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USING THE YIELD CURVE TO FORECAST RECESSIONS
... do you feel lucky?

Executive Summary

Talk of recession is rife. Macroeconomic data prints are discouraging, and most all have slashed economic growth projections for 2022 and beyond. Unsurprisingly, market participants are trying to predict if, and when any recession might occur.

One popular and frequently cited go-to metric said to reliably predict recessions is an 'inverted' yield curve, i.e., when the spread between the yield of a shorter and a longer duration tenor turns negative (typically the yield of the US nominal 2-year and 10-year Treasury). In short, when the yield on short-term debt increases above that of longer-term debt, recessions are said to follow. In this paper, focusing on the US case, we evaluate this claim using an approach based on fictitious Profit and Loss curves (P&Ls) when 'trading' recessions. We also compare the predictability of the yield curve with other contenders.

Our findings can be summarized as follows - inverted yield curves tend to be a good predictor of a recession in one year from the moment of the inversion while a slightly better predictor of recessions comes from the stock market with negative S&P 500 performance preceding recessions with a high level of significance.

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Introduction

There is a near-entrenched dogma that an inverted yield curve – typically the spread between the US 2-year and 10-year nominal yields (2y-10y) – is a reliable predictor of recession.[1]

Anecdotally, this seems reasonable. In figure 1, using monthly data from Global Financial Data (GFD), we plot the US 2y-10y overlapped with official US recessions dating back to the 1940s. This is a version of a plot many readers will be well familiar with. Overlooking the period before the mid-1950s, the 2y-10y inverted before nearly each subsequent recession – albeit with varying lags.
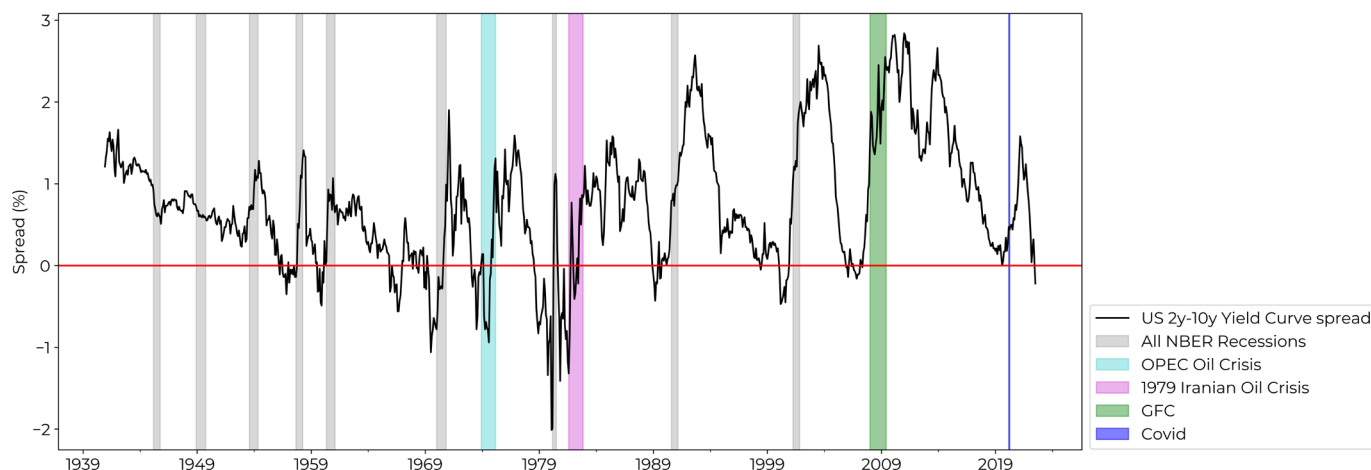
Source: NBER, GFD, CFM

Fig 1. The US 2y-10y using monthly GFD data, overlapped with US recessions. By simple eyeballing, it does seem that a yield curve inversion typically precedes a recession. However, notwithstanding the exceptions where the yield curve inverted and was not followed by a recession, there are also varying lags between the first inversion of the yield curve and the start of a recession.

Why should an inverted yield curve even be predictive of declining economic growth and finally a recession?

The simple logic goes as follows: If a central bank tightens monetary policy – typically to tame inflation by depressing demand (the cycle we find ourselves in today), short-term rates, those most sensitive to central bank tightening, are pushed up. Meanwhile, long-term interest rates – less sensitive to Fed actions – tend to be less reactive, thus mechanically narrowing the spread. Equally, long-term rates are more sensitive to expected inflation, exactly the thing that monetary policy and Fed actions are supposed to manage. Long term rates are typically pulled down if the Fed is successful (or deemed to be successful) in dampening expectations of future inflation, this by raising their key lending rates.

Now, given that asset classes have, historically, displayed divergent performance during periods of recessions (see exhibit 1 A and B in the appendix), one can therefore argue it benefits an investor if recessions could be predicted with a high level of certainty (and timeliness).

In this paper we will not rehash all the arguments for and against an inverted yield curve being predictive of recessions but will propose a technique to evaluate this claim. We endeavoured to include anecdotal data and plots, this to make this document a more comprehensive guide to the salient features of yield curve inversion and recessions.

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[1] There are ample academic and informal resources the reader can reference that examines the relationship between yield curve spreads and economic growth. The work of Dr. Campbell Harvey is one of the first and perhaps most comprehensive to address this question, when, in his 1986 doctoral thesis, he concluded that "there is a link between the yield spread and consumption fluctuations." His dissertation can be found here.

First, a few remarks on 'recessions'

The main authority on classifying US recession is the 'Business Cycle Dating Committee' (BCDC) of the National Bureau of Economic Research (NBER) who has chronicled US recessions dating back to December 1854. Historically, recessions in the US are not all that rare. The US economy has been in a recession 579 months out of 2,011 since 1854 – nearly a third of the time. Recessions, of which there have been 33 in total, lasted, on average, 17 months, with the shortest and longest recessions recorded being 2 months (the Covid contraction) and 65 months (the 'Long Depression' of 1873-79).

The drawback of testing the predictability of a recession using any metric is that the BCDC declares the start of recessions with anywhere from 4, to as much as 21 months of lag – a period "long enough so that the existence of a peak or trough is not in doubt."[2] The reason the BCDC follows the procedure they do, is, for one, the fact that GDP figures are subject to often non-negligible revisions.[3]

What many studies assess – as we do in this paper – is whether any one or set of metrics is good at predicting 'official' recessions ex-post. We recognize the inherent limitation, because it assumes an accurate prediction, if any, only ex-post, and the economy would have been in a recession before being classified as such.

It is therefore not that useful for market participants, nor policy makers, to know when a 'recession' happened in the past but would only be useful when there is a high probability of a slowdown in economic output to be expected in the near future.

An inverted yield curve as predictor of recession?

Nevertheless, the premise that an inverted yield curve is predictive of recessions is anecdotal and popular. We will therefore rely on official recession data to evaluate this claim.

Rather than just counting the number of recessions correctly predicted (making for poor statistical inference), our approach is to create fictitious P&Ls built by using 'predictors' to 'trade' recessions. If any predictor is accurate in correctly predicting recessions, it will yield a positive P&L and vice versa. In so doing, we can measure the total cumulative return of such a strategy over the entire period; not hamstrung by making discretionary calls of when and by how much an inverted yield curve may or may not have been predictive; nor are we encumbered by arbitrarily choosing suitable parameters. We can also determine whether positive results are due to statistical good fortune or are contrarily unlikely and thus "statistically significant."

