993), Estrella and Hardouvelis (1991), and Fama (1990) first showed that the yield curve spread has predictive power for real economic variables. The literature has also considered other predictors. Engstrom and Sharpe (2019) advocate for the use of a near-term forward spread to account for the flattening of the yield curve. Abdymomunov (2013) shows that the entire yield curve, rather than just a spread between two yields, has predictive power for future output growth. Also, Benzoni, Chyruk, and Kelley (2018) and Berganza and Fuertes (2018) use the decomposition of the yield curve into term premia and short-rate expectations to predict recessions. Levanon, Manini, Ozyildirim, Schaitkin, and Tanchua (2015) construct a predictor from financial indicators, and Christiansen, Eriksen, and Møller (2014) propose predictors measuring sentiment. Finally, numerous papers compare the predictors proposed in the literature. Bauer and Mertens (2018) find that the yield curve spread is preferred over other predictors, even in the current low-interest-rate environment. Liu and Moench (2016) agree that it is difficult to systematically outperform the yield curve spread at the 12-month horizon but find that the S&P 500 index return is a useful predictor at shorter horizons. Wright (2006) concludes that a model with the FFR and the yield curve spread is superior at forecasting recessions at various horizons.

VIX–yield curve cycles are related to the co-movement between monetary policy stance and the VIX index, as studied by Bekaert, Hoerova, and Duca (2013). Specifically, they show in a structural vector-autoregressive model that accommodative monetary policy lowers the VIX through the channels of risk aversion and uncertainty. Additionally, Chen and Clements (2007) document that the VIX index declines following the policy announcements of the Federal Open Market Committee. The present paper focuses solely on the information contained in VIX–yield curve cycles for predicting future turning points in the business cycle and leaves the underlying structural relationship between the yield curve and the VIX index for future research.

The paper proceeds as follows: I describe the empirical relationship between the VIX index and the yield curve and construct various cycle indicator measures in Section 2. Section 3 details the probit model, the performance evaluation methods, and the data. The results are presented in Section 4. Extensions and robustness are discussed in Section 5. Section 6 concludes.

2. VIX–yield curve cycles

This paper is motivated by the remarkable empirical insight that the scatter plot of levels of the VIX index and the yield curve spread generates cyclical patterns aligned with the business cycle. Fig. 1 shows this relationship, which I refer to as VIX–yield curve cycles. The data are provided by FRED at the daily frequency from January 1990 to June 2022, smoothed using a two-year moving average. The yield curve spread is computed as the difference between the 10-year Treasury bond yield and the

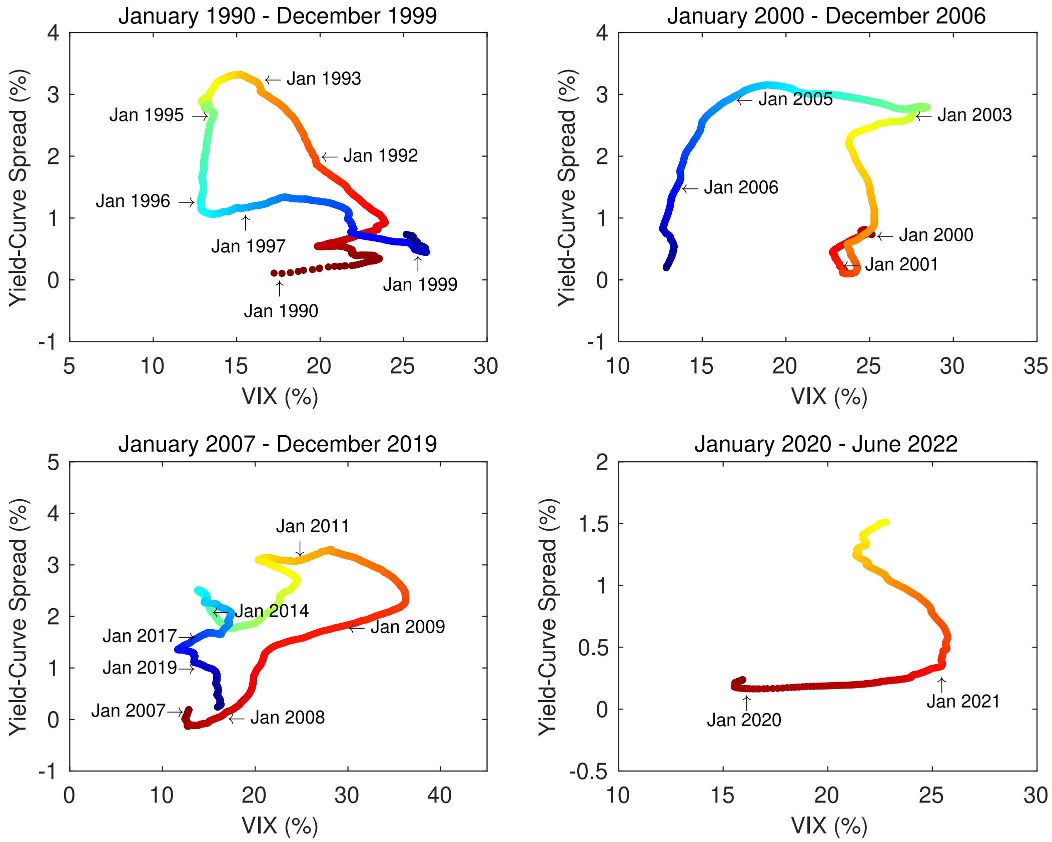

Fig. 1. VIX–yield curve cycles. Line shade (color in online version) indicates the time dimension; dates are superimposed for guidance on the time dimension of the data. The data are at the daily frequency smoothed with a two-year moving average.

three-month Treasury bill rate. The figure is divided into separate charts for each business cycle in the sample. The charts show that the business cycle traces a counter-clockwise movement through the VIX–yield curve cycle. Recessions occur in the lower-right corner, i.e., when yield curve spreads are low and the level of the VIX index is high.

VIX–yield curve cycles express the relationship between the monetary policy decisions of the Federal Reserve (Fed) and financial markets. During periods of recession, the Fed eases monetary policy to support the economy. The resulting decline in the short-term rate causes the yield curve to steepen. Note that this period can be associated with the VIX index declining (as in 1991–1993), remaining nearly constant (as in 2000–2003), or increasing (as in 2007–2009 and 2020). A recovering economy is associated with less fear among investors, and this period is thus characterized by a low value of the VIX index. Following a prolonged expansionary period, the Fed begins to taper the monetary-policy accommodation, which flattens the yield curve. Combined with increasingly pessimistic expectations of the future state of the economy, the yield curve becomes extremely flat, often with a negative spread by the late expansion. These so-called yield curve inversions are well-known signals of impending recession risk. Market expectations of near-term downturns in the business cycle are also reflected in the stock market, where fear and correction increase the VIX index. Eventually, the economy enters a new recession and begins a new cycle.

2.1. VIX–yield curve cycle indicators

This section discusses how VIX–yield curve cycles can be summarized by measures that can be used as inputs in a model for recession prediction. The model is described in Section 3.1.

An immediate approach is to use the VIX index and the yield curve spread as separate measures and let the data determine their relative weights, guided by the chosen model and estimation method. One can also include their product to capture the interaction between the VIX index and the spread, which seems to be important based on the charts of the VIX–yield curve cycles in Fig. 1. However, a single measure that functions as a leading recession indicator is easier to monitor and interpret than multiple measures and may therefore be preferred by policymakers and investors. I therefore consider various methods for constructing a measure of the economy's location on the VIX–yield curve cycle.

