WILEY

RESEARCH ARTICLE

Term Spread Volatility as a Leading Indicator of Economic Activity

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ABSTRACT

In this paper, we examine the macroeconomic predictive power of the volatility of the US Treasury yield curve slope (term spread volatility). Our forecasting exercise shows that US term spread volatility has significant predictive power for US industrial production and employment growth. The predictive power of term spread volatility is stronger at medium- and long-term forecasting horizons and remains robust when well-established predictors of economic activity, such as the term spread and stock market returns, are included. Our results also show that term spread volatility has statistically and economically distinct predictive power compared to other measures of economic uncertainty. Moreover, the predictive power of term spread volatility increases significantly after the 2008 Great Recession, indicating that the relationship between uncertainty about macroeconomic expectations and macroeconomic performance has strengthened in the post–Great Recession period. Finally, our out-of-sample forecasting results show that term spread volatility outperforms the term spread in forecasting economic activity over the longer term.

JEL Classification: C22, E32, E43, E44, E47

1 | Introduction

The term structure of interest rates has been considered as a strong indicator of future economic activity (Aguiar-Conraria et al. 2012; Ang et al. 2006; Chinn and Kucko 2015; Estrella and Hardouvelis 1991; Estrella and Mishkin 1997, 1998; Stock and Watson 1989; Wright 2006). In particular, the slope of the Treasury yield curve is among the most widely known predictors of real output. Existing findings in the literature show that an upward-sloping yield curve is associated with future economic expansions, whereas a flat or downward-sloping yield curve serves as an early warning signal of a recession (Ahmed and Chinn 2025; Bernanke and Blinder 1992; Chinn and Ferrara 2024; Estrella and Hardouvelis 1991; among others).

In recent years, a growing body of literature in macroeconomic forecasting has investigated the relationship between the yield curve and future real economic activity, but the findings remain ambiguous. There is not yet strong evidence in the relevant literature that the yield curve can be used as a robust forecasting tool for real output. Specifically, whereas a few papers document strong predictive accuracy of the yield spread for GDP growth (see Duarte et al. 2005; Yang 2020; among others), several other studies find that the predictive power of yield curve moments for future economic activity is time-varying and may be affected by parameter instability (Chinn and Kucko 2015; De Pace 2013; Estrella et al. 2003; Hännikäinen 2017; Gertler and Lown 1999; Schrimpf and Wang 2010; among others). For example, Estrella and Mishkin (1998) and Estrella et al. (2003) show that the term spread of yield curve provides poor results for output predictions since the mid-1980s. Moreover, Schrimpf and Wang (2010) find that the predictive power of the yield spread on quarterly GDP growth varies when structural breaks are taken into consideration.

There is no universal explanation for the time-varying predictability of yield curve moments in relation to economic activity. One strand of the literature argues that this variability may be linked to monetary policy decisions (Estrella 2005; Giacomini and Rossi 2006; Hännikäinen 2015). For example, Hännikäinen (2015) finds that the term spread of US Treasury notes has had a more pronounced effect on industrial production growth since 2008, particularly during the zero lower bound period. However, D'Agostino et al. (2006) support the view that the informativeness of the term structure of interest rates has been affected by the increased stability of macroeconomic variables since the mid-1980s.

Independently, there is a large and growing body of literature highlighting the importance of uncertainty shocks for the real economy, linking financial and macroeconomic uncertainty to declines in investment and economic activity (see Baker et al. 2016; Bloom 2009; Caggiano and Castelnuovo 2023; Caldara et al. 2016; among others). Additionally, many studies have documented the linkage between the volatility of financial variables (used as a proxy for uncertainty) and output. For example, Campbell et al. (2001) show that the variance of stock returns is a strong predictor of real output, whereas Bakshi et al. (2011) find that the term structure of implied volatilities predicts future GDP growth. Moreover, Cremers et al. (2021) find that the implied volatility of long-term Treasury notes can predict subsequent economic activity. More recently, Megaritis et al. (2025) show that the volatility of the term spread of the US Treasury yield curve has a significant negative impact on US industrial production growth.

Motivated by these strands of literature, in this paper, we construct a measure of uncertainty about the future slope of the US Treasury yield curve. More specifically, we estimate uncertainty in the slope of the yield curve as the monthly realized variance of the daily yield curve slope. According to the expectations hypothesis, the slope of the yield curve reflects expectations about future interest rates and, ultimately, future output growth. Because the yield curve slope is widely used as an indicator of macroeconomic expectations, increasing volatility in the slope (TSRV, henceforth) can be interpreted as higher dispersion in expectations about future macroeconomic outcomes and, therefore, as greater economic uncertainty. Based on this reasoning, we postulate that, similar to other popular uncertainty proxies, rising dispersion in the yield curve slope will be associated with subsequent declines in US output growth. Our goal is to provide a parsimonious and accessible measure for policymakers and market participants that offers additional predictive information about future economic activity.

Our analysis on the forecasting power of the TSRV on economic activity shows that increasing TSRV predicts a drop in US industrial production growth for forecasting horizons ranging from 1 to 12 months ahead. Moreover, the predictive power of TSRV remains robust to the inclusion of well-known indicators of macroeconomic activity like the slope of the yield curve (Estrella and Hardouvelis 1991; Estrella and Trubin 2006), the rate of inflation, the US Treasury bill rate, and popular uncertainty proxies like the VIX (Bloom 2009) and the economic and monetary policy uncertainty (EPU and

TABLE 1 | Descriptive statistics.

Statistics	EMPL	NBER	IPI	INFL	TBILL3M	GOV10Y	BAA	HSTARTS	TS	TSRV	SP500	VIX	EPU	MPU
Mean	0.0091	0.0845	0.0146	0.0258	0.0277	0.0425	0.0230	0.0040	0.0148	0.0004	0.0830	0.1950	109.8732	97.5387
St. dev.	0.0227	0.2785	0.0432	0.0150	0.0229	0.0195	0.0071	0.1869	0.0128	0.0006	0.1574	0.0746	65.2317	66.4323
Min	−0.1621	0.0000	−0.1963	−0.0198	0.0001	0.0062	0.0129	−0.7940	−0.0173	0.0000	−0.5934	0.1013	37.2660	16.5745
Max	0.1261	1.0000	0.1594	0.0862	0.0817	0.0889	0.0601	0.4683	0.0368	0.0069	0.4299	0.6267	536.8998	452.7653
Skewness	−2.2901	2.9981	−1.7232	1.0294	0.2359	0.3222	1.7777	−1.1793	−0.2481	6.0866	−1.2873	2.0240	3.1364	2.0125
Kurtosis	16.0526	7.0218	5.6111	3.2898	−1.2638	−0.6917	5.5286	2.7512	−0.6305	49.5142	2.6664	6.9153	14.2684	6.1324

TABLE 2 | Correlation matrix.

	EMPL	NBER	IPI	INFL	TBILL3M	GOV10Y	BAA	HSTARTS	TS	TSRV	SP500	VIX	EPU	MPU
EMPL	1													
NBER	−0.30	1												
IPI	0.73	−0.49	1											
INFL	0.40	0.08	0.33	1										
TBILL3M	0.20	0.00	0.27	0.38	1									
GOV10Y	0.14	0.08	0.28	0.29	0.83	1								
BAA	0.16	−0.09	−0.02	0.47	0.17	−0.10	1							
HSTARTS	0.31	−0.52	0.46	−0.06	−0.21	−0.16	−0.08	1						
TS	−0.15	0.12	−0.06	−0.23	−0.53	0.04	−0.46	0.14	1					
TSRV	−0.07	0.38	−0.18	0.13	0.02	0.04	0.05	−0.26	0.03	1				
SP500	0.23	−0.55	0.53	0.04	0.13	0.04	−0.02	0.44	−0.18	−0.29	1			
VIX	0.17	−0.09	0.00	0.49	0.14	−0.10	0.98	−0.08	−0.41	0.06	−0.03	1		
EPU	−0.44	0.23	−0.35	0.03	−0.13	−0.17	0.28	−0.06	−0.03	0.12	−0.19	0.32	1	
MPU	−0.13	0.26	−0.17	0.22	0.13	0.06	0.39	−0.12	−0.15	0.31	−0.31	0.42	0.75	1

MPU) indices (Baker et al. 2016). The fact that TSRV remains robust to the inclusion of MPU shows that it contains statistically and economically differentiated predictive power to that of MPU, not necessarily related to uncertainty about future monetary policy. In this way, our findings are the first to show that the TSRV reflects information not solely related (or correlated) to MPU.

Moreover, in order to further assess the forecasting power of TSRV, we conducted a pseudo–real-time out-of-sample forecasting exercise using both recursive and rolling window estimation approaches. Our out-of-sample results show that TSRV has higher predictive power as compared to the yield curve slope (TS) for medium- and long-term forecasting horizons. Our analysis is the first to show that the TSRV outperforms the slope of the yield curve for medium- and long-term real-time forecasts of economic activity. In detail, we find that the TSRV factor provides a rich information content regarding midterm and long-term predictions of industrial production and employment growth. Our results also corroborate the findings of Cremers et al. (2021), who verify the strong predictability of the implied volatility of long-term treasury notes on subsequent real output.

When we examine the time-varying predictive power of TSRV on US economic activity, we find that the TSRV has stronger predictive power on industrial production growth during periods of unconventional monetary policy and increased uncertainty (e.g., during the zero lower bound period). Our empirical results are in line with the findings of Hännikäinen (2015), who identifies stronger predictability of the slope of the US Treasury curve on economic activity during the same period. Our findings provide additional insights into the macrofinance literature, which has extensively identified an increasing interdependence between financial markets and the macroeconomy during and after the 2008 Global Financial Crisis (GFC) period (Abbate et al. 2016; Caldara et al. 2016; Prieto et al. 2016). Additionally, our findings provide new insights for the monetary policy literature identifying the effectiveness of unconventional monetary policy tools like the forward guidance, which was also first deployed during the GFC period (see Swanson 2021). Finally, our results are the first to show that the forecasting power of TSRV remains significant both during and after the COVID-19 outbreak, a period characterized by volatile US Treasury rates, inflationary pressures, and depressed economic activity.

In summary, our paper contributes to the relevant literature in two ways. First, we propose a parsimonious and robust predictor of future economic activity for the medium- and long-run horizons, which contains economically and statistically differentiated predictive information from other commonly used

TABLE 3 | Forecasting OLS regression models.

