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Research

The Near-Term Forward Yield Spread as a Leading Indicator: A Less Distorted Mirror

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The spread between the yields on a 10-year US T-note and a 2-year T-note is commonly used as a harbinger of US recessions. We show that such "long-term spreads" are statistically dominated in forecasting models by an economically intuitive alternative, a "near-term forward spread." This spread can be interpreted as a measure of market expectations for near-term conventional monetary policy rates. Its predictive power suggests that when market participants have expected—and priced in—a monetary policy easing over the subsequent year and a half, a recession was likely to follow. The near-term spread also has predicted four-quarter GDP growth with greater accuracy than survey consensus forecasts, and it has substantial predictive power for stock returns. Once a near-term spread is included in forecasting equations, yields on longer-term bonds maturing beyond six to eight quarters have no added value for forecasting recessions, GDP growth, or stock returns.

Disclosure: The views herein are those of the authors and do not necessarily reflect those of the Board of Governors of the Federal Reserve System or its staff.

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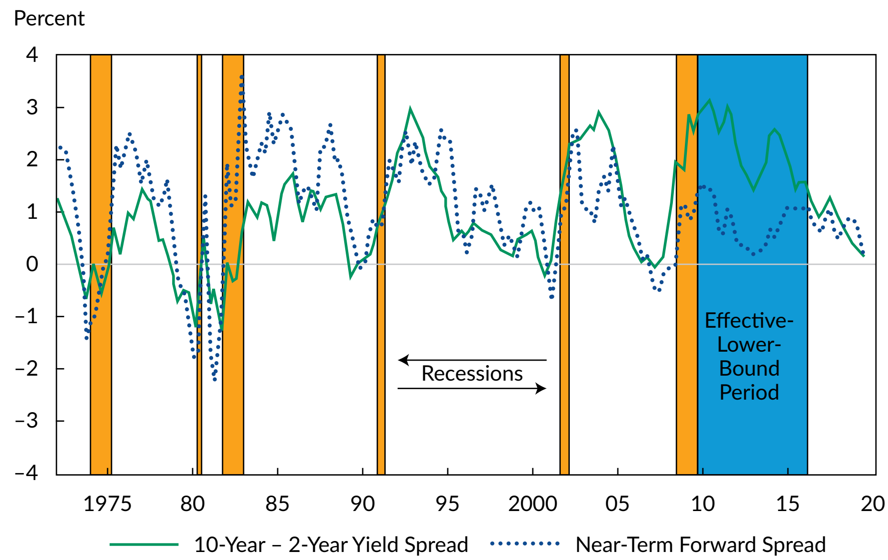
Commonly cited measures of the term spread, such as the difference between the 10-year and 2-year nominal US Treasury yields, dropped to nearly zero by the start of 2019, following several years of decline, as **Figure 1** shows. This phenomenon raised concerns and provoked extensive commentary in the financial press about an impending recession. Those concerns arise from the statistical power that low term-spread levels have shown for predicting recessions over the past several decades. Many studies have documented this predictive power of the term spread—for example, Estrella and Mishkin (1998) and Rudebusch and Williams (2009), to name just a couple. Recently, Bauer and Mertens (2018) and Johansson and Meldrum (2018) have shown that the predictive power of term spreads remains undiminished and is robust to the inclusion of additional predictors.

We show in this article that, for predicting recessions, measures of a "long-term spread"—the spread in yields between a far-off maturity, such as 10 years, and a shorter maturity, such as 1 or 2 years—are statistically inferior to a measure of the interest rate term structure with a more intuitive economic interpretation. In particular, we introduce the "near-term forward spread," which can be construed as a measure of the market's expectations for the trajectory of conventional near-term monetary policy. When negative, it indicates that market participants expect monetary policy to ease over the next several quarters, presumably because they expect monetary policymakers to respond to the threat or onset of a recession. The predictive power of our near-term forward spread indicates that when market participants have anticipated—and priced in—a monetary policy easing over the subsequent year or two, their fears were validated more often than not.[1]

At some level, our findings merely demystify the historical predictive content of the yield curve. We show that the predictive component of yield spreads is highly correlated with market expectations for monetary policy over the coming several quarters. The bond market aggregates the heterogeneous perceptions of traders and

Figure 1. Long-Term Yield Spread and Near-Term Forward Spread



Sources: Federal Reserve Bank of New York; Federal Reserve Board staff estimates.

investors and thereby signals the expectations of the "representative" market participant. So, in some sense, for that typical market participant to infer the likelihood of recession by looking at the yield curve—particularly the near-term forward spread—is akin to that participant looking in the mirror to see whether he or she is anticipating a recession. Of course, to the extent opinions diverge, the yield curve provides onlookers and policymakers a gauge of some average expectation among bond market participants.

Beyond presaging recessions, we found that our near-term forward spread appears to embed other, related information for economists and market observers. For one thing, we show that it has predictive power for the incidence of recession even after conditioning on economists' own consensus forecast of recession probabilities as measured by the Survey of Professional Forecasters (SPF). Perhaps even more interesting, we show that the near-term forward spread has considerable power for forecasting GDP growth over the subsequent four quarters. Here, too, it outperforms the SPF consensus forecast for GDP growth. In contrast, traditional long-term spreads perform relatively poorly for forecasting GDP growth. Finally, we report our tests of whether the near-term forward spread has power to predict excess returns on equities over the year ahead. We found that it has substantial power—indeed, a fair bit more than conventional financial ratios—for predicting market downturns.

