# Asymmetric Phase Shifts in the 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.' We also find that the effects of macroeconomic factors and spillover effects from input-output linkages are asymmetric for the occurrences of industry turning points. While the spillover effects from the other industries are significant only for peaks, the effects of macroeconomic factors are significant for both peaks and troughs.



**Keywords**: Business cycles; Comovement; Turning points; Asymmetries

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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, there has been comparatively little work investigating such feature jointly with the phase-shift property of the business cycle.[1] However, as is evident from the following quotation from Burns and Mitchell (1946, p. 70), 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."

It is also obvious that in this quotation the comovement is defined as the *concentration* of cyclical phases and turning points, rather than cross-correlation between the series.

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) Can we find evidence on the comovement of industries in terms of the concentration of cyclical phases? (ii) Do the distributions

[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.

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?

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 factors and spillovers from input-output linkages, which have been emphasized as two main sources of interindustry comovement by the previous literature (see below).

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, p. 314): "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 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. Empirical work on this topic include Long and Plosser (1987), 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 literatures on infectious disease epidemiology (see, e.g., Padian et al. (1997)), financial crisis contagion (see, e.g., Eichengreen et al. (1996)) and knowledge and technology spillovers (see, e.g., Goolsebee and Klenow (2003)), for instance, we consider that a spillover effect is present if the probability of a phase shift in a particular industry is positively 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 (see Morley (2009) for a recent survey), 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 concentrations 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, 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. major 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.[3]

The remainder of this paper is organized as follows. Section 2 briefly describes the methodology used for dating the industry-specific cycles. Section 3 presents the results for conformity analysis. Empirical results for the asymmetric concentrations 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 turning points in the individual industry cycles 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

[3]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.

inherent in de-trending methods.[4] Second, using a level series is consistent with the practice maintained 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 detrended 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 a time series $\{y_t\}_{t=1}^{T}$ 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 $y_t$ is higher (lower) than two preceding as well as two succeeding observations.

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 2010: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]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.

4-digit level of disaggregation in the 2002 North American Industry Classification System (NAICS).[5]

Before we turn to the industry cycle analysis, Figure 1 compares the NBER business cycle dates to those identified by the Harding-Pagan method applied to the log level of U.S. real GDP for the sample period 1947:Q1 to 2010:Q2. The Harding and Pagan algorithm identifies ten of the eleven NBER recessions during this period. The only one that it miss is the 2001 recession, which was a very mild one. Furthermore, for most cases, two business cycle dates are very close to each other. For instance, for the most recent 2007-09 recession, the Harding and Pagan algorithm selects the exactly same peak and trough dates as those identified by the NBER.[6]

## 2.2. Frequencies and Durations of Industry Cycles

Table 1 reports the summary statistics for frequencies of industry cycles identified by the Harding-Pagan algorithm applied to log IP indices, along with those for durations of expansions, contractions, and whole cycles measured in quarters. For comparison, we include the corresponding statistics for the U.S. business cycle based on the NBER dates. The numbers and durations of whole cycles are measured from trough to trough. Employing peak to peak measures does not change the general features.

Manufacturing industries have experienced more frequent phase shifts than the U.S. economy. During the sample period 1972:Q1 to 2010:Q2, the U.S. economy experienced 5 trough-to-trough cycles, whereas manufacturing industries on average experienced 10.3 cycles. Consequently, the average duration of complete cycles is much shorter for man-

[5] 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).

[6] Despite the similarity between the dates identified by the Harding and Pagan algorithm and the dates established by the NBER, it is of importance to note that the NBER's Business Cycle Dating Committee indeed has no fixed rule to determine turning point dates in the U.S. business activity, nor has it a fixed definition of economic activity. Rather, it examines and compares the behavior of various economic indicators, such as real GDP, industrial production, real manufacturing and trade sales, total non-farm employment, and real personal income less transfers. See the FAQs at http://www.nber.org/cycles/recessions.html for more detailed description of the NBER's business cycle dating procedure.

ufacturing industries (14.2 quarters) than for the U.S. economy (27.4 quarters). Though less pronounced than for the U.S. economy, manufacturing industries also exhibit duration asymmetries between expansions and contractions. The average duration of expansions (8.7 quarters) is about twice as long as that of recessions (5.3 quarters) for manufacturing industries, while the same ratio for the U.S. economy is 6.2.

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 34 quarters in the computer and peripheral equipment (NAICS=3341) industry; meanwhile it drops to 8.3 quarters in the other transportation equipment (NAICS=3369) industry. The semiconductor and other electronic components (NAICS=3344) industry experiences, on average, the longest expansion, with a duration of 31.3 quarters, which is in sharp contrast to the minimum expansion duration of 3.8 quarters recorded for the apparel (NAICS=315) industry. The cross-sectional differences in duration asymmetries are also quite striking. The average duration of expansions, for instance, is ten times longer than that of recessions for the semiconductor and other electronic component (NAICS=3344) industry, while it is just one-half of that of recessions for the apparel (NAICS=315) industry.

# 3. Concentration of Cyclical Phases

In spite of the large cross-sectional differences in the duration properties shown in the previous section, do the timings of phase shifts tend to coincide across industries? That is, do industries comove in terms of the concentration of cyclical phases? To address this question, we in this section briefly discuss two measures of comovement of cyclical phases: diffusion and concordance indices. The diffusion index measures *the fraction of industries* sharing the same phase at a given point of time. The concordance index measures *the fraction of time* that two industries are in the same phase.

Based on the industry cycles identified above, the diffusion index for contraction 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 $i$th 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 share of each industry available from the database of the Federal Reserve Board. Constructed in this way, the diffusion index for contraction, $D_t$, 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 amount of production for the case of output share weights. The diffusion index for expansion is easily computed as one minus the diffusion index for contraction.

The diffusion indices for contraction and expansion phases are plotted in the upper and lower panels of Figure 2, respectively. As can be seen, the fraction of industries experiencing a contraction rises sharply 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 73.1% (67.8%) for the NBER recessions and 33.6% (30.1%) for the NBER expansions when equal (output share) weights are used. By contrast, the fraction of industries experiencing an expansion 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 an expansion is computed to be 66.4% (69.9%) for the NBER expansions and 26.9% (32.2%) for the NBER recessions when equal (output share) weights are used.

The two NBER recessions in 1973-75 and 2007-09 deserve special attention, since the diffusion index for contraction rises close to 1 during these periods. This indicates that almost all industries experienced declines in the *levels* of production during these national recessions. In contrast, during other NBER recessions–1980, 1981-82, 1990-91, and 2001–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. Note that the choice between the two weighting methods does not substantially affect the results.

Our second measure of comovement, called the pairwise concordance index, assesses the fraction of time that two industries are in the same phase using:

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

where $S_{it}$ and $S_{jt}$ are dummy variables defined as above. Similarly, the degree of concordance between the cyclical fluctuations 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.

