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IDENTIFYING THE LATEST STAGE OF THE US BUSINESS CYCLE WITH CLUSTER ANALYSIS

Key points

- *In the US, the current economic expansion has already outlasted all but two post-World War II recoveries, raising concerns that it may soon run its course. To assess the durability of the current US economic expansion, this paper develops a framework capable of identifying the prevailing stage of US business cycle in real time. We use a statistical classification technique known as k-medians clustering to classify the US business cycle into recession, early recovery, mid-cycle expansion and late-cycle expansion.*

- *Conceptually, business cycles are driven by fluctuations in aggregate demand. Aggregate demand, in turn, is jointly determined by the interaction among cycles of real and financial activities of different economic sectors, including the financial cycle, employment cycle, growth cycle, corporate profits / inventory cycle and inflation cycle. By applying k-medians clustering to a set of 20 economic indicators pertaining to these five sectoral cycles, we provide a model-based chronology of the US business cycles between January 1960 and June 2017. Based on the clustering results, we then perform out-of-sample classification of the most recent US business cycle stage, using partially available data for Q3 2017.*

- *Our results show that the US economy could still be designated as being in mid-cycle expansion up to March 2017, but has likely transitioned to late-cycle expansion since then. We also find that late-cycle expansions typically last for 4 years (with a range of 2 to 8 years), suggesting that the current US economic expansion, though likely having entered the late-cycle stage, could still be expected to last for some time.*

- *Yet, late-cycle expansions can be a challenging period for the Fed's conduct of monetary policy, as historical experience suggests that the central bank often found it difficult to perform the balancing act needed during late-cycle expansions to forestall recession risks on one hand and to contain macroeconomic imbalances on the other.*

- *Nonetheless, the classification results could be subject to uncertainties given a number of structural changes in the global and US economy since the Global Financial Crisis (GFC). In particular, compositional changes in the labour force, together with globalisation and technological advancements, may have resulted in structurally lower inflation in the US. Meanwhile, information from financial indicators could be distorted by quantitative easing by the Fed. These structural changes may help prolong the current expansion compared to past recovery episodes.*

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I. INTRODUCTION

A major stylised fact of the US economy is that it goes through cycles of expansions and recessions over time, as first systematically documented in Burns and Mitchell (1946). A business cycle can be customarily divided into four stages, namely, (1) early expansion, (2) mid-cycle expansion, (3) late-cycle expansion and (4) recession, distinguishable by differences in the growth momentum of the overall economy (Chart 1).[1] Table 1 summarises the standard textbook descriptions of the key characteristics of each business cycle stage.

Chart 1: A schematic representation of business cycle and its four stages

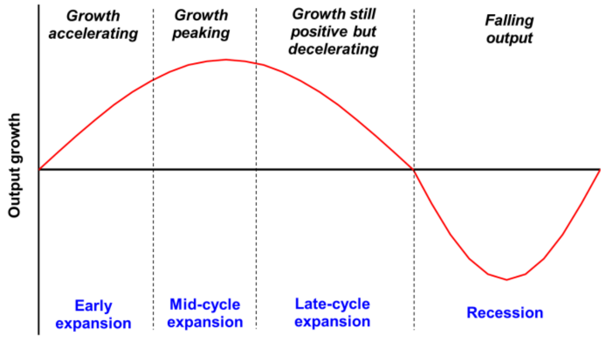


Table 1: Key characteristics of each stage of business cycle

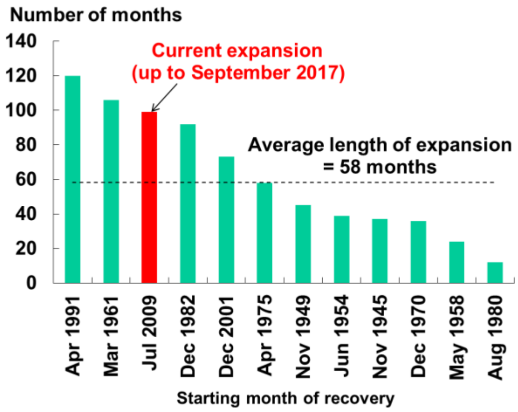
Characteristic	Early expansion	Mid-cycle expansion	Late-cycle expansion	Recession
Economic activity	Stabilises and then begins to increase	Growth accelerates	Growth decelerates	Declines
Employment	● Unemployment stays high ● Average hours worked begin to rise	● Falling unemployment rate ● Overtime hours rise	● Slower pace of job hiring ● Unemployment rate falls, but at a slower rate	● Rising unemployment rate ● Falling average hours worked
Business conditions	● Rising corporate profits ● Inventory stays low while sales improve	● Peaking corporate profits ● Inventory builds up and sales improve further	● Earnings under pressure ● Rising inventory but slower sales growth	● Falling profits ● Falling inventory and sales
Inflation	Remains modest	Picks up moderately	Accelerates	Decelerates, but likely with a lag

Sources: CFA Institute (2017) and HKMA staff compilations.

[1] Other ways of classifying a business cycle into stages are possible. For example, most papers that use Markov-switching models to study business cycle dynamics only distinguish between two stages (expansions and recessions). On the other hand, Layton and Smith (2000) found that the US business cycle could be better described as having three stages (contraction, early recovery and late recovery). Our four-stage characterisation can be thought of as an extension of Layton et al.'s (2000) idea.

According to the National Bureau of Economic Research (NBER), the US economy emerged out of recession since July 2009 and has remained in expansion since then, making it the third longest recovery episode since World War II (Chart 2). While an ageing expansion does not necessarily imply an imminent risk of recession, the extended length of the current expansion has nonetheless raised concerns that the US economy may have already entered the late-cycle stage of expansion.[2]

Chart 2: Length of post-WWII economic expansions in the US



Source: NBER.

Understanding whether the US economy has transitioned to the late-cycle stage of expansion is important. If this were indeed the case, the optimistic earnings prospects, on which the currently elevated US equity market valuations are predicated, would likely be called in question. A maturing expansion could also have profound implications on the future pace of US monetary policy normalisation, as historical experience suggests that late-cycle expansions usually present a dilemma to the Fed, which needs to fend off recession risks on one hand and to contain macroeconomic imbalances accumulated during the earlier phases of expansion on the other.[3]

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[2] Whether an economic expansion will "die of old age" is an unsettled issue. For example, Diebold and Rudebusch (1990) and Durland and McCurdy (1994) found that the probability of an economic expansion ending in any particular month is independent of the age of recovery, i.e., the state transition probability from expansion to recession is duration-independent. On the contrary, Filardo (1994) found that allowing the transition probabilities between recessions and expansions to be time varying could improve the ability of a Markov-switching model to predict business cycle turning points, suggesting that the state transition probabilities could possibly be duration-dependent.

