The Regional Economics Applications Laboratory (REAL) is a cooperative venture between the University of Illinois and the Federal Reserve Bank of Chicago focusing on the development and use of analytical models for urban and regional economic development. The purpose of the **Discussion Papers** is to circulate intermediate and final results of this research among readers within and outside REAL. The opinions and conclusions expressed in the papers are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Chicago, Federal Reserve Board of Governors or the University of Illinois. All requests and comments should be directed to Geoffrey J. D. Hewings, Director, Regional Economics Applications Laboratory, 607 South Matthews, Urbana, IL, 61801-3671, phone (217) 333-4740, FAX (217) 244-9339.

Web page: www.uiuc.edu/unit/real

DOES INDUSTRY MIX MATTER IN REGIONAL BUSINESS CYCLES?

by
Yangsu Park and Geoffrey J.D. Hewings

REAL 03-T-29 November 2003

Does Industry Mix Matter in Regional Business Cycles?

Yangsu Park
Department of Economics and Regional Economics Applications Laboratory, University of Illinois at Urbana-Champaign and The Bank of Korea, Seoul, Korea,
E-mail: yangpark@uiuc.edu

Geoffrey J. D. Hewings
Regional Economics Applications Laboratory, University of Illinois at Urbana-Champaign,
E-Mail: hewings@uiuc.edu

Abstract

This paper tackles two issues: (1) lead and lag relationship among regions and the role of the industry mix effect to this phenomenon are explored; (2) concurrent and lagged effects of the industry mix on the regional economic fluctuations are measured explicitly with the national shock identified from the principal components method. The empirical analysis focuses on five Midwest states. The findings reveal that, the business cycles of Michigan, Ohio, Indiana and Wisconsin coincide with the national cycle while the cycle of Illinois lags the national cycle by 3 to 4 months. This phenomenon turns out to be generated from the differences in industry structure since the manufacturing sector reacts promptly to the national shock while the services sector respond in a few months. As a result, relatively service-oriented Illinois lags other neighboring states. Regression analysis reveals that the industry mix effects explain more than 60 percent of the variance of the state coincident index and around 40 percent of the variation of state total non-farm employment. In addition, the simulation of VAR model demonstrates that the transmission mechanism and autoregressive property of economic activity expand the time differences in the business cycles among regions caused by the industry mix effects.

1. Introduction

Business cycles are empirically characterized by co-movement among a wide variety of economic indicators. This co-movement is generally interpreted as evidence of a common aggregate disturbance in the macroeconomics tradition. This common aggregate shock might have originated from monetary policy (monetary business cycle approach), technology development (real business cycle approach), or an external resource supply such as oil shock (external supply shock argument). The common shock propagates into economic activities (*i.e.* consumption, investment), industrial sectors, and regions. In addition, the co-movement might come from a more diverse set of independent disturbances through some alternative transmission mechanisms. For example, a shock in a specific industry sector (economic activity, region) drives the fluctuations of other industry sectors (economics activities, regions) through interdependence among industries (economic activities, regions). Considering these options, it is clear that business cycle analysis has a hierarchical property: while national economists focus on the common and industry specific disturbances, regional economists need to trace own and neighborhood region specific shocks along with the common and industry shocks.

There has arable research examining the sources of regional fluctuations (*i.e.* national, region-specific and industry-specific disturbance). VAR/error component models, shift-share methods and simple regression analysis have been used in order to decompose the variation of regional economic data into those sources.[1] Since economic variables at the state level are limited, such as GSP (annual), personal income (quarterly) and employment (monthly), most of the analyses have focused on the employment fluctuations in a state. Blanchard and Katz (1992) adapted simple regression methods for annual state employment and found that 66 percent of the annual variation in state employment was due to a national component and 34 percent is due to state-specific components. Clark (1998), and Clark and Shin (1998) applied VAR/error component model to the quarterly employment data for U.S. macro regions. They found that the variance of cyclical innovation in regional employment can be decomposed into roughly 39 percent ascribed

[1] For comprehensive review for the methodology, refer to Clark and Shin (1998).

to national shocks with 41 percent accounted for by region-specific shocks on average.[2] When Clark and Shin (1998) adapted a dynamic factor model, the innovation share of the common component and of region-specific component are 54.3 percent and 45.7 percent respectively. Other research including Long and Plosser (1987), Coulson (1993), Kurre and Woodruff III (1995), Shea (1996), Coulson (1999), Carlino and Sill (2000) has pursued these issues. The findings suggest that both the national disturbances and region-specific shocks are important in the analysis of regional fluctuations. The ratio of each shock to total variance depends on the frequency of the utilized data: the lower the temporal frequency, the higher the portion accounted for by the national components. However, the decomposition methodologies used to date have some limitations in the way that they capture the sources of regional fluctuations. First of all, those methodologies depend on the frequency of data analyzed. Assume that there is a region-specific shock at a point in time; it can propagate to other regions within one or two months. Time aggregation to quarterly data might overestimate the effects of national components by muting the influence of region-to-region shocks. In this respect, it seems that the higher frequency data would be the better choice to distinguish national and regional effects.[3] Secondly, those methodologies tend to underestimate the potential role for common shocks if these shocks influence some sectors but with time lags. Suppose that one sector responds to a common shock a few months later while the another sector reacts promptly. Then the effect of a common disturbance on a region's total employment depends on the industry mix and the time horizon. However, the above model's estimates attribute only concurrent movements among regions to the national shock. Thus, when high frequency data are used, it is possible to undervalue the effect of the national component even more. As can be seen from Long and Plosser (1987), Clark (1998) and Clark and Shin (1998), the contributions of national shocks to the employment of each industry are quite different among industrial sectors. Thus, additional attempts should be made to take into account the explicit influence of the industry mix effects.

Differences in a region's industrial structure may result in different regional business cycle behavior even though there is a common, national macroeconomic disturbance. For example,

[2] When they estimate with the annual data, the portion of national shock and region-specific shock changed to 72 percent and 20 percent respectively.

[3] Long and Plosser (1987) argued this in case of sectoral interaction (p.335).

changes in oil prices might affect oil-producing states differently from oil-consuming states, and the changes yield different impacts among industrial sectors (Davis *et. al*, 1997; Calino and Sill, 2000).[4] Monetary policy might have differential effects among states because of the differences in the mix of interest sensitive industries (Carlino and DeFina, 1998).[5] It is also possible that one sector leads and the other sector follows a common shock; for example, in response to an exogenous demand shock, an export industry will create demands for other industrial sectors through backward linkages, and some of these sectors may not respond contemporaneously and, further, they may be located in states other than the one housing the export industry. Hence, according to the variation in industry mix, regional peaks and troughs may not necessarily be the same among states and may not necessarily coincide with national turning points (heterogeneity of business cycle among regions). There has been some research on this issue. Sherwood-Call (1988) found that states that are smaller in farm and oil sectors and larger in manufacturing sector are linked more closely to the national economy. Kurre and Woodruff III (1995) showed that FIRE (Finance, Insurance and Real Estate) sector had a negative covariance with other sectors while other sector of the U.S. variance-covariance matrix were positive. However, there is little empirical evidence on whether and to what extent regional business cycles differ.

This paper tackles the following issues. First of all, lead and lag relationship among regions and the role of the industry mix effect to this phenomenon are explored. Secondly, concurrent and lagged effects of the industry mix on the regional economic fluctuations are measured explicitly based on the identification of the national shock from the principal components method.[6] Finally, a VAR model in which both national disturbance and regional transmission mechanisms are considered explicitly is set up and simulation is performed to examine the degree to which the model mimics the real economy. The empirical analysis will focus on five Midwest states

---

[4] Daviis *et. al.* (1997) found that the impact of oil prices on the U.S. employment growth is much larger in construction, manufacturing and TPU (Transportation, Communication and Public Utilities) than other industries.

[5] They argued that manufacturing and construction sector are interest-sensitive sectors.

[6] Most of the literature treats the national aggregate of a specific data as a national common shock (*i.e.* in the analysis of state employment fluctuation, national employment is used as a proxy for the common component). In this paper, common disturbances are identified from the principal component analysis.

(Illinois, Indiana, Michigan, Ohio and Wisconsin)[7] and the frequency of the data used is monthly (the highest frequency available in state level). In addition, state coincident indexes developed by the FRB of Philadelphia are utilized to identify the lead and lag relationship among the Midwest states and CFNAI (Chicago Fed National Activity Index) is used as one estimate of the national common shock.

The findings in this paper reveal that, using the cross-correlation analysis with Hodrick-Prescott filtering method and a Granger-causality test, the business cycles of Michigan, Ohio, Indiana and Wisconsin coincide with the national cycle while the cycle of Illinois lags the national cycle by 3 to 4 months. This phenomenon turns out to be generated from the differences in industry structure. Manufacturing, wholesale trade and retail sale sectors react promptly to the national shock while service and FIRE sectors respond to the national disturbance with time lags. As a result, relatively service-oriented Illinois lags other neighboring states. Regression analysis reveals that the industry mix effects explain more than 60 percent of the variance of the state coincident index and around 40 percent of the variation of state total non-farm employment. In addition, the simulation of VAR model demonstrates that the transmission mechanism and autoregressive property of economic activity expand the time differences in the business cycles among regions caused by the industry mix effects.

This paper is organized as follows. The next section explores differences in regional business cycles; section three focuses on the role of industry mix effects. The simulation exercises are presented in section four and the paper concludes with some summary evaluations.

2. Differences in Regional Business Cycles

2.1 Data

This paper uses various data from many sources: total non-farm employment at the national and state level from the Bureau of Labor Statistics (BLS), GSP and personal income data from

[7] As Blanchard *et. al*. (1992, p.29) pointed out, only 26 percent of annual state employment variation is common to Census regions and as such, the majority of state employment is idiosyncratic. In addition, when the share of industry employment to total employment are similar among Census regions. In this regard, data analysis in state level is better choice to capture industry mix effects.

