Asymmetric Phase Shifts in U.S. Industrial Production Cycles

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Abstract

Based on the industrial production of 74 U.S. manufacturing industries, we identify the turning points of industry cycles. Industry peaks and troughs are concentrated around national turning points, confirming that the comovement is a salient feature of the business cycle. However, we find a substantial asymmetry in the distribution of turning points: troughs (upturns) are much more concentrated than peaks (downturns). This is in contrast to the conventional notion of a "sudden stop and slow recovery." While both aggregate shocks and spillover effects from input-output linkages are significant determinants of turning points across industries, their effects are also asymmetric. For example, monetary policy and government spending shocks exhibit larger effects on troughs (upturns) than on peaks (downturns).

Keywords: Business cycles; Comovement; Turning points; Asymmetries

JEL Classification: C14; C33; C35; E23; E32;

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1. Introduction

The comovement of industries over the course of business cycles has been considered a salient feature of market economies (Burns and Mitchell, 1946; Lucas, 1981). The empirical pattern of industrial comovement is of profound importance because it forms the basis for modern (multi-sector) business cycle models. While the previous studies have found a strong degree of comovement across industries based on interindustry correlations, considerably less attention has been paid to the phase-shift property of the business cycle.[1] As is evident from the following quotation, characterizing a cycle as a recurrent sequence of distinct phases is a key ingredient of the business cycle:

> "A period in which expansions are *concentrated* is succeeded by another in which cyclical peaks are *concentrated*, by another in which contractions are *concentrated*, by another in which cyclical troughs are *concentrated*; and this round of events is repeated again and again (Burns and Mitchell, 1946, p. 70)."

The objective of this paper is to examine the patterns of the distribution of business cycle turning points.[2] By doing so we uncover new empirical regularities about the interindustry comovement of turning points that are useful to understand the propagation mechanism of business cycles. We ask the following questions. (i) How do industry turning points shape up over the business cycle? (ii) Do the distributions of industry peaks and troughs exhibit similar dispersion between the national peaks and troughs? (iii) What are the important determinants for the coincidence of phase shifts across industries?

[1] For example, Christiano and Fitzgerald (1998) and Hornstein (2000) find that the pairwise correlations of outputs and inputs across industries are largely positive and quite high, with a mean correlation of about 0.5. Veldkamp and Wolfers (2007) find that the average correlations of industry outputs and inputs with their aggregate counterparts all exceed 0.5. Murphy et al. (1989), Shea (2002), and Kim and Kim (2006) also provide the estimation results of the correlations between industry variables and aggregate business cycle indicators. Using the factor analytic methods, Long and Plosser (1987), Forni and Reichlin (1998), Foerster et al. (2008), and others suggest evidence that common factors account for a large fraction of sectoral fluctuations.

[2] In particular, the timing of turning points (rather than correlations) is of great interest to policy makers, financial analysts, and academics as well as to individual investors.

To answer these questions, we first identify a set of turning points by applying a nonparametric dating algorithm, proposed by Harding and Pagan (2002), to quarterly data on the production series for 74 U.S. manufacturing industries. We then investigate the comovement by examining the distribution of industry turning points around the national peaks and troughs. Comparison of the degrees to which industry peaks and troughs are concentrated around their national counterparts is conducted based on a clustering method proposed by Harding and Pagan (2006). Finally, we employ a panel logit model to investigate whether the coincidence of phase shifts across industries can be attributed to macroeconomic common shocks and spillovers from input-output linkages, which have been emphasized as two main sources of interindustry comovement by the previous literature.[3]

Our empirical analysis confirms a strong comovement across industries even in terms of phase shifts. But more interesting from our point of view are the distributional properties of turning point clusters. We find that industry troughs (i.e., upturns) are much more concentrated than industry peaks (i.e., downturns). This result is robust with respect to various treatments of the data. Our finding of higher concentration of troughs (upturns) is in contrast with the conventional notion of a "sudden stop and slow recovery" dating back to Keynes (1936): *'... the substitution of a downward for an upward tendency often takes place suddenly and violently, whereas there is, as a rule, no such sharp turning point when an upward is substituted for a downward tendency.'* However, our result is consistent with 'sharp' troughs and 'round' peaks documented by McQueen and Thorley (1993) based on the growth rate of industrial outputs.

We find that both the common (aggregate) shocks and the interindustry linkages are important for the joint occurrences of cyclical turns across industries. However, their relative importance differs between peaks and troughs. The downstream spillover effect from input suppliers is significant both for peaks and troughs. The upstream spillover effect from output

[3] For example, Lucas (1981) and Dupor (1999) attribute such comovement to aggregate shocks. The multi-sector RBC models, such as Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (2000), Shea (2002), and Carvalho (2007) attribute comovement to the interindustry linkages.

users is statistically significant only for peaks (i.e., downturns). Finally, we find that both monetary policy shocks (identified by Romer and Romer (2004)) and government spending shocks (identified by Ramey (2009)) have large and statistically significant effects in predicting industry troughs and peaks. However, the effectiveness of policy shocks are substantially stronger for troughs (upturns) than for peaks (downturns).

Our work contributes to various bodies of literature. First, our study sheds new lights on the sources of interindustry comovement. While Lucas (1981) and Dupor (1999) attribute such comovement to aggregate shocks, the proponents of multi-sector RBC models, such as Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (2000), and Carvalho (2007), argue that input-output linkages also play an important role for the comovement of industries. Our results of asymmetric distribution of phase shifts across industries suggest that uncertainty can be an important feature of business cycles (e.g. Bloom (2009) and Nieuwerburgh and Veldkamp (2006)).

Empirical work on this topic include Long and Plosser (1987), McQueen and Thorley (1993), Bartelsman et al. (1994), Forni and Reichlin (1998), Shea (2002), Conley and Dupor (2003), and Foerster et al. (2008). All of these studies analyze continuous quantitative variables like the growth rates of the IP index. On the contrary, we deal with the discrete state variable. As is common in the literature on financial crisis contagion, we consider that a spillover effect is present if the probability of a phase shift in a particular industry is significantly affected by past occurrences of phase shifts in the other industries. An important advantage of this panel logit analysis is that we can estimate the peak and trough equations separately and thus can evaluate whether the sources of comovement have (a)symmetric effects over peaks and troughs.

Second, our result offers another dimension to the literature on the business cycle asymmetries. While previous studies have exclusively focused on the conditional mean or variance properties of aggregate series, asymmetries in the higher moment properties of cross-sectional distribution have received relatively little attention. We complement this literature by adding new evidence on the asymmetric dispersions of industry turning points.

