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SECTORAL TRENDS AND CYCLES IN GERMANY

Yin-Wong Cheung
Frank Westermann*

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CESifo
Center for Economic Studies & Ifo Institute for Economic Research
Poschingerstr. 5, 81679 Munich, Germany
Phone: +49 (89) 9224-1410 - Fax: +49 (89) 9224-1409
e-mail: office@CESifo.de
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Abstract

We examine the comovements between the output indexes of three German sectors (manufacturing, mining, and agriculture) and the three corresponding sectoral stock market indexes. It is found that data with and without seasonal adjustment give mixed results on the long-run interaction between the sectoral indexes. Compared with data that are non-seasonally adjusted, the adjusted data offer a weaker evidence on the cointegration relationship between a) the sectoral output indexes, b) sectoral stock indexes, and c) individual pairs of real and financial indexes. On short-run comovement, seasonally adjusted data offer stronger evidence on the presence of common synchronized and non-synchronized cyclical components.

JEL Classification: E32, C32.

Yin-Wong Cheung

Economics Department
University of California
Santa Cruz, CA 95064
USA

Frank Westermann
CESifo
(University of Munich & Ifo Institute)
Poschingerstraße 5
81679 Munich
Germany
Westermann@cesifo.de

I. Introduction

In this paper, we investigate the interactions between a) the real industrial production indexes of three major sectors in Germany (henceforth referred to as 'real sectors'), b) the sectoral stock market indexes corresponding to the same three sectors (henceforth referred to as 'financial sectors'), and c) the sectoral output and stock indexes. Specifically, the data on the agriculture, manufacturing, and mining sectors are considered. Advanced econometric techniques and data with and without seasonal adjustment are employed to investigate both the long- and short-term common components of the real industrial production sectoral indexes and the associated sectoral stock indexes.

In their seminal work, Burns and Mitchell (1946) adopt the notion of a business cycle to describe the common cyclical movement in a broad range of macroeconomic variables. Implicitly, it is conceived that the broad-based swings in different sectors of the economy are driven by an unobservable aggregate cyclical component. The temporal dynamics of individual macroeconomic series are jointly determined by the common aggregate component and individual idiosyncratic elements.

Using a real business cycle model of Long and Plosser (1983), Engle and Issler (1995) show that the presence of sectoral comovements hinges on the comovements of sector-specific shocks. If the shocks are not common across sectors, comovements among sectors are unlikely. In fact, Durlauf (1989, p. 95) asserts that if "aggregate unit roots are generated by technology, it is unlikely that growth innovations will be common across sectors." For instance, technological shocks to the computer industry do not have the same effect on, say, the agriculture sector.

Stockman (1988), however, argues that both common and sector-specific shocks are important for studying output growth dynamics.

In general, advances in sector-specific technology do not have the same immediate impact on different sectors. However, different economic sectors in a national economy share a common pool of labor and operate in a similar macro-environment. The effects of technology changes will diffuse across sectors and improve overall efficiency, albeit in varying degrees, in different sectors. In this case, there will be non-contemporaneous cross-sectoral dependence. Thus, the evidence of sectoral comovements and importance of sector-specific shocks bear considerable implications for the determination of output dynamics and for business cycle theory.[1]

Further, the issue of sectoral comovement is of particular relevance for the current process of European monetary integration. Suppose countries specialize in production of goods in which they have comparative advantages as a consequence of market integration in the European Union (EU). If cross-sectoral dependence is weak, then the correlation between national business cycles will be low. In this case a common macroeconomic stabilization policy, pursued by the European Central Bank, can have significantly diverse effects on the EU member countries in the absence of autonomous national monetary policies.

Data from the stock market, which represents claims on future output, provide an alternative channel to evaluate the linkages between sectoral shocks. As a forward-looking financial instrument, the stock index is usually perceived as a good predictor of general business conditions and future economic activity. A model illustrating the theoretical link between aggregate production and stock returns is given in, for example, Fama (1990, IIa). Breeden (1986) devises an elaborate consumption-smoothing model in which expected stock returns and expected output growth are positively correlated. Chen (1991) also uses the consumption-smoothing setting to illustrate the relationship between expected stock returns and output growth. Shiller (1989, Chapter 19) contends that stock prices tend to be low in recessions and high in boom times.

