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Predictive Power of Key Financial Variables During the Unconventional Monetary Policy Era

Petri Kuosmanen | Juuso Vataja

University of Vaasa, Vaasa, Finland

Correspondence: Juuso Vataja (jpv@uwasa.fi)

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ABSTRACT

This study investigates the forecasting power of three well-established financial predictors during the prolonged era of unconventional monetary policy: the term spread, the short-term interest rate, and stock returns. The focus is on predicting GDP growth in both the United States and the Euro area. Our out-of-sample forecasting analysis specifically targets the period characterized by the short-term interest rate effectively bounded at or near the zero lower bound. We recognize that the information content of the term spread is likely to change under such circumstances. Similarly, the dynamics of the short-term interest rate could be altered due to unconventional monetary policy measures. To address this, we modify the short rate calculation by incorporating the shadow interest. This shadow interest rate can go much lower on the negative side than normal interest rates, making it a potentially more accurate rate to describe the monetary policy stance of central banks. The forecasting analysis covers the period from 2009:1 to 2022:3. Our results unambiguously reveal that the predictive power of the term spread completely vanishes during the zero lower bound era. Although the shadow rate has minor predictive content, the strongest predictor consistently lies in real stock returns during unconventional monetary policy. Our findings challenge the conventional wisdom and the stylized fact of the term spread as the most reliable financial predictor for economic activity. According to our results, this does not hold true under unconventional monetary policy, and using the shadow interest rate does not make a major difference in that respect. By shedding light on the changing dynamics during unconventional monetary policy, our study contributes novel insights to the existing literature.

Jel Classification: E37, E44, E47

1 | Introduction

Financial data are inherently forward-looking and linked to real economy; hence, financial variables have also potential to forecast future economic activity. Although there exist many plausible financial indicators for forecasting purposes, the term spread (the difference between long- and short-term interest rates), stock returns, and the short-term interest rate have reached the status as the three most established financial variables in predicting future GDP growth or industrial production—arguably the two most focal macroeconomic series describing economic activity. However, the prolonged zero interest rate monetary policy challenges to the predictive association between financial markets and real economic activity in a fundamental manner. This extended period of zero or even negative interest rates is unprecedented in modern economic history in Europe and the United States. Consequently, central banks in the Euro area and the United States have navigated uncharted waters. Therefore, it is crucial to examine the various ramifications of this monetary policy. This study will contribute to the ongoing debate on the predictive association between financial markets and the real economy under unconventional monetary policy (UMP) circumstances.

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The term spread was discovered as the most promising and useful forecast tool for predicting economic activity in many Western economies in the late 1980s. The short end of the term spread is determined by monetary policy authorities, and the long end comes from the investors in the money market. This set of information have been successful in forecasting recessions and economic growth amazing accurately, in fact, so well that it was asked, if we need any more economist to forecast economic growth and business cycles' turning points (Clark 1996). The term spread reached the status as the single most important indicator of economic activity (e.g., Estrella 2005; Wheelock and Wohar 2009). However, quite soon the dark clouds shadowed that optimism, and gradually the Great Moderation (GM) era from the mid-1980 until to the Financial Crisis of 2008 put these results to many test. When volatility of many economic time series diminished during the GM, the term spread had increasing difficulties to convey extra information over and above autoregressive lags for GDP growth. This guided for a search of other useful predictive financial variables in addition to the term spread.

Benati and Goodhart (2008) defined the short-term interest rate as the simplest measure of monetary policy stance. Interestingly, Ang, Wei, and Piazzesi (2006) found that the mere short-term interest rate contains more information for future GDP growth than the term spread in the United States. Similar results have been obtained in Finland, especially under tranquil economic conditions (Kuosmanen and Vataja 2014a). Moreover, the short-term interest rate has been proven to be the single best financial market predictor in the Finnish context (Kuosmanen and Vataja 2014b) and a useful predictor in combination with the term spread and stock returns in forecasting GDP growth in G-7 countries (Kuosmanen and Vataja 2017, 2019).

Stock market movements and trends are normally closely related to underlying economic circumstances, and the stock prices weigh the importance of economic news all of the time and react to them accordingly. Stock markets are therefore an excellent collector and filter of economic information. Regardless of these unique features of stock prices, stock markets are not often considered as a useful economic indicator, because they give far too often wrong signals (e.g., Samuelson 1966). Even though stock returns as a sole financial predictor for GDP growth have performed rather poorly (e.g., Kuosmanen and Vataja 2014a, 2014b), stock prices have proven to be a useful economic indicator in turbulent economic circumstances, especially when used in combination with the term spread in the case of Finland (Kuosmanen and Vataja 2011) or in combination with both the term spread and the short-term interest rate in predicting GDP growth in the G-7 countries (Kuosmanen and Vataja 2017).