Finally, we enlarge the scope of analysis on the stylized facts of the business cycle to include those for industry cycles. Recently, a series of work by Harding and Pagan (2002, 2005, 2006) have revived interest in the classical approach as a tool for collecting business cycle features, and many studies have adopted this method to analyze comovement of international (Artis et al. 2004; Krolzig and Toro, 2005; Camacho et al., 2008), regional (Hall and McDermott, 2007), and U.S. macroeconomic variables (Chauvet and Piger, 2008). As far as we are aware, however, our work is the first attempt to analyze comovement across industries using this method.[4]

The remainder of this paper is organized as follows. Section 2 briefly describes the methodology used for dating the industry-specific and the reference cycles. Section 3 presents the results for conformity analysis. Empirical results for the asymmetric dispersions of industry turning points are given in Section 4. Section 5 conducts the panel logit analysis to investigate the determinants of interindustry comovement. Section 6 concludes the paper.

2. Dating industry cycles

2.1. Algorithm

In order to identify industry business cycle phases we apply Harding and Pagan's (2002) algorithm to the *level* of industrial output. Using this approach has at least three benefits. First, it does not require a particular definition of trend components from the raw series, which is often unobservable to a researcher. Thus it can avoid potential problems inherent in de-trending methods.[5] Second, using a level series is consistent with the practice maintained

[4] Using a multi-level smooth transition model, Fok et al. (2005) analyzed common nonlinear features of industrial production in 19 U.S. manufacturing industries. Unlike ours, their focus was more on developing econometric methodologies and less on collecting business cycle features per se; they did not provide a summary measure for the degree of comovement nor the asymmetric patterns of turning points.

[5] For example, Harvey and Jaeger (1993) and Cogley and Nason (1995) provide analyses of spurious cycles arising from the application of the Hodrick-Prescott filter. Canova (1998) illustrates how the different de-trending methods generate different "stylized facts" of U.S. business cycles.

by the NBER's Business Cycle Dating Committee, which has provided the most authoritative chronology for U.S. business cycles. Third, it is consistent with many previous studies seeking to establish business cycle features based on "aggregate" level time series data (e.g., among others, Watson (1994), Hess and Iwata (1997), and Harding and Pagan (2002)). One of the (potential) shortcomings, however, is that it may fail to detect any turning point in a series with a steady upward or downward trend. Hence, we will check the robustness of our results by considering detreneded data from the Hodrick-Prescott (1997) filter where appropriate.

The implementation of Harding and Pagan (2002), which is a quarterly variant of the Bry-Boschan (1971) algorithm, involves the following stages:

1. Define a peak in $\{y_t\}_{t=1}^{T}$ as occurring at time t if $y_t = max\{y_{t-2}, y_{t-1}, y_t, y_{t+1}, y_{t+2}\}$ and a trough as occurring at time t if $y_t = min\{y_{t-2}, y_{t-1}, y_t, y_{t+1}, y_{t+2}\}$. That is, a peak (trough) occurs at time t if it is higher (lower) than two preceding as well as two succeeding periods.

2. Check whether these peaks and troughs satisfy the predetermined "censoring rules."

Censoring rules make sure that (i) peaks and troughs alternate and that (ii) a phase and a complete cycle have minimum durations. If these requirements are not fulfilled, the least pronounced among adjacent turning points is eliminated. In this paper, we set the minimum duration of a phase to be 2 quarters and that of a cycle to be 5 quarters.

We use the seasonally adjusted quarterly IP indices covering 1972:Q1 to 2009:Q2. The data were extracted from the Board of Governors of the Federal Reserve System. In our data the U.S. manufacturing sector is classified into 74 industries that correspond roughly to the 4-digit level of disaggregation in the 2002 North American Industry Classification System (NAICS).[6]

[6] 70 industries correspond exactly to the 4-digit NAICS. Four industries are at the 3-digit level. They are apparel (315), leather and allied products (316), printing and related support activities (323), and petroleum and coal products (324).

Before we turn to the industry cycle analysis, Figure 1 compares the NBER business cycle phases to those identified by the Harding-Pagan method applied to the log GDP. Two business cycle dates are very close to each other except that the Harding-Pagan method does not detect the 2001 recession, which was a very mild one.

2.2. Summary Statistics

Table 1 summarizes the statistics of industrial business cycle phases identified by the Harding-Pagan algorithm applied to log IP indices. For comparison, we include the corresponding statistics for the U.S. economy based on the NBER dates and aggregate manufacturing cycles based on a multi-variate Harding-Pagan (MHP) method.[7]

Manufacturing industries have experienced more frequent phase shifts than the U.S. economy. During the sample period (1972:Q1 - 2009:Q2) the U.S. economy experienced 4 trough-to-trough cycles, whereas manufacturing industries on average experienced 9.5 cycles. The average duration of a trough-to-trough cycle is 26.8 quarters for the U.S. economy, whereas the average duration of manufacturing industries is just about 14.1 quarters. Manufacturing industries also exhibit duration asymmetries between expansions and contractions. The average duration of expansions (10.8 quarters) is twice as long as that of recessions (5.8 quarters), while the same ratio for the U.S. economy is 7.

Table 1 also shows that there are large cross-sectional differences in the duration properties of industry cycles. For example, the average duration of production cycles goes up to 38 quarters in the computer and peripheral equipment (NAICS=3341) industry; meanwhile it drops to 8 quarters in the iron and steel products (NAICS=3311) industry. The semiconductor and other electronic components (NAICS=3344) industry experiences, on average, the longest expansion, with a duration of 31 quarters, which is in sharp contrast to the minimum expansion duration of 4 quarters recorded for the apparel (NAICS=315) industry. The cross-sectional differences in duration asymmetries are also quite striking. The average

[7]We discuss the multi-variate version of the Harding-Pagan algorithm in Section 4.

duration of expansions, for instance, is ten times longer than that of recessions for the computer and peripheral equipment (NAICS=3341) industry, while it is less than two-thirds of that of recessions for the leather and allied products (NAICS=316) industry.

