Development of a Regional Economic Activity Index for the Chicago Metropolitan Area

Yangsu Park, John Seo and
Geoffrey J.D. Hewings

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

John Seo
Regional Economics Applications Laboratory, University of Illinois at Urbana-Champaign, E-Mail: jseo.frbchi.org

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

Abstract: Even with strong demands for local economic activity indices, there have been relatively few attempts to develop comprehensive indices that are compatible with the national business coincident index developed by NBER and Department of Commerce. In this paper, some experimental methods are explored for generating local economic activity index. Using the Chicago Federal Reserve Bank National Activity Index (CFNAI) and local economic indicators, local and national dynamic factors are extracted by applying partitioned regression and principal components methods. From these results, local economic activity index is generated through combining national components with local dynamic factors. Three local indices for the Chicago Metropolitan area are produced and compared to national indices.

JEL classification: C32, C51, E32, R15
Key Words: business cycle, regional economic activity index, principal components methods

1. Introduction

There are many reasons for monitoring regional economic status; while many state and local economies have become more similar in structure to the national economy over the past two decades (see Schindler, *et al*., 1994), there has been no systematic evaluation of differences and similarities in regional and national economic behavior over time. Further, suitable data, regionally-issued on a monthly basis, is limited; there are monthly regional economic indicators available, such as manufacturing production, employment, retail sales etc. and some of comprehensive economic indicators such as Gross State Products (GSP) and State Personal Income (SPI). However, GSP is issued only annually with lags of several years, and SPI is produced quarterly. Israilevich and Kuttner (1993) developed methods to handle mixed frequency data series but their approach has not been widely used. As a result, it has been difficult to find monthly local economic activity indices, especially based on some common methodological foundation, reflecting local economic status in a comprehensive fashion.

There have been some trials to make local economic activity indices. One is to estimate monthly approximations of GSP or SPI based on regression approach. By regressing interpolated GSP or SPI on economic indicators, one can drive a monthly GSP forecast. Unfortunately, in this regression method, we do not use all information from the available economic indicators, since including many variables would "result in over-fitting and poor performance in forecasts." (Stock and Watson 1999) In fact, the forecasting model can be set up using just two or three data series (see the example: the CRAIN's Chicago Index[1]). Another approach uses the Kalman-Filter method to extract latent economic activity index from some of the local monthly indicators. (Orr *et al*., 1999) Also Crone (1994) applied a composite coincident method used by Department of Commerce to local indicators. In this paper, a new regional economic activity index is developed using a dynamic factors model. This methodology utilizes all information from available economic indicators.

As a matter of fact, regional economy fluctuates according to more factors than those of national economy, since national-level case can ignore regional shocks through aggregation whereas the regional economy moves following both national and local factors with the latter including the influence of neighboring regional economies. In order to identify national components and local components, a great deal of data including regional, neighborhood states' and national-level, are required. The data collection effort has been reduced by the existence of the Chicago Federal Reserve Bank National Activity Index (CFNAI) as an economy-wide factor. Also Forni and Lippi (1997) argue that one or two principal components can almost explain the variance of local indicators caused by economy-wide business fluctuations. Based on this proposition, a local economic activity index is constructed in the following way. First, the national-wide

[1] This may be found at http://www.uiuc.edu/unit/real; it is issued monthly.

components are extracted from local indicators by using the CFNAI and drive the local-shocks-composed indicators. Then, principal components method is applied to those indicators. Finally, a local economic activity index is created through combining CFNAI and local components. In this paper, three monthly indices are presented: Chicago Region Production Activity Index (CRPAI), Chicago Region Real Income Approximate Index (CRRIAI) and Chicago Region Business Activity Index (CRBAI).

This paper is organized as follows. In section 2, a review of the current state of the art in index development is provided and the relevant methodology is presented in section 3. In sections 4 and 5, the estimation results are discussed and a presentation is provided of the new economic activity indices. The final section provides some notes for further research.

2. Literature Review

2.1 Economy-Wide Composite Index

There is a fascination with business cycles that extends from scholars, to businessmen, policy makers and households. There are many ways to analyze business cycle. One of the most important methods seeks to combine macroeconomic indicators into a composite index. For example, the U.S. Department of Commerce produces a coincident index.[2] This is a simple index, which is calculated as a weighted average of changes of individual indicators. More formally, coincident composite index C_t is given by $C_t = \sum_{i=1}^{n} w_i X_t^i$ where X_t^i is the percentage change in the i^{th} indicator and w_i is the weight of X_t^i. The second approach was developed by Stock and Watson (1989). Under the assumption that a single unobserved factor influences the economic activities and thus should be reflected in the various indicators simultaneously, they identify the common factor as a coincident index (say "XCI") using the Kalman Filter method: $\Delta X_t = \beta + \gamma(L)\Delta C_t + \mu_t$,

[2] These days, Conference Board issues the composite index monthly. You can see in more detail at http://www.conference-board.org/economics/leadindicator/indicators.cfm

$D(L)\mu_t = \varepsilon_t$,

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

where X_t denotes an $n \times 1$ vector of the 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. The third approach is the principal components method. This approach tries to utilize all information from the available economic indicators in order to extract unobservable factors.[3] Under the assumption that the fluctuations of economic indicators are explained by many unobservable factors, principal components method is applied to economic data set. The Chicago Federal Reserve Bank National Activity Index (CFNAI) is the first principal component of eighty-five existing, monthly indicators of national economic data. The methodology was developed by Stock and Watson (1999). Along this line, Forni, *et al*. (2000), Forni and Lippi (1997), Forni and Reichlin (1996) also use the principal components method, applying it to the covariance matrix of the spectral density.

2.2 Regional Composite Index

As noted earlier, the regional economy fluctuates according to national economic factors and local factors. Accordingly, regional economy may possibly move quite differently from the nation as a whole. Clearly, differences in economic structure, the position of regional firms in commodity production chains, the region's degree of openness all will play a role; however, the influence that these and other factors might have on regional economic activity remains an empirical question to be explored. Therefore, it makes sense to develop a monthly regional economic activity index that is compatible with a national composite index, such as XCI or CFNAI. There have been a small number of attempts to construct monthly local composite indices using local data; examples would include those developed by Phillips (1988) for Texas and Crone (1994) for New Jersey, Delaware and Pennsylvania. In addition, Orr *et al*. (1999)

[3] Coincident composite index and experimental coincident index are created trough using only four or five economic indicators.

constructed two coincident indices for the New York and New Jersey Region, following the methods adopted by the U.S. Department of Commerce and Stock and Watson (1989). They found out the fact that business cycles of New York and New Jersey have diverged from national cycles. However, one should note that they just use the employment sector data that reveal lagging behavior to business cycle, and as a result, their indices show the same properties. There would appear to have been no attempts to using dynamic factor model for making local economic activity indices.

3. Methodology

Regional economic indicators move according to the national components, local components and idiosyncratic shocks. Thus, a regional model can be written as follows.

$$x_t^i = a_1^i(L)u_{1t} + a_2^i(L)u_{2t} + \ldots + a_h^i(L)u_{ht} + b_1^i(L)v_{1t} + b_2^i(L)v_{2t} + \ldots + b_m^i(L)v_{mt} + \delta_t^i$$

where, u_{1t} is national shock l at time t , l=1,…,h, v_{pt} is regional shock p at time t, p=1,…,m, $a_1^i(L)$, $b_i^p(L)$ are the response functions with the lag operator L, i is region indicator , i=1,…,s, and δ_t^i indicates idiosyncratic shock. In order to estimate above model, many economic indicators for within region and neighborhood regions are required. Since each regional economic indicator includes locally-specific and idiosyncratic noises, application of the principal components method directly to each regional data set, may yield inaccurate national components.[4] Therefore, each indicator needs to be aggregated at a higher level to remove local and idiosyncratic shocks and then, the dynamic factor method can be applied to derive the national components. That is, we need aggregated indicators covering several states in order to get national components. This could turn out to be a tedious process; fortunately, Forni and Lippi (1997) show that when they apply principal components method to the US personal income data, two common shocks are sufficient to account for the co-movements of state-level data. According to their estimate, the first two principal components account for about 96

[4] Dynamic properties between micro-level and macro-level variables may be different from one other, since macro-level variables does not depend on the idiosyncratic components. For example, panel data shows that there are

percent of the total variance of national shocks and the first principal component explains slightly less than 90 percent. Based on this result and data availability, CFNAI can be used as an indicator of national economic shocks without estimating using regional-level data.