Panel A

$$\ln\left(IPI_{t+h} / IPI_t\right) = b_0 + b_1 TSRV_t + \varepsilon_t$$

Horizon (h)	b_0	t-stat (b_0)	b_1	t-stat (b_1)	% R^2
1 month	0.003***	(2.89)	−4.244	(−1.63)	1.57
3 months	0.007***	(3.77)	−8.655***	(−4.47)	3.86
6 months	0.012***	(4.56)	−13.32***	(−3.72)	6.0
12 month	0.021***	(4.40)	−16.91***	(−3.76)	5.84

Panel B

$$\ln\left(EMPL_{t+h} / EMPL_t\right) = b_0 + b_1 TSRV_t + \varepsilon_t$$

Horizon (h)	b_0	t-stat (b_0)	b_1	t-stat (b_1)	% R^2
1 month	0.002***	(3.31)	−2.973	(−1.30)	4.69
3 months	0.004***	(3.49)	−3.511**	(−2.27)	2.32
6 months	0.007***	(4.03)	−5.554***	(−3.51)	3.54
12 month	0.012***	(4.64)	−8.891***	(−4.09)	5.86

Panel C

$$P(NBER = 1)_{t+h} = b_0 + b_1 TSRV_t + \varepsilon_t$$

Horizon (h)	b_0	t-stat (b_0)	b_1	t-stat (b_1)	% pseudo-R^2
1 month	−1.701***	(−15.14)	655.7***	(5.29)	13.3
3 months	−1.617***	(−14.96)	511.7***	(4.34)	8.5
6 months	−1.762***	(−14.54)	811.9***	(5.17)	15.4
12 months	−1.560***	(−14.73)	271.6**	(2.49)	2.65

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

measures of uncertainty. Second, our findings provide further insights into the relevant literature that identifies a time-varying behavior of the yield curve predictability due to monetary policy decisions and tools.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 outlines the empirical methodology. Section 4 presents the main empirical results and robustness checks. Finally, Section 5 concludes.

2 | Data

We obtain daily data for the US Treasury bill rates and the US government bonds from the FRED database in order to estimate the realized variance of the term spread (TSRV) of the yield curve. Following the empirical approach of Estrella and Hardouvelis ([1991](#)), Estrella and Mishkin ([1996](#)), and Estrella and Trubin ([2006](#)), we estimate the daily slope (term spread) of the yield curve as the difference between the daily 10-year US government bond yield and the 3-month US Treasury bill rate. The volatility of the term spread (TSRV) is then calculated as the variance of the daily term spread for each month.

We also collect monthly data on the 3-month Treasury bill rate (TBILL3M) and the 10-year constant maturity Treasury yield (GOV10Y). The term spread (TS), defined as the slope of the US Treasury yield curve, is estimated as the difference between the 10-year and the 3-month Treasury rates (Estrella and Trubin [2006](#)). Furthermore, we collect data on the US consumer price index (CPI), the US industrial production index (IPI), and the US employment rate (EMPL),

TABLE 4 | Forecasting OLS regression models on US industrial production growth (IPI) when controlling for macroeconomic fundamentals.

$$\ln\left(IPI_{t+h}/IPI_t\right) = b_0 + b_1\ln\left(IPI_t/IPI_{t-1}\right) + b_2INFL_t + b_3GOV10Y_t$$
$$+ b_4BAA_t + b_5\ln\left(HSTARTS_t/HSTARTS_{t-1}\right) + b_6TS_t + b_7TSRV_t$$
$$+ b_8\ln\left(SP500_t/SP500_{t-1}\right) + b_9VIX_t + b_{10}MPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	Coef.	−0.0005	−0.004	−0.008	−0.012
	t-stat	(−0.13)	(−0.62)	(−0.80)	(−0.75)
IPI	Coef.	−0.354***	−0.324***	−0.372***	−0.0757
	t-stat	(−4.96)	(−4.47)	(−4.82)	(−0.74)
INFL	Coef.	−0.001	−0.137	−0.439*	−1.154**
	t-stat	(−0.01)	(−0.98)	(−1.81)	(−2.24)
GOV10Y	Coef.	0.104	0.187*	0.337**	0.680**
	t-stat	(1.63)	(1.76)	(2.24)	(2.53)
BAA	Coef.	0.0003	−0.017	−0.033*	−0.028
	t-stat	(0.06)	(−1.28)	(−1.96)	(−1.03)
HSTARTS	Coef.	0.039**	−0.025	−0.002	0.021
	t-stat	(2.31)	(−0.79)	(−0.10)	(0.67)
TS	Coef.	0.104	0.305*	0.429*	0.846**
	t-stat	(1.21)	(1.90)	(1.88)	(2.24)
TSRV	Coef.	−3.604*	−6.620**	−11.83***	−11.62***
	t-stat	(−1.92)	(−2.50)	(−3.34)	(−3.07)
SP500	Coef.	0.052	0.120***	0.106***	0.086***
	t-stat	(1.52)	(4.87)	(5.03)	(3.66)
VIX	Coef.	0.000261	0.00209*	0.00401**	0.00485
	t-stat	(0.51)	(1.83)	(2.49)	(1.64)
MPU	Coef.	−0.0001	−0.00001	0.00005	0.0001
	t-stat	(−1.46)	(−0.45)	(1.25)	(1.51)
% adj. R^2		17.1	17.5	21.7	25.5

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

as well as the binary measure identifying NBER recessions (NBER). The US housing starts index is used as a proxy for construction (HSTARTS). The Baa corporate bond spread (BAA) is used as a proxy for the spread between corporate and government bonds. The return of the S&P500 index (SP500) is used as a measure of the stock market, whereas the VIX index (Bloom 2009) is used as a proxy for stock market volatility (VIX). Inflation (INFL) is measured as the monthly percentage change in the CPI. The EPU and MPU indices (Baker et al. 2016) are used to measure uncertainty related to economic and monetary policy. The data for these series are also sourced from the FRED database. Our monthly dataset covers the period from January 1990 to June 2025 (426 observations).

3 | Methodology

3.1 | In-Sample Regressions

Our empirical approach starts with an in-sample analysis using bivariate and multivariate predictive regression models, followed by an out-of-sample analysis using a pseudo–real-time forecasting framework with similar models. We first estimate a set of bivariate and multivariate predictive regression models on the measures of real economic activity in the United States. The bivariate and multivariate regression models are estimated for various forecasting horizons ranging from 1 to 12 months ahead. We, therefore, estimate bivariate OLS predicting regressions in which we use the

TABLE 5 | Forecasting OLS regression models on US employment growth (EMPL) when controlling for macroeconomic fundamentals.

$$\ln(EMPL_{t+h}/EMPL_t) = b_0 + b_1\ln(EMPL_t/EMPL_{t-1}) + b_2INFL_t + b_3GOV10Y_t$$
$$+ b_4BAA_t + b_5\ln(HSTARTS_t/HSTARTS_{t-1}) + b_6TS_t + b_7TSRV_t$$
$$+ b_8\ln(SP500_t/SP500_{t-1}) + b_9VIX_t + b_{10}MPU_t + \varepsilon_t$$

Horizon (h)		h = 1	h = 3	h = 6	h = 12
Constant	Coef.	0.0008	0.0009	0.002	0.002
	t-stat	(0.44)	(0.18)	(0.23)	(0.14)
EMPL	Coef.	−0.016	−0.146	−0.338	−0.402**
	t-stat	(−0.14)	(−0.79)	(−1.57)	(−2.15)
INFL	Coef.	0.036	0.015	0.008	−0.177
	t-stat	(1.61)	(0.23)	(0.07)	(−1.09)
GOV10Y	Coef.	0.007	−0.005	−0.009	0.043
	t-stat	(0.18)	(−0.06)	(−0.09)	(0.31)
BAA	Coef.	−0.001	−0.006	−0.008	−0.011
	t-stat	(−0.78)	(−1.14)	(−1.00)	(−0.72)
HSTARTS	Coef.	0.0158*	−0.015	−0.008	0.013
	t-stat	(1.72)	(−0.84)	(−0.53)	(1.18)
TS	Coef.	0.0199	0.0756	0.145	0.383
	t-stat	(0.45)	(0.61)	(0.83)	(1.36)
TSRV	Coef.	−2.097	−3.287*	−5.700***	−5.538**
	t-stat	(−1.28)	(−1.89)	(−2.61)	(−2.49)
SP500	Coef.	0.038	0.036**	0.029***	0.046***
	t-stat	(1.41)	(2.32)	(3.01)	(3.91)
VIX	Coef.	0.0001	0.001*	0.001	0.002
	t-stat	(0.95)	(1.82)	(1.54)	(1.47)
MPU	Coef.	−0.00001	0.00001	0.00001	0.00001
	t-stat	(−0.81)	(0.27)	(0.74)	(0.52)
% adj. R^2		13.5	11.1	6.8	9.04

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TSRV as the only predictor of real output, employing the following time-series predictive regression model for IPI growth:

$$\ln(IPI_{t+h}/IPI_t) = b_0 + b_1 TSRV_t + \varepsilon_t. \quad (1)$$

We then estimate a multivariate specification to verify that the TSRV factor remains a robust predictor of real economic activity to the inclusion of other commonly used predictors. In this setting, we additionally control for some key indicators of US real output, such as the lagged value of IPI growth, the CPI inflation (INFL), the 10-year government bond rate (GOV10Y), the Baa corporate bond spread (BAA), the return of the US housing starts (HSTARTS), the S&P500 returns (SP500), the VIX index that reflects uncertainty of the US equities market (VIX), the MPU index (Baker et al. 2016) (MPU), and the slope of the US

Treasury yield curve (TS) (Estrella and Hardouvelis 1991). The multivariate model for IPI growth is specified as follows:

$$\ln(IPI_{t+h}/IPI_t) = b_0 + b_1 \ln(IPI_t/IPI_{t-1}) + b_2 INFL_t + b_3 GOV10Y_t$$
$$+ b_4 BAA_t + b_5 \ln(HSTARTS_t/HSTARTS_{t-1}) + b_6 TS_t + b_7 TSRV_t \cdot \quad (2)$$
$$+ b_8 \ln(SP500_t/SP500_{t-1}) + b_9 VIX_t + b_{10} MPU_t + \varepsilon_t$$

Moreover, for robustness purposes, we estimate identical regressions using an alternative measure of economic activity, namely, the US employment rate (EMPL). We also estimate the probability of the NBER-dated recessions (NBER) by employing bivariate and multivariate probit models using the same regressors with the linear regression specifications provided in Equations (1) and (2). Finally, we perform additional multivariate models with a number of alternative selected variables in Section 4.3.[1]

TABLE 6 | Forecasting the probability of NBER recession when controlling for macroeconomic fundamentals.

$$P(NBER=1)_{t+h} = b_0 + b_1 INFL_t + b_2 GOV10Y_t$$
$$+ b_3 BAA_t + b_4 \ln(HSTARTS_t/HSTARTS_{t-1}) + b_5 TS_t + b_6 TSRV_t$$
$$+ b_7 \ln(SP500_t/SP500_{t-1}) + b_8 VIX_t + b_9 MPU_t + \varepsilon_t$$

Horizon (h)		h = 1	h = 3	h = 6	h = 12
Constant	Coef.	−2.884***	−2.549***	−2.221***	−1.208**
	t-stat	(−7.36)	(−5.97)	(−4.68)	(−2.39)
INFL	Coef.	22.75***	50.58***	65.83***	45.15***
	t-stat	(2.69)	(4.85)	(4.74)	(3.39)
GOV10Y	Coef.	−2.000	2.224	−2.296	−9.835
	t-stat	(−0.34)	(0.35)	(−0.26)	(−1.15)
BAA	Coef.	3.286	45.16**	23.26	−3.113
	t-stat	(0.58)	(2.06)	(1.04)	(−0.24)
HSTARTS	Coef.	−2.611**	−3.090***	−1.419	−4.528***
	t-stat	(−2.00)	(−2.66)	(−1.35)	(−4.53)
TS	Coef.	13.39	−15.62	−80.21***	−110.3***
	t-stat	(1.34)	(−1.40)	(−3.79)	(−5.26)
TSRV	Coef.	506.8***	319.2*	1273.2***	332.3**
	t-stat	(3.17)	(1.78)	(3.58)	(2.18)
SP500	Coef.	−5.339**	−10.59***	−8.561***	−0.0425
	t-stat	(−2.37)	(−4.81)	(−4.69)	(−0.03)
VIX	Coef.	−0.468	−6.468**	−3.465	0.044
	t-stat	(−0.66)	(−2.05)	(−1.09)	(0.03)
MPU	Coef.	0.005***	−0.001	−0.007**	−0.007**
	t-stat	(2.94)	(−0.63)	(−2.09)	(−2.24)
% adj. R^2		65.8	30.1	41	58.4

Note: Reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7 | Out-of-sample results (mean squared forecast errors).