Figure 2 displays the frequencies of industry peaks and troughs over time. It represents the fractions of industries experiencing their own peak (circle) and trough (crosses), respectively, at a given quarter. The fraction of trough industries is multiplied by minus one (-1) to facilitate visual inspection. Shaded areas reflect the NBER recessions. As Burns and Mitchell (1946) pointed out, peaks and troughs tend to be concentrated around national turning points, suggesting a strong comovement across industries. However, it clearly shows asymmetry in the comovement of cyclical turning points, as the fractions of trough industries at the NBER troughs are on average much higher than those of peak industries at the NBER peaks. In other words, troughs (upturns) are much more concentrated than peaks (downturns). We will discuss these features in more depth in the following sections.

3. Concentration of cyclical phases

In this section we briefly discuss two measures of comovement of cyclical phases: diffusion indices and concordance. The diffusion indices measure *the fraction of industries* sharing the same phase at a given point of time. Concordance measures *the fraction of time* that two industries are in the same phase.

Based on the industry cycles identified in the previous section, the diffusion index for contractions is computed as follows:

$$D_t = \sum_{i=1}^{N} w_{it} S_{it}, \quad \sum_{i=1}^{N} w_{it} = 1, \quad t = 1, \ldots, T. \tag{1}$$

where w_{it} is the weight assigned to ith industry at time t, S_{it} is a binary variable taking the value of 1 in contraction phases and 0 otherwise, and N is the cross-sectional dimension. We use two measures of industry weights: one is equal to all industries and the other is the (time-varying) output shares of each industry available from the database of the Federal Reserve Board. Constructed in this way, the diffusion index for contractions, D_t, measures how widely contractions are spread throughout the manufacturing sector in terms of (i) the number of industries (for the case of equal weights) or (ii) the total production of the manufacturing sector (for the case of industry-specific output-share weights). The diffusion index for expansion is easily computed as one minus the diffusion index for contractions.

The diffusion indices for contractions and expansions are plotted in the top and bottom panels of Figure 3, respectively. Note that the fraction of industries experiencing a contraction rises above 65% during every NBER recession period, while it remains low during NBER expansion periods. More precisely, the average of the fractions of industries that are in contraction is 69% (74%) for the NBER recessions and 30% (34%) for the NBER expansions when the industry-specific (equal) weights are used. By contrast, the fraction of industries experiencing expansions stays far above 50% for most of the NBER expansion periods and sharply drops below 50% at about the beginning of the NBER recessions. The average of fractions of industries undergoing expansions is computed to be 70% (66%) for the NBER expansions and 31% (26%) for the NBER recessions when the industry-specific (equal) weights are used.

The two NBER recessions of 1974-75 and 2008 deserve special attention, since the diffusion index for contractions rises close to 1 during these periods, meaning that almost all industries experienced declines in the *levels* of production during these national recessions. By contrast, during two other major NBER recessions–1980 and 1981-82–about 30% of industries continued to increase their production. The figure also shows that there are several periods (i.e., 1984-85, 1995-96, and 2003) when a considerable number of industries experienced a contraction, while the U.S. economy as a whole did not. Finally, the choice between the two weighting methods does not substantially affect the results.

The pairwise concordance measures the fraction of time that two industries are in the same phase:

$$C_{i,j} = \frac{1}{T}\sum_{t=1}^{T}[S_{it}S_{jt} + (1 - S_{it})(1 - S_{jt})], \tag{2}$$

where S_{it} and S_{jt} are dummy variables defined as above. Similarly, the degree of concordance between the production cycles of industry i and the business cycles of the U.S. economy is defined as:

$$C_{i,US} = \frac{1}{T}\sum_{t=1}^{T}[S_{it}S_{US,t} + (1 - S_{it})(1 - S_{US,t})]. \tag{3}$$

where $S_{US,t}$ is a dummy variable taking a value of 1 or 0 in case of the NBER recession or expansion, respectively.

The left panel of Figure 4 presents kernel densities of the concordance indices computed for the 2,701 industry pairs. As is apparent from the figure, there is a high degree of concordance between industry cycles. The estimates of pairwise concordance range from 0.360 to 0.880, with mean of 0.608, suggesting that two manufacturing industries are in the same phase 60.8% of the time on average. The result presented in the right panel of the figure indicates that the degree of concordance between industry cycles and the business cycles of the U.S. economy is on average slightly higher than the degree of pairwise concordance across industries. Taken jointly, the patterns of two measures clearly confirm that comovement across industries is a salient feature of U.S. business cycles.

4. Concentration of turning points

We have already seen from Figure 1 that there is a bunching of cyclical turns around national peaks and troughs. We now ask whether the clusters of turning points have the same dispersion between peaks and troughs. To shed light on this issue, we begin by inspecting the frequencies of industry peaks and troughs computed at the corresponding NBER turning points. The left panel of Table 2 reveals that at the NBER peaks, just about 14% of industries on average experience their peaks as well. On the other hand, when the NBER recession culminates, more than 34% of industries on average simultaneously climb out of their recessions. Thus, the likelihood that industry-level turning points coincide with their national counterparts is clearly asymmetric between peaks and troughs, with troughs being twice as likely to coincide as peaks. This asymmetric pattern does not change substantially during the sample period, although the degree of asymmetry has somewhat increased in the last two NBER recessions.

When determining the U.S. reference-cycle dates, the NBER Business Cycle Dating Committee considers the behavior of various economic indicators besides IP indices. Therefore, the NBER dates may not be the right measure of turning points in the reference cycle specific to the manufacturing sector. To address this problem we extract the reference (or common) cycle for the manufacturing sector by applying a multi-variate version of the Harding Pagan (MHP) algorithm. A detailed description of identifying manufacturing-reference cycles using MHP is provided in the appendix.

The right panel of Table 2 reports the reference-cycle dates for the manufacturing sector obtained by the MHP algorithm and the frequencies of industry turning points corresponding to each reference date. Using the trough-to-trough definition, the MHP algorithm identifies 7 cycles for the period 1972:Q1-2009:Q2, which is 3 more than those for the U.S. economy as a whole recorded by the NBER. Accordingly, the average duration of the manufacturing reference cycles is calculated to be just about one half of that for the NBER cycles, as is shown in Table 1. Among the 8 troughs identified for the manufacturing sector, 5 are associated with the NBER recessions, but the other 3 are specific to the manufacturing sector. Note that for the first 5 cases, the manufacturing sector reaches its troughs exactly at the same time as the troughs of the NBER cycles or just shortly after them. In contrast, peaks for the manufacturing sector generally come earlier than peaks for the U.S. economy, with the leads varying from 1 to 6 quarters. Finally and most important, the fraction of industries experiencing their turning points is still higher at troughs than at peaks, even when we use the MHP reference-cycle dates instead of the NBER dates. Although the degree of difference is smaller than in the case using the NBER dates, the fractions of peak industries computed at the MHP peaks are, on average, just about one-half of those for trough industries computed at the MHP troughs.