Let $S_t = R_t - r_t$ denote the spread between the long-term interest rate, R_t, and short-term interest rate, r_t, and let V_t be the level of the VIX index. Let $\tilde{S}_t$ and $\tilde{V}_t$ denote their two-year moving averages, which are applied to the data to illustrate the VIX–yield curve cycles in Fig. 1. First, I note from the charts in Fig. 1 that past recessions occurred at times where the tangent line from the origin to the VIX–yield curve cycle is flat with the lowest spread during the entire business cycle. One way to summarize this characteristic is to consider the slope of the tangent line, given by

$$\theta_t = \frac{\tilde{S}_t}{\tilde{V}_t}. \tag{1}$$

Note that this cycle indicator is identical to the tangent function of the angle from the origin to $(\tilde{V}_t, \tilde{S}_t)$ in a polar coordinate system: $\theta_t = \tan(\phi_t)$. Since the tangent function is approximately linear for small but positive angles, this transformation does not have an impact on the predictive power. I therefore do not consider a cycle measure defined by the angle ϕ_t.

Since every business cycle is different, better results may be achieved by standardizing the data over a rolling window before computing a VIX–yield curve cycle indicator. I therefore consider the following indicator based on (1):

$$\theta_t^{(z)} = \frac{z(\tilde{S}_t, \tau)}{z(\tilde{V}_t, \tau)}. \tag{2}$$

where the function $z(\cdot, \tau)$ standardizes the data using the mean and standard deviation over a rolling window of τ years. As a baseline specification, I use $\tau = 8$ years, which is the length of a typical business cycle.[3]

Finally, there exist more sophisticated methods to analyze circular or elliptical relationships between data series. I exploit such methods for constructing a cycle indicator by fitting an ellipse to the $(\tilde{V}_t, \tilde{S}_t)$-observations using the following parameters: (i) the center coordinates of the ellipse, (ii) the distances from the center to the perimeter along both axes, and (iii) the tilt angle of the ellipse. Then, I construct a cycle indicator by using the estimated center point to move the VIX–yield curve cycles to the origin of the coordinate system. Letting $\widehat{V_0}$ and $\widehat{S_0}$ denote the estimated center points, I define a cycle indicator by

$$\theta_t^{(0)} = \frac{\tilde{S}_t - \widehat{S_0}}{\tilde{V}_t - \widehat{V_0}}. \tag{3}$$

A useful analogy for interpreting $\theta_t^{(0)}$ is to think of the fitted ellipse as an analog clock with hands given by the implied angle. Rather than time, the direction of the hands thus measures the state of the economy.

The choice of VIX–yield curve cycle indicator ultimately comes down to which measure performs best in terms of predicting recessions. The next section presents the recession prediction framework and the measures used to evaluate model performance. Then, I evaluate the performance of the proposed VIX–yield curve cycle indicators.

[3] I tested specifications with both shorter and longer windows. The results were very similar across different choices of τ.

3. Method

3.1. Model

Let Y_t be a binary variable that is equal to one when the economy is in a recession at time t, and zero otherwise. The objective is to predict the probability that the H-step-ahead economy is in a recession, $Y_{t+H} = 1$, given a set of predictors X_t. Following the literature on recession prediction, consider the following probit model:

$$\Pr(Y_{t+H} = 1|X_t) = \Phi\left(\beta_0 + \beta_1' X_t\right), \tag{4}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. I consider three forecasting horizons: $H = \{6, 12, 18\}$ months.

3.2. Performance evaluation methods

Model performance is evaluated by (i) the fit of the probit model summarized by information criteria and adjusted R-squared values, and (ii) the ability of the model to classify the predicted value of Y_{t+H} correctly. For the assessment of classification ability, I use ROC curves to analyze the tradeoff between the rate of true positives to the rate of false positives for various probability thresholds. A model exhibits better classification performance the closer the associated ROC curve is to the upper-left corner with a high rate of true positives and low false-positive rate. A random guess results in an ROC curve along the 45-degree line. Integrating the area under the ROC (AUROC) curve yields a statistic of classification performance. An AUROC equal to one represents perfect classification ability, whereas values below 0.5 represent an ability worse than a random guess. A detailed description of the construction of ROC curves and AUROC statistics is given in Liu and Moench (2016). To draw inferences about the AUROC and the adjusted R-squared values, I use the block bootstrap method in Politis and Romano (1994), using the estimator of optimal block size proposed by Politis and White (2004).

3.3. Data

I consider monthly data for the analysis. Let the business cycle dates of the NBER define the recession variable, Y_t. The remaining data sources are selected to obtain the longest data sample possible. Since the VIX index is only available beginning in 1990, I proxy the VIX using realized volatility, computed as the monthly sum of squared daily S&P 500 index returns. The return data are sourced from Bloomberg. The VIX index and the realized volatility of the S&P 500 are highly correlated; see Fig. 2. As is well known, realized volatility is lower than the VIX index, due to the variance risk premium (Carr & Wu, 2009). I conjecture that this difference is unlikely to impact the cyclical relationship, with the yield curve spread documented for the VIX index in Section 2.

To compute the yield curve spread, I use the three-month Treasury bill rate from FRED available from 1934. Prior to 1934, I proxy the three-month yield with the

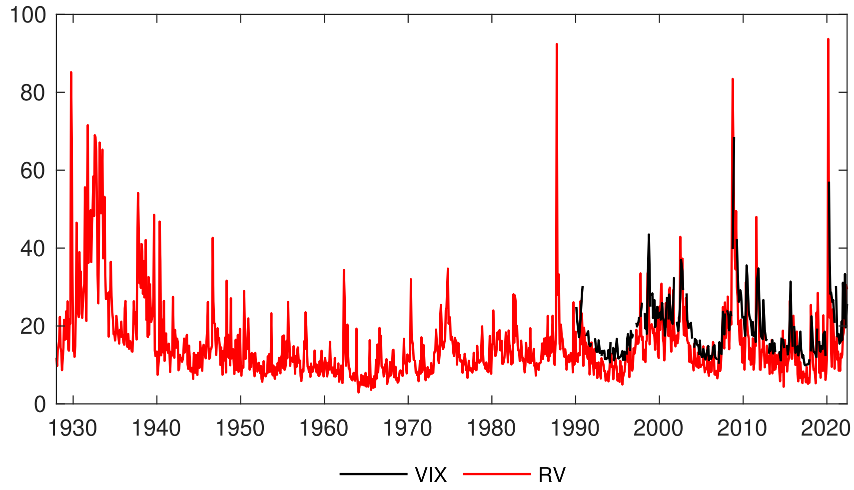

Fig. 2. VIX index and realized volatility. The data are plotted at the monthly frequency. Realized volatility (RV) is computed by the summation of squared daily S&P 500 index returns.

NBER measure of yields on short-term U.S. securities.[4] The yield on 10-year U.S. Treasury bonds is available from 1900 from the website of the European Central Bank.[5] These data choices yield a sample from February 1929 to June 2022.

