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The sectoral analysis of business cycles: the role of aggregate and disaggregate shocks

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The sectoral analysis of business cycles: The role of aggregate and disaggregate shocks

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1 INTRODUCTION

1.1 Preview

A long-lasting consensus in macroeconomics based on Keynesian IS-LM analysis broke down in the early 1970s because of inconsistency between the theory and stylized facts. For example, the traditional consensus could not explain the stagflation phenomenon experienced during the 1970s. Lucas (1976), in his famous "Lucas Critique," also argued that the behavioral relations imposed by the traditional view were not able to evaluate changes in economic policy. Changes in expectations about future economic policy will influence an agent's current decisions, so policy changes also alter the behavioral relationships. Consequently a lot of innovations in macroeconomic theory have been observed during the last two decades even though the innovations are not mutually consistent. Recently Mankiw (1990) has reviewed these developments in macroeconomics. He divided the new trends in macroeconomics into three categories: Expectations, New Classical macroeconomics, and New Keynesian macroeconomics. On the issue of explaining macroeconomic fluctuations, New Classical theorists and New Keynesian theorists take different perspectives.

Mew Classical theorists emphasize technological disturbances, intertemporal substitution of leisure, and real business cycles while New Keynesian theorists emphasize monopolistic competition and coordination failure in explaining macroeconomic fluctuations.

Three of the important unresolved issues concerning macroeconomic fluctuations ("macroeconomic fluctuations" and "business cycles" can be used interchangeably) include

1) What is the main source of macroeconomic fluctuations?

2) Is there only one aggregate shock in the economy or are there many?

3) Do aggregate shocks explain all output fluctuations?

Concerning the first question, there are two classes of theory to explain the main source of business cycles. Monetary business cycle theorists claim that nominal shocks play a major role in explaining macroeconomic fluctuations while real business cycle theorists claim that real shocks are quantitatively more important than nominal shocks.[1]

Two classes of models can be distinguished according to the number of shocks in the economy. A family of single shock theories of business cycles view that a single shock can explain all output fluctuations. On the other hand, the alternative view is that there

[1]There are two versions of the real business theory: A "strong" version of this theory claims that nominal shocks are negligible source of business cycles while a "weak" version of this theory claims that real shocks are more important than nominal shocks.

errors from a restricted VAR representation explaining sectoral output. The sector-specific shocks are viewed as technological in nature, whereas aggregate shocks may have many sources.[3] The second purpose is to determine the number of common shocks in the economy. A family of single shock theories claim one common shock while others claim multiple common shocks in the economy. The third purpose is to measure the relative importance of common aggregate shocks versus sector-specific shocks in explaining aggregate and sectoral output fluctuations. This study will investigate what fraction of the variations in aggregate output growth (or sectoral output growth) can be attributed to sector-specific shocks and what fraction can be attributed to aggregate shocks. This is a very important motivation of this study since there can be two different competing explanations for output comovement among sectors. One explanation is that aggregate common shocks are the dominant source of comovement across sectors and the other explanation is that sectoral shocks have large and rapidly dispersed spillovers. Therefore we would like to ascertain whether common aggregate shocks or propagated sectoral shocks are the source of correlation of real output movements across sectors.

The first goal of this dissertation can be analyzed by a Granger causality test and an impulse response technique which examines the

[3] Schumpeter (1939) viewed technological advancement as the major source of business cycles.

dynamic effects of the various shocks to the system. The second goal can be examined by factor analysis which decomposes a set of random variables into unobserved common factors and a set of unique factors. The third goal can be examined by a forecasting error variance decomposition which examines the contribution of each source of shocks to the variance of the n^{th} period ahead forecast error for each endogenous variable.

1.2 Brief Description of the Korean Economy

General Description

Over the last two decades, the rate of economic growth in Korea has been remarkably high. The real GNP growth rate in the period from 1972 to 1982 was 7.7 percent per year. The primary industry has recorded an average annual rate of 3.3 percent while the manufacturing industry has recorded an average annual rate of 13.2 percent over this period. There are many factors underlying the rapid economic growth in Korea, but one of the major causes of economic development has been the "export-oriented" industrialization strategy adopted by policy makers. This strategy was adopted due to small domestic markets and few natural resources. Exports have grown by an average annual rate of 29.7 percent in the period from 1972 to 1982. The share of manufactured exports relative to total exports increased from 87.7 percent to 93.7 percent over the same period.

This manufacturing industry leads the growth of the overall economy in Korea. Therefore it is useful to investigate growth in the manufacturing sector in detail.

Characteristics of Manufacturing Industries

Some basic descriptive statistics on the manufacturing industries in the period from 1963 to 1979 are presented in Table 1-1. The index of capital intensity differs across sectors. Textiles and Wood are less capital-intensive while Basic metal and Chemicals are more capital-intensive. Since the 1970s, the Korean government has been following an industrial policy aimed at building up the heavy and chemical industries. It is likely that capital-intensive industries can be affected by some form of policy change which affects capital flow.

Industry shares of gross output exported are also reported in Table 1-1 over the period 1963 - 1979. Textiles and Wood exported 52 percent and 41 percent of their gross output respectively. Food, Chemicals and Paper exported less than 10 percent of their gross output. Industries which export a large share of its products such as Textiles and Wood may be less affected by the domestic shocks as opposed to external shocks transmitted through world trade. Sectors that produce more exclusively for home markets may be more sensitive to domestic shocks.

The growth rates of total factor productivity (also called the

Table 1-1 Characteristics of manufacturing industries

Sector	Index of capital intensity (Mfg=100)	Export share from total 63-79 (%)	Rate of TFP growth 63-79 (%)
Non-durable			
Food	159.0[a]	1.05	7.25
Chemicals	190.0	6.98	8.45
Textiles	61.8	52.15	5.88
Paper	87.2	7.2	3.45
Durable			
Glass	91.0	13.1	-2.18
Wood	65.1	41.45	3.83
Basmetal	540.2	21.19	3.23
Fabmetal	108.1	26.58	7.55
Otherman	33.0	47.71	8.0

[a] Based on 1979.

Source: Table 1 - Table 4 in Dollar and Sokoloff (1990).

Solow residual) which measure the part of growth that cannot be explained by either growth of labor or growth of capital, are also presented in Table 1-1. Growth can occur from technological innovation, more efficient organization of production, technology borrowing and scale economies. In addition, growth theory indicates that countries will tend to grow at equal rates in the long run. Therefore, Pacific rim countries which grew relatively slowly in the Post War period might be expected to catch up. This plays an important role in the growth of real output in Korea since Korea economy experienced slow development until 1963. Most industries except Glass have maintained a rapid growth rate of total factor productivity in the period from 1963 to 1979.

It will be also useful to examine the production linkage among industries. One way of measuring the production linkage among industries is the ratio of intermediate consumption to gross output. This ratios are reported in Table 1-2. Table 1-2 shows a strong production linkage in Korean economy. Most manufacturing industries use two-thirds of intermediate goods in producing their final goods. Therefore, it is plausible that a shock which initially affects one sector will be propagated across sectors in the economy through the real production linkage. The statistics also show that the mining sector uses relatively fewer intermediate goods in production, so it may be less affected by technology shocks from other sectors.

1.3 Organization of Study

The plan of this dissertation is as follows. A brief review of business cycle theory is given in Chapter 2. This chapter reviews recent studies of business cycles, concentrating on the definition of business cycle, the identification of the impulse and propagation mechanism, the number of shocks in the economy, the trend versus cycle dichotomy, and aggregate versus disaggregate shocks.

Chapter 3 considers the theoretical framework of this study. An interpretive economic model, a simplified three-sector version of Long and Plosser's (1983) model, is discussed. An econometric model for sector-by-sector analysis, a trivariate Vector Autoregressive (VAR) model, is derived from the interpretive economic model. A multi-sector model, in the form of a restricted VAR model, is also discussed. Strategies for the error structure decomposition for the sector-by-sector and multi-sector models are proposed.

The empirical results for the sector-by-sector model are given in Chapter 4. First, the results of various tests of the time series data such as unit root, cointegration and lag length tests are reported. Then, the results of causality tests, impulse response and Forecasting Error Variance Decompositions (FEVD), are discussed.

The empirical results for the multi-sector model are given in Chapter 5. The model is estimated using Seemingly Unrelated Regression (SUR) method. Factor analysis is used to determine the

2 A REVIEW ON BUSINESS CYCLE THEORY

2.1 Definition of a Business Cycle

One of the most important questions in macroeconomics is to determine the source of macroeconomic fluctuations. A definition of business cycles by Burns and Mitchell (1946) is widely accepted:

> Business cycles are a type of fluctuation found in the aggregate activity of nations that organize their work mainly in business enterprise; a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic (p. 3).

In short, business cycles can be defined as the comovement and recurrences but not strict periodicity among aggregate economic time series.[1] Therefore the objective of any model of business cycles is to explain how and why the characteristics business cycles arise.

[1] Mullineux (1990) surveys various definitions of business cycles (pp. 1-6).

Frisch's framework became a cornerstone in the development of empirical business cycle analysis. After Frisch many studies have attempted to explain macroeconomic fluctuations, considering them as the result of shocks that affect the economy through a complicated dynamic propagation mechanism. For example, Hawtrey (1923) employs a monetary impulses and a monetary propagation mechanism in his explanation of business cycles. He presents a picture in which monetary movements influence the economic system through changes in interest rates and the influence of this change on investment in fixed capital is negligible. Therefore the "deep" structure of production is largely independent of monetary changes. The examination of how shocks to the economy were propagated over time and across sectors in the economy was also the main theme of inter-war business cycle economists such as Mitchell and Von Hayek. Hayek (1933) employs a monetary impulse and real propagation mechanism. He examines primarily the mechanism through which monetary factors influence the real structure of production.

A major concern in macroeconomics in recent years has been to identify empirically the forces that induce fluctuations in economic aggregates. But recent models differ widely according to their characterizations of the ultimate sources of shocks to aggregate economic activity and explaining how these shocks are propagated

across sectors in the economy.[3] Figure 2-1 summarizes how recent models explain the business cycles. Aggregate shock theories, for example Lucas (1972) and Kydland and Prescott (1982), claim that only aggregate shocks are the source of output fluctuations. There is no consensus on the number of aggregate shocks in the economy. These (single or multiple) shocks (denoted by ——> in Figure 2-1) are the sole source of output fluctuations in the economy.
Disaggregate shock theory claims that disaggregate shocks such as sector-specific shocks (denoted by - - -> in Figure 2-1) are the source of output fluctuations (Long and Plosser, 1983). The aggregate shock can be classified as nominal or real and can primarily influence aggregate demand or aggregate supply. Unanticipated money supply is an example of an aggregate demand shock while the unexpected change in oil price is an example of an aggregate supply shock. The propagation mechanism can be either nominal or real. If the structure of production is changed then it is called a real propagation mechanism. Otherwise, it is called a nominal propagation mechanism.

2.3 The Number of Shocks

How many different shocks can affect the economy? This is also

[3]Shiller (1987) surveys recent models.

an important question for current macroeconomists. Business cycle theories can be categorized into two groups, those that assume only one source of aggregate fluctuations and those that assume many sources of these fluctuations. The group which assumes only one major source of aggregate fluctuations can be classified according to the types of shock they assume: monetary and real. Monetarists often single out monetary shocks (nominal shocks) as the main source of business cycles and explain the propagation mechanism through nominal linkages.[4] Lucas regards the business cycles as a result of the optimizing behavior of agents with imperfect information. In his so-called "island economy" agents' decisions are based on relative prices and the "Lucas Supply Function" can be derived from agents' expectations of the current general price level. An increase in the local price level will make agents work more and produce more. In Lucas model money shocks are the source of price movements. This model can explain comovement among price, output and employment. However, a pitfall of this monetary business cycle approach is that

[4]Lucas (1972) argued that business cycles can be explained by introducing imperfect information into an equilibrium model. This approach is called Equilibrium Business Cycle Theory. A change in nominal variables can have temporal real effects but not long-lived effects. This theory stresses the importance of aggregate shock and furthermore consider the aggregate shock as the aggregate demand shock (such as unanticipated nominal money supply) based on the observation that aggregate output and price level move together. For example, Huffman and Lothian (1984) single out monetary factors as the channels of propagation of cyclical fluctuation from one country to the other.

be uncorrelated. Blanchard and Watson (1986) conclude that macroeconomic fluctuations are due to fiscal, monetary, and supply shocks. Fair (1988) reported that there are many sources of fluctuations in his macroeconometric model. Shapiro and Watson (1988) also found multiple sources of shocks. They identified several aggregate supply shocks including labor supply, technology and oil prices shocks. Two aggregate demand shocks were money market and goods market shocks. They concluded that the aggregate demand shocks account for 20 to 30 percent of the variation in short-run output and technological change accounts for roughly one-third of short-run and long-run output variation. The permanent shocks in labor account for at least 40 percent of short and long-run output variation.

Long and Plosser (1983), in their so-called real business cycle model, claim that many independent disaggregate shocks can explain the business cycles. They demonstrated that real trade links among sectors cause sector-specific shocks to be propagated across sectors in the economy.[7]

[7] See the recent essay on real business cycle approach to macroeconomic fluctuations by Plosser (1989) and Mankiw's (1989) skeptical view on real business cycle theory.

2.4 Growth and Cycle Dichotomy

Another interesting issue concerns the dichotomy between trend and cycle. Some define business cycles as deviations of real output from a linear trend. The conventional wisdom is that high-frequency business cycle fluctuations are separated from low-frequency growth fluctuations. Business cycle fluctuations arise from temporary shocks that are sometimes associated with variation in monetary and fiscal policies. These shocks are then propagated by the economic system in ways that result in systematic patterns of persistence and comovement among economic time series. On the other hand, growth fluctuations are viewed as evolving slowly through time and having little influence on the short-run variations in economic variables.

This conventional view of the business cycle and growth dichotomy has been challenged by new research.[8] In the post-war period, even the National Bureau of Economic Research (NBER) has begun to analyze detrended data in order to decompose growth and cycles, although the trend used is not linear. Nelson and Plosser (1982) warn of the danger of this approach, pointing out that the long-run character of many economic time series is well described as a stochastic trend or a random walk with drift. Moreover, they

[8] Harberler (1963) pointed out that there might be an important causal relation between trend and cycle and thus these two sets could not be additive.

present some evidence that innovations in the stochastic trend may account for a significant portion of the short-run, as well as the long-run, variation in such key economic time series as real GNP. More recent developments in macroeconomic theory emphasize that transient economic fluctuations can arise as responses to changes in long-run factors - in particular technology shocks - rather than short-run factors. That is, permanent shifts in technology change the "steady-state" levels of capital stocks, and economic fluctuations are essentially movements along the adjustment path to the new steady-state. These real business cycle theories contend that fluctuations in business cycle and growth are caused by the same shock.[9] Thus there is no meaningful dichotomy between the short-run cycle and long-run growth.

Several recent studies (Blanchard, 1989; Blanchard and Quah, 1989; Shapiro and Watson, 1988) shed greater light on the importance of the permanent component in real GNP. For example, Blanchard and Quah (1989) and King, Plosser, Stock, and Watson (1987) both use forecast error variance decompositions as a guide to assessing the importance of the permanent component. In identifying the permanent component they employ different identification strategies.[10]

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[9]King, et al (1987) examine this issue.

[10]Blanchard and Fisher (1989, Chapter 1) discuss three different decomposition methods. In addition to two methods discussed in this paper, there is another method which looks at other variables as well as variable of interest by assuming that different shocks affect them differently. Blanchard and Quah (1989) use this decomposition method

Blanchard and Quah (1989) identify the permanent component by assuming that it has no permanent effect on unemployment and that demand shocks are transitory.[11] This type of supply-demand decomposition employs an identifying assumption that long-run movements of GNP are generated by "real" factors. In contrast, King, Plosser, Stock, and Watson (1987) identify the permanent component in output by assuming that it is also the permanent component in consumption and investment. The motivation of these studies has been to assess the relative importance of aggregate demand and supply shocks in macroeconomic fluctuations. Both studies conclude that permanent innovations in output play an important role in determining the movements of GNP at horizons typically associated with the business cycle.

2.5 Aggregate and Disaggregate Shocks

One interesting issue concerning the importance of disaggregate shocks was raised in the early 1980s. In discussing aggregate and disaggregate (or sector-specific) shocks the former is defined as the shocks which are responsible for changes in output growth that are shared by all industries (perhaps with different intensity) while the latter are defined as the shocks which are responsible for changes in

by using information from both output and unemployment.

[11] Shapiro and Watson (1988) also use this identification strategy.

output growth that are unique to an industry. Long and Plosser (1983) argued that there exists a possibility that fluctuations in real activity may be due to disaggregate shocks to technology or taste since real trade links among sectors can cause shocks in a sector to be propagated across sectors in the economy.[12] For example, a positive shock to one sector increases the wealth of the individuals in the economy. These individuals respond by increasing their demand for all consumption and investment goods. The increase in consumption explains comovement (or cross correlation) while the increase in investment delineates persistence (or serial correlation). They show that the outputs of individual sectors, even under the assumption that the productivity shocks are independent both across time and across sectors, may exhibit both serial and cross correlation. By simulation, they attempt to provide empirical verification by comparing the implications of their model for the comovement of output across sectors with actual time series data for the post-war U.S experience. Their analysis relied on an aggregate input-output table. The average pairwise cross correlation across sectors is about 20 percent, and the average first-order serial

[12]Most researchers accepted that there could be considerable variation in productivity at the industry level, but they believed that industry-level shocks would theoretically average out in the aggregate since observed variation in aggregate activity is much less than the variation in the industry-level. But one possible explanation for this "stylized fact" is that the service sector (including government sector) in the economy grows during the last few decades.(see Romer (1991) p. 14)

factors (or shocks) are important.

Romer (1991) also examined the relative importance of aggregate versus sector-specific shocks in explaining the variation in disaggregate output, using a simple one common factor model. The fraction of the total variation that is accounted for by a single common factor varies substantially across goods. She found some patterns in the estimated importance of the aggregate factor. One of them is that agricultural goods typically have a lower fraction of total variation explained by the common factor than do mineral or manufactured goods. The other pattern is that the aggregate factor is most important for major mineral and manufactured commodities.

Norrbin and Schlagenhauf (1988, 1990, 1991) attempted to measure the relative contribution of aggregate, region-specific, and industry-specific shocks in generating macroeconomic fluctuations. They define these fluctuations as employment changes or output changes. Using the dynamic multiple indicator-multiple cause (DYMIMIC) model, they show that all three types of shocks are statistically important in explaining variation in employment, suggesting that sector-specific shocks are one of the sources of business cycles. They conclude that theories of macroeconomic fluctuations that stress traditional aggregate shocks may not be complete, and thus we should take account of disaggregate shocks if a complete theory of macroeconomic fluctuations is to be developed.

Altonji and Ham (1990) attempted to investigate the impact of specific country-industry pairs. The variance of output growth at both aggregate and industry levels is then decomposed into these various components. What she found is that the country-specific disturbances explain much, but not all of the steady-state variance of aggregate and sectoral output. She concludes the paper with a suggestion that it is potentially useful to study business cycles at the industry level in order to assess the possible contribution of disturbances which arise at that level of aggregation to movements in both aggregate and industry output.

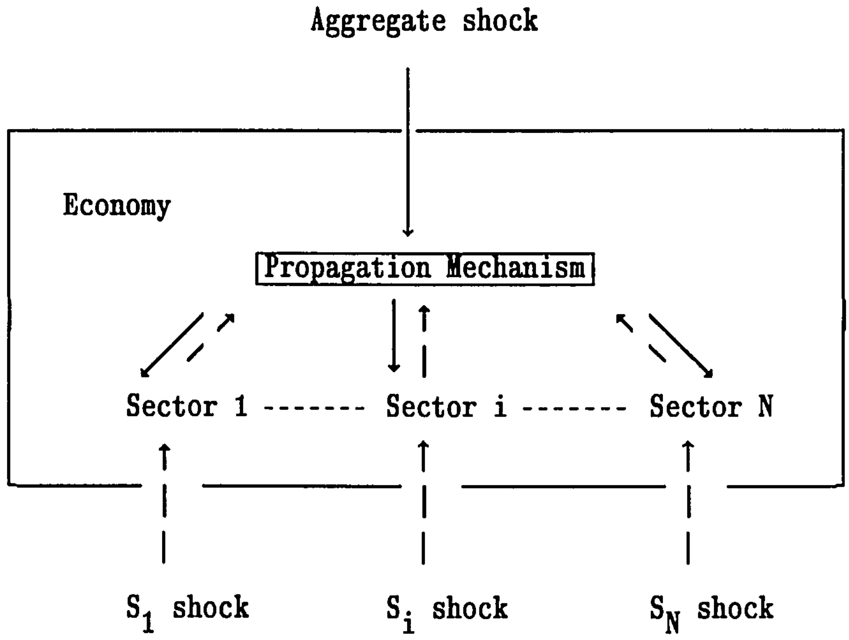

Figure 2-1. Source and the propagation of shocks

then, for analytical tractability, they examine the model's properties under the particular specification of log-utility and Cobb-Douglas technology. We will take the same specification which Long and Plosser used for the convenience of discussion. But our model differs from Long and Plosser in that they assume no contemporaneous correlation in the covariance matrix while we assume that the covariance matrix may be contemporaneously correlated due to the existence of a common shock (see Section 3.2 for details).

Environment

The economy here is populated by a single infinitely lived individual ("Robinson Crusoe") who acts as a price-taker with given initial endowments, production possibilities, and tastes. There is no money and no government.

All activities in the economy may be described as repetitions of the following one-period cycle. At the beginning of each period, he chooses (a) the commodity bundle to be consumed during the period, (b) the amount of leisure time to be consumed during the period, and (c) the commodity and labor inputs to production transformations that will be completed during the period. All of these choices are constrained by the total commodity stocks available at the beginning of the period and by the fixed amount of time available per period. The production process takes one period to be completed, and it is subject to some random exogenous shock. During the period, exogenous random shocks influence the production transformations. These shocks, together with input choices made at the beginning of the period, then determine the total commodity stocks that will be available at the beginning of the next period. The process of exogenous stochastic shocks is assumed to be a time-homogeneous Markov process. Therefore there is no serial dependence in the stochastic elements of the environment.

All commodities in the economy are produced and production of any one commodity requires positive inputs of other commodities. Any given commodity can be used as an input in the production of other commodities. All inputs are assumed to be completely "perishable" in order to facilitate the analysis.

Preference

Let us assume that an individual's preference can be represented with an additively separable log-utility function and furthermore his preference is assumed to be constant over time and unaffected by exogenous random shocks. An individual maximizes the expected value of his lifetime utility given by (as viewed at time 0)

$$U = \sum_{t=0}^{\infty} \beta^t(\theta_0 \ln Z_t + \theta_1 \ln C_{1t} + \theta_2 \ln C_{2t} + \theta_3 \ln C_{3t}) \tag{3-1}$$

where θs are the consumption shares, Z_t is the amount of leisure to be consumed in period t, C_t is a 3×1 commodity vector to be consumed in the period t, and β is a subjective discount factor, $0<\beta<1$.

Production Possibilities

The production possibilities for the three commodities in the economy exhibit well-behaved Cobb-Douglas technology and thus can be represented in the following forms:

$$Y_{1t+1} = \lambda_{1t+1} L_{1t}^{b_1} X_{11t}^{a_{11}} X_{21t}^{a_{21}} X_{31t}^{a_{31}} \qquad (3\text{-}2)$$

$$Y_{2t+1} = \lambda_{2t+1} L_{2t}^{b_2} X_{12t}^{a_{12}} X_{22t}^{a_{22}} X_{32t}^{a_{32}} \qquad (3\text{-}3)$$

$$Y_{3t+1} = \lambda_{3t+1} L_{3t}^{b_3} X_{13t}^{a_{13}} X_{23t}^{a_{23}} X_{33t}^{a_{33}} \qquad (3\text{-}4)$$

where Y_{it+1} is total stock of commodity i (i = 1,2,3) available at time t+1, λ_{it+1} (i = 1,2,3) is a exogenous stochastic shock for total factor productivity in sector i whose value is realized at time t+1 (the sequence $\{\lambda_{it}\}$ is assumed to be time-homogeneous Markov process), X_{ijt} is the amount of commodity i (i = 1,2,3) used to produce commodity j (j = 1,2,3) at time t, b_i is a marginal productivity of labor in producing good i (i = 1,2,3), α_{ij} is a marginal productivity of good i in producing good j (i,j = 1,2,3), and L_{it} is labor input allocated to produce good i (i = 1,2,3) at time t. The parameters b_i and a_{ij} are assumed to be nonnegative and constant. Some special cases of this production technology are assumed: (a) there is no joint production, (b) there is no technological change, i.e., the sequence $\{\lambda_{it}\}$ is assumed to be independent and identically distributed, and (c) given L_t and X_t, Y_{1t+1}, Y_{2t+1} and Y_{3t+1} are independently distributed.

Resource Constraints

The representative agent faces two resource constraints at each date, one on goods and another on time. Labor and leisure choices are constrained at each date by

$$Z_t + L_{1t} + L_{2t} + L_{3t} = H \qquad , t = 0,1,2,.... \tag{3-5}$$

where H is a total time available per period.
Commodity allocations are also constrained at each date by

$$C_{1t} + X_{11t} + X_{12t} + X_{13t} = Y_{1t} \qquad , t = 0,1,2,.... \tag{3-6}$$
$$C_{2t} + X_{21t} + X_{22t} + X_{23t} = Y_{2t} \tag{3-7}$$
$$C_{3t} + X_{31t} + X_{32t} + X_{33t} = Y_{3t} \tag{3-8}$$

where Y_{it} is the endowment of commodity i (or total stocks of commodity i (i = 1,2,3) that is available at the beginning of time t.

<u>Dynamic Optimization Problem</u>

Subject to production possibilities (3-2)-(3-4) and the resource constraints given by (3-5)-(3-8), he chooses a consumption-production plan at time t to maximize

$$E(U|S_t) = E[\sum_{s=t}^{\infty} \beta^{s-t} U(C_s,Z_s)|S_t] \tag{3-9}$$

where $S_t = (Y_t,\lambda_t)$ is a state vector of economy at time t.

It is well-known that if the welfare function, $V(S_t)$, is defined as the maximum value of $E(U|S_t)$, then $V(S_t)$ and the optimal consumption-production plan are jointly the solution to the following Bellman's Equation:

$$V(S_t) = \text{Max } \{U(C_t,Z_t) + \beta\ E[V(S_{t+1})|S_t]\} \tag{3-10}$$

This is the functional equation for the value $V(S_t)$ of (3-9) when an individual is in state S_t and behaves optimally forever.

