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Recession Signals and Business Cycle Dynamics: Tying the Pieces Together

Michael T. Kiley*

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Abstract

Examining a parsimonious, yet comprehensive, set of recession signals yields three lessons. First, signals from financial markets, leading indicators of activity, and gauges of the macroeconomic environment are each useful at different horizons, with leading indicators and financial signals informative at short horizons and the state of the business cycle at medium horizons. Second, approaches emphasizing the yield curve overstate the recession signal from the term spread if other factors are not considered; given correlations among indicators, these differences are often small, but were large in 2022. Finally, simulations of a reduced-form vector autoregression of unemployment and financial conditions, which captures the time-series properties of the series well, suggest the patterns are consistent with a typical hump-shape characterization of business cycle dynamics; this synthesis tightens the connections of the recession prediction literature with the business-cycle literature.

Keywords: Yield Spread, Inflation, Unemployment, Recession Forecast

JEL Codes: E37, E47, G12

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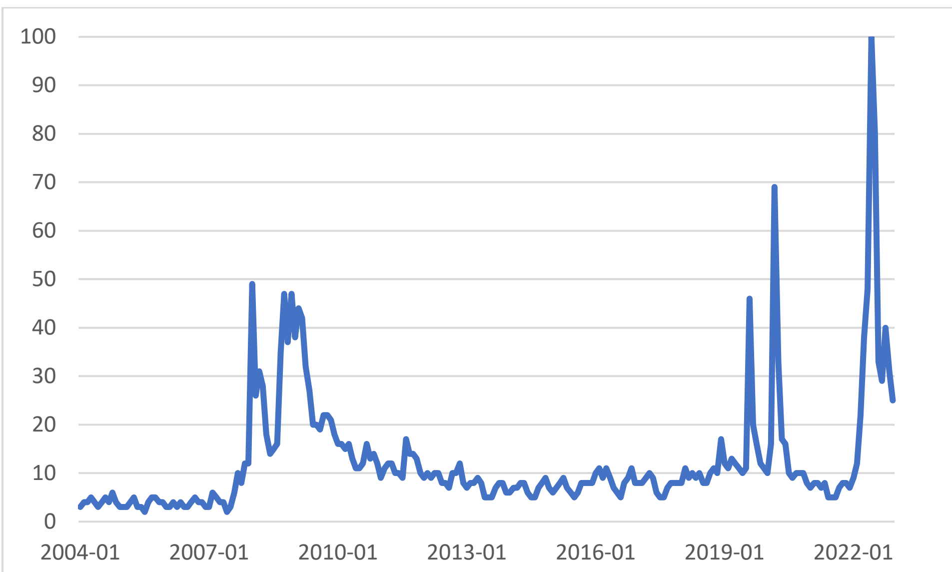
1. Introduction

Recessions in the United States cause substantial economic damage but have been relatively infrequent over the last 50 years. Economists, economic policymakers, financial market professionals, and the public look for signals that a recession may be approaching. In the summer of 2022, web searches for "recession" reached their highest level (as a share of searches) over the period from 2004 according to Google Trends (figure 1), a remarkable development given that the Global Financial Crisis of 2008 precipitated one of the deepest recessions since the Great Depression. This research attempts to integrate a traditional view of business-cycle dynamics into the recession prediction literature, which yields insight into the role of the level of the unemployment rate (and inflation) in typical recession probability models.

Figure 1: Trend in Searches for "Recession" in the United States from Google Trends



Source: Google Trends, downloaded January 3, 2023. Note: Google Trends measures the share of a search term in all search terms in a region (for a sample of searches). The data are normalized so that the maximum value for the term of interest equals 100. For example, the value reported in the figure equals 100 in June 2022, indicated that searches for "recession" reached their highest value as a share of all searches in that month (for the sample shown).

The research literature has extensively investigated indicators that may help predict recessions. While a large variety of approaches have been analyzed, signals can be classified into three broad categories. Financial indicators use data from financial markets, such as components of the yield curve (that is, interest rates at various maturities ranging from overnight interest rates to yields on long-term government bonds), equity prices, exchange rates, and measures of compensation for risk in debt markets. Examples of this approach include Estrella and Hardouvelis (1991), Estrella and Mishkin (1996), Stock and Watson (2003), Chauvet and Potter (2005), Estrella (2005), Chinn and Kucko (2015), and Kiley (2020). Leading indicators broaden the set of indicators from financial variables to include variables that capture near-term economic momentum, such as measures of consumer and business confidence, orders for durable goods, housing starts, or various labor market indicators. Examples of this approach include Burns and Mitchell (1946), Auerbach (1981), Diebold and Rudebusch (1989), Stock and Watson (1989), Hamilton and Perez-Quiros (1996), Marcellino (2006), and Berge (2015). Finally, some work has emphasized the state of the business cycle, as captured by variables like the unemployment rate and/or inflation—indicators that may point to whether economic activity is exceeding a level consistent with stable inflation and hence may be at risk of a slowdown or decline in economic activity. The notion that the unemployment rate and inflation are key summary statistics for the state of the business cycle is consistent with the emphasis on these variables in the mandate of the Federal Reserve (e.g., stable prices and full employment) and in the misery index (e.g., the sum of the unemployment and inflation rates).[2] Examples of research using these variables to forecast recessions include Kiley (2022a, b) and Domash and Summers (2022).

Despite a large body of existing work, the literature on recession prediction is weakly connected to the literature on business cycle dynamics, which is apparent in the tension between recession predictions from the business-cycle and traditional/financial/leading-indicator approaches presented in Kiley (2022b). This tension is apparent in several ways. For example, research, as well as popular discussions, tend to focus on predictions from models with financial variables only, specifically emphasizing the slope of the yield curve. This emphasis is apparent in, for example, Engstrom and Sharpe (2019), Federal Reserve Bank of New York (2022), Ajello et al (2022) and the literature they discuss. Conversely, Domash and Summers (2022) consider only variables like the unemployment rate and inflation—ignoring signals from financial variables or typical leading indicators. In general, the related literature does not tie their analysis to an explicit view of

[2] The misery index is a summary statistic emphasized in popular discussions, and only loosely related to economic theory. The simple index is attributed to Arthur Okun (e.g., Barro, 1999; and Lovell and Tien, 2000).

business-cycle dynamics. The analysis herein ties the approach to recession prediction to a traditional view on business-cycle dynamics (as defined by, for example, Blanchard and Fischer (1989)), integrating results on financial signals, leading indicators, and the levels of the unemployment rate and inflation. Section 2.1 introduces a stylized framework of business-cycle dynamics and its implications for recession prediction.

To empirically assess this integration, we consider a parsimonious-yet-comprehensive set of indicators spanning financial variables, leading indicators, and the state of the business cycle as captured in the unemployment rate and inflation. The set of indicators is relatively comprehensive, but the set is also compact; we use the literature to focus on a set of variables that spans insights from previous work yet allows a thorough analysis of how different indicators interact and thereby shape recession predictions. Specifically, the analysis focuses on the slope of the yield curve (the term spread), a corporate bond spread, a composite leading indicator, the unemployment rate, and inflation. Section 2.2 discusses in detail how this set builds on the literature.

The empirical analysis, presented in section 3, yields three key results. First, signals from financial markets, leading indicators of activity, and gauges of the state of the business cycle such as unemployment and inflation are all useful; focusing on a subset can be misleading. Second, approaches emphasizing the yield curve overstate the recession signal from such variables if other factors are not considered at the same time, because some of the signal contained in the yield curve for recession risk stems from the yield curve's correlations with the business cycle. Finally, some indicators provide more valuable signals at short horizons, such as leading indicators emphasizing momentum, while others provide signals for longer horizons, such as the unemployment rate. This finding highlights how work focused on the short-term—such as Berge (2015) and Liu and Moench (2016)—have emphasized the recession signals from leading indicators of momentum, while work focused on risks over one or two years—such as Kiley (2022a, b) and Domash and Summers (2022)—have emphasized the degree of tightness in the labor market.[3]

The analysis in section 4 examines whether the recession prediction results are consistent with the basic time series properties of unemployment and financial conditions—that is, whether the pattern of coefficients from the prediction equations are what should be expected. A vector-

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[3] Estrella and Mishkin (1998) consider short and long horizons, but generally find that measures of fit are very poor at horizons greater than one year. The results herein and in Kiley (2022a, b) and Domash and Summers (2022) recognize the challenges of prediction, even within sample, at longer horizons, and generally find that inflation and the unemployment rate help at such horizons. The empirical results will demonstrate this finding.

autoregression (VAR) of the unemployment rate and the term spread captures traditional business cycle dynamics of the sort emphasized in Blanchard and Fischer (1989) and described in section 2–generating hump-shaped responses of the unemployment rate to financial shocks. Such dynamics imply the peak effect of shocks appears sometime after the initial impulse. This is expected, as such dynamics emerge from a range of macroeconomic models, as has been known for a long time (e.g., Samuelson (1944)) and as emphasized in textbook treatments (e.g., Sargent (1987)). Kiley (2013) describes how the cyclical component of output (or the unemployment rate, via Okun's law) that emerges from modern modeling techniques resembles the traditional decomposition, consistent with traditional hump-shaped dynamics. Simulation of the VAR equations yields implications for recession predictions in line with the estimated recession prediction equations: momentum, as captured in leading indicators, is important for recession prediction at short horizons as a (positive or negative) shock is initially followed by movements of activity in the same direction; the level of the unemployment rate is important at medium horizons, as the effects of shocks fade and activity returns to its baseline value; and failure to account for these two factors overstates the role of the term spread in recession prediction. In addition, the simulations suggest the results are likely not spurious, as these patterns cannot be replicated in simple frameworks that could generate a spurious role for the level of the unemployment rate.

Pulling all these results together, conditions in early 2022 were in many ways unprecedented: economic momentum and a steep yield curve pointed to essentially no recession risk; low unemployment and high inflation pointed to high recession risk. The data suggest all these signals are valuable and that forecasters should avoid a narrow focus on the term spread or leading indicators, with important roles for the state of the business cycle as summarized by the level of the unemployment rate and inflation. In broad terms, these results support the analyses in Kiley (2018, 2022a, b) and Domash and Summers (2022).

Section 2 discusses business-cycle dynamics and recession indicators. Section 3 presents results on the value of signals over different horizons. Section 4 presents simulation results that highlight the integration of business-cycle dynamics and recession prediction and address the possibility of spurious correlations. Section 5 concludes.