Panel A (recursive window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.431	0.435	0.435	0.450	0.432	0.423	0.435	0.432	0.429	0.433	0.428	0.433	0.426	0.420
3 months	0.775	0.809	0.820	0.886	0.795	0.809	0.850	0.810	0.802	0.839	0.734	0.745##	0.754##	0.764
6 months	1.207	1.275	1.332	1.338	1.256	1.302	1.449	1.284	1.301	1.291	1.155	1.164###	1.265###	1.307
12 months	2.198	2.282	2.636	2.365	2.303	2.468	3.050	2.360	2.455	2.429	2.200	2.950##	3.005###	3.050

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.085*	0.087	0.088	0.096	0.088	0.086	0.090	0.087	0.086	0.086	0.085	0.242	0.242	0.247
3 months	0.242*	0.250	0.253	0.257	0.247	0.246	0.259	0.246	0.246	0.251	0.241	0.426	0.419#	0.423
6 months	0.393**	0.414	0.427	0.433	0.406	0.415	0.444	0.407	0.405	0.421	0.401	0.550	0.525##	0.538
12 months	0.600*	0.653	0.722	0.699	0.625	0.676	0.739	0.642	0.646	0.603	0.581	0.952	0.829###	0.846

Panel B (rolling window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.333	0.333	0.333	0.354	0.329	0.333	0.328	0.329	0.332	0.328	0.326	0.297	0.288##	0.294
3 months	0.382*	0.401	0.407	0.422	0.356	0.406	0.410	0.394	0.401	0.382	0.362	0.388	0.372	0.360
6 months	0.415***	0.490	0.436	0.470	0.408	0.487	0.468	0.506	0.504	0.432	0.441	0.307	0.278	0.269
12 months	0.272**	0.594	0.377	0.455	0.312	0.438	0.665	0.538	0.377	0.280	0.324	1.480	0.452###	0.467

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.016	0.017	0.018	0.030	0.018	0.022	0.017	0.017	0.017	0.017	0.018	0.074	0.074###	0.128
3 months	0.047	0.047	0.052	0.056	0.047	0.046	0.047	0.040	0.042	0.044	0.046	0.235	0.209###	0.233
6 months	0.066**	0.076	0.080	0.087	0.071	0.067	0.070	0.073	0.065	0.054	0.066	0.107	0.053	0.047
12 months	0.063**	0.112	0.089	0.090	0.073	0.064	0.114	0.106	0.083	0.037	0.061	0.339###	0.713###	0.817

Note: This table reports the out-of-sample mean squared forecast errors (MSFEs) when forecasting industrial production (*IPI*) and employment (*EMPL*) growth at 1-, 3-, 6-, and 12-month horizons. Panel A reports the results based on a recursive estimation window, whereas Panel B reports the results based on a rolling estimation window. The table contains the *MSFEs* for a number of bivariate models, using established indicators of economic activity as the main predictor (Columns 1–11), alongside our multivariate settings (Columns 12–14). The models *MULTI, MULTI-TS*, and *MULTI-TS-TSRV* represent gradually reduced multivariate forecasting models. In Columns 1 and 2, the asterisk symbols correspond to the Diebold–Mariano (DM) test comparing the bivariate models with the *TSRV* and *TS* as the main predictors, respectively. In Columns 12–14, the hash symbols correspond to the Clark–West (CW) test comparing the unrestricted model without *TS (MULTI–TS)* with the restricted model without *TS* and *TSRV (MULTI–TS–TSRV)*, respectively.

*, **, and *** denote statistical significance of the DM test at the 10%, 5%, and 1% levels, respectively, whereas #, ##, and ### denote statistical significance of the CW test at the 10%, 5%, and 1% levels, respectively.

3.2 | Out-of-Sample Specifications

We also evaluate the forecasting power of TSRV on real output using a pseudo–real-time out-of-sample specification for similar regression models to those in Equations (1) and (2) across multiple forecasting horizons. In the out-of-sample framework, we apply both a rolling window and recursive methods. Specifically, we start with an 84-month (7-year) initial window to estimate the first OLS regressions for period $t+h$ (where h is the forecasting horizon) using available data up to month t.[2] In the recursive method, the estimation window is extended by 1 month in each step to produce the new out-of-sample forecasts. In the rolling window setting, we follow the "pool forecast" approach of Schrimpf and Wang (2010) in order to also consider structural breaks and shifts in economic conditions over our sample.[3] We evaluate forecasting accuracy by comparing the relative mean squared forecast errors (MSFEs) and mean absolute forecast errors (MAFEs) across the alternative models.

We also conduct predictive accuracy tests to validate the statistical significance of the forecast errors in the out-of-sample framework. Specifically, we perform the Diebold–Mariano (DM) test (Diebold and Mariano 1995) and the Clark–West (CW) test (Clark and West 2007), two widely used statistical tests for comparing the predictive accuracy of two competing models.[4] Finally, we employ the Giacomini–Rossi (GR) fluctuation test, as proposed by Giacomini and Rossi (2010), to assess the predictive value of the TSRV and its robustness to structural breaks.

4 | Empirical Results

Initially, we estimate the descriptive statistics and the correlations among the regressors in our setting. Tables 1 and 2 show the descriptive statistics and correlations for our variables, respectively.

Based on both tables, we observe that regressors are not highly correlated except for the yields of the 3-month Treasury bill and the 10-year Treasury bond, as well as the MPU and EPU indices.[5]

4.1 | In-Sample Forecasting Results

This section discusses the in-sample forecasting results. First, we perform bivariate regression models, and the results are presented in Table 3.

For the bivariate predictive models, TSRV emerges as a robust predictor of subsequent economic activity across multiple forecasting horizons. Specifically, for midterm and long-term predictions of IPI growth and the unemployment rate, the estimated coefficients remain statistically significant across all horizons. Additionally, higher volatility in the yield curve slope (TSRV) is linked to a higher probability of a subsequent recession (NBER), which is observed over the short-term, midterm, and long-term horizons.
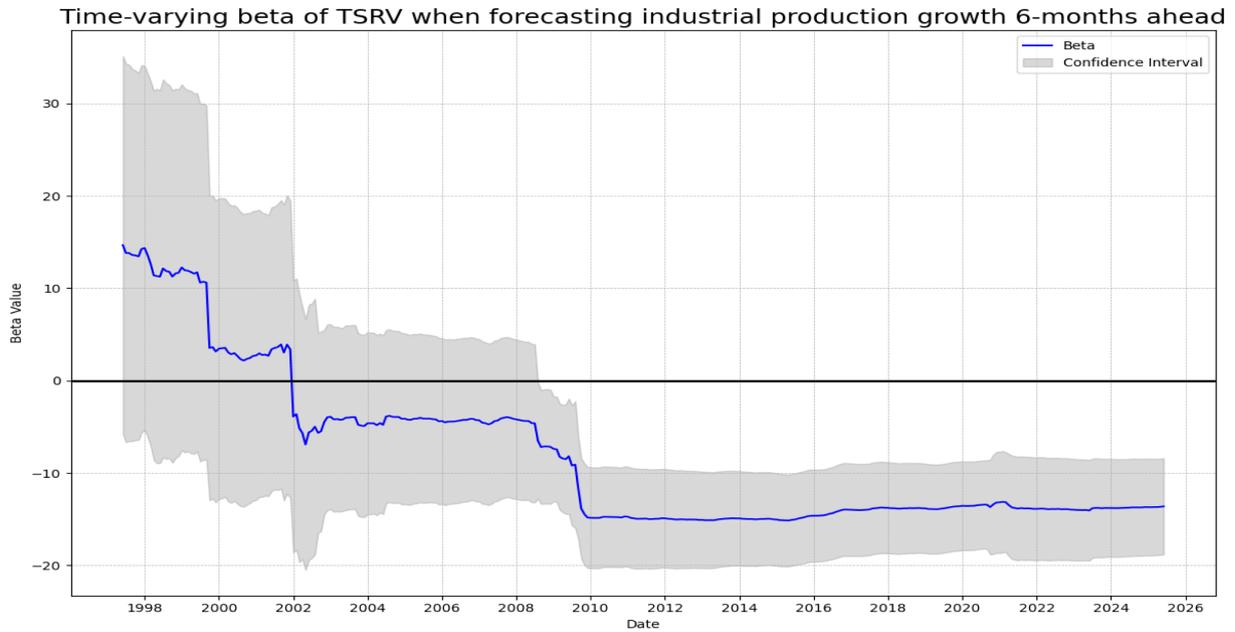
Tables 4–6 display the results of the multivariate regression models for predicting US industrial production growth (IPI), US employment growth (EMPL), and the probability of an NBER recession (NBER), respectively.

TABLE 8 | Fluctuation test results.

Panel A (recursive window)

Dependent variable: *IPI*

Horizon	TSRV vs. TS	MULTI vs. MULTI–TS	MULTI–TS vs. MULTI–TS–TSRV
1 month	Reject	Fail to reject	Fail to reject
3 months	Reject	Reject	Reject
6 months	Reject	Reject	Reject
12 months	Reject	Reject	Reject

Dependent variable: *EMPL*

Horizon	TSRV vs. TS	MULTI vs. MULTI–TS	MULTI–TS vs. MULTI–TS–TSRV
1 month	Reject	Reject	Reject
3 months	Reject	Reject	Reject
6 months	Reject	Reject	Reject
12 months	Reject	Reject	Reject

Panel B (rolling window)

Dependent variable: *IPI*

Horizon	TSRV vs. TS	MULTI vs. MULTI–TS	MULTI–TS vs. MULTI–TS–TSRV
1 month	Fail to reject	Fail to reject	Reject
3 months	Reject	Fail to reject	Fail to reject
6 months	Reject	Reject	Reject
12 months	Reject	Reject	Reject

Dependent variable: *EMPL*

Horizon	TSRV vs. TS	MULTI vs. MULTI–TS	MULTI–TS vs. MULTI–TS–TSRV
1 month	Fail to reject	Reject	Reject
3 months	Fail to reject	Fail to reject	Reject
6 months	Reject	Reject	Reject
12 months	Reject	Reject	Reject

Note: This table reports the results of the Giacomini–Rossi fluctuation tests performed on specific regression models presented in Table 7. Specifically, we perform the fluctuation test under the null hypothesis that the expected loss difference between the two models is zero at all time points, against the alternative that the first model has lower expected losses at some time point. Each column represents the comparisons between two specific regression models. The table reports whether we reject or fail to reject the null hypothesis. Panel A reports the results based on a recursive estimation window, whereas Panel B reports the results based on a rolling estimation window. See Table 7 for additional details.