In order to estimate regional components, nation-wide economic fluctuation effects (the effects of CFNAI) need to be extracted from each local indicator. Notice that CFANI and other economic indicators are not generally orthogonal. Therefore, estimating the effects of CFNAI on each local indicator through the use of a single linear least square regression method could produce misleading results. In this respect, it is better to calculate the partial regression coefficient of CFNAI using partitioned regression.[5] Thus, each local economic indicator is regressed on the set of other economic indicators and a time trend; in addition, CFNAI is also regressed on this same set. Using the residuals from both regressions, the partial coefficient of CFNAI will be obtained with which the effect of CFNAI can be extracted from each local economic indicator. In the second step, the log difference is taken of the national-factor-extracted local indicators and each indicator (y_t) is standardized with mean 0 and variance 1. This step is needed to yield unique solutions in the principal components method. Thirdly, the principal components method is applied to the Y_t, matrix of individual y_t vectors.[6] Finally, the analysis seeks the appropriate methods with which local and national components can be combined into a local economic activity index. For example, if the focus is on a forecasting

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negative first-order autocorrelation in labor income, whereas aggregate labor income indicates a positive first-order autocorrelation. (Forni and Lippi (1997) p.8)

[5] Suppose that the regression has the formula $y = X_1\beta_1 + X_2\beta_2 + \varepsilon$ and X_1, X_2, are two sets of variables. Then the estimated β_2 is calculated by the following form, $\hat{\beta}_2 = \left(X_2' M_1 X_2\right)^{-1}\left(X_2' M_1 y\right)$ where $M_1 = I - X_1\left(X_1' X_1\right)^{-1} X_1'$, M_1, is a residual maker and idempotent matrix. Therefore, $\hat{\beta}_2$ can be obtained by regressing residual vector from least square regression of y on X_1, on the residual vector from that of X_2 on X_1. See in more details on W. Greene (1997) p.245-247

[6] If we have *t* observation on *k* 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 shall be able to obtain uniqueness of *p* and *a*. Our criterion is to select to these vector such that the sum of squares of $Y - pa'$ is minimized. Using matrix algebra, the following can be presented: $a = Y'p$, $\left(YY' - \lambda I\right)p = 0$, $p = \left[1/\lambda\right]Ya$. 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

model of inflation, the search will center on an appropriate method of combination that provides the highest explanatory power for inflation.

4. Estimation of Local Dynamic Factors

4.1 Data

For this phase of the analysis, five local monthly economic indicators are used, namely, Chicago Fed Midwest Manufacturing Index (CFMMI), Chicago Manufacturing Employment (MFGNS), Chicago Non-manufacturing Employment (NMFGNS), Illinois Total Construction (ILCONS), Chicago Retail Sales (RETAILS) as well as CFNAI and Illinois Personal Income (PI). All monthly economic indicators are seasonally adjusted for the period from January 1978 to October 2001 and personal income is seasonally adjusted quarterly data from the first quarter of 1978 to the second quarter of 2001. All variables are real-valued. Mnemonics of data, sources, and units are provided in Appendix 1.

4.2 Estimation

In order to get the national and local principal components, we take several steps of estimations. First of all, each local indicator is regressed on the CFNAI, other indicators and a time trend. Actually, stepwise regression is used to find the significant lag for the explanatory variables, since there is no prior knowledge about the time structure of relationships and our main concern is on obtaining unbiased coefficients of CFNAI in each regression. The estimation results are displayed in Appendix 2. Secondly, based on the regression results described earlier, national component is extracted from each local indicator. Then, the principal components method is applied to the data set that includes log-differenced residuals of CFMMI, MFGNS, NMFGNS, RETAILS and ILCONS. Each series is standardized with mean 0 and variance 1. As a result, five principal component series are obtained. Time sequences of each principal component are displayed in Appendix 3.

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first largest root λ, and the second principal component p is the second largest root and so on. For more details, see Henry (1971) p.46-48

There are several interesting findings at this stage. First of all, as we can see from the regression results of Appendix 2, CFNAI, as a national principal component, affects all of the local economic activity indicators. Especially, the Chicago Fed Midwest Manufacturing Production (LCFMMI) is influenced by CFNAI with the time lag that varies from 0 to 6 months. Furthermore, the CFNAI generates negative effects on employments of non-manufacturing sector with the time lag of 2, 3 and 8 months whereas CFNAI gives positive effects on employments of manufacturing sector with time lag of 3 months.[7] From these results, it appears that CFNAI is the national dynamic factor, which affects all of the economic activity indicators and especially, is closely related with national and regional manufacturing production. Figure 1 shows the fact that CFNAI and the Hodrick-Prescott filtered[8] manufacturing production (CIPMFG) are closely correlated. Actually, CFNAI leads the cyclical component of manufacturing production by about 4 months.

<<insert figure 1 here>>

Secondly, from Table 1, it can be seen that the first principal component explains 26.9 percent of total variations and the second explains 23.9 percent.[9] However, the explanatory powers of the first to the fifth component are not all that different from each other. In this respect, it would appear that all of the components could be used as a source of information in the construction of the local economic activity index.

<<insert table 1 here>>

Thirdly, the explanatory powers of each component to total variance of each indicator were checked.[10] As revealed in Table 2, the national-component-extracted CFMMI (manufacturing production) attributes around 51 percent to the first local principal component and around 42

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[7] We think that this regression result indicates that in the short-run, the employment between manufacturing and non-manufacturing sectors shows a substitution relationship.

[8] 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 we use the penalty weight λ = 14400 in monthly series and λ = 1600 in quarterly series as generally recommended.

[9] When we apply the principal components method, [eigen value(λ) /Trace(Y'Y)] indicates the explanatory power of each principal component to the total variances of the data set (Y).

[10] In our set-up, we can show the following relationship $y_h' y_h = a_{1h}^2 + a_{2h}^2 + a_{3h}^2 + residual$ where y_h is individual 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 normalization.

percent to the fifth component. The national-component-extracted MFGNS (manufacturing employment) attributes around 49 percent to the first local principal component and around 41 percent to the fifth component while the national-component-extracted NMFGNS (non-manufacturing production) attributes around 55 percent to the second local principal component and around 28 percent to the fourth component. For the national-component-extracted ILCONS (construction), the third local principal component dominates (around 81 percent) with the fourth component accounting for 15 percent. The fourth component accounted for 49 percent of the national-component-extracted RETAILS (retail sales) while the second component followed with 34 percent. That is, it appears that the first and the fifth component mainly explain fluctuations of manufacturing production and employment and the second and the fourth component affect mainly on retail sales and non-manufacturing employment whereas the third component dominantly affects on construction. Again, from above results, it can be argued that each component has quite amount of information for the business activity status and therefore, each component would be used complementarily for generating local economic activity index.

<<insert table 2 here>>

Fourthly, the first local principal component moves in a similar fashion with CFNAI. Figure 2 displays the 3 months moving averaged CFNAI and the inverse of the first local principal component (EAIA). They move to the same directions and therefore, CFNAI and the first local principal component moves opposite directions. This can be interpreted as follows: since CFNAI is extracted from each local economic indicator using regression, principal components method applied to the data, generates generically a principal component that follows the opposite movement of CFNAI. From this perspective, it seems that the only one out of CFNAI and the first local principal component can be used as a source of information in the construction of the local economic activity index.

<<insert figure 2 here>>

In summary, from the above exercise, we might confirm that the manufacturing sector still works as a main source of economic fluctuations of both national level and regional level and as a result, CFNAI, closely related with manufacturing production, explains quite well all of the local economic indicators. Also it is needed to recognize that other principal components would be used as an information source for generating local economic activity index in Chicago Metropolitan area since non-manufacturing sector-related indicators such as retail sales, construction and non-manufacturing employments are quite well explained by other principal components. We think it reflects the fact that service sector has the largest share in the economic activity of Chicago Metropolitan area.