Fig. 3 shows the yield curve spread, realized volatility, their interaction, and the proposed cycle indicators from Section 2.1 along with NBER recession periods. The cycle indicators $\theta_t^{(z)}$ and $\theta_t^{(0)}$ are winsorized at the 10th and 90th percentiles. Based on these charts, the cycle indicators θ_t and $\theta_t^{(0)}$ are promising for the purpose of forecasting recessions. Specifically, θ_t dips prior to a recession, reflecting a flattening yield curve and increasing levels of the VIX index; cf. Fig. 1. In contrast, $\theta_t^{(0)}$ peaks immediately before recessions but maintains a persistent pattern over the business cycle, with exception of the first part of the sample. It is, however, unclear from these charts whether these cycle indicators outperform the yield curve spread at predicting recessions. The cycle indicator $\theta_t^{(z)}$ does not exhibit a clear pattern over the business cycle and thus does not hold much promise for predicting recessions.

The figure also reveals that the spread only shows a persistent pattern over the business cycle after the Second World War. I therefore restrict the sample to the post-war period, starting in January 1950.

4. Results

This section presents the main results. First, I test the cycle indicators proposed in Section 2.1, benchmarking against the yield curve spread alone and then against multivariate models with both the spread and volatility. Based on these results, I select an approach for summarizing VIX–yield curve cycles and test this against other well-known predictors from the literature.

4.1. The performance of VIX–yield curve cycles

Tables 1–3 show the in-sample performance at the six-, 12-, and 18-month forecasting horizons for the benchmark model using the yield curve spread (1); the multivariate models using both the spread and volatility (2) and their interaction (3); and the proposed cycle measures θ_t (4), $\theta_t^{(z)}$ (5), and $\theta_t^{(0)}$ (6). Since the cycle measures are constructed based on smoothed data, I also compare the results to models using the smoothed spread (7) and the smoothed spread and smoothed volatility (8).

For forecasting horizons up to 12 months, recession prediction is significantly improved by considering volatility alongside the yield curve spread. In Table 2 for $H = 12$, the AUROC value is significantly higher for models (2) and (3) than for the benchmark using the spread alone (1). The adjusted R-squared values are, however, statistically indistinguishable. In Table 1 for $H = 6$, there are significant differences for both adjusted R-squared and AUROC values. Summarizing S_t and V_t in a single measure by θ_t in (4) generates performance measures that are similar to and statistically indistinguishable from the model that includes S_t and V_t as separate predictors in (2). Recession prediction is thus not improved by letting the probit model determine the coefficients on the spread and volatility separately. It does, however, matter how the spread and volatility are combined. The cycle indicator computed after standardizing the data, $\theta_t^{(z)}$, performs either similarly to or significantly worse than the benchmark model using the spread alone. The cycle indicator computed from ellipse regression, $\theta_t^{(0)}$, predicts recession with precision similar to θ_t. Between θ_t and $\theta_t^{(0)}$, I argue that the former is preferred because it is easier to compute.

For the 18-month forecasting horizon (see Table 3), there is no significant improvement from including

[4] U.S. Yields On Short-Term United States Securities, Three–Six Month Treasury Notes and Certificates, Three Month Treasury. NBER indicator: m13029a.

[5] These data values are similar to the 10-year U.S. Treasury bond yield from FRED. Retrieving these data directly from FRED, however, only allowed me to extend the sample back to 1953.

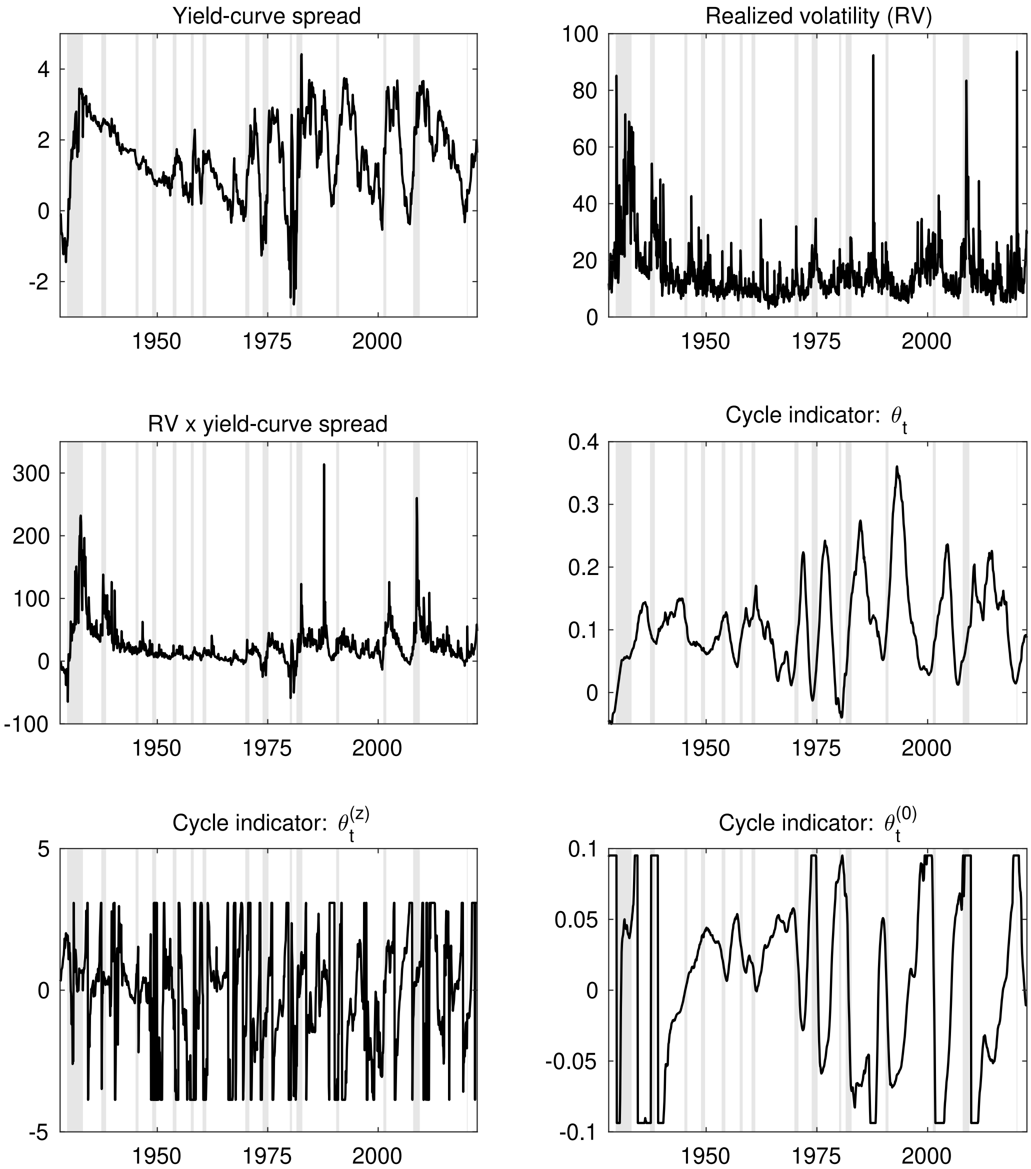

Fig. 3. Cycle indicators, realized volatility, and the yield curve spread. $\theta_t^{(z)}$ and $\theta_t^{(0)}$ are winsorized at the 10th and 90th percentiles. Shaded areas are NBER recessions.

volatility as a separate predictor compared with the model using the spread. But the cycle measure θ_t outperforms the spread alone in terms of classification ability.

