US Economic Viewpoint

A big-data spin on the business cycle

15 October 2018

Key takeaways

- We run a machine-learning algorithm on a large macroeconomic dataset to evaluate the phases of the business cycle.
- Our analysis highlights the unusual nature of the current cycle. It has had no boom phase and several recession scares.
- The real-time signal from our algorithm leads recessions and contains useful information for stock and bond investors.

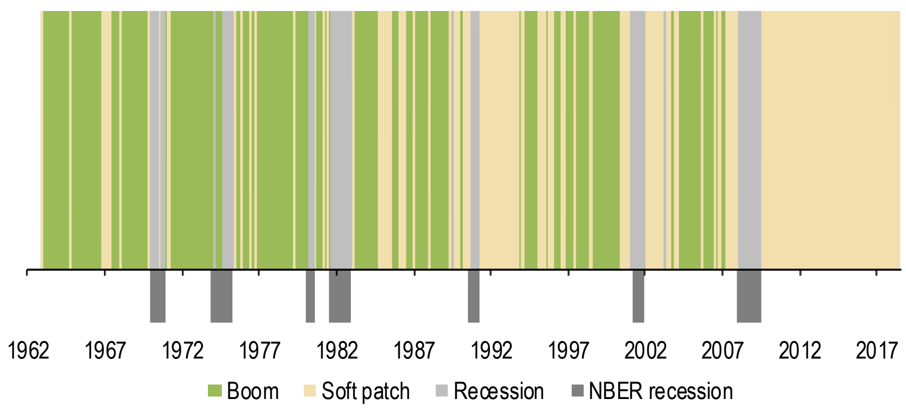
Old questions, new tools

In this piece we take a big-data view of the US business cycle. We apply the "k-means clustering" machine-learning algorithm to a monthly database of over 100 economic variables. The algorithm has no information on what the phases of the business cycle should look like. Even so, when we sort the data into two categories, they closely resemble the NBER's recession indicator. Our results suggest recession is not imminent.

Next, we tweak the algorithm to classify the business cycle into three phases rather than two. In this case it sorts the data into economic booms, soft-patch expansions and recessions. This classification sheds light on the unique nature of the current expansion. Although it is the second-longest in postwar history, it has basically been a very long soft patch, with standard peak business-cycle conditions being elusive so far (Chart 1).

We also look back in history at what the algorithm would have told us in "real time." Because of the timing of data releases, the expansion / recession signal for any given month is received with a three-month lag. But even accounting for this lag, we find that our signal leads recessions. There are also several false alarms, particularly earlier in this cycle. This again highlights the weakness of the ongoing recovery. Finally we show that, even with the lag, the signal might be useful for investors. This is because switches in the signal from expansion to recession are associated with breaks in stock- and bond-market momentum.

Chart 1: The phases of the business cycle according to big data



Source: BofA Merrill Lynch Global Research, FRB St. Louis

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The big dataset

Our dataset is the St. Louis Fed's "FRED-MD database." The Fed maintains this database in order to provide researchers with a standardized starting point for "big data" macroeconomic analysis. The database is updated monthly. It contains observations of 128 US economic and financial variables from January 1959 onwards. The data cover eight categories: 1) output and income, 2) the labor market, 3) housing, 4) consumption, orders and inventories, 5) money and credit, 6) interest and exchange rates, 7) prices, and 8) the stock market. We do some standard data cleaning and processing, the details of which are provided in the Appendix.

What is k-means clustering?

The "k-means clustering" algorithm is a machine-learning technique that classifies data into categories or "clusters." Each cluster is defined by its center point ("centroid"), which is the mean of all the data observations in the cluster. Each observation is assigned to the cluster whose centroid it is closest to. Chart 2 shows how a clustering algorithm with two clusters would work on a hypothetical two-dimensional dataset.

