Forecasting U.S. Recession With a Probit Model

Anna E.W.

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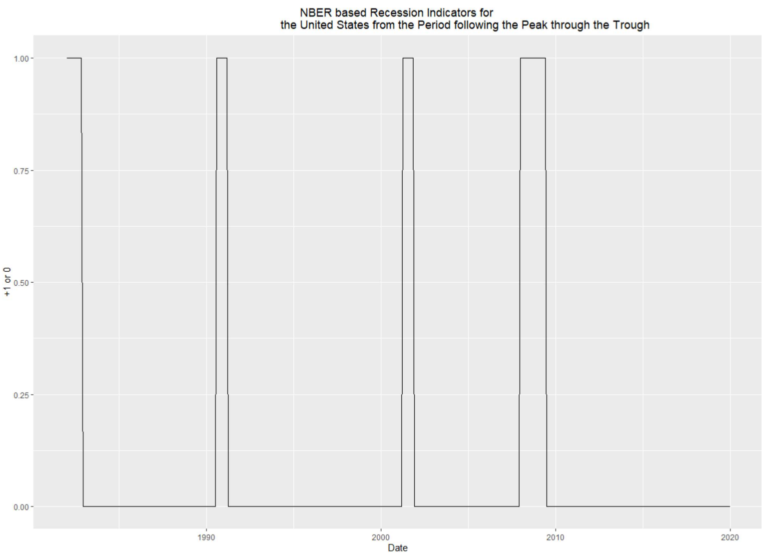
Introduction

Economic turning points are notoriously hard to predict, yet there are no shortage of attempts to find reliable indicators of recession that warn ahead of time. Monthly macroeconomic and other data were downloaded from The Federal Reserve Bank of St. Louis Federal Reserve Economic Data (FRED) for the period January 1982 through January 2020 - a total of 457 observations. The task was to use business cycle data provided by The National Bureau of Economic Research which indicate whether the U.S is in economic recession (defined as two consecutive quarters of a fall in GDP) to forecast recession and the likelihood of recession one month ahead (February 2020). Recessions are coded 1, and expansions coded 0. Explanatory variables that could indicate with a one month warning that the economy was soon to contract were sought.

Following established macroeconomic theory where inputs to production are capital, labour and technology, and output is divided among consumption, investment, net exports, and government purchases, I collect a set of variables suitable for predicting recession and the likelihood of recession.

Explanatory Variables



Explanatory variables were obtained from the FRED portal and assigned the labels below:

- Slope of Yield the Curve on US Government Debt: 10Y2Y
- Average Weekly Hours of Production and Non-supervisory Employees, Manufacturing: AWHMAN
- Unemployment Rate: UNEMP
- Personal Consumption Expenditures: PCE

- Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity: AAA10YM
- Interest Rates and INterest Rate Spreads: TB3MO, TB10, TB5, TB1, T10Y2Y, T10Y3MM
- Housing Starts and Building Permits: HOUST, PERMIT
- Manufacturing Business Confidence: BSCICP
- Consumer Sentiment: UMCSENT
- Normalised Gross Domestic Product: NORMGDP
- The CAPE Ratio: Cyclically-Adjusted Price-to-Earnings Ratio: TRCAPE

Data visualisation and empiric justification

Plotting the data enables a quick visual check for potential leading indicators, the plots I use can be found in Appendix A. Most real world data are skewed. We can visualise the distribution of the variables without temporal ordering with density plots. Heavily skewed data are problematic for simplistic models and require transformation. Appendix A contains the density plots that were created for visual analysis. I also create scatter plots (not included in the appendix) and I find no severe outliers of concern. Furthermore, the data provided by The National Bureau of Economic Research (NBER) are known to be of high quality.

Slope of Yield the Curve on US Government Debt: 10Y2Y

The spread between short and long term interest rates measures the steepness of the yield curve. Inversion of the treasury yield curve has preceded nearly every recession since the 1950s. A considerable body of literature (Estrella and Hardouvelis, 1991, Estrella and Mishkin, 1997, 1998, Wright, 2006, and Ergungor, 2016) supports an inversion of the yield curve as an indicator of recession. The slope of the series inverts when short-maturity rates exceed long-maturity rates. The slope of the yield curve became negative prior to each economic recession since the 1970's, though did not predict the recession of the mid-1960's (Bauer and Mertens, 2018). Estrella and Mishkin (1998) document the strong predictive power of this term spread for recession and economic activity.