2. Recession Signals: The State of Play

2.1 Recession signals and traditional business-cycle dynamics

The traditional view of business-cycle dynamics, as discussed in (among others) Blanchard and Fischer (1989), focuses on the fluctuations in economic activity at business-cycle frequencies. Two approaches have been common in the literature. One, based on Okun (1962), emphasizes that the unemployment rate is a good summary statistic for the state of the business cycle. A second, emphasized in the development of dynamic-general-equilibrium models (of the New-Keynesian and Real Business Cycle varieties, which are now largely integrated), detrends measures of economic activity using various filters (e.g., Cooley and Prescott, 1995). Such decompositions typically yield "hump-shaped" dynamics, in which the univariate properties of activity are well captured by AR(2) dynamics and the system properties of indicators have similar degrees of complexity (or greater). Empirical work has also found hump-shaped dynamics following impulses, as illustrated by the literature on the effects of monetary policy shocks (e.g., Christiano, Eichenbaum, and Evans, 1999).

A simple-reduced form characterization of such dynamics for the unemployment rate (U(t)) and its relationship to financial conditions (denoted FC(t)) is given by equation (1).

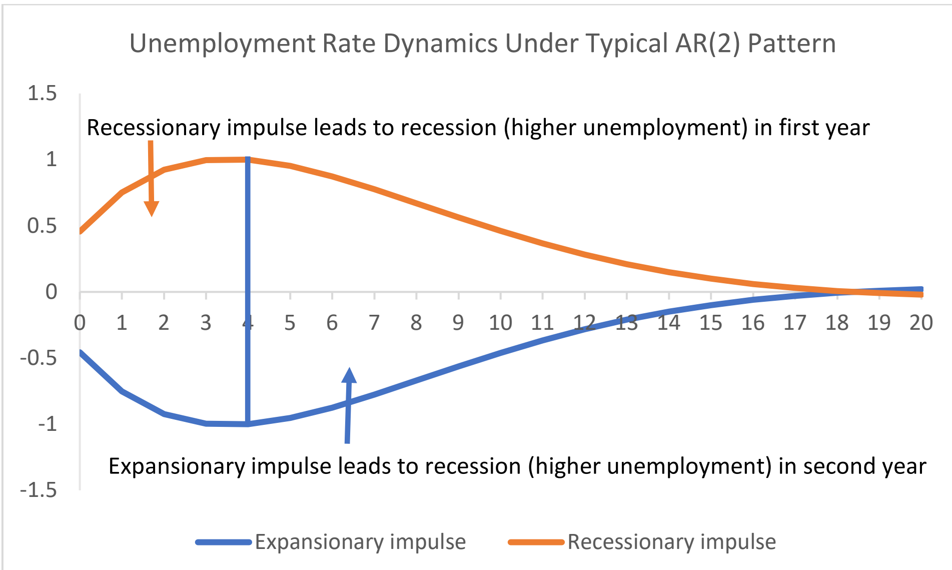
$$(1)\ U(t) = (a1 + a2) * U(t-1) + a1 * a2\ U(t-2) - FC(t).$$

In equation (1), a1 and a2 are the autoregressive roots and the impulse to financial conditions has a negative sign—that is, expansionary financial conditions (a positive value for FC(t)) lower the unemployment rate.

Figure 2 presents the behavior of the unemployment rate following an expansionary and recessionary impulse (which are the mirror-image of each other in this linear equation) and highlights the implications for recession prediction. A recession is defined as an increase in the unemployment rate. Following a recessionary change in financial conditions, the unemployment rate jumps up and rises for the following four quarters—that is, a recession occurs in the year following the shocks. The recessionary impulse to financial conditions occurs prior to the full increase in unemployment, and hence financial conditions are a useful recession predictor. Alternatively, the initial increase in the unemployment rate is followed by further increases over the first year, and hence the momentum in the economic activity is a leading indicator of the recession. Each of these predictions holds over the first year, during the upward portion of the hump-shaped response to the impulse.

After four quarters, the other side of the hump-shape is reached—the initial impulse is reversed. As a result, a recession sets in after a year following an expansionary shock. This recession is preceded by the low level of the unemployment rate: Following an expansionary shock, unemployment falls to low levels, but then reverts to its long-run level, which requires a recession. These dynamics suggest that the level of the unemployment rate may be a recession indicator, especially at longer horizons.

Figure 2: Business Cycle Dynamics of the Unemployment Rate



2.2 A set of recession signals based on previous work

There is a substantial body of existing work on recession signals, which can be classified as *financial indicators*, *leading indicators*, and measures of the *state of the business cycle*.

Financial indicators: Financial markets are forward looking and embed expectations for the economy. For example, monetary policymakers adjust short-term interest rates with fluctuations in economic activity, and hence long-term bond yields—which embed expectations for short-term interest rates—incorporate information on future economic activity.

As a result, a substantial literature uses financial indicators to forecast future economic activity and recession risk. For example, Estrella and Mishkin (1996), Stock and Watson (2003), and Kiley

(2020) consider dozens of variables. As is the norm in research, different studies reach different conclusions. Nonetheless, a consensus appears to have emerged on to types of indicators, even if researchers may differ in findings or preferences over indicators within these classes of indicators. Two indicators that have been identified as strong recession signals are **the slope of the yield curve** and **a corporate bond spread**.

The literature on the slope of the yield curve is very large. The bibliography of Federal Reserve Bank of New York (2022) lists 114 articles on the yield curve as a recession indicator. Prominent studies include Estrella and Mishkin (1996, 1997, 1998), Bernard and Gerlach (1998), Chauvet and Potter (2005), Ang, Piazzesi, and Wei (2006), Wright (2006), Rudebusch and Williams (2007), Wheelock and Wohar (2009), Chinn and Kucko (2015), and Engstrom and Sharpe (2019).

The literature emphasizing the value of the corporate bond spread as an indicator useful for forecasting economic activity or recessions is not as large as the literature on the yield curve, but several recent pieces have suggested that such spreads are powerful indicators. Examples include King, Levin, and Perli (2007), Gilchrist and Zakrajsek (2012), and Faust, Gilchrist, and Zakrajsek (2013), among others. An element of this literature has emphasized the importance of distinguishing between risk premiums in corporate bond spreads and default risk in spreads: the work of Gilchrist and Zakrajsek (2012) highlights this distinction and the forecasting ability of the risk premium component.

In general, these financial indicators are, in the simple framework of section 2.1, impulses and hence would be expected to signal recessions most powerfully in the short run—for example, over a four-quarter horizon.

Leading indicators: While financial indicators, most prominently the slope of the yield curve, dominate work on recession signals, a medium and large body of work examines sets of economic data for coincident and leading indicators—spanning from Burns and Mitchell (1946) to Marcellino (2006). Results vary, but a variety of measures have been found to have some predictive power, including measures of consumer and business confidence and measures of activity in product, housing, or labor markets. Despite this approach's history, researchers continue to make advances in how to combine leading indicators (e.g., Berge, 2015).

To represent this approach, we include the **OECD's composite index of leading indicators for the United States** as one of the recession signals. This indicator is an aggregate of work started for dwellings (housing starts), net new orders for durable goods, a consumer confidence indicator, weekly hours worked in manufacturing, a manufacturing confidence indicator, the term spread of interest rates, and equity prices (the NYSE composite). Note that this composite indicator includes some financial variables, as is typical: for example, Berge (2015), in his own analysis and in reviewing earlier work, finds an important role for term spreads and corporate bond spreads (the financial variables noted above) as well as several labor market, housing, and other variables in his assessment of leading indicators.

Finally, the empirical analysis uses the change in the leading indicator, as these measures momentum, as emphasized in the simple model in section 2.1. Section 2.3 will demonstrate how the change in the leading indicator is related to the change in, and level of, the unemployment rate, further strengthening the connection of the indicator to the simple model. (The change in the leading indicator also has strong predictive content, as the empirical results will show, further justifying the focus on the change.) The simple model suggests that momentum will be important for recession prediction in the short run (less than a year).

State of the business cycle: While leading indicators include measures of economic activity, they are not highly correlated with measures of the business cycle such as the unemployment rate. Recent work has emphasized how the cyclical position of the economy may be useful indicators of recession risk (Kiley, 2022a, b; Domash and Summers, 2022), as we include the unemployment rate and inflation rate in our set of possible recession signals.

Consistent with the simple model of section 2.1, the level of the unemployment rate is expected to be more important at medium horizons—that is, at horizons greater than a year. To the extent inflation reflects the state of the business cycle through a Phillips curve, it would also be expected to have predictive power at longer horizons. Alternatively, high inflation may predict recessions because it brings forth a monetary contraction (Romer and Romer, 1989), and hence may be a recession signal across different horizons.

2.3 Key characteristics of the candidate recession signals

The selected variables are a small subset (five) of possible candidates, but the selected set span the categories of interest, have been emphasized in previous work, and provide a reasonable group for a comprehensive analysis of the possible economic forces underlying empirical relationships. For example, the focus on five variables implies only 31 combinations of variables in estimated equations to fit recession outcomes, which is a large but manageable number. Just as importantly, the set of variables highlight recognizable business cycle co-movements that may be important in understanding the role of different signals. An alternative approach, not considered herein, posits a factor structure for a large number of predictors and uses statistical techniques to extract factors to use in prediction (e.g., Stock and Watson, 2002, 2006); this alternative approach is very useful, but the analysis herein looks at a smaller number of predictors to consider a range of prediction horizons and connect to the substantial bodies of literature that use the yield curve or leading indicators to assess business-cycle turning points.

Table 1 and figure 3 presents some information on the selected signals to introduce some of the business-cycle comovement that may aid understanding of the value of each variable as a recession signal.

