Asymmetric Phase Shifts in the U.S. Industrial Production Cycles

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Abstract

We identify the cyclical turning points of 74 U.S. manufacturing industries and uncover new empirical regularities: (i) Cyclical phase shifts are highly concentrated around the aggregate turning points; (ii) In contrast to the conventional notion of a 'sudden stop and slow recovery,' troughs are much more concentrated than peaks; (iii) Occurrences of phase shifts across industries support the spillovers through input-output linkages; (iv) The common macroeconomic shocks, such as exogenous changes in the federal funds rate, government spending, and oil prices, are significant drivers of industrial phase shifts; (v) Both monetary and fiscal policy shocks are more effective in recessions.

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 business cycle is a salient feature of market economies (Burns and Mitchell, 1946; Lucas, 1977). The empirical pattern of industrial comovement is of profound importance because it forms the basis for modern (one- or multi-sector) business cycle models. While there has been a great deal of empirical work on such comovement, most existing studies have focused on just correlation coefficients.[1] In contrast, relatively little is known about the comovement of phase shifts across industries, while the concentration of cyclical phases is a cornerstone of the classical definition of the cyclical comovement, suggested by Burns and Mitchell (1946, p. 70):

> 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.

The objective of this article is to examine the patterns and sources of the comovement of phase shifts across industries. The timing of turning points (rather than correlations) is of great interest to policy makers, financial analysts, as well as individual investors. The new empirical regularities that we uncover will help us to better understand the sources and propagation of aggregate business cycles. We find the following: (i) Cyclical phases are highly concentrated around the aggregate business cycle; (ii) The distribution of industry troughs (upturns) is much more concentrated than that of industry peaks (downturns); (iii) Occurrences of phase shifts across industries strongly support the spillovers through input-output linkages, a core aspect of multi-sector models; (iv) The standard common macroeconomic shocks, such as exogenous changes in the federal funds rate, government

[1] For the correlations between industrial growth rates, see Murphy, Shleifer and Vishny (1989), Long and Plosser (1987), Shea (2002), Conley and Dupor (2003), and Foerster, Sarte and Watson (2011). For the correlations between detrended industrial variables, see Cooper and Haltiwanger (1990), Christiano and Fitzgerald (1998), Hornstein (2000), Horvath (2000), Kim and Kim (2006), and Veldkamp and Wolfers (2007).

spending, and oil prices, are all significant drivers of phase shifts at the industry level; (v) Both monetary and fiscal policy shocks are more effective in recessions.

We first identify industrial turning points using a nonparametric dating algorithm proposed by Harding and Pagan (2002), which is applied to quarterly production indices for 74 U.S. manufacturing industries. The diffusion and concordance analyses then indicate a strong comovement of phase shifts across industries. But more interesting from our point of view is the asymmetric concentration of clusters between industry peaks and troughs: industry troughs are much more concentrated than industry peaks. This result is robust to various treatments of the data. Our finding of a higher concentration of troughs is in contrast to 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." Our result is instead consistent with 'sharp' troughs and 'round' peaks, as documented by McQueen and Thorley (1993).

We then proceed by investigating the determinants of the industry comovement of phase shifts. We consider two groups of explanatory variables that economic theories suggest are important: spillovers from input-output linkages and common macroeconomic shocks.[2] We distinguish upstream (demand-side) and downstream (supply-side) spillover effects, both of which are measured based on the input-output matrix. A novelty of our approach is that a spillover effect is identified by the change in the probability of an industry experiencing a phase shift resulting from past phase shifts in its neighbor industries.[3] Three macroeconomic shocks considered are (i) Romer and Romer's (2004) indicator of monetary policy shocks, (ii) Ramey's (2011) measure of government spending shocks, and (iii) Hamilton's (2003)

[2]See Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (2000), and Carvalho (2010) for a discussion justifying the role of input-output linkages and Lucas (1977) and Dupor (1999) for a discussion of the importance of aggregate shocks.

[3]Although this approach is new in the industry comovement literature, similar approaches are frequently used in literatures on infectious disease epidemiology (e.g., Padian et al., 1997), financial crisis contagion (e.g., Eichengreen, Rose and Wyplosz, 1996), and knowledge and technology spillovers (e.g., Goolsbee and Klenow, 2002).

oil price shocks. According to our panel data probit estimation, all of these two groups of explanatory variables have a statistically significant effect on the occurrences of industry phase shifts, confirming our economic priors. In addition, both monetary and government spending shocks are shown to have a much greater effect in recessions than in expansions.

Our work contributes to various bodies of literature in the following ways. First, we provide a new empirical characterization of industry comovement. Compared to previous studies focusing only on the correlation coefficient between industries, we provide a more comprehensive picture about the dynamics of industry comovement by demonstrating how the concentration of cyclical phases changes over the course of business cycles.

Second, among previous empirical studies on the determinants of industry comovement, the closest to our work are Bartelsman, Caballero and Lyons (1994), Shea (2002), and Holly and Petrella (forthcoming). While these papers have focused on to what extent the growth rates of industrial variables are affected by changes in the sources of comovement—namely, aggregate shocks and spillovers from input-output linkages, our emphasis is instead on the dynamic responses of the probabilities of industry phase shifts.

Third, our work complements recent studies that find stronger output effects of monetary and fiscal policies in recessions; Weise (1999), Lo and Piger (2005), and Peersman and Smets (2005) for monetary policy, and Christiano, Eichenbaum and Rebelo (2009), Auerbach and Gorodnichenko (forthcoming), Bachmann and Sims (2011), and Woodford (2011) for fiscal policy. While the general message of our analysis are in line with these studies, we find such asymmetric policy effects with respect to phase shifts at the industry level.

Fourth, we offer a new dimension to the analysis of business cycle asymmetries. Traditionally, studies of business cycle asymmetry have been concentrated on the first-moment properties of the fluctuations in aggregate economic activity. Typical examples are the asymmetries associated with durations and steepness of business cycle expansions and contractions.[4] More recently, increasing attention has been paid to the cyclical properties of

[4]See Morley (2009) for an extensive summary.

the cross-sectional dispersion in firm- or industry-level growth rates; e.g., Higson, Holly and Kattuman (2002), Eisfeldt and Rampini (2006), Bachmann and Bayer (2009), Bloom, Floetotto and Jaimovich (2010), and Kehrig (2011). Relative to these papers, we focus on the asymmetric concentration of industry turning points between national peaks and troughs.

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 of conformity analysis. Empirical results for the asymmetric concentration of industry turning points are given in Section 4. In Section 5 we carry out a panel probit analysis to investigate the determinants of inter-industry comovement. Section 6 is the conclusion.

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 advantages. First, it does not require a particular definition of trend components from the raw series, avoiding potential problems inherent in de-trending methods.[5] 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., King and Plosser, 1994; Watson, 1994; Hess and Iwata, 1997; Harding and Pagan, 2002). One of the (potential) shortcomings is that it may fail to detect a turning point in a series with a strong upward or downward trend. Hence, we will check the robustness of our results by considering detrended data from the Hodrick and Prescott (1997) filter where appropriate.

[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.

The implementation of Harding and Pagan (2002), which is a quarterly variant of the Bry and 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 its two preceding and two succeeding observations.

2. Check whether these peaks and troughs satisfy the predetermined 'censoring rules' as described below.

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.[6]

We use disaggregated industrial production (IP) data extracted from the Board of Governors of the Federal Reserve System. The data are quarterly and seasonally adjusted and run from 1972:Q1 through 2010:Q2. 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).[7]

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 period 1947:Q1–2010:Q2. The Harding-Pagan algorithm identifies 10 of the 11 NBER recessions during this period. The only one that the Harding-Pagan algorithm misses is the 2001 recession, which was a very mild one. Furthermore, in most cases, the two business cycle dates are very close to each other. For instance, for the most recent 2007–09

[6]The minimum duration requirement for a phase also prevents a turning point from occurring in the first and last two quarters of the sample.

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

recession, the Harding-Pagan algorithm selects the exact same peak and trough dates as those identified by the NBER.[8]

2.2. Frequencies and Durations of Industry Cycles

Table 1 reports the summary statistics for frequencies and durations of industry cycles identified by the Harding-Pagan algorithm applied to quarterly log IP indices. For comparison, we include the corresponding statistics for the aggregate business cycle based on the NBER dates. The number and duration 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 of 1972:Q1–2010: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 manufacturing 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.

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 industry (NAICS 3341), while it drops to 8.3 quarters in the other transportation equipment industry (NAICS 3369). The semiconductor and other electronic components industry (NAICS 3344) 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 industry (NAICS 315). The cross-sectional differences

[8] Despite this similarity, it is important to note that the NBER's Business Cycle Dating Committee indeed has no fixed rule to determine turning point dates in U.S. economic activity. A detailed description of the NBER's business cycle dating procedure is available at `www.nber.org/cycles/recessions.html`.

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 industry (NAICS 3344), while it is just one-half of that of recessions for the apparel industry (NAICS 315).

3. Comovement: Diffusion and Concordance

In spite of the large cross-sectional differences in the duration properties, phase shifts tend to coincide across industries. To quantify the degree of concentration of cyclical phases we adopt two measures of comovement: diffusion and concordance indices.

The diffusion index measures *the fraction of industries* sharing the same phase at a given point in time. For the case of contractions, it is computed as

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

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

The upper and lower panels of Figure 2 display the diffusion indices for contraction and expansion phases, respectively. 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 fraction of industries in contraction is 73.1% for the NBER recessions and 33.6% for the NBER expansions when equal 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 the beginning of the NBER recessions. The average fraction of industries undergoing an expansion is 66.4% for the NBER expansions and 26.9% for the NBER recessions when equal weights are used. Note that the choice between the two weighting methods does not substantially affect these patterns.