Bureau of Economic Analysis (BEA), the CFNAI from the FRB of Chicago, and state coincident indexes from the FRB of Philadelphia. In industrial sectoral analysis, the SIC 1-digit classification is applied. Most of the data have been seasonally adjusted; if this is not the case, then the X-11 method is applied to remove seasonal factors. Data mnemonics are presented in the Appendix 1.

2.2 Differences in Regional Business Cycles

Regional business cycle behavior depends on both national shocks and region-specific shocks. It also depends on the transmission mechanism driven in part by input-output linkages. One view emphasizing the transmission mechanism is a "locomotive" hypothesis: fluctuations in a larger state drive the fluctuations in smaller states. If this hypothesis works in the Midwest states, Illinois, the biggest state in economic production, should lead the other states.[8] In order to test this hypothesis, Granger-causality test is performed with monthly non-farm employment data from January 1975 to July 2003. The specification of a bivariate VAR model for the Granger-causality test is shown in equation (1).

$$\Delta y_{it} = \alpha + \sum_{l=1}^{L} \beta_l \Delta y_{it-l} + \sum_{l=1}^{L} \gamma_l \Delta y_{jt-l} + \varepsilon_t \tag{1}$$

where Δy_{it} denotes state i's log-differenced employment and ε_t denotes error term. Based on this set-up, joint hypothesis $\gamma_1 = \ldots = \gamma_L = 0$ is tested.

Table 1 reports the results of Granger-causality test. As expected, most of the cases rejected the null hypothesis that employment changes in one state does not affect other neighborhood states at the 5 percent and 10 percent significance levels. That means that the Midwest states display statistically significant business cycle transmissions among themselves. One interesting fact found in this analysis is that the employment fluctuations in the Illinois do not Granger-cause the employment fluctuations of the Indiana and Michigan. The locomotive hypothesis does not seem to hold in the Midwest economy. However, it is not necessarily interpreted that way since

[8] The ratios of GSP of the other Midwest states to that of Illinois in 2000 is as follows: Indiana 41 percent; Michigan 70 percent; Ohio 80 percent; Wisconsin 37 percent.

this Granger-causality test cannot distinguish national and regional shock and transmission effects in the state employment fluctuations. This phenomenon can happen when the industry mix effect of national components on regional business cycles is large enough. For example, if Illinois has a large share of an industrial sector that the national shock affected but with some delay, then Illinois' total employment response would lags those of other states, resulting in the rejection of Granger-causality hypothesis.

<< Table 1 here >>

These results raise some questions about the extent to which regional business cycle differ: which state leads or lags other states? In order to find empirical evidence, state coincident indexes developed by the FRB of Philadelphia are utilized. State coincident index, representing a state's business cycle, is generated from a dynamic factor model. Under the assumption that a single unobserved factor influences the economic activities and thus should be reflected in the various indicators simultaneously, the common factor (C_t) can be identified as a coincident index using the Kalman filter method.

$$\Delta X_t = \beta + \gamma\left(L\right)\Delta C_t + \mu_t \qquad (2)$$

$$D(L)\mu_t = \varepsilon_t \qquad (3)$$

$$\phi(L)\Delta C_t = \delta + \eta_t \qquad (4)$$

where X_t denotes an $n \times 1$ vector of the state macroeconomic indicators, C_t is a common unobserved scalar variable, L is lag operator, μ_t and η_t are idiosyncratic movements in the indicators and in C_t respectively, ε_t is i.i.d error, and β, δ, $\gamma(L)$, $D(L)$, $\phi(L)$ are parameters and lag polynomials respectively (Stock and Watson, 1989; Crone, 2002). The state coincident index is generated with four state level economic indicators: nonagricultural payroll employment, unemployment rate, average hours worked in manufacturing, and real wage and salary disbursements. Generically the state coincident index is a mixture of the national common shocks and regional shocks that show autoregressive processes.

For the purpose of finding the lead and lag relationship among states with the coincident indexes, the Hodrick-Prescott filtering method [9] is applied to the indexes and cyclical parts in the indexes are compared among states. Figure 1 displays the cyclical part of each state index (C__) compared to the national counterpart (CXCI).[10] As can be seen, all Midwest states (CIN, CMI, COH, CWI) except Illinois coincide with the national economy while the Illinois business cycle (CIL) lags the national cycle (CXCI). Cross-correlation coefficients between the state cycle and national cycle (from January 1979 to April 2003) are calculated in Table 2. In the case of the Illinois and the national cycle, the coefficients that lead 3 to 4 month are the highest. In other state cases, the coefficients with 1 month or 0 month are the highest. From this result, it can be said that Illinois business cycle follows the national one 3 to 4 months later while the other Midwest states move concurrently with or lag a month of the national economy.

<< Figure 1, table 2 here >>

2.3 Industrial Structure and Business Cycle

What explains the special feature that reveals a different business cycle between Illinois and other Midwest states compared to the national cycle? Sherwood-Call (1988) found that states that have smaller farm and oil sectors but larger manufacturing sectors are linked more closely to the national economy. The first two factors (farm and oil) seem to be inappropriate to explain the case of Midwest states. The other factor, composition of the manufacturing and service sector, may provide the key. As can be seen at table 3, Illinois has a relatively larger portion of total employment in FIRE and service sectors than those of the nation while other Midwest states have larger portion in manufacturing and smaller in FIRE and service sectors. Further, the nature of the manufacturing sector may vary across states in terms of the "location" of establishments in the commodity chain of production. Establishments that are producing finished products for shipment to final markets may respond more contemporaneously with

---

[9] Hodrick-Prescott filter method decomposes the time series $y(t)$ into trend and cyclical parts. The trend component ($\tau(t)$) minimizes $\sum_{t=1}^{T}(y(t)-\tau(t))^2+\lambda*\sum_{t=1}^{T}\{[\tau(t+1)-\tau(t))]-[\tau(t)-\tau(t-1)]\}^2$. Here the penalty weight λ = 14,400 is used as generally recommended.

[10] National counterpart (called as "experimental coincident index") is available in NBER website.

national shocks; for example, in Ohio and Michigan, there are many automobile assembly plants whose production levels help define the national shocks. Illinois establishments may be further back in the commodity chain and thus respond with some lag.

<< Table 3 here >>

The national common shock has been shown to be closely related to the levels of national and regional manufacturing production (Park *et. al.*, 2002). Thus, if the manufacturing sector reacts to the national common shock promptly and services sector responds with time lags, it is possible for a manufacturing-oriented state to lead the national cycle and for a services-oriented state to follow the national cycle. The top of the figure 2 displays the Hodrick-Prescott filtered cyclical part of the quarterly U.S. GDP and service production. It is clear that the services sector lags the national cycle with smaller variance than that of GDP. The bottom of the figure shows the cyclical part of quarterly wage and salary disbursement in the manufacturing and service sector of the Illinois. This also confirms that the manufacturing sector leads the service sector and that the variance of manufacturing sector is relatively high.

<< Figure 2 here >>

In order to examine the hypothesis that local business cycles depend on industry mix, the cases of two other states, New York and California, that seem to have a similar industrial structure to Illinois, are considered. Table 4 confirms that New York and California have larger services sector and smaller manufacturing sector compared to the national economy. As can be seen in figure 3 and table 5, the business cycles of New York and California lag the national cycle by around 3 months.

<< Tables 4, 5 and figure 3 here >>

3. Industry Mix Effects in the Regional Economic Fluctuations

3.1 Identification of the Common Shock

In contrast to approaches in the current literature in which a national aggregate of specific data is treated as a national common shock (*i.e.* the growth rate of national employment in the analysis of state employment fluctuations), this paper identifies common disturbances using principal components analysis.[11] In this analysis, a linear combination (component) of the variables that explains the maximum amount of the variances in the variables is calculated. Then, a second linear combination is calculated that explains the second greatest amount of the variance, and so on. The square of each combination coefficient in the component matrix provides the explanatory power of that component in the variance of a variable. The eigenvalues indicate the percent of the variance explained by each component (Theil, 1971; Selover, 1999; Park *et. al.,* 2002).[12] Total non-farm employment series for the Midwest states from January 1975 to July 2003 are used. All series are log-differenced and normalized to mean 0 and variance 1 before the principal components method is applied to this data set.

Table 6 displays the results of the principal components analysis. The top part reports the percentage of the total aggregate of employment variances in all Midwest states explained by each component and the bottom part shows the component matrix. The first principal component explains 65 percent of the variance; it appears to be positively related to the employment fluctuations of each state because all the combination coefficients of the first component are positive in the component matrix. This factor can be interpreted as a common factor that the Midwest states share and this common disturbance explains 65 percent of the total variance. As can be seen from the component matrix, this common factor explains 16 percent of Illinois, 23 percent of Indiana, 19 percent of Michigan, 24 percent of Ohio and 18 percent of Wisconsin employment fluctuations respectively. In fact, the principal components method

---

[11] When there is a national common disturbance, it appears as a form of co-movement among a wide variety of economic indicators. Thus, total employment, a national aggregate of specific data, includes the effects of a national common shock and employment-specific disturbances. As a result, when measuring the effects of the national business cycle on the regional economic fluctuations, using a national aggregate as an alternative of a national common shock might result in misinterpretation in the viewpoints of the macroeconomics tradition.