Across all horizons, likelihood ratio tests reject at all significance levels that the goodness of fit of model (1) using only the spread is identical to that of model (2) using both the spread and volatility. Also, the interaction term S_tV_t is insignificant, and the fit and classification performance measures are identical to those of model (2).

In sum, these results show that the cycle indicator, θ_t, outperforms the other considered predictors in predicting recessions six to 18 months ahead. Regressions (7) and (8) in Tables 1–3 show that this result cannot be attributed to data smoothing. Across all horizons, using the smoothed spread and volatility does not generate statistically higher AUROC or adjusted R-squared values compared with the non-smoothed data in (1) and (2).

I also examine out-of-sample performance by re-estimating the probit models over an expanding window starting from January 1950 to January 1975. This choice gives a long sample of data to estimate the probit models, and at the same time leaves six out-of-sample recessions. Table 4 shows that the conclusions based on in-sample results hold out-of-sample as well. Including volatility is beneficial for predicting recessions at short horizons, and volatility can be included in a single measure by the cycle indicator θ_t without loss of classification ability. At long forecasting horizons, θ_t outperforms the yield curve spread even though including the spread and volatility separately does not yield AUROC values that are statistically higher than those of the yield curve spread.

Table 1
In-sample probit model estimation results at the six-month-ahead horizon.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	−0.43*** (0.07)	−0.99*** (0.11)	−1.01*** (0.18)	−0.05 (0.09)	−0.86*** (0.05)	−1.02*** (0.06)	−0.28*** (0.09)	−1.53*** (0.17)
S_t	−0.35*** (0.05)	−0.42*** (0.05)	−0.41*** (0.10)					
V_t		0.04*** (0.01)	0.05*** (0.01)					
$S_t V_t$			−0.001 (0.01)					
θ_t				−8.92*** (0.7.83)				
$\theta_t^{(z)}$					−0.002 (0.001)			
$\theta_t^{(0)}$						6.26*** (0.33)		
$\tilde{S}_t$							−0.47*** (0.06)	−0.65*** (0.07)
$\tilde{V}_t$								0.10*** (0.01)
Log-lik.	−394.47	−366.10	−366.09	−368.93	−424.89	−378.05	−393.61	−350.79
AIC	792.94	738.19	740.7	741.86	853.78	760.09	791.22	707.57
BIC	802.46	752.47	759.21	751.38	863.30	769.61	800.74	684.46
Adj. R^2	0.08 [0.03, 0.14]	0.15 [0.08, 0.21]	0.14 [0.08, 0.21]	0.11 [0.06, 0.16]	0.00 [−0.07, 0.07]	0.12 [0.11, 0.13]	0.07 [0.02, 0.11]	0.17 [0.10, 0.24]
AUROC	0.68 [0.62, 0.74]	0.75 [0.70, 0.80]	0.75 [0.70, 0.80]	0.74 [0.69, 0.79]	0.65 [0.60, 0.70]	0.76 [0.60, 0.91]	0.68 [0.62, 0.74]	0.78 [0.72, 0.83]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1950 to June 2022.

Table 2
In-sample probit model estimation results at the 12-month-ahead horizon.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.10 (0.07)	−0.40*** (0.11)	−0.27 (0.17)	0.61*** (0.10)	−0.60*** (0.05)	−0.79*** (0.06)	0.33*** (0.09)	−0.93*** (0.16)
S_t	−0.57*** (0.05)	−0.65*** (0.06)	−0.73*** (0.10)					
V_t		0.04*** (0.01)	0.03 (0.01)					
$S_t V_t$			0.01 (0.01)					
θ_t				−13.41*** (1.06)				
$\theta_t^{(z)}$					0.0001 (0.002)			
$\theta_t^{(0)}$						7.91*** (0.84)		
$\tilde{S}_t$							−0.76*** (0.07)	−1.00*** (0.08)
$\tilde{V}_t$								0.11*** (0.01)
Log-lik.	−422.56	−396.79	−396.28	−383.07	−502.43	−425.08	−418.14	−369.61
AIC	849.12	799.59	800.56	770.14	1008.97	854.16	840.29	745.22
BIC	858.63	813.85	819.57	779.64	1018.49	863.66	849.80	745.66
Adj. R^2	0.20 [0.11, 0.28]	0.24 [0.16, 0.32]	0.24 [0.16, 0.32]	0.24 [0.16, 0.32]	−0.001 [−0.09, 0.09]	0.20 [0.19, 0.21]	0.18 [0.11, 0.25]	0.27 [0.19, 0.36]
AUROC	0.76 [0.72, 0.81]	0.80 [0.76, 0.84]	0.80 [0.76, 0.84]	0.81 [0.77, 0.85]	0.45 [0.41, 0.48]	0.82 [0.72, 0.91]	0.76 [0.72, 0.81]	0.83 [0.79, 0.87]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1950 to June 2022.

Table 3
In-sample probit model estimation results at the 18-month-ahead horizon.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.47*** (0.08)	0.04 (0.11)	0.26 (0.17)	1.06*** (0.11)	−0.39*** (0.04)	−0.57*** (0.05)	0.78*** (0.09)	0.35* (0.16)
S_t	−0.68*** (0.05)	−0.75*** (0.06)	−0.88*** (0.10)					
V_t		0.04*** (0.01)	0.02* (0.01)					
S_tV_t			0.01 (0.01)					
θ_t				−15.42*** (1.08)				
$\theta_t^{(z)}$					−0.0004 (0.002)			
$\theta_t^{(0)}$						8.77*** (0.84)		
$\tilde{S}_t$							−0.94*** (0.07)	−1.18*** (0.08)
$\tilde{V}_t$								0.11*** (0.01)
Log-lik.	−437.71	−417.57	−416.27	−388.92	−549.17	−451.79	−420.89	−378.50
AIC	879.43	841.13	840.53	781.84	1102.37	907.58	845.78	763.00
BIC	888.92	855.37	859.52	791.33	1111.80	917.07	855.27	777.24
Adj. R^2	0.25 [0.18, 0.32]	0.28 [0.21, 0.35]	0.28 [0.21, 0.36]	0.31 [0.23, 0.39]	−0.001 [−0.07, 0.07]	0.26 [0.25, 0.27]	0.27 [0.19, 0.34]	0.33 [0.25, 0.41]
AUROC	0.80 [0.76, 0.83]	0.81 [0.77, 0.85]	0.82 [0.78, 0.85]	0.84 [0.80, 0.88]	0.47 [0.43, 0.51]	0.84 [0.76, 0.92]	0.81 [0.77, 0.85]	0.85 [0.81, 0.88]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1950 to June 2022.