Table 2 reports the summary statistics for the concordance indices computed over (i) the 2,701 industry pairs (Pairwise) and (ii) the 74 pairs between industry cycles and the U.S. business cycles defined by the NBER (NBER). From this table it is apparent that there is a high degree of concordance between industry cycles. The pairwise concordance indices range from 0.344 to 0.864, with mean of 0.607, suggesting that two manufacturing industries are in the same phase 60.7% of the time on average. The degree of concordance between industry cycles and the business cycles of the U.S. economy is on average 0.674, meaning that most industries exhibit procyclical behavior.[7] Taken jointly, the patterns of two measures constructed in this section clearly confirm that comovement across industries is a salient feature of U.S. business cycles.

[7] The concordance index has a shortcoming that it is positively affected by the expected values of $S_{it}$ and $S_{jt}$. Thus we also contructed the correlation indices proposed by Harding and Pagan (2006). The results also indicated that cyclical fluctuations of most industries are positively synchronized with each other, as well as with the business cycles of the U.S. economy. The results are available upon request.

# 4. Concentration of Turning Points

## 4.1. Evidence for Concentration Asymmetry

We now ask whether the distributions of industry turning points have the same concentration between the NBER peaks and troughs. To shed light on this issue, we define a turning point cluster as a set of industry turning points whose distances from a given NBER date are not greater than a predetermined upper bound. For concreteness, let $\tau_{ij}^P$ be the $j$th peak of industry $i$ and $m_k$ be the $k$th peak in the U.S. business cycles identified by the NBER. Then, the $k$th peak cluster centered around $m_k$ is defined as[8]

$$\Psi_k = \{\, \tau_{ij}^P \mid d(m_k - \tau_{ij}^P) < d(m_\ell - \tau_{ij}^P) \text{ for all } \ell \neq k; \text{ and } d(m_k - \tau_{ij}^P) \leq \bar{d}\,\} \tag{4}$$

where $d(\cdot)$ is a measure of distance and $\bar{d}$ is a predetermined constant. Following Harding and Pagan (2006), we choose $\bar{d} = 8$ for our quarterly data. Clusters of industry troughs are defined in a similar fashion.

It is important to note that the above definition allows an industry turning point to appear in *at most* one cluster. This restriction limits the maximum lag for the 1980 peak and the maximum lead for the 1981 peak to 2 quarters; and the the maximum lag for the 1980 trough and the maximum lead for the 1982 trough to 4 quarters. In addition, due to data availability, the maximum lead for the 1973 peak and the maximum lag for the 2001 trough are reduced to 5 and 2 quarters, respectively. Hence careful attention needs to be paid to the results for the points that miss observations for some clusters. However, as will be seen from Figure 4 below, which displays the turning point distributions for each NBER recession, our conclusion about the general shapes of clusters does not appear to be sensitive to these partial truncations.

[8] This definition is based on Harding and Pagan (2006). The major difference between their and our work is that they use this definition to extract the reference cycle dates which are assumed to be unknown a priori, while we employ the NBER dates as the business cycle reference dates for the U.S. economy. Note that our focus is not on how to identify a common cycle, but on how the peaks and troughs of industry cycles are distributed around the business cycle turning points.

Figure 3 displays histograms of peak and trough clusters. In this figure, the horizontal axis denotes the lead (negative) and lag (positive) time over the NBER turning point dates. The vertical axis is the corresponding fraction of industries, averaged separately over the past 6 NBER peak and trough dates. Inspection of this figure reveals sharp contrasts between the shapes of peak and trough clusters.

First, clusters of industry troughs are highly concentrated at the NBER trough date, whereas clusters of industry peaks are much more dispersed. For troughs, more than 33% of industries, on average, exit simultaneously from the contraction phase at the NBER trough date. For peaks, just about 14% of industries newly enter the contraction phase at the NBER peak date, and this fraction—14%—does not seem to be particularly high compared to the mean fractions for the left side points. Second, trough clusters appear to be slightly skewed toward lags, while peak clusters are skewed toward leads. For troughs, the sums of the industry fractions over the left and right sides of the cluster are 36.7% and 57.7%, respectively. In peak clusters, the respective ratios are 80.0% and 38.8%.[9]

As Figure 4 shows, these asymmetric patterns of peak and trough distributions have emerged relatively consistently over the last 6 NBER recessions. The fraction of coincident industries has almost always been more than two times higher at the NBER trough dates than at the NBER peak dates. One exception was the 1981-82 recession for which the difference reduced to 1.2 times. The maximum difference was found at 6.25 times for the 2001 recession, and for the most recent 2007-09 recession the difference was 3.29 times. With respect to the skewness properties, industry troughs have always been skewed toward lags except for the 1980 NBER trough, and industry peaks always toward leads except for the 1973 NBER peak.

[9] Note that for neither of peak and trough clusters, is the sum of the fractions of industries necessarily equal to one. This is because (i) some industries do not experience any cyclical turns during the time period spanned by the cluster, and because (ii) some industries experience muliple turns during the same time period.

## 4.2. Test results

To test the statistical significance of the distributional asymmetries between peak and trough clusters, we consider an econometric model of the above histogram bars. Recall that we have collected observations on the fractions of industries (i.e., the height of bars) for each $q$th point in a cluster for each $s$th NBER date, where $q = 1, \ldots, 17$ and $s = 1, \ldots, 12$. We can therefore estimate the following panel data model:

$$\begin{aligned} H_{qs} = {} & (\beta_{P0} + \beta_{P,LD} DLD_{qs} + \beta_{P,CI} DCI_{qs}) \times DP_{qs} \\ & + (\beta_{T0} + \beta_{T,LD} DLD_{qs} + \beta_{T,CI} DCI_{qs}) \times DT_{qs} + u_{qs} \end{aligned} \tag{5}$$

where $H_{qs}$ is the fraction of industries for given $q =$ and $s$; $DP_{qs}$ and $DT_{qs}$ are dummy variables indicating peak and trough clusters, respectively; $DLD_{qs}$ is a dummy variable taking the value of 1 in the left side of clusters, and 0 elsewhere; $DCI_{P,qs}$ is a dummy variable taking the value of 1 at the center of clusters, and 0 elsewhere; $u_{rs}$ is an error term with mean zero and variance to be estimated.

In the above specification, $\beta_{P0}$ and $\beta_{T0}$ capture the mean values of the industry fractions for the right side of peak and trough clusters, respectively. Other coefficients reflect additional fractions in other areas of the clusters. Accordingly, we can evaluate the concentration of peak clusters at the NBER peak date by looking at whether $\beta_{P,CI}$ is different from both zero and $\beta_{P,LD}$. Liwewise, the concentration of trough clusters can be evaluated by testing whether $\beta_{T,CI}$ is different from both zero and $\beta_{T,LD}$. We can also compare the estimates of $\beta_{P,CI}$ and $\beta_{T,CI}$ to test whether peak and trough clusters are equally concentrated. Signs and significances of $\beta_{P,LD}$ and $\beta_{T,LD}$ themselves reflect skewness properties of clusters; Significant positive values of $\beta_{P,LD}$ ($\beta_{T,LD}$) can be interpreted as indicating skewness toward lead for peak (trough) clusters.