5. Development of Local Economic Activity Indices

5.1 Production Activity Index

With the estimated national factor and local factors, it is now possible to make a local economic production activity index that is a leading indicator of local production. As already noted, CFNAI is closely related to national production (see figure 1). In order to make a local production activity index, an appropriate method to combine national and local principal components has to be developed. Regression analysis is used to find the weights; a proxy variable is regressed on the dynamic factors. As a proxy variable for production activity, monthly manufacturing production is used. As can be seen in the movement of each principal component of Appendix 3, they show cyclical movements. Thus, manufacturing production is filtered with the Hodrick-Prescott method to yield the cyclical component of production (CCFMMI). Then, CCFMMI is regressed on the principal components. Table 3 reveals that CCFMMI is explained by CFNAI, the second component (EAIB) and the fifth component (EAIE). It is consistent with the analysis of explanatory power of components to the manufacturing production that is presented in Table 2.

<<insert table 3 here>>

Now, it is possible to combine CFNAI, the second and the fifth components into a Chicago Region Production Activity Index (CRPAI). CRPAI is local version of CFNAI and is a leading indicator for production. Figure 3 shows the movements of CCFMMI and CRPAI. At figure 3, FCRPAIMA denotes a 3 months moving average series of normalized CRPAI with mean 0 and variance 1. As can be seen, CRPAI leads Chicago region manufacturing production by a few months.

<<insert figure 3 here>>

5.2 Monthly Real Personal Income Index

Here the attention is focused on a monthly real personal income index. As noted earlier, state personal income (SPI) is issued on a quarterly basis. SPI is estimated with various data sources such as state unemployment insurance programs of the Employment and Training Administration, social insurance programs of Health Care Financing Administration, Social Security Administration, Federal Income Tax program of Internal Revenue Services, etc. Therefore, we cannot say that SPI reflects regional economic status exactly and thus, it has some limits as a business activity indicator. However, the change in personal income is very important factor in regional economic business. This affects on consumption, construction, etc.

H-P filtered real personal income (CRPI) is regressed on national and local principal components. The regression result is displayed in Table 4. CRPI is influenced by CFNAI with the time lag of 3 quarters. It is consistent with the fact that employment adjustment generally lags and SPI is estimated based on the employment data. Also, the second component (EAIB) and the fourth local component (EAID) have the explanatory power to the CRPI. This result also is consistent with the analysis of section 4.2. Since manufacturing and non-manufacturing employments show substitution relationship in the short-run with respect to the fifth components, the fifth component does not give much information for approximating personal income. As a result, coefficients of CFNAI, the second and the fourth component are significant.

From the prior regression analysis, it is possible to generate a monthly Chicago Region Real Income Approximate Index (CRRIAI). Figure 4 shows the quarterly series of the H-P filtered RPI and CRRIAI. FCRRIAI denotes a normalized series of CRRIAI with mean 0 and variance 1. It is clear that CRRIAI follows CRPI well.

<<insert figure 4 here>>

Finally, the local production activity index is compared with the local real personal income approximate index. In figure 5, the 3 months moving averaged CRPAI (FCRPAIMA) and CRRIAI (FCRRIAIMA) are displayed. As has already been noted, CRPAI leads CRRIAI by up to 9 months, since personal income depends on employment data, which typically lags the business cycle.

<<insert figure 5 here>>

5.3 Business Activity Index

Here, an attempt is made to construct a business activity index that is compatible with the national coincident index, reflecting national business cycle status. Conference Board announces the composite coincident index each month and NBER produces the Experimental Coincident Index (XCI) that is developed using the Stock and Watson (1989) methodology. However, one challenging problem in generating the local business index is that it is very difficult to find a proxy variable as before. Also, it is important to consider the fact that the portion of manufacturing production in Chicago Region is not that large (less than 20 percent) and that services account for the largest share of gross regional product. Thus, CRPAI by itself is not enough to reflect the total business activity status in this region.[11] Since employment data lags the business cycle and Illinois total construction data does not reflect Chicago region's business status very well, some other alternatives need to be explored. However, retail sales indicator can contribute to the explanation of the region's business status. With these considerations in mind, a local business activity index has been constructed, with the weights shown in table 2. That is, we weigh each principal component with these weights, reflecting the explanatory power of the variances of manufacturing production and retail sales.[12] Figure 6 shows the 6-month moving average of the normalized Chicago Region Business Activity Index (FCRBAIMA6) and Hodrick-Prescott filtered XCI (CXCI). In fact, the movements of CRBAI show more noise than CXCI, reflecting the properties of local data, including many local shocks and thereafter, we smooth CRBAI for 6 months. From the Figure 6, it can be seen that FCRBAIMA6 matches the turning points of national business fluctuations after the end of 1970s. However, FCRBAIMA6

[11] In national case, CFNAI and XCI do not give the same information. As can be seen the in the graph CFNAIMA and XCI of Appendix 3, CFNAI leads XCI some months at the peak and through of business cycle. Actually the Chicago Federal Reserve Bank's interpretation is that if CFNAIMA<-0.7 following a period of economic expansion, the likelihood that a recession is occurring begins to increase and if CFNAIMA>+0.2 following a period of economic contraction, the likelihood increases that a recession has ended. (see Chicago FRB 2001 p.7)

moves somewhat differently from CXCI in the middle of expansion phases and contraction phases. This reflects the fact that if there is a large national economic shock, its effect dominates local shocks but, otherwise, local shocks strongly affect local business activities.

<<insert figure 6 here>>

Again, the local business index is compared with the local real personal income index, similarly as in previous section. As can be seen in figure 7, FCRBAIMA6 leads FCRPAIMA by 6 to 7 months. From these results, we can think the time structure among newly-generated indices as a following way: production activity index (CRPAI) leads business activity index (CRBAI) by 2 to 3 months and real personal income approximate index (CRRIAI) lags business activity index (CRBAI) by 6 to 7 months. Even though CRBAI and CRPAI are determined mainly by national principal component, CFNAI, CRBAI lags CRPAI a few months due to the effects of local components and moving-averaged effect.[13]

<<insert figure 7 here>>

6. Concluding Remarks

Even with strong demands for local economic activity indexes, there have been surprisingly few attempts to construct comprehensive economic indices. In this paper, some experimental methods for generating local business activity indices are suggested. The basic idea is that given the existence of CFNAI and local economic indicators, it is possible to extract local and national dynamic factors applying partitioned regression and principal component method to this data set. After that, it is possible to generate local economic activity combining the national component with local dynamic factors. From these experiments, three local indices for the Chicago Metropolitan area were generated and those are expected to provide important strategic information to the local business community and policy makers.

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[12] Actually, we put the same weights between manufacturing production and retails sales and sum up a_{ih} with respect to each component.

[13] Generally, when moving average is taken by backward, not centered, direction, moving averaged index lags original index a few months. In this case, FCRPAIMA is 3 months moving averaged series whereas FCRBAIMA6 is 6 months moving averaged series.

Finally, some notes for improvements of the experimental local economic activity indices are suggested along with some further research directions. First of all, more data are needed to generate stable and consistent estimators for local dynamic factors. Secondly, these data need to match with actual economic activity in the region. Thirdly, a search for appropriate weighing methods needs to be conducted to obtain smooth index series. Fourthly, it is important to consider the ways in which economic interaction across regions can be incorporated into the methodology. Finally, it would be useful to consider ways in which these monthly indicators could be integrated with annual, longer-term models, such as the Chicago Econometric Input-Output model.