Many studies have shown that the predictive ability of financial variables is far from permanent and stable over time (e.g., Stock & Watson, 2003; Estrella 2005; Bordo & Haubrich, 2008; Kuosmanen, Nabulsi & Vataja, 2015). However, time-varying predictive content of financial indicators have tendency to move together between countries, and especially during economic turbulent times, the predictive content is enhanced at the same time in the G-7 countries (Kuosmanen and Vataja 2019). Kuosmanen, Rahko, and Vataja (2019) were able to identify several different economic factors and circumstances, where the predictive content of financial variables is either enhanced or reduced in large set of countries. The clear outcome of that study was that increased GDP growth volatility is linked to improved predictive content of financial variables. Moreover, the term spread had increased predictive content at the peaks of business cycle, whereas the term spread and stock returns have enhanced predictive content during recessions.

The Financial Crisis marked the end of the conventional monetary policy era. Consequently, various UMP tools were introduced, including liquidity provision, quantitative easing, asset purchases, and forward guidance. Moreover, during the UMP monetary authorities of the both the Federal Reserve Bank (FED) and the European Central Bank (ECB) have started to affect and direct also long-term interest rates. In practice, this means that the entire term spread is affected by the central banks. Kuosmanen, Rahko, and Vataja (2019) also found that the zero lower bound (ZLB) of interest rates strongly reduces the predictive content of stock returns for GDP growth. It seems possible that the predictive association between financial markets and economic activity is for the most part rigged and weakened by the UMP.

Monetary policy is the key factor that directly affects short-term interest rates, specifically the short end of the term spread. Haubrich (2021) notes that monetary policy plays a critical role in determining whether the term spread can predict GDP growth in the US economy. The severity of the global financial crisis and its aftermath led to significant shifts in monetary policy, with central bank rates being substantially lowered and ultimately reaching the ZLB in many countries. However, Bordo and Haubrich (2020) find that there is at least causality from the term structure to output even in episodes of low interest rates. Moreover, Chinn and Ferrara (2024) found that the term spread is still a significant predictor of industrial production growth during extended zero interest rate policy in the United States.

In the United States, the FED's federal funds rate essentially hit the ZLB in December 2008 and remained there until the end of 2015. The ZLB policy returned in the beginning of the 2020s due to the Covid pandemic and remained in effect until the beginning of the 2022s. Additionally, the ECB's policy rate was significantly decreased already in the beginning of the 2009s, though the ZLB was not reached until the end of the 2014s and remained there until the mid-2022. In the Euro area, the nonconventional monetary policy reached the point where the ECB Deposit Facility Rate turned negative from the mid-2014 and stayed negative until the mid-2022.

The purpose of this study is to reassess the forecasting power of conventional financial variables—the short-term interest rate, the term spread, and stock returns—for future economic activity in the United States and Euro area during the recent UMP era. Although the notion of a potential change in the term spread's predictive power for future economic activity during the ZLB is not new (e.g., Ng and Wright 2013; Chinn and Kucko 2015; Hännikäinen 2015; Kuosmanen, Rahko, and Vataja 2019), this study represents a pioneering effort in testing this empirically. We focus exclusively on the ZLB era, conducting an out-of-sample forecasting analysis using conventional, well-established financial predictors. Additionally, we include the modified versions of the short interest rate and the term spread, which potentially better suit the ZLB era, and compare their predictive ability with the conventional ones.

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In the ZLB environment, relying solely on the short-term interest rate as a predictor is clearly unjustified. To address this, we replace the short-term interest rate with the shadow short rate proposed by Krippner (2020). The use of the shadow interest rate becomes particularly relevant during UMP, because this rate can account for negative values far below zero arising from UMP measures. Similarly, it is logical to modify the conventional definition of the term spread by replacing the short-term interest rate with the shadow rate.

The structure of our paper is as follows: Section 2 introduces the forecasting model and outlines the out-of-sample forecasting period. Section 3 presents the data. Section 4 contains the forecasting analysis, and finally, Section 5 concludes the study.

2 | Forecasting Model and ZLB Era

2.1 | Forecasting Model

Our forecasting methodology draws from the approach popularized in the seminal study by Stock and Watson (2003). Stock and Watson emphasize the essential feature that many macroeconomic variables are inherently history dependent. This is certainly true for economic growth, the variable to be forecasted. The history dependence implies that a univariate autoregressive model constitutes a natural benchmark to which the marginal predictive content of additional financial predictors is compared.

Following this approach, the general form of our forecasting model is as follows:

$$y^h_{t+h} = \alpha + \beta_i \mathbf{X}_{i,t} + \sum_{j=0}^{p} \delta_j y_{t-j} + u^h_{t+h} \tag{1}$$

where $y^h_{t+h} = ln\left(\frac{Y_{t+h}}{Y_t}\right) \times 100$, $y_{t-j} = ln\left(\frac{Y_{t-j}}{Y_{t-j-1}}\right) \times 100$, $\boldsymbol{X}_{i,t}$ = vector of the financial predictors consisting of the term spread (TS), the modified term spread (TS^B), shadow short rate (i^{SR}), and the (quarterly) real stock returns (R); u^h_{t+h} = an error term; and h = the forecast horizon. The forecast horizons of two, four, and eight quarters ahead are considered.