[3] Section 3.3 summarises the historical experiences on how previous late-cycle expansions eventually ended. In brief, most late-cycle expansions since 1960s ended in either (1) monetary tightening amid rising inflation, (2) unwinding of financial imbalances or (3) geopolitical events.

To shed light on this issue, we develop a framework capable of identifying the prevailing stage of US business cycle in real time. This framework is based on a statistical classification technique known as *k-medians clustering*, which divides a set of data objects into distinct groups in such a way that objects in the same group, or cluster, are more “similar” to each other than to those in other clusters. One could then associate the resulting clusters with the notions of recessions, early expansions, mid-cycle expansions and late expansions based on their temporal proximity to NBER recession episodes. Using this framework, we assess (1) whether the US economy has already entered the late-cycle stage of expansion and, if so, (2) how long the economy could be expected to stay in this stage before progressing to the next (i.e. recession).

This paper proceeds as follows. Section II discusses the conceptual foundation of business cycles as well as several common methods of dating US business cycles and their limitations, followed by an explanation of how k-medians clustering can be a useful alternative. Section III presents our cluster analysis model, including a description of the indicators used, the conceptual framework used for selecting the indicators, the classification results and our conclusions regarding the most likely stage of business cycle that the US economy is presently situated, followed by a discussion of how late-cycle expansions ended in the past. Section IV discusses some caveats regarding our classification results, and Section V concludes.

II. DATING US BUSINESS CYCLES

2.1 Common methods and their limitations

As far as the dating of US business cycle turning points is concerned, NBER’s designations are widely regarded as the most authoritative. However, Chauvet and Piger (2003) pointed out that this approach suffers from at least two shortcomings. First, the NBER methodology is neither transparent nor reproducible, because the dating decisions are the consensus among a panel of experts in the Business Cycle Dating Committee, and this involves considerable personal judgement. Second, NBER often announces the timing of business cycle turning points well after the fact, which limits its usefulness as a timely monitor of US business cycle transitions.

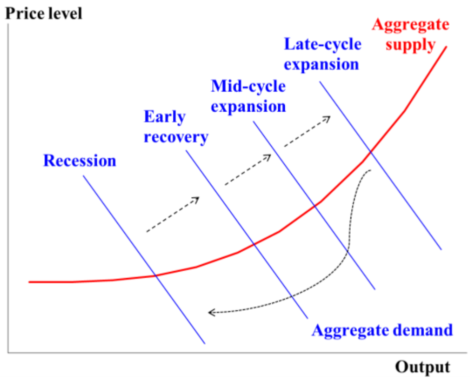
Other dating methods are less judgemental and more reproducible. For example, Boldin (1994) describes a “rule of thumb” that is widely used among economists, by which two consecutive quarters of negative output growth define the start of a recession. However, this method not only fails to capture several NBER recession episodes, but relying on a single variable to identify the current stage of business cycle could be sub-optimal, because many other economic indicators have been found to convey useful information about the contemporaneous or future state of the economy. To address the second criticism, more sophisticated business cycle dating methods that can make use of multiple economic series have been developed, examples including Markov-switching models (e.g. Hamilton (1989)) and dynamic factor models with regime switching (e.g. Kim and Nelson (1998)).

All of the dating methods discussed above, however, suffer from a common drawback that is of primary interest to our paper. They can only distinguish between recessions and expansions, and cannot provide richer information on the nature and evolution of economic expansions. Cluster analysis, on the other hand, can overcome such limitations by classifying expansions into early, mid-cycle and late-cycle stages, as explained in the following sub-section.

2.2 Using cluster analysis to identify stages of US business cycle

Conceptually, business cycle dynamics are driven by fluctuations in aggregate demand, as illustrated by Chart 3. At business cycle frequencies, aggregate supply may be considered as fixed. The fluctuations in aggregate demand, in turn, are jointly determined by the interaction among cycles of real and financial activities of different economic sectors, including the financial cycle, employment cycle, growth cycle, corporate profits / inventory cycle and inflation cycle.

Chart 3: Business cycle fluctuations



Two key features of the US business cycle, as emphasised by Diebold and Rudebusch (1994), are that (1) the business cycle can be divided into separate stages based on differences in the behaviour of the economy, and (2) individual economic series tend to co-move. These two features, taken together, lend support to the idea that different stages of the US business cycle can be identified by grouping together periods in which economic indicators behave similarly. Cluster analysis, which is a statistical technique that can uncover groupings within a data set, is a natural choice for this task.

To be more specific, cluster analysis is a statistical classification technique that divides a set of uncategorised data into a predetermined number of groups (k), in such a way that observations in the same group (or cluster) are more "similar" (in terms of a given metric, usually Euclidean distance) to each other than to those in other clusters. Operationally, cluster analysis is an iterative algorithm that, starting from k (usually randomly-chosen) initial cluster centres, (1) minimises the distance between the group mean (k-means clustering) or median (k-medians clustering) and its members within individual clusters, and (2) maximises the distances of group means / medians among adjacent clusters.

The idea of using cluster analysis to identify business cycle stages is not new. For example, Theis and Weihs (2000) applied a variant of cluster analysis known as *fuzzy-cluster analysis* to a set of 13 economic series to determine the number of distinct stages in Germany's business cycles. More recently, Dawsey (2014) applied *k-means clustering* to 15 US economic series to date the four stages of US business cycle since late-1950s.

While our framework also makes use of cluster analysis, our study improves significantly upon previous studies, including Dawsey (2014), in important ways. Unlike earlier works that lump a large number of economic indicators without much justification of their choices, our study features a systematic approach for selecting different categories of indicators to assess the stage of US business cycle. All variables selected are based on theoretical or empirical studies, as well as taking into account the special features of the US economy. Consequently, many of the variables chosen in our study are different from those of Dawsey (2014). Moreover, we strive to include an approximately equal number of indicators to represent each key aspect of the US economy, such that no particular category of variables would dominate the classification results. Finally, we apply k-medians clustering (instead of k-means clustering as in Dawsey (2014)) because the median is a more robust measure of central tendency in the presence of outliners, which are commonly observed in economic indicators during crisis periods.