An interesting interpretation proposed by Harding and Pagan (2006) about the MHP turning points is that these points can be considered the *central dates of clusters* consisting of individual turning points, in the sense that the average distance from time t and the set of nearest turning points in individual cycles is minimized at those points. Following this interpretation we here build the clusters of turning points to provide a more general picture of the patterns of cyclical turns.

Let r_l be the lth peak in the reference cycle and Ψ_l be the lth cluster of industry peaks centered on r_l. Then, Ψ_l is defined as follows

$$\Psi_l = \{\, \tau_{ij}^P \mid d(r_l - \tau_{ij}^P) < d(r_m - \tau_{ij}^P) \text{ for all } m \neq l; \text{ and } d(r_l - \tau_{ij}^P) \leq \bar{d}\,\} \tag{4}$$

where $\bar{d}$ is a predetermined constant. We choose $\bar{d} = 8$ for our quarterly data, following the suggestion of Harding and Pagan (2005). Clusters of industry troughs can be defined in a similar fashion.

Figure 5 presents the results of the cluster analysis. In this figure, the dotted line indicates nonparametric estimates of the Gaussian kernel densities for the differences between industry peaks and the corresponding central dates of clusters. The solid line represents the Gaussian kernel densities for the differences between industry troughs and the corresponding central dates of clusters. The absolute value of the negative (positive) values on the horizontal axis denotes the number of quarters by which an industry cycle leads (lags) the reference cycle. For the central dates of clusters, we use two sets of the reference-cycle dates: the first set corresponds to the NBER dates and the second set corresponds to the MHP dates. We also include in this figure the results for the deviation cycles, which are extracted from the Hodrick-Prescott (1997) filter. The same nonparametric algorithm as above is applied to the detrended series to identify turning points in the deviation cycles.

Inspection of the plots presented in Figure 4 reveals a sharp contrast between the shapes of peak and trough clusters: the clusters of industry troughs are highly compact and comparably symmetric. On the contrary, the clusters of industry peaks are dispersed and skewed toward leads. Using the MHP reference-cycle dates in lieu of the NBER dates helps correct the skewness of peak distributions, but does not change the general pattern of the asymmetric concentration of turning points between peaks and troughs. Furthermore, the lower panels of Figure 4 show that this asymmetric pattern becomes even more apparent when the deviation cycles are used. We perform a two-sample Komogorov-Smirnov test to evaluate whether the distributions of peaks and troughs are the same and find that the null hypothesis of equal distribution is rejected at the 1% significance level for all the cases considered.[8] Thus, our conclusion that troughs are more concentrated than peaks appears to be robust. Our finding of higher concentration of troughs (upturns) is in contrast with the conventional notion of a "sudden stop and slow recovery" but consistent with 'sharp' troughs and 'round' peaks documented by McQueen and Thorley (1993) based on the growth rate of industrial outputs.

5. Determinants of comovement

5.1. Panel logit model

In this section we analyze the determinants of interindustry comovement to investigate whether the coincidence of phase shifts across industries can be attributed to macroeconomic common shocks and spillovers from input-output linkages, which have been emphasized as two main sources of interindustry comovement by the previous literature. In addition, this section examines whether the effects of these determinants are (a)symmetric between the occurrences of peaks and troughs.

[8] When the null distribution is discrete as is the case for the present study, it is known that the Komogorov-Smirnov test tends to yield conservative results. Therefore, the rejections at the 1% significance level can be considered strong evidence in favor of asymmetry between the distributions of peaks and troughs

Consider a sample of binary variable D_{it}^P that takes the value of 1 if industry i is at *peak* at time t and otherwise takes the value of 0, for $t = 1, \ldots, T$ and $i = 1, \ldots, N$. Similarly, consider another sample of binary variable D_{it}^T taking the value of 1 if industry i is at *trough* at time t and otherwise having the value of 0. To examine the effects of the determinants on the coincidence of peaks or troughs across industries, we estimate the following binary panel logit model with fixed effects:

- Peak equation

$$\Pr(D_{it}^P = 1 \mid x_{it}^P, \alpha_i^P) = \Gamma(X_{it}^{P\prime}\beta^P + \alpha_i^P), \tag{5}$$

- Trough equation

$$\Pr(D_{it}^T = 1 \mid x_{it}^T, \alpha_i^T) = \Gamma(X_{it}^{T\prime}\beta^T + \alpha_i^T), \tag{6}$$

where superscripts P and T denote peak and trough, respectively, $\Pr(\cdot)$ is the probability of an event, $\Gamma(\cdot)$ is a logistic function of the form $\Gamma(z) \equiv \exp(z)/(1+\exp(z))$, X_{it} is the vector of covariates, β is the vector of coefficients, and α_i is the unobserved industry-specific effect. We also allow for the unobserved individual effect α_i to be correlated with covariates X_{it}.

Our approach significantly differs from the previous studies on the comovement of industries in that we deal with the discrete variables rather than continuous variables like the growth rates of IP indices. The model we use is also different from the existing models for predicting recessions (e.g., Estrella and Mishkin, 1998; Sensier et al., 2004) mainly in two respects: we use a panel data model instead of a simple probit model and we estimate peak and trough equations separately, unlike previous studies that use only one equation for the probability of the economy being in a *recession*. Our approach has two potential advantages. First, it enables us to analyze the asymmetric effects of the determinants on the occurrences of peaks and troughs. In addition, our approach provides a convenient way to avoid the problem of serial correlation, which is likely to arise because of employing a "censoring rule" to identify phases of a cycle; see Harding and Pagan (2009) for details.