Table 1: Correlations among recession signals

Sample: 1965Q1 2019Q4 (Included observations: 220)

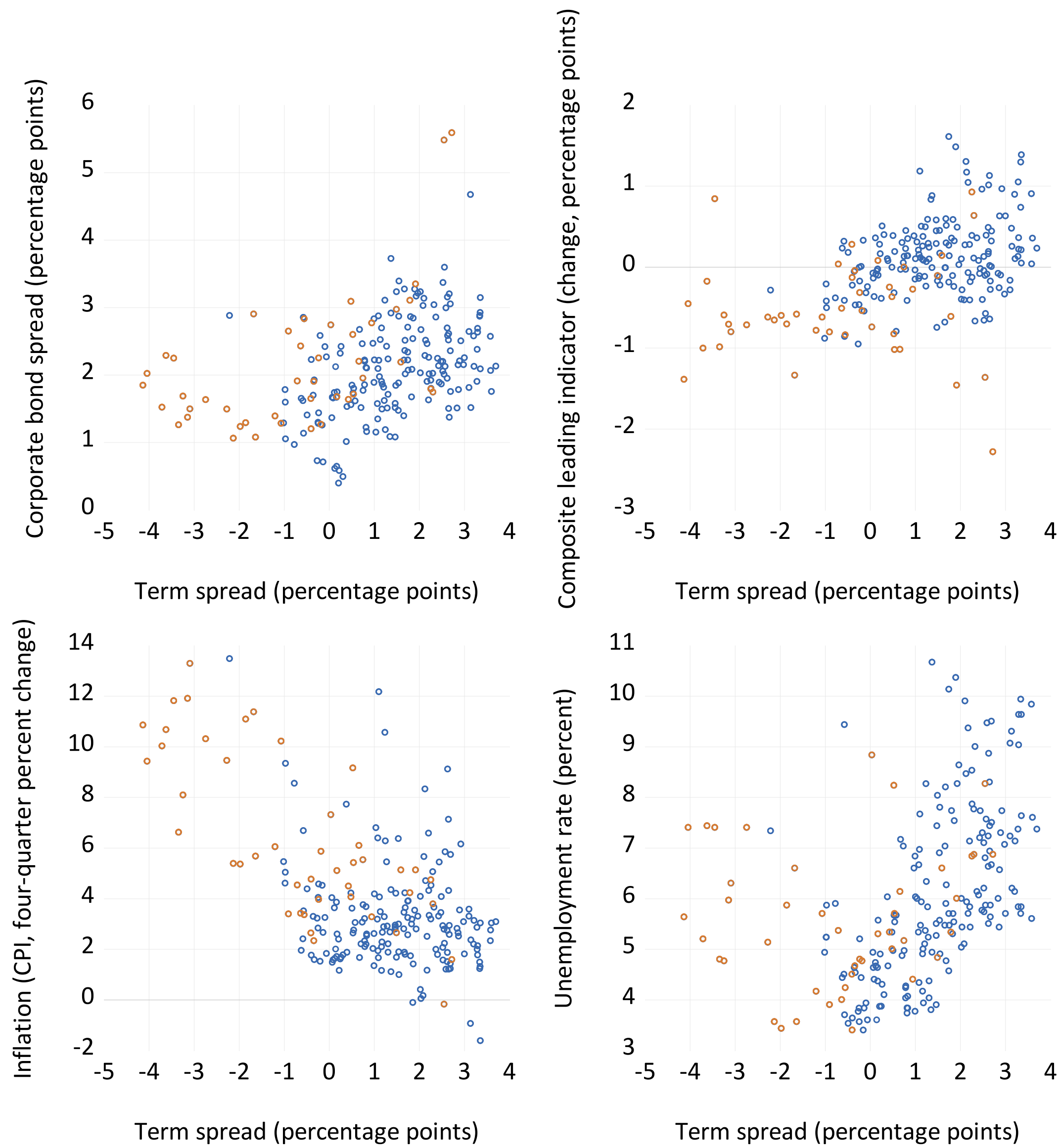
Correlation	TS	CBS	CLI	π	U	ΔU
Term spread (TS)	1.00					
Corporate bond spread (CBS)	0.39	1.00				
Leading indicator (change) (CLI)	0.44	0.00	1.00			
Inflation (π)	-0.57	-0.25	-0.22	1.00		
Unemployment rate (U)	0.43	0.49	0.28	0.13	1.00	
ΔUnemployment rate (ΔU)	-0.16	0.39	-0.32	0.29	0.12	1.00

The signals are highly correlated (table 1), reflecting common business-cycle movements (an issue analyzed more thoroughly in section 4). Inflation and the term spread are highly (negatively) correlated. In addition, the term spread and the unemployment rate are highly positively correlated. These correlations suggest that considering inflation and unemployment, as in Kiley (2018, 2022a, b) and Domash and Summers (2022), may be important for assessing the information in the term spread. The table also shows that the (change in the) leading indicator and the corporate bond spread, as well as the unemployment rate and the corporate bond spread, show sizable correlations.

The (change in the) leading indicator and the unemployment rate are positively correlated—a high unemployment rate is associated with improving economic activity (a positive change in the leading indicator). This is somewhat expected from the business-cycle dynamics in figure 2. This is also consistent with the correlation between the change in the leading indicator and the change in the unemployment rate, which is strongly negative (strong momentum in activity is associated with declining unemployment).

Figure 3 highlights why these signals have been used in previous work. As indicated by the red circles, the period one year before a recession quarter tends to see the following developments: the term spread is low (flat yield curve), the leading indicator is falling, inflation is high, and/or the unemployment rate is low. These patterns are discernably different than those seen outside the period one-year before a recession (the blue circles).

Figure 3: Relationship among Indicators



Note: Scatterplots of data from 1965Q1 to 2019Q4. Red circles indicate data four quarters prior to a recession quarter, as identified by the NBER. Blue circles indicate other periods.

3. Empirical Results

3.1 Approach

Following previous literature, a binary dependent variable regression (logit) is used to predict whether a recession quarter is likely at horizons (h) of the next 2, 4, or 8 quarters; in addition, the analysis considers whether a recession quarter appears within the four quarters that occur four quarters ahead (a 4/4 horizon)—that is, within the year one year after the current year; including this approach will help discriminate across signals useful in the short run and medium run.[4] The approach considers all possible combinations of the five predictors.

The recession event is an adverse tail outcome for economic activity. The analysis considers three definitions of a recession

- An increase in the unemployment rate over horizon h that exceeds the 80th percentile of the change in the unemployment rate over that horizon in the data from 1965Q1 to 2019Q4.
- A change in (the natural logarithm) of real GDP (per capita) over horizon h that falls below the 20th percentile of the change in real GDP over that horizon in the data from 1965Q1 to 2019Q4.
- A recession dummy equal to 1 if the National Bureau of Economic Research identifies a recession within a month that falls within the horizon h.

These measures are similar, reflecting the Okun's law relationship between unemployment and real GDP and the central role these measures play in understanding the business cycle (and hence in NBER determinations). Despite similarities, these three alternative measures provide some sense of robustness and a touchpoint to the literature, as some of the literature. As the results are very similar across approaches, the first approach will be emphasized, as in Kiley (2022a, b): this definition has the advantage that the event being predicted occurs with the same frequency across horizons h (a frequency of 20 percent), whereas the probability that an NBER recession occurs within the prediction window increases as the window expands from the next 2 quarter to the next 8 quarters.

The prediction equation is

$$(2)\ Prob\{\Delta U(t+h) \geq F-1(0.80)\} = G(BX(t)), where$$
$$G(BX(t)) \ = \ 1/[1-\exp{(-BX(t)}].$$

The predictors X(t) are

- The term spread—the difference between the yield on a 10-yr. Treasury security and the federal funds rate;

[4] The binary-dependent variable approach is common in the recession literature and the financial crisis literature (e.g., Kiley, 2020). Another approach is uses quantile regressions, often considering similar predictors (e.g., Adrian, Boyarchenko, and Giannone, 2019; Kiley, 2022a).

- The Baa corporate bond spread;
- The leading indicators—measured as the change in the OECD's composite leading indicator;
- Inflation—measured as the four-quarter change in (the natural logarithm of) the price index for personal consumption expenditures; and
- The unemployment rate of the civilian noninstitutional population over age 16.

3.2 Results summarizing indications from all potential indicators and combinations

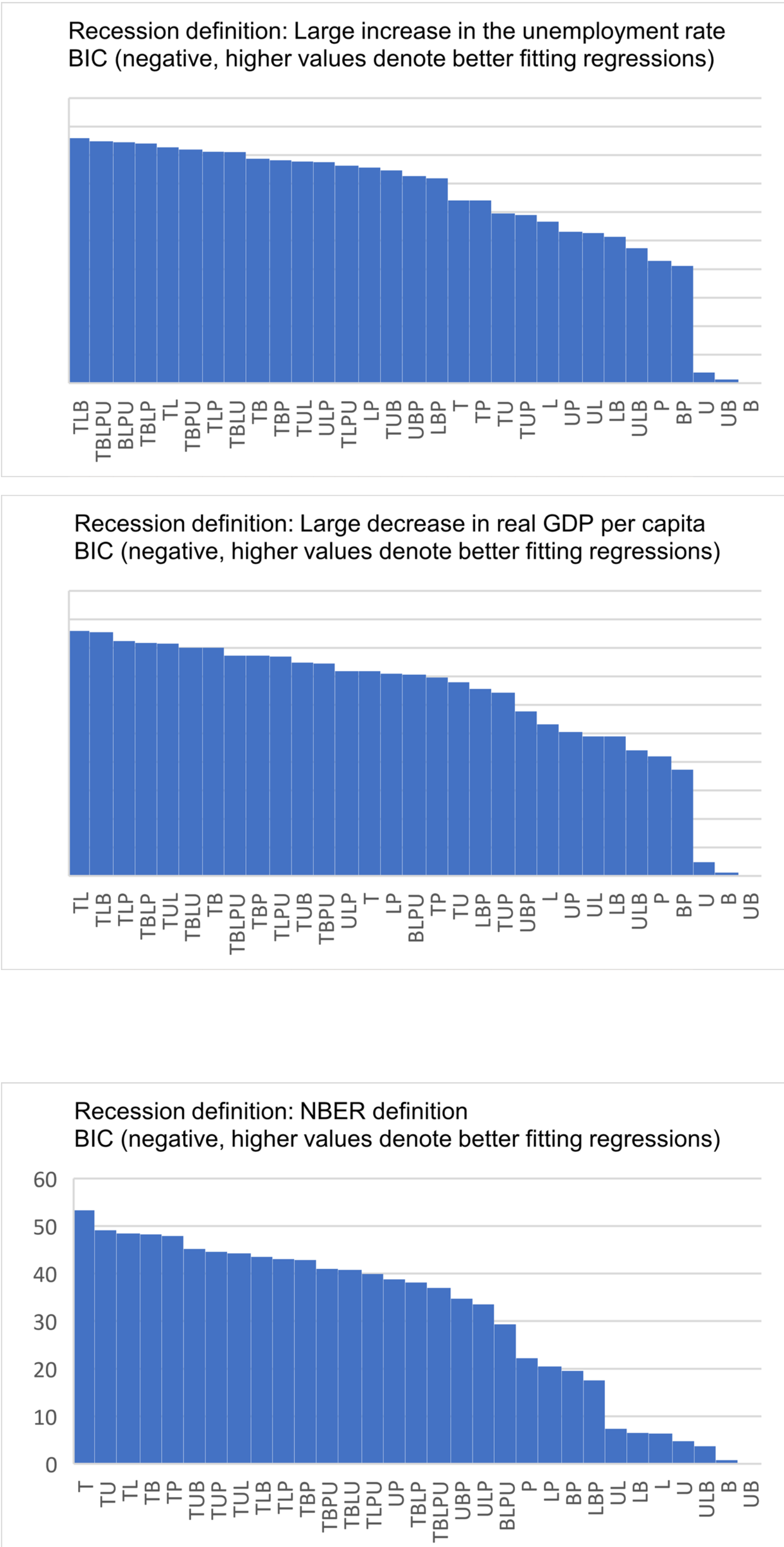
The first step is to consider the set of results for each recession definition, horizon, and combination of predictor variables—a total of 372 prediction equations (i.e., 31 combinations of predictors, 3 recession definitions, and 4 horizons). As the pattern of results is very similar across horizons, the presentation of results focuses on two horizons—four quarters ahead, and four quarters/four quarters from now—and the complete results are contained in the appendix.