The two NBER recessions in 1973–75 and 2007–09 deserve special attention, since the diffusion index for contraction rises to nearly 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.

Our second measure of comovement, the concordance index, measures *the fraction of time* that two cycles are in the same phase over the sample period. This index can be used in two different ways. First, the degree of pairwise concordance between industries is measured by

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

where S_{it} and S_{jt} are binary variables indicating contractions of industry i and j, respectively. Similarly, the concordance of industries with the aggregate U.S. economy is measured by

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

where $S_{US,t}$ is a dummy variable indicating the NBER recession dates.

Table 2 reports the summary statistics for the concordance indices computed over (i) all the 2,701 ($74 \times 73/2$) pairwise combinations of industries (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 across industries. The pairwise concordance indices range from 0.344 to 0.864, with a mean of 0.607, suggesting that a randomly chosen pair of industries are in the same cyclical phase about 60.7% of the time. The degree of concordance between individual industries and the aggregate U.S. economy is on average 0.674.[9] Taken jointly, the patterns of the two measures constructed in this section clearly confirm that comovement across industries is a salient feature of U.S. business cycles.

4. Distribution of Turning Points

4.1. 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 given NBER turning points are less than a predetermined bound (for example, 8 quarters). Formally, the cluster is defined as follows. Let τ_{ij}^P be the jth peak of industry i and m_k be the kth peak in the U.S. business cycles identified by the NBER. Then, the kth peak cluster centered around m_k is[10]

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

where $d(\cdot)$ is a measure of distance and $\bar{d}$ is a predetermined cluster bound. Following Harding and Pagan (2006), we choose $\bar{d} = 8$ for our quarterly data. Clusters of industry

[9] The concordance index has a shortcoming in that it is positively affected by the expected values of the phase indicators. To address this problem, we checked our results using the mean-corrected correlation index proposed by Harding and Pagan (2006). The results also indicated that most industries are positively synchronized with other industries, as well as with the aggregate economy. The results are available upon request.

[10] This definition is based on Harding and Pagan (2006). The major difference between their work and ours 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.

troughs are defined in a similar fashion.[11]

Figure 3 displays histograms of peak and trough clusters. 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. Second, peak clusters are skewed toward leads, whereas trough clusters tend to be skewed to lags. 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%.[12] According to the Kolmogorov-Smirnov test using exact p values (Higgins, 2004), the null hypothesis of equal distribution between the peak and trough clusters is rejected at the 1% level.[13]

These asymmetric patterns of peak and trough distributions have emerged consistently over the last 6 NBER recessions. As Figure 4 shows, the fraction of coincident industries has almost always been more than twice as large at the NBER trough dates than at the NBER peak dates. One exception was the 1981–82 recession, for which this ratio is reduced

[11] 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 2009 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.

[12] Note that for neither the peak nor the 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.

[13] We adopt the randomized permutation test for exact inference, since our data on lead and lag times are discretely recorded on a quarterly basis.

to 1.2. The maximum ratio was 6.25 for the 2001 recession, and for the most recent 2007–09 recession, this ratio was 3.29. With respect to the skewness properties, industry peaks have always been skewed toward leads except for the 1973 NBER peak. Industry troughs have been skewed toward lags except for the 1980 trough.

To check the robustness of asymmetric distribution of peaks and troughs, we use different level of aggregation in Figure 5. We 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 the 6-digit level.[14] In any case, the asymmetric shape of the distribution is very similar to Figure 3 based on 74 4-digit industries.

We also repeat the above dating and clustering analysis using 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 the 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. The general shapes of both peak and trough clusters are almost identical to what we have found using the level series; troughs are much more concentrated than peaks. The exact Kolmogorov-Smirnov test strongly rejects the null hypothesis of equal distribution between peak and trough clusters regardless of the level of aggregation or the de-trending method we use.

4.2. On Relation to Duration Asymmetry

While the concentration of turning points are asymmetric between peaks and troughs, one may suspect that this concentration asymmetry is merely an incidental consequence of the duration asymmetry—i.e., long expansions and short recessions. To address this concern, we consider the following multi-variate system with a common stochastic trend:

$$y_{it} = \gamma_i f_t + \epsilon_{it}, \tag{5}$$

[14] Among the 116 industries we consider, the number of 3-, 4-, 5-, and 6-digit industries is 3, 45, 36, and 32, respectively.

$$f_t = \alpha + f_{t-1} + \eta_t, \tag{6}$$

where y_{it} is the log IP for industry i at time t, f_t represents an unobserved common factor that is assumed to follow a random walk with drift, ϵ_{it} is an idiosyncratic shock, γ_i represents a factor loading, and η_t is a common shock to all industries. For simplicity, we assume that parameters of the model are distributed as

$$\gamma_i \sim N(\bar{\gamma}_i, \sigma^2_{\gamma_i}), \qquad \epsilon_{it} \sim i.i.d.N(0, \nu_i), \qquad \nu_i \sim U(\bar{\nu}_i, \sigma^2_{\nu_i}), \tag{7}$$

and the common shock, η_t, is distributed as the standard normal distribution.

Our goal is to investigate whether a multivariate time series model that captures the duration asymmetry observed in the data tends to generate concentration asymmetry. To achieve this goal, the parameters of the model are estimated by the indirect inference method (see Gouriéroux and Monfort, 1996). Let θ be a vector of parameters. An indirect inference estimator is then defined by

$$\hat{\theta} = arg\,\min_{\theta}\,[\Psi^A - \Psi^S(\theta)]'\,\Omega\,[\Psi^A - \Psi^S(\theta)],$$

where Ψ^A is a vector of key moments from actual data, $\Psi^S(\theta)$ is a vector of simulated moments calculated for given values of θ, and Ω is a weighting matrix. For the target moments we choose the mean and standard deviation of duration asymmetries, as well as those of amplitude asymmetries, pairwise concordances, and durations of complete cycles. The amplitude asymmetry, which is the only one we did not discuss above, is defined by the increase in height of the log IP during an expansion phase, divided by the decrease in height during the following contraction phase.

We calculate the actual moments from 74 IP series disaggregated at the 4-digit NAICS level, and set the size of a simulated data panel equal to that of the actual data panel. The first 100 random draws are discarded in order to eliminate the effect of initial values. The weighting matrix, Ω, is the inverse of the variance-covariance matrix of the actual moments, estimated using the stationary block bootstrap method (Politis and Romano, 1994).[15]

The indirect inference parameter estimates are reported in Table A.1. Actual and simulated moments are reported in Table 3. The multi-variate system with a common stochastic trend does well in reproducing the actual means of the above business cycle features. while it generates somewhat smaller standard deviations than the data. For example, the mean of duration asymmetries in our multi-variate model is 2.25, close to that (1.85) in the data.

Armed with these parameter estimates, we generate an artificial data set whose sample size is identical to that of actual data. We then perform the same cluster analysis with peaks and troughs in the individual series. The center of the cluster is defined by peaks and troughs of the common factor. The resulting turning point distributions, averaged over 1000 simulations, are presented in Figure 7. Obviously, the shapes of peak and trough clusters are almost identical in this figure; both of two clusters are highly concentrated at the turning points of the common factor. This suggests that the concentration asymmetry we found in the U.S. industrial data is not necessarily an artifact due to duration asymmetry.

4.3. Uncovering Leading Industries

Based on the turning points for 4-digit industries, we uncover leading industries over the business cycle. We classify industries into leading, coincident, lagging, and acyclical groups for each NBER peak and trough dates based on the clusters. We define the leading industries as those whose turning points came earlier than the NBER turning points. Consistent with the previous clustering analysis, we restrict the maximum lead time to 8 quarters. Coincident industries are those whose turning points coincide with the NBER turning points. If an industry does not experience a cyclical turning point during the time period spanned by the cluster, we define it as acyclical.[16]

[15] We select a block length of 20, and repeat the bootstrap resampling 1000 times.

[16] Note that an industry may experience multiple peaks (troughs) during the time period spanned by a peak (trough) cluster. In this situation, we consider minimum distance criterion; that is, for instance, if an

Table 4 summarizes the transition probability matrices, estimated separately over the NBER peak and trough dates. The ijth element in the upper (lower) panel of the matrix represents the probability of moving from group i to group j between two adjacent NBER peaks (troughs). Thus, the elements of each row sum to 1 and the diagonal elements represent persistence of a group. For the NBER peak dates, we find a strong persistence among leading industries (0.613), reflecting that many manufacturing industries tend to lead the aggregate peaks. But we find little persistence among coincident (0.089) and lagging (0.107) industries. On the contrary, for the NBER trough dates, we see much less persistence (0.3) for leading industries, whereas the coincident (0.336) and lagging groups (0.346) display higher persistence.

Table 5 lists the industries that have led, lagged, and coincided with the U.S. business cycle on more than 3 occasions over the past 6 NBER peak dates (50% or higher).[17] For the NBER peak dates, 30 (20 durables and 10 nondurables) of the 74 industries are defined as leading industries according to the 50% cutoff rule.[18] We find that 3 industries—cutlery and handtool (NAICS 3322), motor vehicle (NAICS 3361), and furniture and kitchen cabinet (NAICS 3371)—have led all NBER peaks in the past 6 recessions. By comparison, when the same cutoff rule is used, no industry is defined as coincident, and only 2 industries are defined as lagging.

The same list for troughs is presented in Table 6. For the NBER trough dates, the corresponding number of leading industries is significantly reduced to 3—medical equipment and supplies (NAICS 3391), sugar and confectionery product (NAICS 3113), and sawmills and wood preservation (NAICS 3211)—partially reflecting a highly concentrated distribution of troughs, whereas those of coincident and lagging industries increase to 10 and 12, respectively. Interestingly, among the 3 leading industries of the NBER troughs, only the sawmills

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.