5.2. Explanatory variables

The explanatory variables are grouped into two categories. The first group consists of the weighted averages of spillover effects from all the other industries, constructed as:

$$
\begin{aligned}
Z_{it-1} &= \sum_{j\neq i} w_{ij} D^P_{jt-1}, \quad \text{in peak equation,} \\
&= \sum_{j\neq i} w_{ij} D^T_{jt-1}, \quad \text{in trough equation}
\end{aligned} \tag{7}
$$

where w_{ij} denotes the weight capturing the importance of the phase shift of industry j at time $t-1$ with respect to the phase shift of industry i at time t. D^P_{jt-1} and D^T_{jt-1} are constructed in a similar way as explained above.[9]

Following Shea (2002), we distinguish spillover effects depending on the origins of the effects. The first is from input suppliers (*downstream* or supply-side), the second is from output users (*upstream* or demand-side), and the third is unconditional on the input-output structure. Let m_{ij} be the value of products of industry i used as intermediate materials in industry j. Then we measure the importance of industry j as an input supplier to industry i by using the following weight

$$\omega_{ij} = \frac{m_{ji}}{\sum_{j\neq i} m_{ji}}$$

Applying this weight to equation (8), we construct a *downstream* spillover index as an explanatory variable for the probability of the phase shift of industry i. Similarly, the importance of industry j as a user of the product of industry i is computed as

$$\omega_{ij} = \frac{m_{ij}}{\sum_{j\neq i} m_{ij}}$$

Using this weight, we construct an *upstream* spillover index as an explanatory variable for the phase shift of industry i. To construct these two types of weights, we use the 2002 U.S. input-output table provided on the website of the Bureau of Economic Analysis. Finally,

[9] We are thus implicitly assuming a one-period lag in spillovers from other industries.

to control for unconditional spillover effects, which are independent of the input-output structure, we construct an index for which all industries are given equal weight such that $w_{ij} = 1/N$.

The second group of explanatory variables consists of four different macroeconomic shocks. To avoid the problem of endogeneity, we employ the measures of macroeconomic shocks constructed as being exogenous to economic conditions from the previous studies using narrative records. The measure of monetary policy shocks is obtained from Romer and Romer (2004), who analyze narrative records around the meetings of the Federal Open Market Committee (FOMC) and identify monetary policy shocks as the changes in the intended federal funds rate not taken in response to information about inflation and real growth. Government spending shocks are based on Ramey (2009), who constructs the defense news variable as the changes in the expected discounted value of government spending due to foreign political events, divided by the previous quarter's nominal GDP. The measure of tax revenue shocks is provided by Romer and Romer (2008) and constructed as the changes in tax liabilities at the prevailing level of GDP, taken to deal with an inherited budget deficit or to achieve a long-run goal. Finally, the measure of exogenous oil supply shocks is obtained from Kilian (2008) and estimated as the rates of changes in the OPEC-wide oil production shortfall.

We restrict the sample period to end in 1996 because the measure of monetary policy shocks, provided by Romer and Romer (2004), is available only up to that year. In order to avoid the endogeneity problem, we enter the spillover indices in the right-hand side of (6) and (7) only with the first lag, whereas for the macroeconomic shocks, the contemporaneous values as well as the first lags are used, since they are relatively free of the endogeneity problem by definition. In line with other studies using binary variables, we use McFadden's (1974) pseudo$-R^2$ as a measure of goodness-of-fit of the model. Note that though the coefficient estimates in the tables below provide important information due to their signs and significance, they cannot be interpreted as directly representing the marginal effects of the covariates on the probabilities of peaks and troughs because the model used is nonlinear.

5.3. Empirical Results

Table 3 presents the estimation results of the peak equation. The left panel shows the estimation result of the unrestricted model that includes all explanatory variables, and the right panel presents the result of the restricted model that excludes the explanatory variables whose coefficients turned out to be statistically insignificant in the first-stage regression. Both macroeconomic common shocks and spillovers from input-output linkages are significant determinants of the occurrence of a peak (downturn). For the spillover effects, the coefficients of all three indices—downstream, upstream, and unconditional—are significant at the 1% level and have a positive sign. It is worth noting that even after we control for unconditional spillover effects, the upstream and downstream spillover effects are highly significant. An industry is more likely to switch into a contraction if upstream or downstream industries have entered a contraction in the preceding quarter.

The coefficients of both the contemporaneous and the lagged values of monetary policy shocks are significant at the 1% level and have a positive sign, implying that an increase in the federal funds rate due to exogenous reasons yields higher probabilities of switching from an expansion to a contraction in manufacturing. The effects of government spending shocks are estimated to be significant with a one-period lag such that an increase in defense spending lowers the probability of downturns. An increase in tax revenue is also significant with a one-period lag. An exogenous increase in tax leads to a higher probability that a downturn will occur. Finally, the coefficients on the oil supply shocks are significant only for the contemporaneous effects. Oil production shortfalls increase the probability of downturns in manufacturing production. Overall, all four macroeconomic shocks are significant determinants of cyclical turning points and yield signs that conform to our priors.

Table 4 presents the estimation results of the trough equation. What is most striking is that the coefficient of upstream spillover indices is now insignificant even at the 10% level. By contrast, the coefficient of downstream spillover indices is still highly significant and shows a positive sign. According to this estimate, spillover effects from input suppliers are still important for cyclical upturns whereas those from output users are not. Our results raise another interesting question regarding the underlying mechanisms of asymmetric spillover effects in the literature (see Bartelsman et al. (1994), Shea (2002), and Conley and Dupor (2003)).

Turning to the macroeconomic shocks, the coefficients of monetary policy shocks are highly significant and have a negative sign both for the contemporaneous and one-period lagged values. A decrease in the federal funds rate increases the probability of upturns (occurrence of troughs) in manufacturing production. Remarkably, the absolute value of the sum of the coefficients of monetary policy shocks is about twice as large in the trough equation as in the peak equation. This result supports the findings of the previous studies that the effects of monetary policy on output are much greater in recessions than in expansions; see Lo and Piger (2005) and Peersman and Smets (2005), among others. The coefficients of government spending shocks are significant for the first lags of the variable, but not for the contemporaneous values. Comparing the results for government spending shocks between Tables 3 and 4, we find that not only monetary policy shocks but also government spending shocks have larger output effects at troughs than at peaks. The coefficients of tax revenue shocks are significant only for the first lags of the variable and, in that case, have a positive sign. This is a somewhat unusual result, and that goes against common perception.[10] Finally, although the coefficients of oil supply shocks are significant both for the contemporaneous values and the first lags of the variable, the sum of the coefficients is not different from zero, implying that this variable does not have significant effects on the likelihood of upturns in industrial production.

[10] There is no significant difference in other coefficients when we estimate the model excluding tax revenue shocks.

6. Summary

The comovment over the business cycle is a salient feature of the modern economy. The phase shift carries far richer information about the nature of business cycles than a simple correlation. In particular, the timing of turning points is of great interest to policy makers, financial analysts, academics, and individual investors. Based on the IP indices of 74 U.S. manufacturing industries, we identify the turning points of industry cycles using a nonparametric method developed by Harding and Pagan (2002).