Table 4
Out-of-sample AUROC values.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predictors:	S_t	$S_t + V_t$	$S_t + V_t + V_tS_t$	θ_t	$\theta_t^{(z)}$	$\theta_t^{(0)}$	$\tilde{S}_t$	$\tilde{S}_t + \tilde{V}_t$
$H = 6$	0.67 [0.62, 0.73]	0.76 [0.71, 0.81]	0.76 [0.71, 0.81]	0.74 [0.70, 0.79]	0.63 [0.57, 0.68]	0.76 [0.58, 0.93]	0.68 [0.63, 0.73]	0.79 [0.74, 0.83]
$H = 12$	0.76 [0.71, 0.81]	0.80 [0.76, 0.84]	0.80 [0.76, 0.84]	0.82 [0.78, 0.85]	0.59 [0.55, 0.62]	0.82 [0.72, 0.91]	0.77 [0.73, 0.81]	0.83 [0.79, 0.87]
$H = 18$	0.79 [0.75, 0.84]	0.82 [0.78, 0.87]	0.82 [0.78, 0.87]	0.85 [0.81, 0.89]	0.60 [0.56, 0.63]	0.84 [0.78, 0.90]	0.81 [0.78, 0.85]	0.85 [0.82, 0.89]

Notes: Out-of-sample forecasts are obtained by re-estimating probit models (1)–(8) from Tables 1–3 over an expanding window starting from January 1950 to January 1975. The expanding window stops in June 2022. Bootstrapped 0.90 confidence bands in brackets.

4.2. Comparing the cycle indicator with other predictors

This section tests the performance of the cycle indicator θ_t against other predictors suggested in the literature. Specifically, I use the six-month lagged spread (S_{t-6}) and the annual return on the S&P 500 index, as in Liu and Moench (2016). I also test against the federal funds rate (FFR), as in Wright (2006), and a leading economic indicator =, as in Levanon et al. (2015). Specifically, I use the composite leading indicator (CLI) from the OECD. Finally, I use a measure of output, namely the three-month moving average of the Chicago Fed National Activity Index (CFNAI), which is available at the monthly frequency. These data are not available for the long sample of data considered so far. Instead, I use the longest sample possible, which spans from May 1967 to June 2022.

Tables 5–7 show the in-sample results for the univariate probit models using these various predictors in columns (2)–(6) along with those of the cycle indicator in column (1).

At the shortest forecasting horizon, $H = 6$, the performance of the cycle indicator is comparable to the lagged spread, the S&P 500 index return, the CLI, and the output measure CFNAI. The lagged spread also performs similarly to the cycle indicator in forecasting recessions 12 months ahead, but the cycle indicator achieves the lowest information criteria. Finally, at the 18-month horizon, none of the predictors significantly outperforms the cycle indicator in terms of AUROC values. The cycle indicator also obtains the lowest information criteria, but the adjusted R-squared value is not statistically distinguishable from that using the lagged spread.

Columns (7)–(11) in the tables show the results for multivariate probit models using the cycle indicator along with the alternative predictors. Combining the alternative predictors with the cycle indicator significantly improves

Table 5
In-sample estimation results at the six-month-ahead horizon.

	Univariate models						Multivariate models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	0.14 (0.10)	−0.02 (0.09)	−0.72*** (0.06)	−1.67*** (0.11)	45.23*** (4.23)	−0.98*** (0.06)	0.11 (0.11)	0.49*** (0.13)	−0.60*** (0.17)	49.73*** (5.61)	−0.02 (0.11)
θ_t	−11.59*** (1.45)						−3.39** (1.62)	−15.30*** (1.78)	−9.38*** (1.16)	−14.37*** (1.56)	−10.94*** (1.31)
s_{t-6}		−0.75 (0.07)					−0.61*** (0.10)				
S&P 500			−5.01*** (0.46)					−6.01*** (0.61)			
FFR				0.13*** (0.02)					0.09*** (0.02)		
CLI					−0.46*** (0.05)					−0.50*** (0.06)	
CFNAI						−0.77*** (0.11)					−0.37*** (0.13)
Log-lik.	−245.84	−224.16	−239.60	−274.05	−260.76	−269.72	−221.88	−168.66	−229.32	−189.55	−218.34
AIC	495.68	452.32	483.19	552.09	525.51	543.45	449.77	343.32	464.64	385.10	442.69
BIC	504.66	461.30	492.16	561.06	534.48	552.42	463.23	356.78	478.10	398.56	456.15
Adj. R^2	0.19 [0.11, 0.26]	0.34 [0.23, 0.44]	0.27 [0.17, 0.38]	0.17 [0.08, 0.27]	0.23 [0.12, 0.34]	0.22 [0.04, 0.40]	0.32 [0.21, 0.43]	0.47 [0.38, 0.57]	0.26 [0.16, 0.37]	0.42 [0.29, 0.55]	0.29 [0.09, 0.49]
AUROC	0.82 [0.77, 0.86]	0.86 [0.81, 0.91]	0.82 [0.76, 0.87]	0.74 [0.67, 0.81]	0.79 [0.72, 0.86]	0.87 [0.82, 0.92]	0.87 [0.82, 0.91]	0.93 [0.90, 0.95]	0.85 [0.80, 0.89]	0.92 [0.89, 0.95]	0.89 [0.85, 0.93]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from May 1967 to June 2022.

Table 6
In-sample estimation results at the 12-month-ahead horizon.

	Univariate models						Multivariate models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	0.91*** (0.12)	0.49*** (0.10)	−0.44*** (0.06)	−1.57*** (0.11)	26.46*** (4.07)	−0.67*** (0.05)	0.91*** (0.12)	1.36*** (0.15)	0.02 (0.18)	33.10*** (5.21)	0.85*** (0.12)
θ_t	−17.81*** (1.43)						−11.83*** (1.82)	−22.26*** (2.01)	−16.15*** (1.51)	−20.52*** (5.21)	−18.12*** (1.47)
s_{t-6}		−0.89*** (0.07)					−0.43*** (0.09)				
S&P 500			−0.44*** (0.39)					−4.92*** (0.56)			
FFR				0.16*** (0.02)					0.13*** (0.02)		
CLI					−0.47*** (0.04)					−0.32*** (0.05)	
CFNAI						−0.59*** (0.10)					−0.56*** (0.10)
Log-lik.	−229.77	−243.62	−323.72	−311.30	−351.13	−344.28	−218.22	−176.59	−206.24	−203.13	−213.57
AIC	463.53	491.25	651.45	626.61	706.27	692.57	442.44	359.17	418.48	412.26	433.15
BIC	472.48	500.20	660.40	635.56	715.22	701.52	455.87	372.60	431.91	425.69	446.58
Adj. R^2	0.39 [0.29, 0.49]	0.41 [0.31, 0.51]	0.17 [0.13, 0.20]	0.21 [0.13, 0.29]	0.10 [0.09, 0.11]	0.14 [0.12, 0.16]	0.44 [0.33, 0.54]	0.56 [0.45, 0.66]	0.46 [0.34, 0.57]	0.49 [0.39, 0.59]	0.50 [0.40, 0.61]
AUROC	0.89 [0.86, 0.92]	0.88 [0.84, 0.92]	0.74 [0.67, 0.80]	0.76 [0.70, 0.82]	0.68 [0.61, 0.75]	0.77 [0.69, 0.86]	0.91 [0.88, 0.93]	0.94 [0.91, 0.97]	0.91 [0.88, 0.94]	0.92 [0.89, 0.95]	0.93 [0.90, 0.96]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from May 1967 to June 2022.

the AUROC and adjusted R-squared values over the univariate models without the cycle indicator for all predictors at horizons $H = 12$ and $H = 18$. Thus, the cycle indicator improves the performance of other predictors when combined in multivariate models. The same result holds for all but the lagged spread and CFNAI at $H = 6$. Furthermore, at $H = 18$, none of the multivariate models outperforms the univariate model using the cycle indicator with respect to their AUROC and adjusted R-squared values. Finally, it is noteworthy that both the S&P 500 return and the cycle indicator are significant when combined in a multivariate model for all horizons. The stock market return therefore does not erode the predictive power of the combined measure of monetary policy and stock market volatility.