[17] The classification of industries in Tables 5 and 6 is just for expository purposes and not based on rigorous statistical tests. We leave more rigorous statistical testing to follow-up studies.

[18] The classification between durables and nondurables is based on the definition by the Federal Reserve Board.

and wood preservation industry (NAICS 3211) is also identified as a leading industry for the NBER peaks in Table 5.

4.4. On Relation to Sharpness Asymmetry

Our finding of a higher concentration of troughs (upturns) is in contrast to the conventional notion of a 'sudden stop and slow recovery' dating back at least to Keynes (1936). Our empirical findings are, however, consistent with the characterization of sharpness asymmetry documented in McQueen and Thorley (1993).[19] Our analysis helps us to further decompose the sharpness asymmetry into two sources: sharpness asymmetry at the individual industry level and the composition effect due to the concentration asymmetry.

To illustrate the decomposition, suppose that for each group of industries, curvatures (sharpness) of IP indices are the same between the NBER peaks and troughs. 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. (According to our analysis below, the curvatures for coincident industries tend to be sharper than those of non-coincidental industries at both the NBER peaks and troughs.)

Table 7 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 two following quarters. Sharpness asymmetry is then measured by the difference in sharpness between the NBER troughs and peaks. First, the manufacturing sector also supports the notion of sharpness asymmetry at the aggregate level; the mean sharpness for the aggregate manufacturing industry 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 as sharp at the NBER troughs than at the NBER

[19] Hicks (1950, p. 101) 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."

peaks. It also shows that coincident industries tend to exhibit sharper changes than other industries, at both NBER peaks and troughs. When we look at the leading, coincident, lagging, and acyclical industries separately, the sharpness asymmetry is still evident among the individual groups of industries. All groups except for acyclical industries exhibit significant sharpness asymmetry, and the most profound asymmetry is found in coincident industries.

We decompose sharpness asymmetry at the aggregate level as

$$S_T - S_P = \underbrace{\sum_{g=1}^{2}(w_{g,T} - w_{g,P}) \times \frac{1}{2}(S_{g,P} + S_{g,T})}_{\text{Composition effect}} + \underbrace{\sum_{g=1}^{2}(S_{g,T} - S_{g,P}) \times \frac{1}{2}(w_{g,P} + w_{g,T})}_{\text{Individual asymmetry}}, \qquad (8)$$

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 8 reports each term from this decomposition estimated separately for each of the past NBER recessions. According to the decomposition, it is the individual-group-level characteristic that accounts for the lion's share of sharpness asymmetry observed at the aggregate level. However, concentration asymmetry also plays a significant role. It accounts for, on average, 24.3% of the aggregate-level sharpness asymmetry with its least contribution of 9.2% for the 1981–82 recession, and the largest of 74.6% for the 2001 recession.

5. Determinants of Comovement

In this section we investigate what determines the interindustry comovement. Specifically, we ask whether common macroeconomic shocks and inter-industry linkages, emphasized by the existing literature as two main sources of the comovement, are important for the concurrence of industry turning points. We also examine whether the effects of these determinants are (a)symmetric between the occurrences of peaks and troughs.

5.1. Empirical Model

For the occurrence of a peak, the empirical model is

$$d_{it} = \mathbb{1}(X_{it}'\beta + u_{it} > 0), \quad \text{for } i = 1, \ldots, N \text{ and } t = 1, \ldots, T, \tag{9}$$

where d_{it} is a binary variable that takes the value of 1 if industry i is at a peak at time t and otherwise takes the value of 0; $\mathbb{1}(\cdot)$ denotes an indicator function that is equal to 1 if the condition in parentheses is true and 0 otherwise; X_{it} is a vector of observable covariates; β is a vector of index coefficients; and u_{it} is a residual term. The model for the occurrence of a trough can be specified in a similar way.

We assume that u_{it} has the following structure:

$$u_{it} = \tau_i + \epsilon_{it}, \tag{10}$$

where τ_i is an industry-specific time-invariant component that captures unobserved heterogeneity in the mean duration of expansion phases, and ϵ_{it} is an idiosyncratic disturbance that changes across t as well as i. In our baseline specification, we assume that both τ_i and ϵ_{it} are independent from X_{it} and distributed as $\tau_i \sim N(0, \sigma_\tau^2)$ and $\epsilon_{it} \sim$ i.i.d.$N(0,1)$, respectively. This assumption allows for a random effects approach. In the robustness subsection, we discuss whether different assumptions about the error structure would affect the results.

Under the given assumptions, the model parameters are estimated by maximizing the conditional likelihood,

$$L = \prod_{i=1}^{N} \left\{ \int_{-\infty}^{\infty} \left[\prod_{t=1}^{T} \text{Prob}\left(d_{it} | X_{it}, \tau_{it}, s_{it}; \beta\right) \right] \phi(\tau_i | \sigma_\tau^2) d\tau_i \right\}, \tag{11}$$

where $\text{Prob}(d_{it}|X_{it}, \tau_{it}, s_{it}; \beta) = \Phi(X_{it}'\beta + \tau_i)^{d_{it}}[1 - \Phi(X_{it}'\beta + \tau_i)]^{1-d_{it}}$ if $s_{it} = 0$ and 1 if $s_{it} = 1$; s_{it} is a binary indicator that takes the value of 1 where a peak *cannot* appear (i.e., $d_{it} = 0$ with a probability of 1) because of the censoring rule we employ and takes the value of 0 elsewhere;[20] and $\Phi(\cdot)$ and $\phi(\cdot)$ are the c.d.f. and p.d.f. of the standard normal distribution, respectively.[21] We use a 12-point Gauss-Hermite quadrature to approximate the integral over τ_i (see, e.g., Butler and Moffitt, 1982).

As explained in the introduction, our approach significantly differs from the previous studies on the comovement of industries in that we deal with the discrete event variables rather than continuous variables like the growth rates of IP indices. Our approach is also distinguishable from the existing studies trying to predict recessions using a binary response time-series model (e.g., Estrella and Mishkin, 1998; Harding and Pagan, 2011). First, we use a panel data model instead of an aggregate-level time-series model. This choice of model is expected to improve the statistical power of the analysis. Second, while the previous studies have used a binary series representing cyclical phases per se, we use binary series that mark the end of the cyclical phases (i.e., peaks and troughs). This choice enables us to evaluate whether the determinants of comovement have (a)symmetric effects between peaks and troughs.[22] In addition, this approach provides a convenient way to avoid the state dependence problem associated with the constructed binary time series (see Harding and Pagan, 2011), since unlike the cyclical phase itself that is expected to persist over several quarters, the end of a phase cannot happen consecutively.

[20]To be more concrete, in the case of peak equation, $s_{it} = 1$ for a given industry i if t falls in one of the first two quarters of the sample period, the first four quarters after a previous peak, one quarter after a previous trough, and the quarters identified as a contraction phase.

[21]Thus, we assume a probit specification in our baseline analysis.

[22]When we use a binary variable that equals 1 if the economy is in contraction and 0 in expansion, as in the previous work, the probability of expansion is automatically calculated as one minus the probability of contraction. Thus, we cannot separately estimate the responses of the probabilities of expansions from those of contractions.

5.2. Explanatory Variables

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

$$Z_{i,t-p} = \sum_{j \neq i} w_{ij} d_{j,t-p}, \tag{12}$$

where $d_{j,t-p}$ is a dummy variable assigning the value 1 to industry j's peak (in the case of peak equation) or trough (in the case of trough equation) having occurred at time $t-p$ ($1 \leq p \leq p_{max}$), and w_{ij} is a weight capturing the importance of industry j for industry i.

Following Bartelsman, Caballero and Lyons (1994) and Shea (2002), we distinguish spillover effects depending on the origins of the effects. The first is from output users (*upstream* or demand-side), and the second is from input suppliers (*downstream* or supply-side). Let m_{ij} be the value of a commodity (in producers' prices) produced by industry i and used in industry j. Then we measure the importance of industry j as a user of the product of industry i using

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

Similarly, the importance of industry j as an input supplier to industry i is computed as

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

To measure these two types of weights, we use the Benchmark Input-Output tables provided by the Bureau of Economic Analysis (BEA).[23] In contrast to IP data, which are disaggregated by the NAICS system, the input-output tables for years prior to 1997 are available based only on the Standard Industry Classification (SIC) system. Since there is no easy way to convert them to the NAICS codes, we use constant weights drawn from the input-output table for 1997.

[23] We make use of the "Use Tables" at the detailed level, available at `www.bea.gov/industry/io_benchmark.htm`.

The second group of explanatory variables consists of three different macroeconomic shocks, all of which are known to have a statistically significant effect on aggregate output. The first is Romer and Romer's (2004) indicator of monetary policy shocks, derived as changes in the Federal Reserve's target for the federal funds rate, not taken in response to information about future inflation and real growth. The second is Ramey's (2011) measure of government spending shocks, which is the present value of expected changes in future defense spending (as a percent of nominal GDP for the previous quarter) due to foreign political events. The third is Hamilton's (2003) indicator of oil price shocks, constructed as the net oil price increase (in percentage terms) over the previous 3 years (at most).

In estimating the model, we restrict the sample period to end in 1996, the last year for which the monetary shock measure (Romer and Romer, 2004) is available. In order to ensure sufficient propagation of shocks, we include 8 lags for both the inter-industry spillover variables and the macroeconomic shocks. Finally, all explanatory variables are normalized to unit variance after setting the mean to zero, in order to facilitate comparison across shocks.