Panel A (*IPI*)

Time-varying beta of TSRV when forecasting industrial production growth 6-months ahead

Panel B (*EMPL*)

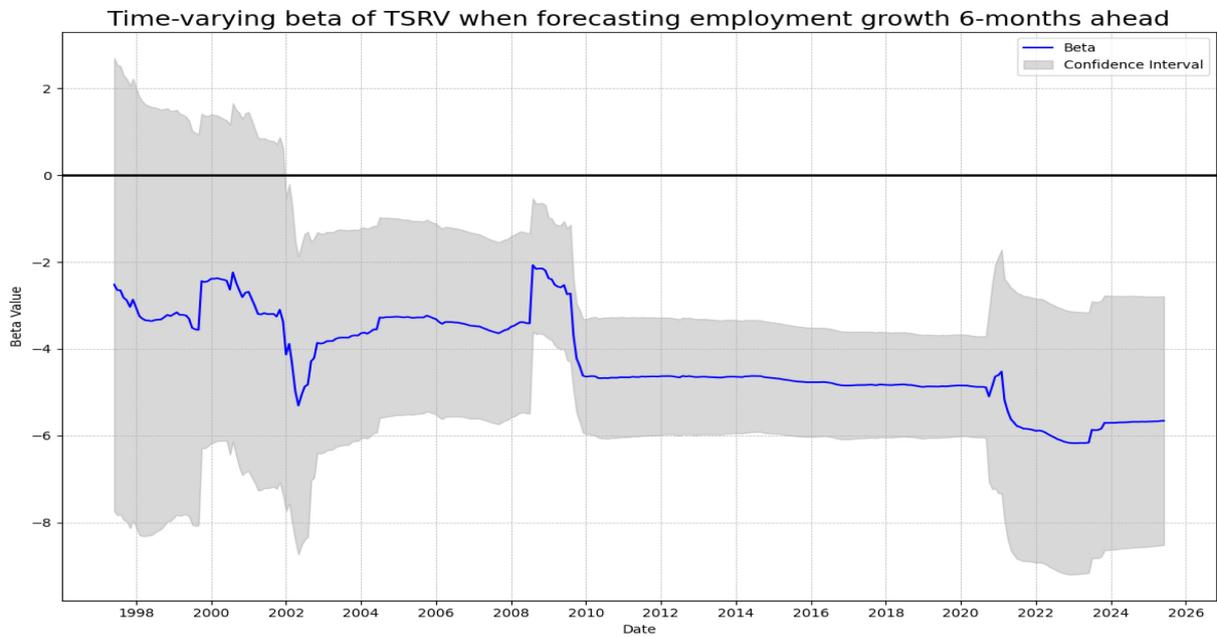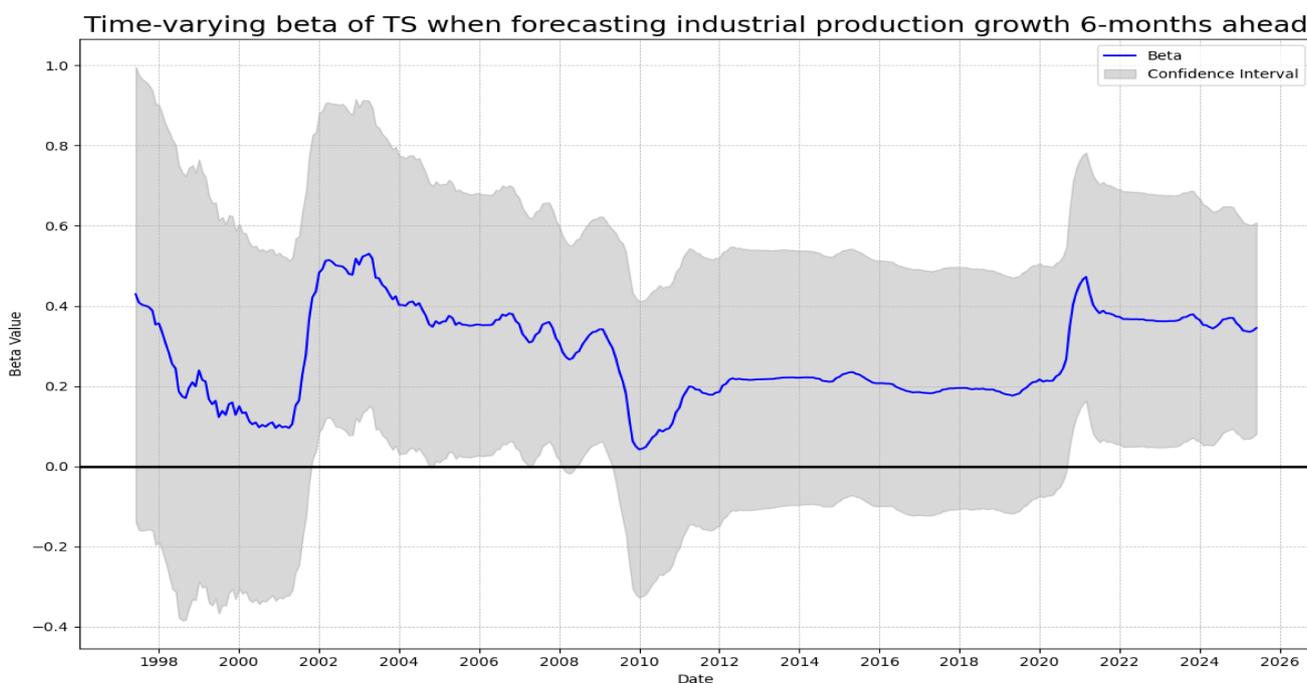Time-varying beta of TSRV when forecasting employment growth 6-months ahead

FIGURE 1 | Estimated *beta* of TSRV when forecasting economic activity 6 months ahead.

The multivariate analysis further confirms the strong predictive power of TSRV, particularly over medium- and long-term horizons. Specifically, the TSRV coefficient is statistically significant for most forecasting horizons. When predicting economic activity (IPI and EMPL), the *t*-statistic of the TSRV coefficient exceeds two over the long-term forecasting horizons. An interesting finding is that the term spread (TS) coefficient itself is found less significant (especially for EMPL), in contrast to its volatility component. In addition, in the NBER recession regressions (Table 6), the TSRV coefficient is found to be positive and significant across all forecasting horizons. These results are consistent with previous

Panel A (*IPI*)

Time-varying beta of TS when forecasting industrial production growth 6-months ahead

Panel B (*EMPL*)

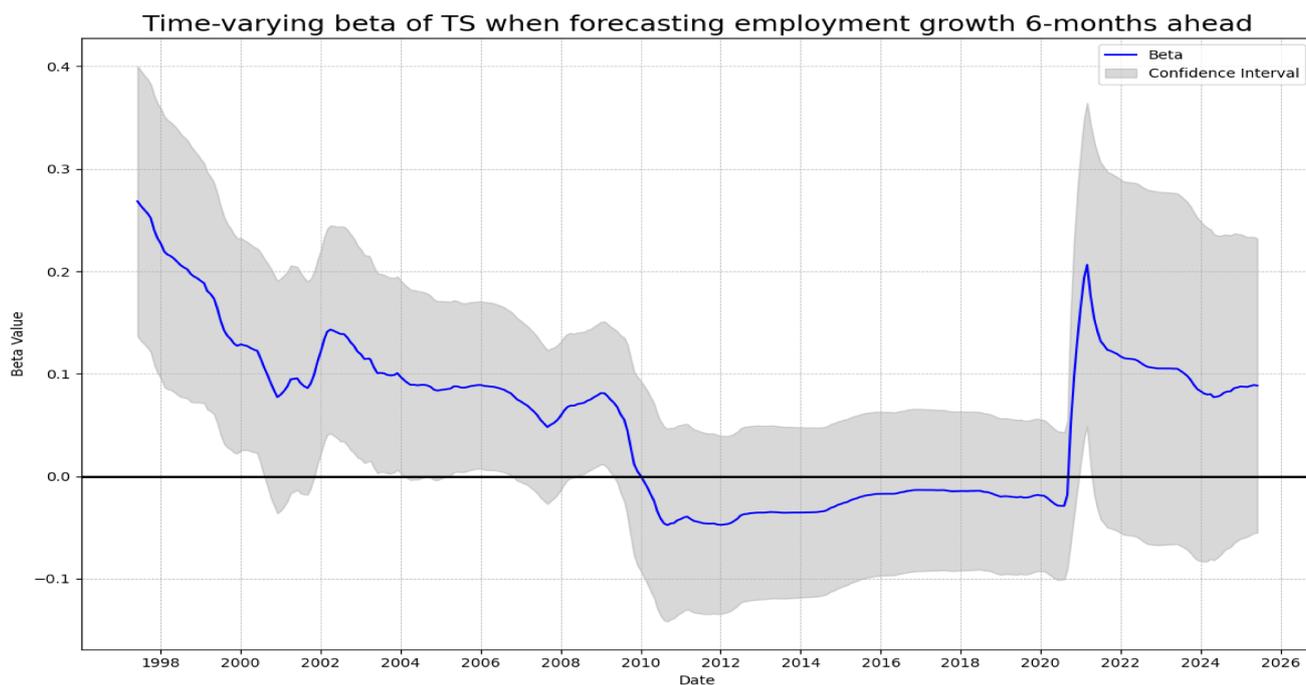### Time-varying beta of TS when forecasting employment growth 6-months ahead

FIGURE 2 | Estimated *beta* of TS when forecasting economic activity 6 months ahead.