I repeat the analysis out-of-sample using an initial estimation window from May 1967 to December 1997; see the resulting AUROC values in Table 8. These results are similar to those obtained by the in-sample analysis. In sum, the cycle indicator has strong predictive power for future recessions at all considered horizons, and the cycle indicator remains significant when combined with other well-known predictors.

5. Robustness and extensions

5.1. Implied bond market volatility and economic policy uncertainty

The cyclical relationship between the VIX index and the yield curve spread is not unique. For instance, the yield curve spread also co-moves in circles with the EPU index from (Baker et al., 2016) and the MOVE index. These cycles are shown in Fig. 4 along with the VIX–yield curve cycles. The volatility and uncertainty measures

Table 7
In-sample estimation results at the 18-month-ahead horizon.

	Univariate models						Multivariate models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	1.48*** (0.13)	0.82*** (0.10)	−0.25*** (0.06)	−1.36*** (0.10)	12.85*** (3.76)	−0.45*** (0.05)	0.91*** (0.12)	1.36*** (0.15)	0.02 (0.18)	33.10*** (5.21)	1.43*** (0.13)
θ_t	−20.68*** (1.50)						−11.83*** (1.82)	−22.26*** (2.01)	−16.15*** (1.51)	−20.52*** (1.74)	−20.51*** (1.52)
S_{t-6}		−0.90*** (0.06)					−0.43*** (0.09)				
S&P 500			−3.12*** (0.37)					−4.92*** (0.56)			
FFR				0.17*** (0.02)					0.13*** (0.02)		
CLI					−0.13*** (0.04)					−0.32*** (0.05)	
CFNAI						−0.48*** (0.10)					−0.28*** (0.10)
Log-lik.	−216.07	−266.60	−370.91	−341.76	−404.14	−388.88	−218.22	−176.59	−206.24	−203.13	−209.01
AIC	436.13	537.20	745.83	687.51	812.27	781.76	442.44	359.17	418.48	412.26	424.02
BIC	445.07	546.14	754.76	696.45	821.21	790.69	455.87	372.60	431.91	425.69	437.42
Adj. R^2	0.50 [0.41, 0.60]	0.41 [0.34, 0.48]	0.12 [0.11, 0.12]	0.20 [0.13, 0.27]	0.58 [0.50, 0.65]	0.09 [0.08, 0.10]	0.44 [0.33, 0.54]	0.56 [0.45, 0.66]	0.46 [0.34, 0.57]	0.49 [0.39, 0.59]	0.55 [0.45, 0.65]
AUROC	0.92 [0.89, 0.95]	0.87 [0.82, 0.92]	0.70 [0.63, 0.76]	0.83 [0.73, 0.93]	0.58 [0.50, 0.65]	0.71 [0.65, 0.77]	0.91 [0.88, 0.93]	0.94 [0.91, 0.97]	0.91 [0.88, 0.94]	0.92 [0.89, 0.95]	0.93 [0.90, 0.96]

Notes: Standard errors in parentheses. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from May 1967 to June 2022.

Table 8
Out-of-sample AUROC values.

Panel A: Univariate models						
Predictors:	(1) θ_t	(2) S_{t-6}	(3) S&P 500	(4) FFR	(5) CLI	(6) CFNAI
$H = 6$	0.82 [0.77, 0.87]	0.86 [0.83, 0.89]	0.75 [0.67, 0.83]	0.79 [0.71, 0.87]	0.71 [0.62, 0.80]	0.77 [0.70, 0.83]
$H = 12$	0.89 [0.84, 0.93]	0.84 [0.78, 0.90]	0.68 [0.62, 0.74]	0.79 [0.73, 0.85]	0.55 [0.47, 0.63]	0.68 [0.61, 0.75]
$H = 18$	0.91 [0.84, 0.98]	0.83 [0.76, 0.90]	0.66 [0.60, 0.72]	0.75 [0.68, 0.82]	0.60 [0.52, 0.67]	0.58 [0.50, 0.66]
Panel B: Multivariate models						
Predictors:	(7) θ_t	(8) S_{t-6}	(9) S&P 500	(10) FFR	(11) CLI	(12) CFNAI
$H = 6$	0.83 [0.77, 0.88]	0.88 [0.85, 0.90]	0.91 [0.89, 0.94]	0.89 [0.85, 0.94]	0.89 [0.85, 0.94]	0.89 [0.80, 0.96]
$H = 12$	0.89 [0.85, 0.93]	0.90 [0.86, 0.93]	0.93 [0.89, 0.96]	0.94 [0.91, 0.97]	0.89 [0.86, 0.92]	0.91 [0.87, 0.94]
$H = 18$	0.91 [0.84, 0.99]	0.92 [0.85, 0.98]	0.93 [0.86, 1.00]	0.93 [0.86, 0.99]	0.93 [0.86, 0.99]	0.92 [0.88, 0.96]

Notes: Out-of-sample forecasts are obtained by re-estimating the probit models (1)–(11) from Tables 5–7 over an expanding window starting from May 1967 to December 1997. The expanding window stops in June 2022. Bootstrapped 0.90 confidence bands in brackets.

are standardized to make the cycles comparable. Note that the VIX– and MOVE–yield curve cycles are generally very similar, whereas the EPU–yield curve cycle stands out. In fact, for 2007–2019, it is debatable whether the scatter plot between the EPU index and the spread forms a counterclockwise cycle. This observation may reflect that the VIX and MOVE indices are measures of volatility in financial markets, whereas the EPU index is a measure of uncertainty about monetary policy.

This section examines the predictive power of cycle indicators constructed using the MOVE and EPU indices:

$$\theta_t^{\text{MOVE}} = \frac{\tilde{S}_t}{\text{MOVE}_t}, \tag{5}$$

$$\theta_t^{\text{EPU}} = \frac{\tilde{S}_t}{\text{EPU}_t}. \tag{6}$$

Due to the limited data availability of the MOVE index, I conduct this analysis using a sample starting in January 1990.

Measures of the model fit and classification ability of these cycle indicators benchmarked against the yield curve spread are shown in Table 9. There are no significant differences between the performance of the cycle indicators computed based on realized volatility and the MOVE index. Also, these models significantly outperform the spread across all forecasting horizons. In contrast, θ_t^{EPU} obtains lower AUROC and adjusted R-squared values that are indistinguishable from those obtained by the spread. These results demonstrate that it is the interaction between monetary policy and financial volatility, rather than policy uncertainty, that holds predictive power for future recessions.