The results from the pooled ordinary least squares (OLS) estimation are given in the first column of Table 3.[10] For trough clusters, the estimate of $\beta_{T,CI}$ is significantly positive, large

[10] For any of the cases reported in Table 3, we could not reject the null hypothesis of the absence of random

enough from an economic perspective, and clearly different from $\beta_{T,LD}$, reflecting a sharp spike at the center of trough clusters. The results quite different for peak clusters. Although the estimate of $\beta_{P,CI}$ is also significantly different from zero, it is not significantly distinguishable from $\beta_{P,LD}$. This indicates that the occurrences of industry peaks are distributed evenly between several quarters ending in the NBER peak date and drop down substantially afterwards. That is, there is no sharp spike for peak clusters.

Turning to the skewness properties, $\beta_{P,LD}$ is estimated to be significantly positive, a result consistent with the visual evidence that peak clusters are skewed toward leads. By contrast, $\beta_{T,LD}$ is estimated to be significantly negative, confirming that trough clusters are skewed toward lags.

## 4.3. Robustness

To check robustness, Figure 5 illustrates how different disaggregation levels of industry definition affect the conclusion on the turning points concentration asymmetry. We here break down the manufacturing sector into (i) 21 3-digit industries and (ii) 116 industries whose IP indices are available in the most disaggregated level up to 6-digit.[11] Comparing this figure with Figure 3, which concerned 74 4-digit industries, one can see that the more disaggregated the industry classification, the less profound concentration of industry turning points for both peaks and troughs. This result may reflect that the relative importance of industry specific shocks versus aggregate shocks increases as the industry classification is more disaggregated. Or it may be just an artifact resulting from noise in the highly disaggregated data. In any case, however, what is important from the perspective of this paper is that the concentration asymmetry is evident regardless of the disaggregation level used.

As an another robustness check, we repeated the above dating and clustering analyses us-

effect at conventional significance levels. When the random effect is absent, pooled OLS is known to be efficient and lead to asymptotically valid hypothesis tests.

[11] Among 116 industries we consider, the numbers of 3-, 4-, 5-, and 6-digit industries are 3, 45, 36, and 32, respectively.

ing the detrended IP series from the Hodrick-Prescott filter. Following Kydland and Prescott (1990) and Harvey and Jaeger (1993), we set the relative variance of trend component equal to 0.000625 to apply the Hodrick-Prescott filter to our quarterly time series. The resulting distributions of industry peaks and troughs are displayed in Figure 6. Strikingly, the general shapes of both peak and trough clusters are almost identical with what we have found using level series; troughs are still much more concentrated than peaks. Note that it is very unusual for two business cycle anayses using classical and growth cycles to produce such similar results.

The last three columns of Table 3 reports the results for pooled OLS estimation of equation (5) using the histograms discussed in this subsection. Although the magnitudes of estimates differ across data used, the general conclusion is the same. First, the estimate of $\beta_{T,CI}$ is significantly positive and different from $\beta_{T,LD}$. Meanwhile, the estimate of $\beta_{P,CI}$ is significantly different from zero but not from $\beta_{P,LD}$. Hence the concentration asymmetry in turning points distributions is confirmed once again. Second, the estimate of $\beta_{P,LD}$ is significantly positive for all cases. In contrast, the estimate of $\beta_{T,LD}$ is found to be negative, but not significant in any case. Therefore, the aforenoted skewness properties appear to be robust only for peak clusters.

## 4.4. Leading, Coincident, and Lagging Industries

We believe that the evidence for turning points concentration asymmetry obtained from this study can provide valuable new insights into the analysis of the business cycle. For example, concerning the prediction of business cycle turning points, our results suggest that the lists of leading, coincident, and lagging industries are likely to vary between the business cycle peaks and troughs. More specifically, we can conjecture that the number of industries that portend future changes in the direction of the U.S. business cycle is fewer at the NBER troughs than at the NBER peaks.

To gauge the empirical relevance of this prediction, we classify industries into leading, coincident, lagging, and acyclical groups for each of the NBER peak and trough dates, based on the above clustering analysis. Our classification of industries is straightforward in that for a given peak cluster, for instance, we define leading industries as those whose peaks are marked in the left half of the cluster. Note that this definition restricts the maximum lead time to 8 quarters. Similarly, we define coincident and lagging industries as those whose peaks are marked at the center and in the right half of the cluster, respectively. If an industry does not experience a cyclical peak during the time period spanned by the cluster, we define it as acyclical.[12] Classification of industries for NBER trough dates is performed in a similar way.

Table 3 contains two transition probability matrices, estimated separately over the NBER peak (upper panel) and trough (lower panel) dates. The $ij$ element in each panel indicates the probability of moving from group $i$ to group $j$ between two adjacent NBER peaks or troughs. Note that the diagonal elements represent persistence of a group. Under the null of no persistence, all elements would be equal to 0.25.

Several interesting observations emerge from this table. For the NBER peak dates, we find evidence of strong persistence among leading industries (0.613), but little persistence among coincident (0.089) and lagging (0.107) industries. With respect to the latter, we instead find that the probability of the transition to leading group always exceeds 0.5 whatever the previous group was. On the contrary, for the NBER trough dates, we find that not only the leading group (0.300) but also the coincident (0.336) and lagging groups (0.346) display persistence significantly exceeding 0.25. Another interesting feature is that the transition to the coincident group occurs with the highest probability for industries that have previously preceded or coincided with the NBER trough. For industries having followed the previous NBER trough, the transition to the coincident group comes about with the same (highest)

[12] Note that an industry may experience multiple peaks during the time period spanned by a cluster. In this situation, we consider minimum distance criterion; that is, for instance, if an industry exhibits two peaks, of which one is marked in the left and the other is marked in the right half of the cluster, and if the lead time is shorter than the lag time, then we classify the industry as leading.

probability as the transition to the lagging group.[13] These patterns are consistent with our previous finding of turning points distributions.

Table 4 presents the list of industries that have led, lagged, and coincided with the U.S. business cycle *more than* 50% of cases over the past 6 NBER peak dates. The same list for the NBER trough dates is presented in Table 5.[14] For the NBER peak dates, 30 among 74 industries are defined as leading according to the 50% cutoff rule. By comparison, when the same cutoff rule is used, none is defined as coincident, and only 2 industries are defined as lagging. For the NBER trough dates, the coresponding number of leading industries is reduced to 3, while those of coincident and lagging industres increase to 10 and 12, respectively. Among the 3 leading industries of the NBER troughs, only the sawmills and wood preservation (NAICS=3211) industry leads the NBER peaks as well more than 50% of cases. Therefore, the lists of leading, coincident, and lagging industries are also asymmetric over the business cycle turning points.