Two spread series were compared: the average ten-year minus three-month term spread (10Y3MM) and the average ten-year minus two-year term spread (10Y2Y). The 10Y3MM is preferred in the literature and by the Federal Reserve for it's predictive power. The data had a slight left skew when plotted as a kernel density plot and did not require transformation.

Average Weekly Hours of Production and Non-supervisory Employees, Manufacturing: AWHMAN

This series has been shown empirically to lead the business cycle (Moore, 1983). Moreover, this metric leads hiring (and firing) trends and logically will lead initial claims; a leading indicator itself. This is because it is easier to adjust employee hours in response to demand than it is to end and create contracts. AWHMAN is a component of the Index of Leading Economic Indicators. The data has a slight right skew and it is not obvious from the visualisation that AWHMAN leads NBER.

Unemployment Rate: UNEMP

This series is the seasonally adjusted unemployment rate which represents the number of unemployed as a percentage of the labor force. The unemployment rate for a healthy economy is around 5% (OECD). Consumption depends on the amount an individual workers. Households without income may struggle to finance debt repayments, as such high levels of delinquency in 2007 contributed to the 2008 housing market crisis and Great Recession. Furthermore, output fluctuation and unemployment rate fluctuations are related (Okun's, 1962; Owyang and Sekhposyan, 2012). A visual analysis of the plotted time series shows that the unemployment rate is falling during periods of expansion, but just prior to a period of contraction the rate of hiring slows, which suggest that the unemployment rate is a leading indicator of recession. The data are not normally distributed, exhibiting a right skew. However, first-diferencing to remove the stochastic trend resulted in a normally distributed data.

Personal Consumption Expenditures: PCE

PCE measures consumer spending on goods and services, a main driver of economic growth. It is the Fed's preferred measure of inflation, which can contribute to, or even indirectly cause economic contraction, especially when inflation is above nominal wage growth and erodes wage increases or when the threat of runaway inflation provokes central banks to tighten monetary or fiscal policy leading to lower aggregate demand. Recessions often follow in the wake of such policies and as such, logically PCE should be a leading indicator. Furthermore, high levels of inflation make planning for the future for individuals and business harder, and given that recession is the mass postponement of investment plans by businesses, changes in PCE should precede recession. Estrella and Mishkin (1998) find PCE to have predictive power for U.S recession. However, in a visual analysis PCE appeared to be a coincident rather than a leading indicator. The data are not normally distributed, however, first-diferencing to remove a stochastic trend resulted in a normally distributed data.

Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity: AAA10YM

This variable indicates risk appetite in the corporate credit market. King, Levin and Perli (2007) show that corporate credit spread had predictive power for one-year ahead probability of recessions. They include a measure of the yield curve to reduce "false positives".The data are approximately normally distributed, however, from a plot is is difficult to tell if there is a clear and consistent reaction before periods of recession.

Interest Rates

The predictive power of the 3-month treasury bill rate rate was compared to the the 10-year, 5-year and 1-year interest rates. Wright (2006) presents a probit model and demonstrates that including a short term interest rate as an explanatory variable alongside a term spread provides a better in-sample fit. The 3-month rose ahead of 4 out of the last 7 recession since 1966. The data are not normally distributed, exhibiting a left skew. However, first-diferencing to remove a stochastic trend resulted in a normally distributed data.

Housing Starts and Building Permits: HOUST, PERMIT

New privately owned housing units building started and the number of new houses authorised by building permits. Unsurprisingly, housing starts have predicted nearly every recession for the past sixty years. Housing's expenditure accounts for approximately fifteen percent of total U.S GDP (National Association of Homebuilders) and as such is a major driver of the economy. Developers are reluctant to begin several months of investment if they fear a recession is imminent. Home-builders are extremely sensitive to changes in consumer spending, because purchasing a home is typically the most expensive good a person will consume in their lifetime. It should logically follow that applications for building permits will follow a similar pattern as they contain information about the future state of the market for new housing. These data appear to lead the NBER, with sharp declines prior to six out of seven recessions, with the exception of the recession in 2001. The data exhibit a slight left skew. However, first-diferencing to remove a stochastic trend resulted in a normally distributed data.