5.3. Results

Direct interpretation of the model parameters is difficult in a binary response model because the model is expressed as a nonlinear function of covariates. Therefore our discussion of the estimation results will be based on the average marginal effects (AME), given by

$$\frac{1}{N}\sum_{i=1}^{N}\left\{\frac{1}{T_i}\sum_{t=1}^{T_i}\left[\frac{\partial\,\mathrm{Prob}\left(d_{it}=1|X_{it},\tau_i,s_{it};\beta\right)}{\partial\,X_{it}}\right]\right\},$$

where T_i is the size of the effective sample in which $s_{it}=0$ (not censored) for given i.[24] The detailed maximum likelihood estimates of the model parameters are provided in Table A.2. Using these estimates, Figure 8 plots the cumulative impacts of a one-standard-deviation

[24]For example, the marginal effect of the kth explanatory variable on the probability of i industry's experiencing a phase shift at time t is calculated as $\beta_k\phi\left(X_{it}'\beta+\tau_i\right)$, where β_k is the coefficient on the kth explanatory variable and $\phi(\cdot)$ is the standard normal density.

increase in the explanatory variables, together with the 68% and 95% confidence bands.[25]

Panel A exhibits the upstream spillover effects for the occurrences of peaks and troughs. Looking at peaks, in response to a one-standard-deviation increase in the fraction of upstream industries (output users) that experienced a peak in the previous quarter, the probability of an industry experiencing a peak increases by 2%. The cumulative effects of this upstream spillover effect continue to rise for seven quarters, suggesting a gradual but strong upstream propagation through the input-output linkages. For troughs, the upstream spillover effect becomes statistically positive only with a two quarters delay, and then begins to fade out after four quarters.

Panel B shows that the downstream spillover effect is also significant. Having more downstream industries (input suppliers) experiencing phase shifts also increases the industry's probability of experiencing a phase shift. In peaks, both upstream and downstream effects are significant and in similar magnitudes. For troughs, unlike the upstream effect, the downstream effect is not only immediately significant but also gradually strengthens over time, reaching its maximum effect after seven quarters. Overall, in troughs, the downstream effect seems stronger than the upstream effect.

Panel C plots the cumulative effects of monetary policy shocks, identified by Romer and Romer (2004). Consistent with the prediction from the standard monetary models, an exogenous increase in the federal funds rate increases the probability of a peak (the end of expansion) and decreases the probability of a trough (the end of contraction). Of importance is its asymmetric effect between peaks and troughs. For peaks, a one-standard-deviation increase in the federal funds rate increases the probability of an industry experiencing a peak by 0.6% in the first quarter. While the probability of a peak slightly increases during the following two quarters, such responses are mostly small and statistically insignificant. In contrast, the probability of a trough exhibits rapid, persistent, and large declines after a rise in the federal funds rate. The cumulative impact is between -6.6% and -9.2% for the

[25] Because no lags of the dependent variable are included in the model, the cumulative effect after m quarters is just the sum of the coefficients on the first m lags of the explanatory variables.

first four quarters, and then declines again, reaching -17.5% at the seventh quarter. The estimated impact is consistently significant even at the 95% confidence level. According to these results, monetary policy is highly effective in recessions: a *decrease* in the federal funds rate *increases* the probability of exiting a recession significantly. This asymmetric pattern is consistent with the view that the effect of monetary policy on output growth is greater in recessions than in expansions; e.g., Weise (1999), Lo and Piger (2005), and Peersman and Smets (2005).

Government policy shocks, measured by Ramey (2011), have significant effects on both peaks and troughs (Panel D). Their effects are also somewhat asymmetric. An exogenous increase in government spending reduces the probability of a peak (the end of expansion). The cumulative effect reaches -7.0% in the fifth quarter, and then returns toward zero. For troughs, increased government spending significantly increases the probability of exiting a contraction phase, with the maximum effect being estimated at 14.9% in the fourth quarter. Hence, the effect of government spending on the occurrence of a phase shift in recessions is almost twice as large as that in expansions. This result is consistent with the recent theoretical (Christiano, Eichenbaum and Rebelo, 2009; Woodford, 2011) and empirical (Auerbach and Gorodnichenko, forthcoming; Bachmann and Sims, 2011) work that finds a larger government spending multiplier in recessions using aggregate-level time-series data.

Finally, Panel E shows that oil price shocks, measured by Hamilton (2003), are also important determinants for industry phase shifts. A one-standard-deviation increase in oil price raises the propensity of a transition from expansion to contraction, with its maximum effect being 7.6% in the fourth quarter. The same magnitude of change in oil price lowers the probability of exiting a recession with its maximum effect of -15.8% in the third quarter after.[26]

[26]Our results for the effects of oil price shocks do not necessarily conflict with the conventional view that an oil price increase has a larger output effect than an oil price decrease; Hamilton (2003) and references therein. The reason is clear because an asymmetry related to the direction of an oil price change does not imply nor is it implied by an asymmetry related to the responses of peaks and troughs to a given change in oil price.

In sum, both the input-output linkages and the three macroeconomic shocks we consider are important determinants of industrial phase shifts over the business cycle. All of them are statistically significant and conform with our economic priors. Moreover, they show interesting asymmetry between peaks and troughs. In particular, both monetary and fiscal policy shocks are more effective during recessions.

5.4. Robustness

In this subsection we examine whether our conclusions are robust to alternative data and model specifications. The results are summarized in Figure 9. In our baseline estimation, we use Hamilton's (2003) measure of oil price shocks, which is constructed in nominal terms and does not distinguish underlying causes of the oil price changes. We re-estimate the probit model using Kilian's (2008) measure of oil price shocks that captures changes in the real price of crude oil driven solely by supply-side disruptions.[27] Our results are generally robust to this alternative measure of oil price shocks. One notable exception is the effect of government spending shocks on the occurrence of a trough: it is much weaker with Kilian's measure.

We also estimate the model using data disaggregated at the 3-digit NAICS level.[28] The use of 3-digit data yields somewhat imprecise estimates with respect to both spillover effects, as the number of observations decreases. However, interestingly, the effects of macroeconomic shocks are much more pronounced, perhaps because they are aggregate common shocks. In particular, the use of 3-digit data considerably increases the effects of government spending shocks on the occurrence of a trough. To check whether applying a detrending method would yield different results, we also estimate the model using the 4-digit data detrended by the Hodrick-Prescott filter. The results are quite robust even to this alternative choice.

[27]We obtain the real oil price shocks as the regression residuals of the growth rate of the real price of oil on the contemporaneous and up to four lags of exogenous oil supply changes documented by Kilian (2008). The real price of oil is obtained by deflating the price of crude oil based on the price index for GDP.

[28]The results of using the 6-digit industry-level data are virtually identical to those reported for the 4-digit industries.

In our baseline model of random effects we implicitly assume that industry-specific factors do not affect the probabilities of phase shifts. This assumption might be too restrictive. To address this problem, we allow industry-specific disturbances, denoted as ϵ_{it} in equation (10), to follow a stationary first-order autoregressive (AR(1)) process.[29] As is clear in the figure, the results are fairly robust to this generalization. We also consider a fixed effects specification to take into account the possibility that the mean durations of expansion phases of industries, which are closely related to their trend growth rates (Harding and Pagan, 2002), may not be independent from the explanatory variables, which account for cyclical movements of industries.[30] To correct the bias due to the incidental parameters problem, we estimate the fixed effects model using the penalized-likelihood-based approximation proposed by Bester and Hansen (2009). Again, the results are very similar to those of the random effects model.

Finally, to check the robustness of our results to structural changes in the input-output linkages during the sample period, we use the 1977 input-output table that is broken down by the SIC codes. In addition, in order to match this input-output table with IP data, we also make use of the vintage IP data disaggregated by the same SIC codes.[31] Despite large time gaps between the two input-output tables, the results do not alter significantly. This evidence is consistent with Carvalho (2010), Foerster, Sarte and Watson (2011), and Holly and Petrella (forthcoming), who find that the observed changes in the structure of input-output relations do not seem to substantially distort the effects of the sources of industry comovement.

[29] We estimate the model using the Geweke-Hajivassiliou-Keane (GHK) simulator; Lee (1997) for details of the procedure.

[30] We note that there is a long-standing debate in economics regarding the relationship between long-term trends and short-term fluctuations in economic variables.

[31] The vintage IP data are constructed by Foerster, Sarte and Watson (2011), and available from Mark Watson's website. We use the vintage IP data disaggregated into 84 industries.

6. Summary

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, 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 inter-industry 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. Second, the comovement across industries appears to be a salient feature of manufacturing business cycles. Third and most important, there is substantial asymmetry in the distribution of turning points between peaks and troughs. Troughs (upturns) are much more concentrated than peaks (downturns). Occurrences of phase shifts across industries strongly support the spillovers through input-output linkages, a core aspect of multi-sector models. We confirm that the standard macroeconomic shocks, such as exogenous changes in the federal funds rate, defense spending, and oil prices, are important determinants of cyclical turning points. Their effects on industry phase shifts are all statistically significant and conform with our economic priors. Finally, we find that both monetary and fiscal policy shocks are much more effective in recessions than in expansions.

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Table 1. Industry Cycles, 1972:Q1–2010:Q2

	No. of cycles	Duration			
		Complete cycle	Expansion (A)	Contraction (B)	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: Complete cycles are measured from trough to trough.

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' measures the concordance between industries. 'NBER' measures the concordance of industries with the aggregate U.S. economy whose turning points are determined by the NBER.

Table 3. Actual and Simulated Moments

		Actual moments		Simulated moments
Duration of a complete cycle	Mean	14.22	(0.63)	13.63
	Std.	4.53	(1.22)	2.15
Duration asymmetry	Mean	1.85	(0.18)	2.25
	Std.	1.47	(0.28)	0.62
Amplitude asymmetry	Mean	-1.82	(0.10)	-2.43
	Std.	2.04	(0.16)	0.62
Pairwise concordance	Mean	0.61	(0.01)	0.72
	Std.	0.08	(0.01)	0.13

Note: The actual moments are estimated from IP series disaggregated at the 4-digit NAICS level. The simulated moments are calculated from a simulated data panel using the common stochastic trend model (5)-(7) and the parameter estimates reported in Table A.1. The values in parentheses are bootstrapped standard errors.