Previous research (e.g., Kuosmanen and Vataja 2019) has found that in terms of predictive power, it is advisable to define nominal variables in real terms. We performed the real transformation for the stock returns but left the shadow short rate untransformed due to its inherently synthetic nature.

It is worth noting that only the current period values (period t) of the financial predictors (the vector $\boldsymbol{X}_i$) enter the forecasting Equation (1). Hence, we conventionally assume that all relevant information is included in the newest observations of the financial data and no further lags are needed. Regarding the model specification, we cover all possible combinations of the financial predictors in the empirical analysis. Although previous research favors using more than a single financial predictor, this may not hold during a ZLB environment. The order of the autoregression (p) was determined based on the Schwarz information criterion (SIC), allowing the number of lags to vary initially between zero and five. The out-of-sample forecasting analysis is conducted recursively using direct forecasts for two, four, and eight quarters ahead.

2.2 | Forecasting Period

Figure 1 graphs the interbank rates for the United States and the Euro area from January 2000 to December 2023, extracted from the OECD Main Economic Indicators. It is clearly visible that in

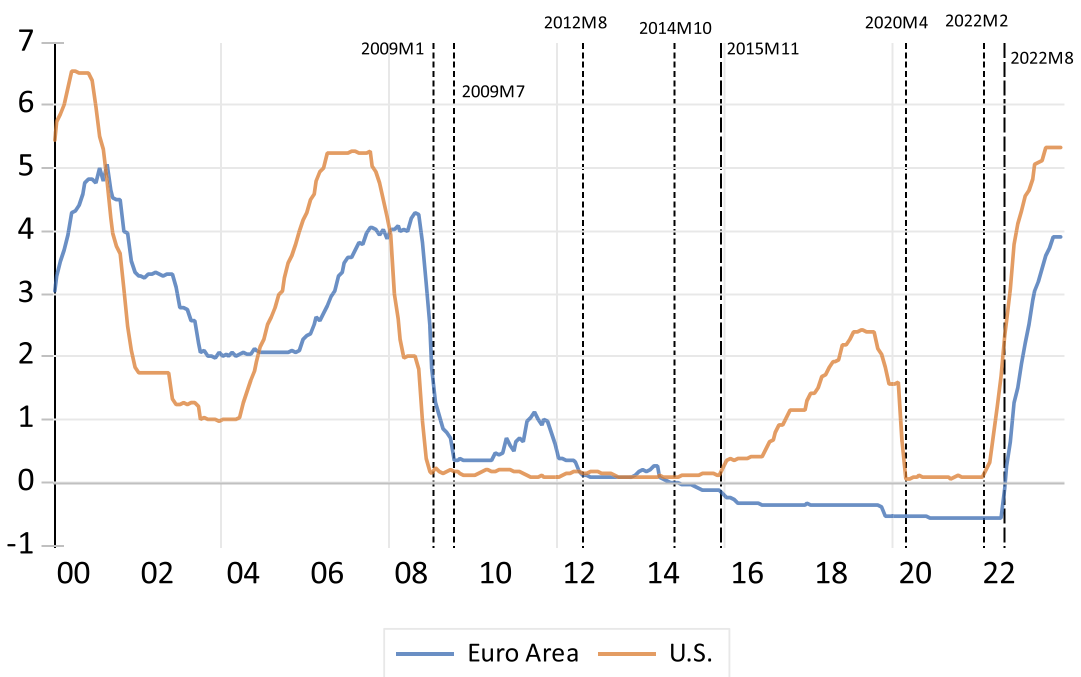

FIGURE 1 | The interbank rates (call money rates) for the United States and the Euro area from January 2000 to December 2023.

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the United States, the ZLB environment became effective over January 2009 to November 2015 and again over April 2020 to February 2022. In the Euro area, this happened later, starting from August 2012 and lasting until August 2022. The interbank rates in the Euro area even turned negative in October 2014 and remained negative until August 2022. Notably, although the ZLB became effective later in the Euro area, the interbank rates fell significantly already in the beginning of 2009. Figure 1 illustrates that the FED typically acts first and vigorously, whereas the ECB follows suit but in a more moderate manner. The era of exceptionally low inflation enabled both central banks to maintain a zero interest rate policy for over a decade. Additionally, sluggish economic growth further motivated this monetary policy. Consequently, the ZLB weakened and likely disrupted the association between economic activity and interest rates in Western economies. Moreover, economic agents have traditionally trusted that large central banks, at least to some extent, follow the Taylor rule. As a result, it was practically impossible to foresee the transition to and from the ZLB.

This study scrutinizes the predictive content of the term spread, the modified term spread (to be defined later), the shadow short-term interest rate by Krippner (2020), and the real stock returns exclusively during the ZLB environment in the United States and the Euro area.

For the sake of comparison, it would be desirable to have a common forecasting period for both countries/economic areas. Hence, we define the first quarter of 2009 as the starting point for the out-of-sample forecasting analysis. This means that the financial information from 2009:1 (together with the lagged GDP growth in Equation 1) is used to generate the first forecasts of GDP growth two, four, and eight quarters ahead. Therefore, the first out-of-sample forecast periods are for 2009:1–2009:3, 2009:1–2010:1, and 2009:1–2011:1, and the forecasting analysis proceeds recursively until the end of the data. The data end at 2022:3, which by and large coincides with the end of the ZLB era.