Defining Near-Term Forward Spreads

Like a standard term-spread measure using yield to maturity, a forward spread gauges the slope of the term structure of Treasury rates. Using forward rates, however, should help identify more precisely than yields to maturity where on the maturity spectrum the signal for a recession lies.[2] The forward rate at a given maturity can be interpreted as representing the market's expected short rate at that horizon, plus a term premium. In contrast, because a yield is an average of the forward rates spanning the period to maturity, yields tend to blur the signal embedded in forward rates.

For this study, we defined the near-term forward spread on any given day as the difference between the implied interest rate expected on a three-month T-bill six quarters ahead and the current yield on a three-month T-bill.[3] Our six-quarter horizon is a common intermediate-term horizon for forecasting and nearly matches the horizon for which Blue Chip consensus forecasts of short-term interest rates are available.[4] To match the quarterly frequency of most macroeconomic data, we constructed the near-term forward spread as a quarterly average of daily values, which is plotted beside the long-term yield spread in Figure 1.[5]

Arguably, changes in this forward spread should be driven largely by changes in the market's expectations for the path of interest rates to be set by monetary policymakers over the subsequent six quarters. This interpretation is an approximation to the extent that term premiums or liquidity premiums embedded in shorter-term Treasury rates change over time. **Figure 2** plots the near-term spread beside a survey-based measure of the expected trajectory of the federal funds rate. Note that the solid green line shows the difference between the Blue Chip consensus forecasts for the average federal funds rate five quarters out and for the current quarter. As can be seen, the two lines in Figure 2 have moved nearly in lockstep since 2001.[6] Thus, the near-term forward spread does, indeed, appear to be a good gauge of expectations regarding monetary policy. In particular, when the near-term forward spread is negative, it is signaling that investors expect the Federal Reserve to ease monetary policy over the specified horizon.[7]

When do investors expect monetary policy easing? Presumably, when they anticipate a substantial slowing or decline in economic activity. Consequently, if market participants have some foresight, a quite logical result is that low readings for the near-term forward spread will tend to precede (and thus can be used statistically to forecast) recessions. This interpretation implies that inversions of the near-term forward spread do not *cause* recessions. Rather, they reflect something that market analysts already track closely—namely, investors' expectations for monetary policy over the next several quarters and, by extension, the economic conditions driving those expectations. Although long-term spreads also incorporate this information, they are likely to be affected by other factors that are unimportant for forecasting recessions, which degrades their forecasting power.[8]

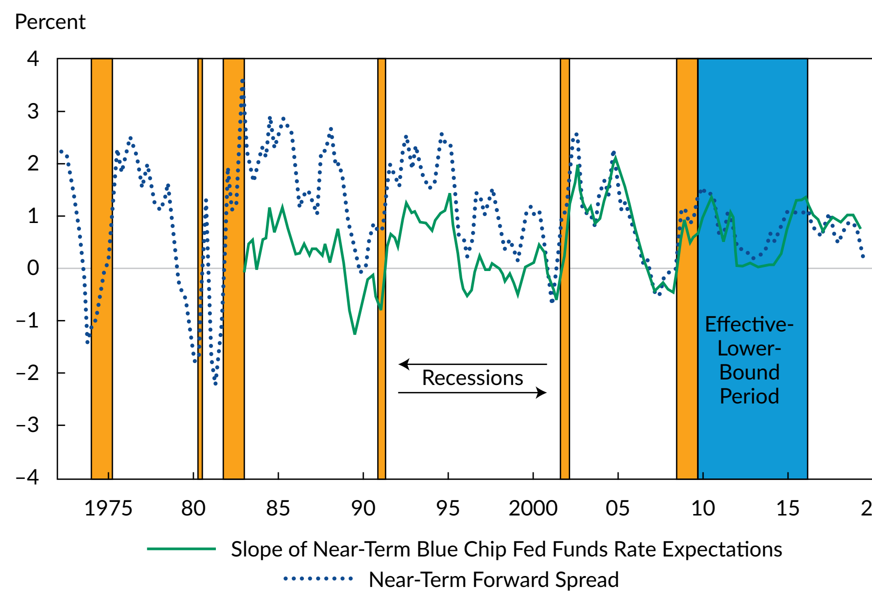
Data

The data used in our analysis are quarterly and span the period from the first quarter of 1972 to the first quarter of 2019.[9] Our macroeconomic data are standard. We used data published by the National Bureau of Economic Research (NBER) to define quarters as periods of either recession or expansion. For GDP growth, we used the four-quarter log difference of real GDP as published by the US Bureau of Labor Statistics. Our financial data are also fairly standard. All of our spread measures begin with daily estimates of the continuously compounded zero-coupon nominal US Treasury curve, estimated as in Gürkaynak, Sack, and Wright (2007). The yield curve for each day is composed of yields at maturities from 1 to 40 quarters out. We took quarterly averages of the daily yield data. We calculated forward rates from the zero-coupon curve using the standard formula,

$$f_t^{n,1} = (n+1)y_t^{n+1} - ny_t^n,$$

where $f_t^{n,1}$ is the (average) forward rate from quarter n to quarter $n+1$ that prevailed during quarter t and y_t^n is the zero-coupon yield for maturity n (expressed at an annual rate). The forward spread was calculated

Figure 2. Near-Term Forward Spread and Market-Expected Path of Short Rates



Sources: Federal Reserve Bank of New York; Blue Chip Financial Forecasts; Federal Reserve Board staff estimates.

as the difference between $f_t^{n,1}$ and the (average daily) three-month T-bill yield during quarter t. Appendix A provides a detailed guide to constructing forward spreads from publicly available data.