Figure 4 presents a measure of the fit, the Bayesian Information Criterion (BIC), of each possible combination of variables at the four-quarter prediction horizon. The BIC is a function of the log-likelihood of the equation (*log(L)*), the number of predictor variables (*k*), and the sample size (*N*)

(3) $BIC = -2 * log(L) + k * ln(N)$.

The BIC is a common measure of fit used in model selection and provides an approximation to the marginal likelihood that can be useful in explicitly Bayesian approaches (Kass and Raftery, 1995). In equation (3), lower values of the BIC indicate a better fit (as indicated by the negative sign in front of the log-likelihood) and models with more parameters are penalized (as indicated by the second term). To ease interpretation, figure 4 presents the negative of the BIC for each possible prediction equation (so larger values are better fitting models). In addition, the lowest BIC value across combinations of predictor variables is subtracted from the BIC for all specifications, implying that the presented value for the worst fitting model is 0. Finally, Kass and Raftery (1995) (and others) emphasize that a difference in BIC values of 3 or more represents strong evidence that a model fits better than the comparison model.

Figure 4: Fit of Recession Prediction Equations: Recession over next four quarters



Legend: Letters indicate variables included in regressions.

T—term spread;

B—corporate bond spread;

L—leading indicator;

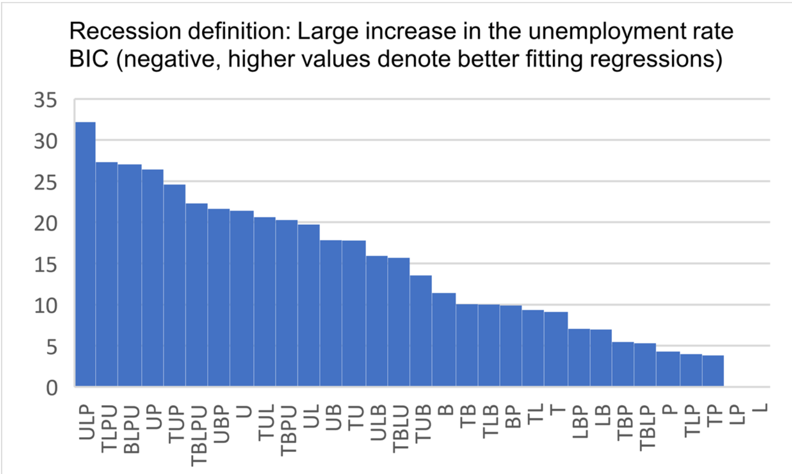
P—inflation;

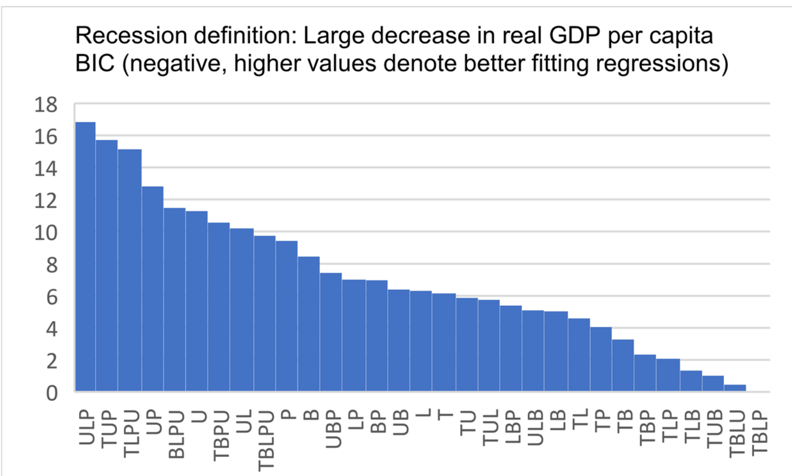
U—unemployment rate.

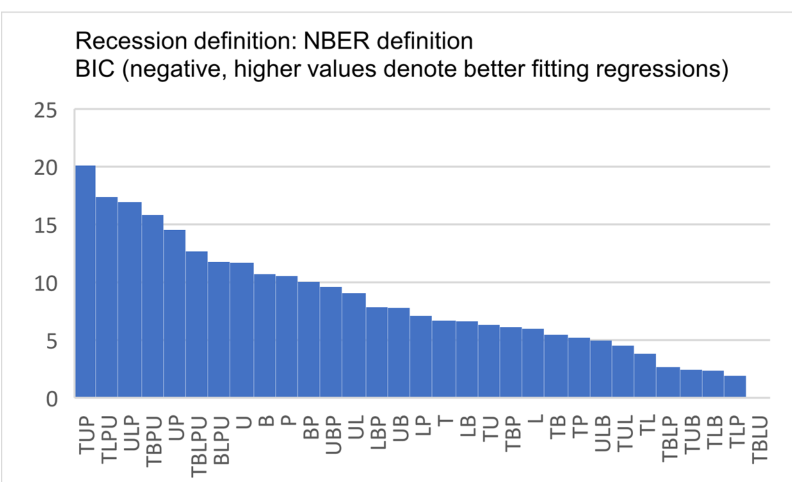
Several results are clear at the four-quarter horizon. First, the term spread is a good predictor—it is in the five best-fitting equations for all three recession definitions except for one case. This clearly supports the emphasis in the literature on this variable at the one-year horizon. Note that the leading indicator is also consistently among the best predictors, although this result reflects "data snooping"—as the leading indicator is constructed to predict activity. Second, each of the other predictors is in one of the five best fitting equations for each recession definition, a result that suggests some value in looking beyond the term spread for recession prediction. Finally, the results are similar, but far from identical, across recession definitions. In particular, the approaches that predict large increases in the unemployment rate or large declines in real GDP per capital tend to have more predictors (3 or more) in the best fitting equations, while the best-fitting equations predicting NBER recessions have few variables (2 or less).

Figure 5 presents analogous results for predicting a recession with the four quarters four quarters ahead—that is, within the second half of an 8-quarter horizon. Again, the results are very similar across definitions of recessions, but very different from the four-quarter horizon. First, the unemployment rate is in the five best fitting equations for each recession definition (i.e., all 15 of the best fitting equations). Second, inflation is in 14 of the 15 best fitting equations. Finally, the term spread, leading indicator, and corporate bond spread appear in some of the best fitting equations, but far less often.

Figure 5: Fit of Recession Prediction Equations: Recession in four quarters/four quarters ahead (i.e., second half of an 8-quarter horizon)







Legend: Letters indicate variables included in regressions.

T—term spread;

B—corporate bond spread;

L—leading indicator;

P—inflation;

U—unemployment rate.

The results in figures 4 and 5 suggest that some of the traditional predictors—financial variables and leading indicators—aid recession prediction at short horizons, whereas unemployment and inflation aid prediction at medium horizons. These results are superficially similar to those predicted by the simple model of business-cycle dynamics in section 2. Table 2 explores this issue more fully by presenting the frequency each predictor is in the 15 best fitting equations (the 5 best fitting equation for the 3 recession definitions) for the 2,4,8 and 4/4 horizons. The summary information in table 2 confirms the patterns in the figures.

The results also shed light on earlier results in the literature highlighting the lack of predictive ability at horizons greater than one year. For example, Estrella and Mishkin (1998) find that prediction is poor beyond a year, with measures of fit (Pseudo-R^2) near zero or negative at such horizons, even within the estimation period and ignoring out-of-sample predictability. Their analysis, and most others, did not consider the state of the business cycle as captured by inflation and the unemployment rate. As highlighted in figure 5, these variables are central to fit at such horizons. Figure 5 reports BIC, not Pseudo-R^2, and the increase in predictability as gauged by a Pseudo-R^2 is even greater (as the BIC includes a penalty for additional predictors). Nonetheless, it is important to keep in mind that these are within-sample results. There are very few recessions in the data, and hence the analysis focuses on in-sample results in a manner consistent with the literature, cognizant of the challenges of out-of-sample prediction. The focus on in-sample results is common in the literature.[5]

The key takeaways are the following. First, the term spread and leading indicator are strong recession predictors in the short run. Second, the unemployment rate and inflation are strong predictors in the medium run. These results hold across recession concepts.

[5] For example, see the discussion of in-sample vs. out-of-sample prediction in the FAQs on the Federal Reserve Bank of New York's monthly release of recession probabilities using the term spread (https://www.newyorkfed.org/research/capital_markets/ycfaq#/overview) or Wright (2006). Stock and Watson (2003) highlight instabilities in empirical models used to forecast economic activity.

Table 2: Frequency Variables Appear in Best Fitting Models

	Term spread	Corporate bond spread	Leading Indicator	Inflation	Unemployment rate
2-Quarter horizon	12	10	15	8	4
4-Quarter horizon	14	6	15	6	4
8-Quarter horizon	10	8	6	11	15
4-Quarter/4-quarter ahead horizon	6	3	6	11	15

Note: Frequency each indicator appears in one of the five best-fitting models according to BIC for each of the three recession definitions (implying that the maximum frequency possible is 15).