studies that highlight the inconsistent predictive power of the term spread for economic activity (Chinn and Kucko 2015; De Pace 2013; Estrella et al. 2003; Hännikäinen 2017). To the best of our knowledge, this is the first study to show that the volatility of the yield curve slope (TSRV) is a strong and robust predictor of economic activity, providing unique information not captured by the level of the term spread and/or other well-known predictors.
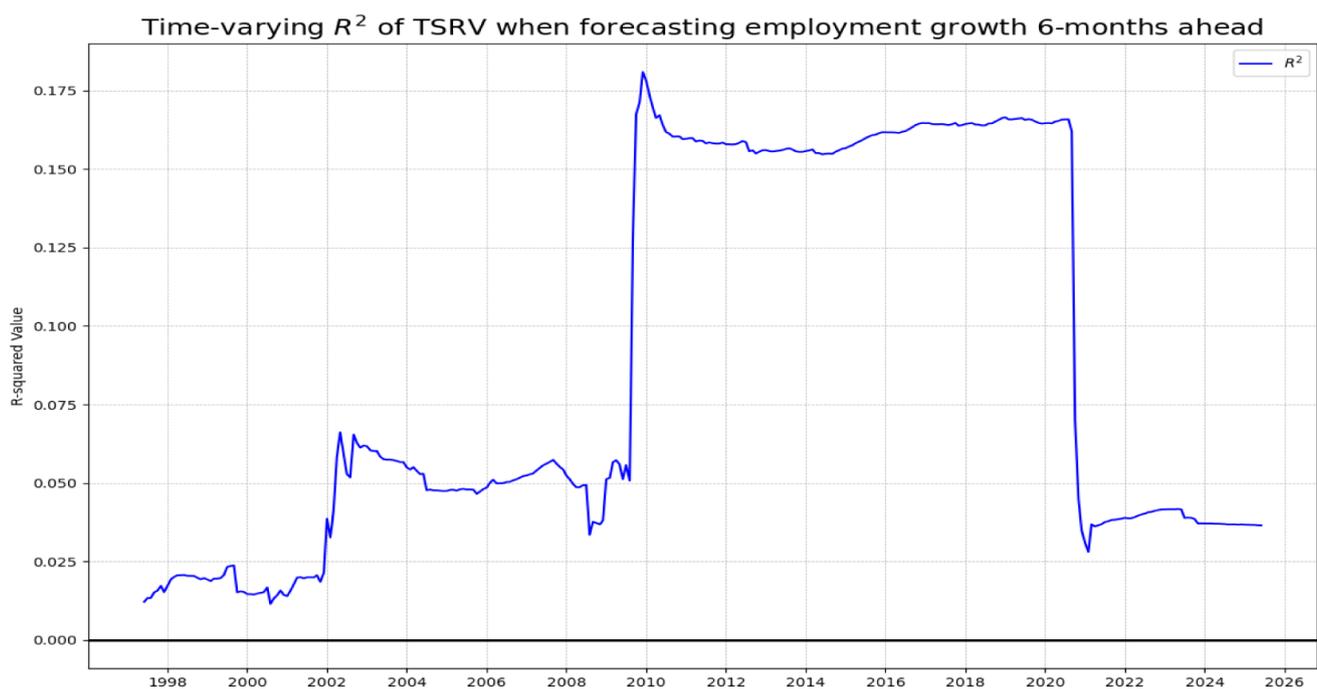
Panel A (*IPI*)
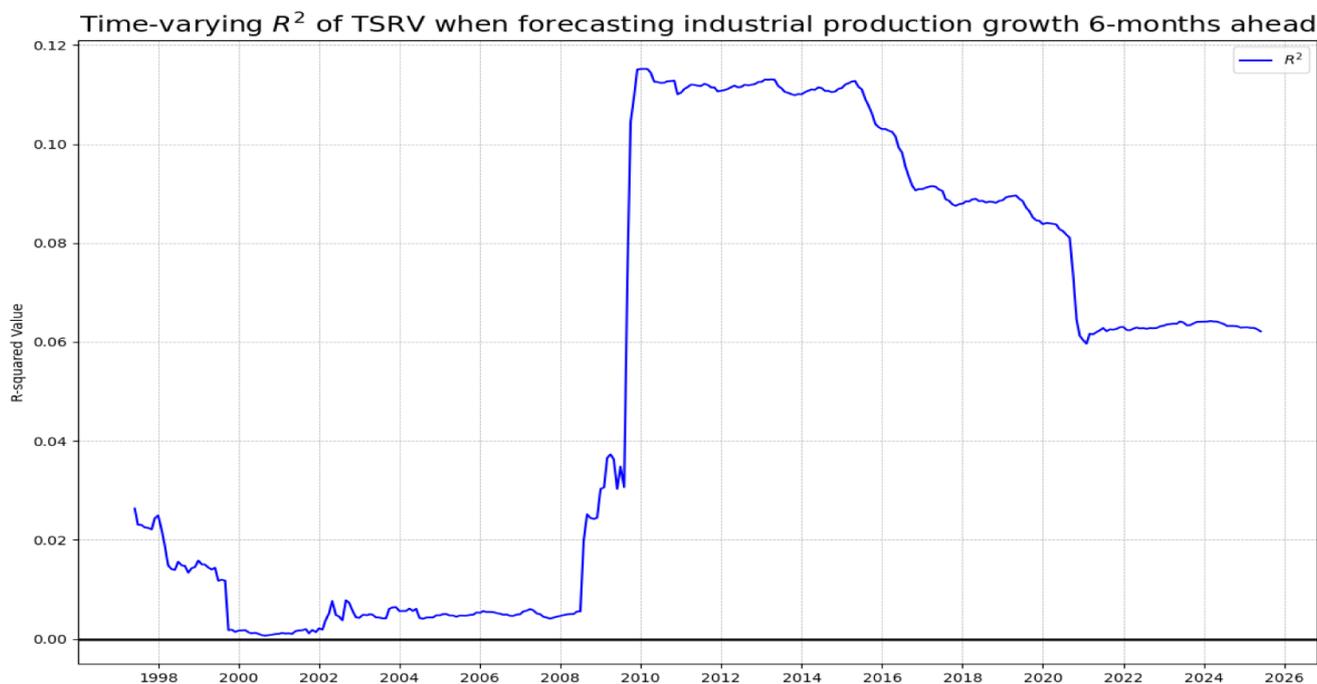
Panel B (*EMPL*)

FIGURE 3 | Estimated R^2 when forecasting economic activity 6 months ahead using TSRV.

4.2 | Out-of-Sample Forecasting Results

This section presents the results of the pseudo–real-time out-of-sample forecasting exercise. As described in Section 3, we use both recursive and rolling window methods in this exercise. Table 7 reports the relative MSFEs in order to evaluate the model performance across a series of bivariate regressions with alternative predictors, as well as our multivariate
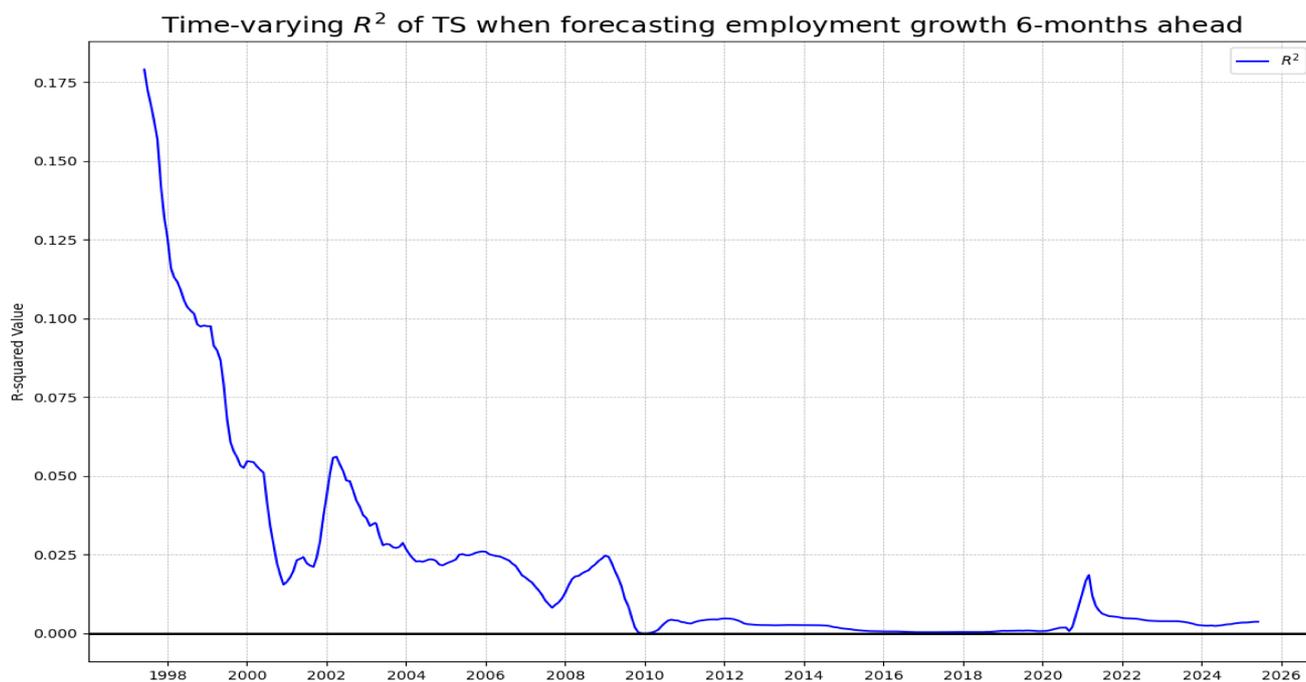
Panel A (*IPI*)
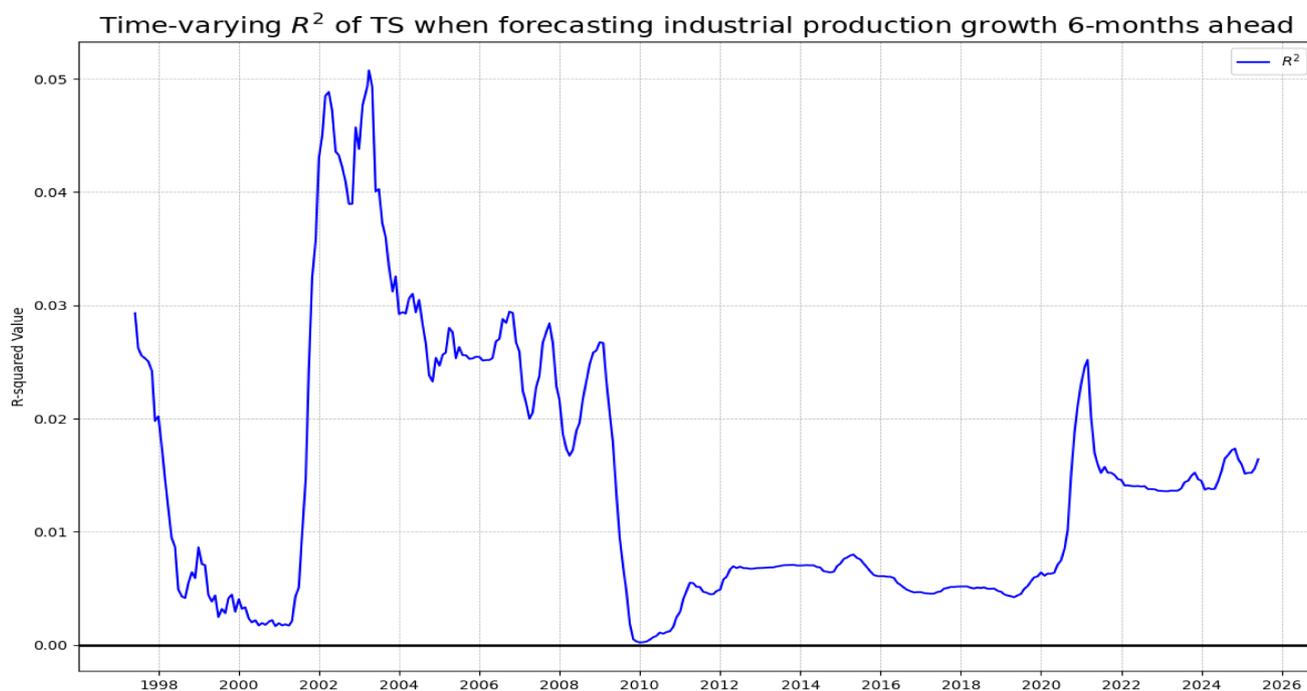
Panel B (*EMPL*)

FIGURE 4 | Estimated R^2 when forecasting economic activity 6 months ahead using TS.

models. Specifically, in Columns 1–11, we present the MSFEs for alternative bivariate models, using the regressors individually employed in our multivariate models, as well as some additional common predictors of economic activity, such as the macroeconomic uncertainty (MU) index of Jurado et al. (2015) and the geopolitical risk (GEOP) index of Caldara and Iacoviello (2022). From the bivariate regressions (Columns 1–11), we observe that the MSFE is consistently lower for the

models with the TSRV measure when compared to those using the TS factor, regardless of whether a rolling or recursive window method is employed. Moreover, the MSFEs associated with the TSRV are generally the lowest among all individual predictive factors. This supports our earlier findings from the in-sample analysis, indicating that the volatility of the yield curve slope (TSRV) is a strong and robust predictor of economic activity even when compared to the term spread level and other well-established predictors.