One way to examine the role of fundamentals on financial sectors is to analyze the comovement between real and financial sectors. For instance, to evaluate stock price rationality, Fama (1990) documents that the U.S. stock returns, especially long-horizon returns, and future economic growth are highly correlated. Similar empirical results on U.S. stock returns and aggregate real activity are reported in Chen (1991) and Ferson and Harvey (1991). Cheung and Ng (1998) also uncover Fama's results in international data. Given the close theoretical and empirical relationships between stock market performance and aggregate economic activity, we anticipate that sectoral stock market indexes contain useful information on sectoral output dynamics.[2] Cyclical movements in sectoral stock indexes should reflect those in sectoral output data. Thus, the common movement between sectoral stock indexes is interpreted as an alternative measure of German sectoral output comovement. In addition, we also examine the comovement between a sectoral output index and the corresponding sectoral stock index.

To anticipate our results, we confirm that seasonal adjustment has significant implications for the empirical common trends and cylces between the German sectors. For instance, the seasonally adjusted data give no indication of cointegration between sectoral indexes while the raw data reveal the presence of seasonal cointegration. On the other hand, synchronized and non-synchronized serial correlation common features (Engle and Kozicki, 1993; Vahid and Engle, 1997) are detected among real sectoral and among financial sectoral data with or without seasonal adjustment. The codependence link between the real sector and its corresponding sectoral stock index, however, is likely to be spurious. The finding of common features is in accordance with the reported lead-lag relationships among German sectors (Entorf, 1991) but different from the result on cyclical comovement in Lucke (1998).

The rest of the paper is organized as follows: Section 2 considers the presence of common trends and common cycles in seasonally adjusted data. After a brief description of the test procedures, we present the cointegration, common feature, and codependence test results. The empirical analysis based on data without seasonal adjustment is reported in Section 3. Section 4 contains some concluding remarks.

II. Sectoral Trends and Cycles in Seasonally Adjusted Data

First we examine seasonally adjusted quarterly data on sectoral industrial net production and real stock market indexes. The sample period covers 1962:I to 1994:IV. The data were provided by the Statistisches Bundesamt in Wiesbaden. The three sectors under consideration are manufacturing, mining, and agriculture. The three sectors sum up to a narrowly defined measure of industrial production. The augmented Dickey and Fuller (ADF) test allowing for both an intercept and a time trend is employed to determine if there is a unit root in each data series. Results of applying the ADF test to the data and their first differences are shown in Panel A of Table 1. The null hypothesis of a unit root is not rejected for the data series and is rejected for the first differenced data. Hence, we infer that there is one unit root in each of the sectoral industrial production and stock index series, a result that is consistent with the literature. In the subsequent analysis, we assume the data are difference-stationary.

The sample correlation statistics for the first differenced data are given in Panels B to D. For the real sectors, the mining production index has the weakest correlation with other sectors.

Excluding the mining sectors, the correlation coefficients are quite large and range from 44% to 99%. Relatively speaking, the correlation among the sectoral stock indexes is stronger than that among the corresponding real sectoral output indexes. The results in Panel D show that the association between a real output index and its corresponding sectoral stock index is quite weak. More vigorous analyses of the interactions between real and financial sectors are given in the following subsections.

IIa. Common Stochastic Trends

Since the sectoral series exhibit unit root persistence, the study of the interactions between these sectoral output and stock data has to distinguish the long-run comovement from the short-term one. First, we use the Johansen (1991) procedure to test for the presence of cointegration, i.e., the presence of common long-run stochastic trends. In addition to common stochastic trends, information about the cointegrating property is essential for specifying an appropriate model to analyze short-run interactions.

The Johansen test for cointegration can be implemented as follows. Suppose a system of sectoral series following a vector autoregression process of order p:

$$\mathbf{X}_t = \mu + \sum_{i=1}^{p} \gamma_i \mathbf{X}_{t-i} + \varepsilon_t, \qquad (1)$$

where $\mathbf{X_t}$ is a *nx1* vector of I(1) sectoral indexes, μ is the intercept term, and ε_t is the vector of innovation terms. The Johansen test statistics are devised from the sample canonical correlations (Anderson, 1958; Marinell, 1995) between $\mathbf{X_t}$ and $\mathbf{X_{t-p}}$, adjusting for all intervening lags.

The cointegration test results are reported in Table 2. The Akaike information criterion is used to determine p, the lag parameter. For all the models presented, there is no significant correlation in the estimated residual; indicating the selected lag structures reasonably capture the data dynamics.[3] In addition to the usual cointegrating relation, we also consider the one that allows for stationarity around a time trend. The estimated time trend is, in general, very small and significant in only a few cases. For the three real sectoral industrial production indexes (manufacturing, mining, and agriculture), there is no evidence of cointegration. The indexes are not significant at the 10% level. Further, allowing for a time trend in the cointegrating relationship does not alter the test result.