3.3 Examining traditional predictors, inflation, and the unemployment rate

The set of results can be understood further by comparing the predictive role of the traditional indicators—the term spread, corporate bond spread, and leading indicator—with those of the business-cycle indicators (the unemployment rate and inflation). Table 3 presents the marginal effect of a one-standard deviation change in the predictors for a model with only the traditional variables and one with all five predictors; the ranges shown are the 90-percent and 95-percent confidence intervals. It is important to note that all the predictors are persistent and recessions are rare, and hence it is likely that confidence intervals (even bootstrapped intervals, as these are) could be misleading; they are presented to be suggestive of the significance of the results. Finally, the definition of a recession used based on a large change in the unemployment rate, although the results for other cases are similar.

To aid reading of the table, the marginal effects are all expected to have a negative sign, as the change is assumed to be in the direction traditionally associated with a reduction in the probability of a recession. Specifically, the marginal effects are for

1. An increase in the term spread (a steeper yield curve is expected to be associated with a lower risk of recession, based on previous research);
2. A decrease in the corporate bond spread (a narrower corporate bond spread is expected to be associated with a lower risk of recession, based on previous research);
3. An increase in the (change in) the leading indicator (as an improving leading indicator is expected to be associated with a lower recession risk, given its construction);

4. A decrease in inflation (as lower inflation is expected to be associated with lower recession risk); and
5. An increase in the unemployment rate (as higher unemployment is expected to be associated with lower recession risk, as discussed in the implications of traditional views of business-cycle dynamics in section 2).

Because of this convention, one can compare the magnitudes of the marginal effects directly.

Focusing first on the term spread, three results are apparent. The traditional financial/leading indicators model has a large marginal effect from term spread movements at all horizons. Inclusion of the business-cycle variables substantially reduces the marginal effect of the term spread, with the point estimate of the marginal effect at horizons of four-quarters or more about ½ the point estimate in the traditional prediction equation without the unemployment rate and inflation. The marginal effect of the term spread is much smaller at the four-quarter/four-quarter ahead horizon than at the four-quarter horizon.

Turning to the leading indicator, which often appeared in the best fitting model, two results are apparent. An improvement in the leading indicator lowers the probability of a recession at short horizons (four quarters or less). An improvement in the leading indicator is not significantly related to a recession, although the point estimate suggests a sign reversal in which it raises the probability of a recession, at medium horizons (at eight quarters or four quarters/four quarters ahead).

Considering the business-cycle state variables (unemployment and inflation), the marginal effects of inflation are larger at the four-quarter/four-quarter ahead horizon than at shorter horizons. The marginal effect of the unemployment rate is much larger at the four-quarter/four-quarter ahead horizon. These results are consistent with the simple model of section 2 and with the emphasis in Kiley (2018, 2022a, b) and Domash and Summers (2022) on medium horizons. The next section considers the consistency of the pattern of coefficients with business-cycle dynamics more rigorously, while also examining whether the results could be spurious.

Table 3: Marginal effects of one-standard deviation change in predictor variable (Recession definition: large change in the unemployment rate over horizon indicated)

	Term spread	Corporate bond spread	Leading indicator	Inflation	Unemploy. rate
		4-quarter horizon			
estimate	-0.12	-0.06	-0.08		
(95-percent interval)	(-0.20,-0.04)	(-0.11,0.00)	(-0.12,-0.04)		
estimate	-0.05	-0.06	-0.05	-0.05	-0.05
(95-percent interval)	(-0.15,0.00)	(-0.14,-0.01)	(-0.09,-0.01)	(-0.14,0.00)	(-0.11,0.00)
		4-quarter/4-quarter ahead horizon			
estimate	-0.07	0.07	0.07		
(95-percent interval)	(-0.15,-0.02)	(-0.01,0.16)	(0.00,0.16)		
estimate	0.02	0.01	0.07	-0.10	-0.16
(95-percent interval)	(-0.05,0.12)	(-0.07,0.08)	(0.01,0.15)	(-0.25,0.01)	(-0.32,-0.05)

Note: Estimate sample is 1965Q1-2019Q4. Confidence intervals obtained via the block bootstrap.

4. Signals and business cycles

4.1 Business cycle dynamics and recession prediction

Kiley (2018, 2022a, b) and Domash and Summers (2022) emphasize the level of the unemployment rate and inflation in recession prediction, and the results herein appear to show the value of these variables are medium horizons—which may surprising, as earlier work did not emphasize these variables. Section 2 suggests, in a stylized way, that this pattern of coefficients is consistent with standard views on business cycle dynamics.

To address the question of recession signals and business-cycle dynamics more closely while preserving intuition in the discussion, I focus on the pattern of coefficients associated with financial conditions (the term spread), momentum (the leading indicator), and the level of the unemployment rate. The empirical analysis finds several key patterns

(i) The term spread has a larger role in prediction when the unemployment rate or leading indicator is not included, and its predictive ability is stronger at the four-quarter horizon than at medium horizons;

(ii) Momentum is important at short horizons—positive momentum lowers the risk of a recession—but this effect fades or reverses at medium horizons; and

(iii) The role of the unemployment rate is larger at medium horizons than a shorter horizon.

To address the pattern of coefficients in a comprehensive manner, a structural model may be desirable, but key aspects can be examined with a reduced-form model. I assume that the unemployment rate and the term spread are governed by a second-order vector-autoregression (VAR(2)). The BIC, Akaike Information Criterion, and Hannan-Quinn Information Criterion all prefer a lag length of 2 for a VAR in these variables over the 1965 to 2019 period. The estimated VAR(2) has the form in equations (4) and (5).

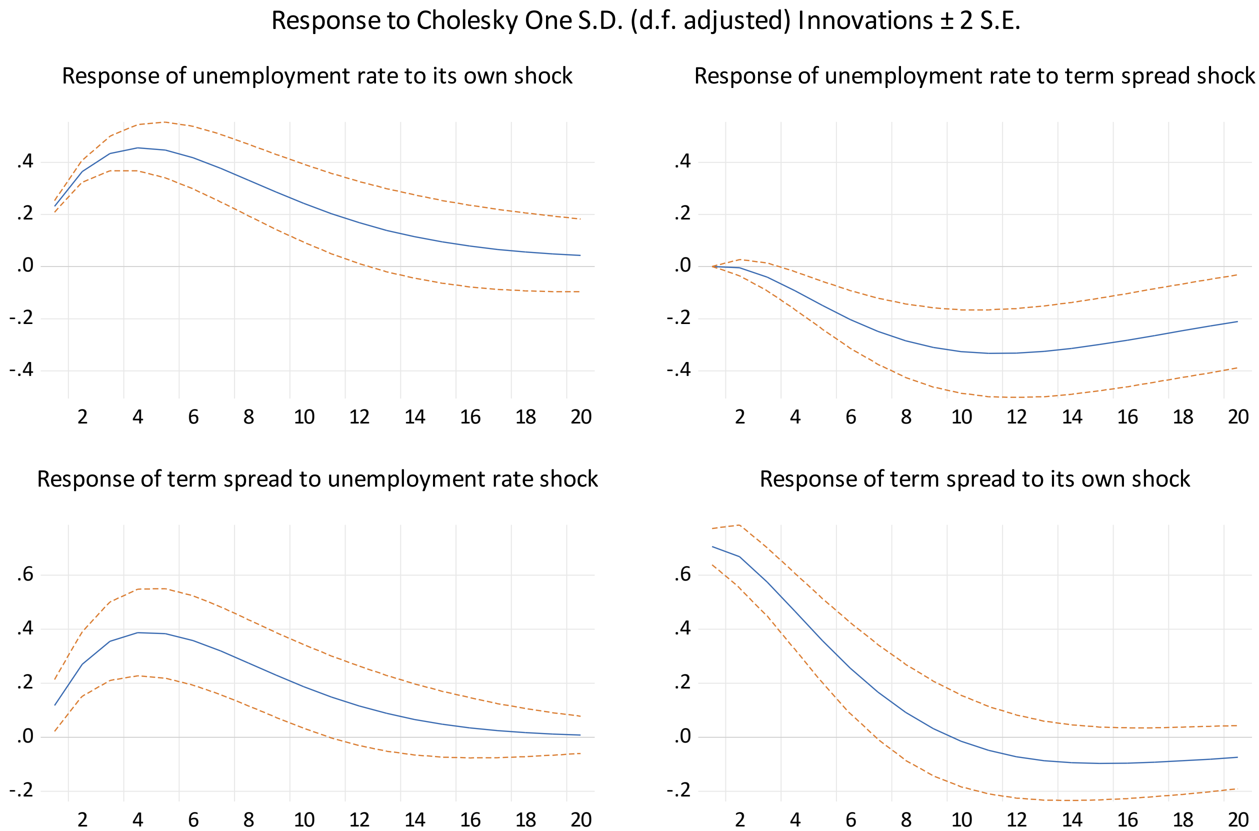
$$(4)\ U(t) = 1.582 * U(t-1) - 0.594 * U(t-2) - 0.006 * TS(t-1) - 0.042 * TS(t-2) + e(t)$$

$$(5)\ TS(t) = 0.688 * U(t-1) - 0.619 * U(t-2) + 0.948 * TS(t-1) - 0.080 * TS(t-2) + v(t).$$

Figure 6 present impulse response to one-standard deviation shocks to this VAR, using a Cholesky decomposition in which the unemployment rate responds to the term spread shock with a lag (to capture the notion that financial conditions, like the term spread, respond contemporaneously to shocks and activity responds with a lag). Importantly, other shock decompositions yield similar results, and these impulse responses are only to capture some intuitive points.

Three results stand out in the responses. The unemployment rate has momentum following shocks-that is, hump-shaped dynamics in which an initial improvement in the unemployment rate (a decrease) is followed by further decreases. This dynamic is suggestive of the role of the leading indicator, where an improvement in the (change in) leading indicator lowers the recession probability at short horizons. This effect reverses at medium horizons, after the hump. An increase in the term spread lowers the unemployment rate initially, but this also reverses, suggesting of a strong near-term role for the term spread in recession prediction. Finally, because an initial change in the unemployment is followed initially by further changes in the same direction, the level of the unemployment rate may be less predictive of a reversal at short horizons than at medium horizons. However, the unemployment rate eventually returns to baseline, so a low value of the unemployment should predict increases in the unemployment rate and a recession.

Figure 6: Impulse response functions



Note: Impulse responses from VAR(2) in the unemployment rate and term spread estimate over 1965Q1 to 2019Q4. The solid blue line is the response and the dashed red lines are the response +/- 2 standard deviations.