Admittedly, our definition of the ZLB era is by no means exact. In the United States, the ZLB was not binding during December 2015 to March 2020, whereas in the Euro area, the ZLB became effective in August 2012, although the short-term interest rates fell significantly already in the beginning of 2009.

3 | The Data

Our dataset is quarterly and spans from 1997:1 to 2022:3. The GDP growth rates are calculated as log-differences of the real GDP time series retrieved from the FRED database. The term spread is determined by the difference between the yield of 10-year government bonds and the 3-month overnight interbank rate, both obtained from the OECD Key Economic Indicators. This definition of the term spread is commonly used in applied forecasting analyses.

Short-term interest rate has been found to be a relevant predictor for GDP growth during conventional monetary policy (e.g., Ang, Wei, and Piazzesi 2006). However, during UMP, the use of short-term interest rate as a predictor for economic activity is clearly unjustified. Therefore, instead of short-term interest rate, we

FIGURE 2 | Three-month overnight interbank rates and shadow short-term interest rates.

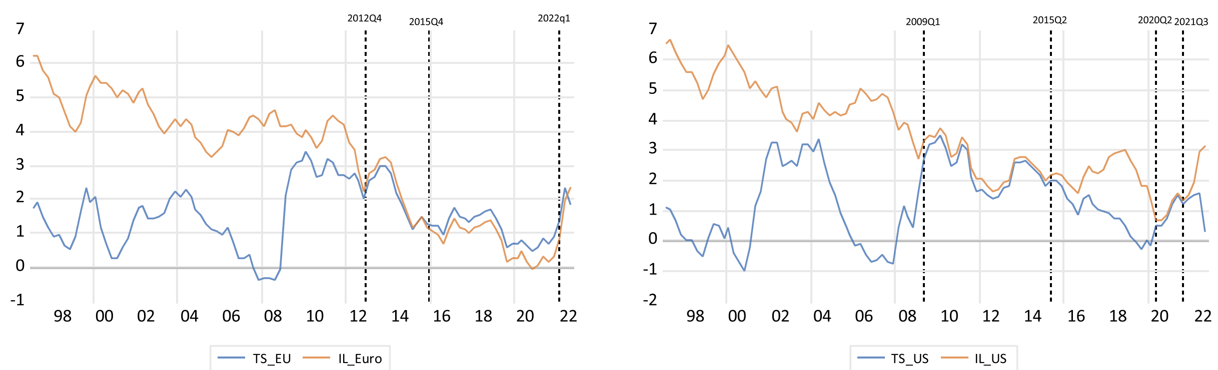

FIGURE 3 | Term spreads (*TS*) and the long-term interest rates (*IL*).

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use the shadow short-term interest rate due to Krippner (2020) as one of the financial predictors. The shadow interest rate provides a quantitative measure of the stance of monetary policy in an UMP environment. Notably, the shadow rate can reach significantly negative values during periods of UMP, but during conventional monetary policy, it closely tracks the 3-month interest rate (Figure 2). The time series for the shadow rate is obtained from Krippner's website (ljkmfa.com).

One should bear in mind that the values of the shadow rate are estimated and, thus, are model and data specific. Consequently, the shadow rates do not directly represent actual market rates, and negative interest rates may not necessarily impact the economy in the same way as actual interest rates. Nevertheless, they serve as a comprehensive measure for the overall stance of the UMP during a ZLB environment (Krippner 2020, 5).

TABLE 1 | Descriptive statistics of the data.