III. EMPIRICAL MODEL: K-MEDIANS CLUSTERING

3.1 <u>*Data and method*</u>

We assume that, at any point of time, the interaction among five aspects of the US economy determines the contemporaneous stage of business cycle: (1) financial conditions, (2) labour market, (3) growth, (4) business conditions and (5) inflation. For each aspect, we select representative economic indicators that (i) are available in a timely manner and (ii) have a long history, as we would like to cover as many business cycles as possible.[4] Based on these considerations, 20 indicators are selected and their definitions are provided in Table 2. The time series plots of these indicators are shown in the Annex. Our data spanned from January 1960 to June 2017 (quarterly data are converted into monthly data by replication), all of which can be readily downloaded from Bloomberg, CEIC, Datastream and the St. Louis Fed. These indicators are then standardised and fed into the k-medians clustering algorithm with an aim of partitioning the intervening 690 months into four (k = 4) clusters.[5]

[4] However, we do not wish to go too far back into history to ensure reasonably uniform data collection for the time series (Chauvet and Potter (2001)). A compromise between data consistency and capturing the maximum number of complete business cycles is made by starting the sample period from January 1960.

[5] We use the **cluster kmed** command in Stata, with k = 4, measure = L2 (i.e. using Euclidean distance as similarity measure) and start = random (i.e. 4 random initial group centres are generated, with values chosen from a uniform distribution over the range of the data).

Table 2: Summary of economic variables used in k-medians clustering

	Variable	Definition
Financial conditions	Treasury yield curve slope	Difference between 10-year and 3-month US Treasury yields
	S&P 500 volatility	Annualised realised volatility of S&P500 index (using daily closing prices)
	Spread between high grade and lower-grade US corporate bonds	Difference between the yields of Baa-rated and Aaa-rated US corporate bonds (as rated by Moody's)
	12-month change in real Fed funds rate	12-month difference of real effective Fed funds rate, which in turn is defined as the difference between the nominal effective Fed funds rate and the year-on-year rate of headline consumer price index (CPI) inflation
	12-month change in bank loans	12-month change in commercial and industrial (C&I) loans provided by US banks, deflated by CPI index
Labour market	Employment gap	Weighted average of unemployment gap and the labour force participation rate gap (as defined in Erceg and Levin (2014))
	Unemployment rate	Monthly headline unemployment rate, seasonally adjusted
	Average weekly hours worked	Average weekly hours worked in manufacturing by production workers
	Real average hourly earnings*	Inflation-adjusted average hourly earnings of production workers (in 1982 – 84 dollar)
Growth	Real GDP growth	Year-on-year change in real GDP index
	Real GDP growth minus potential growth	Difference between actual year-on-year real GDP growth and that of potential GDP (as estimated by the Congressional Budget Office)
	ISM Manufacturing Index	Monthly manufacturing ISM Purchasing Managers' Index (PMI)
	Industrial production	Year-on-year change in industrial production index

	Variable	Definition
Business conditions	Corporate profits	Year-on-year change in nominal corporate profits (with inventory valuation adjustment and capital consumption adjustment)
	Manufacturers' inventory-to-shipment ratio*	Ratio between inventory and shipment in manufacturing industries
	Industrial utilisation rate	Capacity utilisation rate of manufacturing sector (using SIC definition)
Inflation	Core CPI inflation index*	Seasonally adjusted index of CPI (excluding food and energy)
	GDP deflator	Year-on-year change in implicit price deflator of GDP
	Unit labour costs index*	Seasonally adjusted index of unit labour costs (for non-farm businesses)
	Import prices	Year-on-year change in import prices of goods and services

Note: All data series are standardised to have zero mean and one standard deviation. Quarterly data are converted into monthly frequency by interpolation. Indicators marked with (*) are detrended using Hodrick-Prescott (HP) filter prior to standardisation.

A discussion on our choice of economic indicators is in order. The slope of the Treasury yield curve, equity market volatility and corporate bond spreads are known to contain information about the likelihood of future recessions (Estrella and Mishkin (1996), Brunnermeier and Sannikov (2014), and Faust, Gilchrist, Wright and Zakrajšsek (2013)), while the 12-month difference in real Fed funds rate measures changes in the degree of monetary accommodation. Together, these four indicators capture the price dimension of financial conditions of the non-bank sector. As a supplement, bank loan growth is included to capture the quantity dimension of financial conditions of the banking sector.[6]

On labour market conditions, the employment gap, the unemployment rate and average weekly hours worked are included in the model to capture different dimensions of labour market slack, while the real average hourly earnings indicator is included to capture cyclical fluctuations in labour demand. For indicators of growth, the combination of real GDP growth and the difference between actual and potential GDP growth provides the clustering algorithm with

[6] The inclusion of four indicators of the non-bank sector and only one indicator on quantity dimension of the banking sector reflects the greater importance of market financing vis-à-vis bank financing in the US as well as the higher information content of market-based indicators than non-market-based banking indicators.

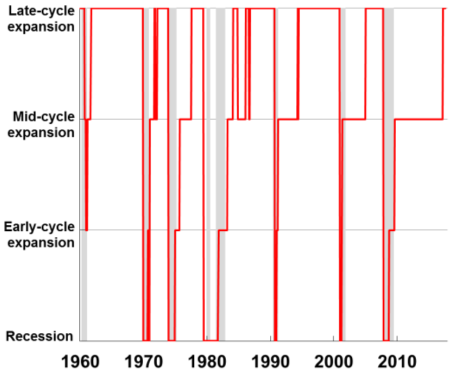
information regarding the current position of the US economy on the business cycle. The ISM manufacturing index and industrial production are also included due to their high degree of pro-cyclicality (in spite of the relatively small size of the manufacturing sector in the US economy). Meanwhile, corporate profits and inventory-to-shipment ratio are included to capture variations of the profits cycle and inventory cycle, and the industrial utilisation rate helps gauge the amount of spare production capacity (i.e. the slack of capital) of the real economy. Finally, to measure the cyclical variations of the inflation cycle, we include core CPI and GDP deflator. In addition, according to Cheung, Leung and Lo (2017), core goods and services components of US inflation are primarily driven by global factors and domestic labour market slack separately, and hence the inclusion of unit labour costs and import price indices in our clustering algorithm to account for the distinct underlying drivers of inflation.

3.2 Classification results

By themselves, the four clusters obtained from k-medians clustering do not have any economic meaning. Nonetheless, they can be associated with the notions of recessions, early expansions, mid-cycle expansions and late-cycle expansions based on their temporal proximity to NBER recessions. More specifically, the clusters that include observations immediately before, during and after NBER recessions can be taken to represent late-cycle expansions, recessions and early-cycle expansions respectively, while the fourth cluster, which happens to straddle early-cycle and late-cycle expansions, is taken to represent mid-cycle expansions.