There are two methods for solving the functional equation (3-10): an iterative and a guess-and-verify method. The second method involves guessing a solution, $V(S_t)$, and verifying that it is a solution to (3-10). There are two classes of specifications of preferences and constraints for which this method yields analytical solutions: linear constraints and quadratic preferences, or

Cobb-Douglas constraints and logarithmic preferences. A solution is a function of state variable in general and we can have a closed form solution given logarithmic preference and Cobb-Douglas technology, therefore the conjectured solution is given by

$$V(S_t) = \phi_1 \ln Y_{1t} + \phi_2 \ln Y_{2t} + \phi_3 \ln Y_{3t} + J(\lambda_t) + K \qquad (3\text{-}11)$$

where $\phi_1 = \theta_1 + \beta(\phi_1\alpha_{11} + \phi_2\alpha_{12} + \phi_3\alpha_{13})$,
$\phi_2 = \theta_2 + \beta(\phi_1\alpha_{21} + \phi_2\alpha_{22} + \phi_3\alpha_{23})$, $\phi_3 = \theta_3 + \beta(\phi_1\alpha_{31} + \phi_2\alpha_{32} + \phi_3\alpha_{33})$,
$J(\lambda_t) = \beta E[\sum_{i=1}^{3} \phi_i \ln\lambda_{it+1} + J(\lambda_{t+1}) | \lambda_t]$, and K is a constant that depends on preference and production parameters.[2]

The procedure for obtaining optimal consumption and input quantities at time t can be described in the following way: Assume $V(S_t)$ is given by (3-11) and substitute it into the left-hand side of (3-10). Then maximize (3-10) with respect to time t control variables such as consumption and input decisions.(see Appendix A for details)

Solving the problem gives the following set of solutions.

$$L_{1t}^{*} = \frac{\beta\phi_1 b_1}{\theta_0 + \beta(\phi_1 b_1 + \phi_2 b_2 + \phi_3 b_3)} H \qquad (3\text{-}12\text{-}1)$$

---

[2]The constant vector is a function of preference parameters. Therefore, preferences also influence the dynamic behavior of outputs since the constant term determines the directions in which outputs are expected to move from any given value in the short-run while it determines the steady-state values of outputs in the long-run.

$$L_{2t}^{*} = \frac{\beta\phi_2 b_2}{\theta_0 + \beta(\phi_1 b_1 + \phi_2 b_2 + \phi_3 b_3)} H \tag{3-12-2}$$

$$L_{3t}^{*} = \frac{\beta\phi_3 b_3}{\theta_0 + \beta(\phi_1 b_1 + \phi_2 b_2 + \phi_3 b_3)} H \tag{3-12-3}$$

$$C_{1t}^{*} = \frac{\theta_1}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})} Y_{1t} \tag{3-12-4}$$

$$C_{2t}^{*} = \frac{\theta_2}{\theta_2 + \beta(\phi_1 a_{21} + \phi_2 a_{22} + \phi_3 a_{23})} Y_{2t} \tag{3-12-5}$$

$$C_{3t}^{*} = \frac{\theta_3}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \tag{3-12-6}$$

$$X_{11t}^{*} = \frac{\beta\phi_1 a_{11}}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})} Y_{1t} \tag{3-12-7}$$

$$X_{12t}^{*} = \frac{\beta\phi_2 a_{12}}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})} Y_{1t} \tag{3-12-8}$$

$$X_{13t}^{*} = \frac{\beta\phi_3 a_{13}}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})} Y_{1t} \tag{3-12-9}$$

$$X_{21t}^{*} = \frac{\beta\phi_1 a_{21}}{\theta_2 + \beta(\phi_1 a_{21} + \phi_2 a_{22} + \phi_3 a_{23})} Y_{2t} \tag{3-12-10}$$

$$X_{22t}^{*} = \frac{\beta\phi_2 a_{22}}{\theta_2 + \beta(\phi_1 a_{21} + \phi_2 a_{22} + \phi_3 a_{23})} Y_{2t} \tag{3-12-11}$$

$$X^*_{23t} = \frac{\beta\phi_3 a_{23}}{\theta_2 + \beta(\phi_1 a_{21} + \phi_2 a_{22} + \phi_3 a_{23})} Y_{2t} \qquad (3\text{-}12\text{-}12)$$

$$X^*_{31t} = \frac{\beta\phi_1 a_{31}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \qquad (3\text{-}12\text{-}13)$$

$$X^*_{32t} = \frac{\beta\phi_2 a_{32}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \qquad (3\text{-}12\text{-}14)$$

$$X^*_{33t} = \frac{\beta\phi_3 a_{33}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \qquad (3\text{-}12\text{-}15)$$

where $\phi_1 = \theta_1 + \beta(\phi_1\alpha_{11} + \phi_2\alpha_{12} + \phi_3 a_{13})$,
$\phi_2 = \theta_2 + \beta(\phi_1\alpha_{21} + \phi_2\alpha_{22} + \phi_3 a_{23})$ and
$\phi_3 = \theta_3 + \beta(\phi_1\alpha_{31} + \phi_2\alpha_{32} + \phi_3 a_{33})$.

These simple decision rules can explain the characteristics of business cycles such as persistence (serial correlation) and comovement (cross correlation).[3] For example, if output of good 1 (Y_{1t}) is unexpectedly high at time t, then the amount of good 1 used to produce time t+1 good 1 (X_{11t}) increases. This is how output shock at time t propagates over time (persistence). Furthermore, the

[3]Following Debreu (1954) and Prescott and Lucas (1972), we can interpret the utility maximizing choices by Robinson Crusoe as the per capita outcomes of a competitive market economy. Crusoe-style analysis can be interpreted as pertaining to the behavior of quantity variable for competitive market economies. Households are alike, there are no externalities, and there is no government.

$$D = \frac{\beta\phi_1 a_{31}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})}.$$

Substituting (3-12-2), (3-12-8), (3-12-11), and (3-12-14) into (3-3) gives

$$Y_{2t+1} = \lambda_{2t+1}(A'H)^{b_1}(B'Y_{1t})^{a_{12}}(C'Y_{2t})^{a_{22}}(D'Y_{3t})^{a_{32}} \qquad (3\text{-}13\text{-}2)$$

where $A' = \dfrac{\beta\phi_2 b_2}{\theta_0 + \beta(\phi_1 b_1 + \phi_2 b_2 + \phi_3 b_3)}$,

$$B' = \frac{\beta\phi_2 a_{12}}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})},$$

$$C' = \frac{\beta\phi_2 a_{22}}{\theta_2 + \beta(\phi_1 a_{21} + \phi_2 a_{22} + \phi_3 a_{23})} \text{ and}$$

$$D' = \frac{\beta\phi_2 a_{32}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})}.$$

Substituting (3-12-3), (3-12-9), (3-12-12), and (3-12-15) into (3-4) gives

$$Y_{3t+1} = \lambda_{2t+1}(A''H)^{b_1}(B''Y_{1t})^{a_{13}}(C''Y_{2t})^{a_{23}}(D''Y_{3t})^{a_{33}} \qquad (3\text{-}13\text{-}3)$$

where $A'' = \dfrac{\beta\phi_3 b_3}{\theta_0 + \beta(\phi_1 b_1 + \phi_2 b_2 + \phi_3 b_3)}$,

$$B'' = \frac{\beta\phi_3 a_{13}}{\theta_1 + \beta(\phi_1 a_{11} + \phi_2 a_{12} + \phi_3 a_{13})},$$

where $y_{1t} = \ln Y_{1t}$, $y_{2t} = \ln Y_{2t}$, $y_{3t} = \ln Y_{3y}$, $\epsilon_{1t} = \ln\lambda_{1t}$, $\epsilon_{2t} = \ln\lambda_{2t}$ and $\epsilon_{3t} = \ln\lambda_{3t}$.

Equation (3-15-1) - (3-15-3) can be written as the following compact notation:

$$y_t = C + Ay_{t-1} + \epsilon_t \tag{3-16}$$

where A is the 3×3 matrix of $\{a_{ij}\}$ (i,j = 1,2,3), C is 3×1 vector of constant, and ϵ_t is the 3×1 stochastic vector.

The elements of A are elasticities of commodity outputs with respect to commodity inputs. Unexpected high time t output of any one of the commodities corresponding to these columns leads to an increase in expected time t+1 outputs of both commodities as long as all elements in A are positive.[5] The A matrix summarizes the propagation mechanism in the sense that it shows how "exterior impulses" are "propagated" through time and across commodities in the model (see Appendix B). Therefore an element a_{ij} in matrix A will be zero if the product of the j^{th} sector is not used as an input into production of the i^{th} sector's product.

[5] A is a null matrix if labor is the only input in production, i.e., non-capitalistic production. As long as A is a non-diagonal matrix, economic activity in one sector will be directly linked to the level of economic activity in the other sectors.

<u>A Sector-by-Sector Model(VAR Model)</u>

The system of equations given by (3-16) is the exact representation of the trivariate Vector Autoregressive(VAR) model.[6]

Equation (3-16) can be written if p^{th} lag is allowed.

$$y_t = C + A(L)y_{t-1} + \epsilon_t \tag{3-17}$$

where y is a 3×1 vector of variables, A(L) is p^{th} order lag polynomial matrix, C is 3×1 vector of constants, and ϵ_t is a 3×1 white noise stochastic disturbance vector.

It may appear that VAR model with lag p in an econometric model and a VAR model with lag one in an economic model are not compatible. But this is not the case. The lag length derived from economic model is one because it takes one time period to produce goods. But if we assume that more than one time period, say up to p, is required to produce goods then we can have a VAR model with lag length p.[7]

The main purpose of this study is to investigate whether aggregate shocks cause sectoral business cycles or sector-specific shocks cause aggregate business cycles. Even though there are many

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[6]Even though some criticize that VAR models are atheoretical, it can be shown that a theoretical model can lead to an exact VAR model.

[7]One period model assumes zero cost of adjustment. Extended length can be due to adjustment lags in recontracting, transportation, and capital adjustment in response to shocks.

sectors, say N in the real economy, it is difficult to take into account all sectors in a VAR model. The more complex the economy (larger N) and the longer the adjustment lags, the greater the likelihood that an unrestricted VAR will have more parameters than available observations. This implies that estimation will require that restrictions must be placed on the parameters of the VAR to make the estimation tractable. The strategy used in this study involved grouping sectors into aggregate industries and then assuming a common transmission mechanism of shocks among sectors in an aggregate industry.

There are two channels by which shocks which initially affect a specific sector or industry can induce total output fluctuations: collective impact and feedback. Collective impact is simply the direct aggregation of sectoral or industry output. Shocks will induce variation in aggregate output directly since aggregate output is a weighted sum of sectoral or industry output. Feedback is the propagation mechanism by which initial shocks to one sector or industry affect subsequent output in all sectors or industries. Sectoral shocks can induce subsequent output fluctuations since various sectors are linked together through input-output relationships or trade linkages. Therefore we need to remove the first channel by constructing the net sectoral and industry output for the sector-by-sector model.

To properly identify sectoral output movements from aggregate or industry output movements, we need to define our empirical measures carefully. Specifically, we cannot include sectoral output in industry output and aggregate output because feedback effects for the own sector will be confused with feedback effects at the industry or aggregate level. To avoid this confusion, industry output is measured by aggregating output from all sectors in the industry except that of sector i. Similarly, aggregate output is measured by aggregating all industry output except that of sector i's industry. That is, from sector i's perspective, the industry output is net of sectoral i output and all aggregate output is net of the output of sector i's and its industry.

To clarify, suppose that the whole economy can be disaggregated by industry, and that an industry can be further disaggregated by sector. Each sector in the economy can trade with other sectors in the same industry group and it can also trade with other sectors outside its own industry group. Take sector i as a representative sector in industry group I. From equation (3-17), let y_{1t} be net aggregate output, defined as aggregate output minus industry group I's output. Let y_{2t} be industry I's net output, defined as industry I output minus sector i output. Let y_{3t} be sector i output.

Let there be S sectors in sector i's industry. Assume that we order the sectors in the following way: first, sector i, then the other S-1 sectors in the same industry as sector i, and finally, the rest of the sectors in the economy.

output (see industry share in Appendix D).

Let y_{1t} be denoted by A_t, y_{2t} by I_t and y_{3t} by S_t respectively. Then we have the following trivariate VAR model:

$$\begin{bmatrix} A_t \\ I_t \\ S_t \end{bmatrix} = \begin{bmatrix} a_{11}(L) & a_{12}(L) & a_{13}(L) \\ a_{21}(L) & a_{22}(L) & a_{23}(L) \\ a_{31}(L) & a_{32}(L) & a_{33}(L) \end{bmatrix} \begin{bmatrix} A_{t-1} \\ I_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{at} \\ \epsilon_{it} \\ \epsilon_{st} \end{bmatrix} \tag{3-19}$$

where $a_{11}(L), \ldots, a_{33}(L)$ are p^{th} order polynomials in lag operator L.

This linear system of stochastic difference equations provides an econometric model for sector-by-sector analysis, i.e., we can perform a causality test, impulse response and forecasting error variance decomposition analysis.

Error Structure

We need to discuss the error structure of the econometric model for the sector-by-sector analysis. Let the covariance of the residual vector be

$$E(\epsilon_t \epsilon_t') = \Sigma \tag{3-20}$$

Σ is a nondiagonal symmetric matrix since the unrestricted VAR residuals may be contemporaneously correlated. The contemporaneous where e_{at}, e_{it}, e_{st} are orthogonalized innovations, i.e., the covariance matrix of $e_t = (e_{at}, e_{it}, e_{st})'$ is diagonal by construction.

A Multi-sector Model(Restricted VAR Model)

There are two different approaches for sectoral analysis of business cycles using a multi-sector model: DYMIMIC and error components models. Norrbin and Schlagenhauf (1989, 1990, 1991) used a DYMIMIC model in analyzing the source of output fluctuations using quarterly data. Altonji and Ham (1990) used an error components model to investigate the source of variation in employment growth in Canada using annual data. Krieger (1989) also used an error components model to examine the role of sectoral and aggregate shocks to industrial output in an open economy using annual data. A completely unrestricted multi-sector model is unestimable due to over-parameterization. Therefore, all of these studies imposed some form of composite-variable restriction on the feedback coefficients of the multi-sector model.[8]

In terms of the number of common shocks, all assume one common factor (or aggregate shock) in the error process. This is consistent with the findings of Long and Plosser's (1987) findings from their

[8]Norrbin and Schlagenhauf (1991) used two more different restrictions. One is a principal component restriction which limits the cross-dependencies between output changes by reducing the dimension of the data matrix. The other is an input-output restriction which is to set the feedback coefficients equal to the input requirements from other industries and the own industry.

examination of the number of common shocks in the economy, using the monthly innovations from a restricted VAR model.

Our strategies to investigate the role of aggregate and disaggregate shocks in the Korean economy using monthly output data. The hope is that monthly data will effectively capture the trade linkage among sectors in the context of a multi-sector model. First, we will try to examine the number of common shocks in the Korean economy using factor analysis. We will use monthly innovations from the multi-sector (restricted VAR) model, which is different from the model Long and Plosser used. Second, we will impose a restriction to estimate the feedback coefficients of the multi-sector model. Our restriction derived from an interpretive economic model is a little different from the composite-variable restrictions used in previous studies. Third, following Altonji and Ham and Krieger we will employ the error components model to identify various shocks in the error process.

Since we are primarily interested in how all sectors in the economy interact we should aggregate over all sectors. Suppose that there are N sectors in the economy. Then we have an N-variate VAR model from the economic model. But the N-variate VAR model might be unestimable due to over-parameterization if N and lags are large enough. Therefore we need to impose some restrictions on the N-variate VAR model to estimate the system of equations.

Suppose that we have the following multi-sector model:

$$S_{1t} = a_{11}(L)A_{t-1} + a_{12}(L)I_{t-1} + a_{13}(L)S_{t-1} + \epsilon_{st}^{1} \qquad (3\text{-}22\text{-}1)$$

$$S_{2t} = a_{21}(L)A_{t-1} + a_{22}(L)I_{t-1} + a_{23}(L)S_{t-1} + \epsilon_{st}^{2} \qquad (3\text{-}22\text{-}2)$$

$$\begin{array}{cccccc} \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{array}$$

$$S_{Nt} = a_{N1}(L)A_{t-1} + a_{N2}(L)I_{t-1} + a_{N3}(L)S_{t-1} + \epsilon_{st}^{N} \qquad (3\text{-}22\text{-}N)$$

This system of equations is a restricted VAR with the restriction that the feedback coefficients ($a_{12}(L),.., a_{N2}(L)$) of other sectors in the same industry group on each sectoral output are the same at each period and also the feedback coefficients ($a_{11}(L),.., a_{N1}(L)$) of other sectors outside its own industry group on each sectoral output are the same at each period. Our restriction is quite similar to composite-variable restriction used by Norrbin and Schlagenhauf, Altonji and Ham, and Krieger. The difference is that we use net industry and net aggregate output while they do not. In their restriction the past history of sectoral output growth are entered three times in each equation. The estimated coefficients could be imprecise and using the residuals from the multi-sector model may contain imprecise information. Therefore our alternative restriction seems to be more reasonable.

Error Structure

As discussed in Section 3.1 the Choleski decomposition imposes restrictions on the error structure in an arbitrary manner.

In particular, the system is recursive and requires prior restrictions on the ordering of the equations. An alternative decomposition, the so called structural decomposition, was proposed and used by some economists who are skeptical of recursive ordering, claiming that most economic theories generate a simultaneous rather than a recursive system of equations (Bernanke, 1986; Sims, 1986; Blanchard and Watson, 1986). They argue that the interpretation of the impulse response function and variance decomposition is questionable since the error structure in the VAR is given recursively rather than structurally.

If there is only one type of disturbance, then the interpretation of sectoral (aggregate) output fluctuations is not too difficult. However, if sectoral (aggregate) output are affected by more than one disturbance, the interpretation is more difficult since the dynamic response of sectoral (aggregate) output represent the mixture of each disturbance. Given the possibilities that sectoral (aggregate) output may be affected by more than one disturbance, it is natural to consider isolating aggregate shocks and disaggregate industry-specific and sector-specific shocks.

Long and Plosser (1983) restrict the vectors in the sequence $\{\epsilon_t\}$ in equation (3-16) to be independent and identically distributed through time and restrict the covariance matrix, $E(\epsilon_t \epsilon_t') = \Sigma$, to be an identity matrix, i.e., no serial and contemporaneous correlation is assumed. These assumptions guarantee that any tendency for output in different sectors to move together arises solely from the nature of the input decision rules and the production technology, not from the existence of a common shock or shocks that are correlated across sectors. Similarly, any serial correlation in output must also arise from the propagation mechanism in the model and not from serially correlated exogenous shocks. But it is generally known that the covariance matrix of the disturbance vector can be contemporaneously correlated. Therefore if we allow contemporaneous correlations in the disturbances, then the comovement across different sectors arise from not only the input decision rules and the production technology but also the existence of a common shock.[9]

Dimension of Common Shocks

Long and Plosser (1987) considered one common factor and two common factor models and Romer (1991) assumed a one common factor model.[10] It seems restrictive that there is only one common factor

[9]Dellas (1986) uses a stochastic, two country, log-linear, infinite horizon model to analyze the generation and transmission of economic fluctuations across countries. He examined three possible sources of output comovement in different countries: common external shocks, adoption of similar economic policies, and world trade interdependence (trade links). His empirical analysis suggests that common shocks rather than trade links are responsible for output comovement across countries.

[10]Our one common factor model is different from Romer's (1991) in that we decompose the innovations to each series while she considers the unconditional residuals. Therefore, the residuals in her study reflect the properties of both the innovations to production and the responses to earlier innovations. The difference may be negligible if the growth rates are not highly correlated.

If an aggregate shock is characterized as one which affects many sectors with potentially different impacts, it can be captured by the "factor loading" vector in a factor analysis model. One rationale of this interpretation is the observation that sectoral outputs move together since a factor analysis is based on the fundamental assumption that some underlying factors are responsible for the covariation among the observed variables (see Kim and Mueller, 1978).

There can be two different explanations for comovement among sectors. One explanation is that aggregate shocks are the dominant source of fluctuations. Another explanation is that sectoral shocks had large and rapid spillovers through trade linkages. That is, the correlation of sectoral outputs may arise either from shocks which are correlated across sectors or from production interdependence (trade linkage) among sectors.

Given that one of main objective is to assess the relative importance of aggregate, sector-specific and industry-specific shocks at either the aggregate, sectoral, or industry levels, we can decompose the disturbance, $\epsilon_t = (\epsilon^1_{st}, \epsilon^2_{st}, \ldots \epsilon^N_{st})'$, for a given sector i in industry j by

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[11]Burns and Mitchell (1947) provide evidence that economic activity in various industries moves together, using over 200 disaggregated production series data in the analysis of short-run movements of economic activity.

$$S_{1t} = \pi_1(L)A_{t-1} + \rho_1(L)I_{t-1} + \phi_1(L)S_{t-1} + f_1c_t + h_1^1g_t^1 + e_{1t} \quad (3\text{-}24\text{-}1)$$

$$S_{2t} = \pi_2(L)A_{t-1} + \rho_2(L)I_{t-1} + \phi_2(L)S_{t-1} + f_2c_t + h_2^2g_t^2 + e_{2t} \quad (3\text{-}24\text{-}2)$$

$$\vdots$$

$$S_{Nt} = \pi_N(L)A_{t-1} + \rho_N(L)I_{t-1} + \phi_N(L)S_{t-1} + f_Nc_t + h_N^Mg_t^M + e_{Nt} \quad (3\text{-}24\text{-}N)$$

where $\pi_1(L),\ldots.\phi_N(L)$ capture the important trade linkage across sectors, c_t represents common shocks due to aggregate demand and/or aggregate supply innovations, $e^i_{st}(i=1,2,\ldots N)$ are sector-specific shocks which capture changes in tastes for an industry's product, sector-specific productivity shocks, and shocks to the price of an industry's input, and g_t^j $(j=1,2,\ldots M)$ are industry-specific shocks.

Estimation of Error Components

The estimation of the parameters in the multi-sector model can be carried out in a two-step procedure:

(Step 1) Estimate the multi-sector model by Seemingly Unrelated Regression(SUR) method to gain efficiency since the disturbances are contemporaneously correlated. The resulting parameter estimates are used to provide estimates $\hat{\epsilon}_t$ of the error ϵ_t.

(Step 2) Estimate the coefficients and variances in the error components model from the sample covariances (or correlations) of $\hat{\epsilon}_t$.

The method of moments technique can be used to estimate the parameters in the error components model. The procedure

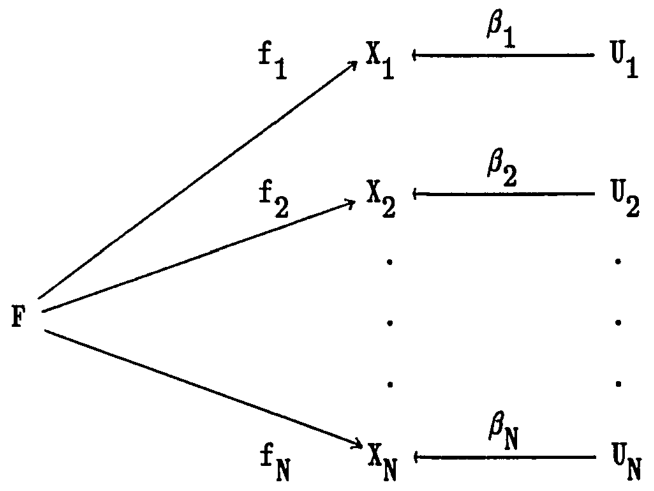

Figure 3-1. Path diagram for an N-variable, one-common factor model

It is not too difficult to analyze and forecast the time series if it is a realization of stationary stochastic process. Therefore it is strongly recommended that one use stationary time series in econometric practice. But most macroeconomic time series is non-stationary. The outstanding characteristics of observed time-series are trend and seasonality.

Decomposition of Time Series

Let the observed economic time-series, X_t, be decomposed in the following way:

$$X_t = T_t \times S_t \times C_t \times R_t$$

where T_t is a trend, S_t is a seasonal factor, C_t is a cyclical factor and R_t is random (irregular) factor. This multiplicative representation of economic time series may be handled with the additive representation by taking logarithmic transformations.

We can determine whether the representation is multiplicative or additive by simply examining the time plot. If the size of seasonal variation does not change as the mean level changes, then it is said to be additive. But if it increases in proportion to the mean level, then it is said to be multiplicative. Figure 4-1 show that the observed time series is additive in logarithms.

Suppose that the economic time series can be decomposed in the following additive way:

$$x_t = t_t + s_t + c_t + r_t$$

where, $x_t = \ln X_t$, $t_t = \ln T_t$, $s_t = \ln S_t$, $c_t = \ln C_t$ and $r_t = \ln R_t$. Since business cycles (or cyclical fluctuations) can be defined as a deviation from the long-run trend path of an economic activity, we are primarily interested in identifying cyclical component (c_t). Therefore we need to be able to extract the cyclical component from observed time series. This can be done by removing trend (t_t) and seasonal (s_t) components from the observed time series. The cyclical components will reflect non-systematic movements in the series.

Data

The data consists of monthly observations on the seasonally adjusted industrial production index for 16 series in Korea. The use of monthly data lessens the possibility that impulses will be confused with the propagation mechanism as could occur in studies that employ longer time intervals. The longer time intervals such as quarterly and yearly are more likely to have both impulses and reactions between observations. That is, using monthly data may get more precise measures of the dynamic interactions among variables. The sample period is 1970:1 - 1990:12. Data were obtained from the Bank of Korea. See the data description in Appendix D.

models since it may distort the true relationship in the model. We will use the officially released seasonally adjusted data instead of adjusting with a regression analysis method.

Trend Removal

The trend is the long-term movements in the series. An economic time series from which the trend has been removed is called a detrended series. Detrending is very important theoretically and econometrically in analyzing business cycles. Most economic time series are non-stationary if trend is not removed. Phillips (1986) and Granger and Newbold (1974) point out the possibility of the misleading regression coefficients when economic time series are dominated by non-stationary near random walk processes. Phillips demonstrated that the usual t- or F-ratio test statistics in this context do not possess standard limiting distributions. Another possible problem is that the "stylized facts" of the business cycle may be sensitive to the detrending method employed.

There are two detrending methods: deterministic and stochastic detrending. One of the controversial issues in economic time series analysis is whether the observed time series is difference stationary (existence of a unit root or stochastic trend) or trend stationary (existence of a deterministic trend). Until recently, statistical inference in economic time series has often been conducted under the assumption that the series are stationary after removing a deterministic trend component. Therefore a time trend is included as a regressor to capture a long-run growth component. It is, however, widely recognized that many macroeconomic series appear to contain a unit root. Dickey and Fuller (1979) developed unit root tests while Nelson and Plosser (1982) applied an augmented Dickey-Fuller procedure to find unit roots in macroeconomic time series. They failed to reject the unit root hypothesis for 13 annual series. Nelson and Plosser claim that the procedure of including a time trend to capture a long-run growth component is likely to confound the growth and cyclical component in the series. In other words, it may overstate the magnitude of the cyclical component and understate the importance of the growth component. They also show that if the trend component of economic time series also contains a stochastic element, it can have important implications for many questions in macroeconomics. A shock to a series has no long-lived effects if the series is trend stationary while a shock to a series has persistent effects if the series is difference stationary.[1] This fact has very

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[1]This can be shown in the following way:
(Case 1) When trend stationarity holds,

$$y_t = \alpha + \beta t + \rho y_{t-1} + \epsilon_t \tag{1}$$

where ϵ_t is white noise and ρ is assumed to be $0 < \rho < 1$.
Suppose there is a ϵ_T shock at time T, i.e., $\epsilon_t = \epsilon_T$ if t=T ant ϵ_t = 0 otherwise. The solution of the first order difference equation give in the equation (1) is

$$y_t = \frac{1}{1-\rho}(\alpha + \beta t) + \sum_{i=0}^{\infty} \rho^i \epsilon_{t-i}$$

We can also represent the solution as

important implications for researchers and policy makers. If the observed time series is trend stationary, then any cyclical fluctuation is considered temporary and long-term growth policy and short-term stabilization policy can be determined independently.