Additionally, Table 7 includes the results from the DM test, which compares the forecast performance of the bivariate model using the term spread (TS) with that of the model using the TSRV.[6] Moreover, the CW test is used to validate whether the addition of the TSRV factor and/or of the TS factor significantly reduces the forecasting errors of the multivariate model.[7]

Specifically, we perform the CW test on the full multivariate model (Equation 2) and on a restricted model (without the term spread), and then we also compare the multivariate model (without the term spread) with a more restricted model that also excludes the TSRV factor. Finally, we perform the GR fluctuation test to ensure that the TSRV adds predictive value and that its performance is robust to structural breaks. Specifically, we conduct a one-sided fluctuation test in which we assess whether the expected loss difference is zero across all time points or whether the model that includes TSRV outperforms in certain subperiods. The results of the GR test for the various cases are reported in Table 8.

The results from both the DM and CW tests in Table 7 again confirm the superior performance of TSRV over TS in forecasting economic activity. Specifically, the DM test (Columns 1 and

TABLE 9 | Forecasting OLS regression models on US industrial production growth (IPI) when controlling for macroeconomic fundamentals (alternative specification).

$$\ln\left(IPI_{t+h}/IPI_t\right) = b_0 + b_1\ln\left(IPI_t/IPI_{t-1}\right) + b_2 INFL_t + b_3 TBILL3M_t$$
$$+ b_4\ln\left(HSTARTS_t/HSTARTS_{t-1}\right) + b_5 TS_t + b_6 TSRV_t$$
$$+ b_7\ln\left(SP500_t/SP500_{t-1}\right) + b_8 VIX_t + b_9 EPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	Coef.	−0.0008	−0.012	−0.023**	−0.036**
	t-stat	(−0.28)	(−1.61)	(−2.10)	(−2.14)
IPI	Coef.	−0.353***	−0.312***	−0.342***	−0.021
	t-stat	(−4.82)	(−4.93)	(−5.59)	(−0.37)
INFL	Coef.	−0.0009	−0.103	−0.385*	−1.142**
	t-stat	(−0.01)	(−0.76)	(−1.76)	(−2.49)
TBILL3M	Coef.	0.085*	0.198**	0.412***	0.845***
	t-stat	(1.65)	(2.03)	(2.79)	(3.21)
HSTARTS	Coef.	0.039**	−0.025	−0.0004	0.023
	t-stat	(2.30)	(−0.87)	(−0.02)	(0.80)
TS	Coef.	0.196	0.532**	0.873***	1.656***
	t-stat	(1.57)	(2.44)	(3.13)	(3.97)
TSRV	Coef.	−4.477**	−7.410***	−11.64***	−11.25***
	t-stat	(−2.20)	(−2.98)	(−3.49)	(−3.20)
SP500	Coef.	0.0544	0.126***	0.109***	0.0903***
	t-stat	(1.55)	(5.00)	(5.77)	(4.35)
VIX	Coef.	0.0002	0.0004	0.001*	0.0023**
	t-stat	(0.75)	(1.12)	(1.87)	(2.25)
EPU	Coef.	−0.00002	0.00004	0.0001**	0.0003***
	t-stat	(−0.46)	(0.82)	(2.19)	(3.62)
% adj. R^2		16.8	22.1	28.2	36.5

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

2) shows that the forecasts generated using the TSRV factor are more statistically significant than those based on the term spread (TS), especially in the medium- to long-term horizons. The TSRV also consistently produces lower mean squared errors over all horizons. Moreover, the CW test (Columns 10–12) indicates that the inclusion of TSRV in the multivariate model significantly improves its forecasting performance, as can be seen from both the rolling and recursive window settings. Interestingly, the addition of TS is not always beneficial. This highlights the distinct predictive information provided by TSRV for economic activity forecasts.[8] Also, the results from the fluctuation test, reported in Table 8, reaffirm the evidence based on the DM and CW tests. Specifically, we find that the null hypothesis (that the expected loss difference between the two models is zero at all time points) is rejected in most cases, indicating that TSRV yields lower expected losses in at least some subperiods of our sample.

Our results provide new evidence about the predictive power of TSRV, thereby contributing to the literature focusing on the macroeconomic predictive power of interest rate and yield curve uncertainty (Cremers et al. 2021; Engle et al. 2013; among others). Another noteworthy finding is the main difference between TSRV and TS in terms of mean squared errors when using the rolling window method, particularly for the industrial production growth forecasts.

To further investigate the time-varying behavior of the TSRV and TS coefficients, we present the figures showing the time-varying R^2 and *beta* coefficients, along with 95% confidence intervals, from the out-of-sample exercise.[9] Figures 1 and 2 show the time-varying *beta* coefficients, whereas Figures 3 and 4 present the time-varying R^2 values for those two coefficients (TSRV and TS).

TABLE 10 | Forecasting OLS regression models on US employment growth (EMPL) when controlling for macroeconomic fundamentals (alternative specification).

$$\ln\left(EMPL_{t+h}/EMPL_t\right) = b_0 + b_1\ln\left(EMPL_t/EMPL_{t-1}\right) + b_2 INFL_t + b_3 TBILL3M_t$$
$$+ b_4\ln\left(HSTARTS_t/HSTARTS_{t-1}\right) + b_5 TS_t + b_6 TSRV_t$$
$$+ b_7\ln\left(SP500_t/SP500_{t-1}\right) + b_8 VIX_t + b_9 EPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	Coef.	0.0003	−0.003	−0.006	−0.01
	t-stat	(0.40)	(−0.61)	(−0.72)	(−0.84)
EMPL	Coef.	−0.015	−0.103	−0.245	−0.261*
	t-stat	(−0.13)	(−0.60)	(−1.39)	(−1.78)
INFL	Coef.	0.038**	0.027	0.014	−0.188
	t-stat	(2.01)	(0.42)	(0.13)	(−1.31)
TBILL3M	Coef.	0.001	0.009	0.0303	0.105
	t-stat	(0.02)	(0.13)	(0.30)	(0.83)
HSTARTS	Coef.	0.016*	−0.015	−0.008	0.013
	t-stat	(1.69)	(−0.89)	(−0.58)	(1.16)
TS	Coef.	0.026	0.088	0.173	0.484
	t-stat	(0.34)	(0.49)	(0.71)	(1.40)
TSRV	Coef.	−2.421	−3.487*	−5.887***	−5.947***
	t-stat	(−1.32)	(−1.93)	(−2.70)	(−2.84)
SP500	Coef.	0.039	0.038**	0.034***	0.051***
	t-stat	(1.38)	(2.27)	(3.11)	(3.91)
VIX	Coef.	0.00003	0.0001	0.0002	0.001*
	t-stat	(0.23)	(0.29)	(0.68)	(1.90)
EPU	Coef.	−0.000004	0.00003	0.0001	0.0001*
	t-stat	(−0.21)	(1.05)	(1.51)	(1.75)
% adj. R^2		10.5	7.96	11.9	26.6

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

These time-varying results validate our main conclusion that TSRV is a more robust predictor of economic activity than the term spread (TS). Our findings align with much of the existing literature (Chinn and Kucko 2015; De Pace 2013; Hännikäinen 2017; among others) that highlights the time-varying predictability of the term spread for subsequent economic activity. However, the estimated time-varying *beta* coefficients for TS are not consistently statistically significant across most periods in the sample. The estimated *beta* coefficients and R^2s shown in Figures 1 and 3 clearly show that the forecasting power of TSRV on US economic activity is low during the 1990s and early 2000s, whereas it jumps during the GFC period and remains high and significant afterwards. For example, the *beta* coefficient of TSRV becomes statistically significant after 2008 when forecasting IPI growth. In addition, the time-varying R^2 rises from approximately 5% to more than 15% when forecasting EMPL growth and as we move from the pre- to the post-2008 GFC period. Our results are broadly in line with the findings of Abbate et al. (2016) and Prieto et al. (2016) who show an increased trend in macrofinancial linkages during the post-2008 recession period.

4.3 | Robustness Checks

In this section, we analytically describe the additional models and estimations employed to confirm the robustness of our main results. First, as we have provided in Tables 3 and 5, we estimate our baseline regression models on the US employment growth (instead of the US industrial production growth), and the regression results are quantitatively and qualitatively similar. Moreover, we estimate probit models on the binary variable indicating the NBER recession periods (Tables 3 and 6), and we show that the TSRV is also a significant predictor of US economic recessions. Furthermore, we include an alternative specification of the multivariate model presented in Equation (2). Specifically, Tables 9–11 report the multivariate regression results when we employ an alternative model specification. In this specification, we replace the 10-year US bond yield and the Baa default spread with the yield of the 3-month US Treasury bills, as well as the MPU with the EPU index. As is evident from Tables 9 to 11, the results remain unaltered under this alternative specification.