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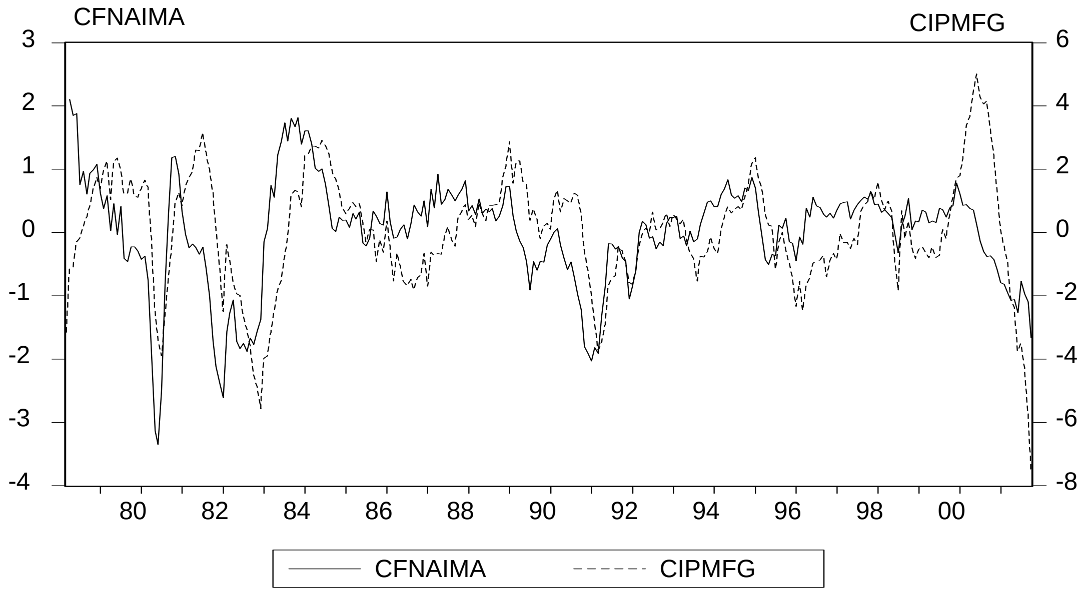


Figure 1 CFNAI and H-P filtered National Manufacturing Production (CIPMFG)

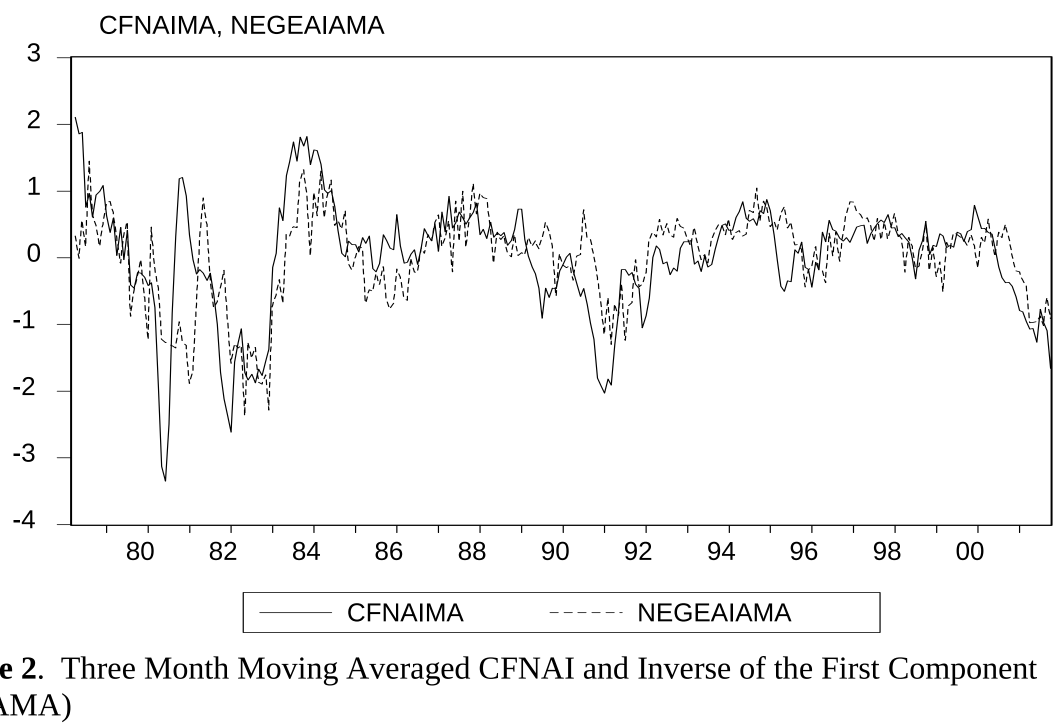


Figure 2. Three Month Moving Averaged CFNAI and Inverse of the First Component (EAIAMA)