We can then also use the same procedure as a template to evaluate and compare other 'predictors'. All of this is of course purely hypothetical since one cannot trade a recession *per se*!

Since the 2y-10y is most cited, this is the spread which we will use as the baseline to evaluate this widely accepted dogma.

To set this baseline, we build a simple predictor using the 2y-10y timeseries. We calculate the spread using GFD which has monthly data available since 1940. We transform the 2y-10y into a binary series, where the predictor is **-1 (0)** when the yield curve is inverted, i.e., **strictly negative (positive).**

We then use official NBER recession dates[4] that indicate whether the US economy was determined to be in a recession or in a growth phase. We also transform this time series into a binary series, assigning **1 (-1)** when the US economy is **expanding (in a recession).**

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[2] https://www.nber.org/business-cycle-dating-procedure-frequently-asked-questions

[3] Interested readers may refer to our "On business cycles… and when trend following works" paper where we highlight the pitfalls of identifying business cycles and the average magnitude of GDP revisions. The paper is available on our website.

[4] https://fred.stlouisfed.org/series/USREC

To build the fictitious P&Ls we multiply our binary yield curve predictor over x lags (can be seen as our fictitious positioning either flat or short recessions) with the binary recession series at each monthly step, i:

$$P\&L_t^x = \sum_{t'<t} P^x(t')R(t')$$

Where:

$P^x(t')$ = Predictor at time t', lagged by x months with $P \in \{-1, 0\}$

$R(t')$ = Recession with $R \in \{-1, 1\}$

x = Number of months of lag with $x \in [-48, 0]$

The table below, using a snippet of actual historical data, visualizes the outcome of this procedure using the yield curve of the previous month as the predictor of the current month.

Date	Yield Curve	Recession	Result
1957 – 05	-1	1	-
1957 – 06	-1	1	-1
1957 – 07	0	1	-1
1957 – 08	-1	1	0
1957 – 09	-1	-1	1
1957 – 10	-1	-1	1
1957 – 11	0	-1	1
1957 – 12	0	-1	0
1958 - 01	0	-1	0
			2

When the yield curve is concomitantly inverted (-1) with a recession (-1), the product yields +1, i.e., a positive P&L result and a correctly identified recession. However, if the yield curve is inverted (-1) and there is no recession (1), then the product is -1, i.e., a negative P&L result and an incorrectly anticipated recession when no such existed. If the yield curve is upward sloping (0) the summation will be 0 irrespective of a recession or not. We do not care whether an upward sloping yield curve predicts a recession or not, we are only interested in evaluating whether a negative yield curve is accurate in predicting a recession (as the dogma dictates).

A cumulative sum of the results is the fictitious P&L through time.

In the tabled example above, the cumulative sum of this hypothetical example yields a positive P&L of 2. To evaluate the future predictive abilities of a yield curve inversion (or for any other predictor), we also lag the predictor by multiple months to see if we get better results.

The obvious question when confronted with measurements of predictability (in our case the fictitious P&L) is whether one could have obtained such an observation just by sheer luck or in other words due to a statistical fluke. For example, instead of using the yield curve as predictor, if one were to use a "head or tail" predictor from the flip of a coin then one would expect a result consistent with statistical noise – neither winning nor losing excessively. Of course, each time the coin is tossed one can use the set of outcomes to describe a single P&L and then a series of P&Ls can be generated to form an "envelope of noise". Such techniques are used daily by quant firms examining the relevance of strategies and to distinguish genuine predictability from the realms of sheer good luck.

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We mimic this 'head or tail' predictor in our context by using a randomized predictor to build 100,000 individual P&Ls. This allows us to obtain a meaningfully large sample from which we can statistically infer and assess where the 'actual' yield curve predictor fits within the statistical envelope (in case of a successful predictor the distance from the noise reveals how significant the predictor is!).

The next question one would like to answer is: if the P&L is above the noise then how likely is it to occur through being lucky? The answer to this involves simple counting – by looking at the terminal point of the P&L and seeing how many of the random P&Ls are above and below it? For example, having generated 100,000 randomized P&Ls it may be that the terminal point of the P&L of a given predictor is above 90,000 randomized P&Ls but below the most successful (through luck) 10,000. One can then make statements such as: achieving (at least) that level of P&L has a 1 in 10 (10%) probability of occurrence through chance. Generally speaking, we would consider probabilities of lower than at least ~5% (1 in 20) as beginning to be statistically meaningful.[5]

The result of the above procedure for the US 2y-10y is presented in figure 2. We highlight the P&L when the predictor is from the close of the previous month as well as the P&L with the yield curve predictor from one year ago. We also plot the P&L of the randomized predictors.[6]
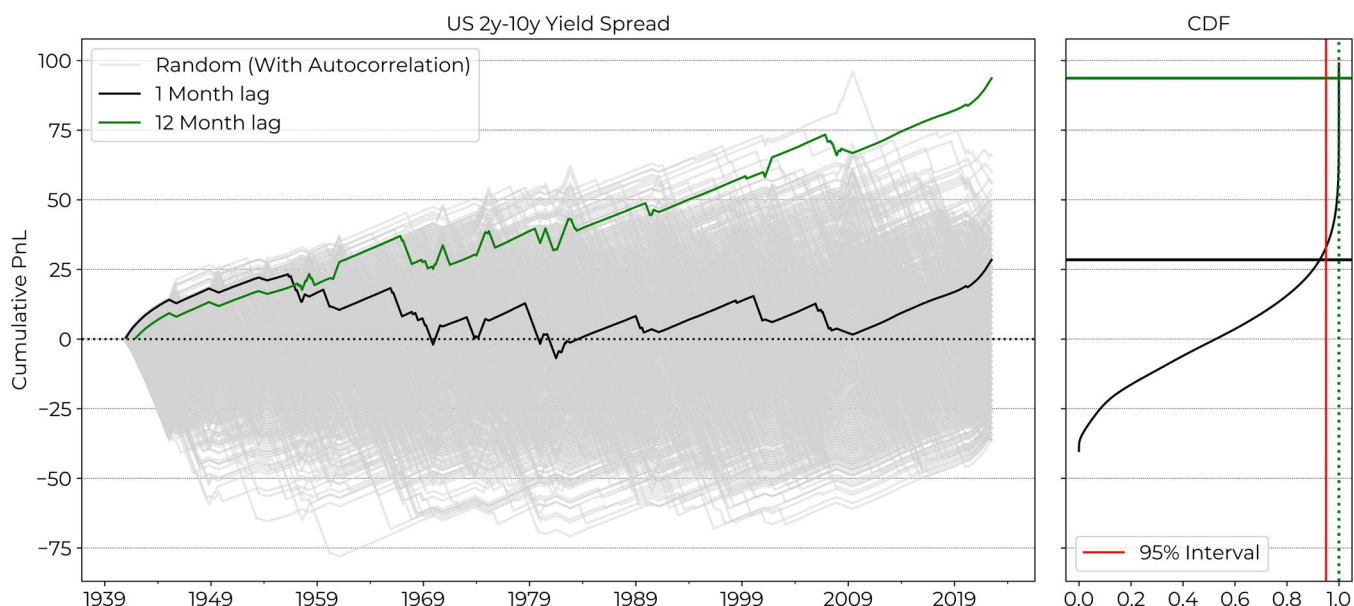
Source: GFD, NBER, CFM

Fig 2. The fictitious P&Ls of an inverted 2y-10y yield curve predicting US recessions. We highlight the P&Ls of the predictor lagged by one month, along with the 12-month lagged predictor. The P&Ls of a randomized 2y-10y yield curve inversion predictor are in light grey[7], producing the "noise envelope". One can conclude that a 2y-10y yield curve inversion is statistically significant in predicting a recession 12-months into the future, in that it falls well outside the statistical noise of the randomized predictors. The yield curve does not predict immediate recessions, however, as the terminal point of the P&L is very much mixed in with the noise. This observation is further developed on the right-hand side, where we plot the cumulative distribution function (CDF) – the result of the counting exercise described above - to give us a probability of seeing such a result through luck. The terminal P&L of the 12-month lagged predictor falls within the critical region, to the right of the red line, which indicates it is statistically significant at the greater than 5% level, meaning the P&L has a statistically significant probability of not being observed through good luck.