Results in Table 2 are consistent with those of Lucke (1998), who finds no evidence of cointegration between quarterly sectoral data in Germany. Thus, these sectoral output series do not share a common long-run component. The difference in the stochastic trends, as stipulated by Durlauf (1989), can be attributed to the possibility that innovations (technology shocks) that spur growth in these sectors are uncorrelated. While these sectors may be influenced by both common aggregate shocks and idiosyncratic sectoral shocks, the absence of cointegration suggests that sector-specific shocks dominate the long-run movements in these sectors.

The cointegration test results from the sectoral stock indexes mirror those from sectoral output data. The statistics in Panel B offer no evidence of cointegration. The fundamental value of the stock market depends, at least in the long run, on the value of its underlying asset. The model of Breeden (1986), for example, shows that stock price depends on output. Thus, the result for sectoral stock indexes follows quite naturally from the no-cointegration results for real sectoral output given in Panel A.

A more surprising finding is the lack of a cointegration relationship between a sectoral output index and the corresponding sectoral stock index. Results in Panel C indicate, with the exception of two cases, the pairs of real and financial indexes are not cointegrated at the 10% level according to both finite-sample and asymptotic critical values. When a time trend is included, the use of asymptotic critical values yield a significant cointegrating relation, at the

10% level, for the agriculture sector pair and the mining sector pair. The no-cointegration result seems to be at odds with the empirical evidence that the stock market and aggregate economic activity are closely related. If the firms which provide data to compile, for example, the manufacturing sectoral output index are not all included in the manufacturing stock index, then it is possible that the real and financial series behave differently in the long run. In addition, it is likely that output is an important factor, but not the only factor, determining stock price in the long run. As a robustness check we adopted different lag structures to conduct the cointegration analysis but found no evidence against the no-cointegration hypothesis. Thus, in the following subsection, we conduct the analysis assuming that the data series are not cointegrated.[4]

IIb. Synchronized and Non-Synchronized Cyclical Comovement

In this subsection, we analyze the sectoral data for similar short-run cyclical components. Specifically, we test for the presence of common serial correlation patterns using the common feature test and codependence test (Engle and Kozicki, 1993; Vahid and Engle, 1993; Vahid and Engle, 1997). The intuition behind the common feature analysis is as follows. Suppose the temporal dynamics of $\Delta\mathbf{X}_t$, a $nx1$ vector of I(0) sectoral series, are driven by a common stochastic process. The effect of this common stochastic component can be removed by choosing an appropriate linear combination of the elements of $\Delta\mathbf{X}_t$. Thus, the presence of a common serial correlation cycle implies the existence of a linear combination of sectoral series that is not correlated with the past information set.

Since the sectoral series are not cointegrated, the test for common features can be constructed directly from the first differenced series $\Delta\mathbf{X}_t$. The procedure amounts to finding the sample canonical correlations between $\Delta\mathbf{x}_t$ and $\mathbf{W}(p) \equiv (\Delta\mathbf{X}'_{t-1},..., \Delta\mathbf{X}'_{t-p})'$.[5] Specifically, the test statistic for the null hypothesis that the number of cofeature vectors is at least s is

$$C(p,s) = -(T-p-1)\sum_{j=1}^{s} \ln(1-\lambda_j)\,, \qquad (2)$$

where $\lambda_n \geq ... \geq \lambda_1$ are the squared canonical correlations between $\Delta\mathbf{x}_t$ and $\mathbf{W}(p)$. The dimension (rank) of the cofeature space is the number of statistically zero squared canonical correlations. Under the null hypothesis, the statistic $C(p,s)$ has a χ^2-distribution with $s^2 + snp - sn$ degrees of freedom.

One technical note on the concept of common feature: it is a measure of contemporaneous comovements and imposes a strong assumption on the way variables respond to shocks. To share a common serial correlation feature, the variables have to respond to the shocks simultaneously. If the variables in the system have different initial responses to a given shock, there will be no common feature. Because of the nature of the shocks and the industry-specific capital/labor input, shocks may propagate through different sectors at uneven speeds. For instance, the agriculture sector may respond to a shock emanating from the manufacturing sector with a time lag. Even with a delay in the initial response, the agriculture sector may react fully to the shock in later periods. Thus the common feature test, which is designed to detect "synchronized" cycles, will have low power to detect common sectoral cycles that are "non-synchronized."