However if the observed time series is difference stationary, then cyclical fluctuations are not temporary but permanent. Therefore theories explaining only growth or only cycles are not appropriate due to interactions between stochastic trend and cycle. Also we should take account of both the short run implications of

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$$y_{T-1} = \frac{1}{1-\rho}(\alpha + \beta(T-1))$$
$$y_T = \frac{1}{1-\rho}(\alpha + \beta T) + \epsilon_T$$
$$y_{T+1} = \frac{1}{1-\rho}(\alpha + \beta(T+1)) + \rho\epsilon_T$$
$$\vdots$$
$$y_{T+s} = \frac{1}{1-\rho}(\alpha + \beta(T+s)) + \rho^s\epsilon_T$$

Therefore $\frac{\partial y_{T+s}}{\partial \epsilon_T} = \rho^s \longrightarrow 0$ as $s \longrightarrow \infty$

(Case 2) When difference stationarity holds, (i.e., $\beta = 0$ and $\rho = 1$) Suppose there is a ϵ_T shock at time T, i.e., $\epsilon_t = \epsilon_T$ if $t = T$ and $\epsilon_t = 0$ otherwise. Then we can have the following dynamics:

y_{T-1} is given.
$$y_T = \alpha + y_{T-1} + \epsilon_T$$
$$y_{T+1} = 2\alpha + y_{T-1} + \epsilon_T$$
$$\vdots$$
$$y_{T+s} = s\alpha + y_{T-1} + \epsilon_T$$

Therefore $\frac{\partial y_{T+s}}{\partial \epsilon_T} = 1 \ \forall \ s \geq 0$

growth policies and the long run implications of stabilization policies (Stock and Watson, 1988).

From a statistical perspective, the differencing method (stochastic detrending) is justified since researchers are misled to incorrect results if they detrend the observed time series by removing the deterministic time trend. Statistical inference of estimates is not standard when the series actually has a stochastic trend. But differencing the series may lose valuable information about the relationship among variables in levels.

In this chapter we analyze a trivariate VAR model, given the system of equations (3-19) in Section 3.2. For the analysis total industry can be disaggregated into three industries: Mining (MIN), Non-durable (NDM) and Durable manufacturing (DM). Also each industry can be further disaggregated into sectors. The Mining industry is disaggregated into three sectors: Coal mining (COAL), Metal ore (ORE) mining and Other mining (OMIN). The Non-durable manufacturing industry is disaggregated into four sectors: Food (FBT), Chemicals (CPRP), Textiles (TWL) and Paper(PPP). The Durable manufacturing industry is also disaggregated into five sectors: Glass (NMMP), Wood (WAF), Basic metal (BMETL), Fabricated metal (FMME) and Other manufacturing (OMAN) (see data descriptions in Appendix D for details). Various tests for unit root, cointegration and lag length are performed. Then the trivariate VAR model for each sector is estimated, allowing an analysis of causality, impulse response and forecasting error variance decomposition.

4.2 Unit Root Test

In the Box-Jenkins' identification stage all the individual time series seem to be non-stationary since the autocorrelation functions diminish linearly. We can write the time series model in the following way if the observed time series is trend stationary and difference stationary respectively:

$$y_t = \alpha + \beta t + \rho y_{t-1} + \epsilon_t \qquad (4\text{-}1)[2]$$

Under $\beta \neq 0$ and $|\rho|<1$ y_t is said to be trend-stationary while y_t is difference-stationary under $\rho = 1$. The usual t-statistic for testing the null hypothesis that ρ is equal to one is not valid here. Therefore we can reparameterize equation (4-1) into (4-2) by adding y_{t-1} on both sides of equation (4-1).

---

[2]The equation (4-1) above is the reduced form of the following model:

$$y_t = \alpha_0 + \alpha_1 t + u_t \qquad (1)$$

where

$$u_t = \rho u_{t-1} + \epsilon_t \qquad (2)$$

and $\{\epsilon_t\}$ is a zero-mean, covariance-stationary stochastic process. The coefficients in equation(4-1) and (1) - (2) are related with $\alpha=[\alpha_0(1-\rho)+\alpha_1\rho]$ and $\beta=\alpha_1(1-\rho)$.

This procedure is called Augmented Dickey-Fuller (ADF) test. This specification allows for more dynamics in the regression of equation (4-2) and thus it is overparameterized in the first order autoregressive model but it is a correct specification in the higher order autoregressive model. The augmented Dickey-Fuller test was performed on the basis of equation (4-3). Also serial correlation of the residual in the regression of equation (4-3) was examined. Most series appear to be serially uncorrelated if we choose autocorrelation adjustment p equal to 1 (see Figure 4-3).

To reject the null hypothesis of unit root for both DF and ADF test, the t-statistic of coefficient of y_{t-1} must be smaller than:

	Significance Level		
Sample Size	0.01	0.05	0.1
250	-3.99	-3.43	-3.13

Since Dickey-Fuller test depends on the nuisance parameter p, we use the Phillips-Perron (1988) test as a secondary test which is known to be robust to nuisance parameters. It allows some amount of weak dependence and heterogeneity of the sample data. The same critical values for their four test statistics, $Z(\alpha^*)$, $Z(\tilde{\alpha})$, $Z(t_\alpha{}^*)$ and $Z(t_{\tilde{\alpha}})$, under the null hypothesis of a unit root can be used as Fuller's reported critical values (1976, p. 371 and 373).

To reject the null hypothesis of unit root, the calculated

Z-statistics must be smaller than:

Critical value(Sample Size=250)

Significance Level	$Z(\alpha^*)$	$Z(\tilde{\alpha})$	$Z(t_{\alpha^*})$	$Z(t_{\tilde{\alpha}})$
0.01	-20.3	-28.4	-3.46	-3.99
0.05	-14.0	-21.3	-2.88	-3.43
0.1	-11.2	-18.0	-2.57	-3.13

Table 4-1 reports Dickey-Fuller (DF), augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for the stationarity of the 16 industrial production indices (one total industrial production index, 3 industry industrial production indices and 12 sector industrial production indices).

We fail to reject the null hypothesis of unit root for all series except Other mining, Paper and Glass in the DF test and PP test, Other mining and Glass in the ADF test.

The residual autocorrelations from the regression of equation (4-2) and (4-3) indicate that ADF test is more appropriate since some significant residual autocorrelations imply that the simple DF test is inappropriate. In sum, all series except Other mining and Glass contain a unit root and are stationary series in first-differences.

4.3 Cointegration Test

One recent development in macroeconometrics is the development of tests for cointegration originated by Granger (1986) and Engle and Granger (1987). Engle and Granger (1987) defined cointegration in the following manner:

(Definition) A vector X_t is said to be cointegrated of order(d,b), denoted $X_t \sim CI(d,b)$, if (i) all components of X_t are integrated of order d (stationary in d^{th} differences) and (ii) there exists at least one vector $\alpha(\neq 0)$ such that $\alpha' X_t$ is integrated of order d-b, b>0.

The idea of cointegration is as follows: although individual series which contain stochastic trend are nonstationary in their levels, there may be stationary linear combinations of the levels if the stochastic trends are common across the series. In other words, cointegration means that two time series possess a common persistent component, so that some linear combination of the series should be free of any persistent component.

The formal definition can be easily reinterpreted if we take the case in which the time series is stationary in first differences. Granger and Engle observed that if two integrated time series, say y_{1t} and y_{2t} that are I(1), are not cointegrated, then the residuals

ϵ_t in the following cointegrating regression

$$y_{1t} = c + \alpha y_{2t} + \epsilon_t \tag{4-4}$$

will contain a unit root. That is, a second-stage regression on the residuals from the cointegrating regression

$$\Delta\epsilon_t = \rho_1\epsilon_{t-1} + \sum_{j=1}^{p} \rho_{1+j}\Delta\epsilon_{t-j} + e_t \tag{4-5}$$

will produce a coefficient ρ_1 equal to zero. The summation terms enter to account for the serial correlation. Two time series are cointegrated if ρ_1 is not equal to zero. The null hypothesis, two time series are not cointegrated, may be tested by computing the t-statistics for ρ_1 in the second-stage regression in equation (4-5).

It is well known that α is unique and the relationship

$$y_{1t} = c + \alpha y_{2t}$$

can be thought of as a long-run (or equilibrium) relationship between y_{1t} and y_{2t} while ϵ_t measures the deviations from the long-run relationship. The vector $(1,-\alpha)$ is called a cointegrating vector. The importance of cointegration test is that we cannot have a VAR representation in differenced series if the original series are cointegrated since a VAR representation ignores the cointegrating relationship in levels (Campbell and Shiller, 1987). Instead, the multivariate data generating process has a Vector Error Correction representation if the series have common stochastic trends.

Two types of cointegration test were performed. First, the cointegration test for two variables is carried out, using the property that the cointegration is transitive. That is, if two series are each cointegrated with a third series, then first two series will themselves be cointegrated. Second, the cointegration test among three variables is performed. We used the cointegration test by Engle and Yoo (1987) which is a natural multivariate extension of the Engle and Granger (1987) bivariate test. They report the critical values for cointegration test. To reject the null hypothesis of cointegration, the calculated value must be greater than:

	N=2 Case(n=200)		N=3 Case(n=200)	
	DF	ADF	DF	ADF
0.01	-4.0	-3.78	-4.35	-4.34
0.05	-3.37	-3.25	-3.78	-3.78
0.1	-3.02	-2.98	-3.47	-3.51

For our trivariate VAR model two independent bivariate cointegration tests were performed: cointegration between aggregate

ϵ_{it} where C is a constant, I_{it} is industry output, and S_{jt} is sectoral output.

Table 4-2 - 4-3 report the results of these two independent cointegration tests while the results of cointegration tests for three variables are reported in Table 4-4. The property of transitivity in cointegration tests seems to work in our data for both DF and ADF tests. In Table 4-4, the DF test implies that all three variable systems (except Food) are cointegrated. However, we fail to reject the null hypothesis that three series are not cointegrated for most trivariate systems (except Coal and Other mining) when the ADF test is applied. The residual plot from the DF regression in second stage indicates that we need an autocorrelation adjustment, so the ADF test would seem to be appropriate (see Figure 4-4). Therefore we can conclude that most three variable systems (except Coal and Other mining) are not cointegrated, which implies that there is no common persistent component among aggregate, industry and sectoral output.[3] This finding validates the use of a trivariate VAR with differenced data.

[3]Durlauf (1990) found that mining and non-durable manufacturing sectoral output are cointegrated with aggregate output while durable manufacturing sectoral output is not cointegrated with aggregate output.

Table 4-2 Bivariate cointegration test between aggregate and industry output

Industry	Sector	DF	ADF[a]
Mining	Coal	-6.61**	-3.8*
	Ore	-3.13+	-0.71
	Othermin	-1.04	-1.33
Non-durable	Food	-2.3	-1.72
	Chemicals	-2.06	-1.65
	Textiles	-3.17+	-2.33
	Paper	-2.17	-1.71
Durable	Glass	-3.96**	-2.66
	Wood	-3.5*	-2.61
	Basmetal	-2.93+	-2.05
	Fabmetal	-3.84*	-2.61
	Otherman	-3.54*	-2.41

[a] Fourth order autocorrelation adjustment is used for the ADF test.

**, *, + denote significance at 1%, 5%, 10% level respectively.

Critical values are given in Engle and Yoo (1987, pp. 157-158).

Table 4-3 Bivariate cointegration test between sectoral and industry output

Industry	Sector	DF	ADF[a]
Mining	Coal	-2.85	-0.16
	Ore	-2.41	0.08
	Othermin	-1.96	0.73
Non-durable	Food	-3.54*	-2.07
	Chemicals	-3.3+	-1.52
	Textiles	-1.78	-1.13
	Paper	-3.42*	-1.42
Durable	Glass	-5.19**	-2.4
	Wood	-3.47*	-2.05
	Basmetal	-2.0	-1.19
	Fabmetal	-4.14**	-2.09
	Otherman	-3.95*	-2.61

[a] Fourth order autocorrelation adjustment is used for the ADF test.

**, *, + denote significance at 1%, 5%, 10% level.

Critical values are given in Engle and Yoo (1987, pp. 157-158).

Table 4-4 Trivariate cointegration test

Industry	Sector	DF	ADF[a]
Mining	Coal	-6.97**	-4.12*
	Ore	-4.73**	-2.3
	Othermin	-7.87**	-4.97**
Non-durable	Food	-2.55	-2.11
	Chemicals	-4.36**	-2.3
	Textiles	-3.18+	-2.32
	Paper	-4.1*	-2.88
Durable	Glass	-3.72*	-2.57
	Wood	-3.51*	-2.61
	Basmetal	-4.18**	-3.22
	Fabmetal	-3.82*	-2.82
	Otherman	-3.53*	-2.41

[a] Fourth order autocorrelation adjustment is used for the ADF test.

**, *, + denote significance at 1%, 5%, 10% level.

Critical values are given in Engle and Yoo (1987, pp. 157-158).

4.4 Lag Length Test

One issue in VAR analysis is the choice of an appropriate number of lags. This choices can be made with the aid of statistical tests. According to Sims (1980) the conventional likelihood ratio test for determining lag length is too conservative in favor of acceptance of the null hypothesis. As an alternative, he suggests a modified test statistic of

$$L(T) = (T - c)(\ln|\Sigma_R| - \ln|\Sigma_U|)$$

where T is the number of observation, c is a correction to improve small sample properties, $|\Sigma_R|$ and $|\Sigma_U|$ are determinants of covariance matrices of restricted and unrestricted model respectively. He suggests using a correction equal to the number of variables in each unrestricted equation in the system. This likelihood ratio test can be used to determine lag length in the system.

Under the null model, the statistic L(T) converges to χ^2 (df) where the degree of freedom (df) is the number of linear restrictions. Table 4-5 contains the results of optimal lag length test. According to the lag length test, 6 lags is appropriate for non-durable manufacturing industry while 12 lags is appropriate for mining and durable manufacturing industries. In order to set the same lag length for all sectors (since it is useful when we are

Table 4-5 Lag length test

Sector	3vs.6[a]	6vs.9	9vs.12	6vs.12
<u>Mining</u>				
Coal	41.1(0.04)	45.8(0.01)	40.8(0.04)	85.9(0.00)
Ore	48.8(0.01)	25.6(0.54)	44.1(0.02)	69.2(0.08)
Othermin	45.6(0.01)	50.5(0.00)	41.8(0.03)	91.4(0.00)
<u>Non-durable</u>				
Food	40.8(0.04)	34.9(0.14)	36.0(0.11)	65.8(0.13)
Chemicals	36.2(0.11)	34.1(0.16)	33.4(0.18)	60.2(0.26)
Textiles	35.9(0.12)	36.4(0.11)	33.3(0.19)	66.3(0.12)
Paper	45.7(0.01)	32.5(0.22)	28.0(0.41)	56.9(0.38)
<u>Durable</u>				
Glass	37.5(0.09)	52.5(0.00)	33.0(0.20)	84.6(0.00)
Wood	43.0(0.03)	36.9(0.09)	34.6(0.15)	72.6(0.05)
Basmetal	48.1(0.01)	56.4(0.00)	40.3(0.05)	92.3(0.00)
Fabmetal	44.3(0.02)	58.2(0.00)	39.3(0.06)	91.7(0.00)
Otherman	38.5(0.08)	30.3(0.30)	47.5(0.01)	75.7(0.03)

[a] Numbers are sample statistic of L(T); numbers in parentheses are marginal significance levels.

analyzing a Multi-sector model) we use 12 lags in analyzing both Sector-by-Sector and Multi-sector model.

4.5 Causality Test

Granger (1969) proposed a concept of "causality" based on prediction error: X is said to Granger-cause Y if Y can be forecasted better using past Y and past X than using just past Y. In other words, X is said to cause Y if taking into account past values of X leads to improved predictions for Y. In his concept he uses the variance of the one-step ahead prediction error as the measure of the accuracy of predictions.

Sims (1972) showed that Y fails to Granger-cause X iff $b_j = 0$ for all $j < 0$ from the distributed lag regression

$$Y_t = \sum_{j=-\infty}^{\infty} b_j X_{t-j} + u_t.$$

In practice, the "Granger test" regresses Y on lagged Y and lagged X and tests the joint significance of lags of X while the "Sims test" regresses X on past, present and future Y, and tests the joint significance of leads of Y (see Harvey, 1981, p. 300-307).

In this study we follow the "Granger" causality test. From the trivariate VAR representation (which is assumed to be linear,

Table 4-6 Causality test on sectoral output

System[a]	Aggregate[b]	Industry	Sector
Mining			
(Coal,I,A)	1.70(0.07)	1.61(0.09)	4.85(0.00)
(Ore,I,A)	1.66(0.08)	1.86(0.04)	5.70(0.00)
(Othermin,I,A)	1.42(0.16)	1.99(0.03)	3.19(0.00)
Non-durable			
(Food,I,A)	1.19(0.29)	1.17(0.31)	2.96(0.00)
(Chemicals,I,A)	0.35(0.98)	1.57(0.10)	3.69(0.00)
(Textiles,I,A)	0.72(0.73)	1.05(0.41)	1.36(0.19)
(Paper,I,A)	0.38(0.97)	1.01(0.44)	3.88(0.00)
Durable			
(Glass,I,A)	2.82(0.00)	1.25(0.25)	1.65(0.08)
(Wood,I,A)	2.34(0.01)	1.02(0.43)	3.11(0.00)
(Basmetal,I,A)	1.16(0.31)	1.60(0.09)	1.00(0.45)
(Fabmetal,I,A)	0.91(0.54)	1.17(0.31)	3.49(0.00)
(Otherman,I,A)	1.42(0.16)	1.00(0.45)	3.50(0.00)

[a] I and A denote industry and aggregate output in the system.

[b] Numbers are F statistics; numbers in parentheses are marginal significance levels.

Table 4-8 Causality test on aggregate output

System[a]	Aggregate[b]	Industry	Sector
Mining			
(Coal,I,A)	2.62(0.00)	1.37(0.18)	1.82(0.04)
(Ore,I,A)	2.48(0.00)	0.82(0.63)	1.51(0.12)
(Othermin,I,A)	2.76(0.00)	2.13(0.02)	1.55(0.11)
Non-durable			
(Food,I,A)	2.72(0.00)	2.02(0.02)	0.97(0.48)
(Chemicals,I,A)	2.40(0.01)	1.86(0.04)	0.50(0.91)
(Textiles,I,A)	2.54(0.00)	0.79(0.66)	2.92(0.00)
(Paper,I,A)	2.28(0.01)	1.52(0.12)	1.03(0.43)
Durable			
(Glass,I,A)	4.58(0.00)	0.65(0.80)	2.29(0.01)
(Wood,I,A)	4.27(0.00)	0.63(0.82)	0.79(0.66)
(Basmetal,I,A)	4.85(0.00)	0.32(0.99)	0.98(0.47)
(Fabmetal,I,A)	4.87(0.00)	1.86(0.04)	0.73(0.72)
(Otherman,I,A)	4.22(0.00)	0.46(0.93)	0.95(0.50)

[a] I and A denote industry and aggregate output in the system.

[b] Numbers are F statistic; numbers in parentheses are marginal significance levels.

caused by aggregate output. We can interpret this result that each sectoral output in durable manufacturing industry has a strong production linkage with other sectors in the economy. Textiles and Basic metal output are not Granger caused by its own history but it has strong causal link to its own industry output.

In aggregate output perspectives some sectoral outputs such as Coal mining, Textiles, and Glass Granger cause aggregate output. But sectoral output in mining industry has the strongest causal link to aggregate output.

In sum, output at every level are Granger caused by their own history. Sectoral output and industry output in durable manufacturing industry is Granger caused by aggregate output. Mining industry has the strongest causal link to aggregate output.

4.6 Impulse Responses and Variance Decompositions

The typical analyses other than causality tests used in VAR are impulse responses and forecasting error variance decompositions (FEVD), which measure the dynamic interactions among the variables in the system. Impulse responses show how one variable in the system responds over time to a surprise movements in itself or in other variables in the system. FEVD shows how much of the forecasting error the model would make is caused by surprise movements in each variables in the model.

Table 4-9 Decomposition of the varance from a sectoral output perspective (evaluated at steady state)

		Fraction of variation explained by		
Industry	Sector	Aggregate	Industry	Sector
Mining	Coal	11.88	6.77	81.35
	Ore	7.53	12.65	78.82
	Othermin	8.51	15.98	75.51
Non-durable	Food	12.54	5.35	82.11
	Chemicals	9.86	15.28	74.86
	Textiles	6.92	13.40	79.68
	Paper	8.06	11.89	80.05
Durable	Glass	16.06	3.98	79.96
	Wood	17.56	7.75	74.69
	Basmetal	15.85	15.65	68.50
	Fabmetal	17.38	12.66	69.96
	Otherman	9.40	7.23	83.37

Table 4-10 Decomposition of the variance from an aggregate output perspective (evaluated at steady state)

	Fraction of variation explained by		
System	Aggregate	Industry	Sector
Mining			
(Coal,I,A)	86.86	5.23	7.91
(Ore,I,A)	87.98	5.08	6.94
(Othermin,I,A)	85.95	7.72	6.33
Non-durable			
(Food,I,A)	88.74	7.86	3.4
(Chemicals,I,A)	90.12	8.28	1.6
(Textiles,I,A)	86.55	3.11	10.34
(Paper,I,A)	87.48	6.51	6.01
Durable			
(Glass,I,A)	87.01	2.49	10.5
(Wood,I,A)	94.5	2.18	3.32
(Basmetal,I,A)	94.85	1.87	3.28
(Fabmetal,I,A)	91.27	5.4	3.33
(Otherman,I,A)	91.8	1.94	6.26

4.7 Conclusions

In this chapter we analyzed what causes business cycles in sectoral and aggregate output levels using a trivariate VAR model. Various statistical tests were performed. Unit root tests indicated that most series contain a unit root, which implies that most series exhibit substantial persistence (or autocorrelation). Cointegration tests which test the existence of common trends across sectors indicated that most three variable systems are not cointegrated. Lag length tests guided us to set twelve monthly lags for all sectors. Causality tests found that sectoral output in durable manufacturing industry has a strong production linkage with other sectors in the economy and mining industry has the strongest causal link to aggregate output. Three types of shocks are assumed to exist: aggregate, industry-specific and sector-specific shocks. The impulse responses of sectoral growth rate to each shock told us that dynamic responses of sectoral output to the aggregate shock are relatively small compared to those to the industry-specific and sector-specific shock. Their contributions in explaining sectoral output fluctuations are calculated using forecasting error variance decompositions. All three shocks play an role in sectoral output fluctuations but the dominant influence comes from the sector-specific shocks.

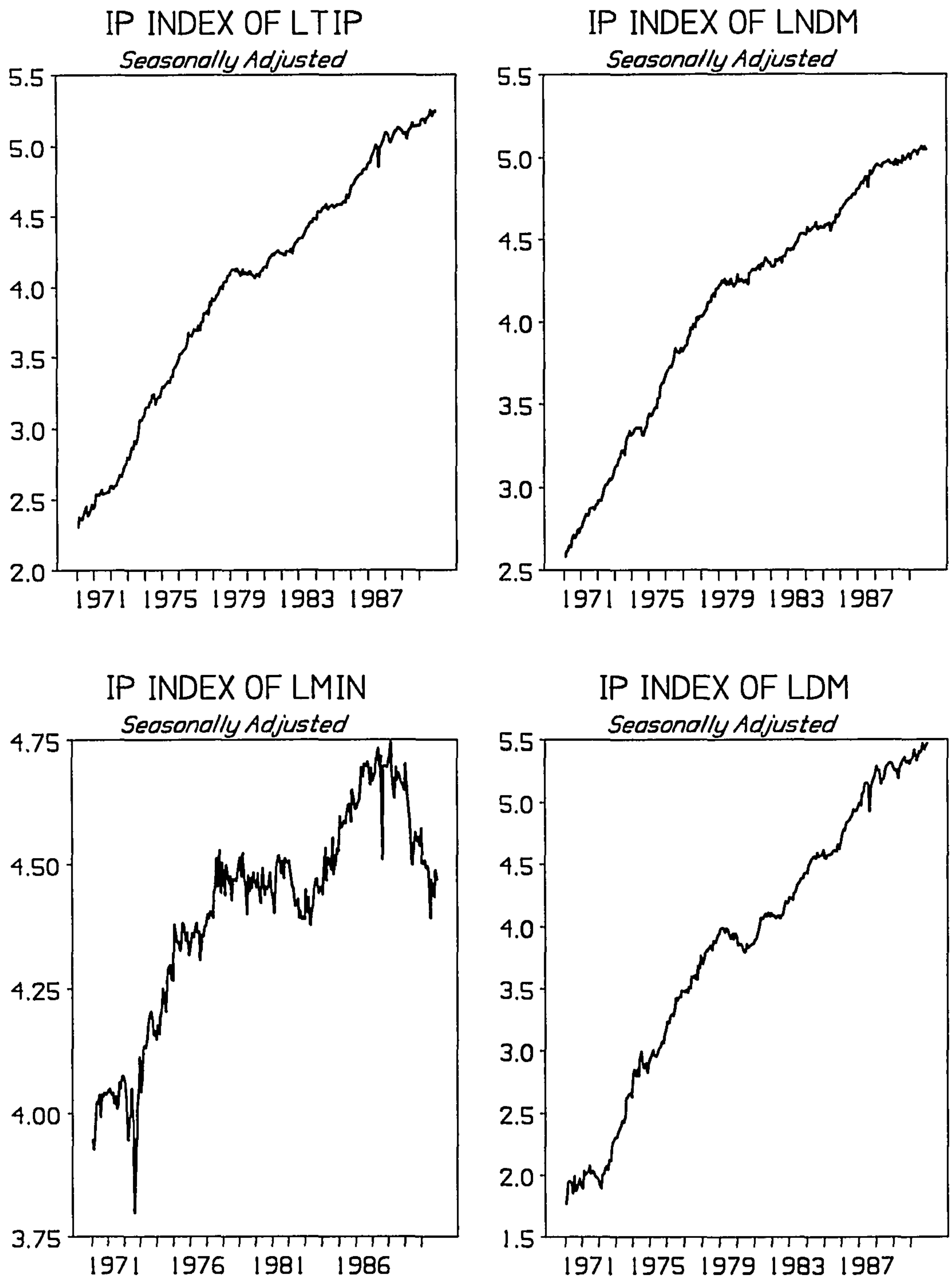


Figure 4-1. Data plot of industrial production index in logarithms

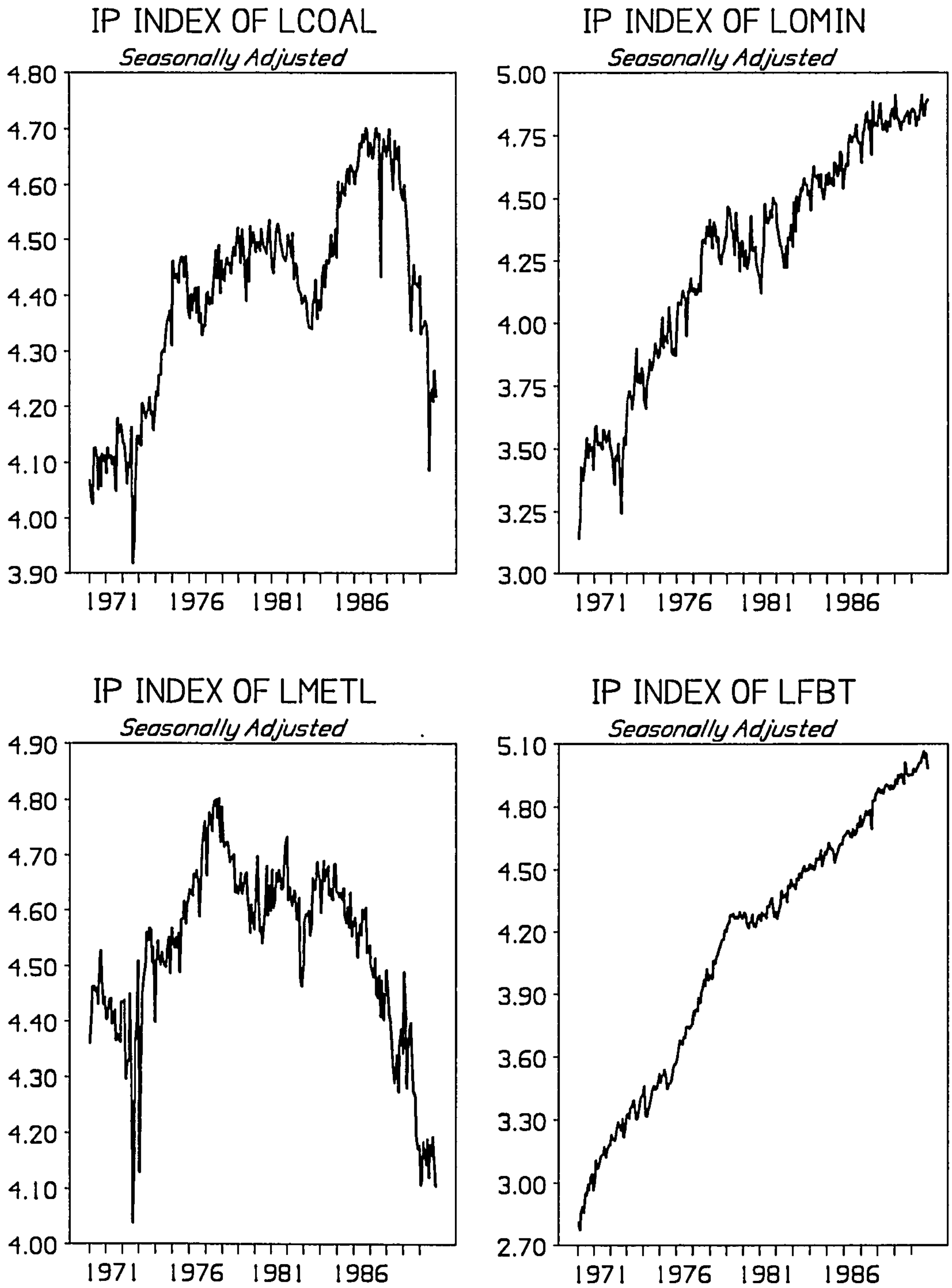


Figure 4-1. (continued)