TABLE 11 | Forecasting the probability of NBER recession when controlling for macroeconomic fundamentals (alternative specification).

$$P(NBER=1)_{t+h} = b_0 + b_1 INFL_t + b_2 TBILL3M_t$$
$$+ b_3 \ln(HSTARTS_t/HSTARTS_{t-1}) + b_4 TS_t + b_5 TSRV_t$$
$$+ b_6 \ln(SP500_t/SP500_{t-1}) + b_7 VIX_t + b_8 EPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	*Coef.*	−3.226***	−2.400***	−1.722***	−0.845
	t-stat	(−7.36)	(−5.34)	(−3.39)	(−1.52)
INFL	*Coef.*	24.16***	45.73***	69.14***	46.99***
	t-stat	(2.92)	(4.83)	(4.86)	(3.15)
TBILL3M	*Coef.*	1.653	−2.182	−5.657	−7.988
	t-stat	(0.29)	(−0.36)	(−0.63)	(−0.87)
HSTARTS	*Coef.*	−2.266*	−2.952***	−1.699	−4.264***
	t-stat	(−1.80)	(−2.59)	(−1.61)	(−4.24)
TS	*Coef.*	12.89	−11.06	−72.48***	−100.2***
	t-stat	(1.18)	(−0.91)	(−2.96)	(−4.19)
TSRV	*Coef.*	616.7***	198.2	1125.4***	286.9*
	t-stat	(4.04)	(1.28)	(3.73)	(1.90)
SP500	*Coef.*	−5.651**	−7.861***	−9.687***	−0.506
	t-stat	(−2.53)	(−4.63)	(−4.82)	(−0.34)
VIX	*Coef.*	−0.133*	−0.191*	−0.328	−0.258*
	t-stat	(−1.84)	(−1.74)	(−1.30)	(−1.70)
EPU	*Coef.*	0.006***	−0.001	−0.014***	−0.013***
	t-stat	(3.51)	(−0.73)	(−3.00)	(−2.71)
% adj. R^2		30.8	38.5	60.1	52.9

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 12 | Out-of-sample results (mean squared forecast errors) using 60-month initial window.

Panel A (recursive window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.439	0.444	0.444	0.458	0.441	0.433	0.441	0.441	0.438	0.439	0.439	0.438	0.433	0.429
3 months	0.757	0.790	0.793	0.858	0.772	0.788	0.824	0.785	0.778	0.812	0.714	0.737	0.752	0.759
6 months	1.157	1.243	1.273	1.276	1.204	1.250	1.392	1.227	1.247	1.239	1.111	1.101	1.195	1.234
12 months	2.114	2.315	2.477	2.247	2.200	2.354	2.881	2.247	2.372	2.322	2.088	2.851	2.886	2.925

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.080	0.082	0.082	0.090	0.083	0.081	0.084	0.081	0.081	0.081	0.080	0.227	0.227	0.231
3 months	0.227	0.235	0.237	0.241	0.231	0.231	0.242	0.230	0.230	0.235	0.226	0.399	0.393	0.397
6 months	0.369	0.393	0.400	0.405	0.381	0.391	0.414	0.381	0.380	0.395	0.376	0.515	0.492	0.505
12 months	0.567	0.641	0.675	0.656	0.588	0.638	0.690	0.603	0.613	0.569	0.545	0.891	0.775	0.791

Panel B (rolling window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.538	0.469	0.474	0.600	0.474	0.479	0.462	0.478	0.458	0.470	0.458	0.625	0.604	0.596
3 months	0.823	0.930	0.908	1.085	0.814	0.854	0.911	0.850	0.869	0.811	0.730	1.500	1.430	1.357
6 months	1.215	1.819	1.612	1.418	1.297	1.580	1.966	1.484	1.855	1.315	1.552	2.227	1.786	2.184
12 months	2.460	5.084	3.812	3.379	2.688	4.898	10.730	3.255	5.873	2.934	4.769	11.811	7.830	7.806

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	0.016	0.017	0.018	0.030	0.018	0.022	0.017	0.017	0.017	0.017	0.018	0.074	0.074	0.128
3 months	0.047	0.047	0.052	0.056	0.047	0.046	0.047	0.040	0.042	0.044	0.046	0.235	0.209	0.233
6 months	0.066	0.076	0.080	0.087	0.071	0.067	0.070	0.073	0.065	0.054	0.066	0.107	0.053	0.047
12 months	0.063	0.112	0.089	0.090	0.073	0.064	0.114	0.106	0.083	0.037	0.061	0.339	0.713	0.817

Note: This table reports the out-of-sample mean squared forecast errors (MSFEs) when forecasting industrial production (*IPI*) and employment (*EMPL*) growth at 1-, 3-, 6-, and 12-month horizons. Panel A reports the results based on a recursive estimation window, whereas Panel B reports the results based on a rolling estimation window. The table contains the *MSFEs* of a number of bivariate models, using established indicators of economic activity as the main predictor (Columns 1–11), alongside our multivariate settings (Columns 12–14). The models *MULTI*, *MULTI-TS*, and *MULTI-TS-TSRV* represent gradually reduced multivariate forecasting models.

TABLE 13 | Out-of-sample results (mean absolute forecast errors).

Panel A (recursive window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	14.587	14.590	14.563	14.793	14.632	14.471	14.580	14.547	14.336	14.747	14.587	13.979	13.987	13.802
3 months	18.095	18.403	18.873	18.802	17.891	18.376	19.314	18.602	18.000	18.575	17.331	18.000	18.425	18.494
6 months	22.916	23.223	24.630	23.795	22.805	23.955	25.216	23.590	23.971	23.302	21.867	24.016	25.442	25.820
12 months	28.682	29.268	35.278	30.363	29.420	32.719	34.243	29.468	33.516	31.501	28.448	40.769	41.093	41.310

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	2.626	2.686	2.738	2.841	2.769	2.703	2.711	2.658	2.594	2.678	2.743	3.484	3.436	3.465
3 months	5.395	5.581	5.766	5.535	5.430	5.438	5.677	5.396	5.427	5.491	5.401	6.698	6.699	6.748
6 months	8.324	8.950	9.599	8.688	8.514	8.609	9.249	8.738	8.702	8.551	8.537	10.389	10.365	10.600
12 months	13.143	14.902	16.251	14.279	13.551	14.173	15.144	14.172	14.811	13.106	13.156	18.163	17.124	17.488

Panel B (rolling window)

Dependent variable: IPI

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	15.218	14.784	14.836	15.277	15.166	15.114	14.761	14.764	14.687	14.865	15.100	15.690	15.315	15.195
3 months	18.935	19.948	19.570	20.185	18.375	18.904	19.689	19.632	19.062	19.342	17.429	21.337	20.887	21.196
6 months	23.922	27.816	26.443	25.679	24.808	25.219	28.284	26.199	26.213	25.185	23.166	30.551	29.499	31.746
12 months	32.556	46.055	38.851	34.704	35.533	37.011	45.953	40.265	38.299	36.464	34.523	69.558	46.886	47.169

Dependent variable: EMPL

Horizon	TSRV	TS	GOV10Y	EPU	MPU	VIX	MU	GEOP	BAA	HSTARTS	SP500	MULTI	MULTI-TS	MULTI-TS-TSRV
1 month	3.682	2.790	2.977	3.326	3.504	3.639	2.717	2.835	2.778	2.982	3.437	5.248	5.061	5.249
3 months	6.323	6.565	6.404	6.361	5.860	5.544	6.069	6.144	5.837	6.018	5.869	11.778	11.387	11.921
6 months	9.564	11.572	11.517	10.121	9.475	8.685	10.563	10.187	9.901	9.756	9.544	18.557	17.796	18.083
12 months	15.426	21.803	20.260	18.264	15.882	15.042	19.528	18.807	17.060	14.979	15.795	33.798	36.470	37.566

Note: This table reports the out-of-sample mean absolute forecast errors (MAFEs) when forecasting industrial production (*IPI*) and employment (*EMPL*) growth at 1-, 3-, 6-, and 12-month horizons. Panel A reports the results based on a recursive estimation window, whereas Panel B reports the results based on a rolling estimation window. The table contains the *MAFEs* of a number of bivariate models, using established indicators of economic activity as the main predictor (Columns 1–11), alongside our multivariate settings (Columns 12–14). The models *MULTI, MULTI–TS,* and *MULTI–TS–TSRV* represent gradually reduced multivariate forecasting models.

Additionally, we re-estimate the real-time forecasting exercise using a different window setting, that is, a 60-month (5-year) window, to ensure that our main findings are not influenced by the out-of-sample setting characteristics. As shown in Table 12, the results of the out-of-sample analysis are similar when using a different initial estimation window. In this way, we show that the out-of-sample predictability of the TSRV factor does not depend on the choice of the initial time-series window. Moreover, in addition to the MSFE, we estimate the

MAFE to evaluate model performance. The relevant results, reported in Table 13, show that our conclusions regarding the out-of-sample forecasting power of TSRV remain unaltered when using the MAFE instead of the MSFE as our forecasting power metric.

We additionally provide further econometric evidence showing the increased forecasting power of TSRV during the post-crisis period. In more detail, we estimate the same multivariate models

TABLE 14 | Forecasting OLS regression models on US industrial production growth (IPI) while controlling for the post-crisis period.

$$\ln\left(IPI_{t+h}/IPI_t\right) = b_0 + b_1\ln\left(IPI_t/IPI_{t-1}\right) + b_2 INFL_t + b_3 GOV10Y_t$$
$$+ b_4 BAA_t + b_5\ln\left(HSTARTS_t/HSTARTS_{t-1}\right) + \left(b_6 + d_6\right)TS_t + \left(b_7 + d_7\right)TSRV_t$$
$$+ b_8\ln\left(SP500_t/SP500_{t-1}\right) + b_9 VIX_t + b_{10}\ln MPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	Coef.	−0.001	−0.002	−0.003	−0.003
	t-stat	(−0.15)	(−0.22)	(−0.20)	(−0.13)
IPI	Coef.	−0.364***	−0.329***	−0.385***	−0.078
	t-stat	(−5.16)	(−4.60)	(−5.21)	(−0.79)
INFL	Coef.	0.008	−0.126	−0.409*	−1.130**
	t-stat	(0.11)	(−0.94)	(−1.80)	(−2.22)
GOV10Y	Coef.	0.091	0.123	0.190	0.449
	t-stat	(1.05)	(0.81)	(0.91)	(1.30)
BAA	Coef.	0.003	−0.016	−0.031	−0.034
	t-stat	(0.53)	(−1.04)	(−1.55)	(−1.06)
HSTARTS	Coef.	0.038**	−0.029	−0.009	0.009
	t-stat	(2.28)	(−0.90)	(−0.43)	(0.29)
TS	Coef.	0.09	0.362***	0.570***	1.144***
	t-stat	(1.13)	(2.87)	(3.21)	(3.36)
TS-Post	Coef.	0.085	−0.07	−0.183	−0.542
	t-stat	(0.53)	(−0.29)	(−0.50)	(−0.98)
TSRV	Coef.	0.246	−2.775	−3.863	−8.296
	t-stat	(0.15)	(−1.37)	(−1.20)	(−1.61)
TSRV-Post	Coef.	−7.027	−6.736*	−13.72***	−5.187
	t-stat	(−1.51)	(−1.94)	(−3.10)	(−0.70)
SP500	Coef.	0.0430	0.117***	0.104***	0.0912***
	t-stat	(1.40)	(4.96)	(4.98)	(3.44)
VIX	Coef.	0.0001	0.002*	0.004**	0.005*
	t-stat	(0.17)	(1.66)	(2.25)	(1.68)
MPU	Coef.	−0.00003	−0.00002	0.00004	0.0001
	t-stat	(−1.59)	(−0.72)	(1.03)	(1.43)
% adj. R^2		18.6	22.4	27.6	30.8