In this exercise, the codependence test (Vahid and Engle, 1997) is used to test for the presence of a common but non-synchronized business cycle. A system of time series is codependent if the impulse responses of the variables are collinear beyond a certain period. That is, codependence allows the series to have different initial responses to a shock but requires them to share a common response pattern after the initial stage. Without restricting the initial effects on the variables, the notion of codependence makes it operationally feasible to model non-synchronized business cycles. In fact, the codependence test is a generalization of the common feature test, which requires the variables to have collinear impulse responses for all periods. A common serial feature is a codependent cycle with the initial period (that allows for differential responses) equal to an empty set. The test statistic for the null hypothesis that there are at least s codependence vectors after the k-th period is

$$C(k,p,s) = -(T-p-1)\sum_{j=1}^{s} \ln\{1-[\lambda_j(k)/d_j(k)]\}, \qquad (3)$$

where $\lambda_n(k) \geq \ldots \geq \lambda_1(k)$ are the squared canonical correlations between $\Delta\mathbf{X}_t$ and $\mathbf{W}(k,p) \equiv (\Delta\mathbf{X}'_{t-k-1},\ldots,\Delta\mathbf{X}'_{t-k-p})$, and $d_j(k)$ is given by

$$d_j(k) = 1, \qquad \text{for } k = 0,$$

and

$$d_j(k) = 1 + 2\sum_{\upsilon=1}^{k} \rho_\upsilon(\alpha'\Delta X_t)\rho_\upsilon(\gamma' W(k,p)) \qquad \text{for } k \geq 1, \qquad (4)$$

where $\rho_\upsilon(y_t)$ is the sample autocorrelation of y_t at the υ-th lag, α and γ are the canonical variates corresponding to $\lambda_j(k)$.[6] Note that when k = 0, the codependence test statistic $C(k,p,s)$ is reduced to the common feature test statistic $C(k,p,0) \equiv C(p,s)$. Under the null hypothesis, the statistic $C(k,p,s)$ has a χ^2-distribution with $s^2 + snp + sr - sn$ degrees of freedom.

The common feature and codependence statistics are reported in Table 3. The test results from the real sectors, the financial sectors, and pairs of real and financial indexes are given, respectively, in Panel A, Panel B, and Panel C. The common feature statistic $C(p,s)$ ($\equiv C(0,p,s)$) indicates that there is one common feature vector in each of the systems under investigation. That is, there are synchronized common cycles among the real sectoral indexes, financial sectoral indexes, and individual pairs of real and financial sectors. As cyclical variations in economic activity are typically modeled by their serial correlation pattern, the test result suggests that the sectoral indexes share a common business cycle.

According to the $C(k, p, s)$ statistics, with k = 1, presented in Table 4, there are two codependence relations among the three real sectoral indexes. The same number of codependence relationships is found between the financial sectoral series. Since the presence of codependence for k = 0 implies codependence for k > 0, one of the two codependence relations follows from the common feature revealed by the $C(p, s)$ statistic. That is, there are synchronized and non-synchronized common cycles among the real sectors and among the financial indexes. The short-term output variations in these three sectors, as attested by both real output indexes and the corresponding stock market indexes, are not independent from each other and they share common cyclical components.

On closer examination of the codependence vectors, however, it is found that not all the three sectors share the common cycles. The GMM codependence vector estimates for the systems of real sectoral and of financial data are given in Panel A and Panel B of Table 4. In three out of four cases, the coefficient associated with the mining sector is not statistically significant. That is, it is mainly the manufacturing and agriculture sectors that share the empirical common cycles. Further, the signs of the codependence coefficient estimates suggest that the manufacturing and agriculture sectors tend to move up and down together along the common cyclical path.

Why is the codependent cycle not shared by the mining sector? One possible explanation is intervention. Among the three economic sectors, the mining sector is the most heavily regulated one. The sector also receives huge subsidies from the government. For instance, to maintain independence in raw materials, there is a tax (“Kohle-Pfennig”) instituted to subsidize the coal industry, which has the historical status of strategic industry. Thus, compared with government regulations and subsidies, technology and demand shocks may have a relatively minor role in determining output in the mining sector.

Taking a first glance at the results in Panel C of Table 3, we tend to conclude that the real and financial sectoral index pairs are codependent with one common non-synchronized cyclical component. However, the results in Panel C of Table 4 show that the codependence results can be spurious for the agriculture pair and mining pair. For these two pairs of real and financial indexes, the codependence coefficient estimates of the real sectors are not significantly different from zero. While theoretical models suggest a close relationship between stock prices and production output, the test results so far indicate weak links between real and financial sectoral indexes in Germany. Apparently, real sectoral output is not the only relevant determinant of German sectoral stock indexes in the long or short run.[7] This is consistent with the difficulty in explaining stock price behavior using fundamentals alone.