To examine the implications of the VAR(2) for recession prediction, the VAR(2) is simulated 1000 times for sample sizes of 200 (the observed sample) and of 200,000 (to provide an accurate approximation of the population values implied by the VAR(2) for the logit coefficients and implied marginal effects). The simulated data are used to estimate the probability of a large increase in the unemployment rate. It is important to note that the model is linear and that accurate forecasts under the assumed data-generating process would be obtained by estimating a VAR(2) and predicting outcomes using the resulting system of equations. However, a large literature focuses on equations for the probability of a recession. The contribution of this analysis is to understand how a standard model of dynamics is (or is not) consistent with the pattern of coefficients in models of the probability of a recession, not to assess the role of nonlinearities.

Table 4 presents results, focusing on marginal effects at the four-quarter and four-quarter/four-quarter ahead horizons and on two specifications—a specification using only the term spread, and a specification with the term spread, the level of the unemployment rate, and the change in the unemployment rate (designed to capture momentum, as in the leading indicator).

Several results are apparent for the specification with all three variables. First, the logit regressions with 200 observations accurately estimate the implied marginal effects for all variables—there are no signs of bias in the small-samples relative to the asymptotic value implied by the VAR(2).

The simulations generally are consistent with the empirical finds. The first two empirical findings were that the term spread and momentum were good short-term indicators. In the simulations, both the term spread and momentum are important at the shorter horizon—the simulated 95-percent interval of estimated marginal effects is centered on sizable effects and well away from zero. The marginal effect of momentum is zero at the medium horizon. The marginal effect of the term spread is still large and negative, but imprecisely estimated, at medium horizons. Finally, the specification with only the term spread has larger marginal effects (in absolute value) than the specification with all variables, as the term spread captures some of the information that would be found in those other variables given the correlations across the variables. These findings are consistent with the empirical results.

Table 4:

Simulated Estimated Marginal Effects from Business-Cycle VAR(2)

	Term spread	momentum Δu(t)	Unemployment rate u(t)
equation with term spread, momentum, and unemployment rate			
4-quarter horizon			
200 observation sample	-0.10	0.09	-0.04
(95 percent interval)	(-0.15,-0.04)	(0.04,0.14)	(-0.10,0.03)
asymptotic value implied by var(2)	-0.10	0.10	-0.04
4-quarter/4-quarter ahead horizon			
200 observation sample	-0.09	0.00	-0.10
(95 percent interval)	(-0.16,0.00)	(-0.07,0.06)	-(0.16,-0.01)
asymptotic value implied by var(2)	-0.10	0.00	-0.09
equation with term spread only			
4-quarter horizon			
200 observation sample	-0.16		
(95 percent interval)	(-0.18,-0.09)		
asymptotic value implied by var(2)	-0.16		
4-quarter/4-quarter ahead horizon			
200 observation sample	-0.12		
(95 percent interval)	(-0.17,-0.04)		
asymptotic value implied by var(2)	-0.13		

Note: The results are from 1000 simulations of the VAR(2). The reported coefficients and confidence intervals are estimated from logit regressions of 200 observations across these simulations. The asymptotic value is obtained from a simulation with 200,000 observations.

The last key empirical result was that the unemployment rate was less useful in the short run and more useful in the medium run. In the simulations, the marginal effect of the unemployment rate is small and less precisely estimated at the four-quarter horizon (with a 95-percent interval across simulations that includes zero). At the medium horizon, the marginal effect of the unemployment rate is much larger, and the 95-percent interval is far from zero. These findings are consistent with the empirical results.

All told, the reduced-form characterization of business-cycle dynamics replicates the key characteristics of the empirical recession-probability equations, highlighting how the results in this analysis are in line with the core of macroeconomic work.

4.2 Spurious results

While the empirical results appear very much in line with expectations given standard business-cycle dynamics, there are important econometric difficulties associated with the analysis. Recessions are infrequent. The set of predictors have substantial persistence. As a result, empirical work in small samples may face challenges.

One challenge is especially salient. The unemployment rate is persistent and estimates of mean-reversion may be biased upward (i.e., estimates of underlying persistence may be biased downward, e.g., Kendall (1949)). The unit-root literature has emphasized the difficulties in discriminating between a process with a unit root and a stationary, but persistent, process (e.g., Cochrane, 1991; Blough, 1992, and Faust, 1996). Moreover, the simple approach herein could spuriously yield results in which the level of the unemployment was found to predict an increase in the unemployment rate because of the challenges associated with predictions using highly persistent regressors.

Two robustness exercises suggest this concern is not salient in the present analysis. First, the results on using the unemployment rate are identical if a long-moving average of the unemployment rate is subtracted from its level when it is used to predict a recession; this approach would, at least in a technical sense, remove the effect of a unit root.

More importantly, simulations of a unit-root process for the unemployment rate cannot replicate the pattern of coefficients on the unemployment rate. In such a case (reported in the appendix), the level of the unemployment rate is found to spuriously predict the change in the unemployment rate/recession in small samples, reflecting the biases emphasized above. However, the coefficient on the unemployment rate is flat as the horizon lengthens. In the data, the coefficient lengthens with the horizon, suggesting this alternative interpretation is not consistent with the results; note that, in contrast, the estimated coefficient on the unemployment rate is larger at longer horizons in the simulation of the business-cycle VAR. While these simulations cannot rule out the possibility that the statistical relationships herein are spurious, they set of results suggests that the results are not simply the result of statistical challenges associated with persistent regressions and long-horizon predictive regressions. Rather, these robustness checks suggest the interpretation of the results in terms of standard business-cycle dynamics is more appropriate than an interpretation as spurious results. That said, explaining recessions is challenging with short samples.

5. Summary

Examining a parsimonious, yet comprehensive, set of recession signals yields three lessons. First, signals from financial markets, leading indicators of activity, and gauges of the macroeconomic environment are all useful for recession prediction. As a result, focusing on a subset of predictors can be misleading. Second, approaches emphasizing the yield curve overstate the recession signal from such variables if other factors are not considered; in particular, the yield curve is highly cyclical and proxies, in part, for the recession signals associated with the state of the business cycle such as inflation and the unemployment rate. Finally, some indicators provide more valuable signals at short horizons, such as leading indicators emphasizing momentum, while others provide signals for medium horizons, such as the unemployment rate. Simulations of a reduced-form VAR of unemployment and financial conditions, which captures the time-series properties of the series well, suggest these patterns are consistent with a typical hump-shape characterization of business cycle dynamics.

Pulling results together, the roles in recession prediction of financial conditions and leading indicators/momentum in the short run and business-cycle indicators in the medium -run are consistent with a traditional view of business cycle dynamics, which suggests value in using the business-cycle indicators emphasized in Kiley (2018, 2022a, b) and Domash and Summers (2022). Given the consistency of the empirical analysis with a traditional view of business-cycle dynamics, consideration of a prediction equation with these variables merits emphasis in future work.

References

Adrian, Tobias; Boyarchenko, Nina; Giannone, Domenico, 2019. Vulnerable growth. American Economic Review, 109:4:1263-89.

Ajello, Andrea, Luca Benzoni, Makena Schwinn, Yannick Timmer, and Francisco Vazquez-Grande, 2022, Monetary Policy, Inflation Outlook, and Recession Probabilities, *FEDS Notes*.

Ang, Andrew; Piazzesi, Monika; Wei, Min, 2006. What does the yield curve tell us about GDP growth? *Journal of Econometrics*, 131:2-Jan:359-403.

Auerbach, Alan J., 1981, The Index of Leading Indicators: "Measurement without Theory," Twenty-Five Years Later, *National Bureau of Economic Research*.

Barro, Robert J., 1999, Reagan vs. Clinton: Who's the economic champ?, *Business Week*, February 22: 22.

Berge, Travis J., 2015, Predicting recessions with leading indicators: Model averaging and selection over the business cycle, *Journal of Forecasting*, 34:6:455-471.

Bernard, Henri, and Stefan Gerlach, 1998, Does the term structure predict recessions? The international evidence, *International Journal of Finance & Economics*, 3:3:195-215.

Blanchard, Olivier, and Stanley Fischer, 1989, Lectures on macroeconomics, MIT press.

Blough, Stephen R., 1992, The relationship between power and level for generic unit root tests in finite samples, *Journal of Applied Econometrics* 7, no. 3: 295-308.

Burns, Arthur F., and Wesley C. Mitchell, 1946, Measuring business cycles, *National Bureau of Economic Research*.

Chauvet, Marcelle; Potter, Simon, 2005. Forecasting recessions using the yield curve. *Journal of Forecasting*. 24:2:77-103.

Chinn, Menzie; Kucko, Kavan, 2015. The predictive power of the yield curve across countries and time. *International Finance*, 18:2:129-156. 2015.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L. Evans, 1999, Monetary Policy Shocks: What have we learned and to what end? *Handbook of Macroeconomics,* 1:65-148.

Cochrane, John H., 1991, A Critique of the Application of Unit Root Tests, *Journal of Economic Dynamics and Control,* 15, no. 2: 275-284.

Cooley, Thomas F., and Edward C. Prescott, 1995, Economic Growth and Business Cycles, *Frontiers of Business Cycle Research*, pp. 1-38, Princeton University Press.

Diebold, Francis X; Rudebusch, Glenn D., 1989. Scoring the leading indicators. Business Cycles.

Domash, Alex and Lawrence H. Summers, 2022. A labor market view on the risks of a U.S. hard landing. NBER Working Paper No. 29910. April.

Engstrom, Eric C; Sharpe, Steven A., 2019. The near-term forward yield spread as a leading indicator: A less distorted mirror. *Financial Analysts Journal*, 75:4:37-49.

Estrella, Arturo, 2005. Why does the yield curve predict output and inflation? *The Economic Journal*. 115:505:722-744.

Estrella, Arturo; Hardouvelis, Gikas A., 1991. The term structure as a predictor of real economic activity. *The Journal of Finance*. 46:2:555-576.

Estrella, Arturo, and Frederic S. Mishkin, 1996, The Yield Curve as a Predictor of US Recessions, *Current Issues in Economics and Finance*, 2:7.

Estrella, Arturo, and Frederic S. Mishkin, 1998, Predicting US recessions: Financial variables as Leading Indicators, *Review of Economics and Statistics*, 80:1:45-61. MIT Press.

Estrella, Arturo, and Frederic S. Mishkin, 1997, The Predictive Power of the Term Structure of Interest Rates in Europe and the United States: Implications for the European Central Bank, *European Economic Review*, 41:7:1375-1401. Elsevier.

Faust, Jon, 1996, Near Observational Equivalence and Theoretical Size Problems with Unit Root Tests, *Econometric Theory* 12, no. 4: 724-731.