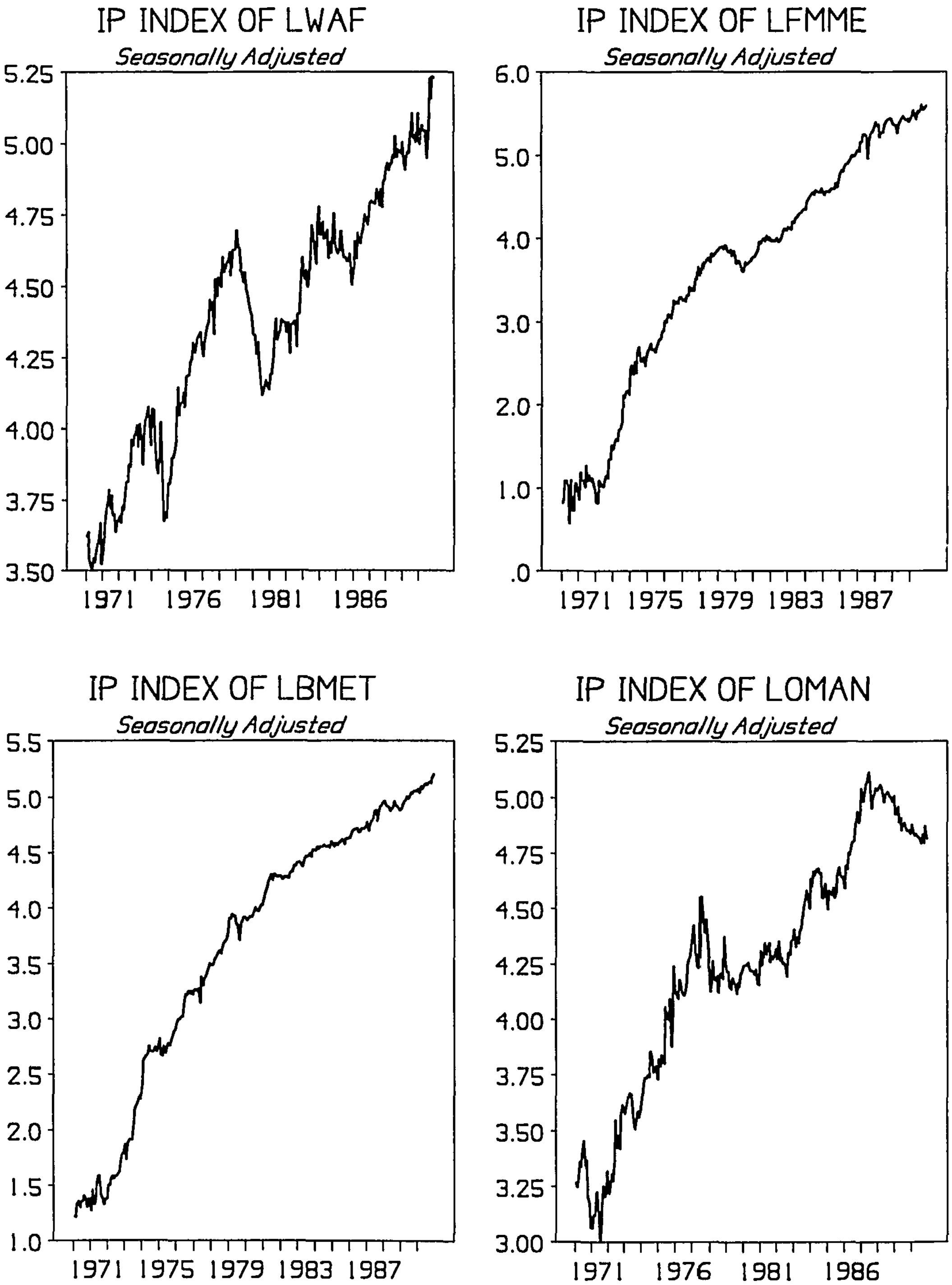


Figure 4-1. (continued)

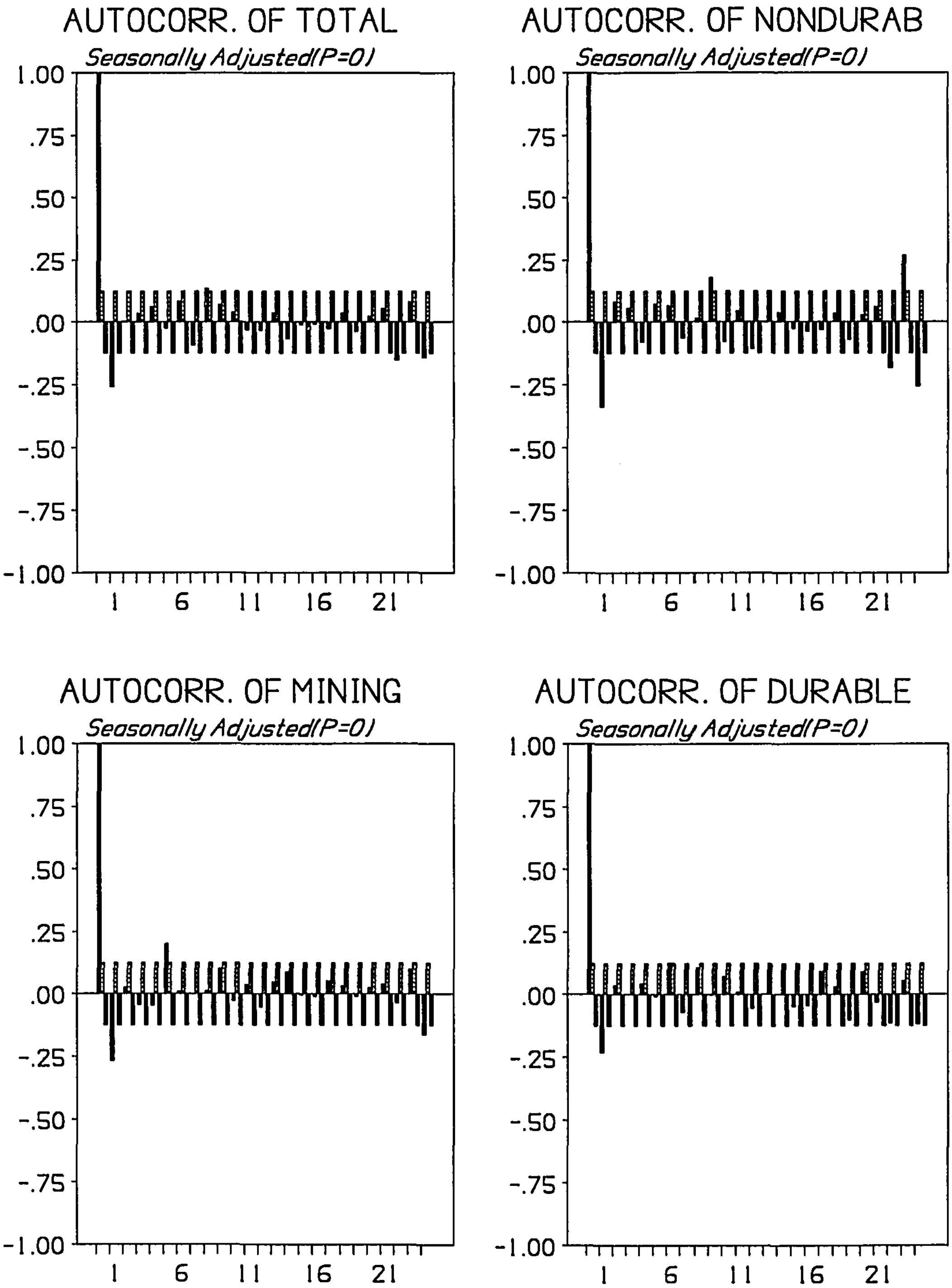


Figure 4-2. Residual autocorrelations from the DF test

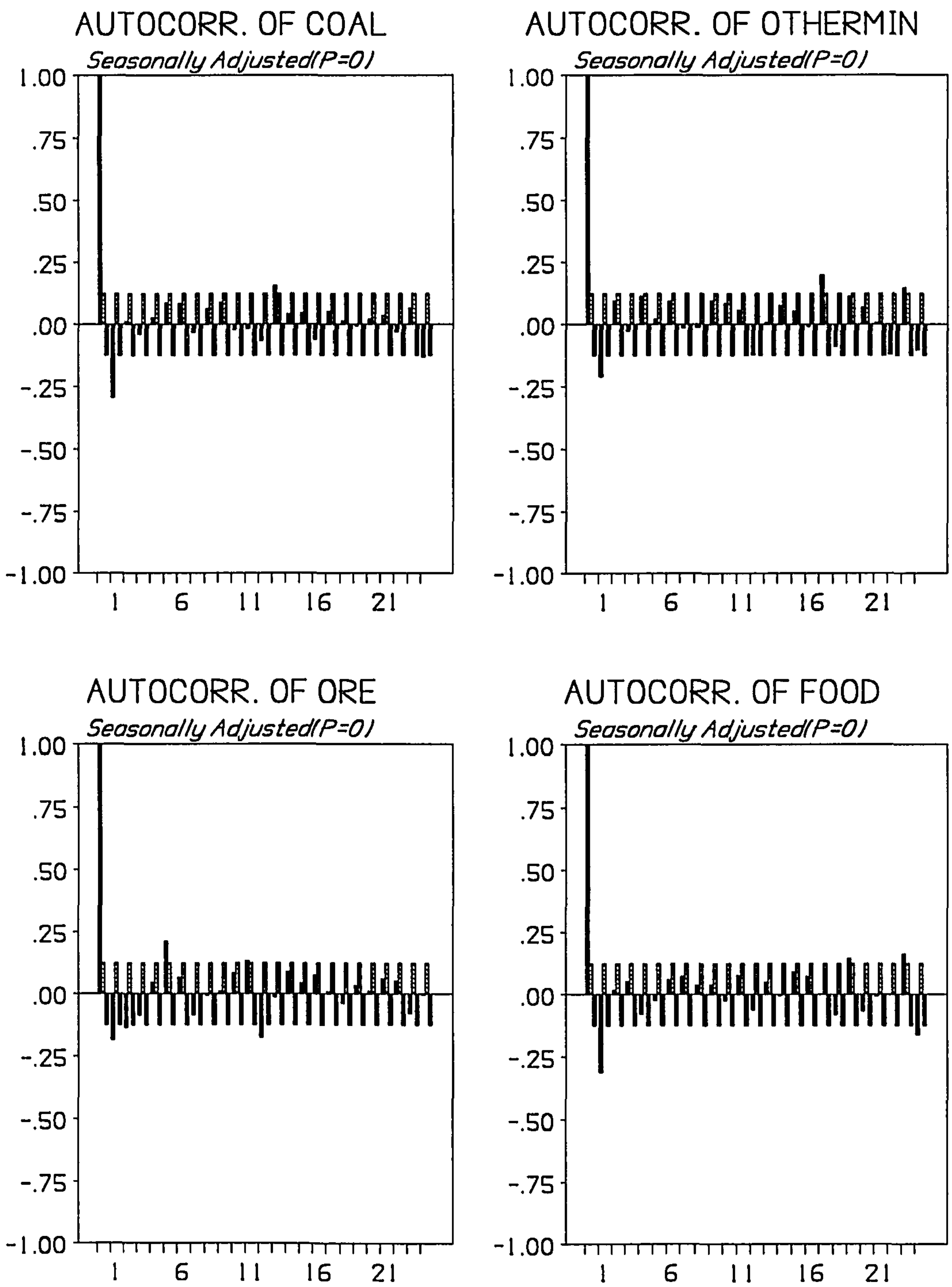


Figure 4-2. (continued)

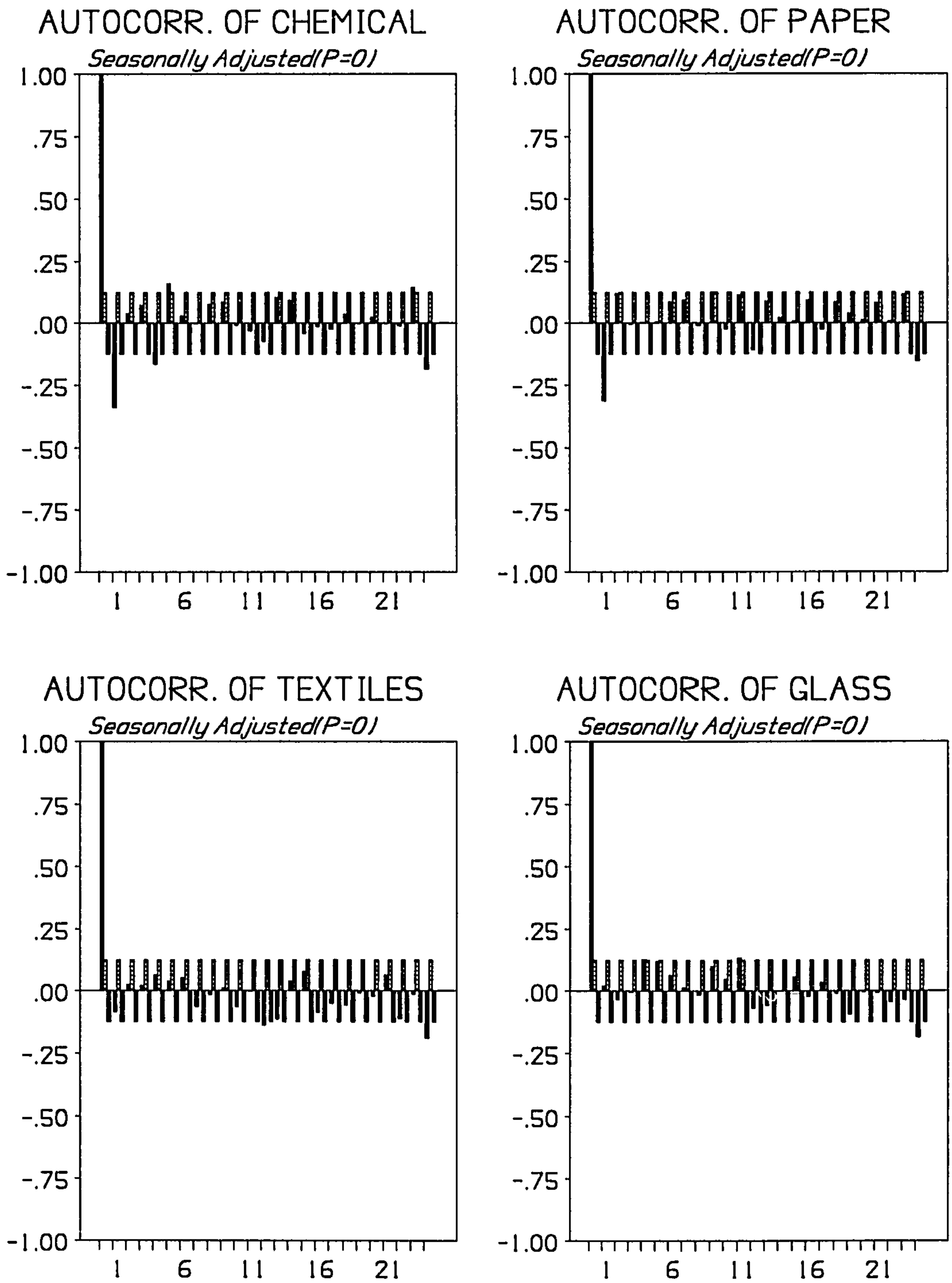


Figure 4-2. (continued)

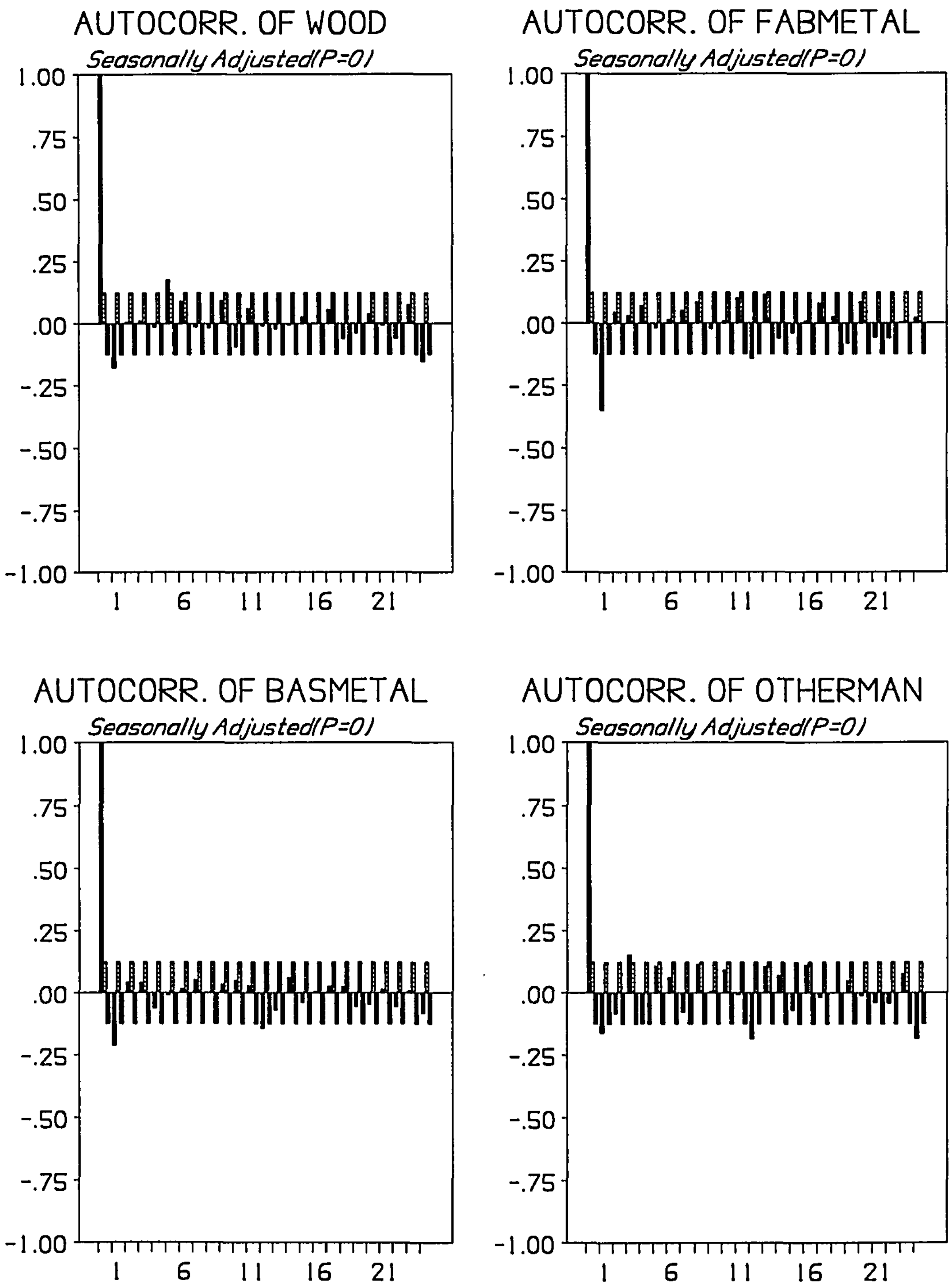


Figure 4-2. (continued)

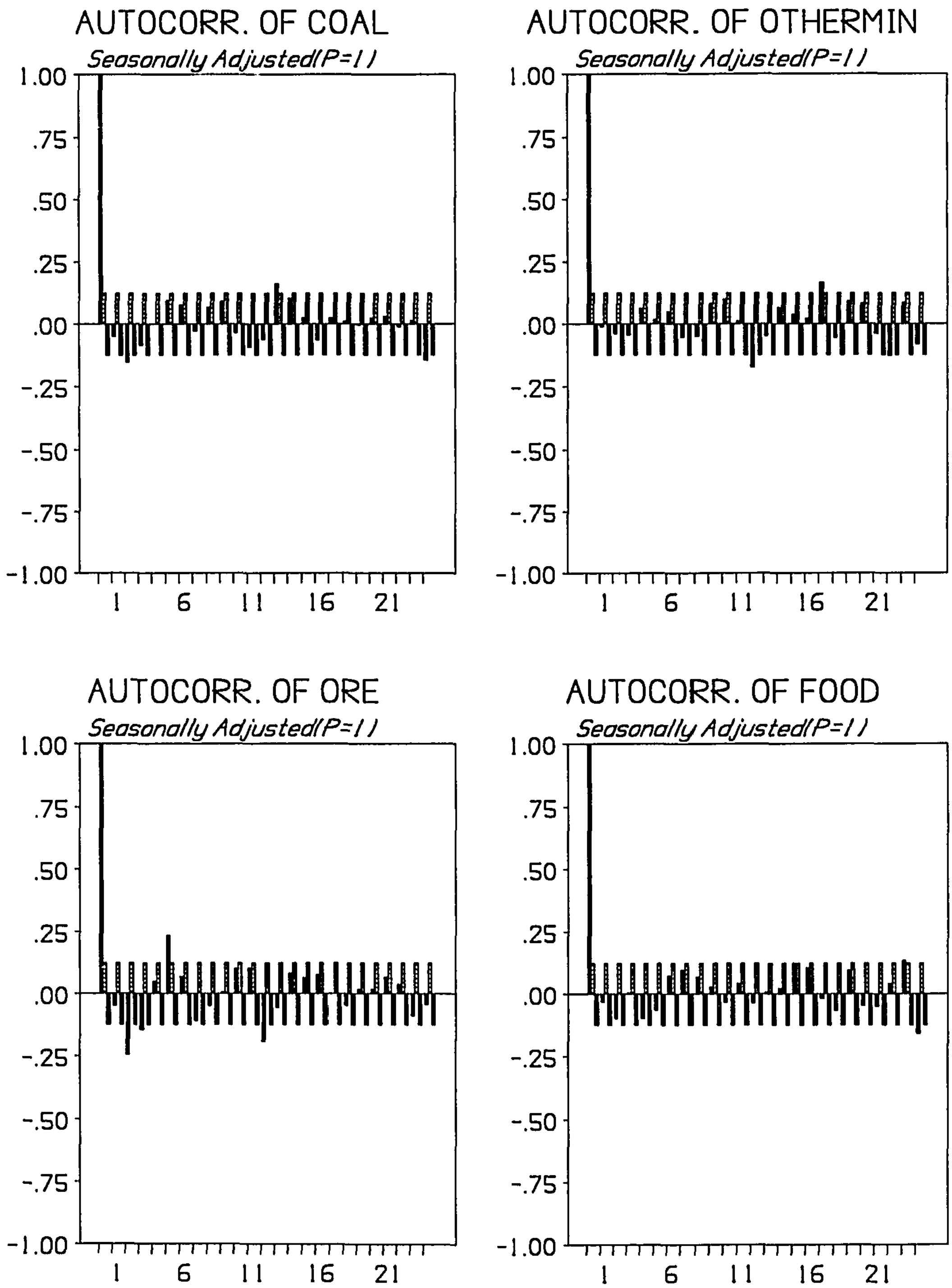
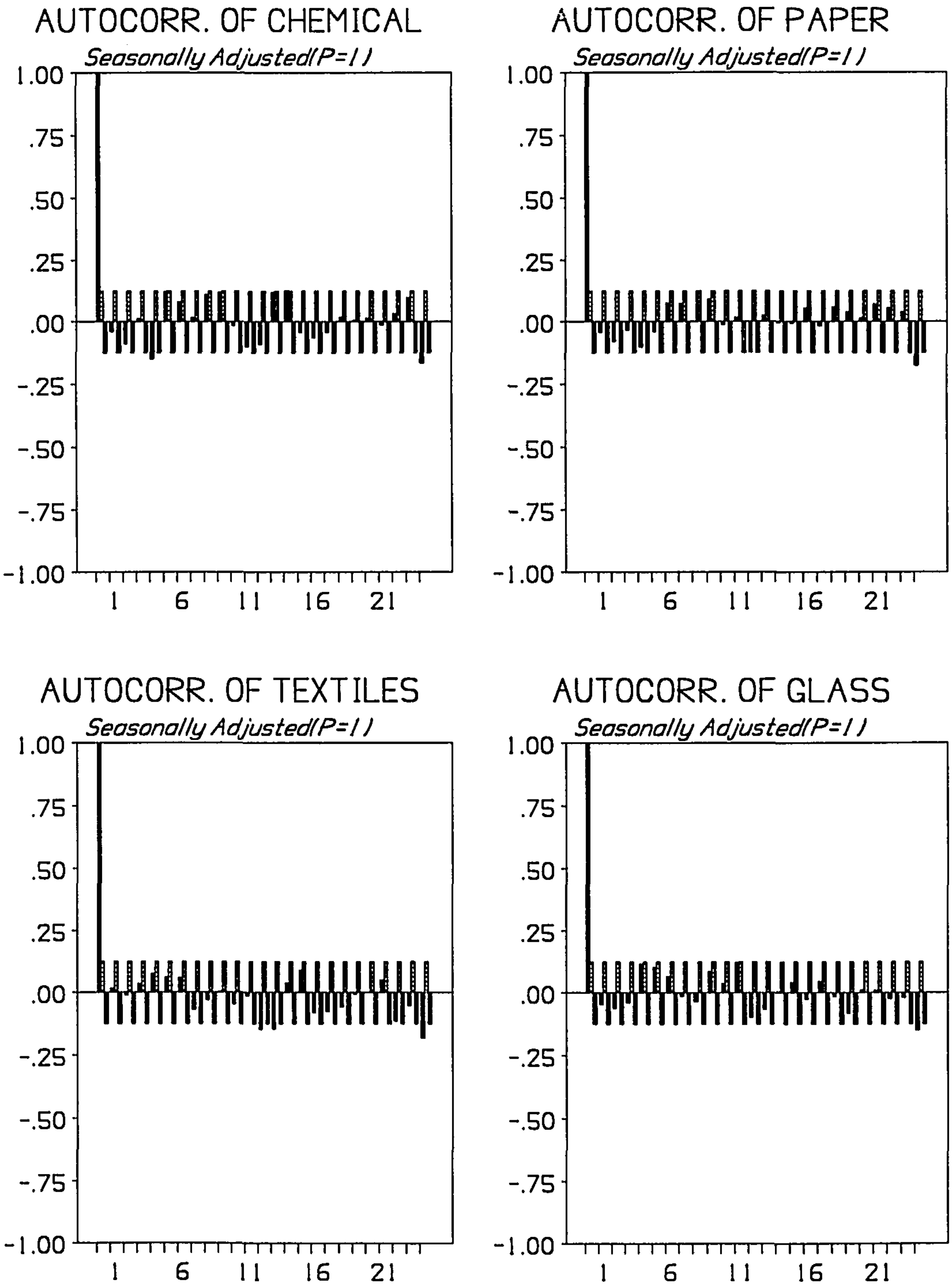