[12] If there are t observations on k regional variables, then Y is $t \times k$ matrix. Principal components method is to find the linear function of small number of other variables, which explains each of k variables. $Y = pa'$ where p is column vector and a' is a k-element row vector. By imposing $p'p = 1$, we can obtain uniqueness of p and a. Our criterion is to select the vectors such that the sum of squares of $Y - pa'$ is minimized. Using matrix algebra, the following can be presented: $a = Y'p,\ (YY' - \lambda I)p = 0,\ p = [1/\lambda]Ya.$ That is, p is a characteristic vector of the $t \times t$ positive semi-definite matrix YY' corresponding to root λ and also a is characteristic vector of the $k \times k$ positive semi-definite matrix $Y'Y$ corresponding to root λ. The first principal component p is the one corresponding to the first largest root λ, and the second principal component p is the second largest root and so on. Also the following relationship holds; $y_h' y_h = a_{1h}^2 + a_{2h}^2 + a_{3h}^2 + residual$ where y_h is regional economic indicator, a_{ih} is a weight of h indicator which is used to calculate i^{th} principal component. Here $y_h' y_h = 1$ due to the normalization.

captures the concurrent effect of the national shock. The value (21 percent on average) is less than the percentage found by Clark (1998) and this difference may be ascribed to different data frequencies that are used (monthly vs. quarterly).

<< Table 6 here >>

The next question to be explored is whether the first principal component is a national common shock or a Midwest-specific common shock. CFNAI is the first principal component of the eighty-five existing, monthly indicators derived from national economic data. The index was suggested by Stock and Watson (1999) and developed by the FRB of Chicago (2001). CFNAI is known as the national dynamic common factor that is closely related with the national and regional manufacturing production (Park *et. al.*, 2002). Thus, it might be reasonable to compare the first principal component of Midwest employment growth rate to the CFNAI. Figure 4 shows the three-month moving average of CFNAI and the first principal component in the analysis. Since two series move in a very similar fashion, it is not that unreasonable to interpret this component as a national common shock. This result is consistent with Forni and Lippi (1997) who argued that national shocks can be found through aggregation of data among a couple of states. From now on, CFNAI is used as a consistent estimator of the national common shock in the analysis.[13]

<< Figure 4 here >>

3.2 Different Lag Effect of the Common Shock

In this section, the hypothesis that the manufacturing sector reacts to the national common shock promptly and services sector responds with time lags is tested. In order to implement the test, the following model is estimated with the U.S. industry sectoral employment and CFNAI as a national common shock.

$$\Delta Y_{it} = \alpha_i + \sum_{l=0}^{L} \beta_{il} \bullet CFNAI_{t-l} + \varepsilon_{it} \qquad (5)$$

---

[13] For referring to the consistency properties of the principal components analysis, see Forni *et. al.* (2000).

where ΔY_{it} denote log-differenced employments in sector *i*. Actually, since there is no monthly alternative to sectoral GDP, monthly sectoral employments data are used. The estimation is performed for the time period of January 1975 to April 2003 and with the time lag (*L*) of 8 months.[14] The results are summarized in the table 7. The table displays only statistically independent variables significant at the 10 percent level. As can be seen, manufacturing and construction sector react relatively soon to the national shock, while wholesale and retail trade respond until 3 months later and transportation and public utilities (TPU) until 6 months later. Finally, FIRE and services sectors are affected until 8 months after the common shock. This finding supports the maintained hypothesis. Additionally, the explanatory power (measured by Adjusted R-square) of national common component (CFNAI) to total variance of the sectoral employment fluctuations are 74 percent for manufacturing, 53 percent for wholesale trade, 42 percent for retail trade, 42 percent for construction, and 38 percent for services sector. There is little explanation derived for the FIRE and TPU sectors. This result confirms that the first national principal component affects manufacturing sector more than other sectors.

<< Table 7 here >>

3.3 Industry Mix Effects in Business Cycles and Employment Fluctuations

Since the responses of different industrial sectors to the common national shock vary in time structure and the degree of impact on industries is different, the state-level impact of the common shock depends on its portfolio of industries. The interaction between the national common shock and a state's industry mix can be captured by the following formula.

$$F_{st} = \sum_{i=1}^{I}\sum_{l=0}^{L}\left(\beta_{sil} \bullet CFNAI_{t-l}\right) \bullet S_{sit} \qquad (6)$$

[14] The duration of one business cycle in the U.S. is 80 months on average since 1975. The length of contraction period is 9 months while that of expansion period is 71 months (refer to http://www.nber.org/cycles.html). In order to capture the effects of the national disturbance on business cycle in a consistent way, maximum length of lag is determined as 8 months.

where S_{sit} denotes the ratio of industry *i* to total production in a state *s*; $\hat{\beta}_l$ is estimated from equation (5). Then, F_{st} capture the effect of the national shock through industry mix including the delayed effects. S_{sit} is constructed by linear interpolation between the ratio of 1977 and the ratio of 2001.[15] This procedure eliminates cyclical changes in industry shares, while incorporating more slow-moving shifts in the state level industry composition (Davis *et. al.,* 1997, p.18). Based on this measure, the following equation is estimated in order to examine the explanatory power of the industry mix effect in state-level business cycles and employment fluctuations.

$$\Delta Y_{st} = \delta_s + \gamma_s \bullet F_{st} + \varepsilon_{st} \qquad (7)$$

where ΔY_{st} denotes log-differenced coincident index (or employments) of state *s*. The estimation period is from May 1979 to April 2003.

First of all, explanatory powers of industry mix effects on the state business cycle are estimated. A state coincident index developed by the FRB of Philadelphia is produced with the dynamic factor model. The cycle of the state index reflects the mixture of the national shocks and state-specific shocks through an autoregressive process. As a result, equation (7) can measure the degree of the industry mix effects on the state business cycle. Table 8 shows the results. As can be seen, the industry mix effects turn out to explain, on average, about 61 percent of the variance state business cycles in the Midwest states. In order to differentiate the direct effects from the industry mix effects, the concurrent CFNAI is used as an independent variable in equation (7). The results reveal that around 52 percent of the variance is from the direct effects on average and the indirect effects account for a further 8 percent of the variance. In case of Illinois , the portion of indirect effects (19 percent) is larger than those of other states. This finding is consistent with the fact that Illinois has relatively services-oriented industrial structure.

<< Table 8 here >>

Secondly, the explanatory power of the national common shock through industry mix effects in the state employment fluctuations is estimated. In the literature, the variances of *annual* state

[15] Since the GSP in 2002 is not available yet, the ratio of 2001 is applied to 2002 and 2003.

employment were divided into 66 percent of nation component and 34 percent of a region-specific shock (Blanchard and Katz, 1992). Using *quarterly* state employment data, the variance of cyclical innovation in regional employments is decomposed into roughly 39 percent of national shock, 41 percent of region-specific shock on average (Clark, 1998; Clark & Shin, 1998). In this paper, *monthly* state employments data are used. Table 9 displays the estimation results of equation (7) with log-differenced state employment series. As shown, the national common shock through the industry mix channel explains 40 percent of the state employment fluctuation on average in the Midwest states. When the direct effect is estimated by substituting F_{st} for CFNAI, the indirect effects turn out to cause, on average, 2 percent of the variance. This result suggests a larger effect of the national shock on regional employment fluctuations compared to the result of the principal component analysis and the previous literature. Even though higher frequency data are used, which tends to lower the national effects from a statistical point of view, considering industry mix effects and identifying the national shock with many national data (that is, using CFNAI) explicitly may results in larger effects of the national shock.

<< Table 9 here >>

4. Simulation with the Static Model and VAR Model

4.1 Simulation with the Static Model

In the previous section, the industry mix effects of the national common shock were found to explain about 60 percent of the variance in state business cycles. It might be interesting to perform a simulation to mimic this phenomenon, especially the degree to which the Illinois business cycle lags those of the other Midwest states, given an arbitrary national shock. Here static simulation based on the equation (6) and (7) is performed. Since S_{sit}, the ratio of industry i to total production in a state s, will change as time goes on and identification of all coefficients are not necessary in the simulation performance, the following equation is directly estimated.

$$\Delta y_{st} = \alpha_s + \sum_{k=0}^{K} \gamma_{sk} CFNAI_{t-k} + \varepsilon_{st} \qquad (8)$$

where Δy_{st} denotes log-differenced coincident index in a state s. K is fixed at 8. The estimation is performed with the data from May 1979 to April 2003. The results are displayed in static equation system of Appendix 2. The coefficients of CFNAI in the Illinois equation are all significant while the coefficients of CFNAI in the other Midwest states are significant only up to lag 2 months. This is consistent with the fact that since Illinois is service-oriented compared to other Midwest states, the direct impacts of national disturbance on the state business cycle continues until 8 months. Based on estimation results of equation (8), static simulation is performed. The arbitrary national shock is generated by moving-averaging the CFNAI with six-months from January 1985 to April 2003. Figure 5 and table 10 show the simulation results. As can be seen in the figure, the Illinois business cycle lags those of the other states; cross-correlation coefficients show that the average time lag of the turning points between Illinois and other states is 2 to 3 months. This model seems to mimic the real economic situation but the time lag between Illinois and other Midwest states is shorter than the Hodrick-Prescott filtering results in section 2.2. In fact, our equation system is static and as such, it does not capture the possibility for the effects of the national shock to expand through autoregressive forces and interactions among states that are generated from interregional input-output structure linkages. In order to make the equation system more realistic, interdependent relationship (transmission mechanism) among states should be implemented.

<< Figure 5, table 10 here >>

4.2 Simulation with the Dynamic Model (VAR Model)

In this section, VAR structure is introduced to reflect interdependent relationship among states.

$$\Delta y_{it} = \alpha_i + \sum_{s=1}^{S}\sum_{l=1}^{L}\beta_{isl}\Delta y_{st-l} + \sum_{k=0}^{K}\gamma_{ik} CFNAI_{t-k} + \varepsilon_{it} \qquad (9)$$

where Δy_{it} denotes log-differenced coincident index is state *i*. Following the previous estimation results and the information criterion of Akaike and Schwarz, *K* is fixed at 8 and *L* is fixed at 2. The choice of two months lag reflects the faster response among regions due to lower transportation costs (see Parr *et al*., 2002). The estimation period is from May 1979 to April 2003. Given the estimation results, simulations are performed. The equation systems can be found in Appendix 2. Again, moving-averaged historical CFNAI is used to obtain the smoothed forecasts.