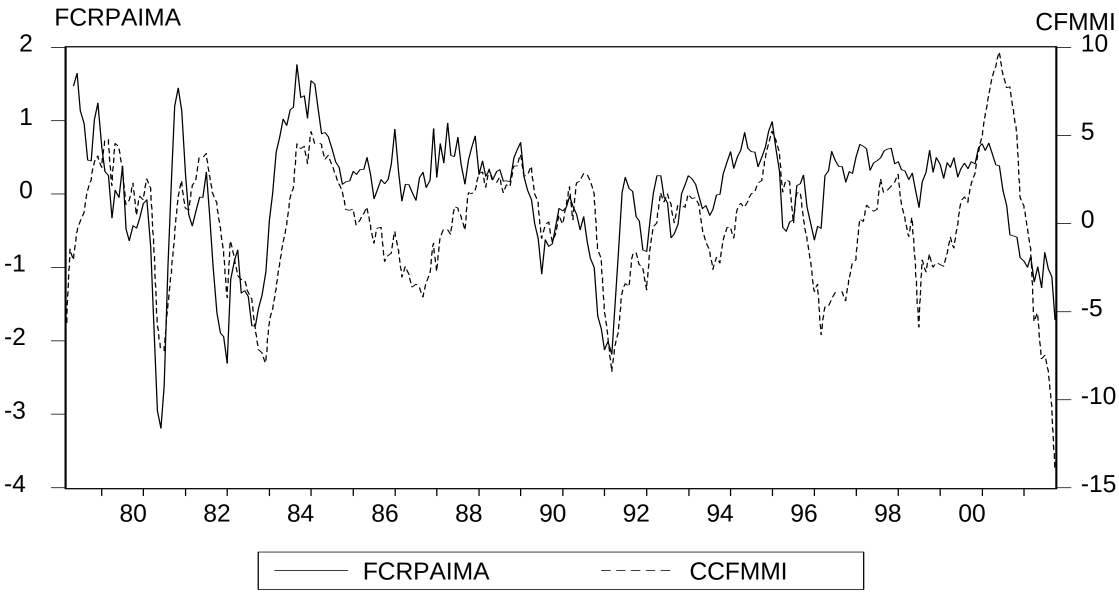


Figure 3 CCFMMI and Three Months Moving Averaged CRPAI

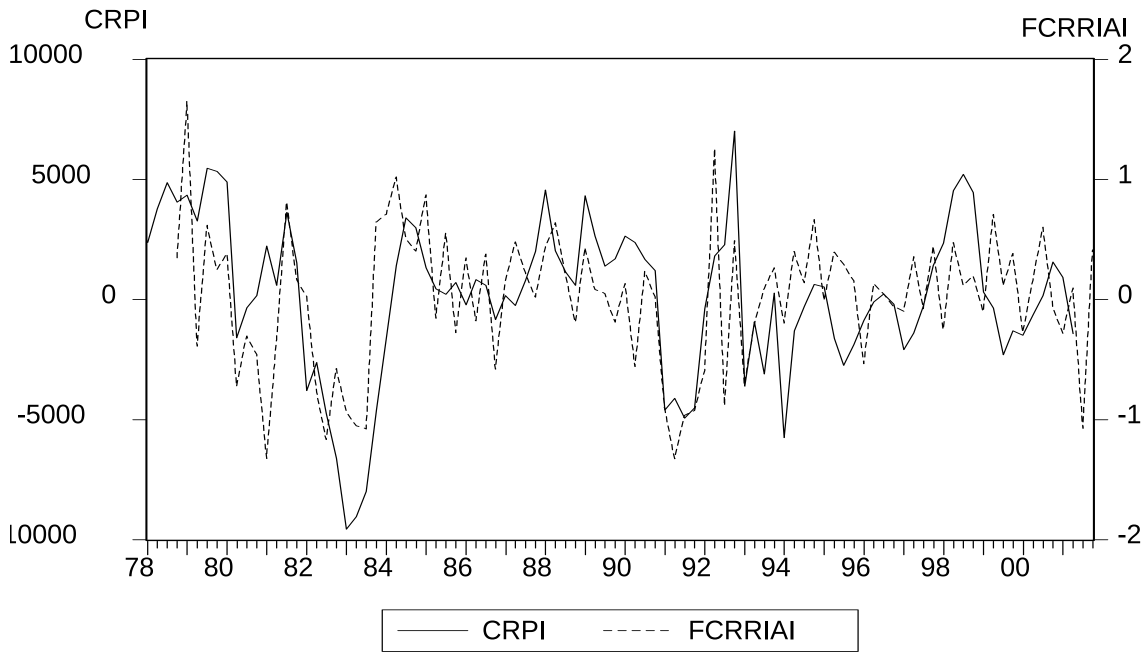


Figure 4 CRPI and Quarterly CRRIAI

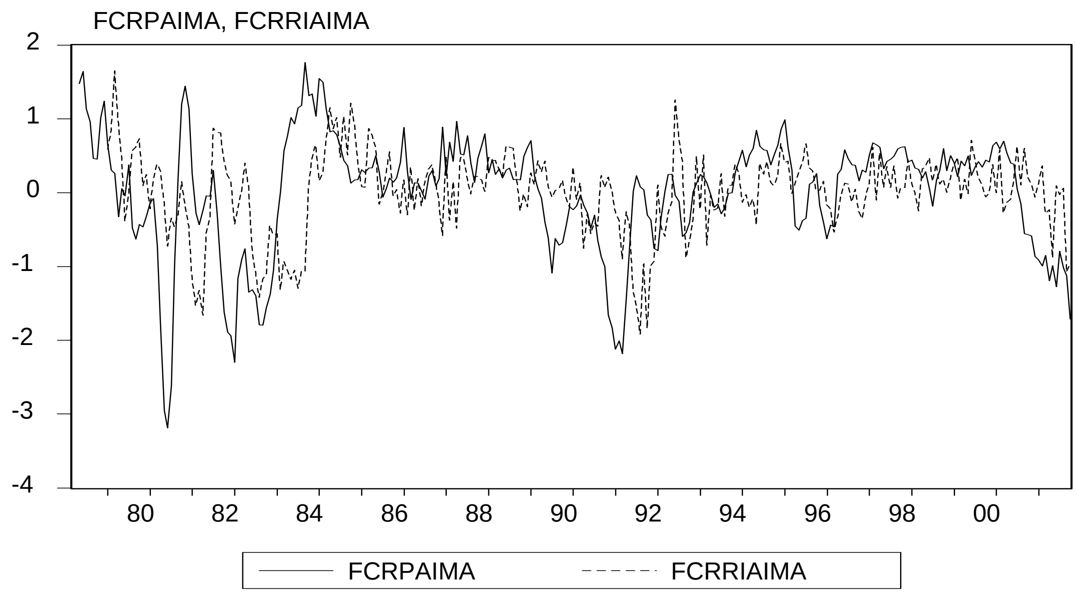


Figure 5 Local Production Activity Index and Real Income Approximate Index

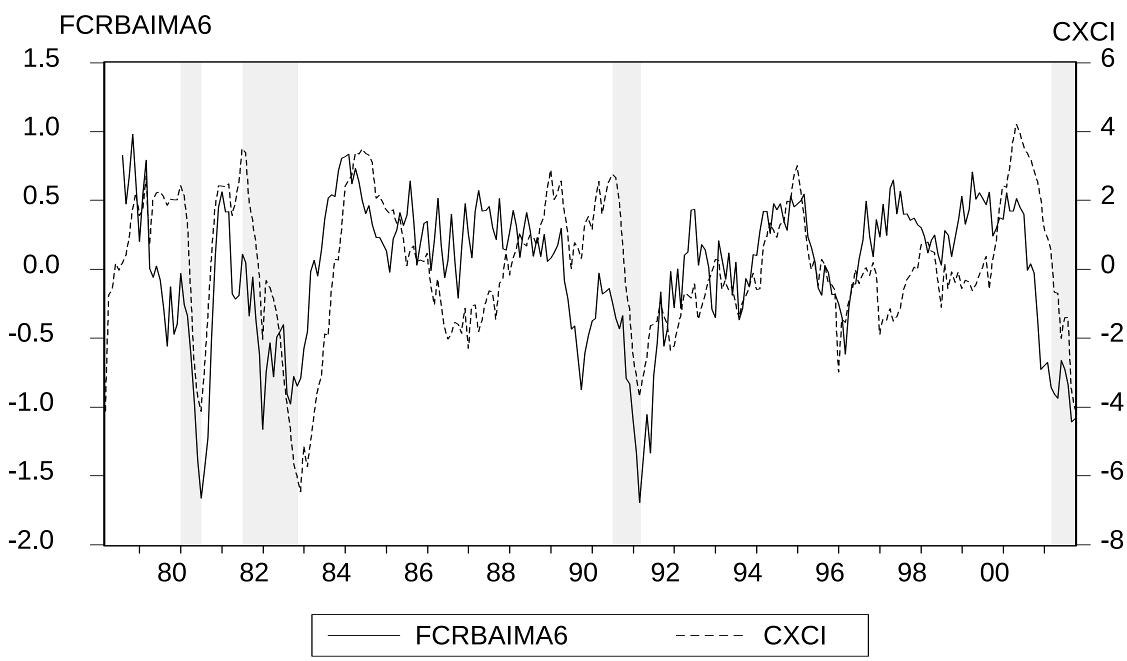


Figure 6 Local Business Activity Index (FCRBAIMA6) and H-P Filtered XCI (CXCI)

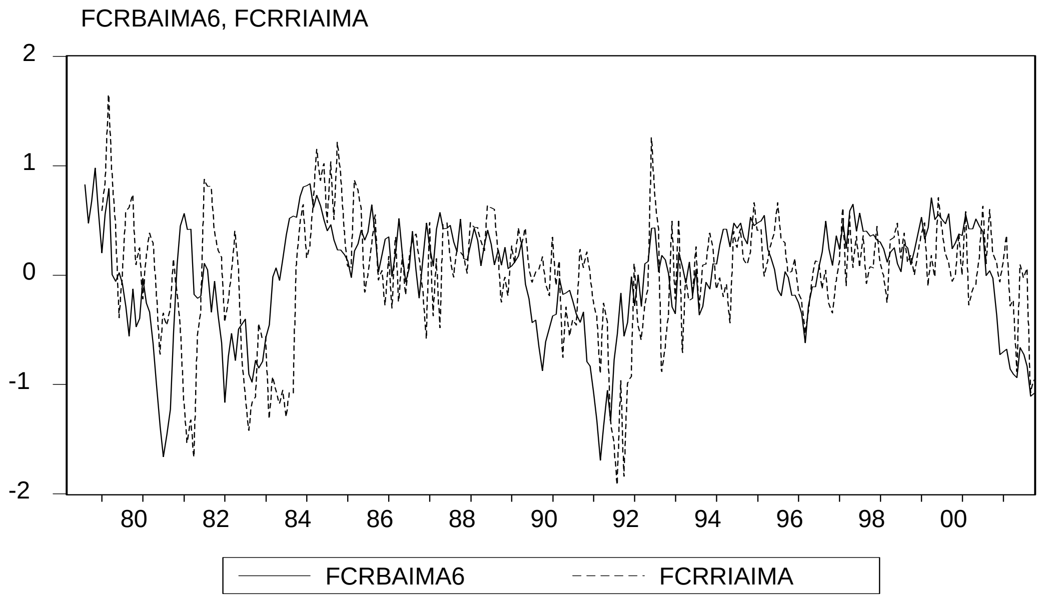


Figure 7 Local Business Activity Index (FCRBAIMA) and Personal Income Approximate Index (FCRRIAIMA)

Table 1 Explanatory Power of Each Component to Total Variances

	First	Second	Third	Forth	Fifth
Eigen value (λ)	382.6847	339.5079	290.0051	243.3285	164.4737
λ/Trace(Y'Y) (%)	26.9	23.9	20.4	17.1	11.6

Table 2 Explanatory Power of Components to the Variance of Each Indicator

	a_{1h}	a_{2h}	a_{3h}	a_{4h}	a_{5h}
ARCFMMI	-0.7124 (1)	0.1832 (4)	-0.0381 (5)	0.1863 (3)	-0.6503 (2)
ARMFGNS	-0.6985 (1)	-0.2239 (4)	-0.0397 (5)	-0.2280 (3)	0.6391 (2)
ARNMFGNS	0.0332 (5)	-0.7392 (1)	0.1241 (4)	-0.5247 (2)	-0.4022 (3)
ARILCONS	0.0570 (5)	0.1658 (3)	-0.9023 (1)	-0.3869 (2)	-0.0736 (4)
ARRETAILS	0.0185 (5)	-0.5851 (2)	-0.4091 (3)	0.6988 (1)	0.0391 (4)

Note: 1) AR_ denotes the national-component-extracted local indicator normalized mean 0 and variance 1.
2) Parenthesis indicates rankings of explanatory power of each component.