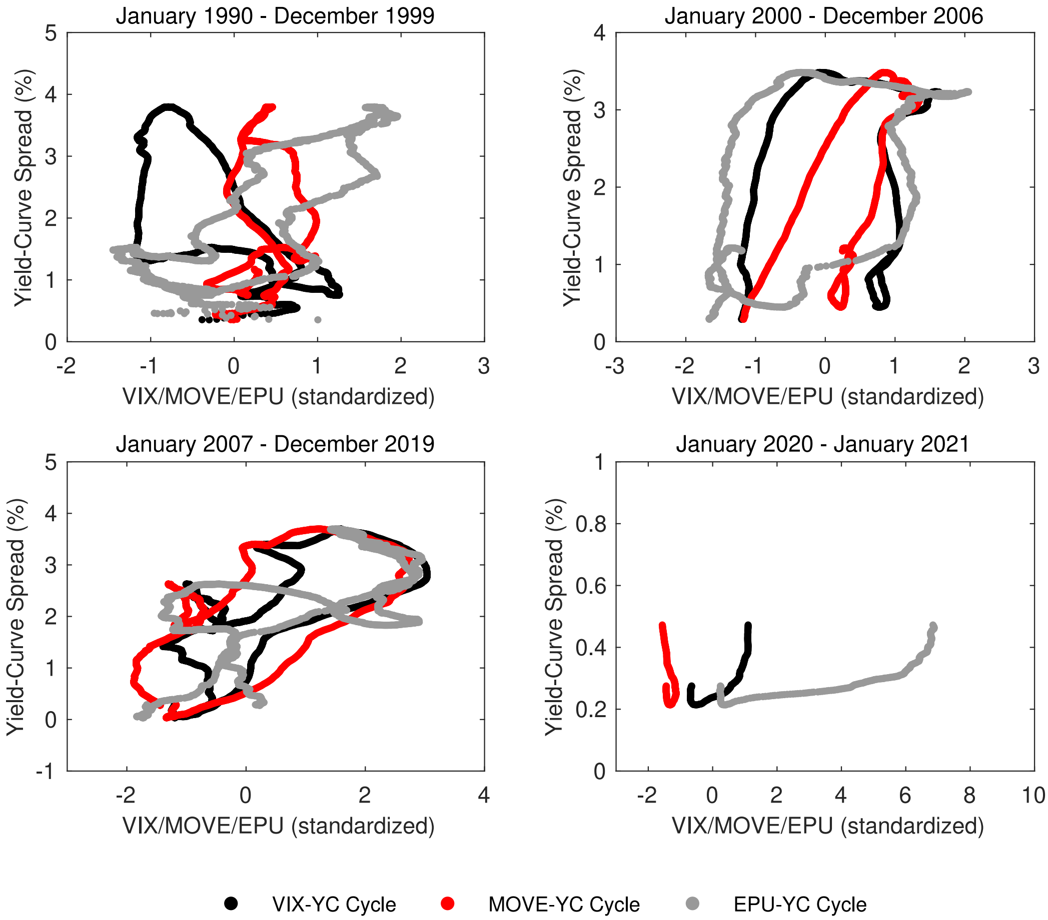

Fig. 4. VIX–, MOVE–, and EPU–yield curve cycles. Cycles using the VIX, MOVE, and EPU indices. The data are at the daily frequency smoothed with a two-year moving average. The VIX, MOVE, and EPU indices are standardized.

5.2. Dynamic probit model

(Kauppi & Saikkonen, 2008) and Nyberg (2010) propose a dynamic probit model, which accounts for autocorrelation in the recession variable Y_t. The dynamic extension of the probit model in (4) is given by

$$\Pr\left(Y_{t+H}=1|X_t,Y_t\right)=\Phi\left(\beta_0+\beta_1'X_t+\beta_2Y_t\right). \tag{7}$$

Table 10 reports measures of model fit and AUROC values using dynamic probit models. The table confirms the results shown in the static probit models, i.e., that the cycle indicator outperforms the yield curve spread at forecasting recessions at all horizons in dynamic models as well.

5.3. Accounting for unconventional monetary policy

Next, I address the concern that the conduct of unconventional monetary policy and the associated flattening of the yield curve may erode the predictive power of the cycle indicator. To examine the impact of unconventional monetary policy, I use the shadow rate from (Wu & Xia, 2016) to construct an adjusted yield curve spread. The shadow rate is defined such that the short rate is $r_t = \max(0, s_t)$. When $s_t > 0$, $r_t = s_t$ and the yield curve spread is not affected by using the shadow rate. In contrast, when the short rate is at the zero-lower bound, the shadow rate is negative, reflecting the degree of unconventional monetary policy accommodation.

I construct the cycle indicator using the shadow rate:

$$\theta_t^{\text{shadow}}=\frac{\tilde{S}_t^{\text{shadow}}}{\tilde{V}_t}, \tag{8}$$

where $S_t^{\text{shadow}} = R_t - s_t$, and $\tilde{S}_t^{\text{shadow}}$ is the two-year moving average of S_t^{shadow}. The shadow rate is only available for January 1990 to February 2022. Table 11 shows the forecasting results over this sample for the probit models using S_t^{shadow} and θ_t^{shadow}. The table shows that the cycle indicator continues to outperform the yield curve spread when adjusting for unconventional monetary policy. Furthermore, using the shadow rate barely changes the AUROC values compared to the results obtained over a similar sample without the adjustment for unconventional monetary policy; cf. Table 9.

5.4. International evidence

Finally, I examine the broader performance of the cycle indicator by considering foreign markets. This section

Table 9
In-sample results for EPU– and MOVE–yield curve cycle indicators.

Regressors:	S_t	θ_t	θ_t^{MOVE}	θ_t^{EPU}
Horizon: 6 months				
AIC	312.59	269.08	280.57	289.50
BIC	320.49	276.98	288.48	297.40
Adj. R^2	0.02	0.09	0.07	0.05
	[−0.02, 0.06]	[0.03, 0.15]	[0.01, 0.12]	[0.00, 0.19]
AUROC	0.63	0.77	0.75	0.72
	[0.53, 0.72]	[0.71, 0.83]	[0.69, 0.82]	[0.65, 0.79]
Horizon: 12 months				
AIC	334.12	271.92	286.29	301.26
BIC	341.99	279.79	294.16	309.13
Adj. R^2	0.14	0.23	0.21	0.17
	[−0.00, 0.28]	[0.12, 0.34]	[0.09, 0.32]	[0.08, 0.26]
AUROC	0.74	0.85	0.84	0.81
	[0.65, 0.83]	[0.80, 0.90]	[0.79, 0.88]	[0.75, 0.87]
Horizon: 18 months				
AIC	340.85	246.19	269.12	284.16
BIC	348.68	254.03	276.96	292.00
Adj. R^2	0.23	0.40	0.35	0.33
	[0.10, 0.36]	[0.27, 0.54]	[0.21, 0.50]	[0.20, 0.45]
AUROC	0.79	0.90	0.89	0.87
	[0.73, 0.86]	[0.87, 0.94]	[0.85, 0.92]	[0.83, 0.92]

Notes: Probit models are estimated with an intercept and one regressor given as indicated. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1990 to June 2022.

Table 10
In-sample results of dynamic probit models.

Horizon:	$H = 6$		$H = 12$		$H = 18$	
Regressor:	S_t	θ_t	S_t	θ_t	S_t	θ_t
AIC	468.57	429.21	457.36	395.75	481.03	387.59
BIC	490.84	451.48	479.59	417.97	503.20	409.76
Adj. R^2	0.28	0.30	0.43	0.49	0.46	0.56
	[0.19, 0.37]	[0.21, 0.40]	[0.33, 0.52]	[0.39, 0.59]	[0.36, 0.57]	[0.45, 0.66]
AUROC	0.83	0.85	0.86	0.88	0.84	0.87
	[0.81, 0.84]	[0.84, 0.87]	[0.84, 0.87]	[0.86, 0.90]	[0.82, 0.87]	[0.85, 0.90]

Notes: Probit models are estimated with an intercept, the lagged recession variable, and one additional regressor given as indicated. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1950 to June 2022.