Manufacturing Business Tendency Survey: BSCICP

These data are from a survey of business opinion and monitor output growth and investment plans, as such they are a very suitable indicator of business cycle turning points (The Conference Board, Business Cycle Indicators, 2001) by asking business people around production, future tendency, orders and stocks of finished goods. A visual analysis reveals that the series reliably falls prior to recession but might produce many "false positives". The data are approximately normally distributed.

Consumer Sentiment: UMCSENT

The data are survey data on consumer optimism. Optimistic consumers spend and invest, stimulating the economy. Pessimistic consumers reduce their spending which could lead to recession. Matsusaka and Sbordone (1995) find that consumer sentiment accounts for 13-26 percent of the variation in GDP, similarliy, Carroll, Fuhrer, and Wilcox (1994) find the relationship accounts for approximately 14 percent of total real household expenditure. On visual inspection, UMCSENT seems to be a good leading indicator post 1990. The data exhibit a slight left skew. However, first-diferencing to remove a stochastic trend resulted in a normally distributed data.

U.S Normalised Gross Domestic Product: NORMGDP

Gross domestic product of the U.S, normalised. Because recession is defined as two consecutive quarters of economic contraction, GDP is a either a very short notice leading indicator of recession, or a coincident indicator. GDP data are characteristically conditionally normally distributed.

The CAPE Ratio: Cyclically-Adjusted Price-to-Earnings Ratio

The series consists of monthly stock price, dividends, and earnings data and the consumer price index (to allow conversion to real values) from the Robert Shiller data bank (Robert Shiller Data). Equity prices reflect market expectations about future corporate profits, and by extension future economic activity. On visual inspection the data are approximately normally distributed and appear to lead periods of recession.

Data

Below is a sample of the data collected. Monthly data were for the period January 1982 to January 2020, creating a sample with 457 observations.

	date	usrec	normgdp	TB10	TB3MO	t10y2y	t10y3mm	TB5	tb1yr	aaa10ym	bscicp0~665s	houst	m2real	permit	pceinfl	umcsent	awhman	unrate	trcape	usslind
1	Jan-82	1	98.4981	14.59	12.28	.026	1.67	14.65	12.77	.59	96.3234	843	1875.4	794	1997.1	71	37.3	8.6	9.25383	-.89
2	Feb-82	1	98.1207	14.43	13.48	-.397778	.15	14.54	13.11	.84	96.3253	866	1873.8	808	2021.2	66.5	39.6	8.9	9.00882	-.38
3	Mar-82	1	97.8086	13.86	12.68	-.333043	.55	13.98	12.47	.72	96.2468	931	1886.5	891	2024.1	62	39.1	9	8.7342	-.15
4	Apr-82	1	97.5493	13.87	12.7	-.330476	.53	14	12.5	.59	96.198	917	1898.8	888	2026.3	65.5	39.1	9.3	9.13576	-.11
5	May-82	1	97.3189	13.62	12.09	-.1545	.91	13.75	11.98	.64	96.1675	1025	1893	953	2044.5	67.5	39.1	9.4	9.06629	-.05
6	Jun-82	1	97.0981	14.3	12.47	-.165909	1.22	14.43	12.57	.51	96.3071	902	1882.5	913	2048.1	65.7	39.2	9.6	8.4515	-.03
7	Jul-82	1	96.8837	13.95	11.35	.149048	2.09	14.07	11.9	.66	96.419	1166	1878.5	1044	2072.2	65.4	39.2	9.8	8.4003	-.06
8	Aug-82	1	96.6852	13.06	8.68	.731364	4.06	13	10.37	.65	96.4778	1046	1888.6	926	2080.1	65.4	39	9.8	8.42275	-.23
9	Sep-82	1	96.5194	12.34	7.92	.555714	4.15	12.25	9.92	.6	96.5416	1144	1902.1	1042	2104.6	69.3	39	10.1	9.39384	-.2
10	Oct-82	1	96.4039	10.91	7.71	.719	2.94	10.8	8.63	1.21	96.6699	1173	1905.9	1149	2125.8	73.4	38.9	10.4	10.1678	.01