Figure 6 and table 11 display the results from the dynamic simulation of the business cycle model. As can be seen in the figure, the Illinois business cycle lags those of the other states; cross-correlation coefficients show that the average time lag of the turning points between Illinois and other states is 3 to 4 months. The time lag of the dynamic model simulation is longer than the simulation of the static model. This model seems to mimic the real economic situation well. From this result, it can be said that the industry mix effects of the national shock end in differences in the business cycle behaviors along with propagation of the national shock through autoregressive forces and transmission mechanism among states.

<< Figure 6, table 11 here >>

5. Conclusion

Does industry mix matter in regional business cycle? Yes; it causes some states to respond more rapidly while others follow a few months later. This paper argues that since industries react to the national common shock with different time structures, different industry combination might be a primary source of the differences in the business cycle behaviors among states. The interpretation may be ascribed to the fact that when there is a national common shock, the manufacturing sector reacts promptly and as such, a manufacturing-oriented state economy is affected more than the services-oriented economy in the early stage while a services-oriented economy becomes affected later as a services sector moves in response to the common shock in a few months. This whole process along with the propagation of the national shock through autoregressive forces and transmission mechanism among states produces the lead and lag relationship in business cycles among states. It also argued that without considering both concurrent and delayed industry mix effects, the portion of the national component in the total regional economic fluctuations might be underestimated. It also shows that the effect of the national shock is larger than that measured by the principal components method and measured by the previous literature that only captured concurrent effects of the shock.

One issue that has been mentioned tangentially is the problem of sectoral aggregation. In this paper, manufacturing was treated in its entirety; with more disaggregation, it might be possible to trace the different responses of say durable versus nondurable sectors to national and other region shocks. The hollowing out process noted for the Chicago metropolitan region in combination with substantially increased interregional trade has generated important changes in the nature of production systems (see Hewings *et al*., 1998a, b). With increased interstate dependencies in production systems, the response mechanisms have become more complex when viewed at more disaggregated levels. In fact, the findings with greater sectoral disaggregation would probably parallel those revealed from changes in the temporal frequencies, with region-region shocks exerting a larger influence.

Finally, this research provides an important insight into the opportunities and limitations state development agencies have in affecting the economic trajectory of their economies. Divergence of the regional business cycle from the national one does not necessarily mean that there occurs a region-specific shock. Thus policy makers and regional economists would better to focus attention on tracing the national shock and the changes in the region's industry composition.

References

Blanchard, O.J., Katz, L.F., Hall, R.E. and Eichengreen, B. (1992). Regional Evolutions. *Brookings Papers on Economic Activity,* 92(1), 1-75

Carlino, G. and DeFina, R. (1998). The Differential Regional Effects of Monetary Policy. *The Review of Economics and Statistics*, 80, 572-87

Carlino, G. and Sill, K. (2000). *Regional Income Fluctuations: Common Trends and Common Cycles*. Working Papers (Federal Reserve Bank of Philadelphia), 00-8

Clark, Todd E. (1998). Employment Fluctuations in U.S. Regions and Industries: The Roles of National, Regional-Specific, and Industry-Specific Shocks. *Journal of Labor Economics*, 16(1), 202-229

Clark, T.E. and Shin, K. (1998). *The Sources of Fluctuations Within and Across Countries*. Research Working Papers (Federal Reserve Bank of Kansas City), 98-04

Coulson, N. Edward. (1999). Sectoral Sources of Metropolitan Growth. *Regional Science and Urban Economics*, 29, 723-743

Coulson, N. Edward. (1993). The Sources of Sectoral Fluctuations in Metropolitan Areas. *Journal of Urban Economics*, 33, 76-94

Crone Theodore M. (2002). *Consistent Economic Indexes for the 50 States*. Working Papers (Federal Reserve Bank of Philadelphia), 02-7

Davis, S.J., Loungani, P. and Mahidhara, R. (1997). *Regional Labor Fluctuations: Oil Shocks, Military Spending, and Other Driving Forces.* International Finance Discussion Papers (Board of Governors of the Federal Reserve System, 578

Diebold, F.X. and Rudebusch, G.D. (1996). Measuring Business Cycles: A Modern Perspective. *The Review of Economics and Statistics*, 78(1), 67-77

Federal Reserve Bank of Chicago. (2001). *CFNAI Background Release*, http://www.chicagofed.org/economicresearchanddata/national/pdffiles/CFNAIbga.pdf.

Federal Reserve Bank of Philadelphia. (2002). *Consistent Economic Indexes for the 50 States*, http://www.phil.frb.org/econ/stateindexes/

Forni, M., Hallin, M. Lippi, M. and Reichlin, L. (2000). The Generalized Dynamic-Factor Model: Identification and Estimation. *The Review of Economics and Statistics*, 82, 540-554

Forni, M. and Lippi, M. (1997). *Aggregation and the Microfoundations of Dynamic Macroeconomics.* Oxford: Oxford University Press.

Hewings, G.J.D., Sonis, M., Guo, J., Israilevich, P.R. and Schindler, G.R. (1998a) The hollowing out process in the Chicago economy. 1975-2015. *Geographical Analysis,* 30, 217-233.

Hewings, G.J.D., Schindler, G.R., and Israilevich, P.R. (1998b) Interstate trade among the Midwest economies. *Chicago Fed Letter*, No. 129 (May)

Kurre, J.A., Woodruff III C.H. (1995). Regional Economic Fluctuations: Portfolio Variance and Industrial Instability Across Metro Area. *The Review of Regional Studies*, 25(2), 159-186

Long, J.B. and Plosser, C.I., (1987). Sectoral vs. Aggregate Shocks in the Business Cycle. *The American Economic Review*, 77(2), 333-336

Park, Y., Seo, J. andand Hewings, G.J.D. (2002). *Development of a Regional Economic Activity Index For the Chicago Metropolitan Area*. REAL Discussion Paper 02-T-5 (University of Illinois at Urbana-Champaign)

Parr, J.B., Hewings, G.J.D, Sohn, J., and Nazara, S. (2002) Agglomeration and Trade: Some Additional Perspectives. *Regional Studies* 36, 675-84

Rao, C. Radhakrishna. (1996). Principal Component and Factor Analyses. in Maddala, G.S. and Rao, C.R. (eds.) *Handbook of Statistics* (volume 14), 489-505

Schindler, G.R., Israilevich, P.R. andand Hewings, G.J.D. (1994). Chicago's Economic Transformation: Past and Future. *Economic Perspectives* (Federal Reserve Bank of Chicago), 19(5), 2-9

Selover, David D. (1999). International Interdependence and Business Cycle Transmission in ASEAN. *Journal of the Japanese and International Economics*, 13, 230-253

Shea, John. (1996). Comovement in Cities. *Carnegie-Rochester Conference Series on Public Policy,* 44, 169-206

Sherwood-Call, Carolyn. (1988). Exploring the Relationships between National and Regional Economic Fluctuations. *Economic Review* (Federal Reserve Bank of San Francisco), summer (3), 15-25

Stock, J. and Watson, M. (1989). New Indexes of Coincident and Leading Economic Indicators. *NBER Macroeconomics Annual*, Washington, D.C., NBER, 351-409.

Stock, J. and Watson, M. (1992). *A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience*. NBER Working Papers 4014

Stock, J. and Watson, M. (1998). *Diffusion Index*. NBER Working Paper 6702

Stock, J. and Watson, M. (1999). Forecasting Inflation. *Journal of Monetary Economics*, 44, 293-335.

Theil, Henry. (1971). *Principles of Econometrics*. New York: John Wiley and Sons

Table 1. Granger-causality (F-test) results

Null hypothesis			Lags 1	2	3	4	5	6
Illinois	$\nrightarrow$	Indiana	1.5918	0.8232	0.3129	1.1220	1.3262	1.3983
	$\nleftarrow$		10.154**	13.558**	7.8758**	5.6288**	4.6354**	5.6309**
Illinois	$\nrightarrow$	Michigan	1.5181	0.5579	0.5017	1.2305	1.3005	1.1487
	$\nleftarrow$		20.498**	15.205**	9.8945**	7.5367**	6.2150**	6.3999**
Illinois	$\nrightarrow$	Ohio	4.1692**	2.4060*	2.2067*	1.9665*	2.3527**	2.3162**
	$\nleftarrow$		22.022**	17.336**	10.909**	8.2450**	6.3686*	6.6843**
Illinois	$\nrightarrow$	Wisconsin	18.773**	10.407**	4.6250**	3.0365**	2.7506**	2.2598**
	$\nleftarrow$		12.622**	29.844**	16.508**	12.114**	10.097**	8.4358**
Indiana	$\nrightarrow$	Michigan	25.700**	9.5707**	4.5677**	2.7880**	2.4752**	2.1907**
	$\nleftarrow$		26.917**	13.802**	14.056**	11.241**	9.1308**	7.9804**
Indiana	$\nrightarrow$	Ohio	16.046**	8.6356**	8.6985**	6.4598**	5.4744**	4.5852**
	$\nleftarrow$		20.075**	6.5642**	3.4441**	2.8645**	2.5517**	2.2109**
Indiana	$\nrightarrow$	Wisconsin	39.427**	16.952**	10.569**	8.8349**	7.1071**	6.1668**
	$\nleftarrow$		15.400**	11.224**	5.7364**	4.9081**	4.2067**	3.4904**
Michigan	$\nrightarrow$	Ohio	18.318**	15.352**	12.709**	10.358**	8.1315**	7.1556**
	$\nleftarrow$		18.566**	4.2352**	1.4265	1.1895	1.0201	1.0988
Michigan	$\nrightarrow$	Wisconsin	41.074**	22.212**	14.659**	11.643**	9.4925**	8.0065**
	$\nleftarrow$		12.682**	5.2828**	2.1224*	1.9617	1.5686	1.4441
Ohio	$\nrightarrow$	Wisconsin	65.553**	25.463**	13.746**	10.574**	8.1857**	6.9151**
	$\nleftarrow$		6.7211**	4.3898**	5.7077**	4.2884**	3.6908**	3.2911**