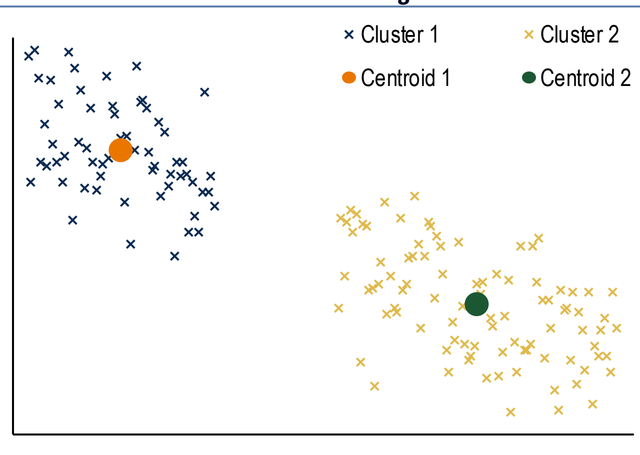
The algorithm is "unsupervised" in the sense that it does not rely on a model to tell it how to categorize the data. The researcher only specifies the number of clusters (k). By contrast a "supervised" learning algorithm includes a model that is chosen by the researcher. To understand the difference, consider the standard exercise of using the slope of the Treasury yield curve as a recession indicator. A supervised learning algorithm would specify a model (e.g. a probit regression) and estimate its parameters using the yield curve slope (independent variable) and the NBER's expansion / contraction indicator (dependent variable) as inputs. But the k-means clustering algorithm with k = 2 would simply assign each historical observation of the slope of the curve to one of two groups. The researcher can later check whether the classification is similar to the NBER's indicator, but the latter would not be used as an input.

We apply the k-means clustering algorithm to the FRED-MD database. Implementation details are explained in the Appendix. Heuristically, splitting up time-series data into clusters is similar to assigning time periods to "states" in state-switching models, which are common in macroeconomic research. In this piece we have three broad objectives.

1. To use data clustering to create an expansion / contraction indicator. We compare our indicator to the NBER's and use it to assess the near-term prospects of recession.

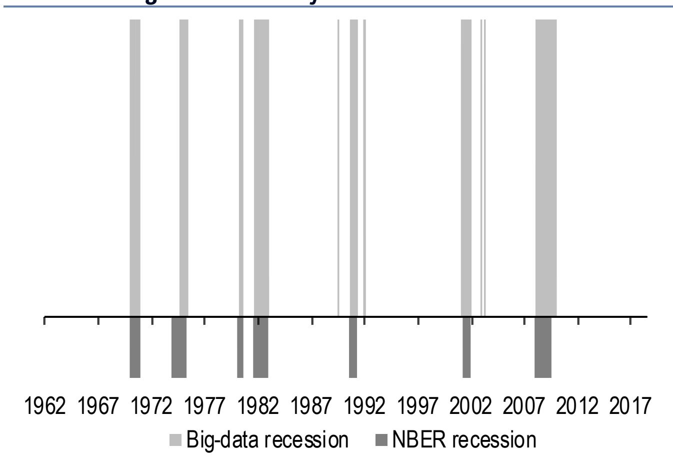
2. To see if the clustering algorithm finds differences between the current expansion and past expansions.

Chart 2: An illustration of k-means clustering with k = 2 clusters



Source: BofA Merrill Lynch Global Research

Chart 3: Our big-data business cycle classification is akin to the NBER's



Source: BofA Merrill Lynch Global Research, FRB St. Louis

3. To assess the performance of the algorithm in "real time," both as a leading recession indicator and as a signal for stock- and bond-market investors.

Let the data speak

The NBER defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales." Instead of relying on just a handful of variables, we use our machine-learning algorithm to divide the entire FRED-MD database into two clusters.

Each month in our dataset is an observation, covering 124 variables (as explained in the Appendix, we drop four of the 128 variables in the database). Note that the data include revisions: they are not "as-reported." We smooth the data over three months, since this provides the closest fit to the NBER's business cycle indicator. Chart 3 illustrates our results. For the most part, one of our clusters corresponds to NBER expansions and the other to recessions. Our approach matches the NBER's indicator in 635 of the 669 months in our sample. There are 18 "false positives," or months that fall into the "recession" cluster even though the NBER classifies them as part of an expansion. There are also 16 "false negatives" which are defined conversely.

More than two-thirds of the false positives occur immediately before or after an NBER recession. In other words, for the most part the clustering algorithm identifies the same downturns as the NBER, but in some cases with either an earlier start date or a later end date. Most notably the NBER contends that the great recession ended in June 2009, but our algorithm identifies a longer downturn, ending in December 2009.

In terms of the false negatives, nine of the 16 occur at the start of the mid-1970s recession (January 1973 to August 1974). That downturn was triggered by the first major oil shock since World War II. Companies were slow to react, and the data only turned substantially in late-1974. For example, nonfarm payrolls, which are typically a coincident indicator, peaked as late as October 1974. So it is intuitive that our algorithm only switches to the recession cluster in September of that year. Besides this instance, the algorithm only "misses" a handful of months when the economy was officially in recession.