III. Common Cycles and Seasonality

Seasonally adjusted economic data are routinely used in empirical analysis. The popularity of seasonally adjusted data can be attributed to the fact that they are usually readily available. Also, the use of seasonally adjusted data can free the researcher from analyzing the deterministic seasonal component and alleviate the sensitivity of empirical results to filtering processes pursued by individual researchers. However, there are concerns on the effects of standard de-seasonalization filters on data dynamics. For instance, Maravall (1995), among others, shows that VAR analysis can be significantly affected by the use of seasonally adjusted data. In the case of common cycle analysis, Hecq (1998) and Cubadda (1999) illustrate that seasonal adjustment can generate spurious comovement results; see also Engle and Hylleberg (1996). In this section we therefore investigate if the use of seasonally adjusted data is responsible for the comovement results in the previous section.

For the same sample period, we apply the test procedures to sectoral output indexes that are non-seasonally adjusted. Consistent with the literature, we detected no deterministic seasonal component in the financial sectoral data. Thus, the financial data are not considered in the current section. First, the seasonal cointegration test is applied to the data to determine cointegrating relations at various seasonal frequencies. Hylleberg *et. al*. (1990) and Cubbada (1999), for example, provide a detailed discussion on seasonal cointegration test. Then, the seasonal common feature and codependence tests (Cubadda, 1999; 2000) are conducted.

The test for codependence that allows for seasonality is similar to the Vahid and Engle procedure described in the previous section. The test statistic for the null hypothesis that there are at least *s* codependence vectors after the k-th period is given by

$$C^*(k,p,s) = -(T-p-k-4)\sum_{j=1}^{s} \ln\left\{1-\left[\hat{\lambda}_j(k)/d_j(k)\right]\right\}, \tag{5}$$

where $\lambda_n(k) \geq \ldots \geq \lambda_1(k)$ are the squared canonical correlations between $\Delta_4\mathbf{X}_t$ and $\mathbf{W}_4(k,p) \equiv (\Delta_4\mathbf{X}'_{t-k-1},\ldots,\Delta_4\mathbf{X}'_{t-k-p},\hat{z}_{1,t},\hat{z}_{2,t},\hat{z}_{3,t},\hat{z}_{4,t})'$, and $d_j(k)$ is given by, for $k = 0$,

$$d_j(k) = 1,$$

and, for $k \geq 1$,

$$d_j(k) = 1 + 2\sum_{\upsilon=1}^{k} \hat{\rho}_\upsilon(\alpha' X_{4,t})\hat{\rho}_\upsilon(\gamma' W_4(k,p)), \tag{6}$$

where $\rho_\upsilon(y_t)$ is the sample autocorrelation of y_t at the υ-th lag, α, γ are the canonical variates corresponding to $\lambda_j(k)$, and $\hat{z}_{1,t},\hat{z}_{2,t},\hat{z}_{3,t},\hat{z}_{4,t}$ are the estimated seasonal error correction terms. Under the null hypothesis, the statistic $C^s(k,p,s)$ has a χ^2-distribution with *k(np+r+k-n)* degrees of freedom, where r is the rank of seasonal cointegration. See Cubbada (1999) for a more detailed discussion of the testing procedure.[8]

The seasonal cointegration and common cycle results for the sectoral real industrial output indexes are reported in Table 5. In contrast to Table 2, the data without seasonal adjustment reveal a much stronger evidence on cointegration between sectoral outputs. One cointegrating vector at the 0 and ½ frequency and two cointegrating vectors at the ¼ frequency are found. The results suggest that the seasonal adjustment process may tarnish the empirical long-run relationship at various seasonal frequencies. While the no-cointegration result is congruous with some aspects of the real business cycle theory, it appears too strong to claim that there is no long-run interaction between these sectors. For instance, labor is a common input in these sectors. While factor mobility is not perfect in the short run, reallocation of resources (including labor) across sectors following sectoral shocks is likely to occur in a longer run. Further, technological advances in one sector can improve long-term overall efficiency even though these sector-specific advances may not have immediate impacts on other sectors. Apparently, the cointegration result fairs better with the usual economic intuition.

Compared with the seasonally adjusted data, the real output data without seasonal adjustment display a much weaker sign of common cycles.[9] The seasonal common feature statistic $C^*(0, p, s)$ indicates the absence of synchronized common seasonal cycles. On the other hand, the seasonal codependence statistic $C^*(k, p, s),$ with k = 1, reveals the presence of one seasonal codependence vector. The decline in the strength of the evidence on common cycles across seasonally and non-seasonally adjusted data is consistent with the results in Hecq (1998) and Cubbada (1999). The standard de-seasonalization process is prompt to induce common cyclical movements. The GMM estimate of the codependence vector is given in the note to Table

5. Similar to the codependence coefficient estimates in Table 4, the coefficient estimate associated with the mining sector series is not statistically significant. Also, the coefficient estimates of the agriculture and manufacturing sectors are significant and have opposite signs. That is, it is only the agriculture and manufacturing sectors that share the common non-synchronized cycles and they tend to move in the same direction throughout the cycles.