Table 1 shows correlations between the near-term forward spread with some other interest rate spreads and additional variables used in our analysis. The first row shows the correlation of the near-term forward spread with the spread between the 10-year and 2-year Treasury yields, a popular measure followed by financial commentators and shown in Figure 1. Although these spreads are reasonably highly correlated, at 0.49, the data suggest a fair amount of unrelated variation. In contrast, the correlation of the near-term forward spread and the 10-year to 1-quarter spread, at 0.83, is quite high. The variable in the third column, the spread between the 10-year-ahead forward rate and the 6-quarter-ahead forward rate, is essentially the complement to the near-term forward spread (added together, the values of these spreads equal the slope of the entire forward curve). This variable has quite a low correlation with the near-term forward spread but a high correlation with the 10y – 2y spread.

The last two columns of Table 1 show the correlation of these spreads with measures of expected economic performance from the SPF. The first is a gauge of the expected recession probability over the next four quarters and is constructed as the average of the SPF probabilities of being in recession during (each of) the subsequent four quarters. The survey probability shows the strongest—and nearly identical—negative correlations with the near-term forward spread and the 10y – 1q spread. The final column shows correlations of spreads with expected growth in GDP over the next four quarters. Here, the near-term forward spread is the spread with the strongest correlation, 0.47.

Horse Race for Recession Predictions

Following long-standing academic practice, our primary recession prediction analysis is based on a probit model.[10] A small departure from most previous studies is that we estimated the probability of *transitioning into* recession. In particular, we estimated the model on the sample that excluded observations for which the economy was already in a recession during the previous quarter.[11] A different model would most likely be appropriate for estimating the probability of *remaining* in recession. As it turned out, however, our main model estimates were not highly sensitive to using the full sample. Finally, as in some other recent studies, we dropped observations for which the effective lower bound on the federal funds rate (around zero) was binding; during those quarters, the near-term forward spread was effectively constrained to be nonnegative.

The statistical results of our probit analysis are shown in **Table 2**. In the first and second rows, we show a comparison of the power of our near-term forward spread and that of the popular 10-year minus 2-year yield spread for forecasting future recessions. As shown in Model 1, a one-standard-deviation decrease in the near-term spread increased the probability of recession by 47 percentage points (pps), an economically large effect that is statistically significant with a p-value of 1%.[12] As shown

Table 1. Correlations among Key Variables, 1972:Q1–2018:Q4

Explanatory Variables	10y – 2y Yield Spread	10y – 1q Yield Spread	10y Fwd. – 6q Fwd. Spread	Survey: Prob. of Recession	Survey: Expected 4-Qtr. GDP Growth
Near-term forward spread	0.49***	0.83***	0.17***	–0.42***	0.47***
10y – 2y yield spread		0.89***	0.93***	–0.32***	0.22***
10y – 1q yield spread			0.69***	–0.41***	0.36***
10y fwd. – 6q fwd. spread				–0.19***	0.02
Survey: Expected prob. of recession					–0.56***

Notes: Data are quarterly. Pearson correlations are reported.

***Significant at the 1% level.

Table 2. Near-Term Spread vs. Far-Term Spreads for Forecasting Recessions, 1972:Q1–2018:Q4

Explanatory Variables	1	2	3	4	5	6	7	8
Near-term forward spread	−0.47			−0.40	−0.28	−0.40		−0.38
	(<0.01)			(<0.01)	(0.04)	(0.01)		(<0.01)
10y – 2y yield spread		−0.36		−0.04				
		(<0.01)		(0.48)				
10y – 1q yield spread			−0.41		−0.09			
			(<0.01)		(0.35)			
10y fwd. – 6q fwd. spread						−0.07		
						(0.23)		
Survey: Expected prob. of recession							0.53	0.29
							(<0.01)	(<0.01)
Mean fitted prob. | future recession	0.64	0.50	0.62	0.64	0.64	0.65	0.58	0.72
Mean fitted prob. | no future recession	0.10	0.15	0.11	0.10	0.10	0.10	0.12	0.08

Notes: Data are quarterly. Observations for which the economy was already in recession in the previous quarter were dropped, as were observations during the zero-lower-bound period (2009:Q1–2015:Q4). Results are for probit regressions in which the dependent variable was an indicator equal to 1 if the economy transitioned from an expansion to a recession one, two, three, or four quarters in the future. Reported are "sensitivity statistics." When the explanatory variable was a term spread, sensitivity was defined as the increase in probability of recession that was estimated to occur when the spread fell by one standard deviation from its unconditional average value while the other explanatory variables remained at their unconditional means. For the survey-based expected probability of recession, sensitivity was defined as the amount by which the probability of recession increased when the survey-based measure increased by one standard deviation from its unconditional mean and all other explanatory variables were held constant at their respective means. Reported in parentheses are the bootstrapped significance levels for a Wald test that the sensitivity was significantly different from zero (bootstrapped under the null hypothesis of no predictability). The bottom two rows report the mean value for the fitted probability of recession in the quarter before (1) a recession occurred in one of the next four quarters or (2) no recession occurred in the next four quarters.