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
USREC	457	0.098468	0.298273	0	1
10Y2Y	457	1.069139	0.836017	-0.41316	2.834211
10Y3MM	457	1.773239	1.11225	-0.7	4.15
TB10	457	5.671926	2.995047	1.5	14.59
TB5	457	5.183151	3.203787	0.62	14.65
TB1	378	4.222593	3.194618	0.09	13.11
TB3MO	457	3.781182	2.999545	0.01	13.48
PCEINF	457	7332.571	3691.238	1997.1	14880.5
UNEMP	457	6.130635	1.704001	3.5	10.8
AWHMAN	457	41.03654	0.698243	37.3	42.3
AAA10YM	457	1.28151	0.492806	-0.13	2.68
BSCICIP	457	99.79537	1.273892	95.52489	103.0265
UMCSENT	457	88.04026	11.79934	55.3	112
HOUST	457	1358.956	394.1268	478	2273
PERMIT	457	1359.934	395.0184	513	2263
TRCAPE	457	25.80364	8.292565	8.400297	48.11097
NORMGDP	457	99.98922	0.995985	96.35713	101.8257

Exploratory Data Analysis

Seasonal Trends

Forecasts that do not account for seasonality will have a high variance, furthermore"seasonally adjusted data" as that has undergone a standardised procedure should be approached with caution as a seasonal pattern might remain, particularly if using a subsample of the data which might have seasonality to a greater or lesser extend than the total span. (Enders, 1995). For the purposes of this assignment, I seek seasonally adjusted data.

The empirical literature overwhelmingly favours non-seasonally adjusted interest rates, as it is claimed that there is no noticeable seasonal pattern in monthly interest or inflation rates (Wooldridge, 1960, ch 10 p340). However, Diller (1969) demonstrates that interest rates do show seasonal variation. I formulate both non-seasonally adjusted and de-seasonalised models and discuss their comparison. Eleven dummy variables representing 12 months in a year were created and found to be significant, though their results are not reported.

Stationarity I - Stochastic Trends

If future data is similar to past data, then historical relationships can be used to forecast the future. If it does change, then the relationship between the past and the future is not stable and historical relationships are unreliable guides to the future. When the future is similar to the past we refer to the series as 'stationary', that is, the probability distribution of the time series variable does not change over time, if not they do not exhibit mean reversions, that is the data generating process of that series does not evolve around zero. Conventional hypothesis testing, confidence intervals and forecasts may be unreliable for non-stationary series. The data were visually inspected for trends that might betray non-stationarity. Yield curve, unemployment, business confidence survey, building permit, consumer sentiment, and GDP data appeared to be stationary. The personal consumption expenditures, corporate bond spread, short term interest rate, real money stock and Cyclically-Adjusted Price-to-Earnings Ratio data appeared to exhibit a trend. It wasn't clear if average weekly hours and housing permits exhibited a trend.

A Dickey-Fuller (DF) test was used to test the null hypothesis that a unit root is present in the autoregressive series versus the alternative hypothesis that the series is stationary. The lag length was selected using the AIC suggested lags, as the literature suggest that too many lags are preferred OVER too few (Stock, 1994). Series found to be non-stationary were transformed using differencing. Because DF assumes that errors are independent and have a constant variance but the true data generating process is usually unknown, we are faced with the problem that to test the coefficients of interest we need to include all the autoregressive terms in the estimating equation, and therefore must use the correct lag length. The results of visual inspection and formal testing are below. Critical values for the ADF test are -3.96(1%), -3.41 (5%) and -3.12 (10%).

Stationarity II - Structural Breaks

Commonly, researchers do not have an *a priori* knowledge of the nature and timing of structural breaks. Therefore in recent literature break dates are assumed unknown and approached as additional change point parameters to be estimated (Andrews, 1993).

Below are some hypothesised breaks that might affect my results;

- 1986: Tax reform repeals many of the 1981 tax incentives that were meant to encourage real estate investment.
- 2005: Growth in the gross domestic product slowed, unemployment and inflation rates start to rise. The housing market falls sharply, and the U.S. dollar weakened against international currencies
- 2008: The Great Recession. In November 2008 the Federal Reserve began it's first round of quantitative easing.