The classification results from k-medians clustering are illustrated in Chart 4, which shows the model-based chronology of the US business cycles between January 1960 and June 2017. Our results appear to be reasonable, being able to capture all but one NBER recessions in the sample period and depicting smooth transitions of the US economy from recession to early, mid and late-cycle stages of expansion over time (except the relatively erratic results in mid-1980s). Based on our model results, the US economy could still be classified as being in the mid-cycle stage of expansion until March 2017, but has since transitioned into the late-cycle stage of expansion from April 2017 onwards.

Chart 4: Chronology of US business cycles based on K-medians clustering



Note: Periods shaded in grey are recessions as defined by NBER.
Sources: NBER and HKMA staff calculations.

Next, we perform out-of-sample classification of the latest US economic business cycle stage using partially available data for Q3 2017. To do so, we compute the centroids of the four clusters, followed by a comparison of the Euclidean distances between the latest data vector and the four centroids, with a shorter distance implying a closer match to that particular cluster.[7] A summary of the centroids of the four clusters, together with their Euclidean distances from the vector of latest observations, is provided in Table 3.

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[7] In our case, a centroid is a 20-dimensional vector of the arithmetic means of the 20 data series within a cluster. The Euclidean distance between the centroid of a cluster (x) and the data vector (y) is given by

$$dist(x, y) = \sqrt{\sum_{i=1}^{20}(x_i - y_i)^2}$$

The Euclidean distances between the centroids and the vector of latest data for each of the five sub-sets can be calculated similarly.

Table 3. Means of individual indicators by cluster, and distances between cluster centroids and latest observations

Variable	**Cluster centroid (standardised value)**				**Latest obs**	*As at*
	Recession	**Early**	**Mid**	**Late**		
Treasury yield curve slope	-1.00	0.80	0.90	-0.49	-0.23	*Sep 2017*
12-month change in real Fed funds rate	-0.22	-0.40	-0.17	0.20	0.03	*Sep 2017*
Realised S&P 500 volatility	0.60	1.09	-0.06	-0.13	-1.00	*Sep 2017*
12-month change in real C&I loans	-0.05	0.39	-0.21	-0.69	-0.55	*Sep 2017*
Corporate bond yield spread	0.73	2.39	0.12	-0.39	-0.67	*Sep 2017*
(A) Euclidean distance of latest observations from centroid: *Financial conditions*	*2.32*	*3.89*	*1.69*	*1.35*		
Employment gap	0.21	-1.57	-0.79	0.50	0.78	*Sep 2017*
Unemployment rate	0.10	1.70	0.67	-0.44	-0.99	*Sep 2017*
Average hours worked	-0.50	-1.14	0.12	0.12	0.95	*Sep 2017*
Real average hourly earnings	-1.14	-0.56	0.02	0.28	-0.26	*Sep 2017*
(B) Euclidean distance of latest observations from centroid: *Employment*	*2.09*	*4.15*	*2.44*	*1.17*		
GDP growth	-0.93	-1.81	-0.17	0.45	-0.36	*Q3 2017*
Actual minus potential GDP growth	-0.92	-1.88	0.12	0.31	0.28	*Q3 2017*
ISM manufacturing PMI	-1.70	-0.77	0.09	0.26	1.08	*Sep 2017*
Industrial production	-0.58	-1.47	-0.23	0.18	-0.29	*Sep 2017*
(C) Euclidean distance of latest observations from centroid: *Growth*	*2.30*	*3.99*	*1.02*	*1.24*		
Industrial utilisation rate	-0.07	-1.69	-0.76	0.59	-0.94	*Sep 2017*
Corporate profits	-0.99	-0.64	0.36	-0.02	-0.08	*Q2 2017*
Manufacturing inventory / shipping ratio	-0.15	2.45	0.07	-0.32	-0.45	*Sep 2017*
(D) Euclidean distance of latest observations from centroid: *Business conditions*	*3.53*	*3.34*	*0.70*	*0.93*		
Core CPI inflation	0.64	1.72	0.10	-0.43	0.05	*Sep 2017*
Unit labour costs	1.01	1.63	-0.23	-0.24	-0.83	*Q3 2017*
GDP deflator	1.56	0.89	-0.29	-0.09	-0.60	*Q3 2017*
Import prices	1.87	-0.47	-0.31	-0.04	-0.16	*Q3 2017*
(E) Euclidean distance of latest observations from centroid: *Inflation*	*1.30*	*3.05*	*0.71*	*1.54*		
Overall distance from cluster centroid	5.40	8.29	3.29	2.82		

Note: Cells highlighted in yellow refer to the closest match to the latest observations (as measured by absolute distance).
Source: HKMA staff calculations.

The classification results in Table 3 are broadly in line with intuition. In terms of financial conditions, the recent flattening of the Treasury yield curve, subdued equity market volatility and compressed corporate bond spreads are common indicators of a late stage of financial upcycle, and the results from the clustering algorithm have arrived at the same conclusion (A). At the same time, the progressive tightening of labour market conditions (with the unemployment rate falling to 4.2% in September, below the Fed's estimated natural rate of 4.6%) suggests a late-expansion-stage of the employment cycle (B). On the other hand, the unusually weak pickup of GDP growth compared with previous recoveries, the earlier slump in corporate profits and the recent softening of inflationary pressures have led the model to classify the prevailing growth (C), business conditions (D) and inflation (E) sub-cycles as in the mid-cycle stage of expansion. Taking all 20 economic indicators together, the latest data vector has the shortest Euclidean distance to the cluster corresponding to late-cycle expansion stage (2.82, see the last row of Table 3), affirming the in-sample classification results that the US economy has transitioned to the late-cycle stage of expansion since Q2 2017.

As the final step of our analysis, we calculate the historical average length of each of the four stages of the business cycle based on results from the classification exercise, with results summarised in Table 4. Of particular interest is that the late-cycle expansion stage in the US typically lasted for 4 years on average, with a range between 2 and 8 years (column highlighted in yellow). These results suggest that the current US economic expansion, while just having entered the late-cycle stage, could possibly last for some more time before transitioning to a recession based on past experience.

Table 4: Summary statistics on the past length of the four business cycle stages (in years)

	Recession	Early	Mid	Late
Average length	0.9	0.8	3.0	4.2
Range	0.3 – 2.3	0.2 – 1.8	0.6 – 7.6	1.8 – 8.3

Source: HKMA staff calculations.

3.3 *What could happen when late-cycle expansions come to an end?*

With our classification results suggesting that the US economy has just transitioned to the late-expansion stage of the business cycle, it would be useful to examine how late expansions ended in the past, in order to shed more light on the likely endgame of the current expansion.