The seasonal cointegration and common cycle test results for the real and financial pairs are given in Table 6. While there is no evidence on cointegration at the zero frequency, one cointegrating vector at the ½ and ¼ frequency are found for each pair of real and financial sectoral indexes. Again, the cointegration test result verifies that de-seasonalization can noticeably distort the seasonal interaction between data series. The seasonal common factor statistics $C^*(k, p, s)$, with $k = 0$ and $k = 1$, reject the hypothesis of the presence of any common feature or codependence vectors. The finding of no common cycles reinforces the notion that the codependence results for the seasonally adjusted real and financial pairs are likely to be spurious.

Tables 3 to 6 highlight the sensitivity of empirical common trends and cycles to seasonal adjustment. The use of seasonally adjusted data obviously hinders the effort to uncover (seasonal) cointegrating relations. On the other hand, seasonal adjustment appears to inject spurious cyclical comovement to the data. Thus, the use of data with or without seasonal adjustment has significant implications for inferences on common trends and common cycles.

IV. Concluding Remarks

Using seasonally adjusted and non-seasonally adjusted German sectoral data, we study the long- and short-term sectoral comovements. The seasonally adjusted data indicate only limited cointegrating relations between a) the agriculture, manufacturing, and mining sectoral output indexes, b) the corresponding sectoral stock indexes, and c) individual pairs of sectoral real and stock indexes. On short-term interactions, these data series exhibit considerable evidence of synchronized and non-synchronized common business cycles. The data not subject to seasonal adjustment, however, yield different results. Without seasonal adjustment, these sectoral data series are found to be cointegrated and display a lower level of common cyclical components. For both data with and without seasonal adjustment, the evidence suggests that the empirical cyclical comovement between real and financial sectors is likely to be spurious.

The use of sectoral data offers a good opportunity to illustrate the idiosyncratic elements of different economic sectors, to compare different views on the sources of (sectoral) growth, and to examine synchronized and non-synchronized sectoral cycles. Our empirical findings, however, show that the inferences on the relative contributions of common and sector-specific shocks and their short- and long-term interactions depend critically on the choice between seasonally adjusted and non-seasonally adjusted data. Specifically, the two types of data offer distinctly dissimilar descriptions of sector-specific forces that define the patterns of sectoral growth and cyclical movement. In order to assess a theory's empirical implication for sectoral comovement, one has to determine whether the intrinsic dynamics are better captured by data before or after de-seasonalization. Apparently, the results pertaining to data without seasonal adjustment are more in line with the usual wisdom – the sectors are related in the long run while short-run sector-specific shocks can generate idiosyncratic cyclical patterns.

Both data with and without seasonal adjustment offer a similar inference on the interaction between real and financial sectors. The real sector and the corresponding stock index are likely to be linked in the long run. However, there are only weak cyclical cross-relations between sectoral output index and the corresponding stock index. The empirical relationships reinforce the linkages between stock prices and economic activity established in the theoretical literature. While the stock market and economic activity are related, the financial market is inherently difficult to explain/predict in the short-run and factors other than production have a non-negligible effect on stock prices.

Footnotes

1. The effect of sectoral shocks on aggregate economic activity is also an intensely contested issue in the literature of sectoral shifts (Lilien, 1982; Brainard and Cutler, 1993).
2. Brainard and Cutler (1993), for example, use sectoral stock indexes to construct measures of sectoral shocks.
3. Vahid and Issler (1999) show that standard information criteria may lead to a lower order VAR specification in the presence of common serial correlation. Diagnostic checks on the residuals alleviate such a possibility.
4. It can be argued that the no-cointegration result follows from the low power of the Johansen test. As a robustness check, we also a) assumed the sectoral data are cointegrated and included an error correction term in the common feature and codependence analyses and b) considered different lag structures. The results, which are available from the authors, are qualitatively the same as those reported.
5. If the series are cointegrated, then an error correction term is added to **W**(p). See Vahid and Engle (1993) for a detailed discussion.

6. If the series are cointegrated, then an error correction term is added to **W**(k,p). See Vahid and Engle (1997) for a detailed discussion.
7. Of course, the results do not rule out the possibility that, when combined with other fundamentals, output helps explain variations in stock prices. See, for example, Fama (1981) and Cheung and Ng (1998).
8. The results reported in this section were generated from computer codes generously provided by Professor Cubbada.
9. Again, as a robustness check, we conducted the seasonal common cycle tests in this section a) assuming there is no cointegration and b) with different lag structures. The results, which are available from the authors, are qualitatively the same as those reported.