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[5] Scientists tend to use "5 standard deviations" as the limit of significance for discovery purposes which corresponds to a probability of less than 1 in 3.5 million!

[6] For the purposes of illustration and interpretation, we 'updrift' the P&Ls of the randomized and actual, lagged predictors with the mean of the randomized predictors added at each step so that the mean of the terminal randomized P&Ls is zero. Without this updrift procedure the noise has an average negative performance since recession periods exist in less than half of the sample (actually, 579 months out of 2,011 months or ~29% of the sample is defined as recessionary). For those of a more technical nature, one can think of the corrected P&L of a predictor under consideration as being thus converted to a residual with respect to the (negative) P&L of recessions.

[7] Since the yield curve predictor displays a high level of autocorrelation – when a yield curve is inverted it tends to remain inverted for a short time – random reshuffling of the actual data will destroy this autocorrelated feature and render the randomized predictor incomparable. Therefore, we reshuffle the actual predictor but reintroduce the same level of autocorrelation into each of the individually generated random time series. We also impose that the randomized predictors have exactly as many -1s as the predictor being tested – the yield curve being less frequently inverted than upward sloping means less -1s than 0s in the predictor and the randomized timeseries.

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Some further observations to highlight:

The fictitious P&L lagged by one month, which is whether an inverted yield curve accurately predicts an imminent recession in the next time step, is flat and falls roughly within the noise of the random predictors.

Using multiple lags we observed, in fact, the predictor that yielded the best result, is the predictor lagged by 12-months of which the P&L falls well outside the statistical noise. **We can conclude that an inverted yield curve, 12-months in the past, is in fact, a much better predictor than random**.

Now, with this procedure in hand, we can use it as a template to evaluate other viable 'predictors' of recession and compare with the 2y-10y baseline.

Better predictors of recession?

The intention of this paper is not to propose an exhaustive list of potential predictors of recession (whether macro fundamental or price-based). It is, however, prudent to evaluate other predictors which can then be compared to the baseline 2y-10y yield inversion predictor.

To start, we evaluate the claim that another localized yield curve spread, that of the US 3-month and 10-year nominal yields (3m-10y) is more reliable than its more frequently cited 2y-10y cousin. We repeat the process as above, creating a binary series of the 3m-10y and duplicate the procedure. Data for the 3m-10y spread goes back further, since January 1920. However, to remain consistent and allow for comparison, we limit the time window to that of the 2y-10y.

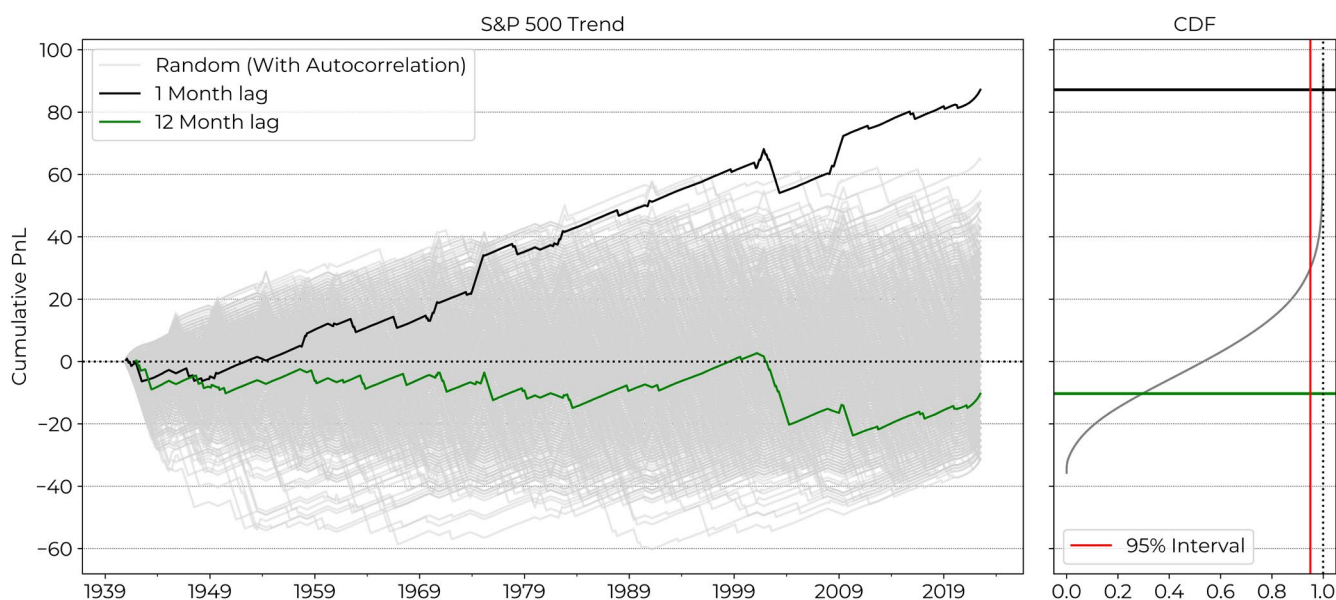The results are shown in figure 3.
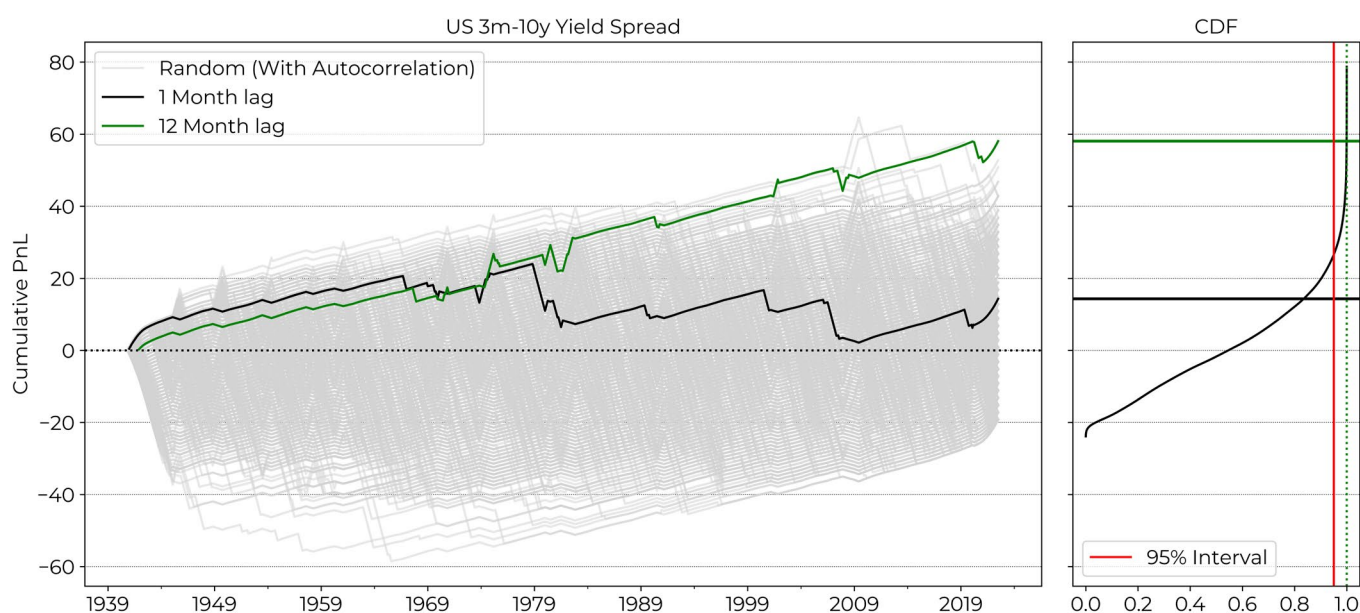
Source: GFD, NBER, CFM