We uncover new empirical regularities about the interindustry comovement of turning points. First, industry peaks and troughs are concentrated around national turning points, confirming that the comovement is a salient feature of the business cycle. Second and most important, we find a substantial asymmetry in the distribution of turning points between peaks and troughs. Troughs (upturns) are much more concentrated than peaks (downturns). This is in contrast to the conventional notion of a "sudden stop and slow recovery." Finally, we find that both aggregate shocks and spillovers from input-output linkages are significant determinants of turning points. However, their effects are also asymmetric between upturns and downturns. For example, upstream spillover effects are more important for downturns, whereas downstream spillover effects are significant for both upturns and downturns. Monetary policy and government spending shocks are important for occurrences of both downturns and upturns, yet they exhibit much larger effects on upturns than on downturns. Our results of asymmetric distribution of phase shifts across industries suggest that uncertainty can be an important feature of business cycles (e.g. Bloom (2009)).

A Appendix

The multi-variate Harding-Pagan (MHP) algorithm used to identify the manufacturing reference cycle proceeds as follows:

1. Let τ_{ij}^P and τ_{ij}^T be the dates to the jth peak and trough in the ith industry cycle, respectively, for $i = 1, \ldots, N$. Define d_{it}^P and d_{it}^T as the distance from time t and the nearest peak and trough in the ith industry cycle, respectively, for $t = 1, \ldots, T$; that is, $d_{it}^P = \min d(t - \tau_{ij}^P)$ and $d_{it}^T = \min d(t - \tau_{ij}^T)$ for all j, where $d(\cdot)$ is a measure of distance.

2. For each t, compute the cross-sectional averages of the distances from time t and the nearest peak and trough in industry cycles, respectively. Let's denote these results as d_t^P and d_t^T. Harding and Pagan (2006) propose to use the median as the measure of the average distance. But since we have the information on the output shares of each industry, we instead employ the weighted average of d_{it}^P and d_{it}^T to measure the average distance. Formally, $d_t^P = \sum_{i=1}^N w_{it} d_{it}^P$ and $d_t^T = \sum_{i=1}^N w_{it} d_{it}^T$ for $t = 1, \ldots, T$, where w_{it} is the weight assigned on the ith industry and $\sum_{i=1}^N w_{it} = 1$.

3. Determine the local minima in d_t^P and d_t^T, respectively. Then the peaks and troughs in the reference cycle are defined as the dates of these local minima.

4. Finally, apply the "censoring rule" to ensure that the identified peaks and troughs yield a cycle satisfying the requirement explained in Section 2 of this paper.

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Table 1. Average numbers and durations of completed cycles, expansions, and contractions

	Number of cycles		Average duration in quarters				
			Cycles		Expansions	Contractions	
	T to T	P to P	T to T	P to P	T to P (A)	P to T (B)	A/B
U.S. economy	4.0	5.0	26.8	27.2	23.8	3.4	7.0
Manufacturing	7.0	8.0	16.1	16.5	10.8	5.8	1.9
Summary of industry cycle features							
Mean	9.5	10.3	14.1	14.0	8.8	5.1	2.0
Median	10.0	10.0	12.9	13.0	7.5	4.7	1.6
Max	15.0	16.0	38.7	34.5	31.3	10.1	10.3
Min	3.0	4.0	8.3	8.3	4.0	2.6	0.6
Std.	2.5	2.5	5.0	4.6	4.7	1.4	1.6

Note: 'T' denotes trough and 'P' denotes peak. Manufacturing cycle dates are based on the multi-variate Harding-Pagan method applied to the industrial production indices of 74 industries.

Table 2. Frequencies of industry peaks and troughs at the reference dates

NBER dates				MHP dates for manufacturing			
Peak	% of industries	Trough	% of industries	Peak	% of industries	Trough	% of industries
1973:Q4	14.9	1975:Q1	37.8	1974:Q1	16.2	1975:Q2	37.8
1980:Q1	21.6	1980:Q3	41.9	1978:Q4	12.2	1980:Q3	41.9
1981:Q3	23.0	1982:Q4	25.7	1981:Q1	6.8	1982:Q4	25.7
—	—	—	—	1984:Q4	13.5	1985:Q4	9.5
1990:Q3	12.2	1991:Q1	32.4	1989:Q1	16.2	1991:Q2	18.9
—	—	—	—	1995:Q1	20.3	1996:Q1	23.0
2001:Q1	5.4	2001:Q4	35.1	2000:Q2	20.3	2001:Q4	35.1
—		—	—	2002:Q3	18.9	2003:Q3	20.3
2007:Q4	9.5	—	—	2007:Q1	6.8	—	—
Average	14.4		34.6	Average	14.6		26.5

Note: "MHP dates for manufacturing" denote reference-cycle dates for the manufacturing sector identified by the multi-variate Harding and Pagan (MHP) algorithm.

Table 3. Estimation result of peak equation

	Unrestricted model		Restricted model	
	Coefficient	s.e.	Coefficient	s.e.
Spillover effects				
Unconditional $(t-1)$	0.056***	(0.009)	0.056***	(0.009)
Downstream $(t-1)$	0.028***	(0.009)	0.028***	(0.009)
Upstream $(t-1)$	0.027***	(0.009)	0.027***	(0.009)
Common macroeconomic shocks				
Monetary policy shocks (t)	0.863***	(0.243)	0.895***	(0.234)
Government spending shocks (t)	-0.002	(0.043)		
Tax revenue shocks (t)	0.113	(0.240)		
Oil supply shocks (t)	-0.072**	(0.036)	-0.072**	(0.035)
Monetary policy shocks $(t-1)$	0.730***	(0.266)	0.706***	(0.257)
Government spending shocks $(t-1)$	-0.060*	(0.033)	-0.061*	(0.034)
Tax revenue shocks $(t-1)$	0.580**	(0.235)	0.614***	(0.236)
Oil supply shocks $(t-1)$	0.050	(0.041)		
Log likelihood	-1425.01		-1425.87	
Pseudo-R^2	0.134		0.134	
Number of observations	4914		4914	