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Table 1: Unit Root Test Results and Correlation Statistics

A. Unit Root Test Results

	Levels	First Differences
rip	-1.71 (3)	-4.86* (2)
rmi	0.46 (3)	-6.21* (2)
rma	-1.76 (3)	-4.96* (2)
rag	-1.28 (3)	-6.15* (2)
fip	-1.92 (3)	-5.55* (2)
fmi	-2.60 (2)	-5.05* (2)
fma	-1.72 (2)	-5.58* (2)
fag	-1.39 (2)	-4.65* (2)

B. Correlations Among Real Sectors

	rip	rag	rma	rmi
rip	1			
rag	0.414	1		
rma	0.988	0.441	1	
rmi	0.289	-.014	0.231	1

C. Correlations among Financial Sectors

	fip	fag	fma	fmi
fip	1			
fag	0.701	1		
fma	0.994	0.672	1	
fmi	0.720	0.521	0.695	1

D. Correlations Between Real and Financial Sectors

rip-fip	0.201
rag-fag	0.095
rma-fma	0.219
rmi-fmi	-.011

Note: The sectors are represented as follows: rip = real industrial production index, rag = real production index of the agriculture sector, rma = real production index of the manufacturing sector, rmi = real production index of the mining sector, fip = real sectoral stock index corresponding to the industrial production index, fag = real sectoral stock index for the agriculture sector, fma = real sectoral stock index for the manufacturing sector, and fmi = real sectoral stock index for the mining sector. Panel A reports the ADF test statistics. The lag parameters selected by the Akaike information criterion are given in parentheses. In all cases, the reported lag parameter coincides with the one selected according to the last-significant-lag criterion (Ng and Perron, 1995). These specifications do not display any significant serial correlation in their residuals. Asymptotic and finite-sample critical values (Cheung and Lai, 1995) give the same inference. “*” indicates significance at the five percent level. Panels B to D report the correlation coefficients between the first log differences of the sectoral indexes.

Table 2: The Johansen Test Results

H(0)	Trace Statistic (No trend)	Trace Statistic (With Trend)
A. Real Sectors		
r = 0	25.32	28.07
r = 1	8.78	11.50
r = 2	0.26	2.36
B. Financial Sectors		
r = 0	18.90	29.90
r = 1	5.50	9.37
r = 2	1.44	2.89

C. The Real and Financial Sectoral Pairs

	rip/ fip	rag/ fag	rma/ fma	rmi/ fmi	rip/ fip	rag/ fag	rma/ fma	rmi/ fmi
r = 0	9.91	8.60	10.96	10.51	22.92	23.44*	22.89	24.83*
r = 1	1.45	1.28	1.64	0.39	7.43	6.47	6.47	4.70

Note: Panel A reports the results of testing for cointegration in the three real sectoral series - agriculture, manufacturing, and mining. Panel B reports the results from the financial sectoral series. Panel C reports the results of testing for cointegration between a sectoral real output series and its corresponding financial sectoral series. Results from the Johansen tests with or without a time trend in the cointegrating relation are reported. The lag parameter is set to two according to the Akaike information criterion. The Q-statistics computed from the first five and ten lags of the estimated residuals are all insignificant. "*" indicates statistical significance at the 10% level according to asymptotic critical values. All statistics are not significant at the 10% level according to finite-sample critical values (Cheung and Lai, 1993). See the "Note" to Table 1 for the definitions of rip, rag, rma, rmi, fip, fag, fma, and fmi.

Table 3. Common Feature and Codependence Tests

Null Hypothesis	C(0,p,s)	C(1,p,s)
A. Real Sectors		
s = 1	7.71	3.90
s = 2	32.52*	12.62
s = 3	82.53*	30.68*
B. Financial Sectors		
s = 1	6.02	2.06
s = 2	16.32	5.19
s = 3	36.01*	28.47*
C. The Real and Financial Sectoral Pairs		
a. rip/fip		
s = 1	16.01*	4.08
s = 2	50.52*	31.18*
b. rag/fag		
s = 1	9.93*	7.79
s = 2	46.05*	20.35*
c. rma/fma		
s = 1	13.94*	4.01
s = 2	48.52*	30.47*
d. rmi/fmi		
s = 1	12.26*	1.22
s = 2	28.41*	13.69*

Note: The common feature and codependence test results for the real sectors (Panel A), the financial sectors (Panel B), and the real and financial sectoral pairs (Panel C) are reported. The degrees of freedom of the common feature statistic C(0,p,s) and codependence statistic C(1,p,s) are calculated with n = 3 and p = 2 in Panels A and B and with n = 2 and p = 2 in Panel C . See the “Note” to Table 1 for the definitions of rip, rag, rma, rmi, fip, fag, fma, and fmi. “*” indicates significance at the five percent level.