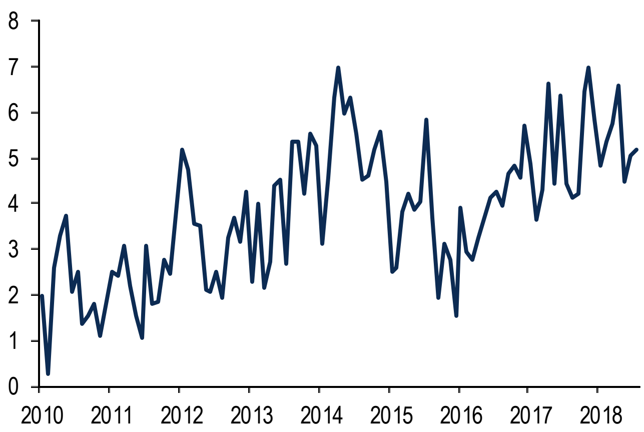
The Matthews correlation coefficient between the NBER's indicator and our clustering classification is 77%. This is a measure used in the machine-learning literature to assess the performance of a clustering algorithm when the clusters are of substantially different sizes, as is the case here (i.e., expansions are more frequent than recessions). Overall, we think the performance of the algorithm is quite impressive, since our approach is completely agnostic: we do not tell the algorithm how any of the variables typically behave in expansions and recessions.

The Benjamin Button business cycle

Next we ask what our algorithm is telling us about the current cycle. According to the NBER, the expansion started in July 2009. Our algorithm assigns January 2010 as the start date. Either way, this has been one of the longest cycles in postwar history. Is it due to die of old age? One way to answer this question is to see whether the data are moving closer to the recession cluster. We find the opposite: in recent quarters, the data have been moving further away from recession cluster relative to the expansion cluster. In other words the economy has trended away from recession (Chart 4). This is consistent with our view that a recession is not imminent. Business cycles die of excesses, not of old age, and we are not seeing most of the excesses that typically cause recessions, such as aggressive Fed tightening, financial bubbles and bubbles in cyclical sectors of the real economy.

The cyclical excess that seems most imminent is a large oil shock. Spikes in oil prices have played a part in four postwar recessions, including the most recent one. And as we argued here, the Iran sanctions could push crude oil prices above $100/barrel. But owing

Chart 4: Distance from centroid of recession cluster minus distance from centroid of expansion cluster



Source: BofA Merrill Lynch Global Research, FRB St. Louis

Table 1: Average monthly growth rate of headline indicators in each of our three clusters

	Cluster 1 ("booms")	Cluster 2 ("soft patches")	Cluster 3 ("recessions")
Nonfarm pay rolls	0.3%	0.1%	-0.2%
Industrial production	0.5%	0.1%	-0.9%
Real personal income less transfer pay ments	0.4%	0.2%	-0.2%
Real manufacturing & trade sales	0.5%	0.2%	-0.6%

Note: The average for real manufacturing & trade sales is taken from February 1967 onwards because prior data are not available.
Source: BofA Merrill Lynch Global Research, FRB St. Louis

to the shale boom the US is now both a major producer and consumer of oil. Far from causing a recession, we estimate that $100 oil would take only about a tenth off GDP growth next year.

The cycle that won't go boom

Despite its resilience, a great deal has been written about the weakness of the ongoing economic expansion. In order to address this issue with data clustering, we need an approach that does not group all expansion periods into a single cluster. That is, we need to allow for more than two business cycle phases. There are multiple ways to do this but we find that the simplest one—adding a third cluster (i.e., a third business-cycle phase)—works best.

When we run k-means clustering with k = 3, we find that the "recession" cluster is little-changed from the two-cluster results, while expansions get broken up into two clusters. In fact the algorithm with three clusters does a slightly better job of fitting the official recession data, with only seven false positives and 17 false negatives, of which 8 are again associated with the 1970s recession (Chart 1). The correlation with the NBER data rises to 83%.

Although the algorithm does not put labels on the clusters, the growth rates of several headline coincident indicators suggest that one of the expansion clusters corresponds to economic "boom" periods, while the other corresponds to soft patches in the economy that often occur early or late in the cycle (Table 1). Note that the algorithm captures the transition of the US economy from boom-bust cycles to the great moderation. Most expansionary periods from the 1960s through the early 1980s fall into the boom category. However from the mid-1980s onwards, soft-patch expansions become more frequent and boom periods become rarer.