Table 5 lists the instances of late-cycle expansions in the US as identified by k-medians clustering since 1960, together with changes in the Fed funds rate target, CPI inflation and period-end Shiller price-earning (P/E) ratio of the S&P 500 index over those periods. As shown in the table, the majority of late-cycle expansions ended in one of the following three ways: (1) monetary tightening in the midst of accelerating inflation (episodes highlighted in red); (2) geopolitical events (e.g. Gulf War, the episode highlighted in green); or (3) unwinding of financial imbalances (as reflected by the elevated Shiller P/E ratio in the episodes highlighted in blue).

While geopolitical events are clearly outside the Fed's control, the episodes highlighted in red and blue reflect the Fed's less-than-stellar track record in terms of performing the balancing act needed during late expansions, to forestall recession risks on one hand and to contain macroeconomic imbalances on the other. Looking ahead, with inflation currently subdued but equity valuation arguably at stretched levels, it can be argued that an unwinding of financial imbalances could be a more likely catalyst in bringing an end to the current expansion.

Table 5: Late-cycle expansions as identified by cluster analysis since 1960

Late-cycle expansions as identified by cluster analysis		Cumulative Fed rate hikes (% pt)	Core CPI (% yoy)	Period-end Shiller P/E (ratio)
Beginning	End			
Oct 1961	Dec 1969	+3.00	1.3 → 6.2	17.3
Mar 1972	Dec 1973	+4.00	3.3 → 4.7	13.5
Aug 1977	Jun 1979	+4.25	6.2 → 9.3	8.9
Mar 1984	Nov 1984	-1.50	5.0 → 4.6	9.7
Mar 1986	Sep 1990	+0.75	4.1 → 5.5	15.3
Jul 1994	Dec 2000	+2.25	2.9 → 2.6	37.3
Feb 2005	Oct 2007	+2.00	2.4 → 2.2	27.3
Apr 2017	Sep 2017	+0.25	1.9 → 1.7	30.6
(Still ongoing)				

Sources: CEIC, Datastream, Multpl.com and HKMA staff calculations.

IV. Some Caveats of Classification Results

As a purely statistical technique, clustering algorithms solely rely on patterns of historical data to classify current observations. Nonetheless, the latest classification results may be subject to uncertainty, due to a number of structural changes in the global and US economy since the GFC that may lengthen the longevity of the current expansion, thereby introducing the risk of mis-classification. For one, the latest signal of a late-stage financial upcycle, arising from the flattening of Treasury yield curve, could partly be the result of distortions by the Fed's past large-scale asset purchases. With the Fed having begun its balance sheet normalisation programme since October 2017, the suppressing effect of its past quantitative easing programmes on term premia could be unwound going forward, possibly resulting in a re-steeping of the US Treasury yield curve. Moreover, it is uncertain whether the notable post-GFC decline in labour force participation rate is transitory or permanent. While the labour market hysteresis argument tends to support the latter view, if instead such a drop is transitory, this could imply an over-estimation of the natural rate of unemployment and a larger-than-expected degree of labour market slack, which could help prolong the current expansion relative to historical norms. Finally yet importantly, a number of structural changes in the global and US economy in recent years could have resulted in structurally lower inflationary pressures in the US. For example, the advancement of labour-substituting technology may erode the wage-bargaining power of workers, while globalisation means greater price competition among producers. Meanwhile, recent research (e.g. Daly and Hobijn (2016)) finds that compositional changes in the US labour force (e.g. retirement of high-pay baby boomers and entry into the job market by workers, who were previously outside the labour force, at below-average wages) could also constrain wage pressures. Diminished inflationary pressures would allow the Fed to keep an accommodative monetary policy longer, which, in turn, helps prolong the current expansion.

V. CONCLUDING REMARKS

In summary, our clustering results suggest that the US economy has just transitioned to the late-cycle stage of expansion, though it could be expected to last for some more time based on past experience. Yet, late-cycle expansions can be a challenging period for the Fed's conduct of monetary policy, as historically the central bank experienced difficulties in performing the balancing act needed during late expansions to forestall recession risks on one hand and to contain macroeconomic imbalances on the other. That being said, structural changes in the US economy since the GFC could suggest upside risks to the longevity of the current expansion compared with past episodes.