Fig 3. The fictitious P&Ls of an inverted 3m-10y yield curve predicting US recessions. We highlight the P&Ls of the predictor lagged by one month, along with the 12-month lagged predictor. The P&Ls of a randomized 3m-10y yield curve inversion predictor are in light grey. We can conclude that a 3m-10y yield curve inversion is also statistically significant in predicting a recession 12-months into the future, in that it falls well outside the statistical noise of the randomized predictors. The results using the 3m-10y inversion are broadly comparable to the 2y-10y inversion.

The claim from some that the 3m-10y yield spread is a more reliable predictor of recession does not seem to hold true with any level of significance. The overall performance of the P&L is slightly poorer than the 2y-10y predictor but slightly better at a 10-month lag – see figure 5 below – although we do not believe this difference to be in any way meaningful.

We subsequently evaluate whether equity markets could be considered predictors of recession. The a priori case is sound: equity investors capture a vast set of information to assess expectation of firms' future earnings. This is discounted and reflected in the current market price. One can reasonably expect falling equity prices to incorporate (and be reinforced by endogenous trading activity) future expectations of economic growth.

To evaluate whether equity markets are predictive of recessions, we construct a generic 5-month trend strategy on the S&P 500 and convert the predictor into a binary series using the same procedure as for the other predictors where a **'short'** **('long')** signal is transformed to **-1 (0)**. However, to make a like-for-like comparison with the 2y-10y predictor, we set the threshold of the S&P 500 trend signal such that the distribution (or ratio) of the binary -1s to 0s trend predictor is equal to that of the benchmark predictor, the US 2y-10y spread. The US 2-10y yield curve (using monthly data) has been inverted ~17% of the time within the available history. We therefore set the threshold of the negative S&P trend predictor at a level such that the ratio of -1s and 0s matches this ~17%.

The results of a trend on the S&P 500 predicting recessions are presented in figure 4. The P&L is highly significantly positive for predicting imminent recessions.[8]
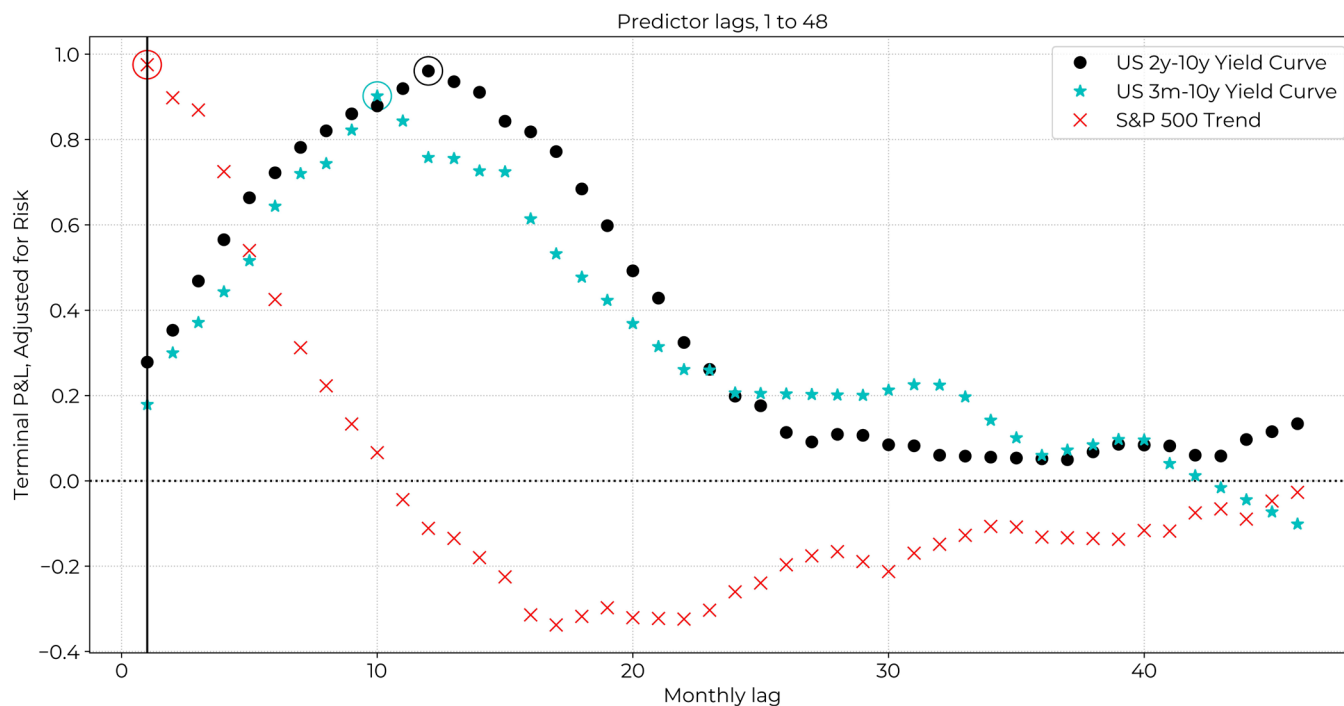

Source: GFD, NBER, CFM

Fig 4. The fictitious P&Ls of a trend signal on the S&P 500 predicting US recessions. We highlight the P&Ls of the predictor lagged by one month, along with the 12-month lagged predictor as before. The P&Ls of a randomized trend predictor are in light grey. Here, only the one month lagged predictor is statistically significant in predicting a recession in the very-near future, in that it falls well outside the statistical noise of the randomized predictors.

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[8] Note, however, that in some cases it may well be that the drop of the S&P causes the subsequent recession! We briefly address this in the conclusion.

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The summary results for the three above predictors over 1 to 48 monthly lags are shown in figure 5 below.

Source: GFD, NBER, CFM

Fig 5. The summary results of all the above predictors with lags from 1 month, as described in the text, up to 48-months in the past. The lag of each predictor that yielded the best terminal P&L adjusted for risk is circled. The predictability of the 2y-10y is superior to that of the 3m-10y over most lags. The trend on equities is typically a better predictor of recessions in the very near-term, up to 4-months into the future given the superior terminal P&Ls. As previously discussed, the P&L (gain on the y-axis) is statistically significant (there is genuine predictability), as it is inconsistent with typical levels of statistical fluctuation through chance.