	United States			**Euro area**		
	1997:1–2008:4	**2009:1–2019:4**	**2020:1–2022:3**	**1997:1–2008:4**	**2009:1–2019:4**	**2020:1–2022:3**
$\boldsymbol{y_t}$						
Mean	0.66	0.51	0.39	0.49	0.26	0.22
Std	0.69	0.45	3.82	0.53	0.63	5.47
Min	−2.21	−1.17	−8.87 (2020:2)	−1.84	−3.16	−12.12 (2020:2)
Max	1.80	1.28	7.56 (2020:3)	1.21	0.96	11.47 (2020:3)
J-B	76.44 (0.00)	33.96 (0.00)	10.71 (0.00)	118.70 (0.00)	826.50 (0.00)	7.29 (0.03)
$\boldsymbol{TS_t}$						
Mean	0.89	1.74	0.93	1.09	2.05	1.10
Std	1.34	0.96	0.58	0.77	0.79	0.59
Min	−1.02 (2009:4)	−0.31 (2019:3)	−0.15 (2021:1)	−0.38 (2007:4)	0.56	0.47
Max	3.35	3.51	1.56	2.35	3.40	2.32
J-B	4.47 (0.11)	0.75 (0.69)	1.04 (0.60)	2.18 (0.33)	3.30 (0.19)	5.06 (0.08)
$\boldsymbol{TS_t^B}$						
Mean	1.33	3.04	1.85	1.53	3.52	2.17
Std	1.43	1.83	1.19	0.81	0.53	0.59
Min	−0.52	0.20	−0.13	0.27	2.37	1.30
Max	3.81	5.70	3.37	3.55	4.46	2.86
J-B	4.78 (0.09)	4.04 (0.13)	0.69 (0.71)	1.13 (0.57)	1.95 (0.38)	1.19 (0.55)
$\boldsymbol{i_t^{SR}}$						
Mean	3.55	−0.56	−0.27	3.05	−1.19	−1.55
Std	2.00	1.83	1.83	0.88	1.29	1.25
Min	0.34	−3.74 (2012:4)	−2.44	1.72	−3.80 (2019:3)	−2.74
Max	6.55	2.42	3.24	4.85	1.18	0.96
J-B	4.79 (0.09)	2.05 (0.36)	0.96 (0.62)	2.05 (0.36)	1.11 (0.57)	2.16 (0.34)
$\boldsymbol{R_t}$						
Mean	0.09	1.50	−0.29	0.22	0.92	−1.05
Std	7.50	4.93	7.18	9.93	6.27	8.05
Min	−33.97 (2008:4)	−11.02 (2009:1)	−10.63 (2020:2)	−30.16 (2008:4)	−17.14 (2011:3)	−13.64 (2020:2)
Max	11.23	11.61	9.31	18.60	12.32	9.71
J-B	180.64 (0.00)	1.97 (0.37)	1.97 (0.37)	7.85 (0.02)	4.58 (0.10)	0.91 (0.64)

Note: The value in parentheses is the p-value for the Jarque–Bera test.
Abbreviations: *Std* = standard deviation, *J-B* = the Jarque–Bera test for the null hypothesis of normally distributed data.

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The conventionally defined term spread is the difference between long-term and short-term interest rates. It is noteworthy that in the ZLB environment, short rates are bound to zero; hence, all the variation in term spread is due to changes in long rates (Figure 3). This changes the information content of the term spread and, consequently, the predictive content of the term spread as well. For example, when the ZLB binds, a decrease in long rates due to UMP brings about a decrease in term spread, which is conventionally interpreted as tightening of monetary policy. However, at the ZLB, decreasing term spread is actually associated with easing monetary policy (e.g., Krippner 2013). In view of this, it seems logical to modify the conventional term spread by replacing the short-term interest rate with the shadow short-term interest rate. We include the modified term spread (TS^B), defined by the difference between the long-term interest rate and the shadow rate, in the financial predictors set as well.