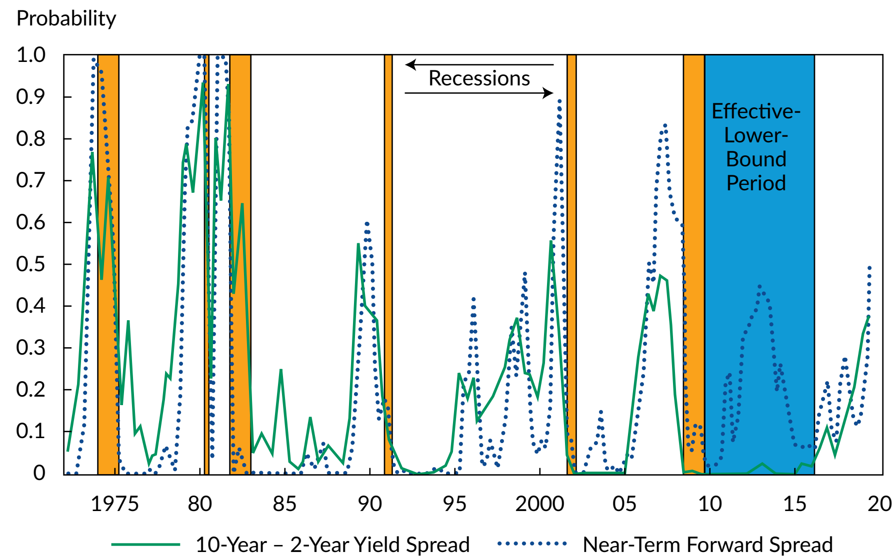
at the bottom of Table 2, the average value of the model-implied probability of a recession was 64% for those observations for which recessions did occur within the specified four-quarter window, in contrast to the 10% average probability preceding periods in which no recession occurred. This result suggests that the model delivers a fairly discriminating signal. In comparison, the results of Model 2 indicate that the 10-year minus 2-year spread delivered a smaller effect, together with a notably less accurate in-sample fit.

Figure 3 shows the fitted conditional probabilities of recession from Model 1, based on only the near-term forward spread (the dotted line), compared with those from Model 2, the more conventional model using the long-term spread (the solid line). Generally, our model exhibits somewhat steeper spikes before recessions, again indicating a more accurate prediction. Notably, this model provided a clearer signal before the 2007–09 "Great Recession." As of the end of the sample period in early 2019 (and the time of this writing), the near-term forward spreads forecasted a substantially elevated probability of a recession.[13]

Returning to Table 2, Model 3 considers an alternative measure of the long-term spread used in the academic literature, the 10-year yield minus the 1-quarter T-bill rate. This measure has more overlap, in some sense, with the near-term spread than does the 10-year minus 2-year spread. Indeed, the coefficient on the spread in Model 3 indicates an effect closer in magnitude to that of our near-term spread, while the fitted probabilities indicate that this measure discriminates almost as well as the near-term spread.

To gauge whether the near-term forward spread and a long-term spread contribute independent information for recession prediction, we included

Figure 3. Estimated Recession Probabilities



Sources: Federal Reserve Bank of New York; Federal Reserve Board staff estimates.

in Models 4 and 5 one of the long-term spreads together with the near-term spread. In both of these models, the magnitude of the coefficient on the near-term forward spread is somewhat smaller than its estimate in Model 1, but it remains statistically significant. In contrast, the estimated marginal effect on the probability of recession of the competing long-term spread is economically small in both cases and not statistically different from zero. Also, fitted probabilities did not improve relative to Model 1. This result is consistent with the hypothesis that essentially all of the information in the long-term spread is subsumed by the near-term forward spread.

Perhaps a better approach to testing whether the term structure contains additional information beyond six quarters would be to include the 10-year forward minus 6-quarter forward spread, which is the complement to our near-term forward spread. (That is, maturities do not overlap with our near-term forward spread; summed, the two spreads equal the slope of the forward rate curve out to 10 years.) Model 6 provided such a test. The results appear, again, to reject the hypothesis that the term structure contains additional information beyond what is contained in our near-term forward spread.

A final question we considered is whether the near-term forward spread contains information over and above that reflected in economists' forecasts. The SPF asks respondents to write down (four) probabilities that the US economy will be in recession in each of the next four quarters. Rudebusch and Williams (2009) tested the relative forecasting power of the 10-year to 1-quarter yield spread against each of these recession probability forecasts and found that, particularly for three and four quarters out, the yield curve was clearly more informative about recession risk than the SPF.

In Models 7 and 8, we show the predictive content of these survey-based recession probabilities in a univariate specification analogous to Models 1–3. As noted earlier, we aggregated probabilities into a signal regarding the year ahead by taking the average of the four quarterly probabilities.[14] The SPF is conducted during the first month of each quarter. We used the survey data from the month that followed the quarter over which interest spreads were measured, so survey respondents had access to all information reflected in market interest rates *prior* to providing their forecasts. In Model 7, where the only regressor is the survey probability, its estimated effect is highly significant. By itself, the survey probability demonstrates prediction accuracy that exceeds that of the 10-year minus 2-year spread, but its performance is inferior to that of the near-term forward spread.

In Model 8, we examined the marginal contribution of the near-term spread when we included it with the recession probability forecast. Here, the coefficient on the near-term spread is only modestly smaller than in Model 1, whereas both the spread and the survey probability are statistically significant. Because Model 8's performance is notably better than that of Models 1 and 7, we conclude that the near-term spread and the survey each bring some independent information to the table. That said, note that the survey-based estimates do not subsume more of the information in the near-term forward spread, given that the survey-based predictions were collected a month later.