Faust, Jon, Simon Gilchrist, Jonathan H. Wright, and Egon Zakrajšek, 2013, Credit Spreads as Predictors of Real-time Economic Activity: a Bayesian Model-Averaging Approach, *Review of Economics and Statistics*, 95:5:1501-1519. MIT Press.

Federal Reserve Bank of New York, 2022, *The Yield Curve as a Leading Indicator*. https://www.newyorkfed.org/research/capital_markets/ycfaq.html

Gilchrist, Simon, and Egon Zakrajšek, 2012, Credit Spreads and Business Cycle Fluctuations, *American Economic Review*, 102:4:1692-1720.

Hamilton, James D; Perez-Quiros, Gabriel, 1996. What do the leading indicators lead? *Journal of Business*. 27-49.

Kass, Robert E., and Adrian E. Raftery, 1995, Bayes Factors, *Journal of the American Statistical Association* 90, no. 430: 773-795.

Kendall, Maurice G., 1949, The Estimation of Parameters in Linear Autoregressive Time Series, *Econometrica: Journal of the Econometric Society*: 44-57.

Kiley, Michael T., 2021. What macroeconomic conditions lead financial crises? *Journal of International Money and Finance*, 111, 1023-16.

Kiley, Michael T., 2020, Financial Conditions and Economic Activity: Insights From Machine Learning, FEDS Working Paper.

Kiley, Michael T., 2022a. Unemployment risk. *Journal of Money, Credit and Banking*.

Kiley, Michael T., 2022b. Financial and Macroeconomic Indicators of Recession Risk, FEDS Notes. Washington: Board of Governors of the Federal Reserve System, June 21, 2022, https://doi.org/10.17016/2380-7172.3126.

King, Thomas B., Andrew T. Levin, and Roberto Perli, 2007, Financial Market Perceptions of Recession Risk, FEDS Working Paper.

Liu, Weiling, and Emanuel Moench, 2016, What Predicts US Recessions? *International Journal of Forecasting*, 32:4:1138-1150. Elsevier.

Lovell, Michael C., and Pao-Lin Tien, 2000, Economic discomfort and consumer sentiment, *Eastern Economic Journal* 26: 1-8.

Marcellino, Massimiliano, 2006, Leading Indicators, *Handbook of Economic Forecasting*, 1:879-960. Elsevier.

Romer, Christina D., and David H. Romer, 1989, Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz, *NBER Macroeconomics Annual,* 4:121-170.

Rudebusch, Glenn D, and John C. Williams, 2009, Forecasting Recessions: the Puzzle of the Enduring Power of the Yield Curve, *Journal of Business & Economic Statistics*, 27:4:492-503. Taylor & Francis.

Stock, James H., and Mark Watson, 1989, New Indexes of Coincident and Leading Economic Indicators, *NBER Macroeconomics Annual*, 4:351-394. MIT Press.

Stock, James H., and Mark Watson, 1993, A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience, *Business cycles, indicators and forecasting*, 28:95-156.

Stock, James H; Watson, Mark, 2002. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20:2:147-162.

Stock, James H; Watson, Mark, 2003. Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*, 41:3:788-829.

Stock, James H; Watson, Mark, 2006. Forecasting with many predictors. *Handbook of economic forecasting*, 1:515-554. Elsevier.

Wheelock, David C; Wohar, Mark E., 2009. Can the term spread predict output growth and recessions? A survey of the literature. *Federal Reserve Bank of St. Louis Review*, 91:5 Part 1:419-440.

Wright, Jonathan H., 2006, The Yield Curve and Predicting Recessions, FEDS Working Paper.

Data Appendix

All data were retrieved from FRED, Federal Reserve Bank of St. Louis. The series used in the paper are their sources are described below.

Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS, January 3, 2023.

Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis [DGS10], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10, January 2, 2023.

Federal Reserve Bank of St. Louis, Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity [BAA10YM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BAA10YM, January 2, 2023.

Federal Reserve Bank of St. Louis, NBER based Recession Indicators for the United States from the Period following the Peak through the Trough [USREC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USREC, January 2, 2023.

Organization for Economic Co-operation and Development, Leading Indicators OECD: Leading indicators: CLI: Normalised for the United States [USALOLITONOSTSAM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USALOLITONOSTSAM, January 3, 2023.

U.S. Bureau of Economic Analysis, Real Gross Domestic Product [GDPC1], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPC1, January 3, 2023.

U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, January 12, 2023.

U.S. Bureau of Labor Statistics, Population Level [CNP16OV], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CNP16OV, January 6, 2023.

U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, January 6, 2023.

Appendix tables and charts (online working paper only)

Legend for all figures on following pages:

Letters indicate variables included in regressions.

T—term spread;

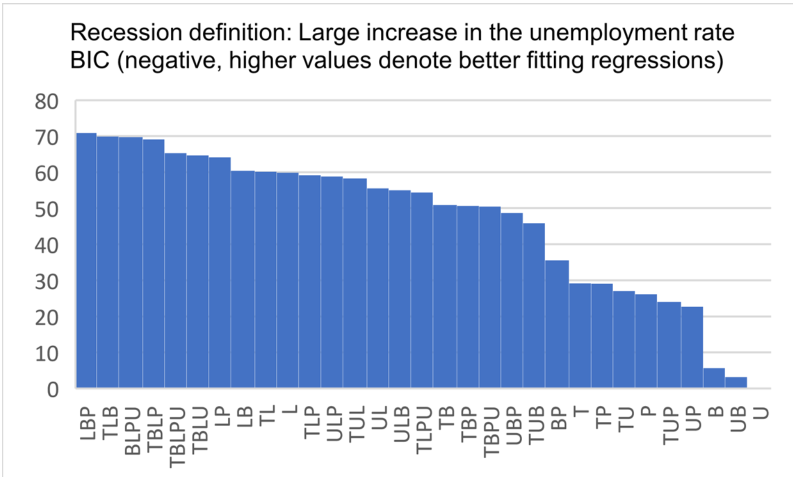
B—corporate bond spread;

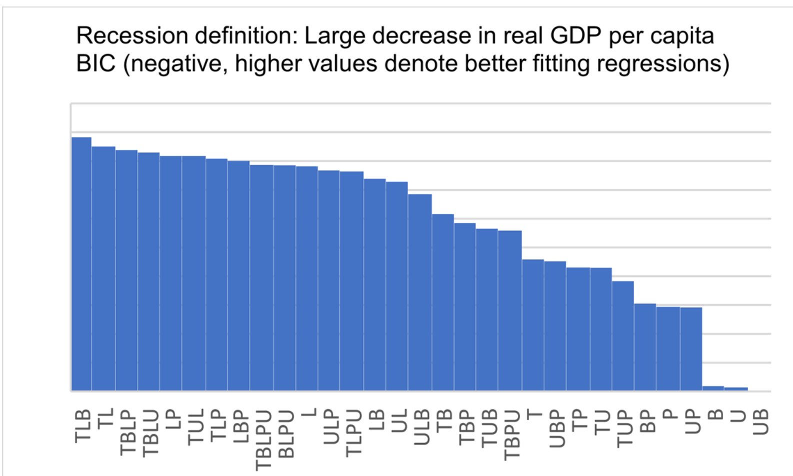
L—leading indicator;

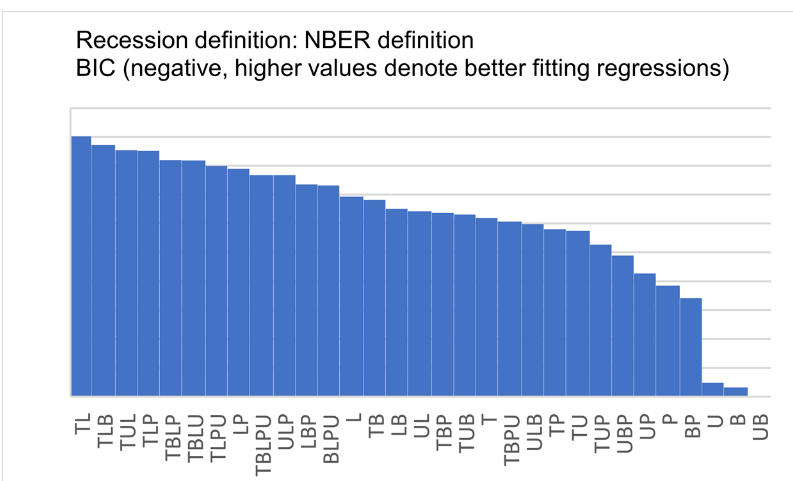
P—inflation;

U—unemployment rate.

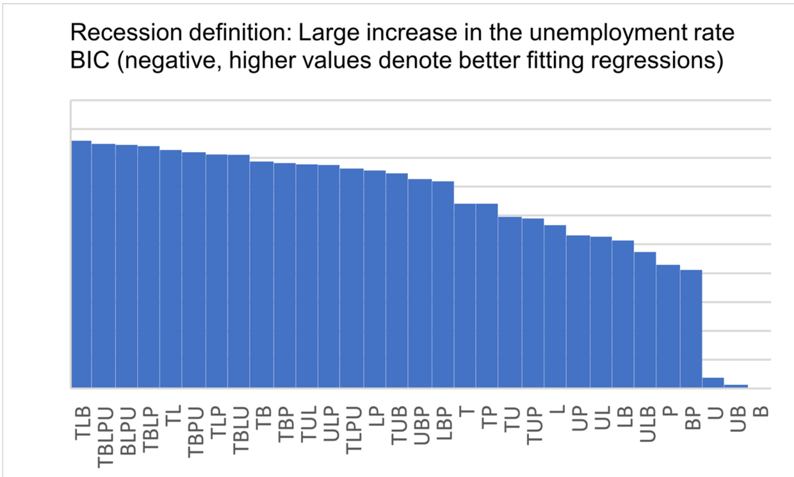
A1: Fit of Recession Prediction Equations: Recession over next two quarters