But even compared to recent history the current cycle is truly exceptional. From July 2009 to January 2018, the economy was stuck in the "soft patch" cluster. That period, 103 months, is longer than all but two business cycles in postwar history. The data finally shifted to the "boom" cluster this February, but then reverted the following month. Therefore just one of the 108 months in the current expansion falls into the boom cluster, even though the algorithm classifies 70% of the previous expansionary periods in our dataset into that cluster.

We don't yet have time machines

So far we have used the full history of data to assign time periods to clusters or business cycle phases. So, for example, it is possible that data from 2018 could have influenced the algorithm's classification of months in the 1960s as either expansionary or contractionary. This is not an issue for descriptive purposes. But our next step is to see whether clustering can provide a leading indicator for recession and market performance. To do this we must take a different approach.

Starting in January 1989, we run the clustering algorithm using the data through that month only. This approach basically ensures that we are only using data that were available in real time (a caveat is that we cannot account for data revisions, since as we mentioned above, the data are not "as reported"). We reduce the number of clusters back to two and keep track of the real-time "signal" for the latest month. Why do we start in 1989? First, the prior data, which cover over 26 years and four recessions, are used to train the algorithm. This allows it to produce sensible results from the get go. Second, we want to include any potential real-time signals of the 1990-91 recession in our analysis, since there have been only two more recessions after that.

This time really is really different

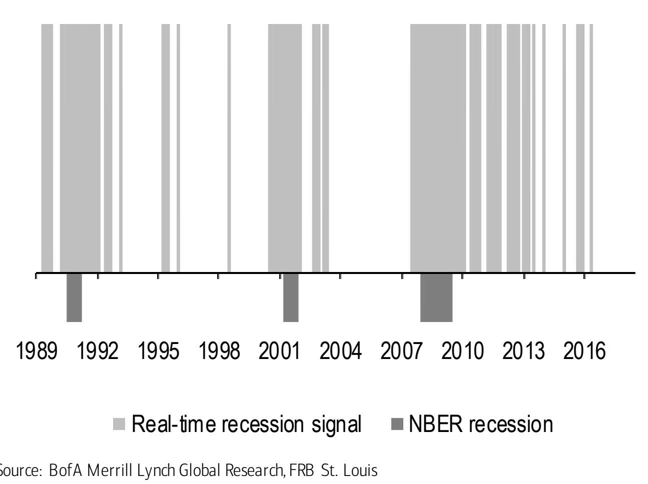
To see if our signals truly lead recessions we must account for the three-month lag in our data. For example, at the time of writing (October 2018) the last month in our dataset is July 2018 and so the last-available signal is from that month. We find that our signals are noisy (Chart 5), but they do flag all three recessions in our sample—1990-91, 2001 and 2008-09—more than three months in advance. This means that the signal from the algorithm would have been available before the recessions started. By contrast, the NBER is always late to date the turn in the cycle. It called the last three recessions more than three quarters after they began.

In terms of false alarms, note that until the current expansion they predominantly occurred early in the cycle, when the data were still sufficiently weak that the algorithm thinks the economy was still in recession. But this cycle is different. The signal indicator repeatedly switched between expansion and recession from the start of the cycle through mid-2013. This is not very surprising because the labor market was still very weak. Moreover, US financial markets were strained by the Eurozone sovereign debt crisis for some of that period. Our indicator also flashed red in 2015-16, when US growth (and in fact global growth) hit a soft patch.

There are two takeaways. First, the fact that these periods are no longer classified as recessions when we use the full dataset through 2018 suggests that data from the current cycle have altered the algorithm's view of what an expansion looks like. This notion of lowered expectations jibes well with the fact that when there are three clusters, essentially the entire cycle gets classified as a soft-patch expansion.

Second, the real-time indicator has not had a false alarm since the spring of 2016. This was when the global economy troughed. Since then there has been across-the-board

Chart 5: Our real-time indicator leads actual recessions but is noisy



Source: BofA Merrill Lynch Global Research, FRB St. Louis

Table 2: Switches in our signal from expansion to recession are associated with reversal in market momentum

	Baseline		Signal switch to recession		Signal switch to expansion	
	Prior rally	Prior selloff	Prior rally	Prior selloff	Prior rally	Prior selloff
S&P 500						
1-month change (%)	0.83	0.50	-0.05	2.83	1.38	1.11
Rally frequency	64%	59%	59%	82%	76%	58%
Relative to baseline (pp)			-0.88	2.33	0.55	0.61
10-year yield						
1-month change (bp)	-2.67	-0.65	4.12	-7.88	-0.92	-6.91
Rally frequency	53%	54%	46%	67%	44%	67%
Relative to baseline (bp)			6.78	-7.23	1.75	-6.26

Source: BofA Merrill Lynch Global Research, FRB St. Louis improvement in the economy and financial conditions, turbocharged recently by highly expansionary fiscal policy. This is consistent with our earlier finding that the economy seems to be moving away from a recession for now.