Figure 4-3. (continued)



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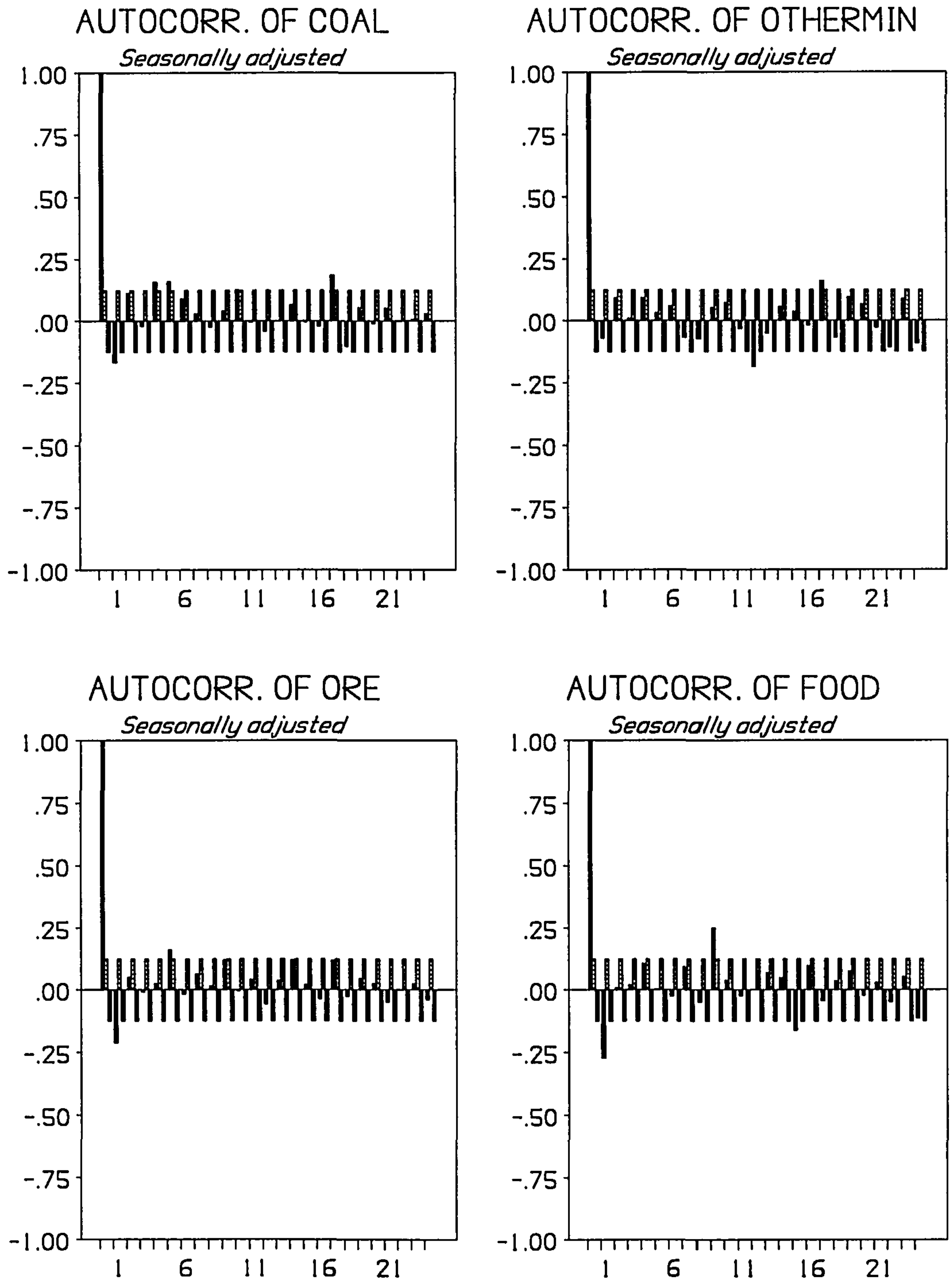
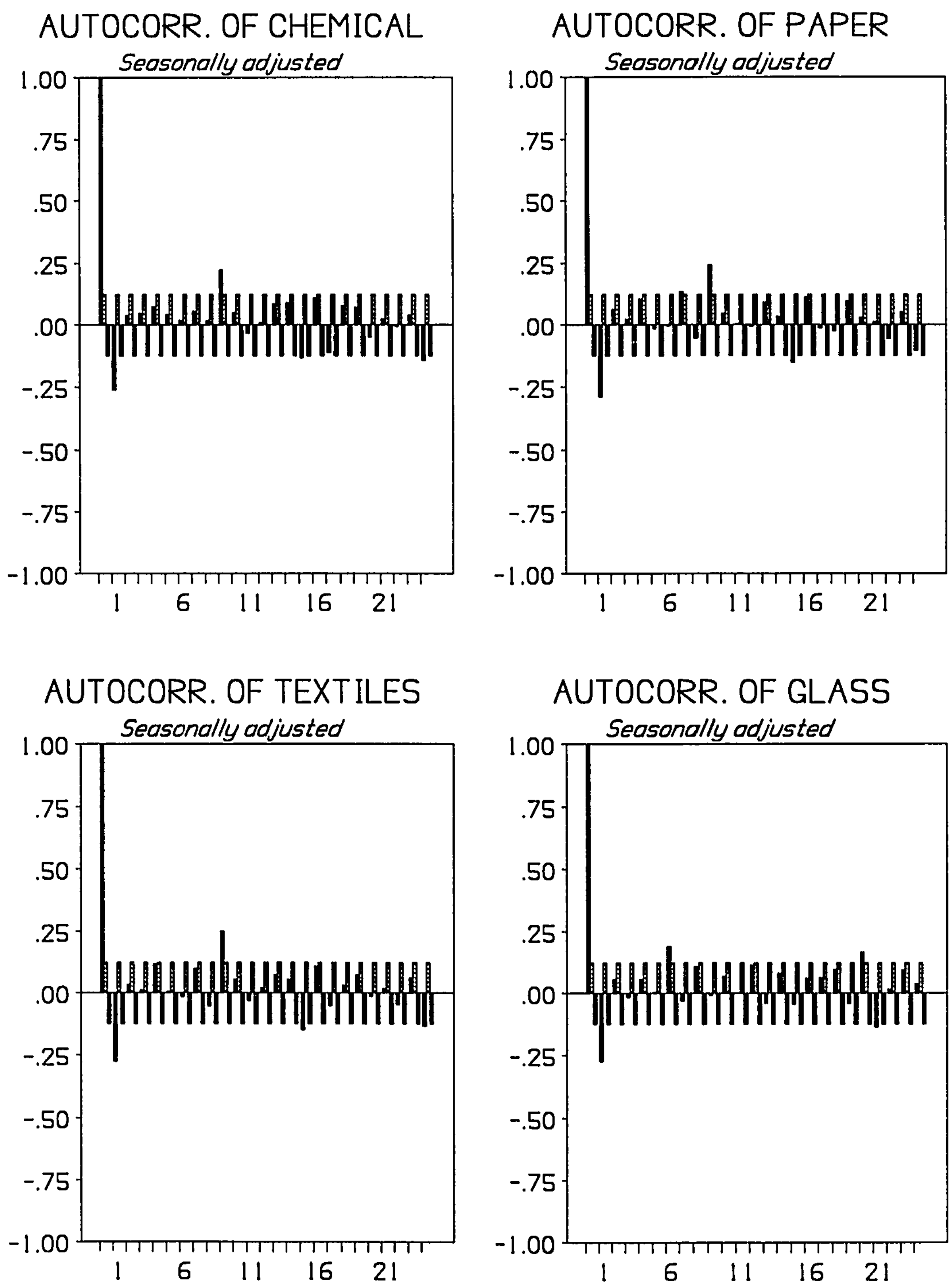


Figure 4-4. Autocorrelations from cointegrated residuals in DF test



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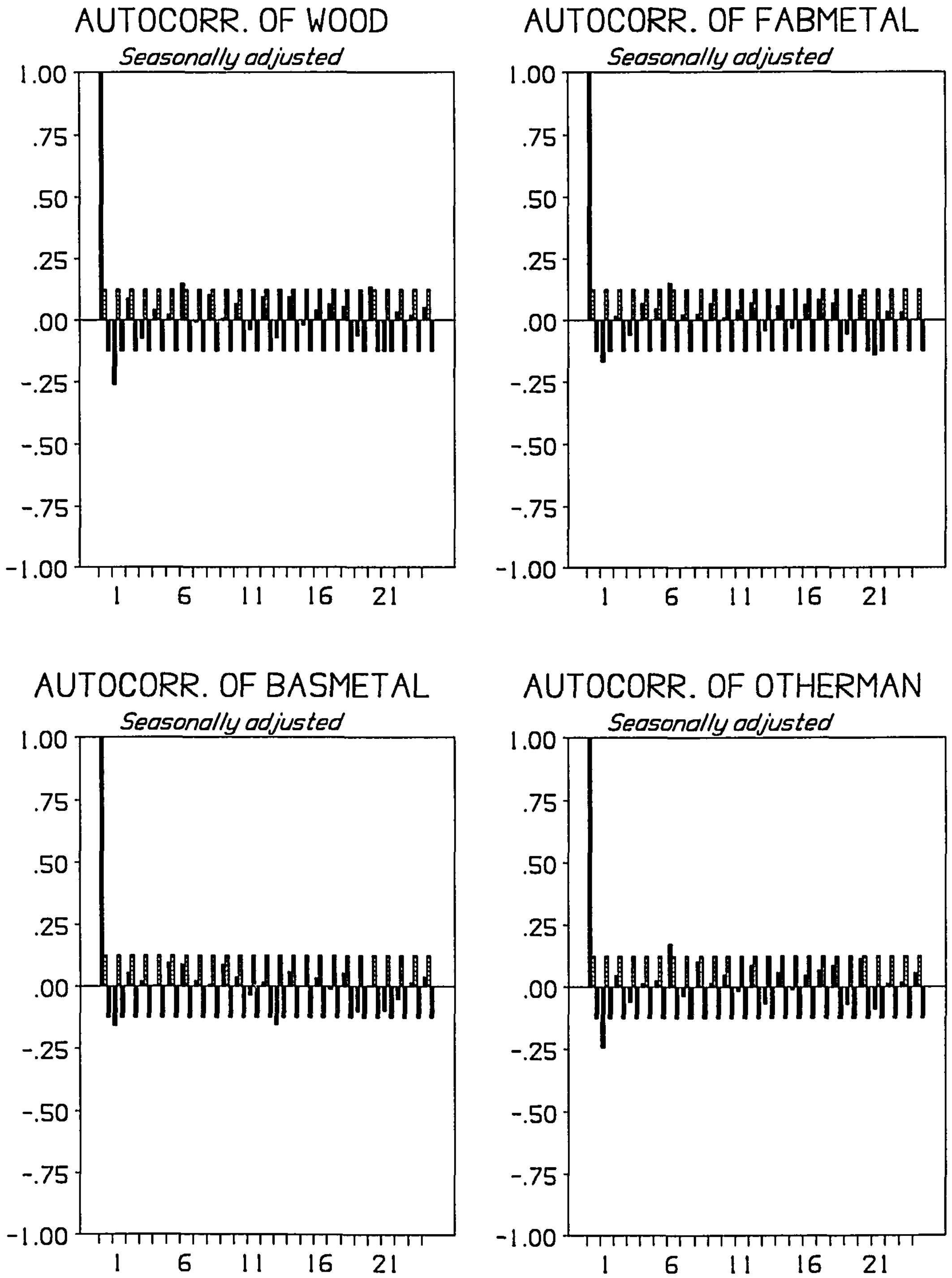


Figure 4-4. (continued)

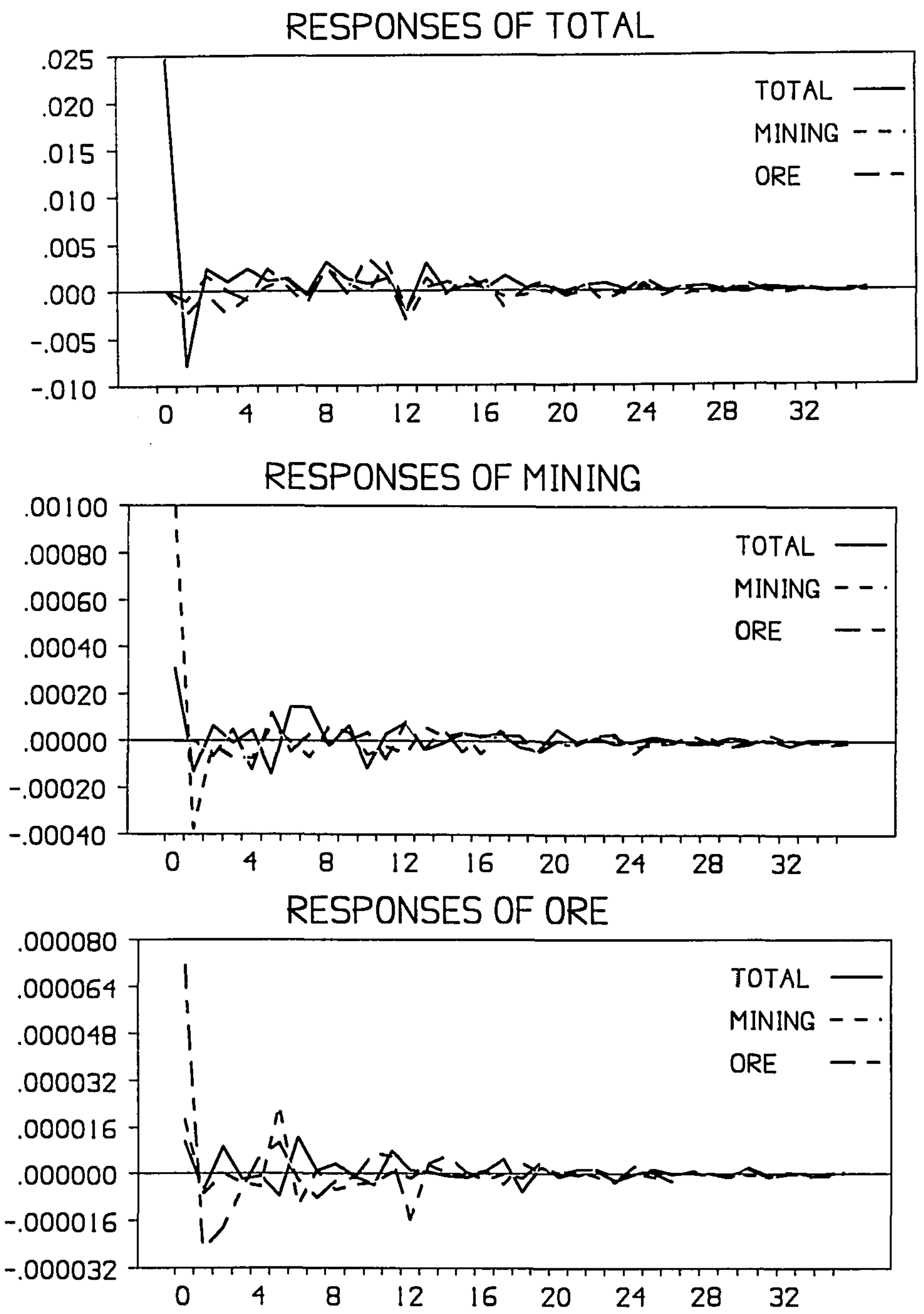


Figure 4-5. (continued)

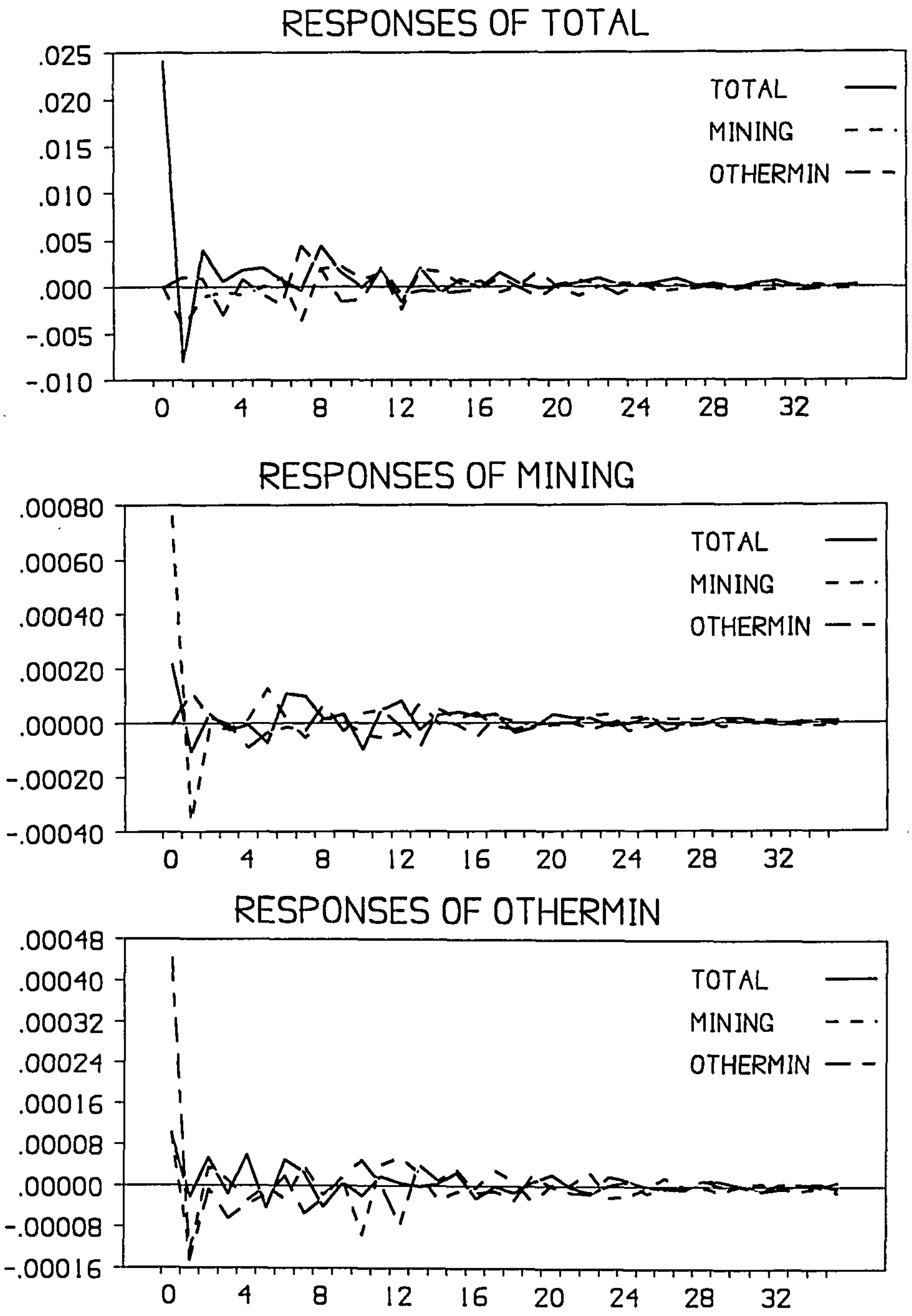


Figure 4-5. (continued)

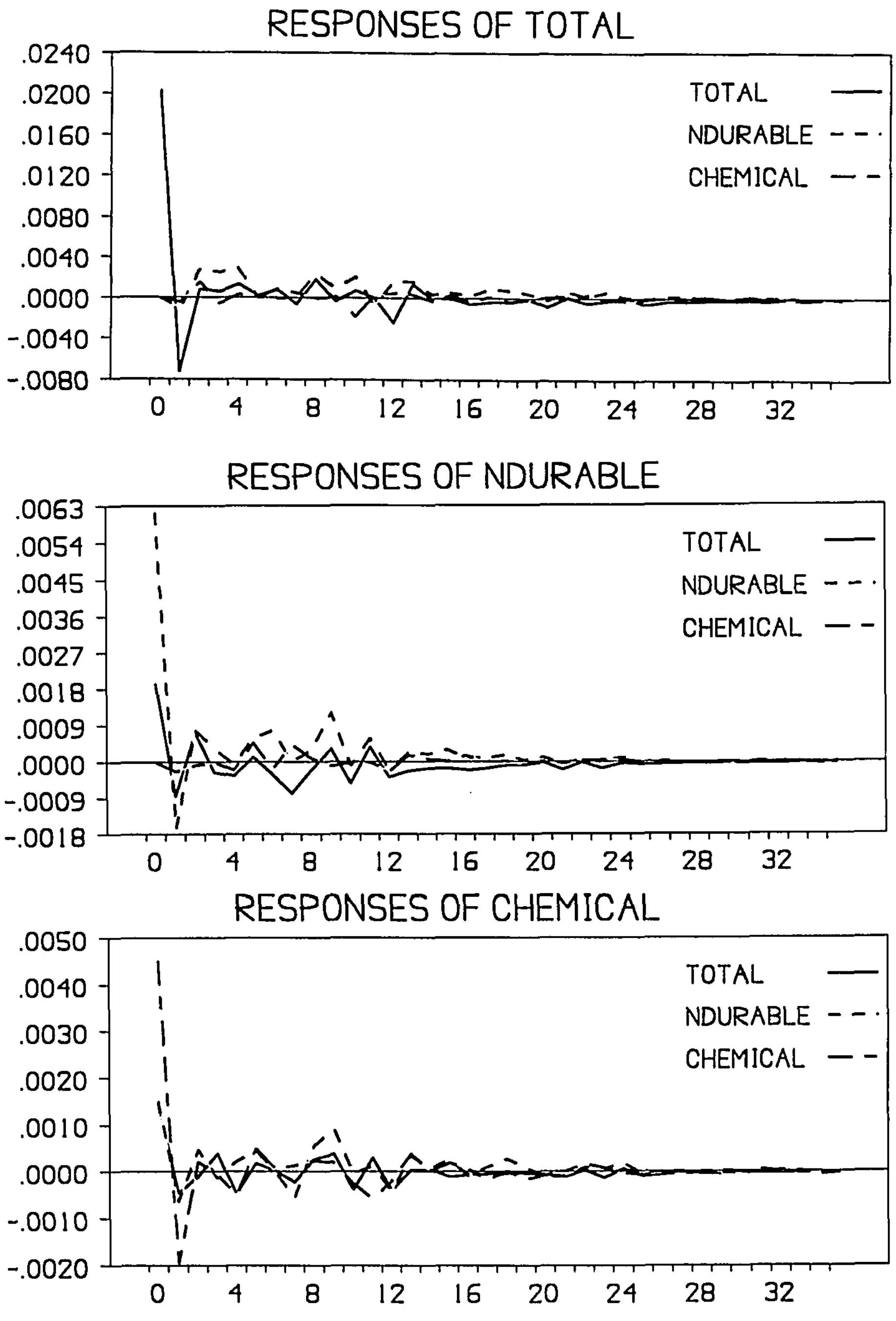


Figure 4-5. (continued)