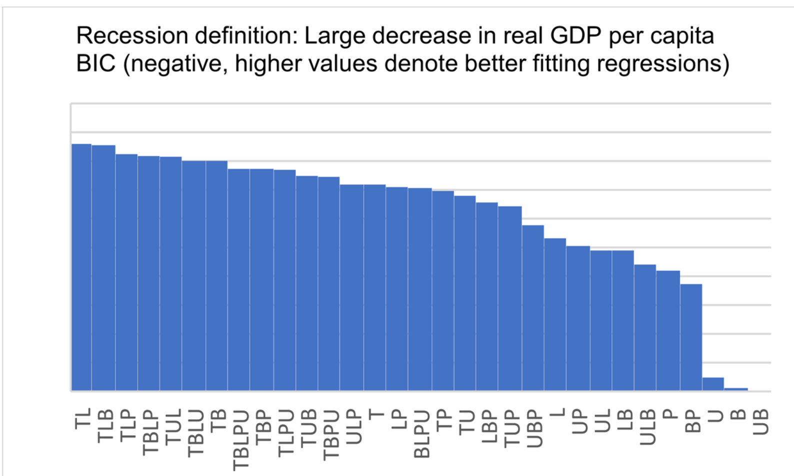


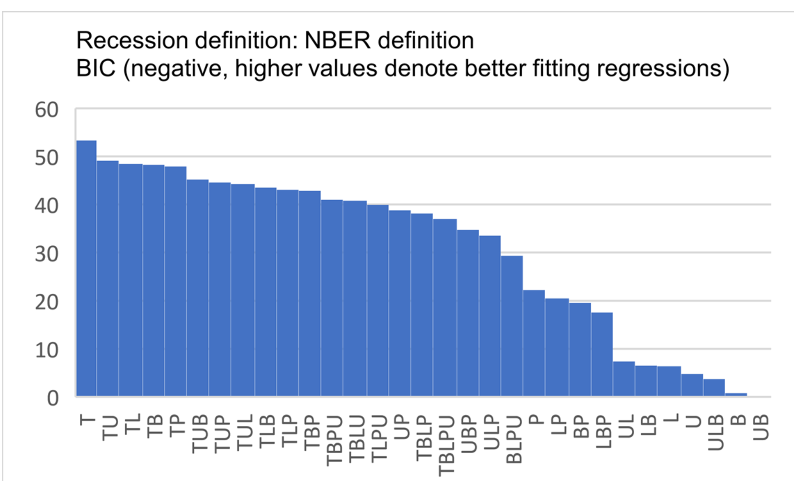




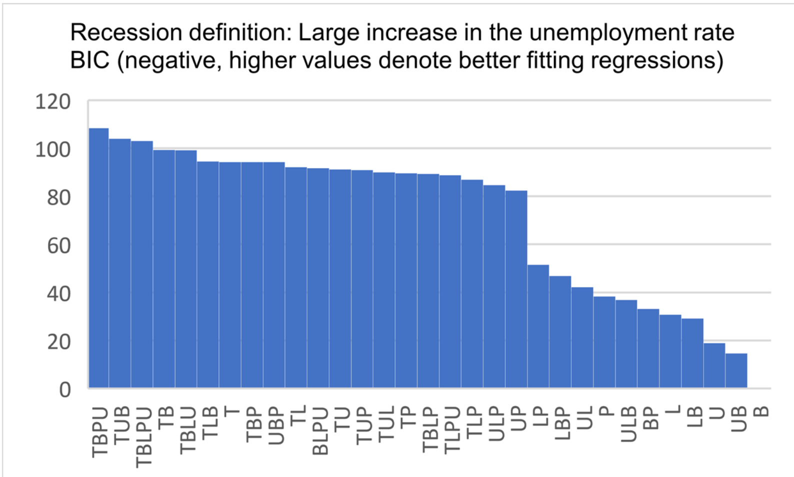
A2: Fit of Recession Prediction Equations: Recession over next four quarters

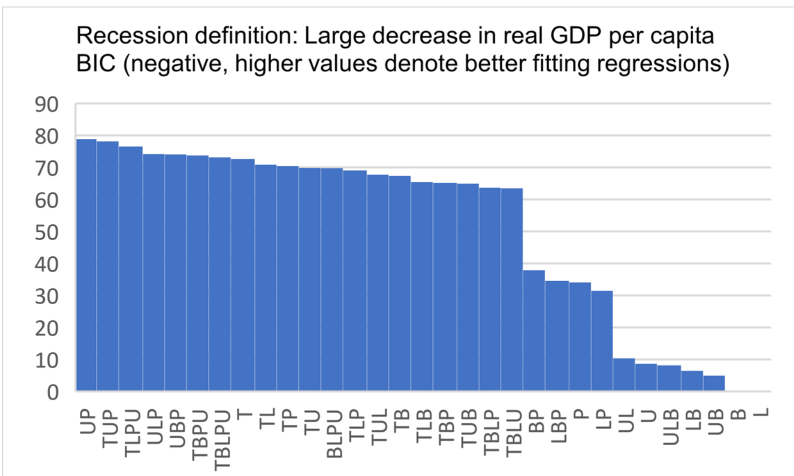


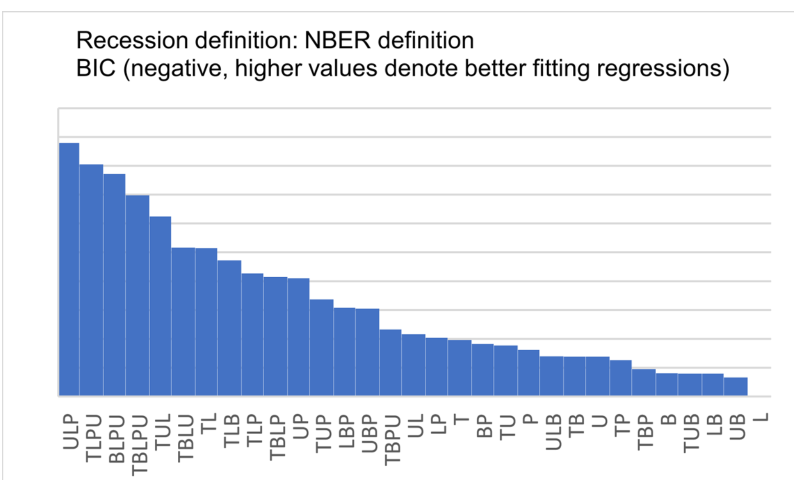




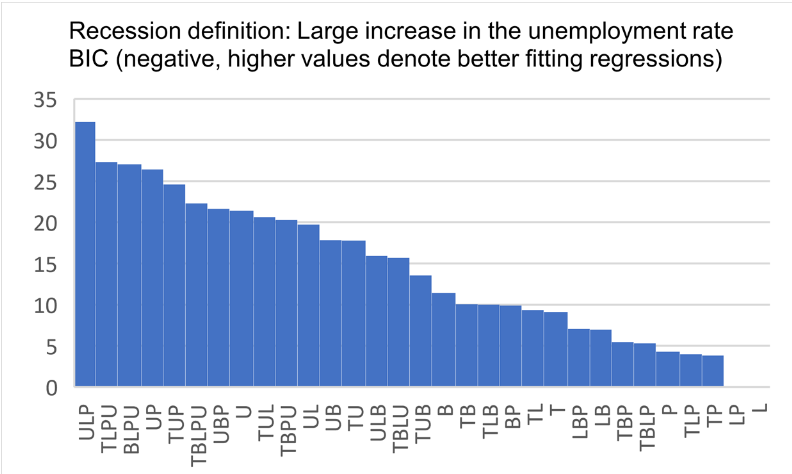
A3: Fit of Recession Prediction Equations: Recession over next eight quarters

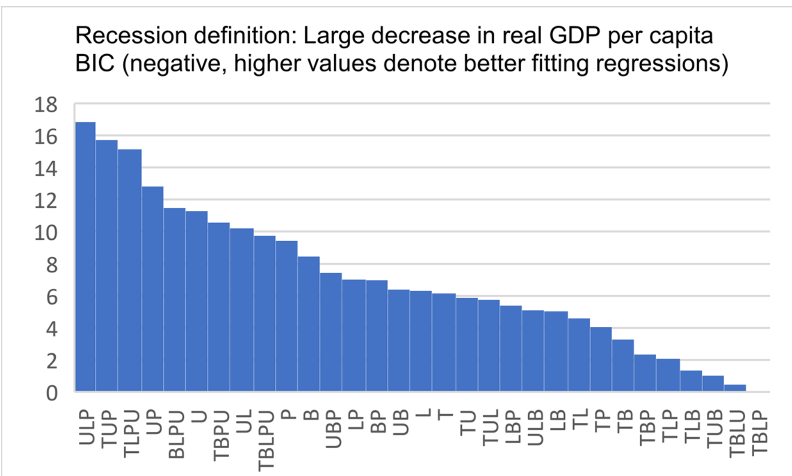






A4: Fit of Recession Prediction Equations: Recession in four quarters/four quarters ahead (i.e., second half of an 8-quarter horizon)





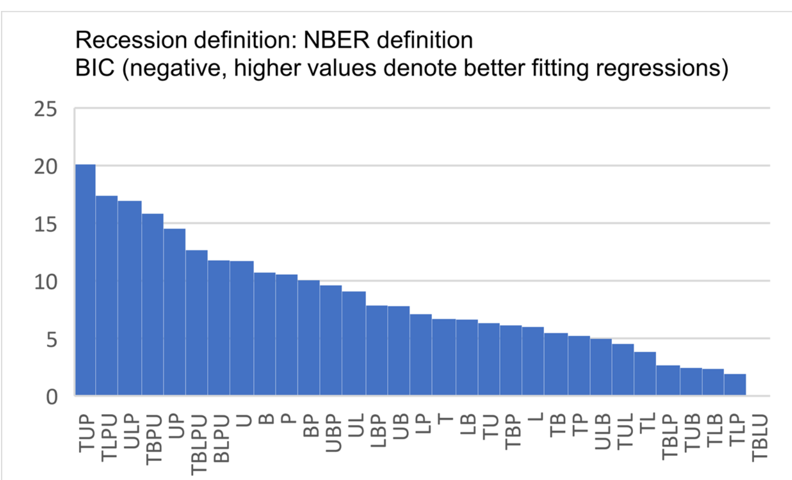


Table A:

Estimated Marginal Effects from Random Walk (RW) for Unemployment Rate

4-quarter horizon	
200 observation sample	-0.06
(95 percent interval)	(-0.13,0.02)
asymptotic value implied by RW	0.00
4-quarter/4-quarter ahead horizon	
200 observation sample	-0.06
(95 percent interval)	-(0.13,-0.03)
asymptotic value implied by RW	0.00

Note: The table reports the median and 95-perccent interval of the estimated marginal effect of the level of the unemployment rate on the probability of an increase in the unemployment rate greater than the 80th percentile across 1000 samples of 200 observations when the unemployment rate follows a random walk (and hence for which the changes are unpredictable).