## 4.5. On Relation to Sharpness Asymmetry

As mentioned in the introduction, our finding of higher concentration of troughs (upturns) is in contrast with the conventional notion of a 'sudden stop and slow recovery' dating back at least to Keynes (1936). Instead it is in support of the characterization of turning point asymmetry by 'sharp' troughs and 'round' peaks, as documented in McQueen and Thorley (1993).[15] These authors, however, paid attention only to the movements in the aggregate IP index. Our contribution in this context is to demonstrate that sharpness asymmetry at the aggregate level comes from two sources: sharpness asymmetry inherent at the individual industry level and the composition effect due to the concentration asymmetry.

[13] Only for the industries that have been acyclical to the previous NBER trough, the transition to the leading group takes place with the highest probability.

[14] It is important to note that the classification of industries conducted in Table 4 and 5 is just for giving insight, and not based on rigorous statistical tests; see Diebold and Rudebusch (1989) for the tests of predictive ability between binary indicators.

[15] Hicks (1950) also noted that "falls in output do not induce disinvestment in the same way as rises in output induce investment. There is a marked lack of symmetry (p. 101)."

To gain insight, let us suppose as an extreme example that for each group of industries, curvatures of IP indices are the same between the NBER peaks and troughs. However, according to the dating algorithm we use, the curvatures for coincident industries tend to be sharper than those for other industries at both the NBER peaks and troughs. As a result, if the fractions of coincident industries are higher at the NBER troughs than at the NBER peaks (as we found), then sharpness asymmetry may arise at the aggregate level even if there is no sharpness asymmetry at the individual group level.

Table 5 compares the degrees of sharpness asymmetry between coincident and other industries. Following McQueen and Thorley (1993), we measure the sharpness of IP changes by the mean absolute difference between changes in the log IP during the two quarters ending in the NBER turning points and those during the following two quarters. Sharpness asymmetry is then measured by the difference in sharpness between the NBER troughs and peaks.

The results contained in Table 5 support the notion of sharpness asymmetry at the aggregate level; the mean sharpness for whole manufacturing is 0.062 at the NBER peaks and 0.126 at the NBER troughs, suggesting that the curvature of the aggregate IP index is on average twice sharper at the NBER troughs than at the NBER peaks. The results also clearly confirm that coincident industries tend to exhibit sharper changes than other industries, at both NBER peaks and troughs. As the lower panel of the table shows, even if we look at the results for leading, coincident, and acyclical industries, separately, this conclusion does not change. Another noticeable feature is that sharpness asymmetry is still evident among the individual groups of industries. Indeed all groups except for acyclical industries exhibit significant sharpness asymmetry, and the most profound asymmetry is found in coincident industries. Therefore, with respect to the emergence of sharpness asymmetry at the aggregate level, the effects from the above-mentioned two sources appear to operate in the same direction.

To evaluate quantitatively the relative contributions of two effects, we decompose sharpness asymmetry at the aggregate level as:

$$S_T - S_P = \underbrace{\sum_{g=1}^{2}(w_{g,T} - w_{g,P}) \times \frac{1}{2}(S_{g,P} + S_{g,T})}_{\text{Composition effect}} + \underbrace{\sum_{g=1}^{2}(S_{g,T} - S_{g,P}) \times \frac{1}{2}(w_{g,P} + w_{g,T})}_{\text{Individual asymmetry}} \tag{6}$$

where the subscript $g$ distinguishes coincident industries ($g = 1$) from other groups ($g = 2$), $P$ and $T$ indicate that the statistics are constructed at the NBER peaks and troughs, respectively, $w$ denotes the fraction of industries belonging to each group, and $S$ denotes the sharpness for each group at the NBER turning point dates.

Table 7 reports each term from this decomposition estimated separately for each of the past NBER recessions. According to this table, it is the individual-group-level characteristic that accounts for the lion's share of sharpness asymmetry observed at the aggregate level. However, the concentration asymmetry also plays a significant role. It accounts for, on average, 24.3% of the aggregate-level sharpness asymmetry. Its minimum share of explanation is 9.2% for the 1981-82 recession, and the maximum is 74.6% for the 2001 recession.

# 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.

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

$$\Pr(D_{it}^P = 1 \mid x_{it}^P, \alpha_i^P) = \Gamma(X_{it}^{P\prime}\beta^P + \alpha_i^P), \tag{7}$$

- Trough equation

$$\Pr(D_{it}^T = 1 \mid x_{it}^T, \alpha_i^T) = \Gamma(X_{it}^{T\prime}\beta^T + \alpha_i^T), \tag{8}$$

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, $\beta$ is the vector of coefficients, and $\alpha_i$ is the unobserved industry-specific effect. We also allow for the unobserved individual effect $\alpha_i$ 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:

$$
\begin{aligned}
Z_{it-1} &= \sum_{j \neq i} w_{ij} D^P_{jt-1}, \quad \text{in peak equation,} \\
&= \sum_{j \neq i} w_{ij} D^T_{jt-1}, \quad \text{in trough equation}
\end{aligned}
\tag{9}
$$

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.[16]

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,

[16] 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 8 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 9 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 8 and 9, 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.[17] 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.

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

# 6. Summary

The comovement 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 that will help us to better understand the nature of business cycles. First, manufacturing industries on average have experienced more cycles than the U.S. aggregate economy. Asymmetries in durations between expansion and contraction phases are much weaker at the industry-level than at the aggregate level. The average duration of expansions is only twice that of recessions. We also find significant heterogeneity across industries for the durations of complete cycles and for the degrees of the duration asymmetries. Second, despite this heterogeneity, comovement across industries appears to be a salient feature of manufacturing business cycles. Third 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 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.

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Table 1. Numbers and Durations of Industry Cycles, 1972:Q1-2010:Q2

| | No. of cycles | Duration: Complete cycle | Duration: Expansion (A) | Duration: Contraction (B) | Duration: Duration asymmetry (A/B) |
|---|---|---|---|---|---|
| NBER cycle | 5.0 | 27.4 | 23.8 | 3.8 | 6.2 |
| Industry cycles | | | | | |
| Mean | 10.3 | 14.2 | 8.7 | 5.3 | 1.8 |
| Median | 10.0 | 13.5 | 7.6 | 5.1 | 1.5 |
| Max | 16.0 | 34.0 | 31.3 | 8.9 | 10.4 |
| Min | 4.0 | 8.3 | 3.8 | 2.6 | 0.5 |
| Std. | 2.5 | 4.5 | 4.3 | 1.3 | 1.5 |

*Note*: All the numbers and durations of complete cycles are measured from trough to trough. The summary statistics for durations of industry cycles and phases are based on the average length of corresponding measures for each industry.