Note: ** significant at 5 percent level, * significant at 10 percent level

Table 2. Cross-Correlation Coefficients between State Cycle and National Cycle

		Month	CIL	CIN	CMI	COH	CWI
National Cycle (CXCI)	Lead	6	0.7964	0.4057	0.3368	0.4290	0.5858
		5	0.8367	0.5279	0.4421	0.5449	0.6871
		4	0.8556	0.6510	0.5545	0.6661	0.7782
		3	0.8497	0.7627	0.6611	0.7794	0.8521
		2	0.8179	0.8510	0.7503	0.869	0.8997
		1	0.7607	0.9014	0.8140	0.9214	0.9142
		0	0.6796	0.9079	0.8366	0.9254	0.8875
	Lag	1	0.5897	0.8676	0.806	0.8793	0.8232
		2	0.4887	0.7935	0.7372	0.7965	0.7332
		3	0.3876	0.6981	0.6424	0.6934	0.6230
		4	0.2789	0.5911	0.5352	0.5851	0.5027
		5	0.1769	0.4845	0.4245	0.4828	0.3808
		6	0.0833	0.3820	0.323	0.3894	0.2691

Table 3. Ratio of Industry Production to GSP (2000)

Industry	Illinois	Indiana	Michigan	Ohio	Wisconsin	U.S.
Agriculture, forest., fish	0.89	1.16	0.89	0.93	1.64	1.36
Construction	4.77	5.12	5.11	4.51	4.86	4.66
Manufacturing	15.71	30.65	26.27	23.99	25.38	15.37
TPU	8.82	7.51	6.56	7.27	7.17	8.18
Wholesale Trade	7.92	5.96	7.24	7.11	6.47	7.04
Retail Trade	8.06	9.04	9.23	9.71	9.35	8.97
FIRE	20.73	13.23	14.27	16.36	15.81	19.99
Services	23.04	17.04	19.93	18.76	18.21	21.40

Table 4. Ratio of Industry Production to GSP (2000)

Industry	Illinois	New York	California	U.S.
Agriculture, forest., fish	0.89	0.42	1.83	1.36
Construction	4.77	3.25	4.10	4.66
Manufacturing	15.71	10.06	14.06	15.37
TPU	8.82	7.15	6.84	8.18
Wholesale Trade	7.92	6.06	6.83	7.04
Retail Trade	8.06	6.77	9.07	8.97
FIRE	20.73	33.47	22.34	19.99
Services	23.04	22.79	23.64	21.40

Table 5. Cross-Correlation Coefficients of New York and California

		Month	CNY	CCA
National Cycle (CXCI)	Lead	6	0.6244	0.6141
		5	0.6803	0.6558
		4	0.7238	0.6877
		3	0.7478	0.7033
		2	0.7516	0.6990
		1	0.7309	0.6727
		0	0.6899	0.6197
	Lag	1	0.6274	0.5533
		2	0.5492	0.4685
		3	0.4598	0.3772
		4	0.3623	0.2669
		5	0.2641	0.1609
		6	0.1663	0.0594

Table 6. Principal Components Analysis

<Principal Components>

Component	Eigenvalue	Pct. of Variance
1	1,111.6	65.0
2	209.4	12.3
3	171.2	10.0
4	124.4	7.3
5	93.4	5.5

<Component Matrix>

	1	2	3	4	5
Illinois (NDLILX)	0.3945	0.8670	-0.0270	-0.3023	0.0225
Indiana (NDLINX)	0.4765	0.0526	0.0901	0.7288	-0.4805
Michigan (NDLMIX)	0.4402	-0.3482	0.6171	-0.4969	-0.2395
Ohio (NDLOHX)	0.4891	-0.1628	0.0622	0.2274	0.8238
Wisconsin (NDLWIX)	0.4293	-0.3128	-0.7788	-0.2808	-0.1804

Table 7. Regression Results for Lag Effects of National Common Shock

	Dependent Variable						
	DLCONS	DLMANU	DLTPU	DLWHOL	DLRETA	DLFIRE	DLSERV
Constant	0.001815 (0.00035)	-0.00028 (0.00010)	0.00118 (0.00022)	0.001256 (0.00009)	0.001855 (0.00010)	0.001918 (0.00010)	0.003275 (0.00008)
CFNAI	0.005913 (0.00037)	0.002322 (0.00016)	0.001567 (0.00026)	0.001012 (0.00014)	0.001333 (0.00015)	0.000391 (0.00013)	0.000738 (0.00010)
CFNAI(-1)		0.00111 (0.00016)		0.000583 (0.00014)	0.000381 (0.00016)		
CFNAI(-2)		0.000522 (0.00015)		0.000235 (0.00014)			
CFNAI(-3)				0.000462 (0.00013)	0.000292 (0.00014)	0.000405 (0.00013)	0.000444 (0.00012)
CFNAI(-4)							
CFNAI(-5)							0.00026 (0.00012)
CFNAI(-6)			0.000833 (0.00025)				
CFNAI(-7)							
CFNAI(-8)						0.000406 (0.00011)	0.000199 (0.00010)
Adjusted R-squared	0.42389	0.73791	0.158957	0.525692	0.424185	0.176771	0.381191

Note: Parenthesis shows standard deviations.

Table 8. Explanatory Power to Regional Business Cycle

	Including Lagged Industry Mix Effects				Concurrent Industry Mix Effects			
	Variable	Coefficient	Std. Error	Adjusted R-squared	Variable	Coefficient	Std. Error	Adjusted R-squared
DLIL	Constant	-0.00067	0.000211	0.578865	Constant	0.00206	0.000213	0.388189
	FILA	1.853908	0.093222		CFNAI	0.003275	0.000242	
DLIN	Constant	0.000591	0.000154	0.614696	Constant	0.002257	0.000154	0.557746
	FINA	1.429338	0.066725		CFNAI	0.003329	0.000175	
DLMI	Constant	-0.00117	0.000312	0.552368	Constant	0.002027	0.000292	0.53183
	FMIA	2.547264	0.135166		CFNAI	0.005998	0.000332	
DLOH	Constant	-0.00053	0.000193	0.667026	Constant	0.002071	0.000197	0.574647
	FOHA	2.030982	0.084629		CFNAI	0.00441	0.000224	
DLWI	Constant	0.000997	0.00012	0.613036	Constant	0.002406	0.00012	0.529443
	FWIA	1.119307	0.052435		CFNAI	0.002451	0.000136	
Average				0.605198	Average			0.516371

Table 9. Explanatory Power to Regional Employment Fluctuation

	Including Lagged Industry Mix Effects				Concurrent Industry Mix Effects			
	Variable	Coefficient	Std. Error	Adjusted R-squared	Variable	Coefficient	Std. Error	Adjusted R-squared
DLEIL	Constant	-0.00044	0.000193	0.255993	Constant	0.000826	0.000167	0.207647
	FILA	0.850917	0.085199		CFNAI	0.001653	0.000189	
DLEIN	Constant	-0.00014	0.000179	0.416106	Constant	0.001161	0.00017	0.393703
	FINA	1.110583	0.077467		CFNAI	0.002641	0.000193	
DLEMI	Constant	-0.00063	0.000222	0.388792	Constant	0.001025	0.000201	0.401477
	FMIA	1.304342	0.096272		CFNAI	0.00318	0.000229	
DLEOH	Constant	-0.00047	0.000127	0.572577	Constant	0.000953	0.000118	0.551139
	FOHA	1.094583	0.055751		CFNAI	0.002511	0.000134	
DLEWI	Constant	0.000361	0.000152	0.369357	Constant	0.001458	0.000143	0.330021
	FWIA	0.868552	0.066794		CFNAI	0.001934	0.000162	
Average				0.400565	Average			0.376797

Table 10. Cross-Correlation Coefficients of Simulated State Cycles (Static)

		Month	DLINFM	DLMIFM	DLOHFM	DLWIFM
Illinois Business Cycle (DLILFM)	Lead	6	0.4744	0.4556	0.4930	0.5864
		5	0.5358	0.5134	0.5536	0.6488
		4	0.6054	0.5801	0.6219	0.7154
		3	0.6794	0.6527	0.6945	0.7825
		2	0.7544	0.7275	0.7675	0.8464
		1	0.8244	0.7995	0.8358	0.9029
		0	0.8862	0.8652	0.8952	0.9494
	Lag	1	0.9269	0.9110	0.9334	0.9727
		2	0.9506	0.9405	0.9548	0.9801
		3	0.9565	0.9520	0.9586	0.9711
		4	0.9448	0.9460	0.9454	0.9467
		5	0.9175	0.9238	0.9166	0.9093
		6	0.8757	0.8864	0.8741	0.8607

Table 11. Cross-Correlation Coefficients of Simulated State Cycles (Dynamic)