Table 11
In-sample results using the shadow-rate yield curve spread.

Horizon:	$H = 6$		$H = 12$		$H = 18$	
Regressor:	S_t^{shadow}	θ_t^{shadow}	S_t^{shadow}	θ_t^{shadow}	S_t^{shadow}	θ_t^{shadow}
AIC	299.89	271.01	316.76	280.03	317.42	258.81
BIC	307.77	278.89	324.61	287.88	325.24	266.63
Adj. R^2	0.03	0.08	0.14	0.20	0.24	0.36
	[−0.00, 0.07]	[0.02, 0.13]	[0.01, 0.28]	[0.10, 0.31]	[0.10, 0.39]	[0.22, 0.51]
AUROC	0.67	0.76	0.77	0.83	0.82	0.89
	[0.59, 0.75]	[0.69, 0.82]	[0.70, 0.84]	[0.78, 0.88]	[0.77, 0.88]	[0.85, 0.93]

Notes: Probit models are estimated with an intercept and one regressor given as indicated. The yield curve spread is computed using the shadow rate from Wu and Xia (2016). Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1990 to February 2022.

Table 12
In-sample results for U.K.

Horizon:	$H = 6$		$H = 12$		$H = 18$	
Regressor:	S_t	θ_t	S_t	θ_t	S_t	θ_t
AIC	373.52	348.77	413.98	377.76	442.76	401.25
BIC	381.76	357.01	422.20	385.97	450.95	409.44
Adj. R^2	0.02	0.07	0.07	0.14	0.12	0.19
	[−0.04, 0.08]	[−0.01, 0.16]	[−0.04, 0.19]	[0.01, 0.28]	[−0.02, 0.26]	[0.03, 0.34]
AUROC	0.61	0.68	0.66	0.72	0.70	0.74
	[0.51, 0.72]	[0.59, 0.78]	[0.56, 0.76]	[0.63, 0.80]	[0.62, 0.77]	[0.66, 0.82]

Notes: Probit models are estimated with an intercept and one regressor given as indicated. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from January 1984 to June 2022.

Table 13
In-sample results for Germany.

Horizon:	$H = 6$		$H = 12$		$H = 18$	
Regressor:	S_t	θ_t	S_t	θ_t	S_t	θ_t
AIC	355.35	284.71	355.29	294.74	354.66	297.11
BIC	363.21	292.56	363.11	302.56	362.45	304.90
Adj. R^2	0.26	0.38	0.30	0.41	0.32	0.46
	[0.15, 0.37]	[0.27, 0.48]	[0.20, 0.41]	[0.30, 0.53]	[0.21, 0.44]	[0.34, 0.58]
AUROC	0.80	0.87	0.82	0.88	0.83	0.89
	[0.73, 0.87]	[0.83, 0.92]	[0.77, 0.88]	[0.84, 0.93]	[0.77, 0.89]	[0.83, 0.96]

Notes: Probit models are estimated with an intercept and one regressor given as indicated. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from September 1990 to June 2022.

Table 14
In-sample results for Japan.

Horizon:	$H = 6$		$H = 12$		$H = 18$	
Regressor:	S_t	θ_t	S_t	θ_t	S_t	θ_t
AIC	444.53	440.61	458.66	455.20	435.81	434.02
BIC	452.15	448.23	466.25	462.79	443.36	441.57
Adj. R^2	−0.00	0.01	−0.00	0.01	−0.00	0.01
	[−0.02, 0.01]	[−0.02, 0.03]	[−0.03, 0.02]	[−0.01, 0.02]	[−0.04, 0.04]	[−0.01, 0.02]
AUROC	0.52	0.56	0.49	0.56	0.51	0.56
	[0.46, 0.57]	[0.48, 0.63]	[0.43, 0.56]	[0.50, 0.62]	[0.43, 0.58]	[0.48, 0.64]

Notes: Probit models are estimated with an intercept and one regressor given as indicated. Bootstrapped 0.90 confidence bands in brackets. The data sample spans from February 1994 to June 2022.

specifically focuses on the U.K., Germany, and Japan. I construct cycle indicators, as in (1), using daily returns on the FTSE 100 index, DAX index, and Nikkei index, respectively. For the U.K., I use the 10-year minus 10-month U.K. government bond (gilt) yield spread computed from yields published by the Bank of England.[6] For Germany and Japan, I use the 10-year minus three-month spread computed from yields obtained from Bloomberg. The data samples are from January 1984 to June 2022 for the U.K., September 1990 to June 2022 for Germany, and February 1994 to June 2022 for Japan. Recession dates for the three economies are collected from the Economic Cycle Research Institute.

Performance measures of the cycle indicator and the spread are reported in Tables 12, 13, and 14, for the U.K., Germany, and Japan, respectively. For the U.K., the cycle indicator achieves lower information criteria, higher adjusted R-squared values, and higher AUROC values compared to the spread for all forecasting horizons. However, the confidence bands are wide, reflecting low precision in estimation, and it is therefore not possible to statistically distinguish the performance of the cycle indicator from that of the spread. For Germany, the cycle indicator achieves significantly higher adjusted R-squared and AUROC values than the spread for all horizons. Finally, the results for Japan show that the cycle indicator performs better than the spread, but none of the predictors are successful in the sense that their AUROC values are not significantly different from 0.5, i.e., the AUROC of a random guess. The difficulty of predicting Japanese recessions based on the yield curve has also been confirmed by the literature (Hasegawa & Fukuta, 2011; Hirata & Ueda, 1998).

These results provide preliminary evidence that volatility–yield curve cycles have predictive power for future recessions in some economies beyond the U.S. However, due to data limitations, it is difficult to establish

6 The three-month yield contains many missing data points at the monthly frequency. The 10-month maturity is the shortest maturity for which the data set has no missing monthly observations.

the robustness and significance of these results. I leave the further exploration of non-U.S. economies and the challenge of constructing a cycle indicator with a long history of data for future research.

6. Conclusion

The scatter plot between the VIX index and the yield curve spread reveals counterclockwise cycles that repeatedly align with the business cycle. This paper used this empirical observation to predict changes in the business cycle.

I constructed a cycle indicator that summarizes the economy's location on the VIX–yield curve cycle. The cycle indicator significantly outperformed the yield curve spread in predicting recessions from 1950–2022. This conclusion holds both in- and out-of-sample and in static and dynamic probit models. The cycle indicator also outperformed other leading indicators in predicting U.S. recessions. The predictive power comes from the interaction between monetary policy and corrections in financial markets, rather than the co-movement between monetary policy and policy uncertainty. Using shadow rates, I found no evidence that the predictive power of the cycle indicator has weakened with the flattened yield curve and the use of unconventional monetary policy.

The analysis of this paper focused solely on predictive power and did not consider causal effects. Indeed, it is highly likely that, rather than actually causing a recession, the combination of a flat yield curve and a high VIX index merely reflects that investors are incorporating the risk of a recession into market prices. Future research may focus on understanding the results of this paper in a structural model. Further work may also explore how to exploit the entire course of the VIX–yield curve cycle to predict other stages of the business cycle.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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