We finally repeat the same procedure as for all the above predictors but, in addition, applied to US employment, inflation, and commodities. We also compare results with a different threshold on the 2y-10y yield curve, i.e., being in recession (or a predictor of -1) when the spread narrows to 0.2% or lower.

The results of these additional individual predictors are all presented in detail in exhibit 2 of the appendix. None of these predictors, however, yield better results at predicting recessions than that of an inverted yield curve (both the 2y-10y and 3m-10y in the medium term), and few outperform the US equity market in the short term.

Conclusion

Forecasting macroeconomic events is a tricky business and relying on dogma to draw conclusions about the future based on a few isolated events – each with its own idiosyncratic nuance – is risky.

There is a rich and extensive literature on predicting recessions, including the reliance on yield curve inversions and the reasons why such predictability might be plausible. In this paper we did not attempt to debunk, nor challenge the mostly macroeconomic and econometric approaches but instead let the results do the talking.

We deployed a novel and simple approach to evaluate the veracity of the US 2y-10y spread inversion as predictor of recession over an 80-year period. **Our approach suggests that an inverted US 2y-10y yield curve is statistically significant at predicting an upcoming recession in 1 year as compared to a random predictor derived from the same yield spread inversion.** Our approach shows that an inverted 3m-10y yield curve inversion is at best as good as the 2y-10y inversion in predicting recessions.

It seems, therefore, that as of the first yield curve inversion it takes approximately one year before the slowdown actually materializes in the real economy and causes a slowdown. The Fed began its tightening cycle some months ago now and the first yield curve inversion (of the 2y-10y) occurred at the end of March 2022 – briefly, while it has been inverted (looking at daily data) since the first week of July 2022. The results of this paper suggest that the next recession is in perhaps Q2-Q3 of 2023.

The current US macroeconomic environment, although not officially (but technically[9]) in recession, looks ever bleaker given the high levels of inflation (with simultaneous monetary tightening), geopolitical risk and deteriorating global trade conditions. Yet, it is only the vibrant jobs market that keeps the NBER from making the recession proclamation official. Only time will tell if this predictor is prescient!

In any event, any serious forecaster relies on many inputs to decide whether we are truly in a recession.

Our approach also allowed us to evaluate other 'predictors', and we show that the US equity market has historically been a better predictor of imminent recessions. It is worth bearing in mind, however, that the results of the equity market being predictive of recession might be conflated with falling equity markets being itself contributory to recessions. One such channel is declining household wealth when equity markets fall, which is likely to impact consumer spending – an outsized component in the US economy.

Also, of note for the reader though, is that even if a yield curve inversion (or any other macroeconomic derived proxy) could consistently predict recessions, the recessions themselves are not directly tradable for financial gain. The only way to generate returns from such predictions, is by taking positions in hard assets such as stocks or futures and it is not a given that these same predictors capture the future returns of said assets.

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[9] The US GDP advanced estimate figure for Q2 2022 printed -0.9%, this following the -1.6% recorded in Q1. These two consecutive negative quarters of GDP growth constitute a 'technical recession'.

Appendix

Exhibit 1A. Average performance of different asset classes during periods of recession

In the figure below we show the average annualized returns of key benchmark asset classes using GFD data[10]. No distinction is made here between the severity or magnitude of any given recession, since we simply take the average annualized returns of the asset classes within each of the periods classified as recession. Nor do we consider the periods before or after a recession, which will require assigning arbitrary time windows to track performance.
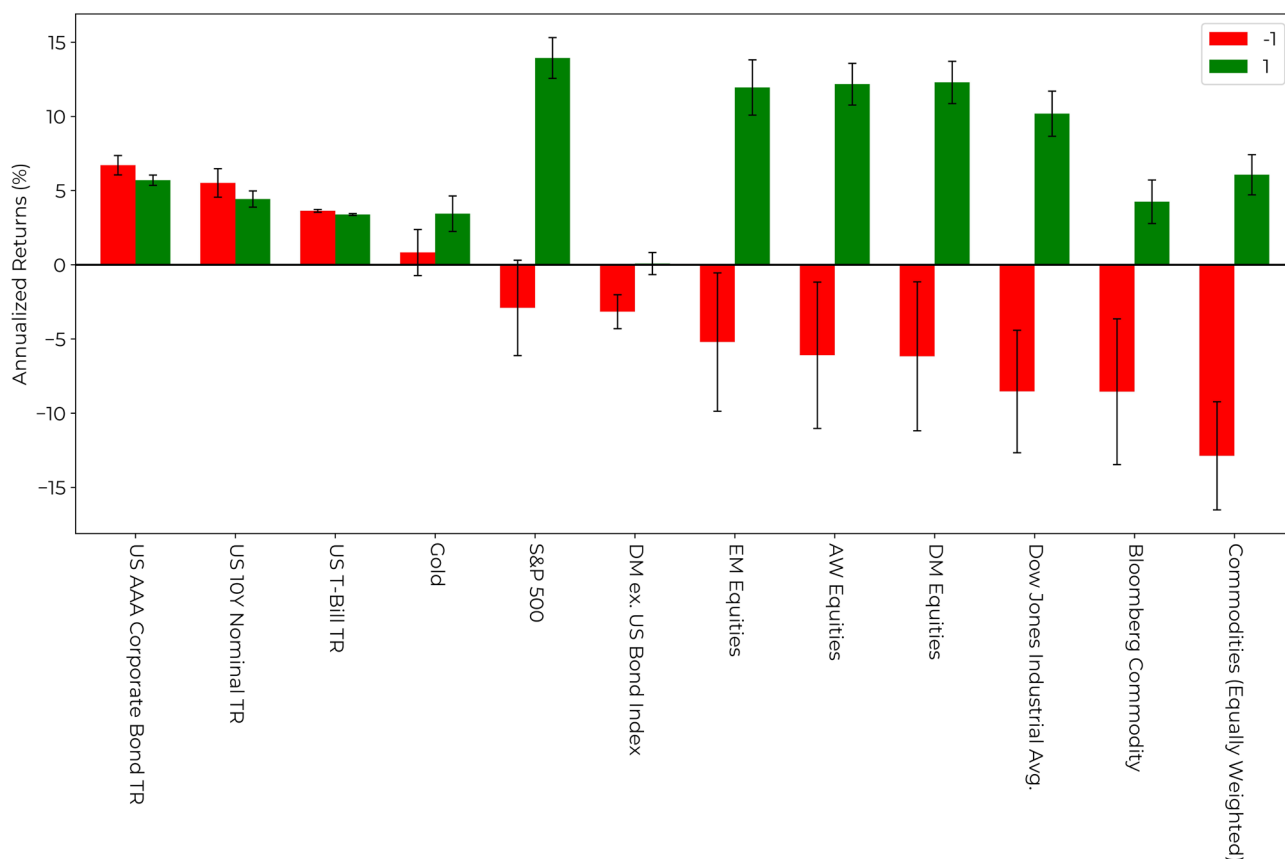
Source: GFD, NBER, CFM

The average annualized returns of key benchmark asset classes during periods of recession, ranked, right-to-left, the worst-to-best performing asset class during recessions (labelled -1 in red) and correspondingly the return in the non-recessionary period (labelled 1 in green). The returns are calculated using monthly data. Unsurprisingly, commodities have historically performed poorly during recession, while equities also substantially underperformed during recessions vis-à-vis during a growth phase. The error bars are larger for the recessionary periods given the lower frequency of these periods.