Table 4. Transition Probability

Previous	Current			
	Leading	Coincident	Lagging	Acyclical
(A) For 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) For 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 ijth element 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.	Industry 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: 'D' and 'ND' stand for durables and nondurables, respectively. 'Prob.' denotes the unconditional probability of being classified in a group at a NBER peak. 'Mean' and 'Std.' are the conditional mean and standard deviation of leads or lags at the NBER peaks, given that the industry belongs to the specified group.

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

Code	Dur.	Industry 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 5.

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 two quarters following the NBER peak dates. S_P measures the mean sharpness of the log IP at the NBER peak date, defined as the absolute difference between $D_{P,-2}$ and $D_{P,+2}$. For troughs, $D_{T,-2}$, $D_{T,+2}$, and S_T are defined in a similar way. Sharpness asymmetry is measured by the difference between S_T and S_P. Asterisk indicates that the Welch t-test rejects the null of no sharpness asymmetry at the 5% level or less.

Table 8. Decomposition of 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. 'Individual 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 parentheses are the share of sharpness asymmetry (in percentage terms) explained by each source.

Table A.1. Indirect Inference Estimates for the Common Stochastic Trend Model

	Estimates	S.E.
$\sqrt{\bar{\nu}_i}$: mean standard deviation of idiosyncratic shock	0.33	(0.29)
σ_{ν_i}: standard deviation of idiosyncratic volatility	1.20	(0.40)
$\bar{\gamma}_i$: mean of factor loadings	1.29	(0.00)
σ_{γ_i}: standard deviation of factor loadings	0.68	(0.00)
α: drift of the common stochastic trend	0.35	(0.03)

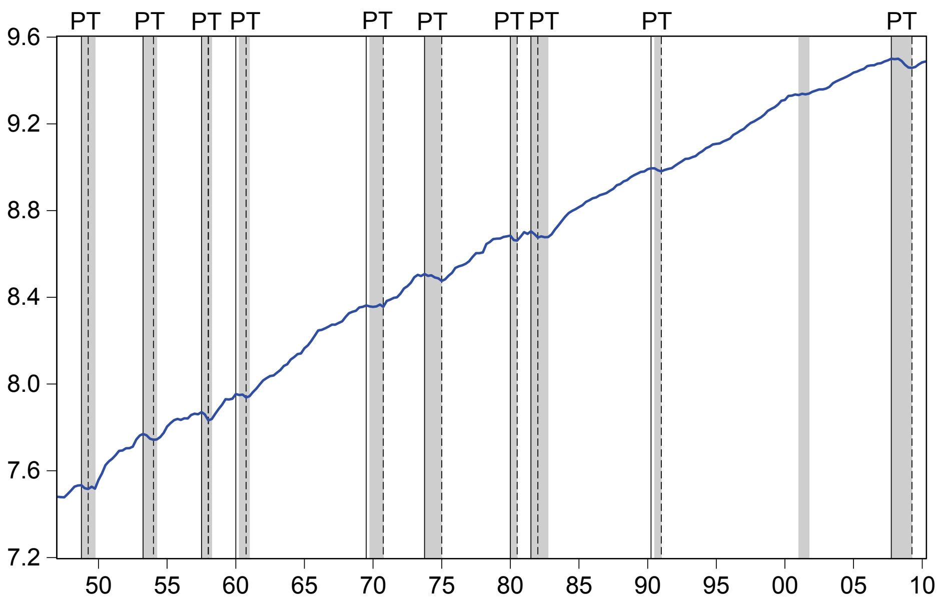
Note: The values in parentheses are numerical standard errors based on the Hessian matrix.

Table A.2. Maximum Likelihood Estimates of Models for Industry Phase Shifts

Variable	Peak equation				Trough equation			
Lag	Index coefficient		AME		Index coefficient		AME	
Upstream spillover								
$t-1$	0.105*	(0.030)	0.021*	(0.007)	0.010	(0.040)	0.003	(0.012)
$t-2$	0.036	(0.034)	0.007	(0.007)	0.178*	(0.045)	0.049*	(0.013)
$t-3$	0.022	(0.036)	0.004	(0.008)	0.000	(0.054)	0.000	(0.016)
$t-4$	0.039	(0.035)	0.008	(0.008)	0.012	(0.056)	0.003	(0.017)
$t-5$	0.025	(0.033)	0.005	(0.007)	-0.098	(0.051)	-0.027	(0.015)
$t-6$	0.061	(0.033)	0.012	(0.007)	-0.062	(0.042)	-0.017	(0.013)
$t-7$	0.015	(0.034)	0.003	(0.007)	-0.031	(0.042)	-0.009	(0.013)
$t-8$	-0.044	(0.036)	-0.009	(0.008)	0.029	(0.043)	0.008	(0.013)
Downstream spillover								
$t-1$	0.124*	(0.030)	0.024*	(0.007)	0.116*	(0.041)	0.032*	(0.012)
$t-2$	0.021	(0.035)	0.004	(0.008)	0.000	(0.048)	0.000	(0.014)
$t-3$	0.020	(0.037)	0.004	(0.008)	0.047	(0.051)	0.013	(0.015)
$t-4$	0.040	(0.036)	0.008	(0.008)	0.017	(0.055)	0.005	(0.016)
$t-5$	-0.010	(0.035)	-0.002	(0.008)	0.006	(0.049)	0.002	(0.015)
$t-6$	-0.061	(0.036)	-0.012	(0.008)	0.099*	(0.045)	0.027*	(0.013)
$t-7$	0.023	(0.034)	0.004	(0.007)	0.004	(0.047)	0.001	(0.014)
$t-8$	-0.033	(0.037)	-0.007	(0.008)	-0.137*	(0.051)	-0.038*	(0.015)
Monetary policy shock								
$t-1$	0.029	(0.041)	0.006	(0.009)	-0.272*	(0.041)	-0.075*	(0.011)
$t-2$	0.067	(0.041)	0.013	(0.009)	0.033	(0.054)	0.009	(0.016)
$t-3$	0.024	(0.041)	0.005	(0.009)	-0.094	(0.051)	-0.026	(0.015)
$t-4$	-0.101*	(0.044)	-0.020*	(0.010)	0.065	(0.054)	0.018	(0.016)
$t-5$	0.014	(0.047)	0.003	(0.010)	-0.283*	(0.054)	-0.078*	(0.016)
$t-6$	0.033	(0.048)	0.006	(0.010)	-0.083	(0.048)	-0.023	(0.014)
$t-7$	0.165*	(0.048)	0.033*	(0.011)	0.001	(0.047)	0.000	(0.014)
$t-8$	-0.004	(0.041)	-0.001	(0.009)	0.183*	(0.047)	0.051*	(0.014)
Government spending shock								
$t-1$	-0.114*	(0.036)	-0.023*	(0.008)	0.368*	(0.054)	0.102*	(0.017)
$t-2$	-0.098*	(0.032)	-0.019*	(0.007)	0.075*	(0.038)	0.021	(0.011)
$t-3$	-0.084*	(0.035)	-0.017*	(0.008)	0.087	(0.045)	0.024	(0.014)
$t-4$	-0.015	(0.039)	-0.003	(0.009)	0.009	(0.038)	0.003	(0.011)
$t-5$	-0.044	(0.041)	-0.009	(0.009)	-0.028	(0.041)	-0.008	(0.012)
$t-6$	0.119*	(0.044)	0.023*	(0.010)	-0.220*	(0.043)	-0.061*	(0.013)
$t-7$	0.056	(0.045)	0.011	(0.010)	-0.054	(0.044)	-0.015	(0.013)
$t-8$	0.055	(0.054)	0.011	(0.012)	0.053	(0.047)	0.015	(0.014)
Oil price shock								
$t-1$	0.020	(0.039)	0.004	(0.009)	-0.063	(0.054)	-0.017	(0.016)
$t-2$	0.267*	(0.047)	0.053*	(0.010)	-0.206*	(0.063)	-0.057*	(0.019)
$t-3$	0.092	(0.061)	0.018	(0.013)	-0.289*	(0.054)	-0.080*	(0.017)
$t-4$	0.006	(0.075)	0.001	(0.016)	-0.014	(0.035)	-0.004	(0.011)
$t-5$	-0.004	(0.053)	-0.001	(0.011)	0.140*	(0.040)	0.039*	(0.012)
$t-6$	-0.100*	(0.045)	-0.020	(0.010)	0.099	(0.052)	0.028	(0.015)
$t-7$	-0.039	(0.037)	-0.008	(0.008)	-0.032	(0.056)	-0.009	(0.017)
$t-8$	-0.085*	(0.037)	-0.017*	(0.008)	0.104	(0.055)	0.029	(0.016)
Constant	-1.108*	(0.044)			-0.706*	(0.047)		
σ_τ	0.257*	(0.042)			0.208*	(0.051)		
$ln\, L$	-1277.8		-950.1					
No. obs.	3588		1935					

Notes: The estimated model is given by equations (9) and (10). Index coefficients are the model parameters. AME is the abbreviation for "Average Marginal Effect." The values in parentheses are asymptotic standard errors. The asymptotic standard errors of index coefficients are obtained from the inverse of the Hessian at the maximum likelihood estimates, and those of AMEs are computed using the delta method. Asterisk indicates significance at 5% level or less.