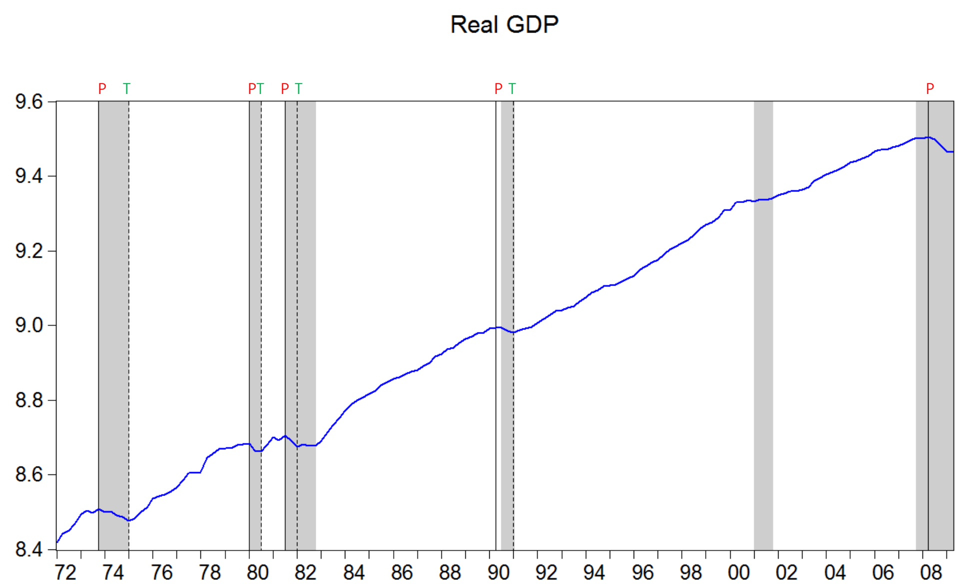
Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in parentheses are standard errors.

Table 4. Estimation result of trough equation

	Unrestricted model		Restricted model	
	Coefficient	s.e.	Coefficient	s.e.
Spillover effects				
Unconditional $(t-1)$	0.045***	(0.007)	0.048***	(0.006)
Downstream $(t-1)$	0.038***	(0.010)	0.038***	(0.010)
Upstream $(t-1)$	0.013	(0.009)		
Common macroeconomic shocks				
Monetary policy shocks (t)	-1.189***	(0.260)	-1.155***	(0.257)
Government spending shocks (t)	0.056	(0.039)		
Tax revenue shocks (t)	-0.042	(0.193)		
Oil supply shocks (t)	0.122***	(0.044)	0.115***	(0.043)
Monetary policy shocks $(t-1)$	-1.717***	(0.196)	-1.714***	(0.196)
Government spending shocks $(t-1)$	0.114**	(0.046)	0.114***	(0.046)
Tax revenue shocks $(t-1)$	0.808***	(0.232)	0.821***	(0.236)
Oil supply shocks $(t-1)$	-0.106**	(0.043)	-0.118***	(0.042)
Log likelihood	-1356.56		-1358.69	
Pseudo-R^2	0.168		0.166	
Number of observations	4836		4836	

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in parentheses are standard errors.

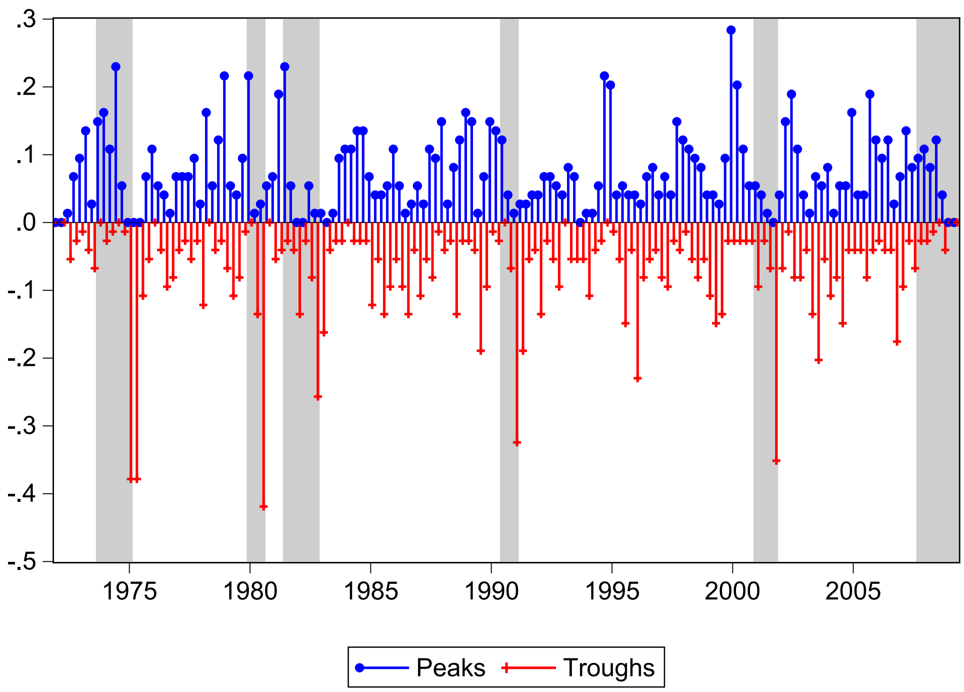
Figure 1. Business Cycle Dates: NBER vs Harding and Pagan



Note: P and T denote peaks and troughs, respectively.

Note: 'P' and 'T' corresponds to the peaks and troughs identified by the Harding-Pagan method applied to the GDP. The shaded areas are recessions defined by the NBER.

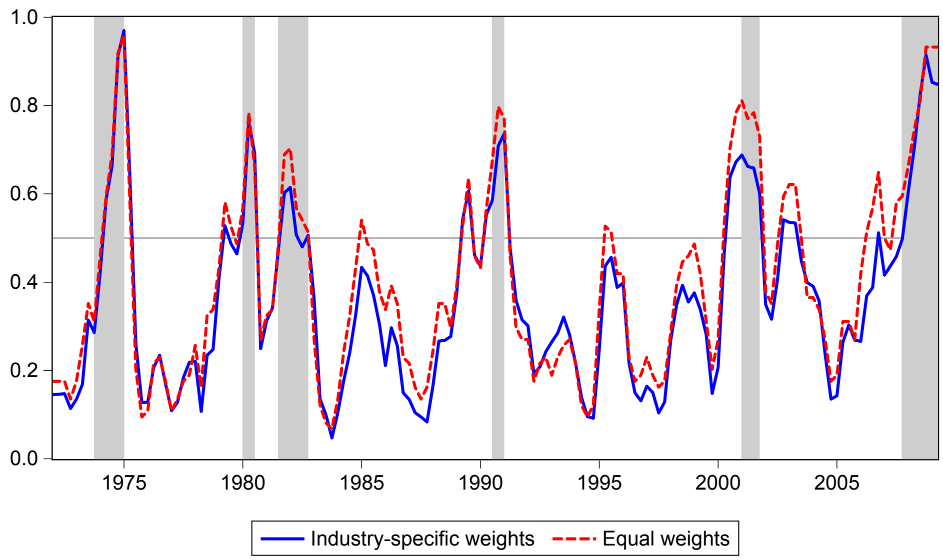
Figure 2. Frequencies of industry turning points over 1972:Q1-2009:Q2



Note: 'Peaks (circle)' and 'Troughs (cross)' denote the fractions of industries experiencing peaks and troughs, respectively, at a given quarter. For visualization purpose, the fractions of trough industries are multiplied by minus one. Shaded areas are NBER recessions.