Table 3 Regression of CCFMMI on Principal Components

Dependent Variable: CCFMMI				
Sample: 1978:03 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFNAI	0.670967	0.073468	9.132838	0.0000
EAIB	0.071419	0.035688	2.001191	0.0463
EAIE	-0.312305	0.060635	-5.150616	0.0000
AR(1)	0.962143	0.020243	47.52978	0.0000
R-squared	0.903188	Mean dependent var		0.041914
Adjusted R-squared	0.902150	S.D. dependent var		3.449339
S.E. of regression	1.078984	Akaike info criterion		3.003902
Sum squared resid	325.9781	Schwarz criterion		3.055296
Log likelihood	-422.5541	F-statistic		870.7321
Durbin-Watson stat	1.275214	Prob(F-statistic)		0.000000

Table 4 Regression of CRPI on Principal Components

Dependent Variable: CRPI				
Sample(adjusted): 1979:2 2001:2				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFNAI(-3)	830.6740	347.7409	2.388773	0.0191
EAIB	-691.8483	437.5415	-1.581218	0.1175
EAID	1116.616	502.4030	2.222551	0.0289
AR(1)	0.687615	0.080596	8.531612	0.0000
R-squared	0.580127	Mean dependent var		-50.21186
Adjusted R-squared	0.565308	S.D. dependent var		3164.131
S.E. of regression	2086.148	Akaike info criterion		18.16793
Sum squared resid	3.70E+08	Schwarz criterion		18.27978
Log likelihood	-804.4728	F-statistic		39.14745
Durbin-Watson stat	2.005137	Prob(F-statistic)		0.000000

Appendix 1 Data Description

Series	Description
CFMMI	Chicago Fed Midwest Manufacturing Index, 1992=100 (1/78-10/01) Source: Federal Reserve Bank of Chicago
CFNAI	Chicago Fed National Activity Index, (1/78-10/01) Source: Federal Reserve Bank of Chicago
ILCONS	Illinois Total Construction, Millions of Dollars (1/78-10/01) Source: Dodge Construction Bulletin
IPMFG	U.S. Index of Manufacturing Production, 1992=100 (1/78-10/01) Source: Federal Reserve Board
MFGNS	Chicago Manufacturing Employment, Thousands (1/78-10/01) Source: Bureau of Labor Statistics
NMFGNS	Chicago Non-manufacturing Employment, Thousands (1/78-10/01) Source: Bureau of Labor Statistics
RETAILS	Chicago Retail Sales, Millions of Dollars (1/78-10/01) Source: Illinois Department of Revenue and estimates by REAL
RPI	Illinois State Income deflated by GDP Deflator, (Q1/78-Q2/01) Source: Bureau of Economic Analysis
XCI	Experimental Coincident Index Source: NBER
ARCFMMI	National-component extracted LCFMMI, Normalized mean 0 and variance 1
ARILCONS	National-component extracted LILCONS, Normalized mean 0 and variance 1
ARMFGNS	National-component extracted LMFGNS, Normalized mean 0 and variance 1
ARNMFGNS	National-component extracted LNMFGNS, Normalized mean 0 and variance 1
ARRETAILS	National-component extracted LRETAILS, Normalized mean 0 and variance 1
CCFMMI	Cyclical Component of CFMMI: CFMMI – HP filtered trend
CFNAIMA	3 months moving averaged CFNAI
CIPMFG	Cyclical Component of IPMFG: IPMFG – HP filtered trend
CRBAI	Chicago Region Business Activity Index
CRPI	Cyclical Component of RPI: RPI – HP filtered trend
CRPAI	Chicago Region Production Activity Index
CRRIAI	Chicago Region Real Income Approximate Index
CXCI	Cyclical Component of XCI: XCI – HP filtered trend

Series	Description
EAIA	First Principal Component
EAIB	Second Principal Component
EAIC	Third Principal Component
EAID	Fourth Principal Component
EAIE	Fifth Principal Component
FCRBAI	Normalized CRBAI, Mean 0 variance 1
FCRPAI	Normalized CRPAI, Mean 0 variance 1
FCRRIAI	Normalized CRRIAI, Mean 0 variance 1
FCRBAIMA6	6 months moving averaged FCRPAI
FCRPAIMA	3 months moving averaged FCRPAI
FCRRIAIMA	3 months moving averaged FCRRIAI
LCFMMI	log(CFMMI)
LILCONS	log(ILCONS)
LMFGNS	log(MFGNS)
LNMFGNS	log(NMFGNS)
LRETAILS	log(RETAILS)

Appendix 2 Regression Results

(1) Manufacturing Production

Dependent Variable: LCFMMI				
Sample: 1978:10 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
@TREND	0.004301	0.000140	30.73546	0.0000
CFNAI	0.012807	0.003443	3.720017	0.0002
CFNAI(-1)	0.011208	0.003581	3.129514	0.0019
CFNAI(-2)	0.012832	0.003608	3.556926	0.0004
CFNAI(-3)	0.008848	0.003716	2.381042	0.0180
CFNAI(-5)	0.008882	0.003552	2.500460	0.0130
CFNAI(-6)	0.010149	0.003163	3.208695	0.0015
LNMFGNS	-1.277685	0.062977	-20.28804	0.0000
LILCONS(-1)	0.036963	0.011832	3.123943	0.0020
LILCONS(-2)	0.037807	0.012042	3.139608	0.0019
LILCONS(-5)	0.039156	0.011594	3.377138	0.0008
LILCONS(-6)	0.033263	0.011575	2.873650	0.0044
LRETAILS	0.220901	0.050845	4.344609	0.0000
LRETAILS(-3)	0.109068	0.050710	2.150817	0.0324
LMFGNS(-6)	1.602340	0.041103	38.98367	0.0000
R-squared	0.978697	Mean dependent var		4.647739
Adjusted R-squared	0.977558	S.D. dependent var		0.239768
S.E. of regression	0.035919	Akaike info criterion		-3.762497
Sum squared resid	0.338017	Schwarz criterion		-3.566250
Log likelihood	536.1058	F-statistic		859.7516
Durbin-Watson stat	0.298064	Prob(F-statistic)		0.000000

(2) Total Construction

Dependent Variable: LILCONS				
Sample: 1978:10 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.67668	0.656112	-20.84504	0.0000
CFNAI(-2)	0.067954	0.014025	4.845320	0.0000
CFNAI(-7)	0.038001	0.013748	2.764127	0.0061
LNMFGNS	2.553089	0.082190	31.06328	0.0000
R-squared	0.793434	Mean dependent var		6.690073
Adjusted R-squared	0.791164	S.D. dependent var		0.418615
S.E. of regression	0.191301	Akaike info criterion		-0.455603
Sum squared resid	9.990722	Schwarz criterion		-0.403270
Log likelihood	67.10098	F-statistic		349.5373
Durbin-Watson stat	1.618246	Prob(F-statistic)		0.000000