Table 2. Concordance Indices

| | Pairwise | NBER |
|---|---|---|
| Mean | 0.607 | 0.674 |
| Median | 0.604 | 0.669 |
| Max | 0.864 | 0.883 |
| Min | 0.344 | 0.455 |
| Std. | 0.080 | 0.082 |

*Note*: 'Pairwise' signifies that the indices are constructed from each pair of industry cycles. 'NBER' denotes that the indices are constructed between each of industry cycles and the business cycles defined by the NBER.

Table 3. Tests for Concentration Asymmetry

| | IP in levels | | | Detrended IP |
|---|---|---|---|---|
| | 4-digit | 3-digit | 6-digit | 4-digit |
| $\beta_{P0}$ | 0.049** | 0.043** | 0.060** | 0.060** |
| | (0.009) | (0.012) | (0.008) | (0.010) |
| $\beta_{P,LD}$ | 0.052** | 0.057** | 0.036** | 0.050** |
| | (0.013) | (0.019) | (0.011) | (0.013) |
| $\beta_{P,CI}$ | 0.093** | 0.116** | 0.058** | 0.086* |
| | (0.025) | (0.044) | (0.019) | (0.034) |
| $\beta_{T0}$ | 0.076** | 0.074** | 0.079** | 0.085** |
| | (0.013) | (0.017) | (0.010) | (0.013) |
| $\beta_{T,LD}$ | -0.030* | -0.037 | -0.017 | -0.029 |
| | (0.014) | (0.019) | (0.013) | (0.015) |
| $\beta_{T,CI}$ | 0.257** | 0.378** | 0.197** | 0.274** |
| | (0.026) | (0.036) | (0.017) | (0.025) |
| R2 adjusted | 0.440 | 0.445 | 0.353 | 0.426 |
| Hypothesis tests | | | | |
| $\beta_{P,CI} = \beta_{P,LD}$ | 2.642 | 1.722 | 1.356 | 1.171 |
| $\beta_{T,CI} = \beta_{T,LD}$ | 142.037** | 159.412** | 189.115** | 170.480** |
| $\beta_{P,CI} = \beta_{T,CI}$ | 20.457** | 21.369** | 29.152** | 19.875** |

*Note*: **and *indicate significance at the 1% and 5%, respectively. The numbers in parentheses under coefficients are heteroskedasticity-robust standard errors.

Table 4. Transition Probability Matrix

| | Leading | Coincident | Lagging | Acyclical |
|---|---|---|---|---|
| (A) Peaks | | | | |
| Leading | 0.613 | 0.131 | 0.157 | 0.100 |
| Coincident | 0.554 | 0.089 | 0.179 | 0.179 |
| Lagging | 0.547 | 0.187 | 0.107 | 0.160 |
| Acyclical | 0.500 | 0.167 | 0.146 | 0.188 |
| (B) Troughs | | | | |
| Leading | 0.300 | 0.338 | 0.263 | 0.100 |
| Coincident | 0.256 | 0.336 | 0.296 | 0.112 |
| Lagging | 0.185 | 0.346 | 0.346 | 0.123 |
| Acyclical | 0.371 | 0.171 | 0.286 | 0.171 |

*Note*: The $ij$ element in this table indicates the probability of moving from group $i$ at the previous NBER peak (trough) to group $j$ at the current NBER peak (trough).

Table 5. Leading, Coincident, and Lagging Industries at the NBER Peak Dates

| Code | Dur. | Title | Prob. | Leads (-) or lags (+) | |
|---|---|---|---|---|---|
| | | | | Mean | Std. |
| *Leading industries* | | | | | |
| 3322 | D | Cutlery and handtool | 1.00 | -3.00 | 1.41 |
| 3361 | D | Motor vehicle | 1.00 | -3.00 | 1.79 |
| 3371 | D | Furniture and kitchen cabinet | 1.00 | -1.83 | 1.17 |
| 3325 | D | Hardware | 0.83 | -4.40 | 2.07 |
| 3362 | D | Motor vehicle body and trailer | 0.83 | -4.40 | 2.70 |
| 3255 | ND | Paint, coating, and adhesive | 0.83 | -3.80 | 2.68 |
| 3212 | D | Veneer, plywood, and engineered wood product | 0.83 | -3.60 | 2.07 |
| 3219 | D | Other wood product | 0.83 | -3.40 | 1.95 |
| 3221 | ND | Pulp, paper, and paperboard mills | 0.83 | -3.40 | 2.30 |
| 3352 | D | Household appliance | 0.83 | -3.00 | 2.35 |
| 3274 | D | Lime and gypsum product | 0.83 | -3.00 | 2.92 |
| 3252 | ND | Resin, synth. rubber, fibers, and filaments | 0.83 | -2.80 | 1.64 |
| 3253 | ND | Pestic., fertil., and agric. chemical | 0.83 | -2.60 | 2.07 |
| 3351 | D | Electric lighting equipment | 0.83 | -2.40 | 1.34 |
| 3372A9 | D | Office and other furniture | 0.83 | -2.20 | 1.30 |
| 3315 | D | Foundries | 0.67 | -4.75 | 2.87 |
| 3211 | D | Sawmills and wood preservation | 0.67 | -4.50 | 2.08 |
| 3363 | D | Motor vehicle parts | 0.67 | -4.50 | 2.08 |
| 3122 | ND | Tobacco | 0.67 | -4.25 | 3.77 |
| 3334 | D | Ventilat., heat., air-cond., and refrig. equip. | 0.67 | -4.00 | 2.16 |
| 3149 | ND | Other textile product mills | 0.67 | -4.00 | 2.45 |
| 3118 | ND | Bakeries and tortilla | 0.67 | -4.00 | 2.94 |
| 3133 | ND | Textile and fabr. finishing and fabr. coating mills | 0.67 | -3.75 | 1.26 |
| 3343 | D | Audio and video equipment | 0.67 | -3.75 | 1.71 |
| 3131 | ND | Fiber, yarn, and thread mills | 0.67 | -3.75 | 2.36 |
| 3353 | D | Electrical equipment | 0.67 | -3.75 | 2.36 |
| 3273 | D | Cement and concrete product | 0.67 | -3.25 | 1.50 |
| 3329 | D | Other fabricated metal product | 0.67 | -3.25 | 3.30 |
| 3279 | D | Other nonmetallic mineral product | 0.67 | -3.00 | 2.12 |
| 3141 | ND | Textile furnishings mills | 0.67 | -2.25 | 0.50 |
| *Lagging industries* | | | | | |
| 3113 | ND | Sugar and confectionery product | 0.67 | 1.50 | 1.00 |
| 3345 | D | Navig., measur., electromed., and contr. instr. | 0.67 | 2.50 | 1.29 |

*Note*: In the column 'Dur. (Durability)', 'D' and 'ND' stand for durables and nondurables, respectively. 'Prob.' denotes the unconditional probability of being included in the specified group at a NBER peak date, which is equal to the sample proportion. 'Mean' and 'Std.' are the conditional mean and standard deviation of leads or lags at the NBER peak dates, given that the industry belongs to the specified group.