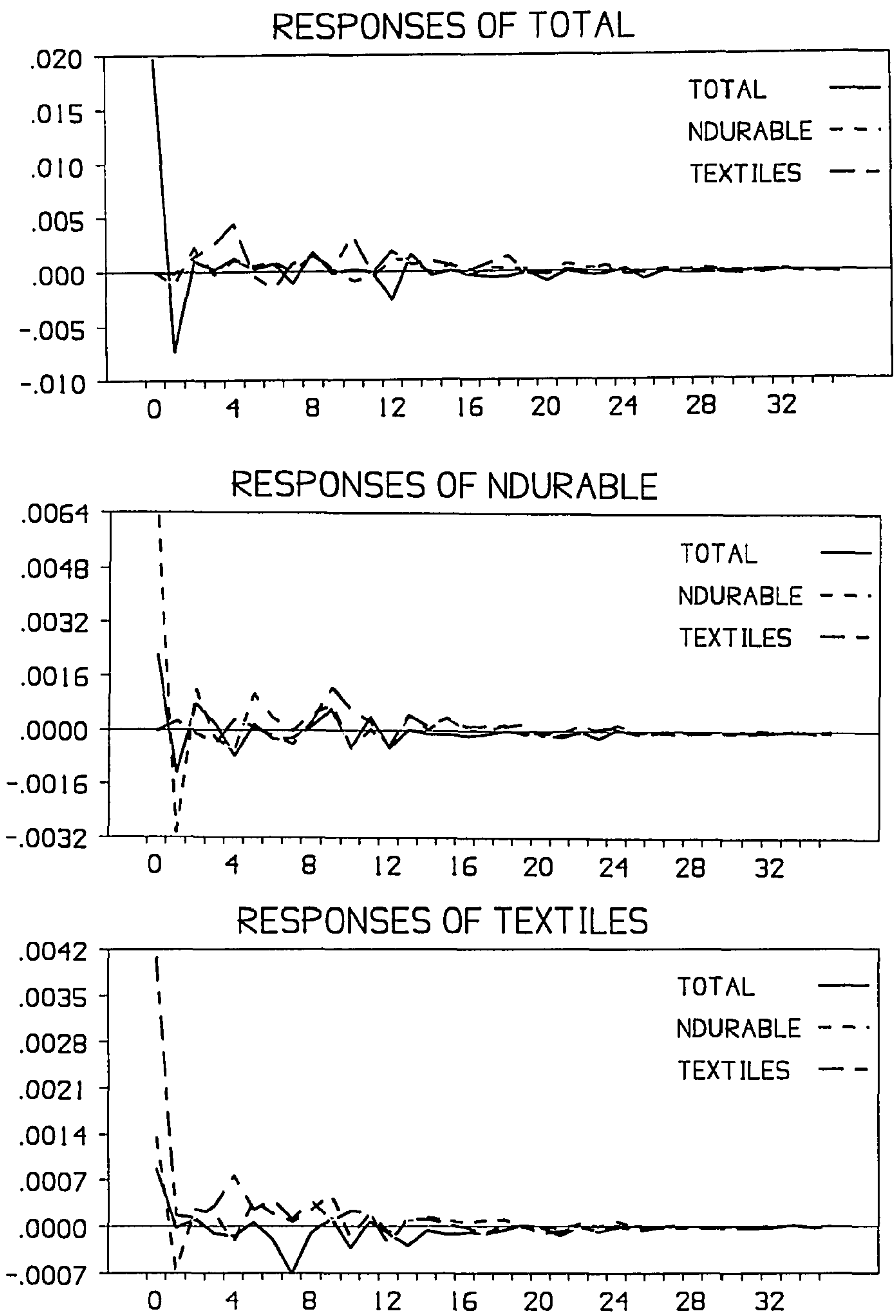
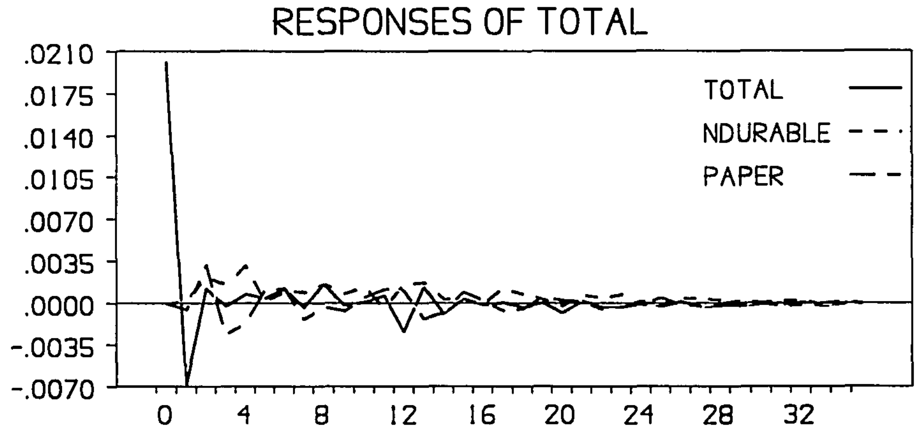
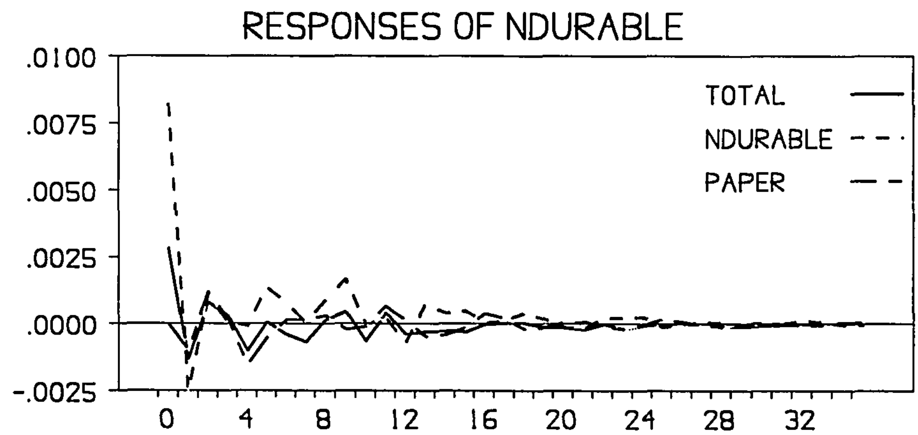


Figure 4-5. (continued)





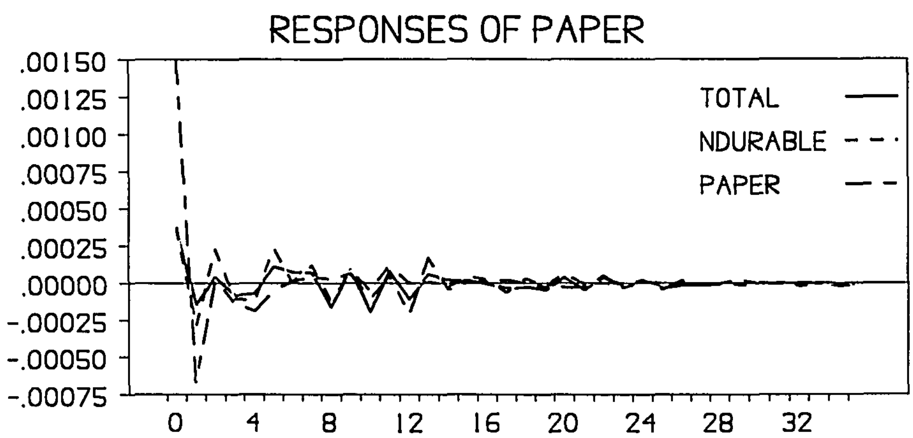


Figure 4-5. (continued)

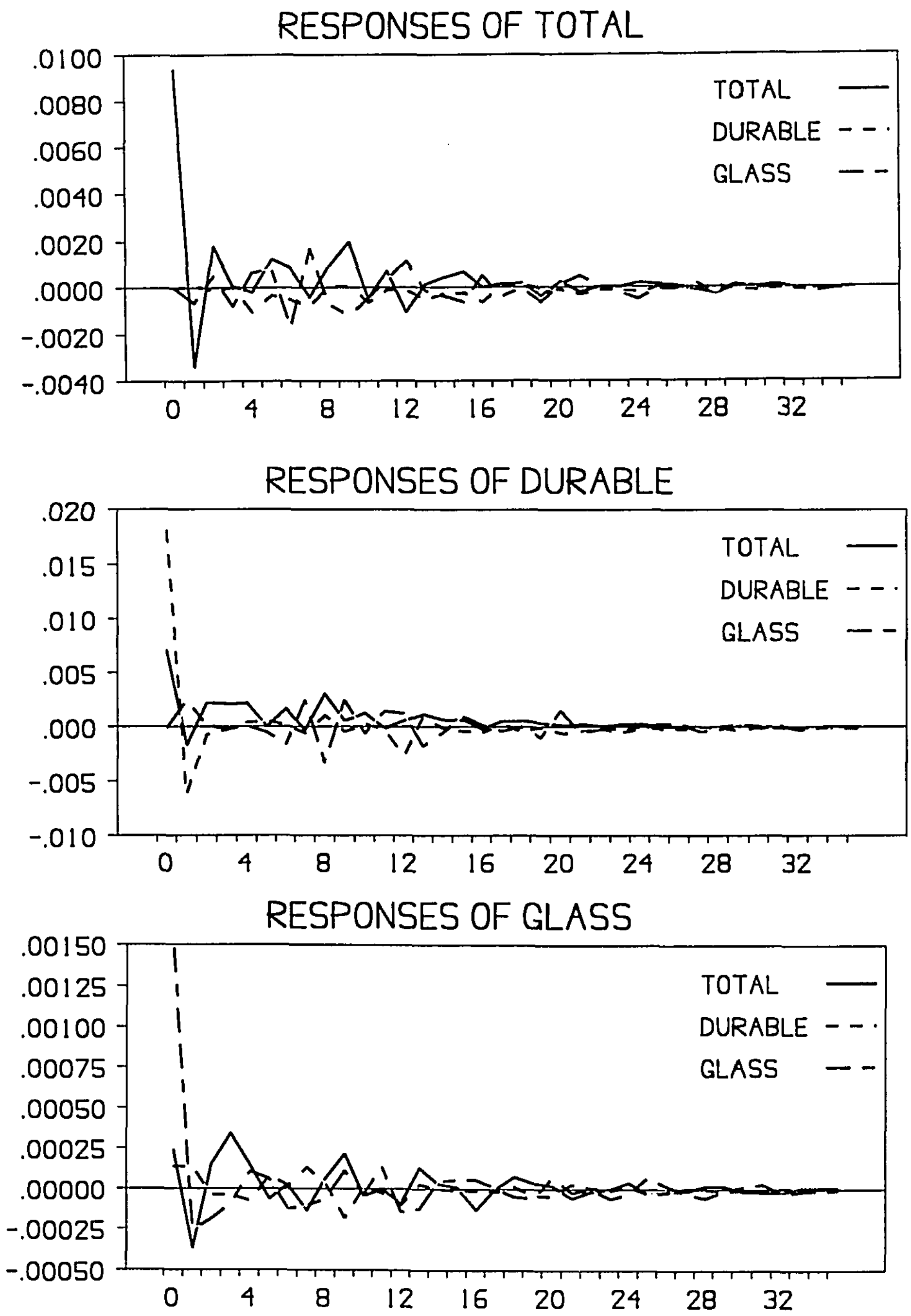


Figure 4-5. (continued)

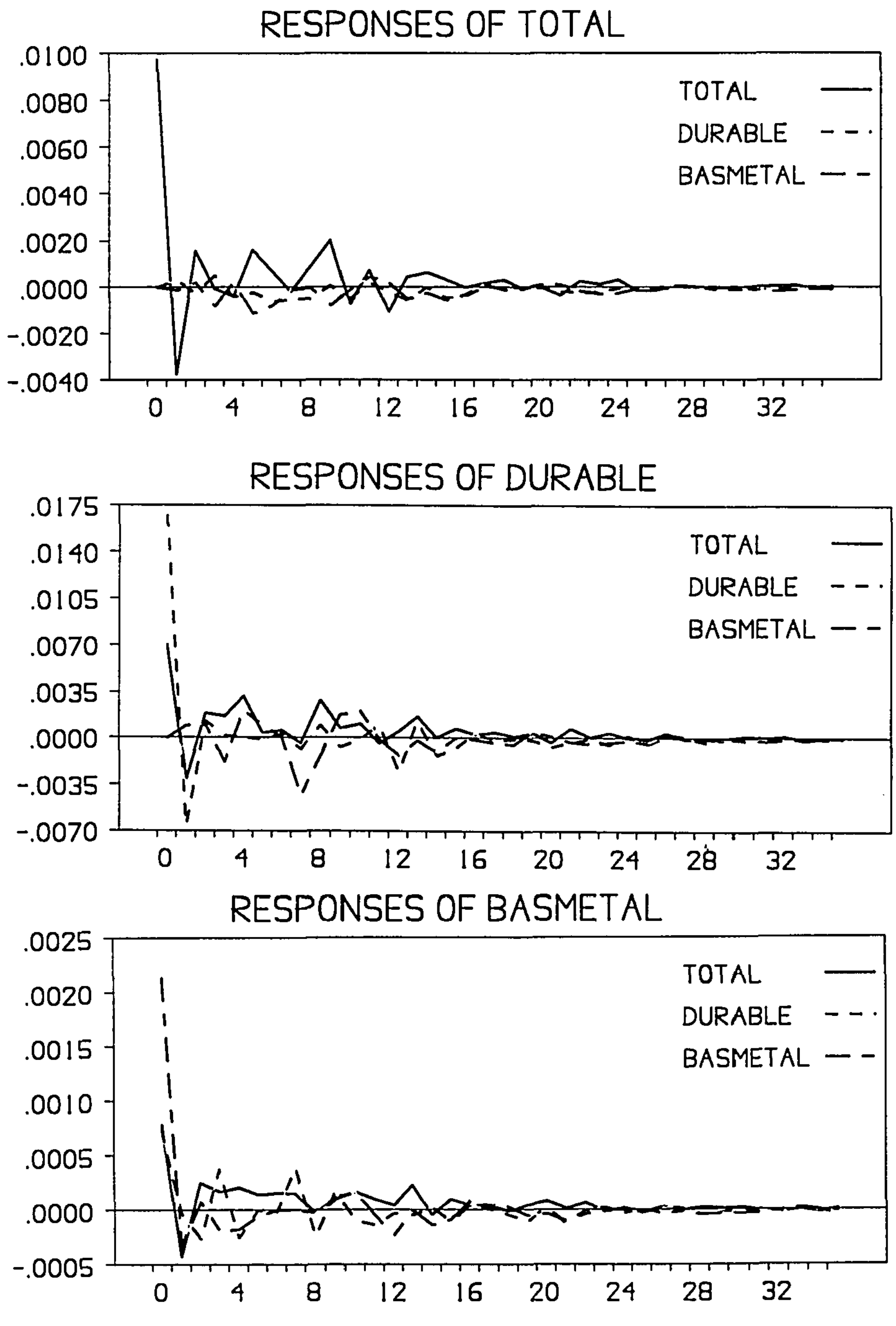


Figure 4-5. (continued)

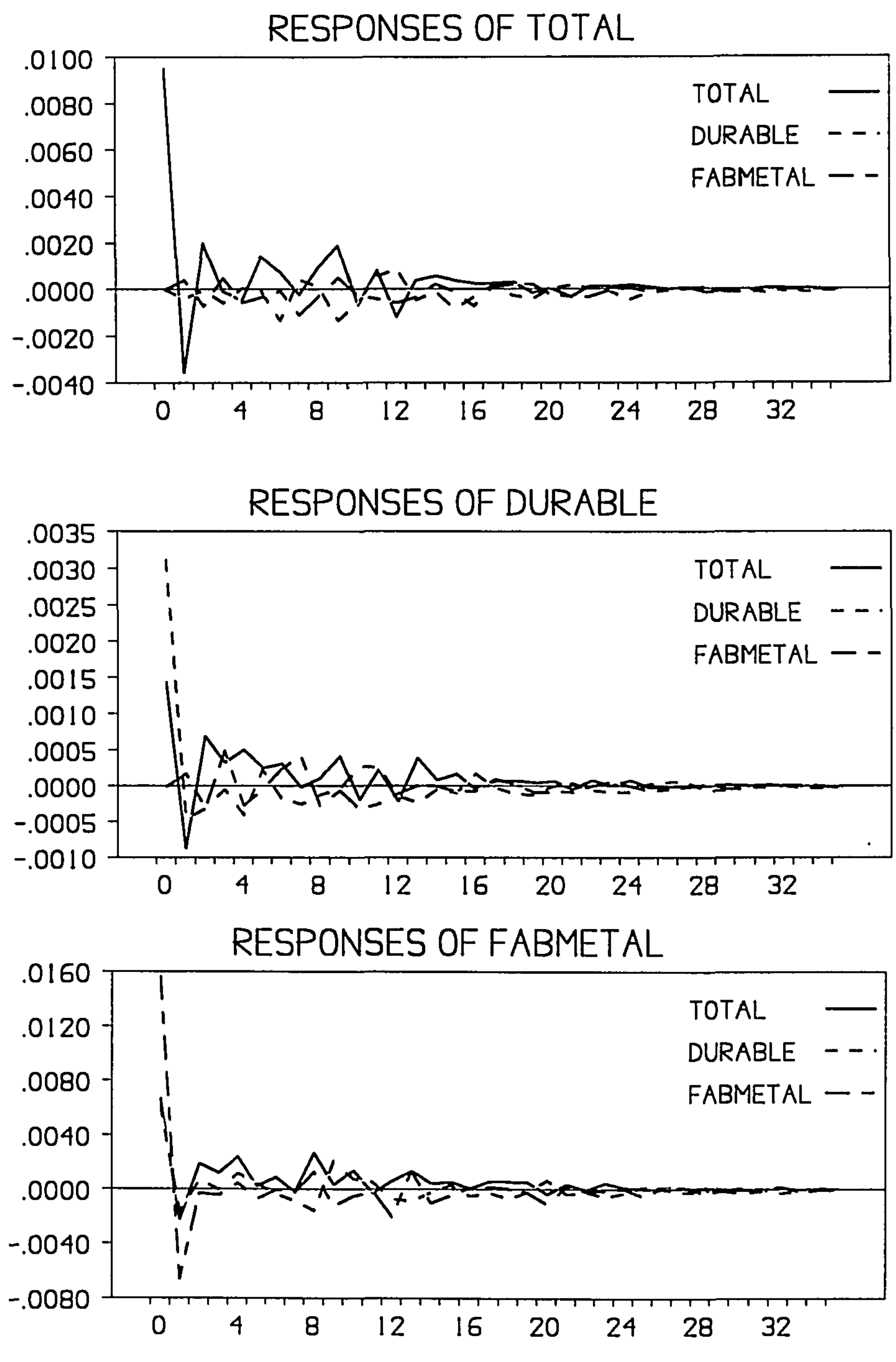


Figure 4-5. (continued)

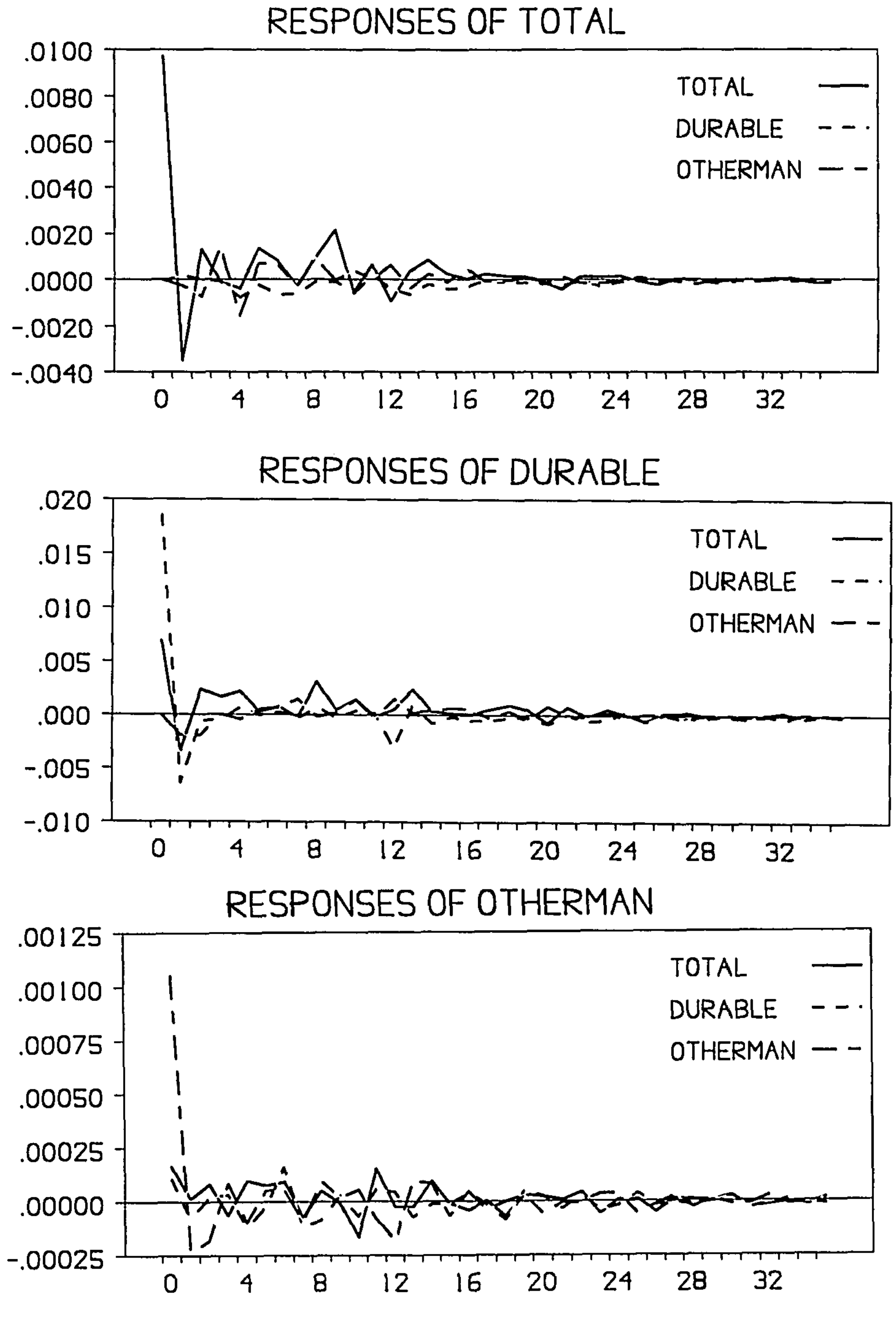


Figure 4-5. (continued)

5 EMPIRICAL RESULTS OF A MULTI-SECTOR MODEL

5.1 Introduction

In this chapter a Multi-sector Model (restricted VAR model) is estimated by Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. The SUR and OLS residuals from the VAR model are used in the factor analysis and covariance analysis observed below. The first task is to examine how many common factors (or aggregate shocks) are causing the comovement among residuals from the restricted VAR model. There is no consensus on the number of common shocks in the economy. Therefore, it is useful to examine empirically the dimensionality of the common shocks. This can be done by evaluating the relative size of eigenvalues and statistical tests such as χ^2 goodness-of-fit test in factor analysis. The common shocks are defined as the shocks which affect all sectoral outputs. There can be many aggregate shocks in the economy. The candidates of these common shocks are aggregate demand and supply shocks.

After determining the dimension of common shocks we can decompose the disturbance for each sectoral output into various sources. Three types of shocks are assumed: aggregate shocks, industry-specific shocks and sector-specific shocks. The error components in the disturbance can be estimated using the method of moments technique in covariance analysis. The impulse response function which traces the system's responses to the impact of various shocks is calculated to examine the transmission of shocks. The relative importance of various shocks can be measured by calculating the j-step ahead forecasting error variance and decomposing it according to its sources.

5.2 Estimation of a Multi-sector Model

In this section we are going to discuss the estimation of the multi-sector model given in Section 3.2. The growth rate of an individual sectoral output is regressed on the past history of its own growth rate, the growth rate of other sectors in the same industry, and the growth rate of sectors outside its own industry group. The lag length is chosen to be twelve monthly lags. We have a system of twelve equations since the industry production index is disaggregated into twelve two-digit SIC industries.

We specified the multi-sector model based on the given system of equations (3-22-1) - (3-22-N).

$$w_i s_{it} = \sum_{j=1}^{12} \alpha_{ij}(w_i s_{it-j}) + \sum_{j=1}^{12} \beta_{ij}\left(\sum_{k=1}^{S} w_k s_{kt-j}\right) + \sum_{j=1}^{12} \gamma_{ij}\left(\sum_{l=S+1}^{N} w_l s_{lt-j}\right) + \epsilon_{it}$$

5.3 Factor Analysis

The residuals from the estimation of the multi-sector model using either OLS or SUR methods can be used in factor analysis. Factor analysis is a statistical procedure that decomposes a set of random variables into unobserved common factors and a set of unique disturbances. A common factor is an unobservable variable that contributes to the variance of all observed variables while a unique factor is an unobservable variable that contributes to the variance of only one of the observed variables (see Figure 3-1). The model for common factor analysis posits one unique factor for each observed variable.

Model

The multiple common factor model can be represented as a linear combination of unobserved (or hypothetical) common factors and a specific factor. Because there are twelve equations, There are twelve series of innovations to be used in the factor analysis. There will be at most six common factors, but it is expected that the dimensionality of the common factors, m, will be less than six.[1] Then the model can be written as

---

[1]The number of common factors cannot exceed the largest integer satisfying

$$m < (2p + 1 - \sqrt{8p + 1}) / 2$$

for a fixed number of p (see Morrison, 1976, p. 315).

$$\underset{p\times 1}{X} = \underset{p\times m}{\Lambda}\ \underset{m\times 1}{F} + \underset{p\times 1}{e}$$

where $X = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ x_{12} \end{bmatrix} = \begin{bmatrix} \text{residuals of Coal mining} \\ \text{residuals of Metal ore mining} \\ \cdot \quad \cdot \quad \cdot \\ \text{residuals of Other manufacturing} \end{bmatrix}$,

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots\lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \cdots\lambda_{2m} \\ \cdot & \cdot & \cdot \\ \lambda_{p1} & \lambda_{p2} & \cdots\lambda_{pm} \end{bmatrix},\quad e = \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ e_p \end{bmatrix},\quad F = \begin{bmatrix} F_1 \\ F_2 \\ \cdot \\ F_m \end{bmatrix}$$

λ_{ik} is called factor loading (or factor pattern) and Λ is called factor loading matrix.

There are three critical assumptions (normality is only needed for maximum likelihood estimation):

(1) The common factors (F_k, k = 1,2,..m) are uncorrelated with each other and F follows an m-dimensional standard normal distribution, i.e.,

$$F \overset{\ell}{=} N_m(0, I_m)$$

(2) The unique factors (e_i, i = 1,2,..p) are uncorrelated with each other and e_i follows a normal distribution, i.e.,

$$e \overset{\ell}{=} N_p(0,\Psi)$$

where $\Psi = \mathrm{diag}(\Psi_1, \Psi_2, \ldots \Psi_p)$.

(3) The unique factors are uncorrelated with the common factors,i.e.,

$$\mathrm{Cov}(F,e') = 0$$

The procedure for estimating the factor loading is first to parameterize the cross-correlation matrix in terms of the λ_{ik}s and then choose the $\hat{\lambda}_{ik}$s to minimize the difference between the actual sample cross-correlation and the estimated cross-correlation. This yields estimates of λ_{ik}s. The square of the $\hat{\lambda}_{ik}$s provide estimates of the fraction of the variance of observable variables that can be explained by the unobserved common factor. This is often called communality or common variance. Therefore we can interpret this fraction as the relative importance of common shocks in explaining the variation in sectoral output since a factor model attributes all of the comovement to the common factors. The factor analysis is performed using both SUR residuals and OLS residuals.

<u>Comovement</u>

The residuals (innovations) from the multi-sector model (restricted VAR model) are serially uncorrelated but may be contemporaneously correlated. Therefore the comovement among innovations across the sectors can be measured by the contemporaneous cross-correlations among sectors. The contemporaneous correlations are only due to common shocks because of the assumptions that unique factors are uncorrelated with each other and also uncorrelated with common factors. Table 5-1 reports the contemporaneous cross-correlations among residuals from SUR and OLS estimation of the restricted VAR model. In the SUR residuals, 48 pairwise correlations out of 66 are statistically significant at the 10^{th} percentile level of significance. This provides evidence of comovement in innovations among the sectors. This is also true for the OLS residuals, even though less strong comovement is found. In the OLS residuals, 46 pairwise correlations are statistically significant at the 10^{th} percentile level of significance. Table 5-2 contains further evidence of comovement. The extent of the comovement among the sectors can be measured by the average pairwise correlation between each sector with all other sectors. All sectors show some amount of comovement with other sectors though the degree of comovement differs. Root mean square (RMS) which weights large correlations (both positive and negative) more than averaging also exhibits some extent of comovement (see Table 5-2).

Goodness-of-fit

The difference between the correlation predicted by the common factor model and the actual correlation is the residual correlation.