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

discussed in Section 3.1 (Equation 2), introducing a dummy variable for the post-crisis period, which interacts with both the TSRV and TS factors. The results from Tables 14 and 15 further support our argument, as they show that the TSRV coefficients become more negative (and significant) when controlling for the crisis period. Similarly, we perform a Bayesian forecast combination approach (see Koop and Korobilis 2012) for US economic activity and show that the statistical significance of TSRV

increases significantly after the 2008 GFC period, confirming our previous out-of-sample exercise.[10]

Furthermore, we present in the Supporting Information the time-varying *beta* coefficients for TSRV and TS (similarly to those shown in Figures 1 and 2) for the 12-month forecasting horizon. The results presented in Figures A1 and A2 of the Supporting Information show that the macroeconomic forecasting power of

TABLE 15 | Forecasting OLS regression models on US employment growth (EMPL) while controlling for the post-crisis period.

$$\ln\left(EMPL_{t+h}/EMPL_t\right) = b_0 + b_1\ln\left(EMPL_t/EMPL_{t-1}\right) + b_2 INFL_t + b_3 GOV10Y_t$$
$$+ b_4 BAA_t + b_5\ln\left(HSTARTS_t/HSTARTS_{t-1}\right) + \left(b_6 + d_6\right)TS_t + \left(b_7 + d_7\right)TSRV_t$$
$$+ b_8\ln\left(SP500_t/SP500_{t-1}\right) + b_9 VIX_t + b_{10}\ln MPU_t + \varepsilon_t$$

Horizon (h)		$h=1$	$h=3$	$h=6$	$h=12$
Constant	Coef.	0.000876	0.00247	0.00493	0.00629
	t-stat	(0.32)	(0.35)	(0.46)	(0.40)
IPI	Coef.	−0.0212	−0.142	−0.343*	−0.402**
	t-stat	(−0.19)	(−0.79)	(−1.66)	(−2.21)
INFL	Coef.	0.0410*	0.0241	0.0252	−0.147
	t-stat	(1.66)	(0.40)	(0.24)	(−0.94)
GOV10Y	Coef.	−0.00582	−0.0515	−0.0969	−0.0940
	t-stat	(−0.12)	(−0.46)	(−0.60)	(−0.42)
BAA	Coef.	0.000119	−0.00458	−0.00776	−0.0116
	t-stat	(0.04)	(−0.57)	(−0.65)	(−0.56)
HSTARTS	Coef.	0.0148*	−0.0183	−0.0122	0.00697
	t-stat	(1.74)	(−1.00)	(−0.79)	(0.55)
TS	Coef.	0.0191	0.112	0.230**	0.534***
	t-stat	(1.05)	(1.61)	(2.32)	(2.86)
TS-Post	Coef.	0.0306	−0.0329	−0.119	−0.228
	t-stat	(0.31)	(−0.19)	(−0.51)	(−0.63)
TSRV	Coef.	0.0323	0.0268	−1.280	−1.069
	t-stat	(0.04)	(0.02)	(−0.82)	(−0.38)
TSRV-Post	Coef.	−3.814	−5.857	−7.542*	−7.758*
	t-stat	(−0.94)	(−1.45)	(−1.96)	(−1.79)
SP500	Coef.	0.0334	0.0338**	0.0286***	0.0480***
	t-stat	(1.46)	(2.33)	(3.11)	(4.20)
VIX	Coef.	0.000113	0.000621	0.00104	0.00203
	t-stat	(0.76)	(1.21)	(1.21)	(1.22)
MPU	Coef.	−0.0000133	−0.000000462	0.00000830	0.00000949
	t-stat	(−0.96)	(−0.03)	(0.41)	(0.29)
% adj. R^2		13	8.66	11.3	24.4

Note: Reported *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey–West (1987) estimator.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TSRV is similar for medium-term (6-month) and long-term (12-month) forecasting horizons.

Moreover, we conduct another robustness check regarding the estimated realized volatility measure of the term spread. Specifically, we estimate the TSRV as the realized volatility of the difference between the 10-year and 1-year Treasury yields (instead of the difference between the 10-year Treasury yield and the 3-month Treasury bill rate). This robustness check ensures that the predictive power of the term spread volatility for economic activity is not sensitive to the specific definition of the term spread. We thus re-estimate Equation (2), replacing TSRV with the 10-year minus 1-year term spread volatility (TenOneRV, henceforth). The results reported in the Supporting Information (Tables A1–A3) are consistent with our baseline findings, confirming that the evidence on the forecasting power of term spread volatility is robust to alternative definitions of the term spread.

In order to examine whether the TSRV contains statistically and economically distinct information beyond that of long-term yield volatility (see Cremers et al. 2021, among others), we estimate our baseline forecasting regression models while controlling for the predictive content of long-term yield volatility (LongRV). In particular, we re-estimate a multivariate model (as shown in Equation 2) that also includes the LongRV factor in the right-hand side of the regression equation. In addition, we conduct our analysis in an out-of-sample setting. To do this, we estimate a trivariate model with TSRV and LongRV, along with the relevant measure of economic activity, in the pseudo–real-time forecasting exercise, and we plot the corresponding time-varying *beta* coefficients of TSRV and LongRV, similar to those in Figures 1 and 2. The results are reported in Tables A4–A6 (in-sample regressions) and in Table A7 and Figures A3–A6 (out-of-sample exercise) of the Supporting Information. We can observe that including the long-term yield does not affect the predictive power of the TSRV. More specifically, Figures A3–A6 show that the TSRV yields a statistically significant coefficient for most of the sample period, whereas LongRV fails to do so, especially in the case of industrial production growth.

5 | Conclusions

Our study demonstrates that term spread volatility (TSRV), defined as the monthly realized variance of the daily term spread, is a more robust and consistent predictor of US economic activity than the term spread (TS). The term spread is defined as the difference between the 10-year Treasury note and the 3-month Treasury bill. The predictive power of TSRV is stronger at medium- and long-term forecasting horizons and remains robust even when well-established predictors of economic activity, such as the term spread and stock market returns, are included. The results also show that TSRV has statistically and economically significant predictive power, distinct from other measures of economic uncertainty. Moreover, although the predictive power of TS fluctuates across different periods, particularly before the 2008 financial crisis and after the dot-com bubble, TSRV consistently exhibits stronger predictive ability across various time horizons. The time-varying *beta* and R^2 coefficients further confirm that TSRV is a

valuable tool for forecasting economic activity, especially during periods of heightened uncertainty. These findings provide new insights into the role of yield curve volatility in economic forecasting and suggest that TSRV offers unique and more reliable information for predicting economic downturns, making it a valuable indicator for policymakers and market participants.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] Specifically, we include the rate of the 3-month US Treasury bill instead of the 10-year government bond rate and the Baa corporate bond spread, as well as the EPU index instead of the MPU index. We do not include these two variables in the main multivariate model due to their high degree of correlation with the rest of the variables. Moreover, for the purpose of robustness check, we estimate our multivariate model by also including the macroeconomic uncertainty (MU) index of Jurado et al. (2015) and the geopolitical risk (GEOP) index of Caldara and Iacoviello (2022), and our results remained unaltered. These additional results are available upon request.

[2] We also perform the same rolling and recursive window forecasting settings with a spectrum of initial windows starting from 60 to 120 months. The results based on these alternative windows are qualitatively similar. The estimates based on the 60-month window can be found in Section 4.3, whereas the additional results are available upon request.

[3] In the rolling window setting, we follow the empirical approach of Pesaran and Timmermann (2007) and Schrimpf and Wang (2010). Namely, we estimate an average forecast across multiple selected forecasting windows, named "pooled forecast" in Schrimpf and Wang (2010). In Section 4.3, we also perform a rolling setting using a 60-month window. The results remain qualitatively the same as those from the "pool forecast" approach.

[4] Furthermore, we have employed the model confidence set (MCS) test (Hansen et al. 2011) to identify which of the set of models is statistically equivalent in predictive ability, assessing whether differences in forecast accuracy are significant or due to random variation. The results based on the MCS test are available from the authors upon request.

[5] We have thus estimated our main multivariate models without these correlated regressors, and then, in Section 4.3, we examine alternative specifications using the alternative variables, and the results remain unaltered. These additional results are available upon request.

[6] The DM test evaluates whether the forecasts from one model are statistically significantly different (and potentially better) than those from an alternative model. In this case, we compare two competing forecasting models by examining their forecast errors. Specifically, we report the DM test results for the bivariate model with the TSRV factor versus the model with the TS factor to assess whether the former performs better than the latter.

[7] The CW test is a modified version of the DM test, specifically designed for comparing forecasts from nested models. It allows for comparison between a parsimonious null model and a larger model that nests the null. The test explicitly adjusts for the bias introduced by estimating additional parameters in the extended model relative to the restricted model.

[8] Finally, we have also performed the MCS test of Hansen et al. (2011) to check which models are excluded by the MCS test at the 5% significance level. The results based on this test confirm the main evidence provided by the DM and CW tests and are available from the authors upon request.

[9] For brevity, we present the plots of the time-varying TSRV and TS coefficients based on the 6-month ahead forecasts, which are the two main predictive factors we aim to compare. The reported coefficients are estimated using a recursive forecasting method. In our Supporting Information, we also provide the time-varying coefficients for the 12-month ahead forecasting horizons. More details can be found in Section 4.3.

[10] The results based on the Bayesian forecast combination approach are available from the authors upon request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table A1:** Forecasting OLS regression models on US industrial production growth (IPI) when controlling for macroeconomic fundamentals (alternative measure of term spread). **Table A2:** Forecasting OLS regression models on US employment growth (EMPL) when controlling for macroeconomic fundamentals (alternative measure of term spread). **Table A3:** Forecasting the probability of NBER recession when controlling for macroeconomic fundamentals (alternative measure of term spread). **Table A4:** Forecasting OLS regression models on US industrial production growth (IPI) when controlling for macroeconomic fundamentals (including the volatility of long-term yield). **Table A5:** Forecasting OLS regression models on US employment growth (EMPL) when controlling for macroeconomic fundamentals (including the volatility of long-term yield). **Table A6:** Forecasting the probability of NBER recession when controlling for macroeconomic fundamentals (including the volatility of long-term yield. **Table A7:** Out-of-sample results for TSRV and LongRV (Mean Squared Forecast Errors). **Figure A1:** Estimated *beta* of TSRV when forecasting economic activity twelve months ahead. **Figure A2:** Estimated *beta* of TS when forecasting economic activity twelve months ahead. **Figure A3:** Estimated *beta* of TSRV when forecasting economic activity six months ahead (based on the trivariate model with TSRV and LongRV). **Figure A4:** Estimated *beta* of LongRV when forecasting economic activity six months ahead (based on the trivariate model with TSRV and LongRV). **Figure A5:** Estimated *beta* of TSRV when forecasting economic activity twelve months ahead (based on the trivariate model with TSRV and LongRV). **Figure A6:** Estimated *beta* of LongRV when forecasting economic activity twelve months ahead (based on the trivariate model with TSRV and LongRV).