Figure 1. U.S. Log Real GDP and 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

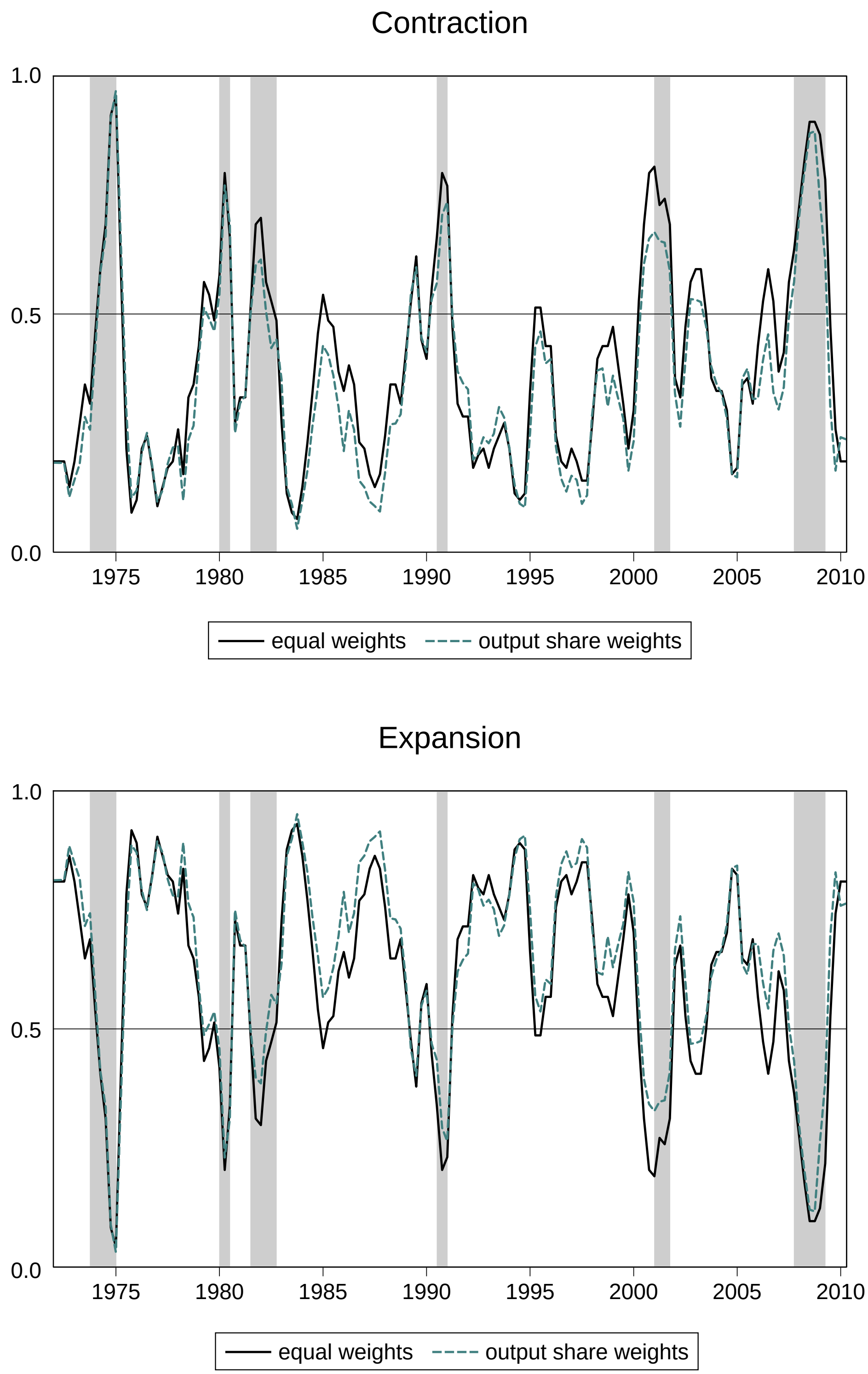


Figure 3. Distributions of Industry Turning Points, 1972:Q1–2010:Q2

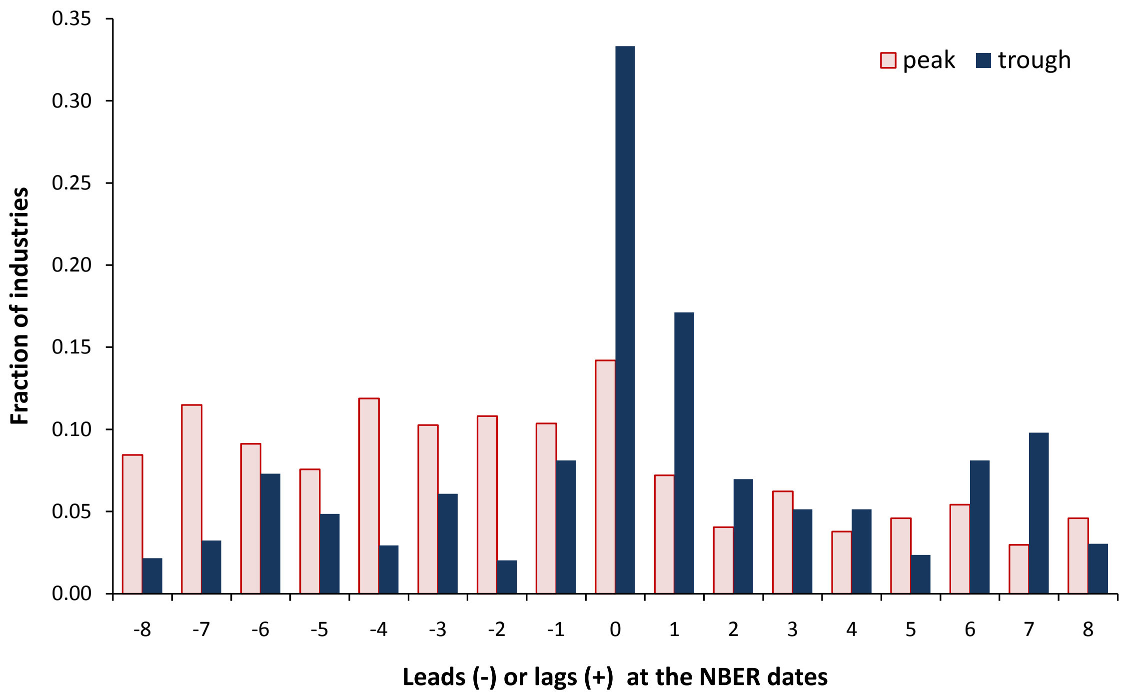


Figure 4. Distributions of Industry Turning Points for Each NBER Recession

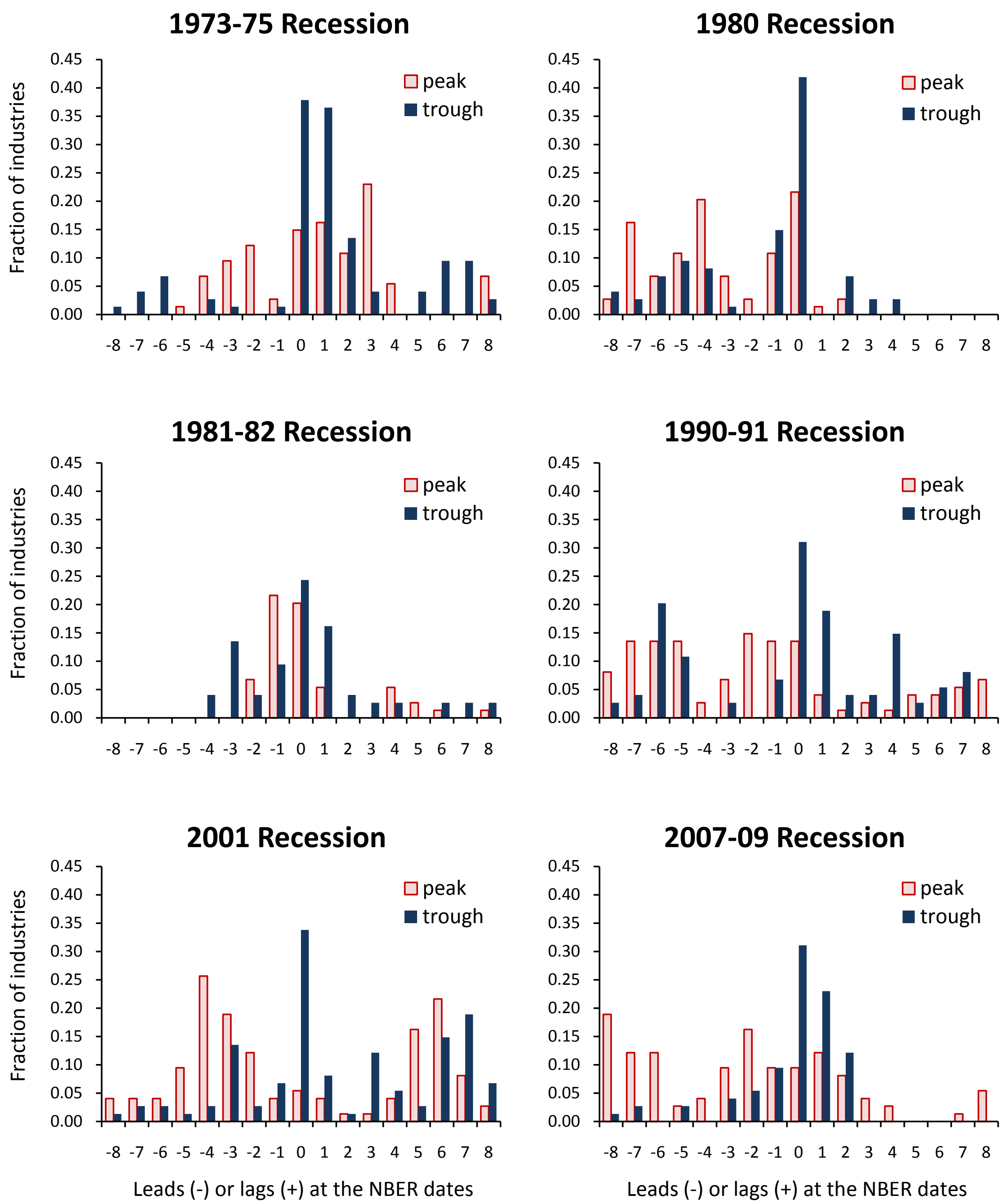


Figure 5. Distributions of Industry Turning Points: 3- and 6-digit NAICS

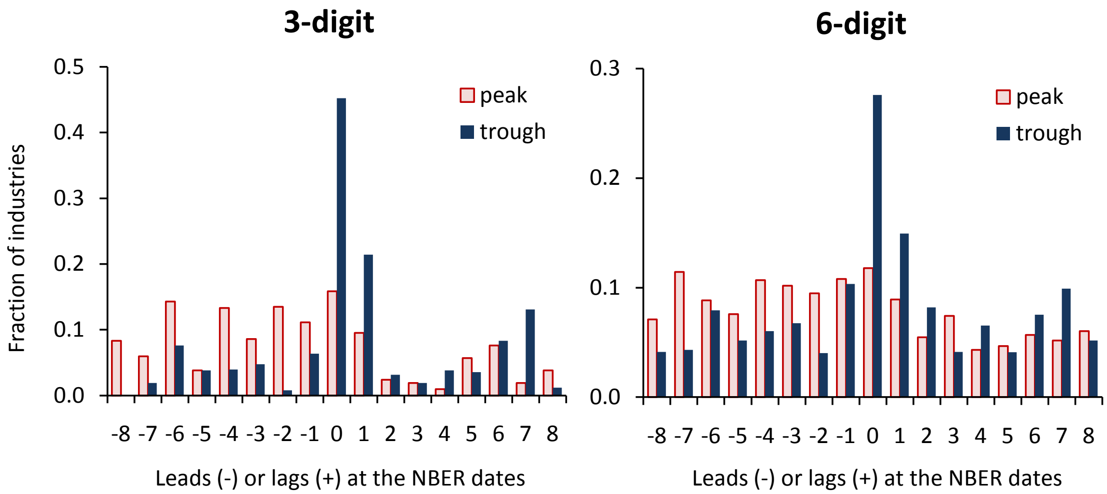