Table 5-1 Contemporaneous cross-correlations among VAR residuals

	COAL	METL	OMIN	FBT	CPRP	TWL	PPP	NMMP	WAF	BMET	FMME	OMAN
COAL	.	[b].17^{+}	.25^{+}	.16^{+}	.21^{+}	.09	.15^{+}	.04	.21^{+}	.19^{+}	.19^{+}	.16^{+}
METL	[a].18^{+}	.	.27^{+}	-.00	.00	.10	.11^{+}	-.08	.20^{+}	-.00	.11^{+}	.12^{+}
OMIN	.26^{+}	.29^{+}	.	.20^{+}	.06	.07	.11^{+}	.25^{+}	.18^{+}	.10	.14^{+}	.02
FBT	.20^{+}	-.01	.25^{+}	.	.19^{+}	.20^{+}	.14^{+}	.14^{+}	.15^{+}	.09	.15^{+}	.04
CPRP	.25^{+}	.03	.08	.23^{+}	.	.28^{+}	.24^{+}	.23^{+}	.16^{+}	.21^{+}	.25^{+}	.12^{+}
TWL	.10	.12^{+}	.09	.22^{+}	.30^{+}	.	.23^{+}	-.06	.19^{+}	.20^{+}	.19^{+}	.07^{+}
PPP	.17^{+}	.13^{+}	.12^{+}	.16^{+}	.29^{+}	.27^{+}	.	.00	.15^{+}	.27^{+}	.19^{+}	.10
NMMP	.06	-.10	.31^{+}	.18^{+}	.27^{+}	-.06	-.01	.	.14^{+}	.06	.13^{+}	.09
WAF	.25^{+}	.22^{+}	.22^{+}	.16^{+}	.17^{+}	.22^{+}	.17^{+}	.16^{+}	.	.20^{+}	.27^{+}	.07
BMET	.21^{+}	.00	.11^{+}	.09	.22^{+}	.21^{+}	.28^{+}	.08	.22^{+}	.	.38^{+}	-.01
FMME	.24^{+}	.13^{+}	.17^{+}	.16^{+}	.27^{+}	.23^{+}	.22^{+}	.14^{+}	.31^{+}	.41^{+}	.	.16^{+}
OMAN	.20^{+}	.14^{+}	.02	.04	.13^{+}	.08	.13^{+}	.08	.09	-.01	.18^{+}	.

[a] Correlations among SUR residuals from a restricted VAR are in the lower diagonal.

[b] Correlations among OLS residuals from a restricted VAR model are in the upper diagonal.

+ denotes significance at 10^{th} percentile level.

Table 5-2 Average pairwise correlations using SUR residuals

Sector	Average	RMS	RMSE1[a]	RMSE2[b]
<u>Mining</u>				
Coal	0.19	0.20	0.06	0.05
Ore	0.10	0.15	0.11	0.09
Othermin	0.17	0.20	0.11	0.03
<u>Non-durable</u>				
Food	0.15	0.17	0.07	0.06
Chemicals	0.20	0.22	0.08	0.07
Textiles	0.16	0.19	0.07	0.06
Paper	0.18	0.19	0.06	0.05
<u>Durable</u>				
Glass	0.10	0.16	0.11	0.10
Wood	0.20	0.21	0.05	0.04
Basmetal	0.17	0.20	0.08	0.07
Fabmetal	0.22	0.24	0.06	0.05
Otherman	0.10	0.12	0.06	0.06

[a] Root mean square of residuals after taking into account the estimated one common factor model.

[b] Root mean square of residuals after taking into account the estimated two common factor model.

A good way to assess the goodness-of-fit of the common factor model is to examine the residual correlation. It is expected that off-diagonal elements of the residual correlation matrix will be small if we choose an appropriate common factor model for our observable variables. The common factor model also implies that the partial correlations among the variables, removing the effects of the common factors, must all be 0. When the common factors are removed, only unique factors remain. Table 5-3 reports the residual correlation and the partial correlation matrix of the one common factor model. Most residual and partial correlations are quite small. Most are less than 0.1, but some of them are larger than 0.2. However, if more common factors are important, then the root mean square of residuals reported in Table 5-2 should decrease as more factors are added. In fact, there is little difference between the one factor versus the two factor root mean squared errors, implying that one common factor model is appropriate.

Dimension of Common Shocks

Long and Plosser (1987) attempted to determine the number of common shocks using factor analysis. They claimed that there is only one common shock in their growth rates of thirteen industry group, even though the second factor is statistically significant. There are many ways to determine the number of common factors in factor analysis. The Scree graph which plots the eigenvalues of the sample

Table 5-3 Residual correlations/ partial correlations matrix

	COAL	METL	OMIN	FBT	CPRP	TWL	PPP	NMMP	WAF	BMET	FMME	OMAN
COAL	.	.08[b]	.09	.03	.02	-.11	-.05	-.07	.03	-.01	-.05	.11
METL	.07[a]	.	.22	-.12	-.14	.03	.03	-.17	.12	-.13	-.01	.09
OMIN	.08	.19	.	.12	-.14	-.09	-.06	.24	.04	-.08	-.08	-.08
FBT	.03	-.11	.10	.	.05	.08	-.01	.09	-.03	-.10	-.07	-.05
CPRP	.01	-.12	-.11	.04	.	.12	.08	.17	-.11	-.02	-.03	.02
TWL	-.09	.02	-.07	.07	.09	.	.10	-.18	.02	.02	-.02	-.02
PPP	-.04	.02	-.05	.01	.06	.08	.	-.14	-.06	.10	-.06	.03
NMMP	-.06	-.16	.21	.08	.14	-.16	-.12	.	.04	-.04	-.01	.02
WAF	.02	.10	.03	-.02	-.08	.01	-.05	.03	.	-.01	.04	-.03
BMET	-.01	-.11	-.07	-.08	-.01	.01	.08	-.03	-.01	.	.21	-.14
FMME	-.03	-.01	-.06	.05	-.02	-.02	-.04	-.01	.03	.16	.	.06
OMAN	.09	.08	-.07	-.05	.02	-.02	.03	.02	-.02	-.12	.05	.

[a] Residual correlations are in the lower diagonal matrix.

[b] Partial correlations are in the upper diagonal matrix.

correlation matrix is helpful to determine the dimensionality of the common shocks. Generally the number of eigenvalues greater than one is equal to the number of common factors (Kaiser Rule). The Scree graph (Figure 5-1) shows one common factor.

Another way of determining the dimensionality of the common factor is a statistical test, which is called the chi-square goodness-of-fit test. The null hypothesis is

$$H_0: \Sigma = \Lambda\Lambda' + \Psi$$

where Λ has dimension $p \times m$, and the alternative hypothesis is that Σ is any $p \times p$ symmetric positive definite matrix. Use of the likelihood ratio principle gives the test statistic

$$Q = [n - (2p + 5)/2 - 2m/3] \ln \frac{|\hat{\Psi} + \hat{\Lambda}\hat{\Lambda}'|}{|R|}$$

where $\hat{\Psi}$, $\hat{\Lambda}$ are the solutions of the maximum-likelihood equations, R is the sample correlation matrix and $n = N-1$. Under the null hypothesis, the test statistic(Q) is distributed as a chi-squared variate with degrees of freedom $s = [(p - m)^2 - (p + m)]/2$ as N becomes large.[2]

[2]The degrees of freedom is the difference between the number of elements in a covariance (or correlation) matrix $(p(p + 1)/2)$ and the number of parameters to be estimated $(pm + p - m(m-1)/2)$.

Table 5-4 reports the results of the χ^2 test for goodness-of-fit. The null hypothesis of no common factors is rejected and the null hypothesis of one common factor is also rejected at the 5 percent significance level. We reject the null hypothesis of two and three common factors with SUR residuals but we fail to reject the null hypothesis of three common factors with OLS residuals. This χ^2 test tends to accept more common factors than are actually present. Therefore it is recommended to pick a very small significance level. Akaike's Information Criterion (AIC) and Schwartz's Bayesian Criterion (SBC) also can be used to aid in determining the dimensionality of the common factor, with the dimension set by the smallest value for the AIC and SBC. Table 5-4 shows mixed results when AIC and SBC are considered. That is, AIC indicates that the three common factor model is appropriate while SBC indicates one common factor. The SBC seems to work better, based on various simulation studies since AIC tends to select models with too many parameters when the sample size is large. Nonetheless, we experiment with both one common factor and two common factor models in the following section.

Contribution of Common Shocks

One and two common factor models are estimated in two different ways: principal axis method and maximum likelihood estimation. The two results are quite similar. Table 5-5 contains the results of

Table 5-4 χ^2 test for the dimension of common factors

no.of factor	Q[a]	d.f	p-value	AIC	SBC
0	339.0(307.9)	66	.0001(.0001)		
1	148.9(108.2)	54	.0001(.0001)	44.5(2.8)	-143.3(-184.9)
2	103.4(71.5)	43	.0001(.004)	20.1(-12.5)	-129.4(-162.0)
3	62.8(41.6)	33	.0013(.1442)	-1.4(-23.1)	-116.1(-137.9)

[a] The first set of numbers refers to the SUR residuals; numbers in parentheses refers to the OLS residuals.

factor pattern and communality (common variance) based on maximum likelihood estimation. The estimates of the factor pattern are all positive and all are statistically significant, so that all sectoral outputs respond positively to the common factor. Fabricated metal, Chemical and Wood are the most responsive to the common factor while Other mining, Metal ore and Non-metallic mineral are the least responsive. This is true for both the SUR and OLS residuals. The relative importance of common factors can be measured using the communality which is defined as the fraction of the variance explained by common factors. The common shocks, as measured by communality ($R^2 1F$), can explain 6 to 34 percent of the variation in sectoral output when the one common factor model is estimated using SUR residuals.[3] The two common factor model does not improve the explanatory power ($R^2 2F$) across all sectors, implying that a second factor is not common across sectors.

5.4 Identification of the Error Components

In this section we will try to identify various shocks, i.e., to estimate the response coefficients and the variance of each shock in an error components model. After identifying these shocks using PROC

[3]This finding is consistent with Long and Plosser (1987)'s finding. In their results, the common shocks can explain 1 to 40 percent of the variation in sectoral output measured by 13 industrial production indices.

Table 5-5 Contribution of common factors

	Factor1 Pattern[a]	t-value	Communality($R^2$1F)	$R^2$2F
<u>Mining</u>				
Coal	0.466(0.420)	6.50(5.63)	0.218(0.177)	0.208(0.172)
Ore	0.240(0.222)	3.23(2.91)	0.058(0.049)	0.097(0.084)
Othermin	0.374(0.339)	5.12(4.49)	0.140(0.115)	1.0(1.0)
<u>Non-durable</u>				
Food	0.369(0.342)	5.05(4.53)	0.137(0.117)	0.140(.117)
Chemicals	0.501(0.476)	7.03(6.43)	0.251(0.226)	0.285(0.262)
Textiles	0.422(0.401)	5.82(5.36)	0.178(0.161)	0.203(0.185)
Paper	0.446(0.419)	6.18(5.61)	0.199(0.176)	0.219(0.189)
<u>Durable</u>				
Glass	0.253(0.223)	3.41(2.92)	0.064(0.050)	0.111(0.081)
Wood	0.491(0.451)	6.88(6.08)	0.241(0.204)	0.221(0.185)
Basmetal	0.478(0.472)	6.67(6.37)	0.229(0.223)	0.259(0.252)
Fabmetal	0.583(0.545)	8.34(7.46)	0.340(0.297)	0.357(0.309)
Otherman	0.232(0.210)	3.11(2.74)	0.054(0.044)	0.059(0.045)

[a] The first set of numbers refer to the SUR residuals; numbers in parentheses refer to the OLS residuals.

CALIS in SAS we will calculate the system's response to a shock (or an impulse) and measure the the relative importance of these shocks at the sectoral, industry and aggregate levels. For this analysis, we use the residuals from the SUR estimation of the multi-sector model.

Estimation

The components of disturbances in the multi-sector model can be estimated by the method of moments techniques. Altonji and Ham (1990) and Krieger (1989) used this technique to estimate the error components in their models. The idea behind the method of moments technique is to the compare sample covariance (or correlation) matrix with the predicted covariance (or correlation) matrix generated by the parametric structure imposed on the errors (or the hypothesized model). Thus this type of analysis is called the 'analysis of covariance structures'.[4] Therefore the analysis of covariance structures refers to the formulation of a model for the variances and covariances (or correlations) among a set of variables and the fitting of the model to an observed covariance (or correlation) matrix.

[4]See Aigner, Hsiao, Kapteyan, and Wansbeck (1984) for discussion of these model.

Computer program

There are many computer programs available for the analysis of covariance structures. Altonji and Ham used LISREL (Linear Structural Relations) in SPSS.X while Krieger used GAUSS to make her own program. LINCS (Linear Covariance Structures) is also available in GAUSS. We will use CALIS (Covariance Analysis of Linear Structural Equations) which is available in SAS. CALIS is well-suited for our study since it allows the use of hypothetical latent variables or measurement errors in the models and it can deal with systems of linear structural multiple and simultaneous equations.

Suppose that there are three types of shocks in the economy: an aggregate shock, industry-specific shocks and sector-specific shocks. For our study, there are twelve sectoral outputs which are further classified into three different industries (see the data description in Appendix D). The disturbance for a given sector i in industry j can be decomposed by

$$\epsilon_{it}^{j} = f_i c_t + h_i^j g_t^j + e_{it} \tag{5-1}$$

where c_t is an aggregate shock, g_t^j is an industry-specific shock, and e_{it} ia a sector-specific shock. This is a system of twelve equations since there are twelve sectors in the economy.

We need to estimate the response coefficients ($f_1, \ldots f_{12}$, $h_1^1, \ldots, h_3^1$, $h_4^2 \ldots h_7^2$, $h_8^3, \ldots h_{12}^3$) and the variance of various shocks (σ_c^2, $\sigma_{g1}^2, \ldots \sigma_{g3}^2, \sigma_{e1}^2, \ldots, \sigma_{e12}^2$). Then we can analyze the system's responses to an impulse and measure the relative importance of various shocks in explaining output variations.

The model (5-1) predicts that Σ, the covariance matrix of $\epsilon_t = (\epsilon_{st}^1, \ldots \ldots \epsilon_{st}^{12})'$, takes the form:

$$
\begin{aligned}
E(\epsilon_{it}^{j}\epsilon_{i't}^{j'}) &= f_i^2\sigma_c^2 + h_i^{j2}\sigma_{gj}^2 + \sigma_{ei}^2 && \text{if } i=i' \text{ and } j=j' && (5\text{-}2\text{-}1)\\
&= f_i f_{i'}\sigma_c^2 + h_i^j h_{i'}^j \sigma_{gj}^2 && \text{if } i\neq i' \text{ and } j=j' && (5\text{-}2\text{-}2)\\
&= f_i f_{i'}\sigma_c^2 && \text{if } i\neq i' \text{ and } j\neq j' && (5\text{-}2\text{-}3)
\end{aligned}
$$

The contemporaneous output comovement across sectors rises due to aggregate and industry-specific shocks in this framework.

Estimation Procedure

The procedure for estimating the parameter vector is as follows: First, calculate the observed sample covariance matrix (S), which is a consistent estimate of the predicted covariance matrix (Σ). Second, stack the elements of S into a 78×1 vector since covariance terms are counted only once (symmetric), so that there are $n(n + 1)/2$ independent elements in S. Therefore there will be 78 elements if we are analyzing twelve sectoral outputs. Third, choose the parameter vector to minimize the difference between the observed sample covariance and the predicted covariance matrix.

CALIS, which uses both covariance and correlation matrix, provide three methods of estimation: unweighted least-squares estimation, generalized least-squares estimation and maximum-likelihood estimation for multivariate normal distributions. Each estimation method is trying to find parameter estimates that maximize (or minimize) the discrepancy (or goodness-of-fit) between the observed sample covariance matrix and the predicted covariance matrix given the model and the parameter estimates. The maximum-likelihood estimation routine was chosen because it is the preferred method for most applications, especially for statistical inference. The response of each sectoral output to its own shock is normalized to one for all sectors.

We tried to use a covariance matrix of the SUR residuals from the multi-sector model but the CALIS procedure failed to converge, giving the diagnostic message that the sample covariance matrix was not positive definite. While theoretically impossible, this problem can happen in numerical optimization, particularly in applications with large covariance matrices and many parameters. However CALIS could successfully estimate the parameters when the correlation matrix was used. Then, the covariance matrix was recalculated based on the estimates from the correlation matrix.

Since we have twelve sectors and three different types of shocks (see the system of equations (5-1) we need to estimate 40 parameters from 78 the elements of correlation matrix. The 40 parameters include 12 sectoral variances, three industry variances, one aggregate variance, twelve parameters giving the sectoral response to the industry shock and twelve parameters giving the sectoral response to the aggregate shock. The estimation revealed one negative variance for the Basic metal specific shock.[5] In addition, all response coefficients of sectoral output in durable manufacturing to the durable manufacturing industry shock were statistically insignificant. The model was then reestimated, restricting the durable manufacturing industry shock to be zero. This saved six degrees of freedom (five response coefficients and the durable goos industry variance), so 34 parameters remained. This more restricted model yielded reasonable results.[6]

As noted above, the numerically estimated covariance matrix was not positive definite, so estimation used the correlation matrix. There is a one-to-one correspondence between the covariance and correlation matrices because the latter is the covariance matrix of the standardized variables. This allows the parameters of the

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[5]Altonji and Ham (1990) and Krieger (1989) also found negative variances for some shocks.

[6]The test statistics for the null hypothesis that there was no durable manufacturing industry shock is distributed chi-square with six degrees of freedom. The test statistic was 15.9 which exceeds the critical value at the 5 percent significance level but it is not at the 1 percent significance level.

covariance matrix to be recaptured. Let R be the correlation matrix, let Σ be the covariance matrix and D_Σ (= diag(σ_{ii}, i = 1,2,..12) be the diagonal matrix of standard deviations of the observed variables. Then the following relation hold:

$$D_\Sigma R D_\Sigma = \Sigma$$
$$\text{or } R = D_\Sigma^{-1} \Sigma D_\Sigma^{-1}$$

In addition, $R = (P_R D_R)(P_R D_R)'$ where P_R is the matrix of response parameters to standardized shocks and D_R is the vector of standardized shock. Similarly, $\Sigma = (P_\Sigma D_E)(P_\Sigma D_E)'$ where P_Σ is the matrix of response coefficients to an impulse and D_E is the vector of standard deviations of the shocks. The relation between the standardized and non-standardized parameters is:

$$D_\Sigma^{-1} P_\Sigma D_E = P_R D_R$$
$$\text{or } D_\Sigma P_R D_R = P_\Sigma D_E$$

Therefore if we have a problem in numerical optimization using a covariance matrix, then we can first estimate $P_R D_R$ using the correlation matrix and then recover the estimates $P_\Sigma D_E$ by premultiplying $P_R D_R$ by D_Σ.

We need $P_\Sigma D_E$ to simulate the impulse responses to unstandardized shocks while we need $P_R D_R$ for simulating impulse responses to standardized shocks. Therefore we need to decompose $P_\Sigma D_E$ into P_Σ and D_E so that we can establish the relative size of the various shocks. In doing so, we developed a two-step procedure: First, calculate a new predicted covariance matrix, $\hat{\Sigma}$, based on the parameter estimates from the correlation matrix with $\hat{\Sigma} = (P_\Sigma D_E)(P_\Sigma D_E)' = (D_\Sigma P_R D_R)(D_\Sigma P_R D_R)'$. This matrix $\hat{\Sigma}$ will be positive definite by construction. In the second stage use the predicted covariance matrix, $\hat{\Sigma}$, instead of the observed sample covariance matrix, S, to estimate P_Σ and D_E.

Table 5-6 - 5-8 presents the maximum likelihood estimates of the response coefficients P_Σ (P_R)as well as the variances of the various shocks D_E (D_R), based on the residuals from SUR estimation. All response coefficients are statistically significant. Fabricated metal, Chemicals and Textiles are the most responsive to the aggregate shock while Metal ore and Other mining are the least responsive to the aggregate shock. Sectors in the manufacturing industry are more responsive while sectors in the mining industry are less responsive to the aggregate shock. Other mining is the most industry-specific shock and Textiles and Paper are the most responsive to the non-durable manufacturing industry-specific shock. This implies that Textiles and Chemicals are more sensitive to the policy or taste change which is specific to the nondurable industry.

Table 5-6 Maximum likelihood estimates from SUR residuals (Sectoral coeffficients (P_{Σ}) on various shocks)

Industry	Sector	Aggregate	Industry	Sector
Mining	Coal	0.8308(5.17)[a]	0.9843(2.53)	1.0*[b]
	Ore	0.0332(2.29)	0.1881(1.78)	1.0*
	Othermin	0.3746(3.99)	1.3485(4.64)	1.0*
Non-durable	Food	2.2276(3.76)	0.9551(2.05)	1.0*
	Chemicals	5.4086(5.29)	2.3595(3.32)	1.0*
	Textiles	3.6065(4.09)	2.763(4.22)	1.0*
	Paper	1.4847(4.56)	0.6644(2.35)	1.0*
Durable	Glass	0.0733(3.33)	-	1.0*
	Wood	0.8574(5.94)	-	1.0*
	Basmetal	3.0171(5.94)	-	1.0*
	Fabmetal	28.3107(90.19)	-	1.0*
	Otherman	0.5894(2.87)	-	1.0*

[a] Numbers in parentheses are t-value.

[b] * denotes a normalization to 1.0.

Table 5-7 Maximum likelihood estimates from SUR residuals (Sectoral coefficients (P_R) on various shoks)

Industry	Sector	Aggregate	Industry	Sector
Mining	Coal	0.8672(6.46)[a]	0.4946(2.33)	1.0*[b]
	Ore	0.3601(2.40)	0.9833(2.64)	1.0*
	Othermin	0.6484(4.58)	1.1246(3.22)	1.0*
Non-durable	Food	0.6106(4.23)	1.0857(2.21)	1.0*
	Chemicals	0.8784(6.64)	1.5888(3.09)	1.0*
	Textiles	0.6644(4.72)	2.1097(3.92)	1.0*
	Paper	0.7563(5.48)	1.3601(2.77)	1.0*
Durable	Glass	0.5215(3.59)	-	1.0*
	Wood	0.9725(7.34)	-	1.0*
	Basmetal	1.2605(9.92)	-	1.0*
	Fabmetal	1.2605(9.92)	-	1.0*
	Otherman	0.4455(3.03)	-	1.0*

[a] Numbers in parentheses are t-value.

[b] * denotes a normalization to 1.0.

Impulse Responses and Variance Decompositions

In this section we will simulate the system's responses to the impact of various shocks using our parameter estimates and the moving average representation of the multi-sector model. Once the moving average representation is obtained, a useful decomposition of output variance can be derived by calculating the variance of j-step ahead forecasting error.

Impulse Responses

The impulse response from an initial unit shock to each of hypothetical latent variables are presented in Figure 5-2 - 5-16. Dynamic responses of sectoral output growth rates in the mining industry to the aggregate shock are relatively insignificant compared to those in the non-durable and durable manufacturing industries. However, the impact of various shocks on sectoral growth rates mostly disappears within two years. The exception is Fabricated metal's response to some shocks. The implication is that sectoral output growth rates responds completely to various shocks within 24 months. Dynamic responses of sectoral output growth rates in the mining industry are more responsive to the mining industry-specific shock than others. The same is true of sectoral output growth rates responses in the non-durable manufacturing industry. There is some dynamic responses of sectoral output growth rates in the durable manufacturing industry to the non-durable industry-specific shock.

Table 5-9 Variance decompositions from a sectoral perspective (When the shock is not propagated)

Sector	Fraction of variation explained by			
	Aggregate	Mining	Non-durable	Sector
<u>Mining</u>				
Coal	19.51	5.07	-[a]	75.42
Ore	3.36	20.02	-	76.61
Othermin	10.91	26.19	-	62.90
<u>Non-durable</u>				
Food	9.67	-	5.55	84.78
Chemicals	20.03	-	11.90	68.06
Textiles	11.45	-	20.97	67.58
Paper	14.84	-	8.71	76.45
<u>Durable</u>				
Glass	7.05	-	-	92.95
Wood	24.55	-	-	75.45
Basmetal	27.07	-	-	72.93
Fabmetal	41.23	-	-	58.77
Otherman	5.15	-	-	94.85

[a] - denotes a negligible percentage, i.e., less than 1 percent..

Table 5-10 Variance decompositions from a sectoral perspective (When the shock is allowed to be propagated)
(24 period ahead)

	Fraction of variation explained by				
Sector	Aggregate	Mining	Non-durable	Own Sector	All other Sectors
Mining					
Coal	18.83	4.64	-[a]	68.58	7.49
Ore	4.92	18.26	-	65.23	11.04
Othermin	11.63	22.04	-	54.04	11.93
Non-durable					
Food	15.07	-	5.75	72.74	6.43
Chemicals	19.47	-	12.01	64.62	3.90
Textiles	12.13	-	19.93	62.77	5.16
Paper	16.46	-	9.97	69.04	4.53
Durable					
Glass	9.92	-	3.65	77.23	9.16
Wood	21.04	-	3.76	64.40	10.76
Basmetal	26.67	-	1.97	63.13	8.22
Fabmetal	37.78	-	1.78	54.08	6.35
Otherman	9.06	-	2.24	80.13	8.55

[a] - denotes a negligible percentage, i.e., less than 1 percent.

across sectors. The aggregate shock is transmitted across sectors immediately but the a priori restrictions impose that it takes one time period for disaggregate shocks to be transmitted across sectors.

The aggregate shock accounts for 3 to 19 percent of the variance in the innovation of sectoral output growth rates in the mining industry when the shock is not propagated. The mining industry-specific shock explains 5 to 26 percent of the variance in the innovation of sectoral output growth rates in the mining industry. The sector-specific shock explains the rest of the variance. The aggregate shock accounts for 10 to 20 percent of the variance of sectoral output growth rates while the non-durable manufacturing industry-specific shock can explain 6 to 21 percent of the variance of sectoral output growth in non-durable manufacturing industry. The sector-specific shock accounts for 67 to 85 percent of the variance. In durable manufacturing industry the aggregate shock is relatively more important, accounting for 7 to 41 percent of the variance of its sectoral output growth rates. The sector-specific shock explains the rest of the variance since there is no durable manufacturing industry-specific shock.

In sum, the aggregate shock accounts for 3 and 41 percent of the variance in the innovation of sectoral output growth rates when a propagation mechanism is not considered. The industry-specific shock accounts for 5 to 26 percent of the variance in the innovation of sectoral output growth rates in its industry while sector-specific shocks account for 59 to 94 percent of the variance in the innovation of sectoral output growth rates. While the results indicate that all three types of shocks play an important role in the fluctuations of sectoral output growth rates, the dominant influence comes from sector-specific shocks. Relatively speaking, the aggregate shock is more important in durable manufacturing industry than mining industry. This finding may implies that durable goods industries are more sensitive to aggregate shocks.

We have qualitatively similar results when the shock is allowed to be propagated across sectors and time. Sector-specific shocks continue to play the dominant role in generating sectoral output growth rates In addition, these shocks explain four to twelve percent of the variance of output in other sectors. Aggregate and industry-specific shocks also do not change much in their relative importance in explaining output fluctuations. The aggregate shock accounts for 5 to 38 percent of the variation in sectoral output growth rates.[7] Non-durable industry-specific shocks propagated into the durable manufacturing, but not into the mining industry. Mining industry shocks do not affect output elsewhere in the economy. All in all, sectoral shocks are propagated across sectors more rapidly than industry shocks.