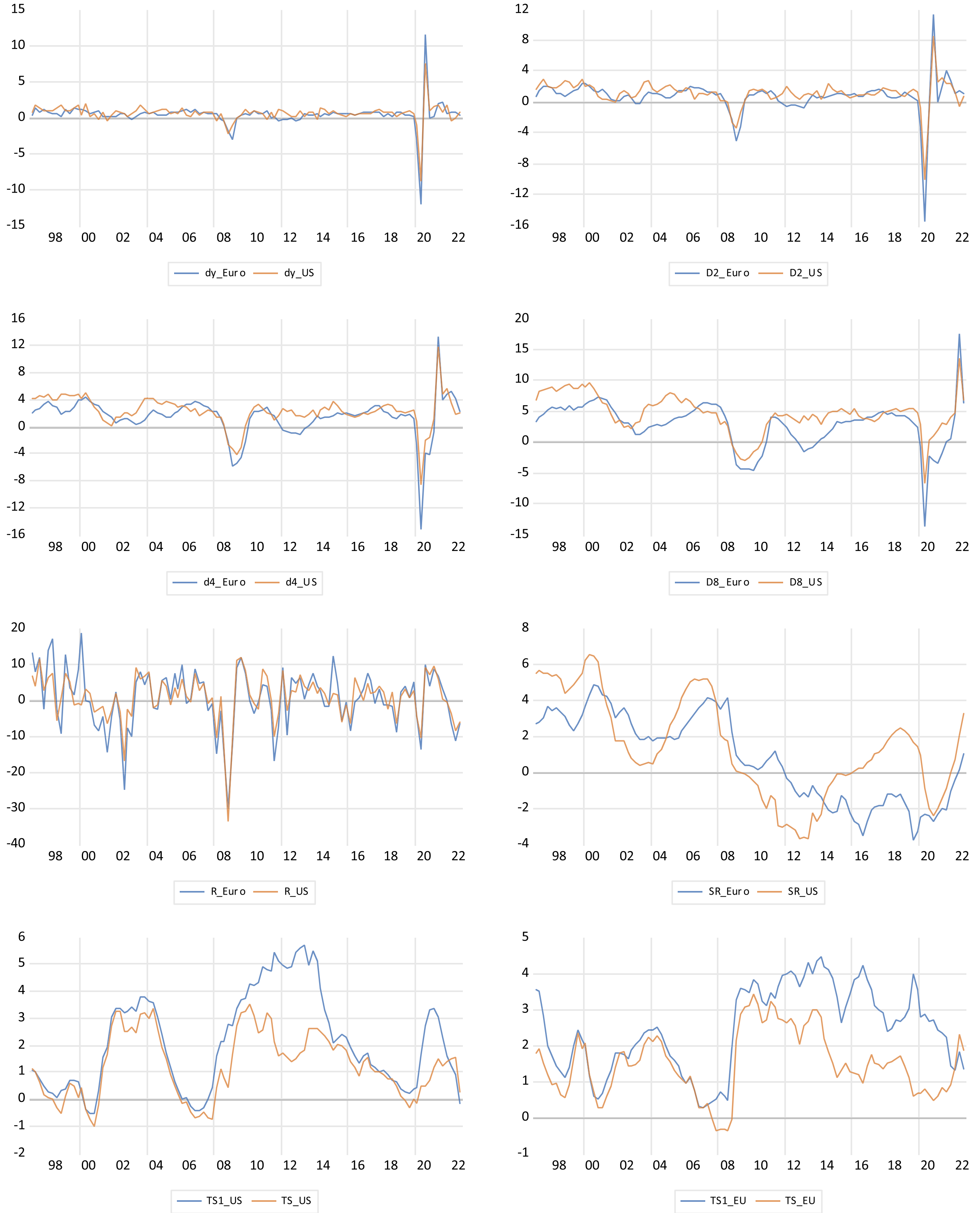

FIGURE 4 | The data. TS1 stands for the modified term spread TS^B.

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Stock returns are based on the stock price indices retrieved from the OECD Main Economic Indicators. The stock price indices were deflated using consumer price indices (CPI), and the real stock returns were obtained using log differences. The source for the CPI data is the FRED database.

Our data extends up to 2022:3. As is well known, the COVID-19 pandemic caused unusually large fluctuations in many macroeconomic time series, including GDP growth. In order to control the impact of the pandemic on forecasting results, we conduct out-of-sample forecasting analyses for two periods: 2009:1–2019:4 and 2009:1–2022:3. Table 1 provides descriptive statistics of the data, but the data are visualized in Figure 4.

The graphical illustration in Figure 4 and the descriptive statistics in Table 1 clearly reveal a significant increase in the variation of GDP growth during the pandemic in 2020, with the increase and slowdown being more pronounced in the Euro area on average. Additionally, the average value of the term spread rises distinctly during the ZLB period from 2009:1 to 2019:4. This phenomenon reflects the fact that when short-term interest rates are stuck at zero, the term spread is effectively determined by the long-term interest rate. The increase in the average value of the modified term spread during 2009:1–2019:4 is even stronger, reflecting the fact that negative values of the shadow rate increase the values of the modified term spread.

The shadow short-term interest rates have indeed been negative in both the United States and the Euro area on average since 2009, which corresponds to the out-of-sample forecasting period in this study. The minimum value is −3.74 for the United States (2012:4) and −3.80 for the Euro area (2019:3).

As expected, real quarterly stock returns exhibit the highest volatility among the three financial predictors. The negative effects of the COVID-19 pandemic are reflected in the negative average stock returns from 2020:1 to 2022:3 in both the United States and the Euro area.

Inversions of the term spread have garnered significant attention due to their ability to signal impending recessions (e.g., Wheelock and Wohar 2009). During the ZLB period, term spread inversions were detected in the United States (2019:3, 2021:1), but interestingly, none occurred in the Euro area.

The time series properties of the data were formally tested using the DF-GLS unit root test (Elliott, Rothenberg, and Stock 1996). The results are presented in Table 2. The null hypothesis of a unit root was rejected for all series except the shadow short-term interest rates and the modified term spread for the Euro area. However, the test statistic (−1.92) for the Euro area modified term spread is very close to the 5% critical value (−1.94). Therefore, we are willing to reject the unit root also in this case. Moreover, considering the well-known low power of unit root tests and the economic rationale for interest rates to exhibit stationarity (Cohrane 1991), we conducted the forecasting analysis using both the level and difference specifications for the shadow rate. Generally, the difference specification resulted in lower forecast errors; therefore, we present results based solely on the difference specification of the shadow interest rate. The results using the level of shadow rate are available upon request.

TABLE 2 | Unit root test results.

	United States	Euro area
y_t	−4.34***	−12.99***
TS_t	−2.81***	−2.79***
TS_t^B	−2.00**	−1.92*
i_t^{SR}	−1.83*	−0.88
R_t	−2.40**	−4.32***

***Significance level at 1%. **Significance level at 5%. *Significance level at 10%.

4 | Forecasting Results

The central premise of the out-of-sample forecasting analysis in this study is that it is conducted solely for the ZLB period, that is, when monetary policy is unconventional. This allows us to assess the forecasting ability of financial predictors when the ZLB is binding. Although not completely uniform for both the United States and the Euro area, the time period spanning from 2009:1 to 2022:3 was considered consistent enough for the analysis. The forecasting analysis was carried out recursively, and the forecasting performance was evaluated based on the root mean squared error (RMSE), with a lower RMSE indicating better forecasting ability. The RMSE of a simple univariate model serves as a natural benchmark against which the marginal predictive ability of the financial predictors is compared. This pseudo-out-of-sample forecasting approach has been followed in the vast majority of forecasting studies since the classic Stock and Watson (2003) study. The forecast horizons considered are two, four, and eight quarters ahead. Previous research has found the four-quarter forecast horizon to be the most suitable for financial predictors (e.g., Kozicki 1997; Wheelock and Wohar 2009). However, other forecast horizons are of interest as well. In particular, this applies to the use of the shadow short rate as one of the financial predictors in the study.