Plainly, all else being equal, there has historically been a sizeable divergence of asset class performance during periods of recessions.

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[10] We use the maximum length of available data for each asset class to overlap as much as possible with the US recession data going back to 1854. However, not all asset classes have the same length of available data.

Exhibit 1B. Key asset class performance during each US recession since 1940.

In the table below we show the performance of these asset classes within each of the individual recessions since the early 1940s (the date from which all these asset classes have data). Bar the returns of fixed income proxies that were universally positive during each of these periods, asset classes show divergent, and inconsistent returns during recessionary periods classified as such. This should not be surprising, since each recession has idiosyncratic features, and of which the genesis is also unique.

	Bloomberg Commodity	US 10Y Nominal TR	US AAA Corporate Bond TR	DM Equities	S&P 500	Gold	EM Equities	DM ex. US Bond Index	AW Equities	Commodities (Equally Weighted)	US T-Bill TR	Dow Jones Industrial Avg.
1945-03-01 → 1945-10-31	12.1	5.9	3.0	9.7	31.2	3.1	17.2	-2.3	10.2	2.3	0.4	25.5
1948-12-01 → 1949-10-31	-8.8	5.0	4.7	4.4	17.3	-1.3	-12.6	-28.7	3.3	-20.7	1.1	11.7
1953-08-01 → 1954-05-31	15.1	8.8	6.9	30.3	28.9	-6.7	3.6	4.4	29.2	6.4	1.3	23.1
1957-09-01 → 1958-04-30	-3.2	18.0	11.4	-6.6	-1.8	0.2	-13.0	3.2	-6.8	-6.0	2.3	-8.7
1960-05-01 → 1961-02-28	-1.0	9.2	6.6	23.1	24.5	-0.3	5.3	-2.1	22.7	2.5	2.4	12.2
1970-01-01 → 1970-11-30	4.7	20.2	6.9	-7.3	-2.0	7.3	9.9	7.3	-6.9	0.4	6.6	-0.9
1973-12-01 → 1975-03-31	0.7	0.6	2.8	-4.2	-6.0	52.5	-7.3	0.3	-4.3	0.4	7.5	-5.0
1980-02-01 → 1980-07-31	-2.4	16.9	16.2	18.0	19.8	-11.5	56.7	-0.8	20.0	9.0	11.0	14.0
1981-08-01 → 1982-11-30	-3.5	34.5	30.6	3.8	10.4	5.5	-25.6	0.3	2.2	-12.0	11.9	6.8
1990-08-01 → 1991-03-31	-11.6	12.1	12.6	-3.0	12.2	-6.6	-7.0	-10.5	-2.8	-10.4	6.8	0.4
2001-04-01 → 2001-11-30	-19.8	7.0	8.4	-7.3	-1.4	10.5	-6.5	4.6	-7.2	-12.3	3.0	-0.4
2008-01-01 → 2009-06-30	-24.0	6.3	6.7	-26.0	-25.0	7.9	-25.9	1.1	-25.9	-11.1	0.9	-26.0
2020-03-01 → 2020-04-30	-60.1	32.4	21.2	-19.9	-6.5	40.0	-37.8	-1.5	-22.4	-51.6	0.1	-22.6

Source: Bloomberg, GFD, NBER, CFM

Exhibit 2. Alternative predictors of recession

We evaluated whether an inverted yield curve, both the 2y-10y and 3m-10y, as well as a trend strategy on the S&P 500 are predictive of recessions. For completion, we evaluated other potential predictors of recession, some well-discussed in the literature and others we consider feasible extensions.

Throughout, even if deeper historical data exist, we limit the look-back window to match that of the available data of the US 2y-10y spread, i.e., since 1940 for a fair comparison. In the figure below, we show, as above, a summary plot of the terminal P&Ls over all the various lags for the 'alternative' predictors.
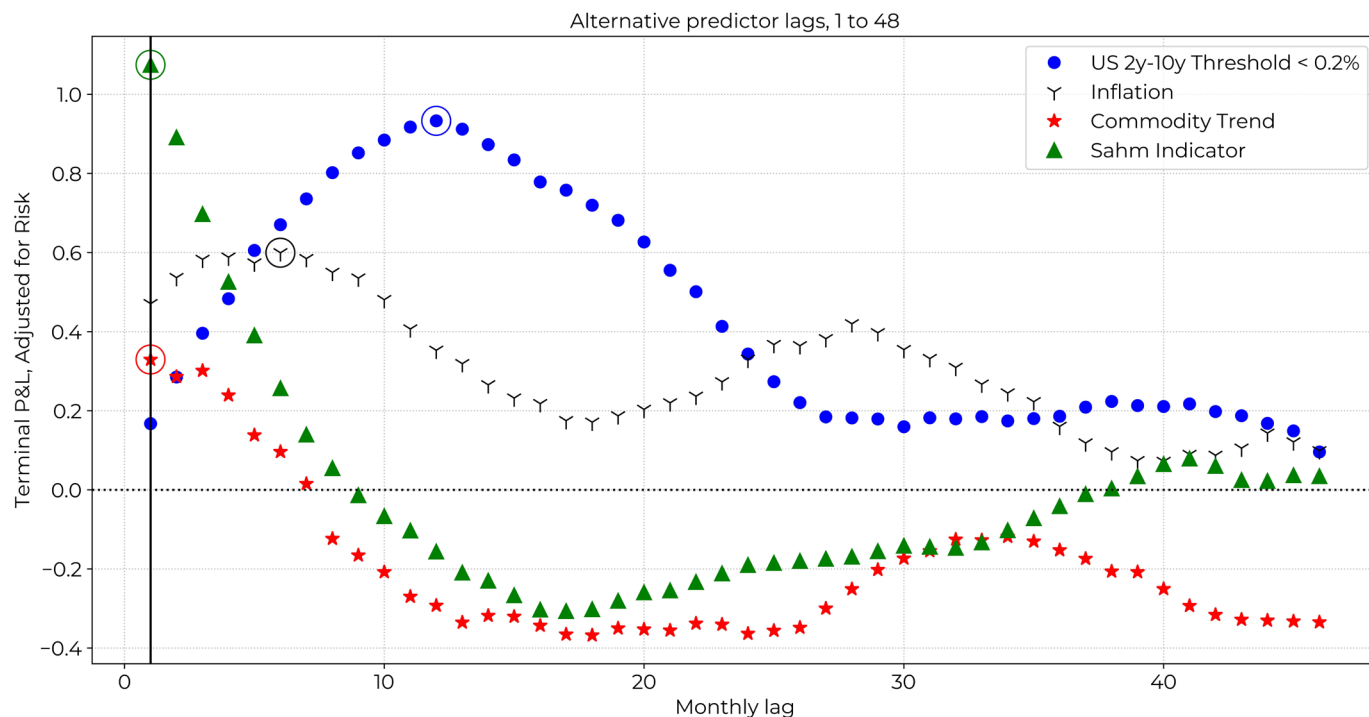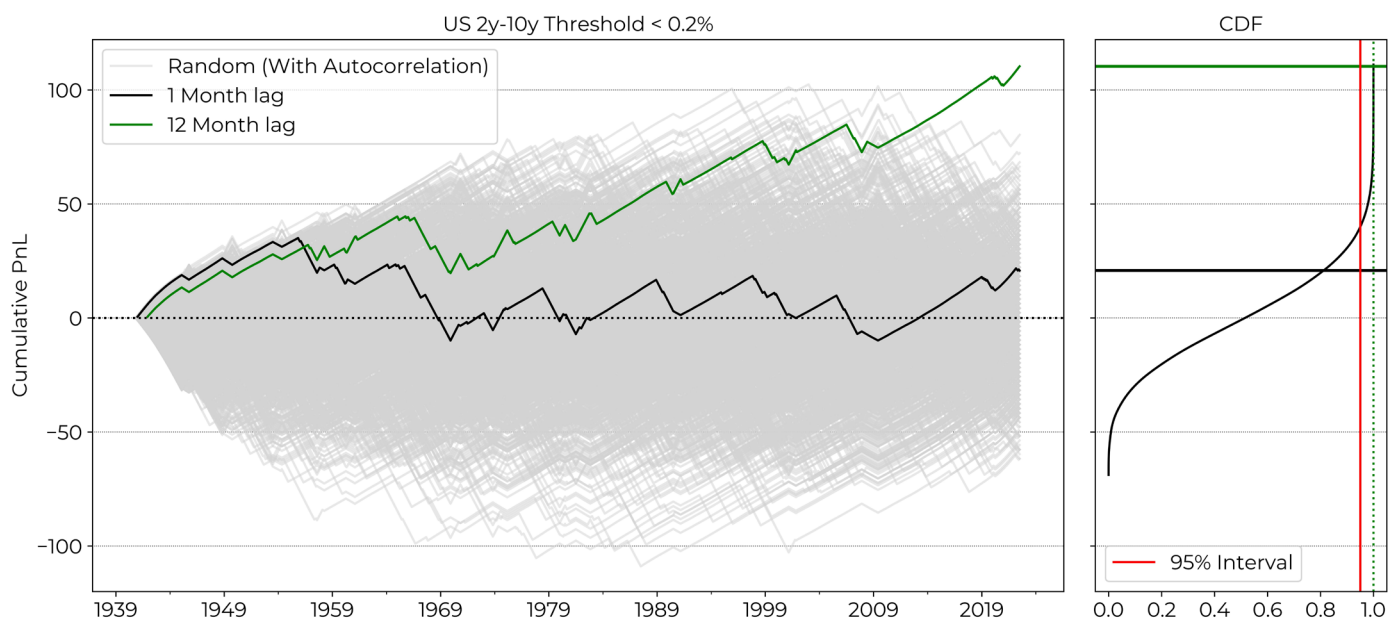
Source: GFD, NBER, CFM