Table 2: Stationarity

Label	k	AIC Value	ADF Statistic	p-val	Diagnosis
10Y2Y	9	-1.22781	-3.431*	0.0474	Stationary
10Y3MM	9	-.175297	-3.723 *	0.0209	Stationary
TB10	4	-.099668	-3.447 *	0.0454	Stationary
TB5	4	.006728	-4.298***	0.0032	Stationary
TB1	4	-.498541	-3.528 ***	0.0365	Stationary
UNEMP	7	-.815517*	-3.227*	0.0792	Non-stationary
AWHMAN	3	-.12064*	-4.226	0041	Stationary
PCE	3	.866399*	-0.046 ***	0.9937	Non-stationary
AAA10YM	7	.875807*	-3.955 *	0.0102	Stationary
TB3MO	3	1.04787*	-2.984	0.1366	Non-stationary
BSCICP	8	-1.39887*	-6.757 ***	0.0000	Stationary
CSI	3	5.53247*	-2.794	0.1992	Non-stationary
HOUST	3	12.169*	-2.482	0.3368	Non-stationary
PERMIT	10	11.575*	-3.800	0.0166**	Non-stationary
M2REAL	2	7.80094*	1.591	1.0000	Non-stationary
TRCAPE	2	2.43612*	-2.126	0.5317	Non-stationary
GDP	14	-8.34075*	-5.003	0.0002	Stationary

$* = p \leq 0.05, ** = p \leq 0.01, *** = p \leq 0.001$

- 2019: U.S equity markets markets suffered their biggest losses in modern U.S. history due to concerns regarding the coronavirus pandemic and the Russia-Saudi Arabia oil price war.

Stata trims samples by 15% to avoid estimating breaks near the end or near the beginning of the sample for which we do not have enough observations to estimate the parameters. Therefore, we don't have to worry about events very early and very late in the series. In practice, it is very difficult to know the exact date of a structural break. I use a test that allows for this uncertainty. A modified version of the Chow Test (Chow, 1960) called the Quandt Likelihood ratio statistic (Quandt, 1960) tests for breaks at an unknown date. Furthermore it is useful because it can detect multiple breaks, and slowly evolving coefficients as well as discrete changes. Individual variables were tested for coefficient stability and the results are below.

Table 3: Quandt Likelihood ratio statistic structural break test

Variable	k	QLR-statistic	p-val	Break Date
10Y2Y	9	68.6816	0.0000	Break at 1982m10***
10Y3MM	9	30.6722	0.0003	Break at 1988m7***
TB10	4	14.411	0.0959	Break at 2007m7
TB5	3	22.613	0.0039	Break at 2007m7***
TB1	4	22.613	0.0039	Break at 2007m7***
UNEMP	7	41.853	0.0000	Break at 2010m12***
PCE	3	49.4422	0.0000	Break at 1979m12***
AAA10YM	7	24.4388	0.0379	Break at 2007m11**
TB3MO	3	19.0528	0.0169	Break at 1989m4**
BSCICP	8	16.5651	0.4661	NO Break
HOUST	3	24.4388	0.0376	2005m10
PERMIT	10	25.6841	0.1170	NO Break
M2REAL	2	23.6377	0.0007	Break at 1995m5***
AWHMAN	3	35.7742	0.0000	Break at 2009m6**
TRCAPE	2	11.5581	0.1222	Break at 1982m7
NORMGDP	14	779.8166	0.0000	1982m6***

$* = p \leq 0.05, ** = p \leq 0.01, *** = p \leq 0.001$

Model selection

Studies relating macroeconomic and financial variables to the probability of recession typically employ a probit model. Additional lags of the explanatory variables were considered for inclusion. Whilst including additional lags of the independent variables will reduce the sum of squares of the residuals, degrees of freedom will be lost to estimating additional coefficients. This is associated with a loss of forecasting performance (Enders, 1995). Information criterion AIC and BIC balance good fit with parsimony. Whilst BIC is best for parsimony, AIC is best for prediction as it is asymptotically equivalent to cross-validation. I estimate a probit model of the form

$$Pr(USREC_{t+k} = 1) = \phi(\gamma_0 + \gamma_t X_t + \epsilon_t), \tag{1}$$

where k is the length of the forecast horizon and USREC a binary indicator that is coded 1 if there is a recession in the period $t+i$ and ϕ is the standard normal cumulative distribution function. Additional coefficients increase the fit of a model at the expense of eating degrees of freedom. Parsimonious models are preferred for their ability to produce better forecasts by approximating the true relationship rather than explain the exact process. To ensure the models are parsimonious all coefficients should be statistically different to zero (joint significance test) and the coefficients should not be strongly correlated (Enders, 1995). All models pass tests for joint significance and tests for multicollinearity show that coefficients are not strongly correlated with each other.