The forecasting results are presented in Table 3. The row titled AR gives the RMSE of the univariate benchmark model. The subsequent rows present the relative RMSE of the competing models (the RMSE of the competitive model relative to the univariate benchmark model). The financial predictors included in the model (together with AR terms) are given in the first column of the table.

Before analyzing the forecasting performance in more detail, a couple of general notions appear noteworthy. Firstly, the forecast errors increase dramatically due to the Covid pandemic, regardless of the forecast horizon. The forecast errors more than double and at worst almost quadruple. The remarkable increase in RMSEs is not surprising, given the unexpected nature of the pandemic and serves to illustrate the inherent difficulties in forecasting during exceptional circumstances. Prior to the pandemic, over the forecast period 2009:1–2019:4, the RMSEs remain moderate. Secondly, the RMSEs are systematically lower for the United States than for the Euro area, again regardless of the forecast horizon.

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TABLE 3 | Out-of-sample forecasting results.

	United States		Euro area	
Forecast horizon: two quarters ahead				
	2009:1–2019:4	2009:1–2022:3	2009:1–2019:4	2009:1–2022:3
AR	0.61	2.75	1.06	4.02
TS	1.02	1.00	0.98	1.00
TS1	1.02	1.01	1.00	1.00
R	**0.97*****	**0.95****	**0.89*****	0.97**
Δi^{SR}	1.03	1.00	1.03	1.01
R, TS	1.02	0.96**	0.90***	0.98
R, TS1	1.00	0.97**	0.90***	**0.96****
Δi^{SR}, *TS*	1.05	1.01	1.01	1.00
Δi^{SR}, *TS1*	1.05	1.01	1.01	1.01
Δi^{SR}, *R*	1.00	0.96**	0.93***	0.99
Δi^{SR}, *R, TS*	1.03	0.97	0.93***	1.00
Δi^{SR}, *R, TS1*	1.03	0.97	0.93***	0.98
Forecast horizon: four quarters ahead				
	United States		**Euro area**	
AR	0.94	3.43	1.56	4.87
TS	1.06	1.01	1.12	1.02
TS1	1.07	1.02	1.04	1.02
R	**0.91*****	**0.93*****	**0.87*****	0.94***
Δi^{SR}	0.98***	1.00	1.05	0.96**
R, TS	1.02	0.95***	1.02	0.97**
R, TS1	1.02	0.95**	0.94***	0.95***
Δi^{SR}, *TS*	1.05	1.01	1.13	0.98**
Δi^{SR}, *TS1*	1.05	1.01	1.05	0.97**
Δi^{SR}, *R*	0.91***	0.94***	0.93***	**0.93*****
Δi^{SR}, *R, TS*	1.02	0.96**	1.05	0.95***
Δi^{SR}, *R, TS1*	1.03	0.96**	0.97***	0.94***
Forecast horizon: eight quarters ahead				
	United States		**Euro area**	
AR	1.12	4.25	2.21	5.39
TS	1.54	1.11	1.46	1.18
TS1	1.62	1.10	1.23	1.13
R	**0.97****	**0.93*****	**0.91*****	**0.93*****
Δi^{SR}	1.01	1.01	1.05	0.97**
R, TS	1.60	1.06	2.29	1.07

(Continues)

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TABLE 3 | (Continued)

Forecast horizon: eight quarters ahead				
	United States		Euro area	
R, TS1	1.70	1.04	1.22	1.03
Δi^{SR}, *TS*	1.55	1.12	1.46	1.14
Δi^{SR}, *TS1*	1.63	1.11	1.23	1.06
Δi^{SR}, *R*	0.98**	0.93***	0.95***	0.96**
Δi^{SR}, *R, TS*	1.62	1.05	1.37	1.10
Δi^{SR}, *R, TS1*	1.71	1.04	1.21	1.04

Note: AR row gives the RMSE of the univariate bench mark model; the subsequent rows give the relative RMSEs (RMSE of the competing relative to the RMSE of the bench mark model). Superscripts refer to the significance level of the Clark–McCracken test (Clark and McCracken 2001). The null hypothesis is equality of RMSE with the univariate bench mark model. Bolded values indicate the model with the lowest (relative) RMSE. Significance levels:
**Significance level at 5%. ***Significance level at 1%.