The summary results of the additional predictors with lags from 1 up to 48-months in the past. The Sahm unemployment measure is, as the macro literature asserts, a comparably better predictor in the very-near term. Setting a 0.2% threshold of the yield curve yields comparable results with the best terminal P&L of the strictly negative yield curve predictor, also at a 12-month lag. The commodity trend and inflation predictors yield results that fall broadly in line with randomized noise.

Below we give a brief description of each of the alternative predictors summarized in the figure above.

I. US 2y-10y Threshold

While an inverted yield curve (the spread being strictly negative) is the widely recognized shorthand of recession prediction, we also investigate a 'threshold' of a yield curve flattening. We first set an arbitrary threshold spread of < 0.2% to capture those periods where the yield curve has flattened, albeit not to zero, as opposed to strictly using periods of an inversion. Following the same procedure as with the 2y-10y yield curve inversion, we created a binary series where the predictor is -1 (0) when the yield curve spread is < 0.2% (> 0.2%). We assess whether a flattening itself yields different results. The 12-month lagged predictor also falls well outside the random noise, with the P&L comparable to that of a strictly inverted yield curve.

When, in addition, we arbitrarily increase the threshold, the terminal P&Ls degrade slowly. We can conclude that an inverted yield curve, the spread being strictly negative, is as robust a signal of future recessions as relying on only a significantly flattened yield curve and other implementations do not yield significantly different results.
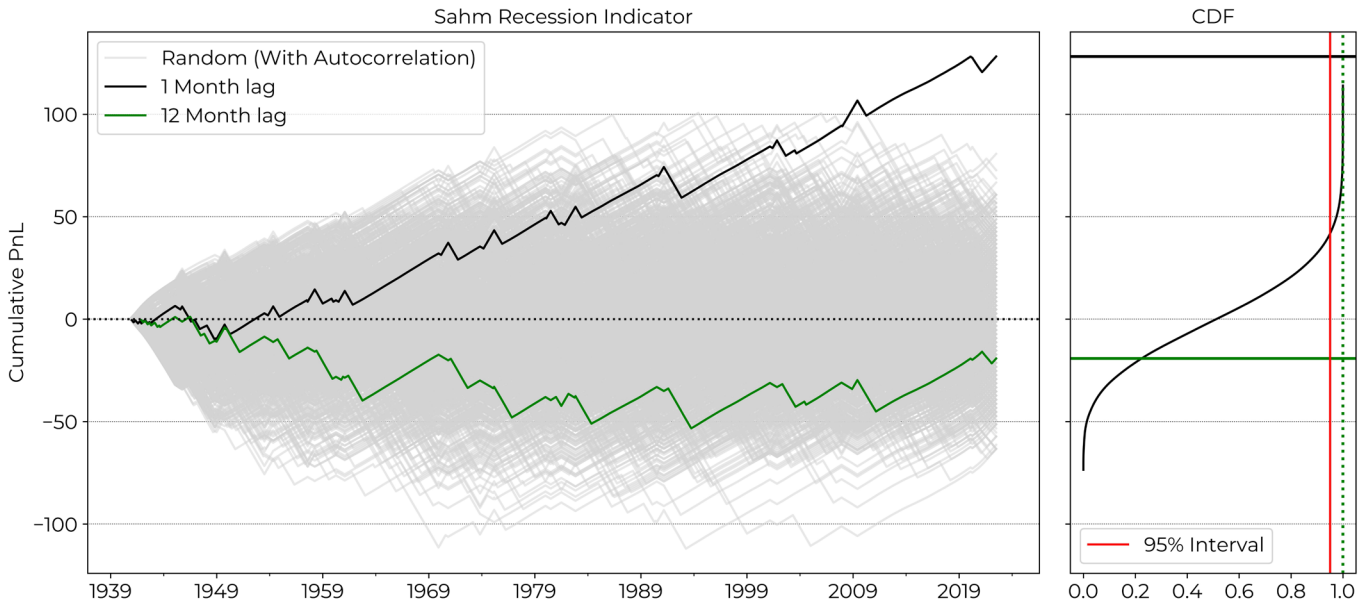
Source: GFD, NBER, CFM

II. US Employment

The 'Sahm Rule Recession Indicator' is considered a reliable 'real time' indicator of US business cycles. The indicator is derived by calculating the difference between the three-month moving average of the US national unemployment rate to its low during the previous 12 months. When this quantity rises by 0.5 percentage points or more, recessions have tended to follow. The indicator is available from the Fred database from March 1949[11], however, to extend the look back-period to overlap with the same historical length of the US 2y-10y yield curve, we reproduce the procedure as per the Fed but using unemployment data from GFD. Our reproduced Sahm indicator has a ~97% correlation with the index on the Fred database.