The probit models presented in Table 2 allow a nonlinear relationship between the level of spreads and the future incidence of recession, but a great deal of attention has been paid in popular discourse to a particular form of nonlinearity in this context—namely, inversions of yield spreads (i.e., when they fall below the knife edge of zero). The importance of an inversion seems intuitive, given that the near-term forward spread would tend to turn negative when investors decide that the Fed is likely to switch soon from a tightening to an easing stance. To explore the relative performance of the near-term forward spread in this respect, Appendix C presents results from linear models in which the probability of recession depends simply on dummy variables indicating whether a given spread has inverted. In a nutshell, these results are consistent with the probit models in that little or no information for forecasting recessions appears to be embedded in inversions of the long-term spreads that is not already captured by inversion of the near-term spread.

Extension to GDP Growth Prediction

Our finding of the statistical dominance of the near-term spread for forecasting economic activity might be attributable to the use of a probit framework, which accounts for only two possible outcomes—recession or no recession. If some additional signal is embedded further out on the yield curve, perhaps it can be teased out with forecasts of a more granular measure of economic activity. Considering this possibility, we focused on predictions of GDP growth over the four quarters ahead, the same period over which the probability of recession was being predicted. We also examined whether these spreads contain substantial information about future growth that is not reflected in SPF forecasts of GDP.

For predicting recessions, the probit specification allowed for nonlinearity in the effect of spreads on recession probability. Our forecasting apparatus for GDP growth used linear regressions, but we allowed for a simple form of nonlinearity by including, in addition to the value of the spread, a dummy variable equal to 1 when the spread was negative, thus allowing for a discontinuity in predicted GDP growth around a spread of zero.

Models 1–3 in **Table 3** show the results for GDP growth predictions for each of the three candidate spreads. In each case, we included the spread in question plus a dummy indicating when that spread was negative. In Model 1, which used the near-term forward spread, we found that both terms contributed to predicting GDP growth. The coefficient on the spread indicates that a 1 pp increase in the spread boosted expected four-quarter GDP growth by 0.69 pp. In addition, the coefficient on the dummy indicates that seeing a negative spread lowers expected growth by more than 2 pps. The adjusted R^2 indicates that this simple model explains 39% of the variation in realized GDP growth.

In comparison, using the 10-year minus 2-year spread in the analogous specification, Model 2, explained only 17% of the variation in realized GDP growth. Here, only the dummy, with a coefficient of –2.6, contributed to the explanatory power. The explanatory power of the 10-year to 1-quarter spread, Model 3, falls between the first two regressions, with an R^2 of 27%. The coefficient estimate on the linear term is 0.4, but it is not statistically significant at conventional levels. In the columns for Models 4 and 5, we report tests of whether knowledge of either long-term spread contributed to the GDP growth prediction when the model also included the near-term forward spread (and its indicator). When the 10-year minus 2-year spread was included, as in Model 4, neither the linear nor the indicator term was significant whereas the coefficients on the near-term spread variables were largely unaffected and the adjusted R^2 increased only marginally—from 39% to 41%. A similar result occurred when we added the 10-year to 1-quarter spread. We, again, conclude that virtually all of the useful information for prediction is contained in the near-term forward spread.

A final consideration about the information value of the near-term spread for predicting GDP growth is whether it reflects information different from that contained in the consensus survey forecasts of GDP growth.[15] Model 6, using survey data collected toward the end of the first month of the first of the four quarters, simply regressed four-quarter GDP growth on the consensus forecast for four-quarter GDP growth. (As with the recession probits, this process gives a one-month informational advantage to SPF forecasters relative to the bond market.) As shown in Table 3, the coefficient on the survey

Table 3. Near-Term Spread vs. Far-Term Spreads for Forecasting GDP Growth, 1972:Q1–2018:Q4

Explanatory Variables	1	2	3	4	5	6	7
Near-term forward spread							
Level	0.69			0.80	1.28		0.31
	(0.08)			(0.09)	(0.10)		(0.47)
Inversion dummy	–2.10			–2.03	–1.89		–2.30
	(0.05)			(0.05)	(0.09)		(0.03)
10y – 2y yield spread							
Level		0.07		–0.56			
		(0.85)		(0.29)			
Inversion dummy		–2.61		–1.05			
		(0.01)		(0.29)			
10y – 1q yield spread							
Level			0.40		–0.59		
			(0.22)		(0.31)		
Inversion dummy			–2.36		–0.73		
			(0.05)		(0.53)		
Survey expected GDP growth						1.04	0.66
						(0.01)	(0.08)
Root-mean-square error (RMSE)	1.75	2.04	1.91	1.70	1.71	1.95	1.63
Adjusted R^2	0.39	0.17	0.27	0.41	0.41	0.25	0.47

Notes: Data are quarterly; the zero-lower-bound period (2009:Q1–2015:Q4) was excluded. Results are for ordinary least-squares (OLS) regressions in which the dependent variable is real GDP growth over the subsequent four quarters. Bootstrapped significance levels for the coefficients are reported in parentheses (bootstrapped under the null hypothesis of no predictability). The standard deviation of the dependent variable is 2.27%.

forecast is 1.04, close to unity and thus statistically unbiased and consistent with the traditional definition of forecast rationality. But the R^2 is only 25%, notably below the 39% R^2 for the near-term forward spread and its inversion indicator. The final specification, Model 7, includes the forward spread and its inversion indicator together with the survey forecast. Here, both the inversion indicator and the survey forecast are statistically significant, although the forecast has a *p*-value of only 8%. Nonetheless, the adjusted R^2 of 47% implies that economist forecasts contributed materially to the multivariate forecast.