Figure 6. Distributions of Industry Turning Points: Detrended IP Series

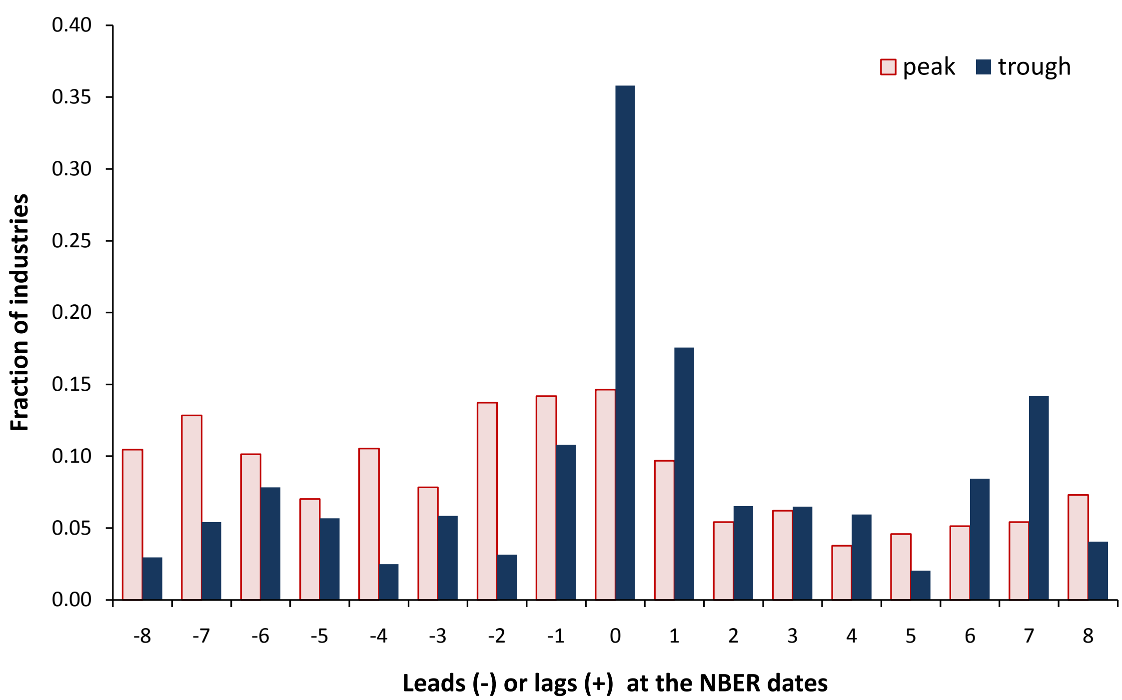


Figure 7. Distributions of Industry Turning Points: Simulation Results from the Common Stochastic Trend Model

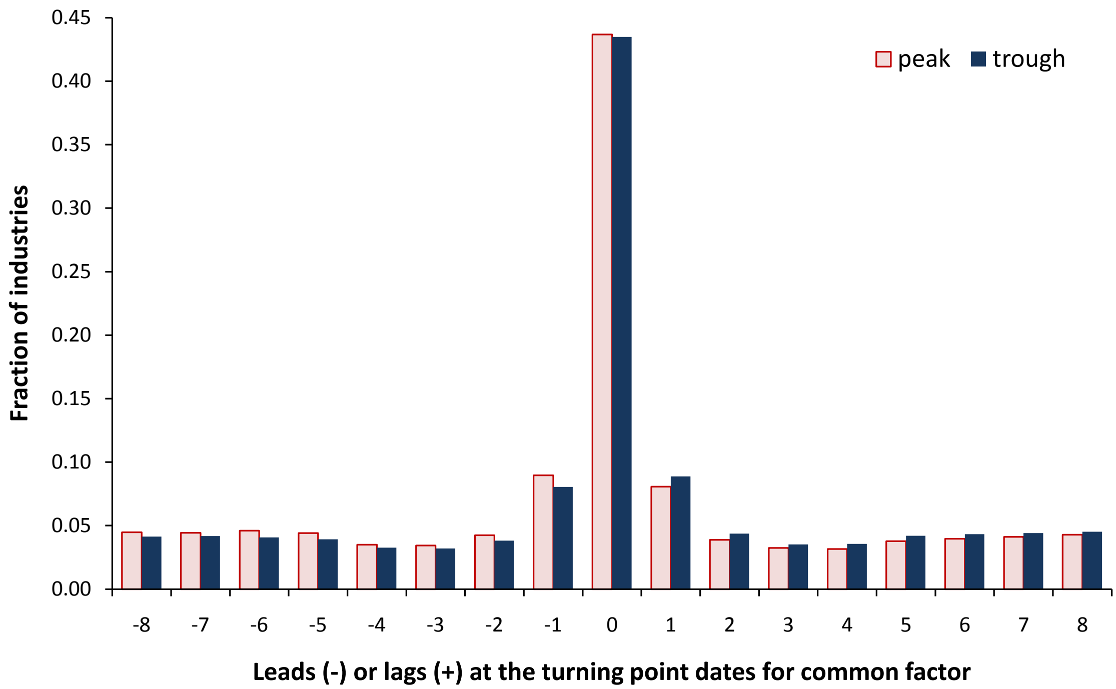


Figure 8. The Cumulative Marginal Effects of a One-standard-deviation Increase in the Explanatory Variables on the Probabilities of Industry Phase Shifts

(with 68% (dashed line) and 95% (dotted line) confidence intervals)