(3) Retail Sales

Dependent Variable: LRETAILS				
Sample: 1978:10 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.963620	0.978812	3.027772	0.0027
CFNAI(-1)	0.007453	0.003683	2.023445	0.0440
LNMFGNS	1.920510	0.299104	6.420879	0.0000
LNMFGNS(-6)	-0.763008	0.284929	-2.677886	0.0079
LILCONS(-2)	-0.035324	0.014534	-2.430409	0.0157
LMFGNS(-3)	-0.889882	0.071330	-12.47559	0.0000
LCFMMI(-4)	0.488146	0.037285	13.09241	0.0000
R-squared	0.979623	Mean dependent var		8.435371
Adjusted R-squared	0.979170	S.D. dependent var		0.313481
S.E. of regression	0.045243	Akaike info criterion		-3.328583
Sum squared resid	0.552675	Schwarz criterion		-3.237002
Log likelihood	468.0088	F-statistic		2163.381
Durbin-Watson stat	0.915600	Prob(F-statistic)		0.000000

(4) Manufacturing Sector Employment

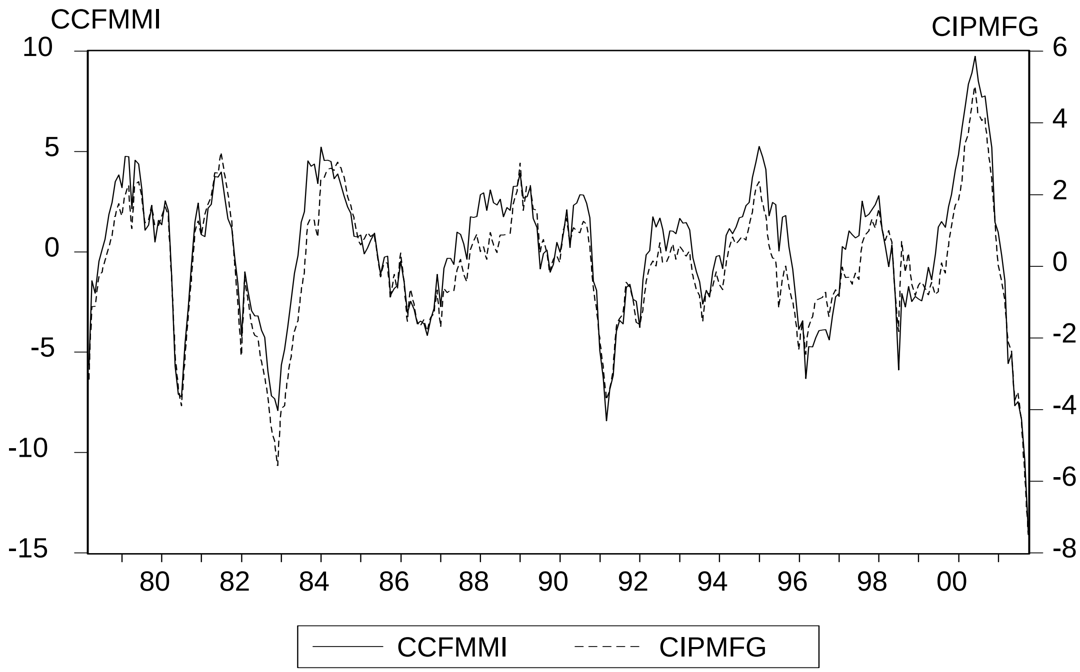
Dependent Variable: LMFGNS				
Sample: 1978:10 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.088843	0.349099	26.03514	0.0000
CFNAI(-3)	0.004902	0.002238	2.190534	0.0294
LNMFGNS	0.563813	0.195833	2.879051	0.0043
LNMFGNS(-6)	-0.656036	0.176592	-3.714985	0.0002
LILCONS(-5)	0.024047	0.008606	2.794109	0.0056
LILCONS(-6)	0.022248	0.008566	2.597165	0.0099
LRETAILS	-0.159359	0.042703	-3.731805	0.0002
LRETAILS(-1)	-0.109535	0.045891	-2.386866	0.0177
LRETAILS(-2)	-0.142345	0.043978	-3.236765	0.0014
LRETAILS(-6)	-0.077014	0.038853	-1.982178	0.0485
LCFMMI(-6)	0.423465	0.015945	26.55763	0.0000
R-squared	0.893716	Mean dependent var		6.516370
Adjusted R-squared	0.889721	S.D. dependent var		0.081893
S.E. of regression	0.027195	Akaike info criterion		-4.332634
Sum squared resid	0.196731	Schwarz criterion		-4.188720
Log likelihood	611.0698	F-statistic		223.6735
Durbin-Watson stat	0.208315	Prob(F-statistic)		0.000000

(5) Non-Manufacturing Sector Employment

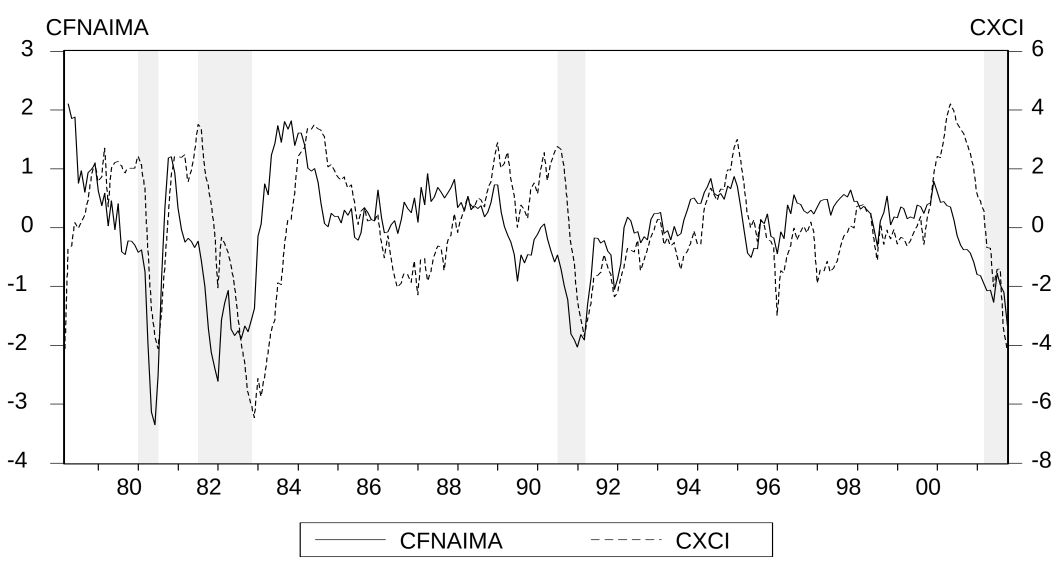
Dependent Variable: LNMFGNS				
Sample: 1978:10 2001:10				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.513098	0.038102	118.4476	0.0000
CFNAI(-2)	-0.004808	0.001649	-2.915856	0.0039
CFNAI(-3)	-0.004139	0.001667	-2.482773	0.0137
CFNAI(-8)	-0.004899	0.001399	-3.502903	0.0005
LILCONS	0.014702	0.006005	2.448481	0.0150
LILCONS(-1)	0.018519	0.006100	3.036035	0.0026
LILCONS(-2)	0.019712	0.006003	3.283587	0.0012
LILCONS(-3)	0.014962	0.006194	2.415422	0.0164
LILCONS(-4)	0.013154	0.006094	2.158404	0.0318
LILCONS(-6)	0.018781	0.005937	3.163186	0.0017
LRETAILS	0.082096	0.024972	3.287485	0.0011
LRETAILS(-4)	0.068541	0.029984	2.285873	0.0231
LRETAILS(-5)	0.079566	0.031457	2.529357	0.0120
LRETAILS(-6)	0.102237	0.029038	3.520742	0.0005
R-squared	0.983770	Mean dependent var		7.980506
Adjusted R-squared	0.982968	S.D. dependent var		0.140598
S.E. of regression	0.018349	Akaike info criterion		-5.109252
Sum squared resid	0.088549	Schwarz criterion		-4.926088
Log likelihood	721.6314	F-statistic		1226.277
Durbin-Watson stat	0.299539	Prob(F-statistic)		0.000000