		Month	DLINFVM	DLMIFVM	DLOHFVM	DLWIFVM
Illinois Business Cycle (DLILFVM)	Lead	6	0.3562	0.3562	0.4349	0.5335
		5	0.4128	0.4066	0.4920	0.5939
		4	0.4799	0.4673	0.5579	0.6596
		3	0.5546	0.5368	0.6305	0.7268
		2	0.6344	0.6125	0.7056	0.7934
		1	0.7128	0.6912	0.7775	0.8532
		0	0.7855	0.7707	0.8411	0.9073
	Lag	1	0.8420	0.8295	0.8879	0.9418
		2	0.8824	0.8741	0.9184	0.9611
		3	0.9050	0.9009	0.9319	0.9642
		4	0.9100	0.9105	0.9288	0.9521
		5	0.8988	0.9029	0.9104	0.9270
		6	0.8730	0.8804	0.8791	0.8906

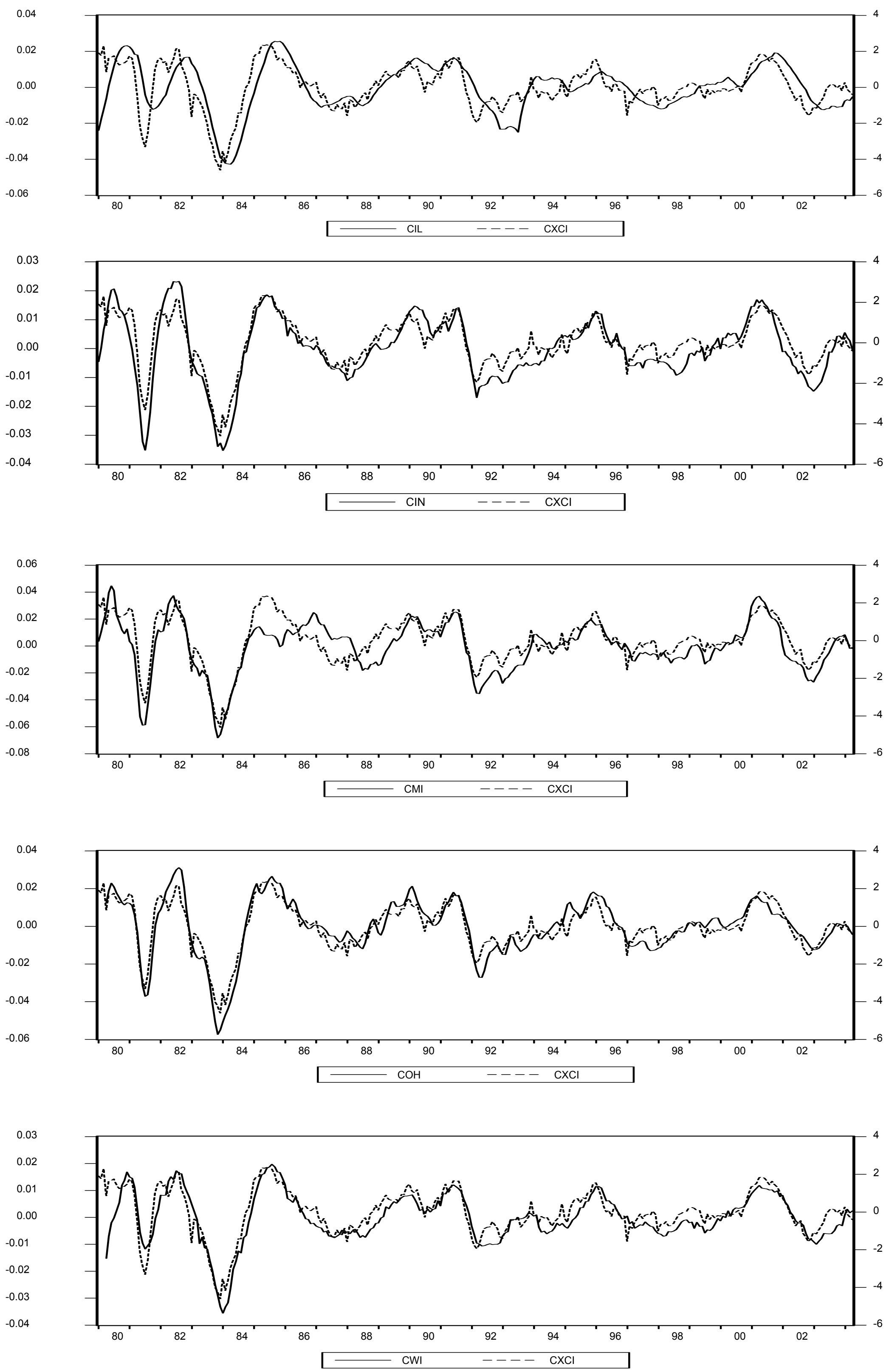
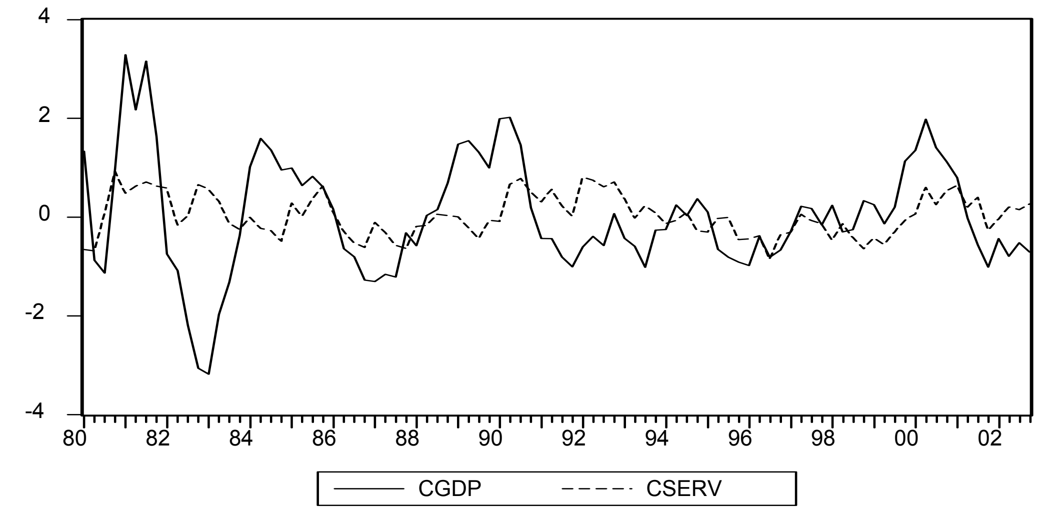