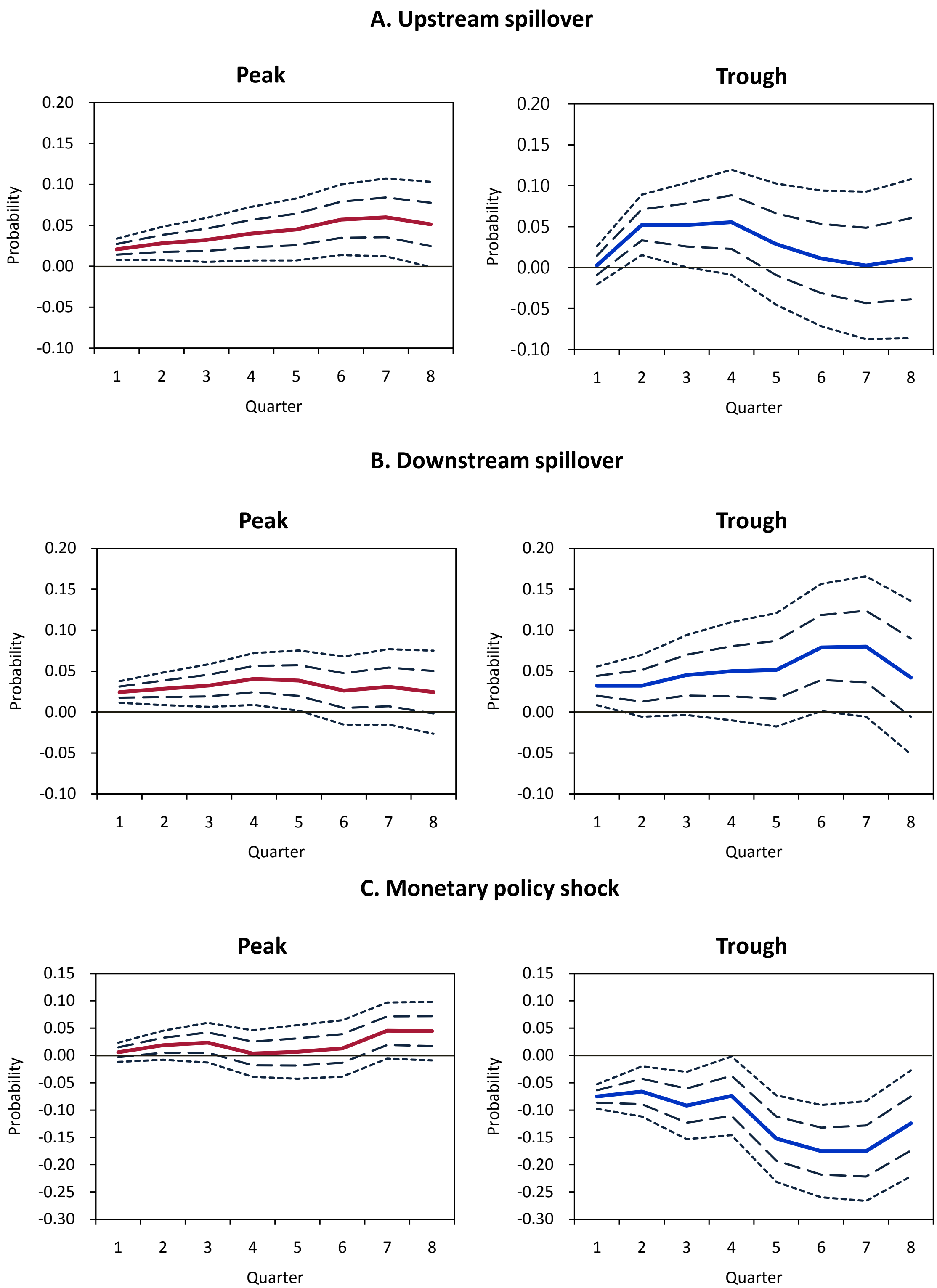


Figure 8. -Continued.

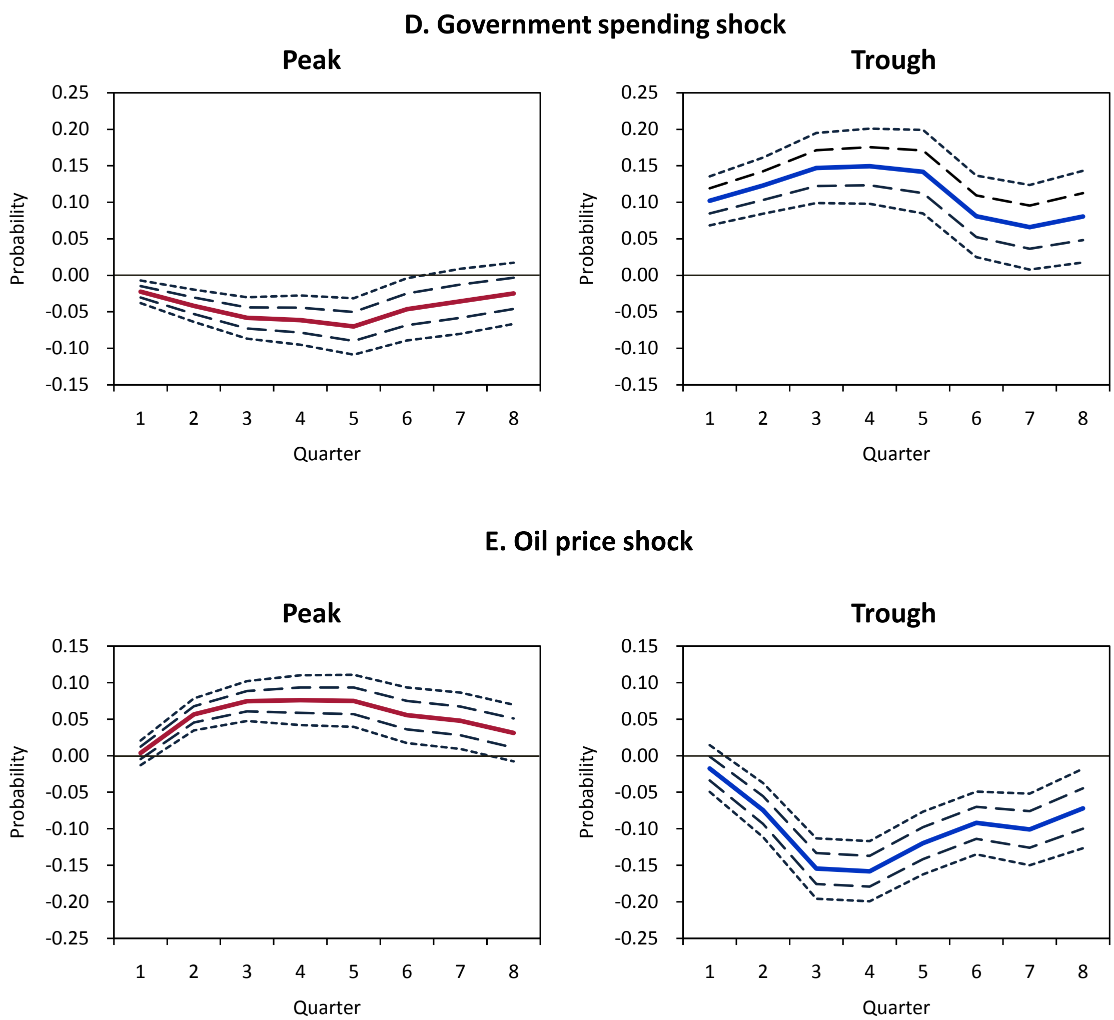


Figure 9. Results of Various Sensitivity Exercises

(Baseline model: Hamilton's oil price shocks, 4-digit classification, Random effects model without idiosyncratic dynamics, 1997 IO table)

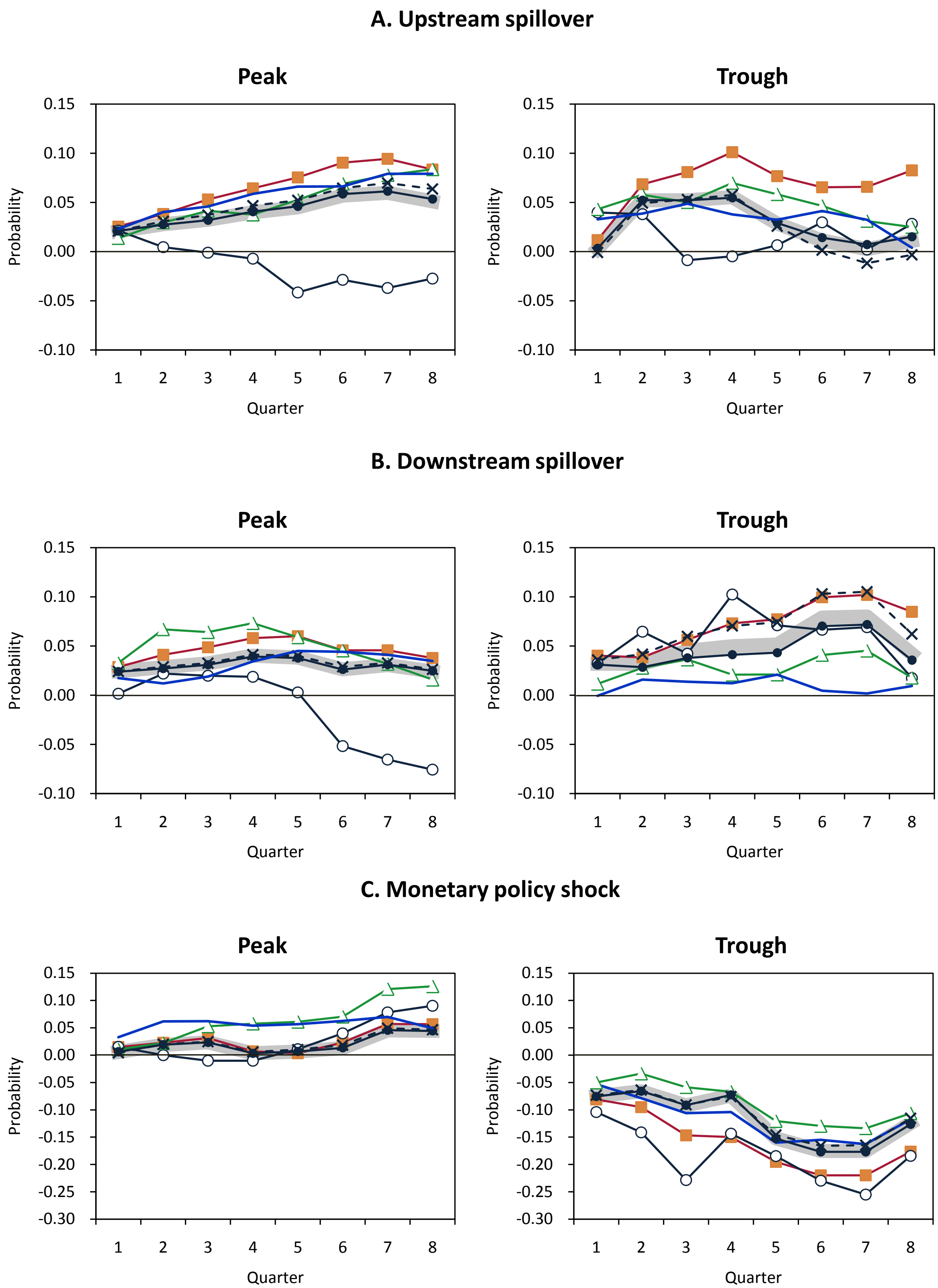


Figure 9. -Continued.