Table 6. Leading, Coincident, and Lagging Industries at the NBER Trough Dates

| Code | Dur. | Title | Prob. | Leads (-) or lags (+) | |
|---|---|---|---|---|---|
| | | | | Mean | Std. |
| *Leading industries* | | | | | |
| 3391 | D | Medical equipment and supplies | 0.67 | -3.50 | 3.32 |
| 3113 | ND | Sugar and confectionery product | 0.67 | -3.20 | 2.28 |
| 3211 | D | Sawmills and wood preservation | 0.67 | -3.00 | 2.45 |
| *Coincident industries* | | | | | |
| 3149 | ND | Other textile product mills | 0.83 | 0.00 | 0.00 |
| 3325 | D | Hardware | 0.83 | 0.00 | 0.00 |
| 3311A2 | D | Iron and steel products | 0.83 | 0.00 | 0.00 |
| 3132 | ND | Fabric mills | 0.67 | 0.00 | 0.00 |
| 3133 | ND | Textile and fabr. finishing and fabr. coating mills | 0.67 | 0.00 | 0.00 |
| 3327 | D | Machine shop; screw, nut, and bolt | 0.67 | 0.00 | 0.00 |
| 3371 | D | Furniture and kitchen cabinet | 0.67 | 0.00 | 0.00 |
| 3261 | ND | Plastics product | 0.67 | 0.00 | 0.00 |
| 3272 | D | Glass and glass product | 0.67 | 0.00 | 0.00 |
| 3315 | D | Foundries | 0.67 | 0.00 | 0.00 |
| *Lagging industries* | | | | | |
| 3333A9 | D | Commercial and service industry machinery | 0.83 | 1.80 | 1.30 |
| 3336 | D | Engine, turbine, and power trans. equipment | 0.83 | 2.40 | 2.61 |
| 3118 | ND | Bakeries and tortilla | 0.83 | 2.40 | 2.61 |
| 3353 | D | Electrical equipment | 0.83 | 2.80 | 2.39 |
| 3256 | ND | Soap, cleaning compound, and toilet preparation | 0.83 | 3.00 | 2.55 |
| 3345 | D | Navig., measur., electromed., and contr. instr. | 0.67 | 2.25 | 1.50 |
| 3321 | D | Forging and stamping | 0.67 | 2.75 | 0.96 |
| 3331 | D | Agriculture, construction, and mining machinery | 0.67 | 2.75 | 2.06 |
| 3122 | ND | Tobacco | 0.67 | 3.00 | 1.41 |
| 3111 | ND | Animal food | 0.67 | 3.00 | 1.41 |
| 3335 | D | Metalworking machinery | 0.67 | 3.20 | 2.77 |
| 3365 | D | Railroad rolling stock | 0.67 | 4.50 | 2.38 |

*Note*: See footnote of Table 4.

Table 7. Sharpness Asymmetry for Each Group of Industries

| | Peaks | | | Troughs | | | Sharpness asymmetry |
|---|---|---|---|---|---|---|---|
| | $D_{P,-2}$ | $D_{P,+2}$ | $S_P$ | $D_{T,-2}$ | $D_{T,+2}$ | $S_T$ | $(S_T - S_P)$ |
| Total | -0.003 | -0.046 | 0.062 | -0.077 | 0.038 | 0.126 | 0.065** |
| Coincident | 0.034 | -0.063 | 0.097 | -0.120 | 0.089 | 0.209 | 0.112** |
| Others | -0.009 | -0.043 | 0.056 | -0.056 | 0.012 | 0.085 | 0.029** |
| Leading | -0.029 | -0.068 | 0.059 | -0.020 | 0.055 | 0.096 | 0.037** |
| Lagging | 0.034 | 0.013 | 0.049 | -0.083 | -0.018 | 0.083 | 0.035** |
| Acyclical | 0.003 | -0.031 | 0.056 | -0.035 | 0.024 | 0.070 | 0.013 |

*Note*: For peaks, $D_{P,-2}$ and $D_{P,+2}$ indicate the mean changes in the log IP during the two quarters ending in the NBER peak dates and those during the following two quarters. $S_P$ measures the mean sharpness of the log IP at the NBER peak date, which is defined as the absolute difference between $D_{P,-2}$ and $D_{P,+2}$. For troughs, $D_{T,-2}$, $D_{T,+2}$, and $S_T$ can be defined in a similar way. Sharpness asymmetry is measured by the difference between $S_T$ and $S_P$. $^{**}$and $^{*}$indicate that the Welch $t$-test rejects the null of no sharpness asymmetry at the 1% and 5% level, respectively.

Table 8. Decomposition of Sharpness Asymmetry

| | Sharpness asymmetry | | | | |
|---|---|---|---|---|---|
| NBER recessions | $S_T - S_P$ | Composition effect (%) | | Individual asymmetry (%) | |
| 1973-75 | 0.151 | 0.030 | (19.5) | 0.122 | (80.5) |
| 1980 | 0.045 | 0.010 | (22.5) | 0.035 | (77.5) |
| 1981-82 | 0.028 | 0.003 | (9.2) | 0.026 | (90.8) |
| 1990-91 | 0.029 | 0.014 | (48.5) | 0.015 | (51.5) |
| 2001 | 0.022 | 0.017 | (74.6) | 0.006 | (25.4) |
| 2007-09 | 0.112 | 0.022 | (19.3) | 0.090 | (80.7) |
| Mean | 0.065 | 0.016 | (24.3) | 0.049 | (75.7) |

*Note*: The second column shows sharpness asymmetry at the aggregate level, estimated for each NBER recession. 'Composition effect' corresponds to the sharpness asymmetry due to changes in the fraction of coincident and other industries. 'Micro asymmetry' corresponds to the sharpness asymmetry attributed to the changes in sharpness for each group of industries between NBER troughs and peaks. The values in parenthesis are the share of sharpness asymmetry (in percentage terms) explained by each source.