Implications for Stock Market Predictability

In light of the strong predictive power of the near-term forward spread for economic outcomes, even relative to survey forecasts, our findings raise the question, Does this spread measure have power for predicting stock returns? Given that the onset of recession is generally preceded or accompanied by a substantial stock price decline, an affirmative response seems a reasonable possibility. One might expect, however, that much of the information driving movements in the yield curve would already be reflected in equity prices. Indeed, long-term spreads frequently have appeared in the set of conditioning variables used in the predictability literature and have usually contributed little to those regressions.

In **Table 4**, we show the result of our examination of the question of aggregate stock return predictability. We regressed annual (four-quarter) excess stock returns on interest spreads (each measured as an average of the daily values over the quarter preceding the annual return period)—that is, using the same periodicity as the tests for economic predictions.

Table 4. Near-Term Spread vs. Far-Term Spreads for Forecasting Excess Equity Returns, 1972:Q1–2018:Q4

Explanatory Variables	1	2	3	4	5	6
Near-term forward spread						
Level	–1.53				–1.78	
	(0.59)				(0.53)	
Inversion dummy	–22.69				–27.35	–23.59
	(<0.01)				(<0.01)	(<0.01)
10y – 2y yield spread						
Level		1.03				
		(0.73)				
Inversion dummy		–5.40				
		(0.40)				
10y – 1q yield spread						
Level			1.76			
			(0.43)			
Inversion dummy			–7.18			
			(0.40)			
Short rate				–1.85	–1.31	–1.36
				(0.15)	(0.29)	(0.26)
Earnings yield				2.69	3.28	3.28
				(0.05)	(0.02)	(0.02)
RMSE	16.22	17.70	17.35	17.22	14.90	14.96
Adjusted R^2	0.16	0.00	0.04	0.05	0.28	0.28

Notes: Data are quarterly. The zero-lower-bound period (2009:Q1–2015:Q4) was excluded. Results are for OLS regressions in which the dependent variable was excess equity return over the subsequent four quarters. Bootstrapped significance levels for the coefficients are reported in parentheses (bootstrapped under the null hypothesis of no predictability). The standard deviation of the dependent variable is 17.96%.

Of course, the earlier results for economic predictions suggested that the near-term forward spread would have the best shot at predicting returns. The first regression (Model 1) shows the results from predicting excess returns with both the level of the forward spread and the inversion dummy. The coefficient on the spread level is insignificant, but the coefficient on the dummy, –22, is highly significant, and the adjusted R^2 is 0.16. Indeed, this inversion dummy exhibits impressive predictive power relative to other explanatory variables considered in the literature; the result implies a 22% lower average excess return when the spread is negative, a very meaningful effect.

As shown for Model 2, neither the level of the 10-year minus 2-year yield spread nor its inversion dummy has any predictive power. Model 3 results suggest some joint predictive power from the level and inversion indicator of the 10-year to 1-quarter yield spread, but the adjusted R^2 of 0.04 is small relative to the near-term spread regression. Not surprisingly, adding neither long-term spread measure to a regression with the near-term spread (not shown) boosted the overall predictive power relative to Model 1.

To make a connection with the broad return predictability literature, in the column for Model 4, we show results for the more conventional predictors from that literature—the short interest rate and the earnings yield for the S&P 500 Index (the inverse of the price–earnings ratio), each measured at quarter-end preceding the four-quarter prediction period.

The earnings yield is fairly strongly significant, and the adjusted R^2 from this regression is 0.05. In Model 5, we added the near-term spread measures to the regression and found that the inversion dummy coefficient is even larger and, again, highly significant. The earnings yield is also significant, with a positive coefficient, and the adjusted R^2 rises to 0.28—clearly at the high end of explanatory power found in such regressions reported in the academic literature. Finally, because the spread level and inversion indicator are, presumably, highly correlated, in Model 6, we dropped the spread level, which was not significant, to get a clean measure of the inversion dummy effect. The inversion indicator received a coefficient estimate of about –23, which is, again, an economically large effect.

These results suggest a simple market-timing strategy that might dominate a portfolio always invested in the equity market. In particular, they suggest that a dominating strategy in any given quarter would involve being fully invested in equities if and only if the near-term spread was positive during the preceding four quarters. Otherwise, the practitioner should shift the portfolio into the riskless asset (T-bills). Such a rule would seem to follow naturally from the four-quarter return regression and our initial four-quarter recession prediction framework, although a careful analysis of any such rule is beyond the scope of this article.[16]

Conclusion

We have documented, at least on an in-sample basis, that the near-term forward spread subsumes essentially all of the information in other popular measures of term spreads when it comes to forecasting recessions and GDP growth. We argue that this superior performance reflects that the near-term forward spread is simply a cleaner measure of the expectations of market participants—a less distorted mirror. Moreover, the near-term forward spread adds meaningfully to the accuracy of survey-based economic forecasts of real activity, particularly when using a fairly granular measure of activity, such as GDP growth. Somewhat surprisingly, the near-term forward spread also has significant information for predicting equity returns.

The strength and consistency of our findings may tempt one to treat these statistical relationships as a reliable guide for the future. But remember the assumptions required to extrapolate from our findings. In a regime that is targeting a short-term interest rate, extrapolating from the narrow lesson in this exercise does seem reasonable: Once you observe the near-term forward spread or a similar measure of the expected near-term trajectory for short-term interest rates, looking to the 10-year minus 2-year spread or other long-term spreads will reveal little or no additional information about expectations for monetary policy or an economic slowdown in the year ahead. Nonetheless, even this inference is subject to the conditions that (1) interest rates are not too near their lower bound and (2) monetary policy is not being conducted through changes in plans for long-term asset purchases.