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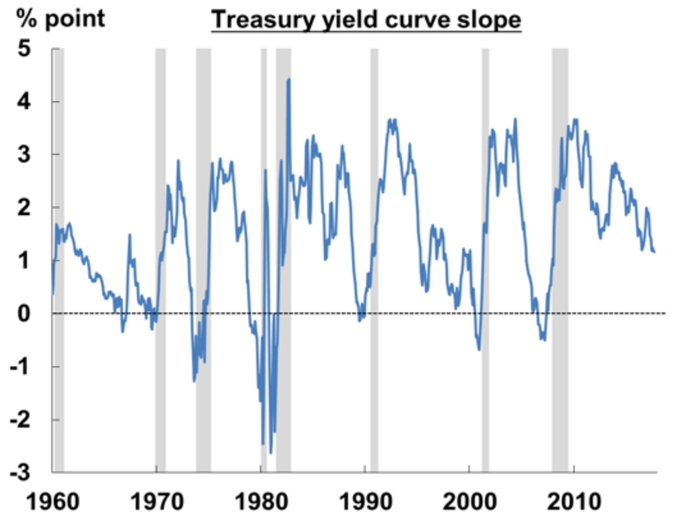
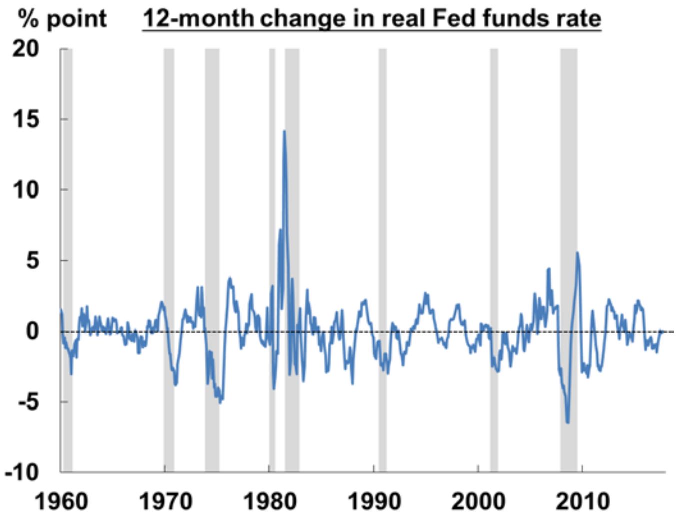
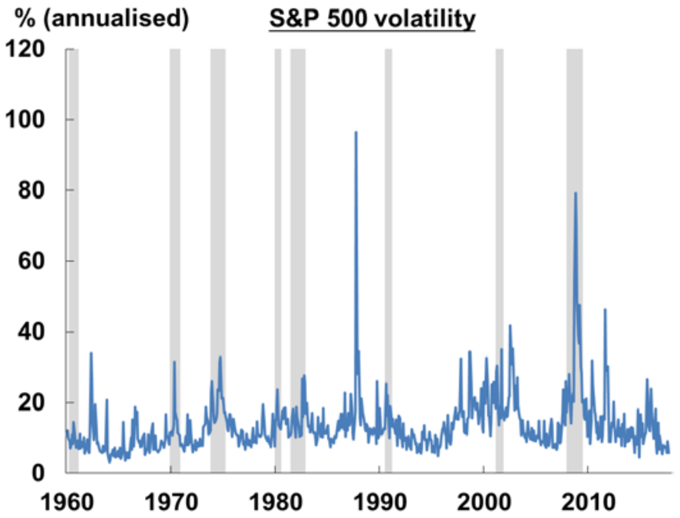
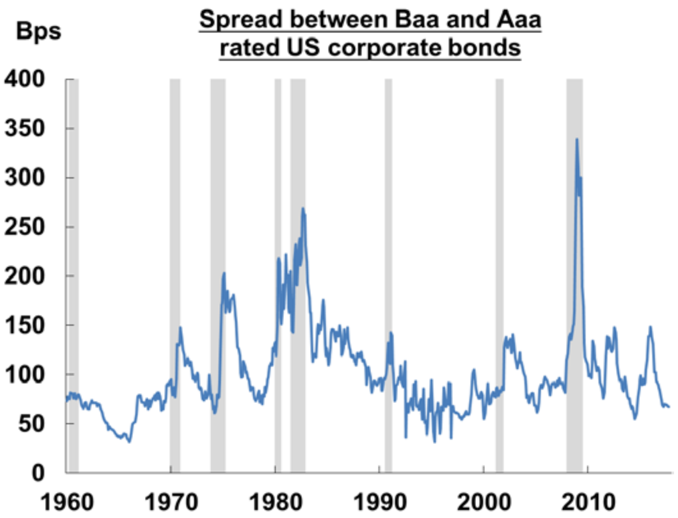
Annex: Economic indicators used as inputs to k-medians clustering