Despite three different forecasting horizons, the basic forecasting results are surprisingly uniform regardless of the forecast horizon. The lowest RMSEs, that is, the best forecasts, are consistently obtained by using only a single financial variable: real stock returns as the predictor. This holds true in 10 out of 12 cases. In the remaining two cases, the use of more than a single financial predictor yields marginally lower RMSEs than what is obtained using mere stock returns as a predictor. However, the difference in RMSEs is not statistically significant according to the Clark and McCracken (2001) test. This pattern emerges in Euro area forecasts spanning from 2009:1 to 2022:3 for two and four quarters forecast horizons. Specifically, for the two-quarter forecast horizon, using both real stock returns and the modified term spread predictors yields the RMSE of 3.85, whereas using mere stock returns yields the RMSE of 3.88—the difference being insignificant. Similarly, for the four quarters forecast horizon, using both stock returns and the change of shadow rate as predictors yields the RMSE of 4.52, but using mere stock returns as the predictor also yields an RMSE of 4.57. Again, the difference in RMSEs is insignificant.

Another remarkable finding is the complete vanishing of the predictive power of the term spread during the ZLB environment. Only in 1 case out of 24 (Euro area during 2009:1–2019:4), the use of the term spread—either conventionally defined or the modified one—as a single predictor is capable of yielding a lower RMSE than the autoregressive benchmark model, but the difference is insignificant. In the other 23 cases, the RMSEs from the term spread models even fail to match the benchmark model. This result is novel and completely contradicts a vast body of previous research, including Chinn and Kucko (2015), Bordo and Haubrich (2020), and Chinn and Ferrera (2024), among others, to mention a couple of the most recent ones.

Although the use of the shadow interest rate as a financial predictor appears well founded in the ZLB environment, our results provide only minor support for its ability to forecast future economic activity. The change in the short-term shadow rate was capable of better forecasting performance than the autoregressive benchmark in only 3 out of 12 cases, and the decrease in RMSEs was smaller than what was gained by using mere stock returns as the predictor. These results are broadly consistent with Hännikäinen (2017) and Carriero et al. (2021).

Previous research has strongly favored the use of several financial predictors when forecasting future economic growth to obtain the best forecasting performance. However, according to our results, this does not hold true during the ZLB environment. Despite using all possible financial predictor combinations, the forecasting performance did not improve compared to using stock returns as the sole financial predictor. This result aligns with the findings of Stock and Watson (2003), who suggested that a single financial predictor is sufficient for forecasting economic activity in the G-7 countries.

Overall, improvements in forecasting performance relative to the autoregressive benchmark model vary between 9% and 13%, with the largest improvement observed for the Euro area during the entire forecasting period 2009:1–2022:3 for the four-quarter-ahead forecast horizon. The variation in forecasting performance is rather limited for two- and four-quarter forecast horizons, but increases considerably for the eight-quarter forecast horizon, particularly during the pre-pandemic forecast period (2009:1–2019:4).

5 | Conclusions

This study analyzes the forecasting ability of the three most established financial predictors: the term spread, the short-term interest rate, and stock returns, for future GDP growth in the United States and the Euro area. Our study differs from previous literature in that we consider the predictive ability solely during the prolonged UMP era, when short-term interest rates are effectively constrained and stuck at the ZLB. In these circumstances, the predictive content of short-term interest rates and the term spread is likely to change. Hence, it is of vital importance to reevaluate the predictive power of the term spread, which has previously been considered the most established single financial predictor for forecasting economic activity in the United States and other countries. We also test the predictive ability of the short-term shadow interest rate (Krippner 2020) as one of the financial predictors, instead of the conventional short rate. The shadow short rate takes into account UMP by including distinctly negative values for the shadow rate due to various measures of UMP. Finally, given

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the use of the shadow rate, we also carried out the forecasting exercise using the modified term spread, in which the conventional short-term interest rate was replaced with the shadow rate.

Our empirical results are distinct and robust: During UMP, the term spread lost its forecasting power entirely. The same applied to the modified version of the term spread as well. In turn, real stock returns possessed significant forecasting power across all forecasting horizons. The shadow short rate showed some minor forecasting ability, but it was consistently lower than that of the real stock returns. Interestingly, the lowest forecast errors were captured by using only a single financial predictor—the real stock returns—although many previous studies have favored using several financial predictors.

The main result of the study—the collapse of the predictive ability of term spread for future economic activity—is startling, considering the term spread's long-lived status as the single most important financial predictor for future economic activity. This result is novel; there exist no previous forecasting studies concentrating exclusively on the ZLB era. The strong support for the predictive power of stock returns is also remarkable given the usual suspects due to high volatility of stock returns. The robust forecasting performance of stock returns also contrasts strongly with the recent negative view expressed by Nobel laureate Paul Krugman regarding stock markets' ability to forecast the future economic activity (Krugman 2024).

Our results consider only the United States and the Euro area; hence, an important future research topic will be to extend the analysis to a broader group of countries to uncover the robustness of the key findings in this study. Moreover, Japan has experienced prolonged periods of extremely low interest rates since the mid-1990s. Therefore, an in-depth analysis of the association between interest rates and economic activity could provide valuable insights into this issue.

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Data Availability Statement

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

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