Figure 1. Cyclical Part of State Coincident Indexes

<GDP and Service Production in the U.S.>



<Wage and Salary Disbursement of Manufacturing and Services Sector (Illinois)>

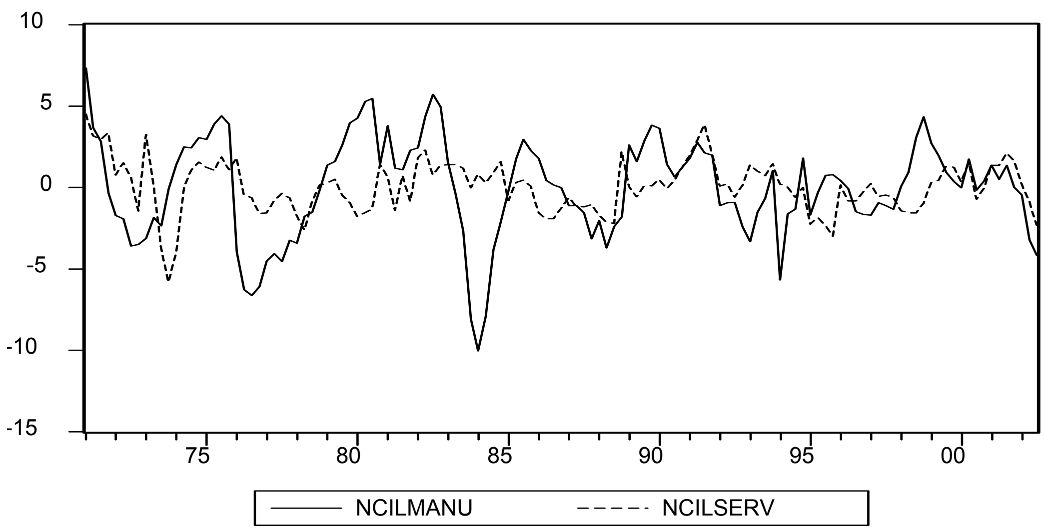


Figure 2. Cyclical Part of GDP, Manufacturing, and Service Sector

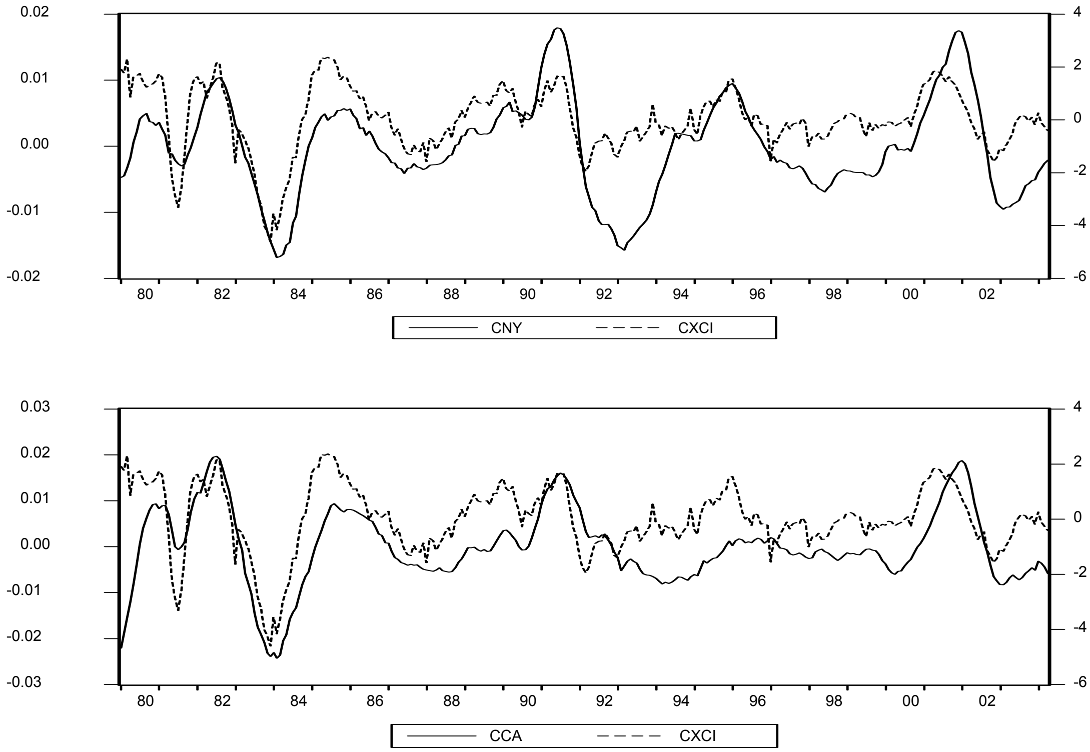


Figure 3. Cyclical Part of New York and California Coincident Indexes

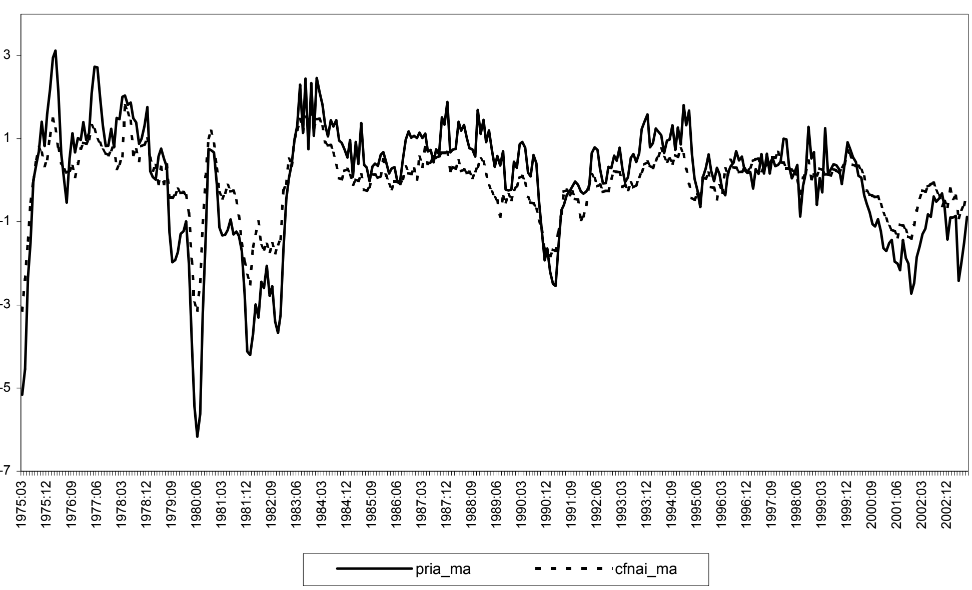


Figure 4. CFNAI and the First Principal Component (pria_ma)