Figure 3. Diffusion indices for cyclical phases

a) Contractions



b) Expansions

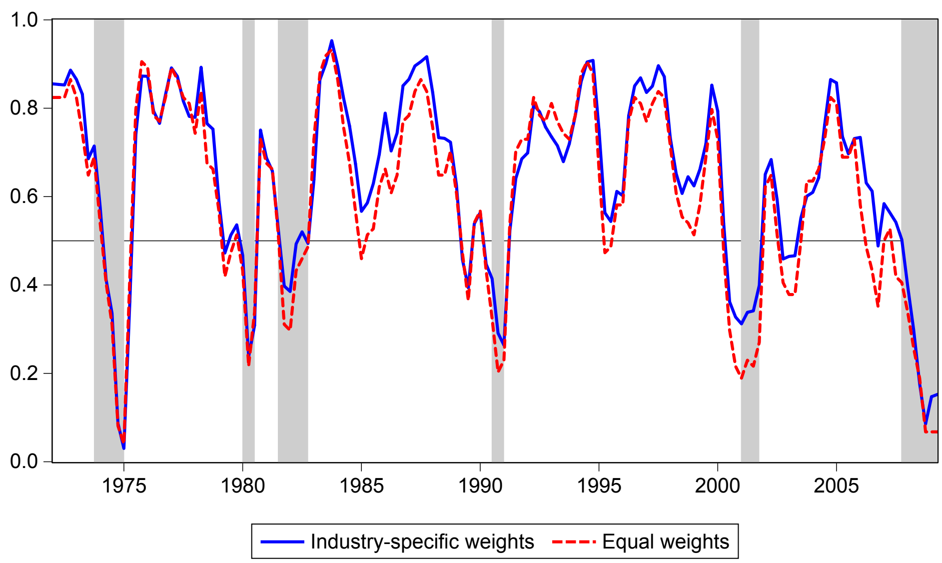


Figure 4. Kernel densities of the concordance and correlation indices

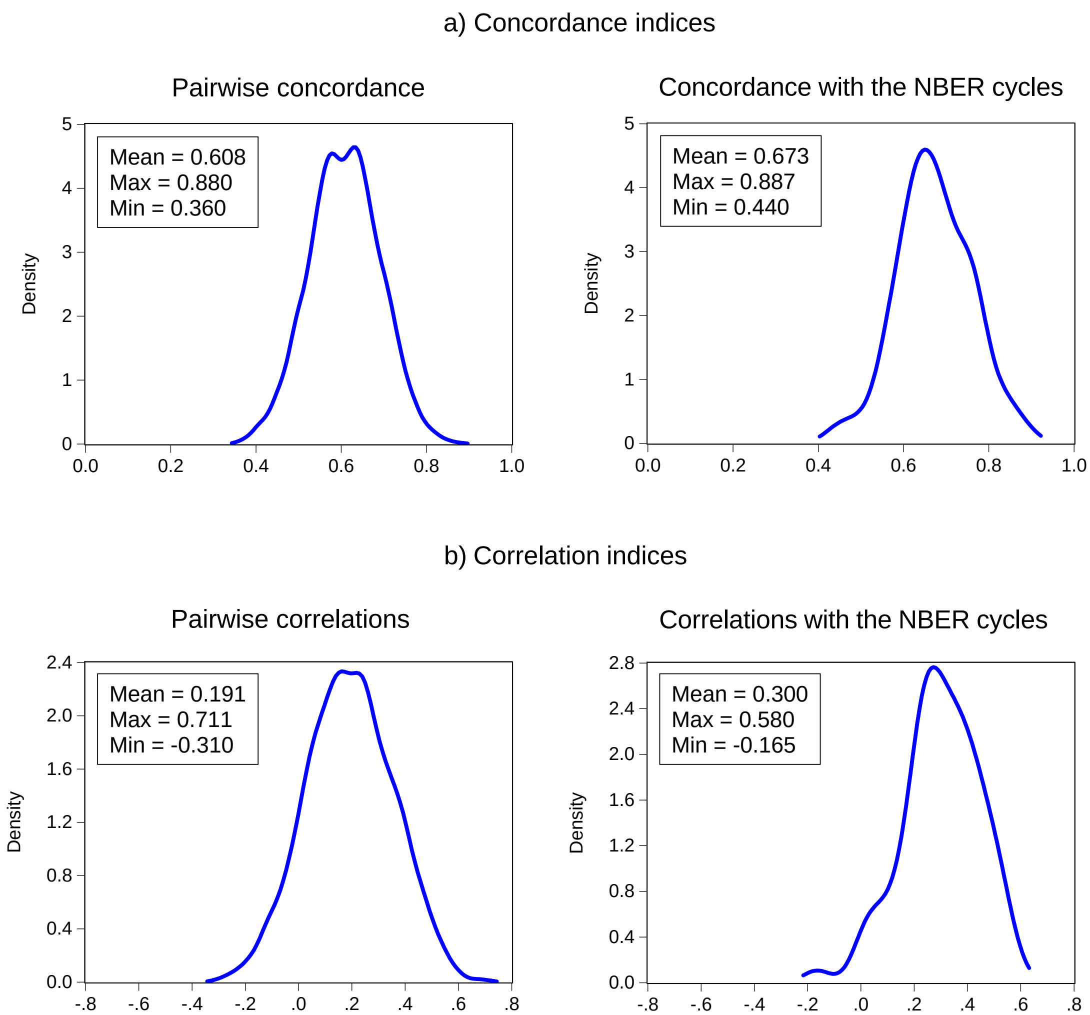


Figure 5. The shapes of clusters of peaks and troughs