Since the macroeconomic literature surmises (with an ex-post view) that when the Sahm indicator breaches a threshold of 0.5 a recession is likely to follow, we transform the indicator to a binary vector of **-1** when the **Sahm indicator >= 0.5 and 0** (when the **Sahm indicator < 0.5**). We then apply the same procedure as throughout.

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[11] https://fred.stlouisfed.org/series/SAHMCURRENT

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Using the yield curve to forecast recessions … do you feel lucky?

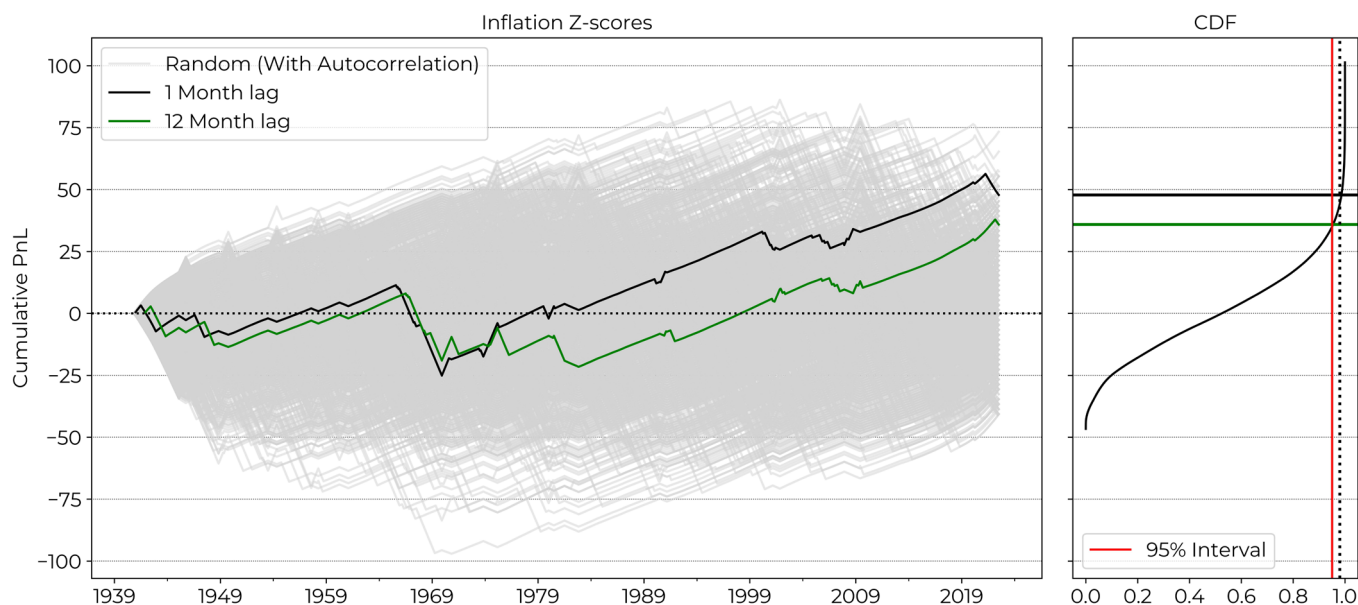Source: GFD, NBER, FRED, CFM

III. Commodities

Commodities, especially energy, is a major input into economic activity. It stands to reason that negative demand shocks captured by a downward trending price in commodities could be indicative of a recession. We use the Bloomberg Commodity Index as a proxy for commodities and construct, like the S&P 500 above, a 5-month trend predictor – where, as for the S&P 500 trend, we fix the ratio of binary predictors to that of the 2y-10y. A trend on commodities as predictor, as with the trend on equities, is more predictive at smaller lags. However, as opposed to the trend on the S&P, less convincing (and statistically significant).
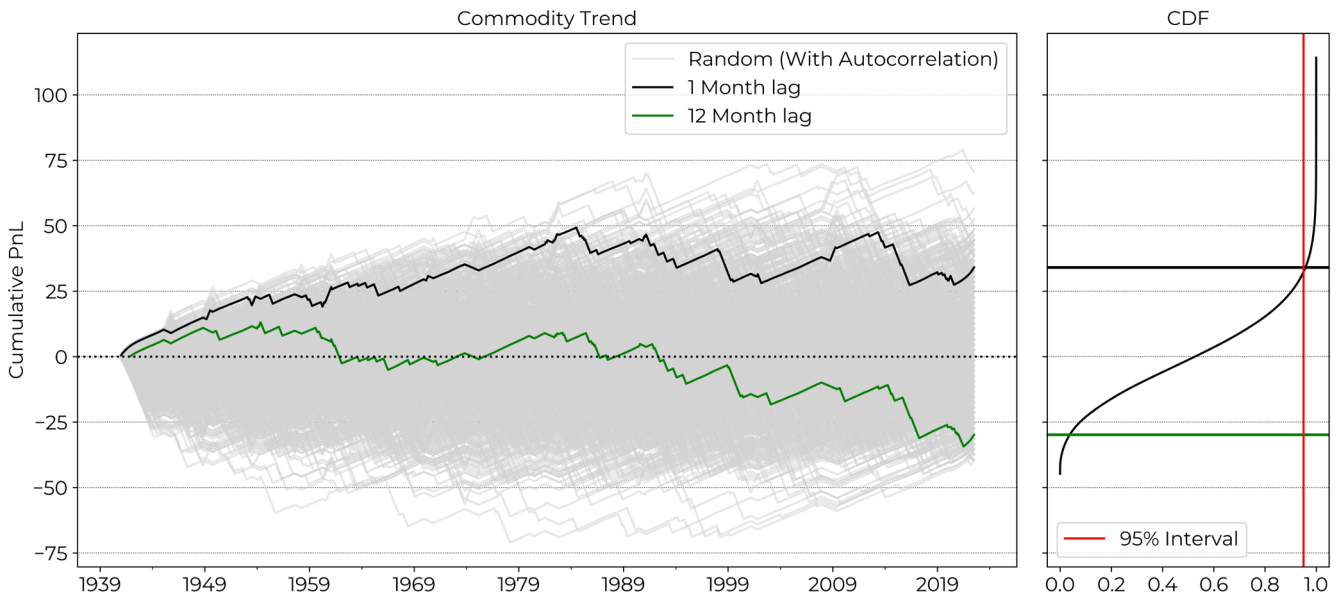
Source: GFD, NBER, FRED, CFM

IV. Inflation

Given the relationship between prices and the Fed's mandate of inflation targeting, higher levels or accelerating inflation is typically accompanied by a Fed response of tighter monetary policy. If inflation levels are meaningfully higher, higher interest rates should drive short term yield higher, flattening the yield curve. To evaluate the predictability of higher levels of inflation (as compared to its own historical mean) of recession, we convert US inflation into z-scores[12] and set the ratio of **high, -1 (low, 0)** inflation to be equal to that of the ratio of the inverted yield predictor. The ratio is such that the threshold is 1.5 sigma, above which inflation is considered high. The terminal P&L of the best lagged inflation predictor is, however, 6-months – as in the summary plot above. However, it falls outside what could be considered statistically significant (at a 5% level of significance).

Source: GFD, NBER, FRED, CFM

Disclaimer

[12] We calculate a rolling 7-year Z-score of YoY changes in inflation (monthly headline CPI NSA).

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A good time for Trend Following … but, then again, its always been!

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