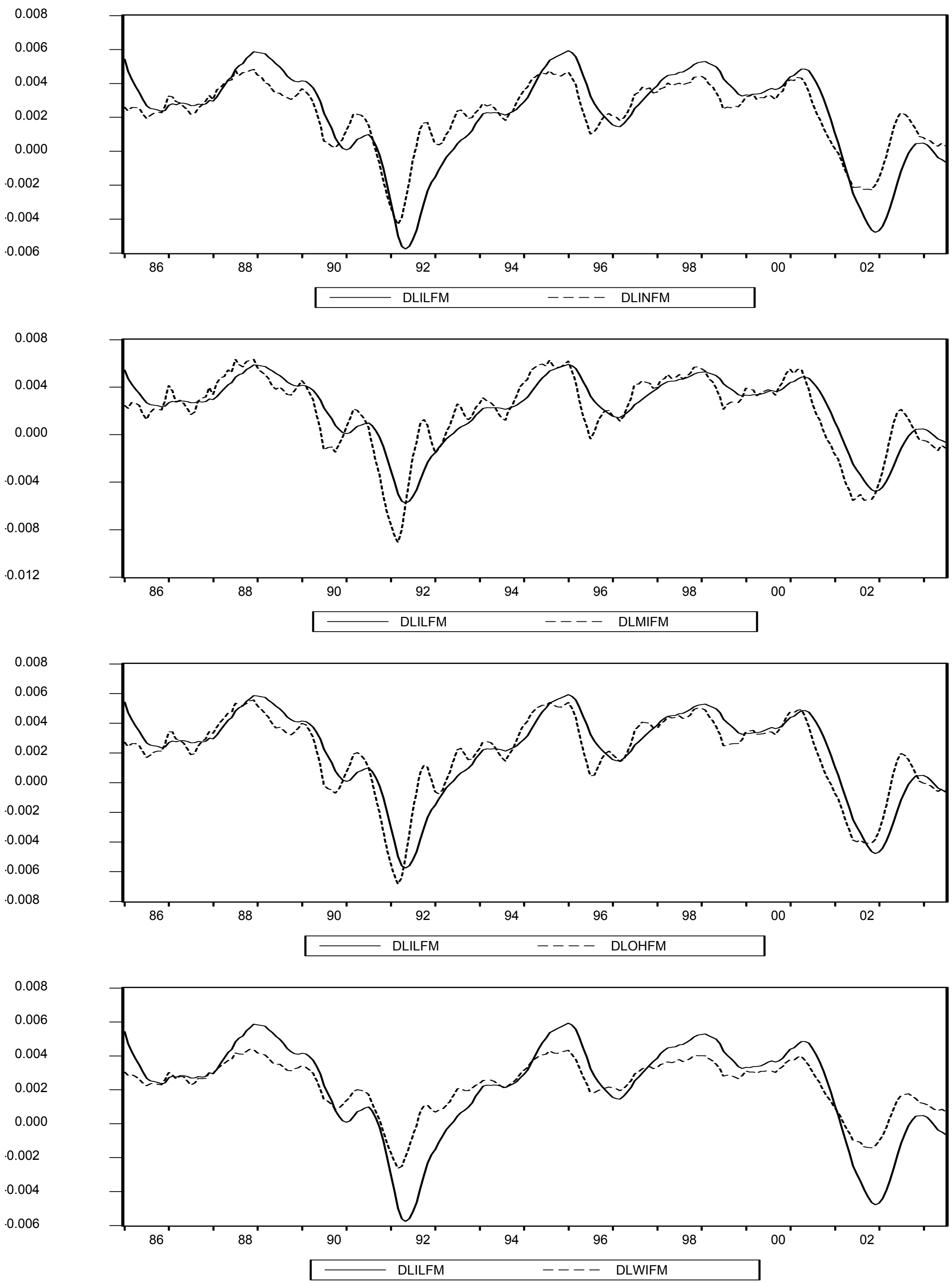


Figure 5. Static Simulation of Structural Model

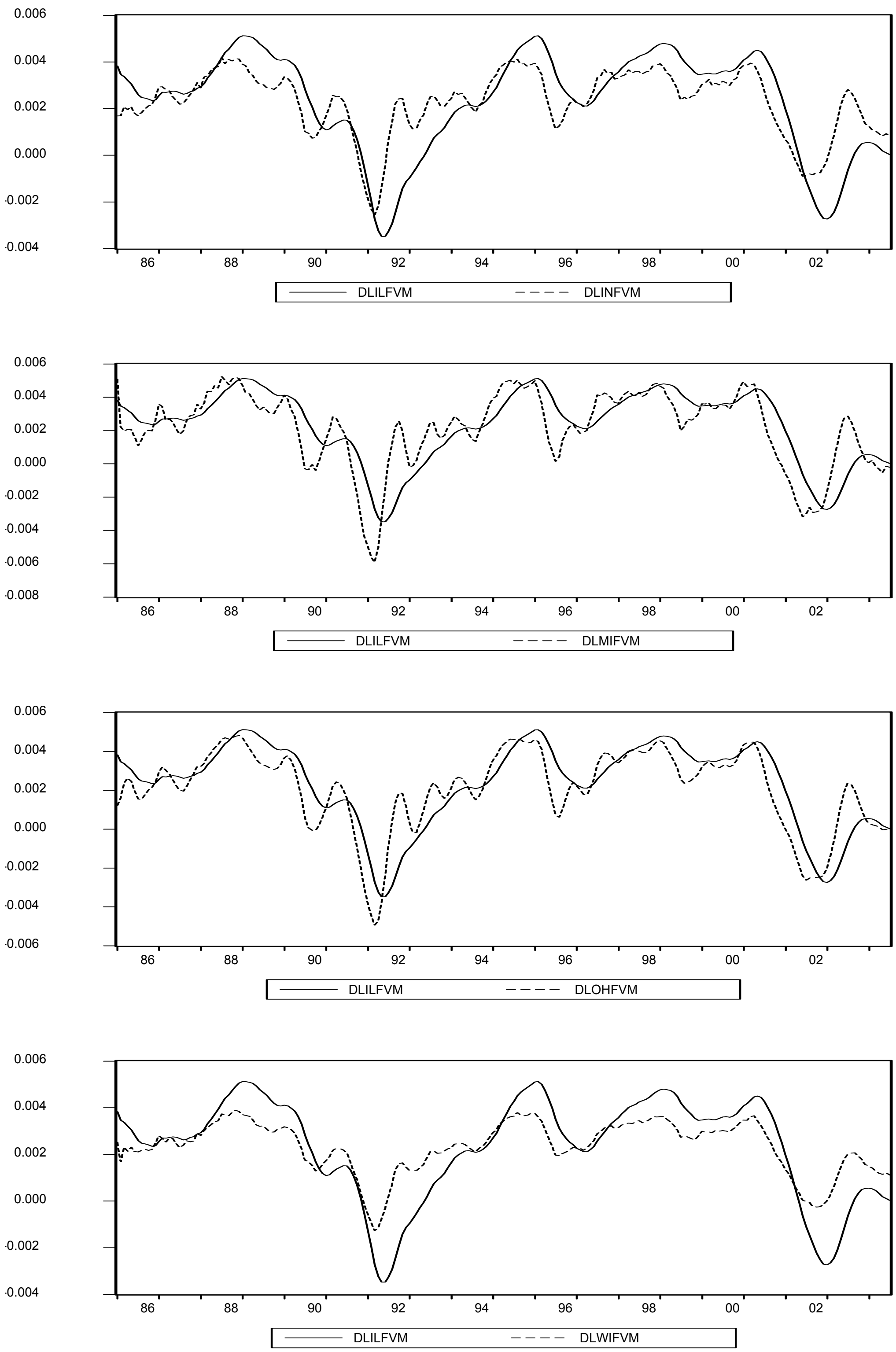


Figure 6. Dynamic Simulation of VAR Model

<Appendix 1>

Series	Description
C______	Cyclical part of coincident index of the FRB of Philadelphia ____ : IL (Illinois), IN (Indiana), MI (Michigan), OH (Ohio), Wi (Wisconsin) CA (California), NY (New York), XCI (U.S.)
CFNAI CFNAIM	Chicago Fed National Activity Index 6 months moving averaged CFNAI
CGDP CSERV	Cyclical part of GDP Cyclical part of Services production
DL______	Log differenced U.S. employment in a sector _____ : CONS (construction), MANU (manufacturing), TPU (transportation and public utilities), WHOL (whole sale trade) RETA (retail sales) FIRE (finance, insurance and real estate) SERV (services)
DL______	Log differenced coincident index of the FRB of Philadelphia ____ : IL (Illinois), IN (Indiana), MI (Michigan), OH (Ohio), WI (Wisconsin)
DL____FM DL____ FVM	Forecast of DL___ by the static model Forecast of DL___ by the dynamic model
DLE______	Log differenced non-farm employment of each states ____ : IL (Illinois), IN (Indiana), MI (Michigan), OH (Ohio), WI (Wisconsin)
F____A	F_{st} in a state ____ : IL (Illinois), IN (Indiana), MI (Michigan), OH (Ohio), WI (Wisconsin)
NDL____X	Log differenced non-farm employment of each states, normalized to mean 0 variance 1 ___: IL (Illinois), IN (Indiana), MI (Michigan), OH (Ohio), WI (Wisconsin)
NCILMANU NCILSERV	HP-filtered wage and salary disbursement in manufacturing of Illinois HP-filtered wage and salary disbursement in Services of Illinois

<Appendix 2>

1. Static Structural Model of Business Cycle Index

DLIL = **0.00248327075** + **0.001040603683***CFNAIM + **0.001105412515***CFNAIM(-1) + **0.0007457972538***CFNAIM(-2) + **0.0005552517332***CFNAIM(-3) + **0.0004162070538***CFNAIM(-4) + **0.0004840112329***CFNAIM(-5) + **0.0006726103241***CFNAIM(-6) + **0.0007221869993***CFNAIM(-7) + **0.0004371518108***CFNAIM(-8)

DLIN = **0.002476373769** + **0.002231058867***CFNAIM + **0.001192078375***CFNAIM(-1) + **0.0008856761186***CFNAIM(-2) - 4.835443491e-06*CFNAIM(-3) - 0.0002308106768*CFNAIM(-4) - 0.0002409076075*CFNAIM(-5) + 0.0001958074554*CFNAIM(-6) + 0.00012352756*CFNAIM(-7) - 0.0004604756081*CFNAIM(-8)

DLMI = **0.002398194055** + **0.004686914352***CFNAIM + **0.002484567581***CFNAIM(-1) + 0.0002235440089*CFNAIM(-2) - 0.0002465504051*CFNAIM(-3) - 0.0007458161518*CFNAIM(-4) - 0.0002136541675*CFNAIM(-5) + 0.0004730494417*CFNAIM(-6) + 0.0001485066588*CFNAIM(-7) - 0.0006483115616*CFNAIM(-8)

DLOH = **0.002362427979** + **0.002633883631***CFNAIM + **0.002214826488***CFNAIM(-1) + **0.0009315568783***CFNAIM(-2) + 0.0001405813861*CFNAIM(-3) - 0.0002801399479*CFNAIM(-4) - 0.0003765249171*CFNAIM(-5) - 2.836688865e-05*CFNAIM(-6) + 0.0001898725719*CFNAIM(-7) - 0.0003018827851*CFNAIM(-8)

DLWI = **0.002481120686** + **0.001528014683***CFNAIM + **0.0008789167419***CFNAIM(-1) + 0.0002204892223*CFNAIM(-2) + 0.0001575708496*CFNAIM(-3) + 0.0002557162099*CFNAIM(-4) + 6.515825984e-05*CFNAIM(-5) + 0.0001147021139*CFNAIM(-6) + 5.773758157e-05*CFNAIM(-7) - 0.0001049313329*CFNAIM(-8)

Note: bold shaped coefficients represent significant ones at the 5 percent significance level.

2. VAR Model of Business Cycle Index

DLIL = 0.6230832962*DLIL(-1) + 0.1633310803*DLIL(-2) + 0.09102140392*DLIN(-1) + 0.02470977496*DLIN(-2) + 0.01746976391*DLMI(-1) + 0.001136375859*DLMI(-2) + 0.02795263446*DLOH(-1) - 0.03930054659*DLOH(-2) + 0.003188788334*DLWI(-1) + 0.05568024553*DLWI(-2) + 0.0001002902984 + 0.000524549621*CFNAIM + 0.0001741861914*CFNAIM(-1) - 0.0001863219899*CFNAIM(-2) - 9.416627617e-05*CFNAIM(-3) - 2.601532803e-05*CFNAIM(-4) + 9.435957226e-05*CFNAIM(-5) + 0.0002584424371*CFNAIM(-6) + 3.640350269e-05*CFNAIM(-7) - 0.0001528660887*CFNAIM(-8)

DLIN = - 0.08843350404*DLIL(-1) + 0.1930071982*DLIL(-2) + 0.1799431549*DLIN(-1) + 0.3575670174*DLIN(-2) - 0.03239806032*DLMI(-1) + 0.06884878236*DLMI(-2) + 0.09652627536*DLOH(-1) - 0.113657493*DLOH(-2) + 0.06182774594*DLWI(-1) + 0.1024548983*DLWI(-2) + 0.0004281996312 + 0.001715445152*CFNAIM + 0.0004466481519*CFNAIM(-1) - 0.0002389201133*CFNAIM(-2) - 0.0006013998206*CFNAIM(-3) - 0.0005934880782*CFNAIM(-4) - 0.0004049548614*CFNAIM(-5) + 0.000215727647*CFNAIM(-6) + 0.0001512254332*CFNAIM(-7) - 0.0004873929627*CFNAIM(-8)

DLMI = - 0.01149466508*DLIL(-1) + 0.2931101147*DLIL(-2) + 0.1059230297*DLIN(-1) + 0.3268469565*DLIN(-2) + 0.4655150907*DLMI(-1) - 0.03737419233*DLMI(-2) + 0.297662143*DLOH(-1) - 0.0952794748*DLOH(-2) - 0.3139304278*DLWI(-1) - 0.0669442788*DLWI(-2) + 6.217801077e-05 + 0.003234472855*CFNAIM + 0.0001885526242*CFNAIM(-1) - 0.00138234264*CFNAIM(-2) - 0.0007366816073*CFNAIM(-3) - 0.001111893337*CFNAIM(-4) - 6.133452858e-05*CFNAIM(-5) + 0.0006532264427*CFNAIM(-6) - 0.0001244934831*CFNAIM(-7) - 0.000628445914*CFNAIM(-8)

DLOH = 0.08393231721*DLIL(-1) + 0.09032829038*DLIL(-2) + 0.01542712636*DLIN(-1) + 0.1966463405*DLIN(-2) + 0.03453076902*DLMI(-1) + 0.06367563932*DLMI(-2) + 0.8370267815*DLOH(-1) - 0.5092997432*DLOH(-2) - 0.02358753152*DLWI(-1) - 0.05954579503*DLWI(-2) + 0.0005915280268 + 0.001461983241*CFNAIM + 0.000554969438*CFNAIM(-1) - 0.000226813298*CFNAIM(-2) + 1.238727642e-05*CFNAIM(-3) - 0.000359582242*CFNAIM(-4) - 0.0002215028094*CFNAIM(-5) + 0.0002777053527*CFNAIM(-6) - 2.680585939e-05*CFNAIM(-7) - 0.0004073018048*CFNAIM(-8)

DLWI = 0.09042378355*DLIL(-1) + 0.02566006287*DLIL(-2) + 0.06760863122*DLIN(-1) + 0.08659032549*DLIN(-2) - 0.01699046984*DLMI(-1) + 0.0004106920324*DLMI(-2) + 0.09947303752*DLOH(-1) + 0.03281715374*DLOH(-2) + 0.005451474617*DLWI(-1) + 0.3215723551*DLWI(-2) + 0.0007193749543 + 0.001152069964*CFNAIM + 0.0003023905014*CFNAIM(-1) - 0.0006929600334*CFNAIM(-2) - 0.0003843445878*CFNAIM(-3) - 1.388574597e-05*CFNAIM(-4) - 0.0001094599858*CFNAIM(-5) + 1.6269694e-05*CFNAIM(-6) + 1.303656552e-05*CFNAIM(-7) - 0.0001465104322*CFNAIM(-8)