I examine the selected variables individually and in combination. I present the results of several estimations. I began with a simple baseline model that includes three explanatory variables; the slope of the yield curve, a measure of employment, and personal consumption expenditures as as measure of the inflation rate. Different yield curves and measures of employment rates were experimented with. The literature demonstrates that the yield curve's predictive power is reinforced when short term interest rates and the corporate bond spread are included in the explanatory variables and so this was added to the baseline model. Lags of the slope of the yield curve were added, and this was the final specification of the baseline model. Next, I test several theoretically important macroeconomic and financial variables relating to homebuilding, financial market returns and sentiment.

Results and Discussion

Below are the results for the probit regression with a single regressor. We see that 10Y3MM is significantly better at predicting recession than 10Y2Y, which was not statistically significant in the single regressor model. The short term interest rate TB3MO, employment measures and confidence surveys were all statistically significant at the 1 percent level and have good predictive power.

Table 4: Probit regression with a single regressor results

Variables	CE	Psudo R^2	Log-liklihood
10Y2Y	0.0052 (.0895)	0.0000	-144.689
10Y3MM	0.0473 (.0653)	0.0014	-144.493
TB3MO	-1.6071 (.5498)	0.1132	-126.229
TB10	0.0687 (.0275)*	0.0255	-140.996
TB5	0.0592 (.0264)	0.0218	-141.54
TB1	0.0745 (.0311)*	0.0329	-114.875
UNEMP	5.6820 (.8007)	0.3161	-97.3424
AWHMAN	-1.1977 (.1491)	0.2949	-102.024
AAA10YM	1.6665 (.7511)	0.0248	-138.815
PCE	-0.0102 (.0041)**	0.0655	-133.015
BSCICP	-1.2155 (.1218)	0.5921	-59.0264
UMCSENT	-0.0775 (.0098)*	0.3489	-94.2148
HOUST	-0.0009 (.0007)***	0.0041	-141.756
PERMIT	-0.0018 (.0012)**	0.0091	-141.045
NORMGDP	-0.2812 (.0903)	0.0521	-137.148

$* = p \leq 0.05, ** = p \leq 0.01, *** = p \leq 0.001$

Below are the results of the probit multivariate regressions.

Table 5: Results of the probit multivariate regressions

Model No.	1	2	3	4	5	6	7	8
Variable								
10Y2Y	1.8934	1.9778	1.7817	1.5073	3.6973	1.1076	1.6355	
	(0.061)	(0.079)	(0.101)	(0.117)	(0.001)	(0.257)	(0.220)	
10Y3MM								9.4627
	(0.008)							
AWHMAN	-0.9213	-0.5917	-.5404	-.592	1.6431	-0.0553		
	(0.0000)***	(0.013)*	(0.029)*	(0.023)*	(0.0000)***	(0.833)		
UNEMP							6.8540	12.007
							(0.000)	(0.000)
PCE	-0.0156	-.0101	-.0092	-.0068	-.0040	-.0066	-.0034	-.0126
	(0.0000)***	(0.002)**	(0.019)*	(0.066)	(0.343)	(0.175)	(0.701)	(0.099)
AAA10YM	0.8406	.1778	1.4044	1.3412	3.4738	-.272	9.4938	24.58
	(0.363)	(0.845)	(0.128)	(0.12)	(0.006)**	(0.783)	(0.001)***	(0.000)***
TB3M0	-0.3661	-.0368	-0.4949	-.7217	2.1163	-1.4394	8.0013	8.1416
	(0.0000)***	(0.961)	(0.128)	(0.318)	(0.015)*	(0.085)	(0.001)**	(0.003)*
TRCAPE		-0.3085						
		(0.029)*						
HOUST			-.0031					
			(0.007)**					
PERMIT				-0.0048				
				(0.029)*				
BSCICP					-1.8348		-3.0876	-5.9823
					(0.0000)***		(0.0000)***	(0.000)***
UMCSENT						-.1035		
						(0.0000)***		
NORMGDP							1.2271	3.1032
							(0.0000)***	(0.000)***
Cons	38.2682	21.8293	19.9924	21.942	111.2997	9.4178	31.9158	270.6918
Pseudo R2	0.5969	0.5988	0.5326	0.5375	0.7428	0.6765	0.8306	0.8907
Log likelihood	-38.9061	-49.2419	-57.3765	-56.7657	-31.5687	-39.7037	-23.3022	-14.7802
Correctly Classified	94.84%	94.18%	93.96%	93.96%	97.32%	96.20%	98.23%	98.89%
Sensitivity	55.56%	48.57%	48.57%	48.57%	80.00%	74.29%	90.24%	95.00%
Specificity	97.95%	98.06%	97.82%	97.82%	98.79%	98.06%	99.03%	99.27%
Rate of False Positives	2.05%	1.94%	2.18%	2.18%	1.21%	1.94%	0.97%	0.73%