What is more, extrapolation is somewhat dicey considering the possible evolution in the relationship between expectations for monetary policy easing and the likelihood of future recessions. The strength of that statistical relationship during the past 45 years reflects the observation of only six actual recessions, coupled with the relative paucity of false signals, in which expectations of policy easing by market participants did *not* precede a recession. The most prominent false positive during our sample was associated with the anticipation of easing triggered by the spread of the Asian financial crisis in 1998, which did not result in a recession in the United States. We can easily imagine that similar scenarios could generate additional false positives in the future. The near inversion of the near-term forward spread at the end of 2018 seems to have been associated with market perceptions of significant risks to the global economic outlook, including the threat of escalating trade disputes. Despite expectations, whether those risks are realized and result in a recession remains to be seen.

Appendix A. Replicating and Updating the Near-Term Forward Spread

Readers wishing to construct and update the near-term forward spread for themselves can do so by using the following three-step procedure (based on the methodology in Gürkaynak et al. 2007) and using data published by the Federal Reserve System.

1. Calculate the six-quarter-ahead forward rate by using the following formula from Gürkaynak et al. (2007), which specifies forward rates in terms of six parameters and the maturity of the forward date, n, in years:

$$f_t(n,0) = \beta_0 + \beta_1 \exp\left(-\frac{n}{\tau_1}\right) + \beta_2\left(\frac{n}{\tau_1}\right)\exp\left(-\frac{n}{\tau_1}\right) + \beta_3\left(\frac{n}{\tau_2}\right)\exp\left(-\frac{n}{\tau_2}\right),$$

where $f_t(n,0)$ is the forward rate and the coefficients that determine the forward rate in each time period are $[\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2]$. The Gürkaynak et al. formulation defines the *instantaneous* forward rate, whereas we used the six-quarter-ahead *three-month* forward rate, which is an average of instantaneous forward rates over the interval of maturities from 1.50 to 1.75 years. To easily approximate the measure used in our article, we advise calculating the instantaneous forward rate for the maturity at the midpoint of that interval, n = 1.625 years. This choice yields a forward rate that rarely differs by more than 1 basis point from the forward rate used in our article.[17] At the time of this writing, updates of daily values of the six parameters needed to calculate Gürkaynak et al. forward rates were published by the Federal Reserve Board at www.federalreserve.gov/econresdata/researchdata/feds200628.xls.

2. Obtain the three-month T-bill rate. At the time of this writing, this series could be obtained from the FRED Economic Data webpage of the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/TB3MS.
3. Calculate the near-term forward spread as the difference between the forward rate and the three-month T-bill rate.

Appendix B. Bootstrapping Procedures

The statistics that we report from the probit and linear regressions in Tables 1–3 used overlapping observations. For example, for the observation of the dependent variable representing "any recession in the period from 1980:Q1 through 1980:Q4," the adjacent observation for the dependent variable represents "any recession in the period from 1980:Q2 through 1981:Q1." The overlapping nature of the data effectively reduced the number of independent observations and created artificial serial correlation in the dependent variable. Although using standard techniques to calculate point estimates in this situation is valid (maximum likelihood for the probits and OLS for the linear regressions, as shown, for instance, by Hedegaard and Hodrick 2016), the overlapping structure rendered standard asymptotic inference invalid.

To produce p-values that are valid in this setup and appropriate for our relatively small dataset, we used a bootstrapping procedure. We first generated synthetic samples of the (overlapping) dependent variable by bootstrapping randomly, with replacement, from the data in blocks of 12 quarters. Bootstrapped samples each had the same length as our data sample. Independently, we block-bootstrapped the vector of explanatory variables. Putting together the bootstrapped dependent and explanatory variables, we created a synthetic dataset in which the effects of overlapping data were present (e.g., artificial serial correlation in the dependent variable) but the model coefficients were zero in population, by construction, as is true under the null hypothesis of "no predictability." We calculated point estimates for each of 1,000 such bootstrapped data samples by using the same estimation procedure as for our actual data sample. Our inference was based on the frequency with which the coefficients in the bootstrapped data exceeded (in magnitude) those calculated in the data sample. For instance, if we found that the magnitude of a particular coefficient in our bootstrapped samples exceeded that from the actual data in only 1% of bootstrapped samples, we reported a p-value of 0.01.

We also calculated standard errors for the portfolio statistics in Table 4 and calculated p-values (in parentheses) representing hypothesis tests for whether the statistics for the active portfolios differ significantly from those of the market portfolio. (Overlapping data were not used for portfolio statistics, except for the maximum drawdown statistic.) For the standard errors of the univariate portfolio statistics, we simply bootstrapped (in blocks of 12 quarters, with replacement) the portfolio returns and calculated the standard deviations of the portfolio statistics across 1,000 bootstraps. To test whether the portfolio statistics for the active portfolios are statistically different from the market portfolio, we used a different bootstrap procedure. We bootstrapped, separately, two samples of the market return and calculated the difference in portfolio statistics that occurred across the two bootstrapped samples of market returns. These portfolio statistics, by construction, have zero difference in population. With 1,000 pairs of bootstrapped market statistics in hand, we calculated the frequency with which the difference in the two synthetic market statistics exceeded what we observed in the actual data (the difference between the statistics for the market and for the active portfolio). For example, only if the observed sample statistic differed from the market statistic by more than 95% of bootstrapped differences under the null did we indicate the difference as statistically significantly different from zero at the 5% level.