Appendix 3 Reference Graphs

- Hodrick-Prescott filtered CFMMI (CCFMMI) and national manufacturing production (CIPMFG)



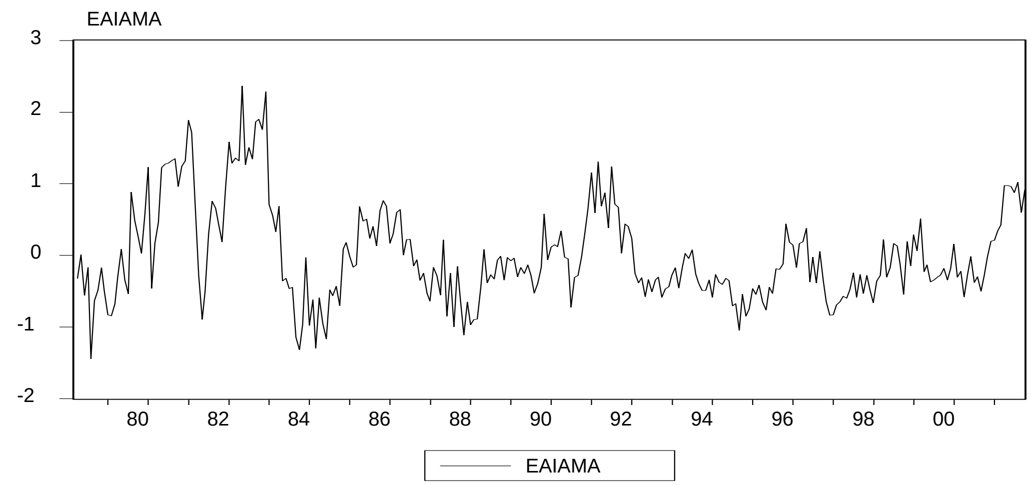
- CFNAI and XCI

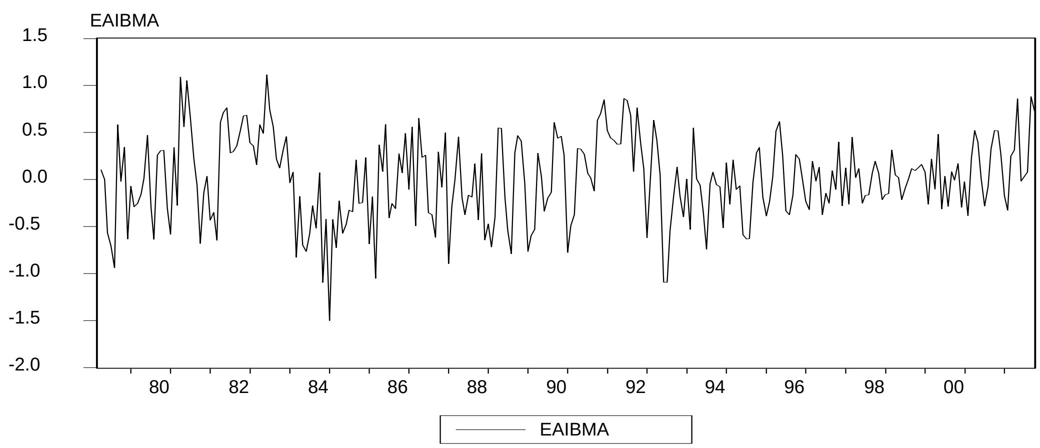


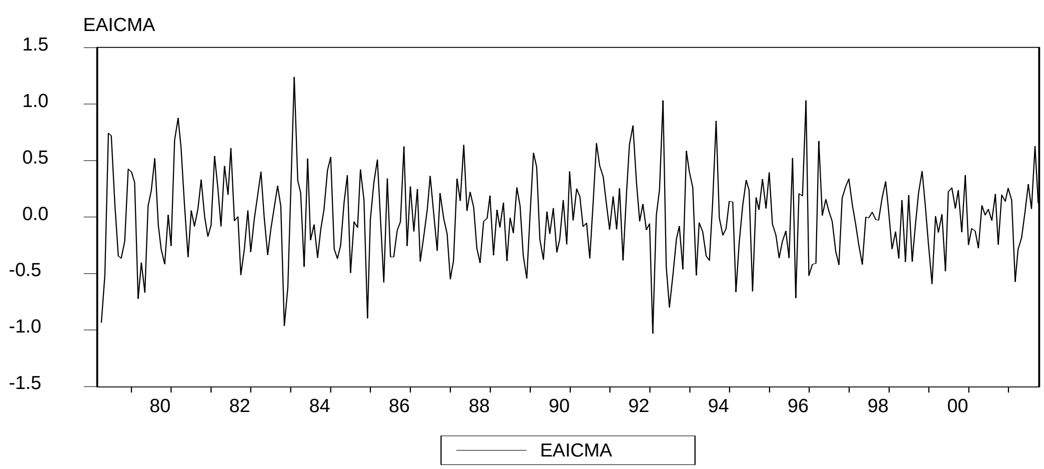
- Local Principal Components

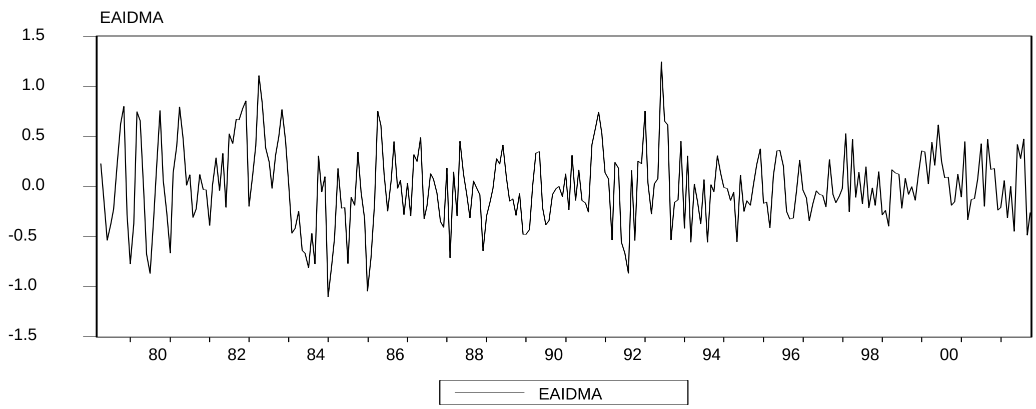
First component: EAIA, Second component: EAIB, Third component: EAIC

Fourth component: EAID, Fifth component: EAIE





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94
96
98
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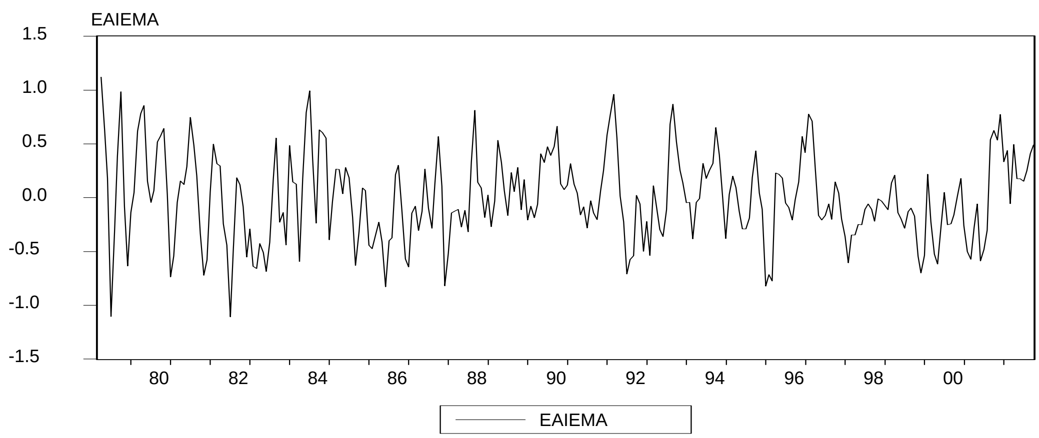
EAIDMA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84
86
88
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94
96
98
00
EAIEMA