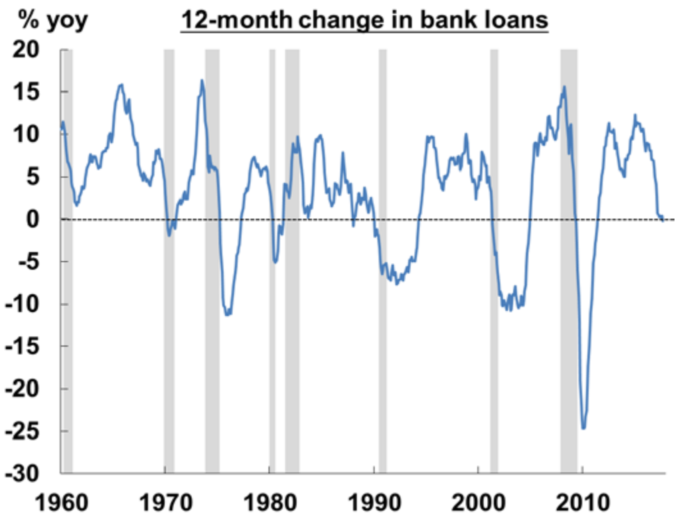
Financial conditions



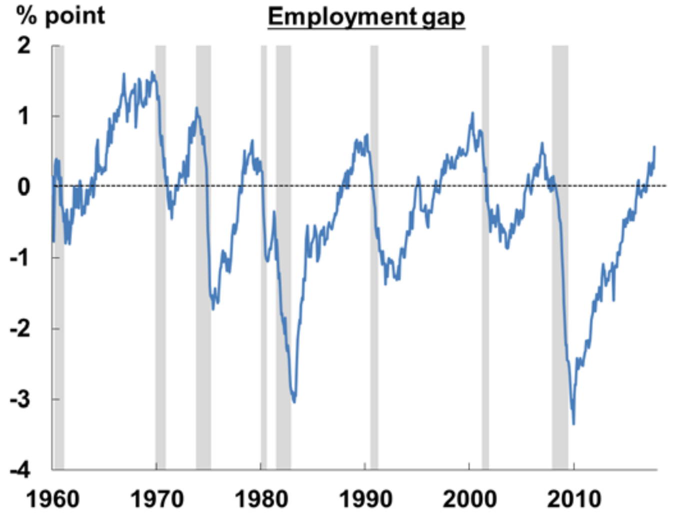


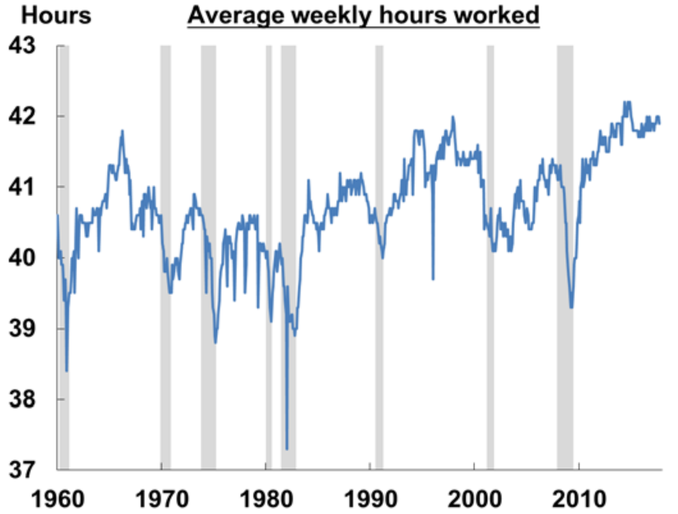


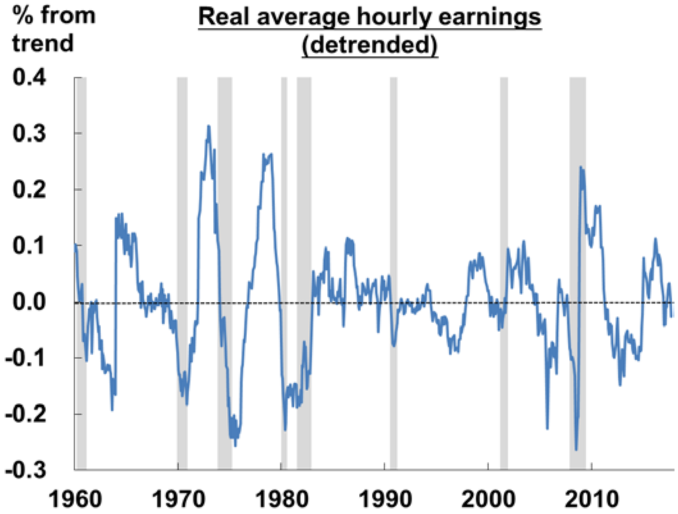




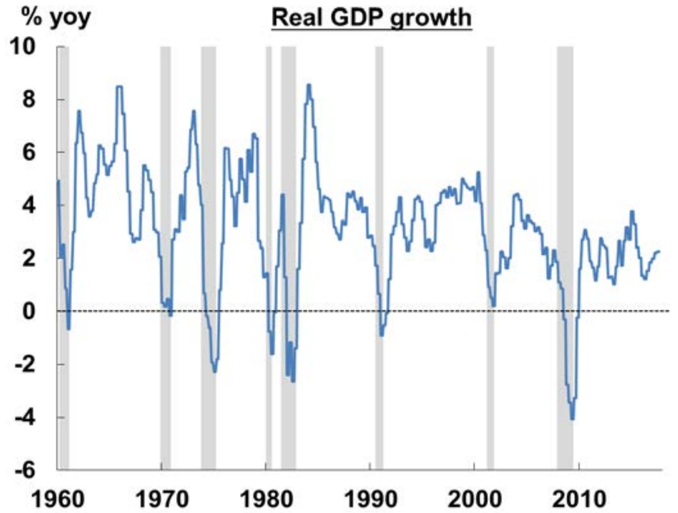
Labour market

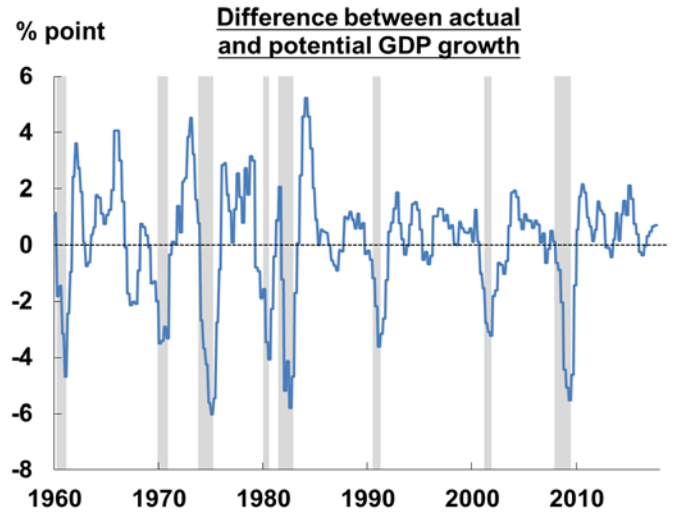




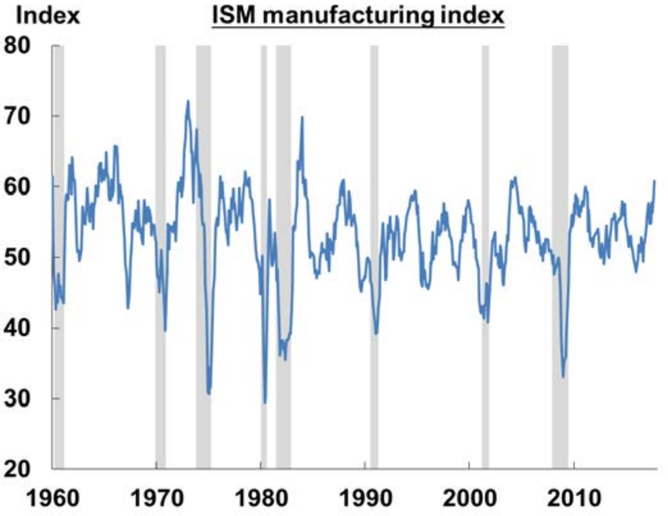