Appendix C. Inversions and Recessions

Table C1 displays results from linear models in which the probability of recession depends simply on dummy variables indicating whether a given spread has inverted. As shown in Model 1, for the near-term spread, the probability of recession increases from 6% to 6% + 85% = 91% when the spread inverts and the coefficient on the spread is highly significant. Models 2 and 3 document that the long-term spread measures are slightly less powerful for predicting recessions. Models 4 and 5 show that when the near-term forward spread is included with the far-term spreads, the near-term forward spread retains its economically large coefficient but the coefficient on the long-term spreads falls to essentially zero.

Editor's Note

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Table C1. Using Inversions to Predict Recessions, 1972:Q1–2018:Q4

Explanatory Variables	1	2	3	4	5
Constant	0.06	0.13	0.13	0.06	0.06
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Near-term forward spread	0.85			0.81	0.84
	(<0.01)			(0.18)	(0.08)
10y – 2y yield spread		0.61		0.07	
		(<0.01)		(0.88)	
10y – 1q yield spread			0.75		0.02
			(<0.01)		(0.82)
Mean fitted prob. | future recession	0.71	0.42	0.49	0.71	0.71
Mean fitted prob. | no future recession	0.08	0.16	0.14	0.08	0.08

Notes: Data are quarterly. Observations for which the economy was already in recession were dropped, as were observations during the zero-lower-bound period (2009:Q1–2015:Q4). Results are for linear probability regressions in which the dependent variable is an indicator equal to 1 if the economy transitioned from an expansion to a recession one, two, three, or four quarters in the future. The explanatory variables are dummy variables equal to 1 if the indicated spread was inverted. Reported are slope coefficients. Reported in parentheses is the bootstrapped significance level for a Wald test that the coefficient is significantly different from zero (bootstrapped under the null hypothesis of no predictability). The bottom two rows report the mean value for the fitted probability of recession in the quarter before (1) a recession occurred in one of the next four quarters or (2) no recession occurred in the next four quarters.

Notes

1. Benzoni, Chyruk, and Kelley (2018), in a paper circulated subsequent to the initial draft of this article, also found support for this interpretation.

2. Another interesting approach for decomposing the yield curve, one that appears to dominate the long-term spread, was used by Johansson and Meldrum (2018). They examined the predictive power of the three principal components of the yield curve.

3. As we describe more fully later in the article, the forward rate six quarters ahead is inferred from the yields to maturity on zero-coupon T-notes maturing six quarters ahead and seven quarters ahead. In particular, it is the rate that would have to be earned on a three-month T-bill purchased six quarters from now to equate these two investment strategies: (1) simply investing in a T-note that matures in seven quarters and (2) investing in a T-note that matures six quarters from now and reinvesting the proceeds in that three-month T-bill.

4. Inferences are nearly identical for all horizons between five and eight quarters.

5. When we used end-of-quarter measures for interest rate spreads, such as average values over the last month of the quarter, our inferences were unaffected, although the predictive value of the spreads was a bit lower.

6. Starting in 1997, the survey-based measure is the Blue Chip expected federal funds rate five quarters ahead minus the T-bill yield. Prior to 1997, the five-quarter-ahead forecast was not available, so a four-quarter-ahead forecast scaled by a factor of 5/4 was used instead.

7. Benzoni et al. (2018) followed our approach of focusing on the near-term segment of the yield curve but took the additional step of estimating a decomposition of the near-term forward rates into expected short-term real rates, expected inflation, and risk premiums in order to determine which components of the near-term spread contribute to forecasts of recession probability.

8. One such factor could be a secular decline in the inflation risk premium on long-term bonds.

9. Data for 2019:Q1 were available through January only.

10. We characterize this analysis as estimating recession prediction models, but we acknowledge that our estimates, like those of previous studies, are based on a purely in-sample analysis. Given the relatively small number of recessions in the sample periods of similar studies, the approach does not lend itself well to out-of-sample analysis.

11. Because NBER-defined turning points are not available concurrently or even with a one-quarter lag, an additional step would be required for use in real time. Replicating NBER turning points from data that are available with only a short lag has, however, been done quite accurately (Chauvet and Piger 2008). Our main results are robust to using such real-time measures to determine whether a recession is already under way at the time the forecast is constructed.

12. Our use of overlapping observations rendered standard statistical inference invalid. Instead, we used bootstrapped *p*-values and standard errors. These procedures are described in Appendix B.

13. The near-term spread model forecasts a higher probability of recession during the effective-lower-bound period because it does not reflect the monetary authority's desired trajectory for policy at that time, as the federal funds rate (and three-month T-bill rate) could be lowered no further. The near-term spread thus arguably was not reflective of expectations for macroeconomic performance in this period.

14. We examined whether using a more flexible approach that incorporated the four separate survey probabilities into the prediction model (rather than just their average) would indicate that these survey forecasts contained more information but found only slight improvement to their forecasting power.

15. Rudebusch and Williams (2009) also touched on this issue but only with the limited goal of testing for "rationality" of survey forecasts—that is, whether the (10-year to 1-quarter) term spread they used had any ability to predict GDP forecast errors. Indeed, they documented some evidence against the null hypothesis of no error prediction ability.

16. A brief analysis of such a rule is discussed in an earlier draft of this article (FEDS Working Paper 2018-055, available at www.federalreserve.gov/econres/feds/files/2018055pap.pdf).

17. In daily data for 1971–2018, the two measures differed by more than 1 basis point on only 0.13% of days.

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