TABLE 9. 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 | |

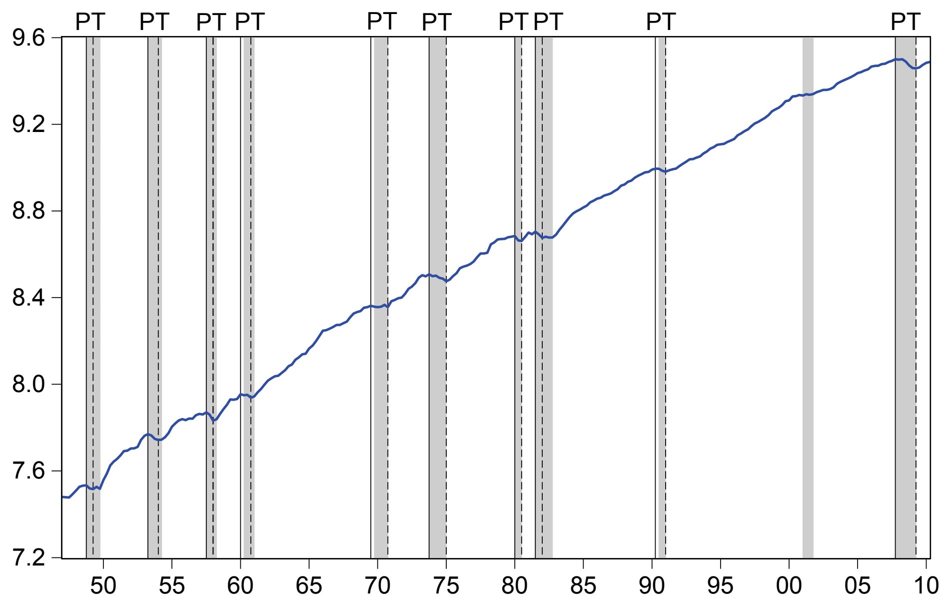
*Notes*: **, *, and indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in parentheses are standard errors.

Table 10. 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% and 5% level, respectively. The numbers in parentheses are standard errors.

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




*Note*: 'P' and 'T' correspond to the peaks and troughs identified by the Harding-Pagan method applied to the log level of U.S. real GDP. The shaded areas are recession periods established by the NBER.