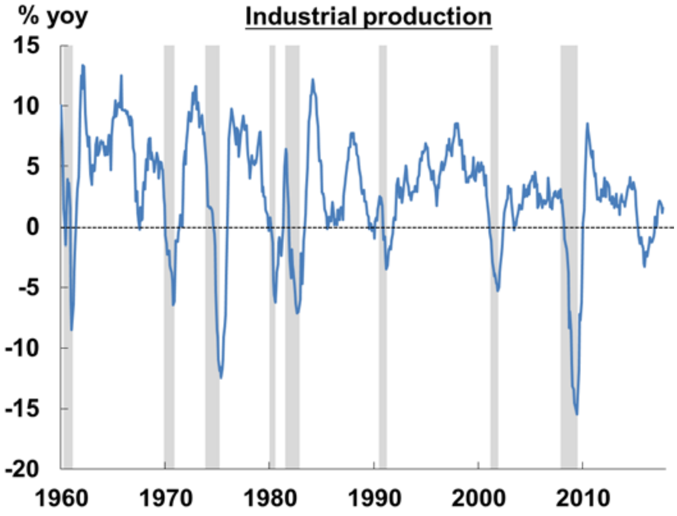
Growth

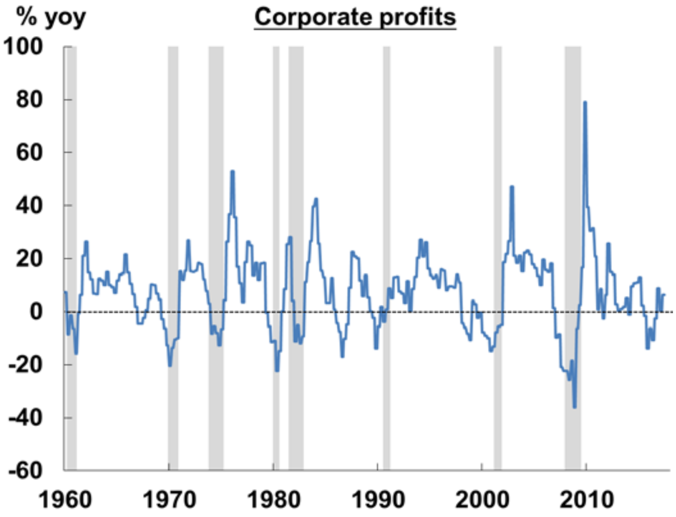


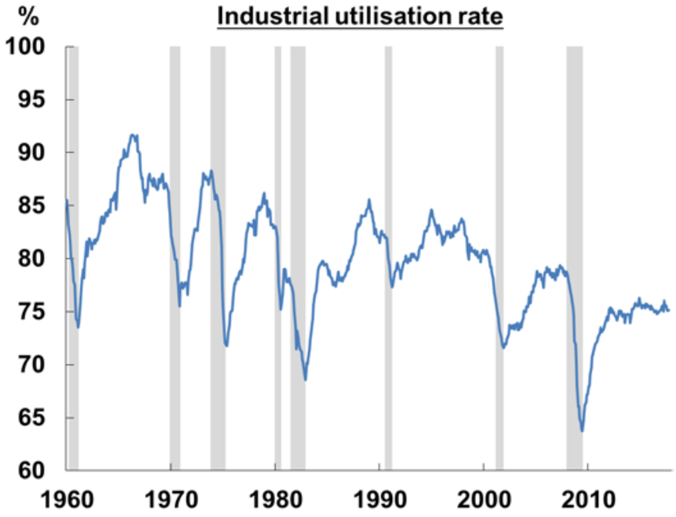


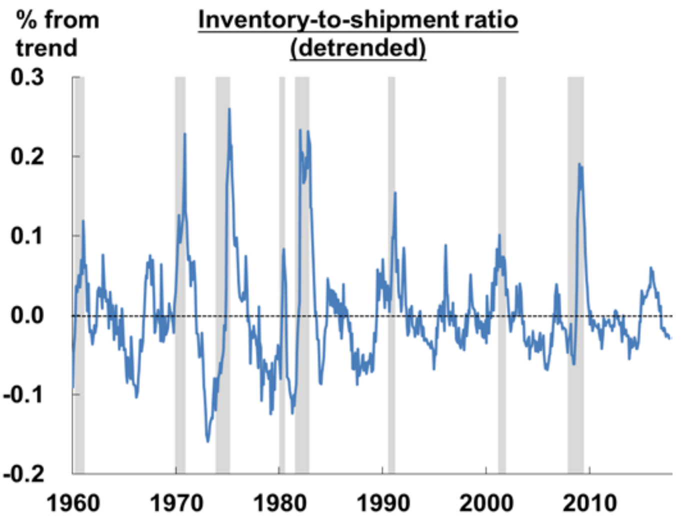
Growth (continued)



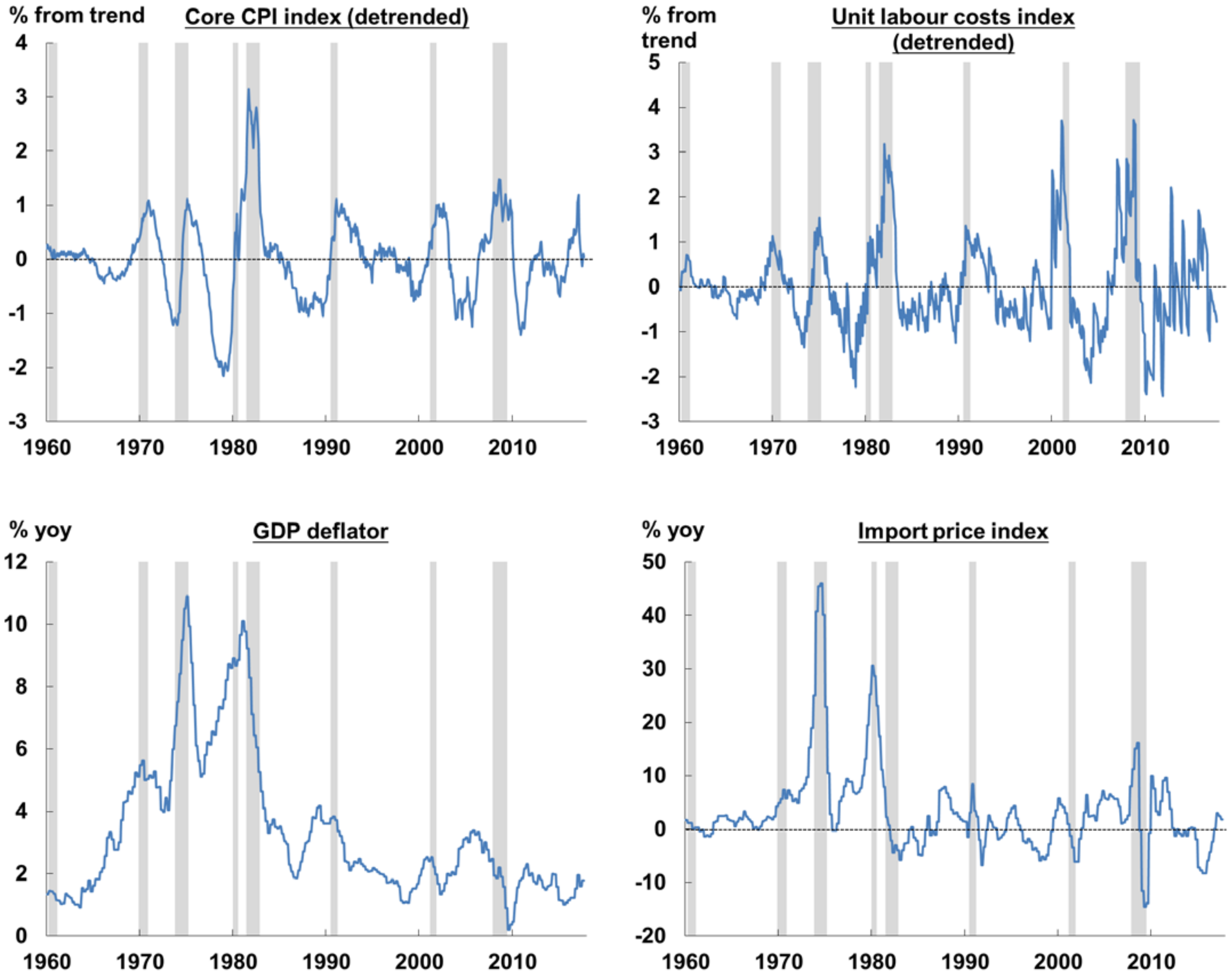








Inflation



(Note: Shaded areas denote NBER recessions)