$* = p \leq 0.05, ** = p \leq 0.01, *** = p \leq 0.001$

Marginal Effects

Probit estimated parameters do not have as straightforward an interpretation as OLS regression. The column dy/dx is the probability, in percentage points, that the variable adds to the probability of a positive outcome in the probit model, evaluated at the sample mean. Evaluating at other values allows testing for the sensitivity of a positive outcome to the explanatory variables. For example, in Nov 2008 the unemployment rate accelerated. Evaluating at UNEMP$= 0.3$ (where the seasonally adjusted unemployment rate was 6.8%), we see that UNEMP adds 28 percentage points to the probability of recession next month. Below is a table of the marginal effects.

Table 6: Marginal effects

dy/dx	1	2	3	4	5	6	7	8
Variable								
10Y2Y	0.1174	0.0844	0.1100	.1088	2.5568	.1205	.03681	
	(0.100)	(0.238)	(0.118)	(0.113)	(0.021)*	(0.101)	(0.417)	
103MM								.1766
								(0.000)***
AWMAN	-0.0609	-0.0667	-.0673	-.0709	.9445	-.0603		
	(0.001)***	(0.0000)***	(0.0000)***	(0.000)***	(0.001)***	(0.001)		
UNRATE							.1811	.2241
							(0.0000)	(0.000)
AAA10YM	0.0540	.0062	.0535	.0431	1.7367	.0590	.0945	.4588
	(0.413)		(0.415)	(0.503)	(0.085)	(0.447)	(0.008)	(0.000)***
TB3MO	-0.0942	-1.2456	-.0968	-.1077	.1221	-.093	-.0256	.151983
	(0.046)*	(0.035)*	(0.037)*	(0.18)	(0.815)	(0.047)*	(0.148)	(0.000)***
PCE	-0.0006	-.0061	-.0006	-.0004	-.0026	-.0006	-.0000 (0.871)	-.0002
	(0.050)	(0.106)	(0.056)	(0.157)	(0.531)	(0.050)*	(0.871)	(0.073)
TRACEP		-.2258						
		(0.087)						
HOUST			-.0002					
			(0.013)*					
PERMIT				0.157				
				(0.037)*				
BCICP					-1.7626		-.0645	-.1117
					- (0.000)***		(0.000)***	(0.000)***
UMCSENT						.0005		
						(0.861)		
NORMGDP							.0316	.0579
							(0.000)***	(0.000)***

From the results we see that all interest rates, UNEMP, AAA10YM, TRACEP, PERMIT, BSCICP AND NORMGP are all strong predictors but AWHMAN, PCEINF are UMCSENT wake predictors.

MSFE Over Pseudo-out-of-Sample Period February 2019 to January 2020

The sample standard deviation of the pseudo-out-of-sample is an estimator of the MFSE. It is a measure of the forecast error. The very low forecast errors are consistent with the good fit of the model (R^2). The final model, model 8, performs the best with a very low forecast error.

Table 7: MSFE

Model	MSFE
1	0.0001403
2	0.0001291
3	0.0000821
4	0.00011
5	0.0004927
6	0.0001234
7	2.00e-07
8	8.28e-09

Forecasts for February 2020

All models give extremely low probability for recession in February 2020.

Table 8: Probability of recession in February 2020

Model	Probability of recession
1	0.0078313
2	0.0040928
3	0.0040928
4	0.0033903
5	0.0180773
6	0.0066691
7	0.0000215
8	0.00000148

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