FIGURE 2. DIFFUSION INDICES FOR CYCLICAL PHASES

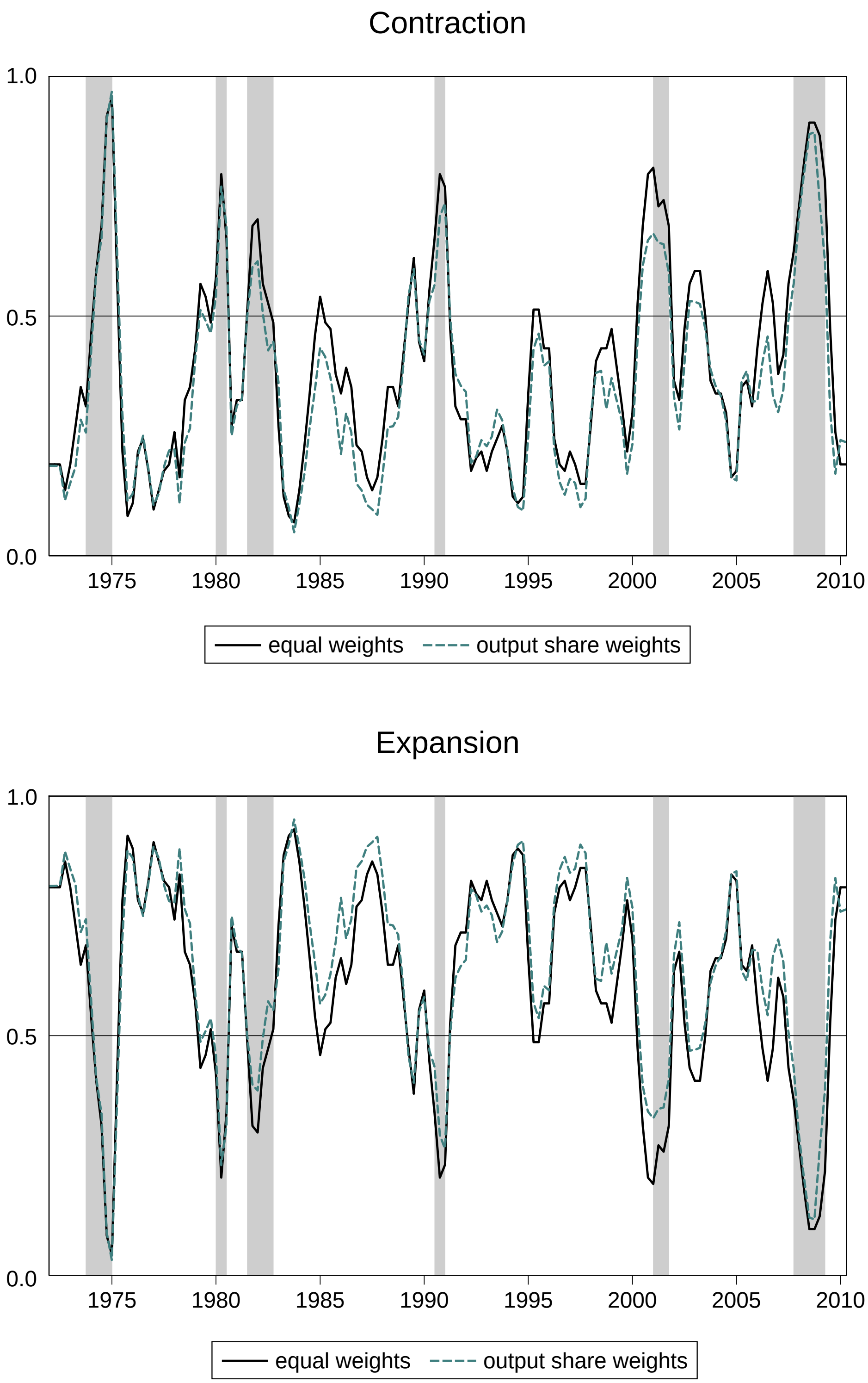


Figure 3. Distributions of Industry Turning Points, 1972:Q1-2010:Q2

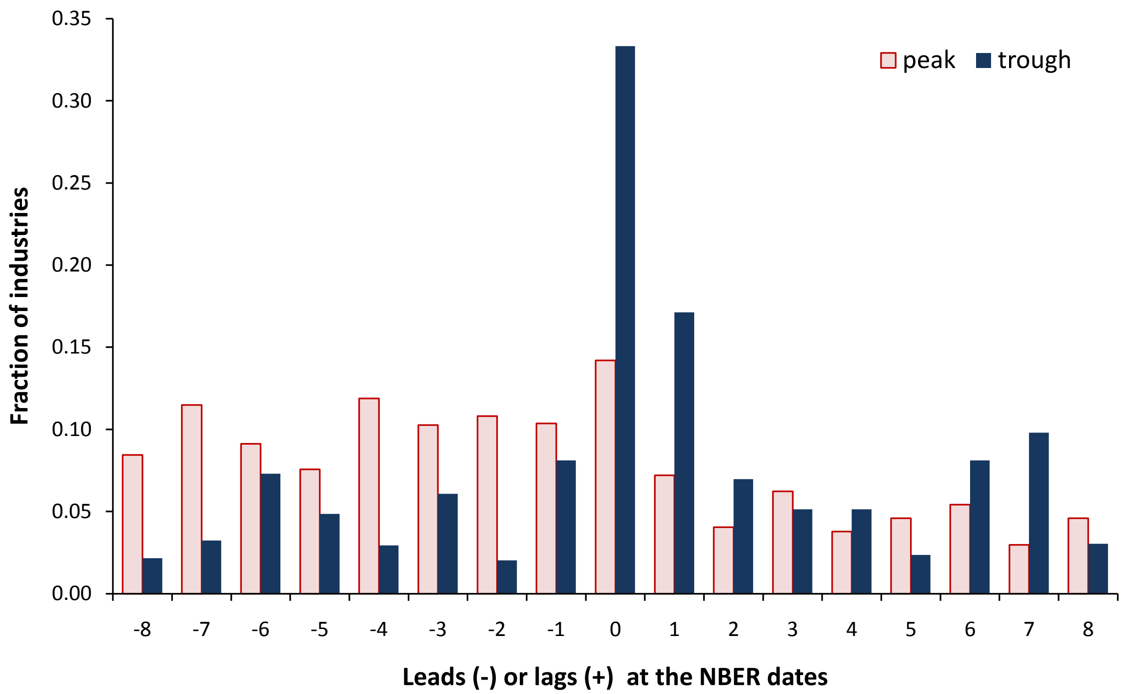


Figure 4. Distributions of Industry Turning Points for Each NBER Recession

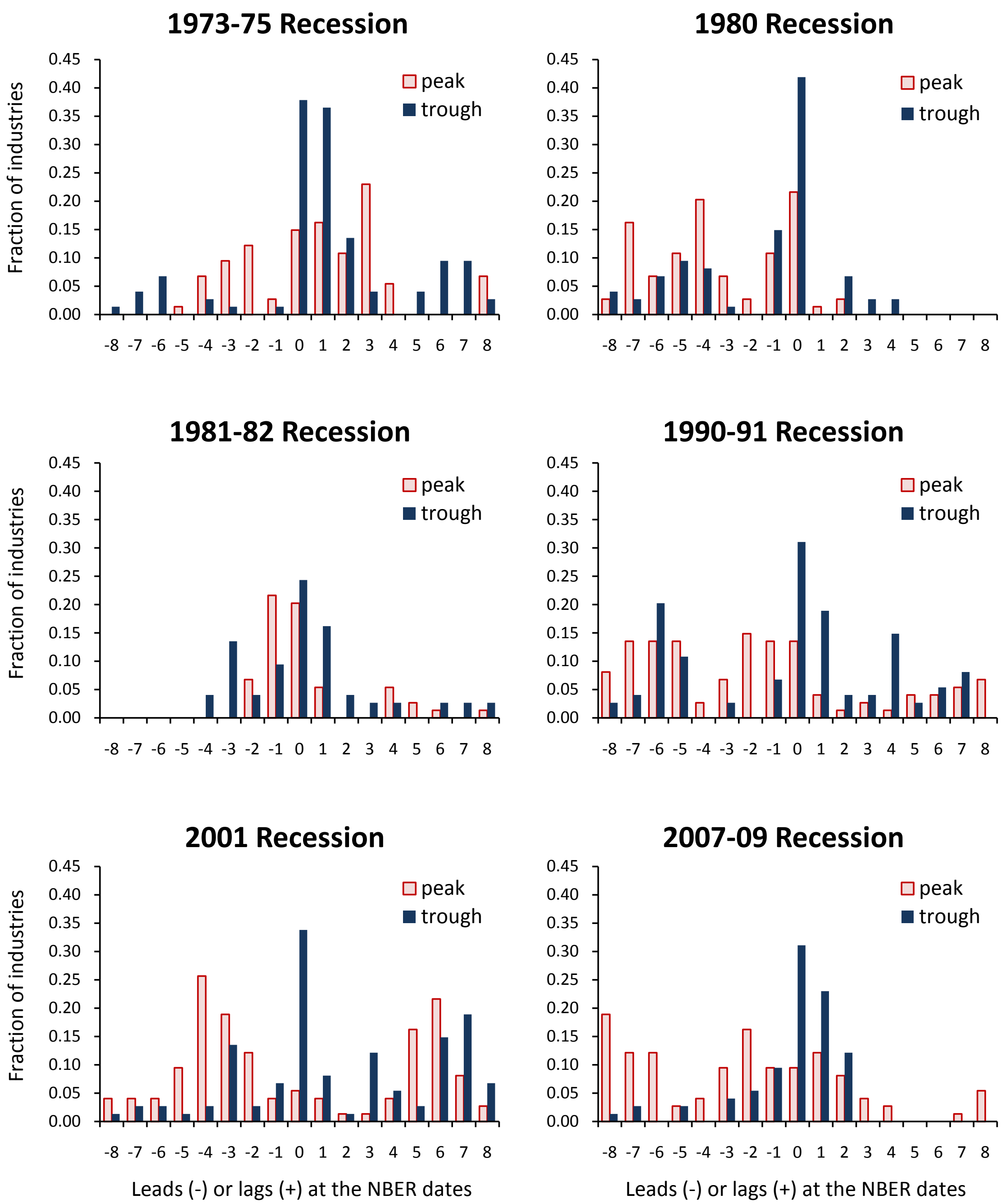


Figure 5. Distributions of Industry Turning Points: 3- and 6-digit NAICS

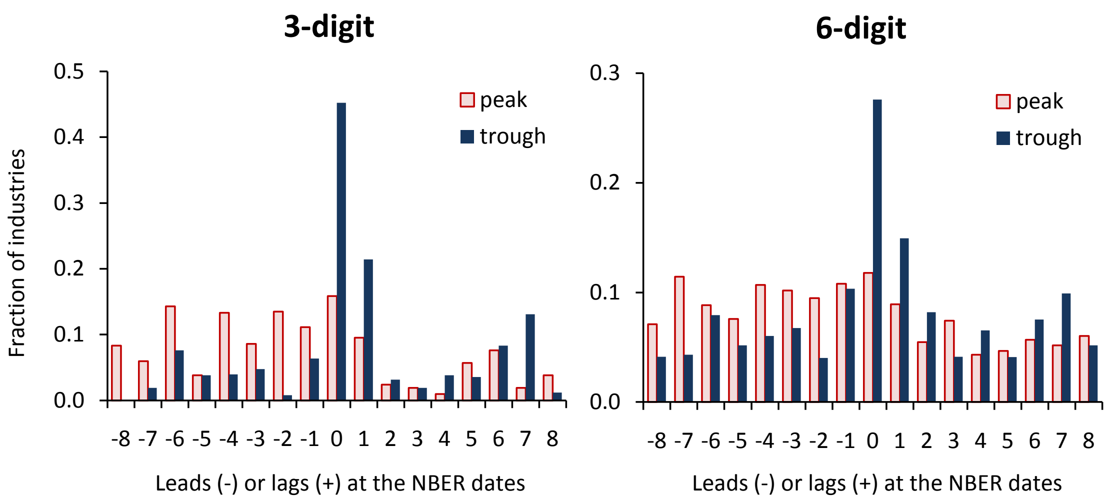



Figure 6. Distributions of Industry Turning Points: Detrended IP Series