Breaking from the past

Our last step is to investigate whether our signal is useful for investors. Again, we must account for the three-month lag with which an investor would *receive* the signal from our data. It is possible that the markets might observe the state of the economy "live" and price it in, rendering the signal useless three months later. But in fact this is not the case.

Here we look at the one-month performance of the S&P 500 and 10-year Treasuries when the real-time signal switches from expansion to recession or vice versa. There are 33 instances of each between January 1989 and July 2018. We break out the cases in which the markets rallied and sold off in the prior three months, i.e., the lag period of the signal. These rallies and selloffs would reflect the extent to which the markets price in changes in the economy before our algorithm produces its signal.

Our baseline is all three-month rallies and selloffs. We find that on average, stocks and bonds both rally regardless of price action in the prior three months. This is consistent with the upward trend in stocks and the downward trend in bond yields over the last few decades (Table 2).

However, when the signal switches from expansion to recession, both markets tend to have breaks in momentum. Rallies are followed by selloffs and vice versa. This is true both in absolute terms and relative to the baseline. The magnitudes of the changes in market direction are also large relative to the baseline.

When the signal switches from recession to expansion, the bond market again tends to see a reversal in momentum. But the stock market rallies regardless of its prior move, and the average rally is larger than the baseline. We conclude that in all cases, our signal can provide useful information to investors at the time it is received.

In conclusion, we're just getting started

In this piece we have shown that machine learning is useful in understanding many features of the business cycle. It can not only generate a close match to the NBER's "small data" business-cycle classification, but also go a step further by generating a distinction between booms and soft-patch expansions. In real time, the signal from our algorithm leads recessions and provides potentially-useful information for investors. These are promising results and we think we are only scratching the surface on the use of big-data techniques in our research.

Appendix

Data cleaning

The FRED-MD database[1] does not have the full history of observations for all data series. Therefore some data cleaning is required. Specifically, we do the following.

1. Several variables have missing observations in the late 1950s and early 1960s. In order to work with a long dataset while still keeping as many variables as possible, we start our sample in July 1962. That is, we drop the first 36 months in the database, from January 1959 to June 1962.

2. Again due to incomplete data, we drop the last month in the database (August 2018).

3. Even in this attenuated database, four variables (out of the total of 128) have missing observations. They are: new orders for consumer goods, new orders for nondefense capital goods, the trade-weighted U.S. dollar index versus major currencies and the University of Michigan consumer sentiment index. We drop these variables.

4. The database is also missing the S&P dividend yield for July 2018 and the S&P PE ratio for May-July 2018. We use Haver Analytics to fill out these data. In the case of the PE ratio, the data in Haver do not exactly match the FRED-MD series. Therefore our extrapolation is not precise.

Data processing

Using the guidelines provided[2] by the St. Louis Fed, we transform the variables to make them stationary. We then smooth the data by taking the three-month weighted rolling averages of the series, with each month getting double the weight of the previous month. Finally we scale each variable so it has a mean of zero and a standard deviation of one. That is, we transform all variables into z-scores.

Clustering algorithm

After cleaning and transforming the data as described above, we then run the "k-means clustering" algorithm. The algorithm always converges, in the sense that every observation gets assigned to the cluster whose centroid it is closest to, and every centroid is the average of the observations in its cluster.

However, the solution to k-means clustering is not necessarily unique: it depends on the initial input for the centroids. To get around this issue, we run the algorithm 1000 times. In each instance, we initialize the centroids with a different vector of pseudo-random normal variables (we also set a seed for the random number generation so that the results are replicable). Of the 1000 potentially-different clustering allocations, we select the one in which the observations are, on average, closest to the final centroids.

[1] See https://research.stlouisfed.org/econ/mccracken/fred-databases

[2] https://s3.amazonaws.com/files.fred.stlouisfed.org/fred-md/Appendix_Tables_Update.pdf

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