Table 4: Codependence Vectors

		First Codependence Vector	Second Codependence Vector
A.	*Real Sectors*		
	rma	23.85* (2.24)	71.80* (2.64)
	rmi	22.00* (2.05)	-5.16 (-0.39)
	rag	81.78* (2.65)	-53.58* (-1.87)
B.	*Financial Sectors*		
	fma	50.12* (4.15)	6.15* (4.16)
	fmi	8.65 (0.69)	-10.99 (-1.48)
	fag	-22.67* (-2.78)	-41.89* (-2.80)
C.	*The Real and Financial Sectoral Pairs*		
	a. rip	-21.04* (-3.02)	
	fip	97.84* (4.48)	
	b. rag	33.44 (0.67)	
	fag	61.29* (2.33)	
	c. rma	-21.03* (-3.11)	
	fma	93.54* (4.37)	
	d. rmi	-7.12 (0.84)	
	fma	93.54* (4.37)	

Note: The GMM codependence vector estimates for the real sectors (Panel A), the financial sectors (Panel B), and the real and financial sectoral pairs (Panel C) are reported. The codependence vector estimates correspond to the test results in Table 3. The asymptotic t-statistics are given in parentheses next to the estimated codependence coefficients. See the "Note" to Table 1 for the definitions of rip, rag, rma, rmi, fip, fag, fma, and fmi. "*" indicates significance at the five percent level.

Table 5: Common Features and Seasonality: Real Sectors

A. Seasonal Cointegration

	Frequency 0	Frequency ½	Frequency ¼
r = 0	28.31**	29.74**	65.57*
r = 1	9.24	13.35	31.84*
r = 2	0.01	1.57	12.74

B. Seasonal Common Feature/Codependence

	$C^*(0,p,s)$	$C^*(1,p,s)$
r = 1	29.49*	10.38**
r = 2	113.82*	33.17*
r = 3	315.77*	68.72*

Note: Panel A reports the results of testing for seasonal cointegration in the three non-seasonally adjusted real sectoral series, agriculture, manufacturing, and mining. Panel B reports the results for common feature test statistic $C^*(0,p,s)$ and codependence test statistic $C^*(1,p,s)$. "*" indicates significance at the 5% level and "**" indicates significance at the 10% level. The degrees of freedom of the common feature statistic C(0,p,s) and codependence statistic C(1,p,s) are calculated with n = 3 and p = 2. Using a GMM estimator, the codependence relatioship is: $\underset{(2.47)}{1.00}\,\Delta_4 rma_t + \underset{(0.01)}{0.02}\,\Delta_4 rmi_t - \underset{(3.55)}{0.30}\,\Delta_4 rag_t$, with asymptotic t-statistics in parentheses. See the "Note" to Table 1 for the definitions of rip, rag, rma, rmi, fip, fag, fma, and fmi.

Table 6: Common Features and Seasonality: Real and Financial Pairs

A. Seasonal Cointegration

	Frequency 0	Frequency ½	Frequency ¼
1. rma			
r = 0	11.42	29.25*	32.30*
r = 1	3.11	2.50	8.65
2. rag			
r = 0	17.02	37.36*	20.07
r = 1	2.73	5.44	5.75
3. rmi			
r = 0	15.22	32.04*	37.33*
r = 1	0.01	8.92	13.28

B. Seasonal Common feature/Codependence

	$C^*(0,p,s)$	$C^*(1,p,s)$
1. rma/fma		
s = 1	181.02*	31.79*
s = 2	454.48*	71.06*
2. rag/fag		
s = 1	45.45*	16.01*
s = 2	277.95*	49.57*
3. rmi/fmi		
s = 1	110.01*	27.64*
s = 2	353.99*	65.19*

Note: Panel A reports the results of testing for seasonal cointegration in the pairs of real and financial sectoral indexes. Panel B reports the results for common feature test statistic $C^*(0,p,s)$ and codependence test statistic $C^*(1,p,s)$. "*" indicates significance at the 5% level. The degrees of freedom of the common feature statistic C(0,p,s) and codependence statistic C(1,p,s) are calculated with n = 2 and p = 2. See the "Note" to Table 1 for the definitions of rip, rag, rma, rmi, fip, fag, fma, and fmi.