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[7]Norrbin and Schlagenhauf (1991) also found that aggregate factor (or shock) accounts for 0.08 to 34.38 percent of output variation at steady-state. In their results, the aggregate factor play more important role in durable industries than mining.

We can also assess the relative importance various shocks at the industry output level since the growth rate of industry output is approximately equal to the weighted sum of the growth rates of sectoral outputs in the industry. In a similar way we can assess the relative importance of various shocks at the aggregate level. Table 5-11 contains the results of variance decompositions at the industry and aggregate output levels. The aggregate shock accounts for 16 percent of output growth rates in the mining and non-durable goods industries, and 32 percent of output growth rates in durable goods. As before, the aggregate shock plays a more important role in durable manufacturing industry than elsewhere. The non-durable industry-specific shock explains 13 percent of the non-durable industry output growth rates, 2 percent of the durable industry variation in growth rates, and a negligible share of mining output growth rates variation. Sector-specific shocks account for 59 to 66 percent of the own-industry output growth rates variance, and from 5 to 9 percent of other industry output growth rates.

When looking at aggregate output growth, the aggregate shock accounts for 26 percent of the variance in growth rate, while all industry-specific shocks explain 8 percent and all sector-specific shocks account for 66 percent of aggregate output growth rates.

5.5 Conclusions

In this chapter the multi-sector model (restricted VAR model) is estimated by SUR method. The residuals from the multi-sector model are analyzed using factor analysis to determine the extent and the dimensionality of comovement in the residuals. Descriptive statistics indicate one common factor while a χ^2 test statistic, which is biased to reject the null hypothesis, accepts more common factors. We choose one common factor in covariance analysis so as to make interpretations easy. Three types of shocks are assumed to exist: an aggregate shock, industry-specific shocks, and sector-specific shocks. The error components model is estimated using the method of moments technique, yielding estimates of the response coefficients and the variances of the various shocks. The response coefficients of sectoral output growth to the aggregate shock differ across sector. In general, manufacturing sectors are more responsive to the aggregate shock than are mining sectors. The possible candidate for the aggregate shock is either aggregate demand or aggregate supply shock. But our model, a version of real business cycles models, predicts the aggregate shock to be aggregate supply shock such as technological shock. Therefore we can say that the impact of technological change differs across sectors. Relatively speaking, technological change plays more important role in manufacturing industry than mining industry. The dynamic responses of sectoral output growth rates to various shocks are simulated and confirm the results of the error components model in that the dynamic responses of sectoral output growth rates in mining industry to the aggregate shock are relatively insignificant compared to those in manufacturing. We can assess the relative importance of various shocks to the variance in sectoral, industry and aggregate output level by decomposing the forecasting error variance into various sources of shocks. The results indicate that all three types of shocks play a significant role in all level of output fluctuations but the dominant influence comes from sector-specific shocks. This finding is consistent with the "weak" version of real business cycle theory that disaggregate disturbances play very important role in aggregate fluctuations.

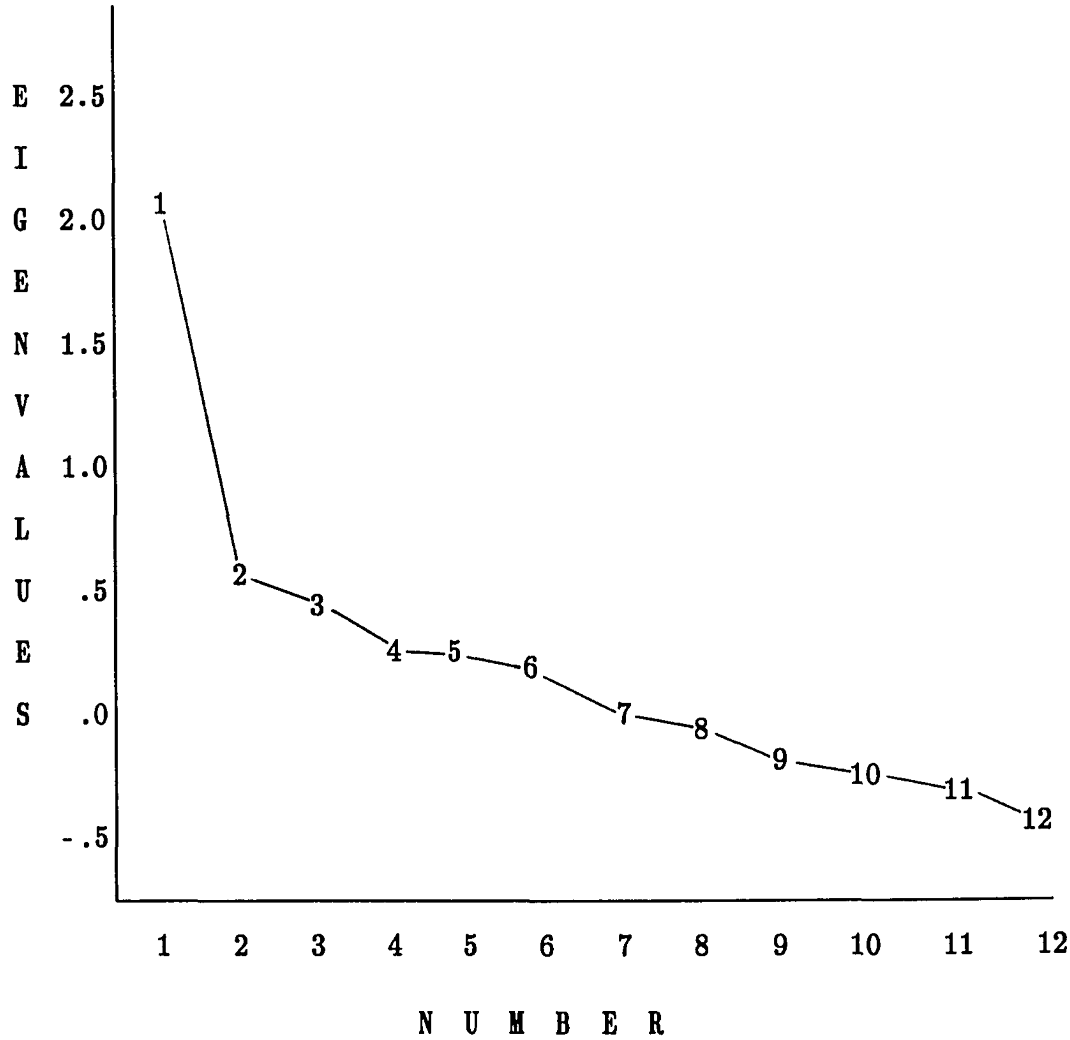
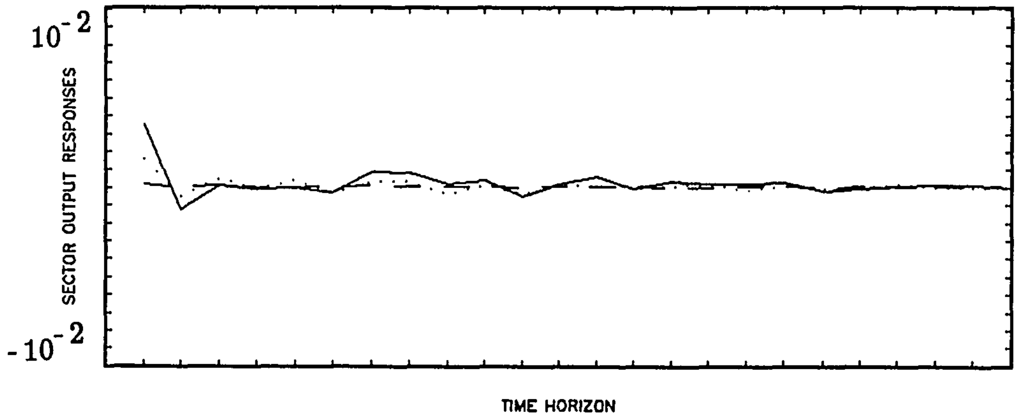
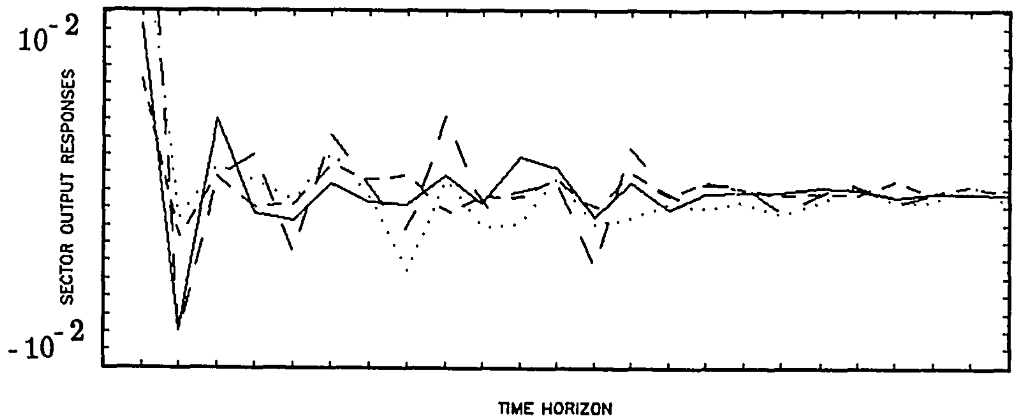


Figure 5-1. Scree graph

Mining



Non-durable



Durable

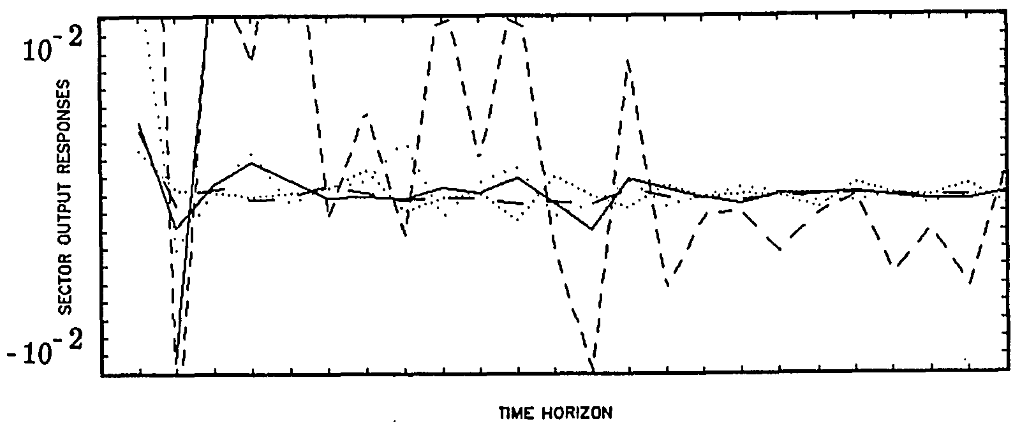


Figure 5-2. Output responses to the aggregate shock

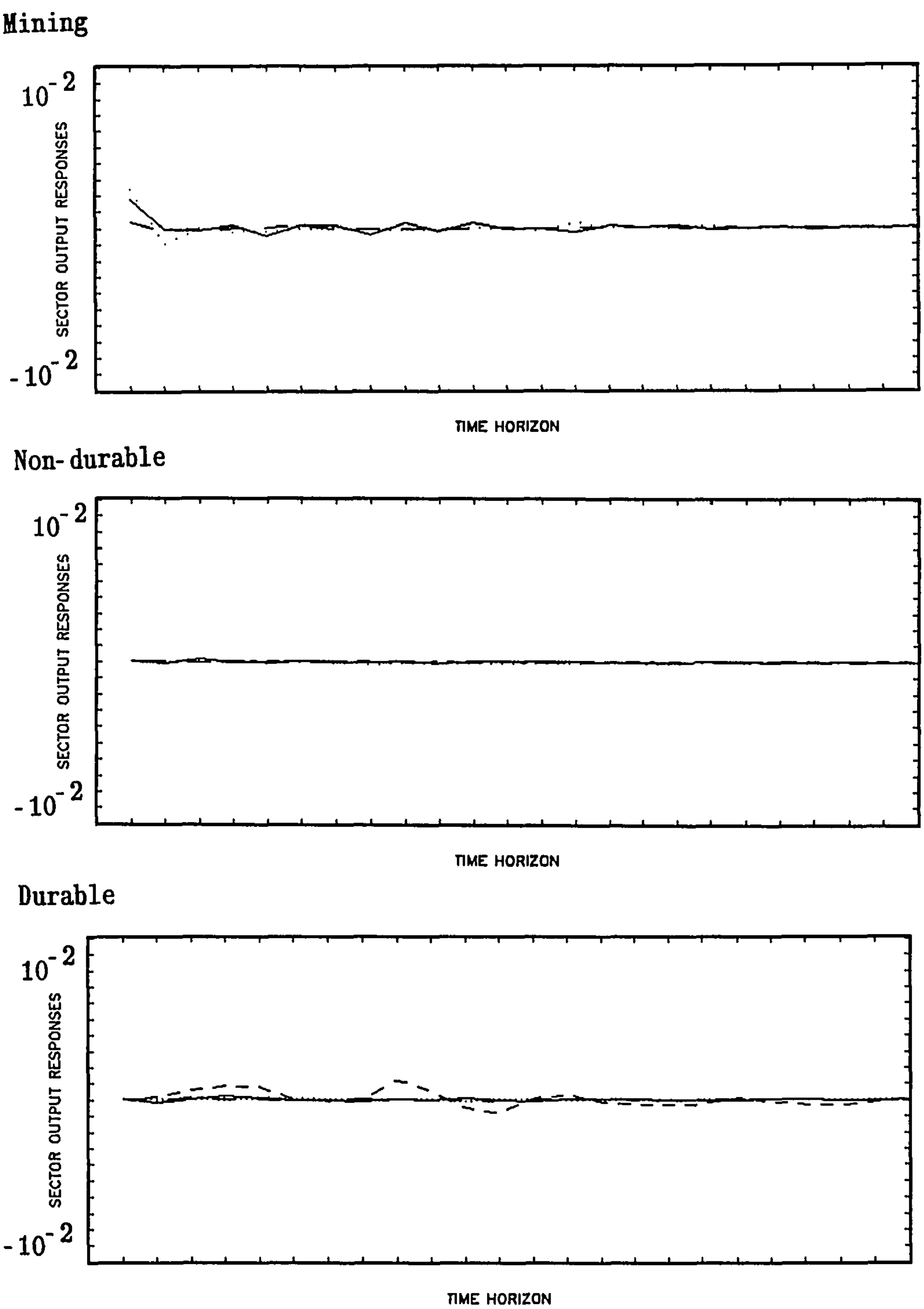
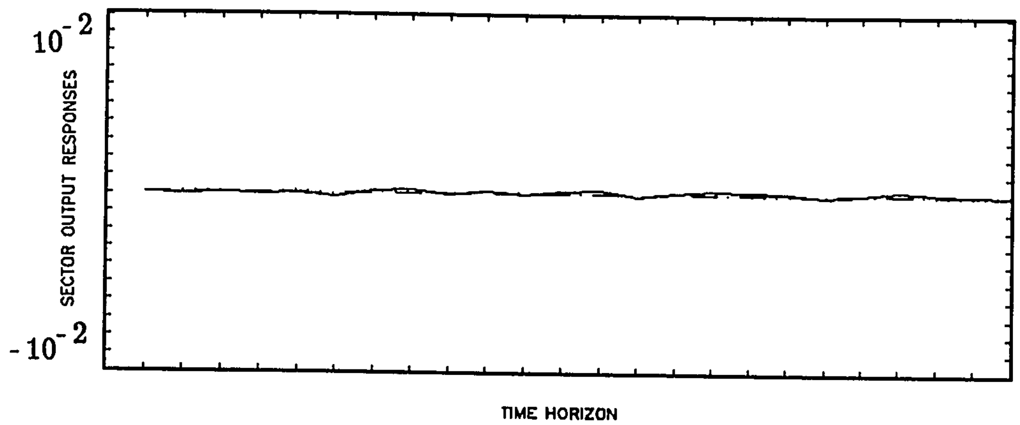
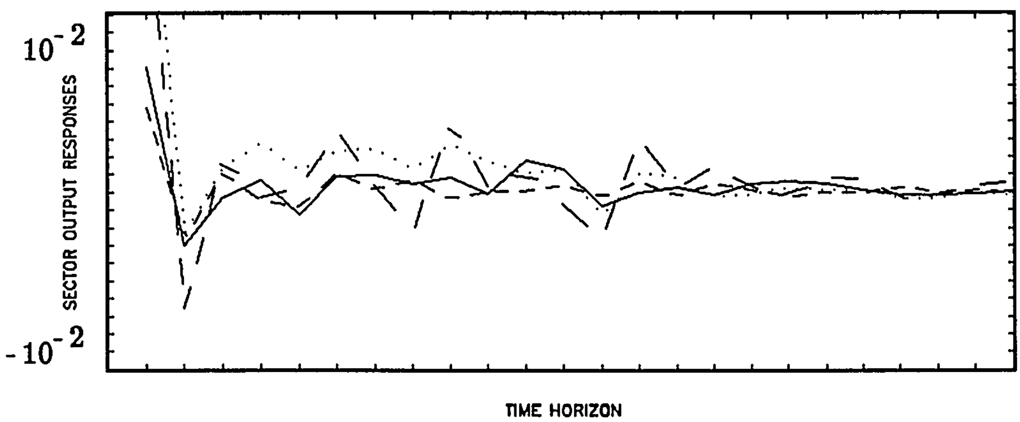


Figure 5-3. Output responses to the mining industry shock

Mining



Non-durable



Durable

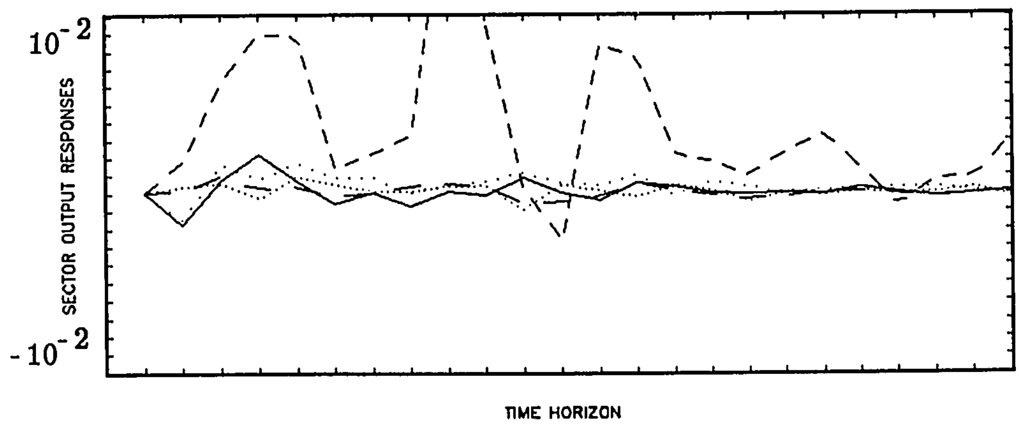


Figure 5-4. Output responses to the non-durable manufacturing industy shock

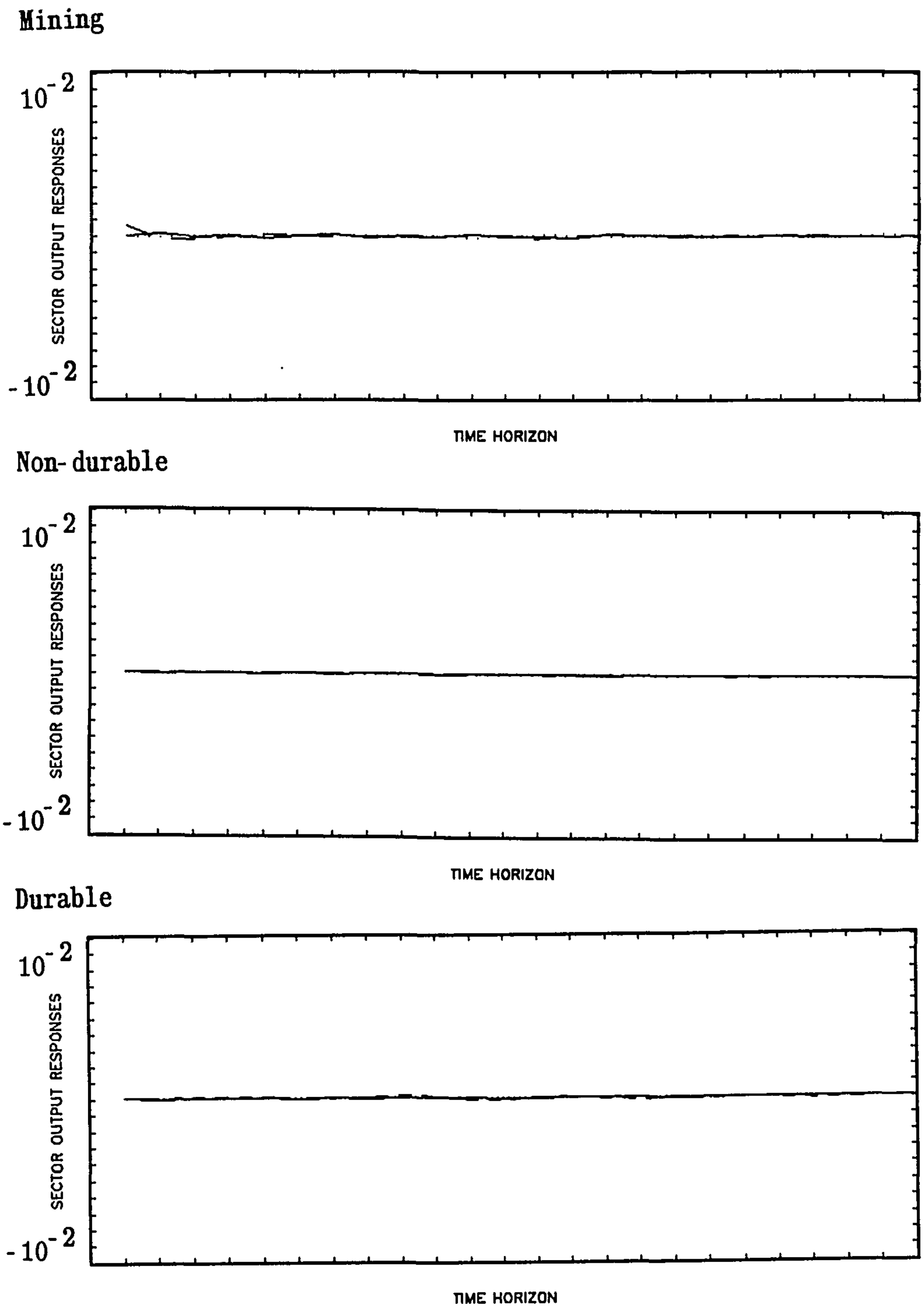
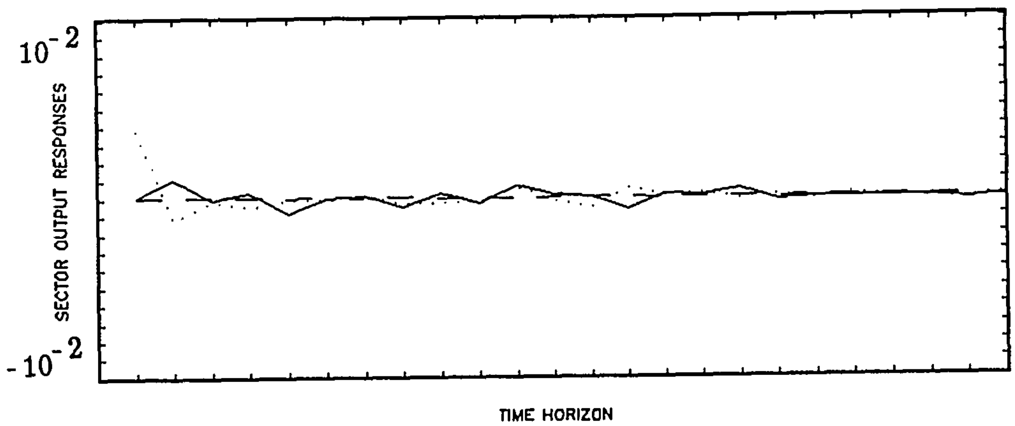
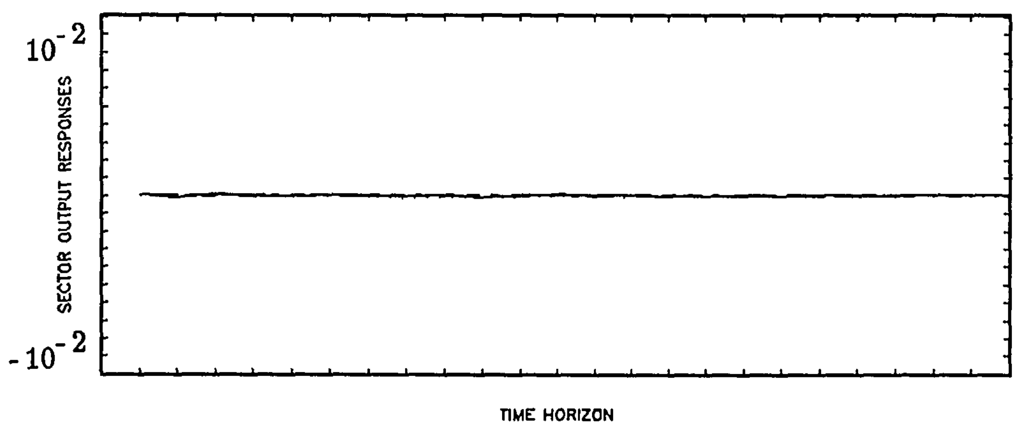


Figure 5-6. Output responses to the Ore sector shock

Mining



Non-durable



Durable

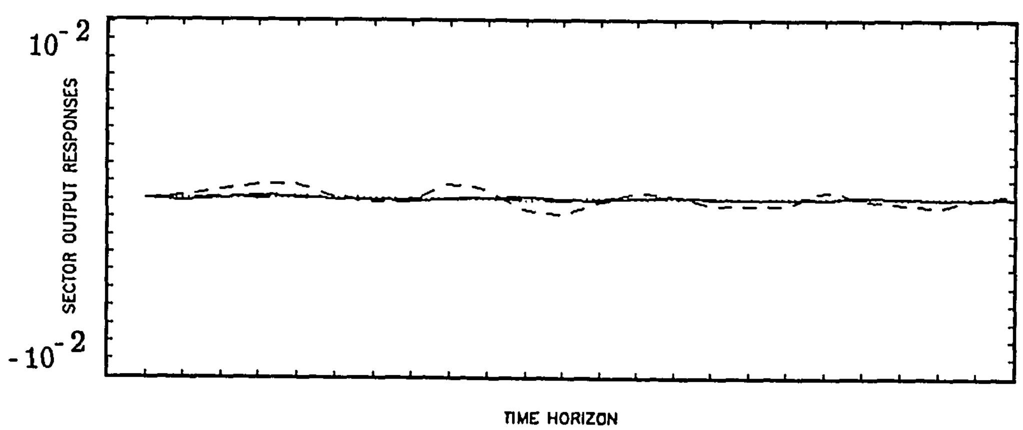
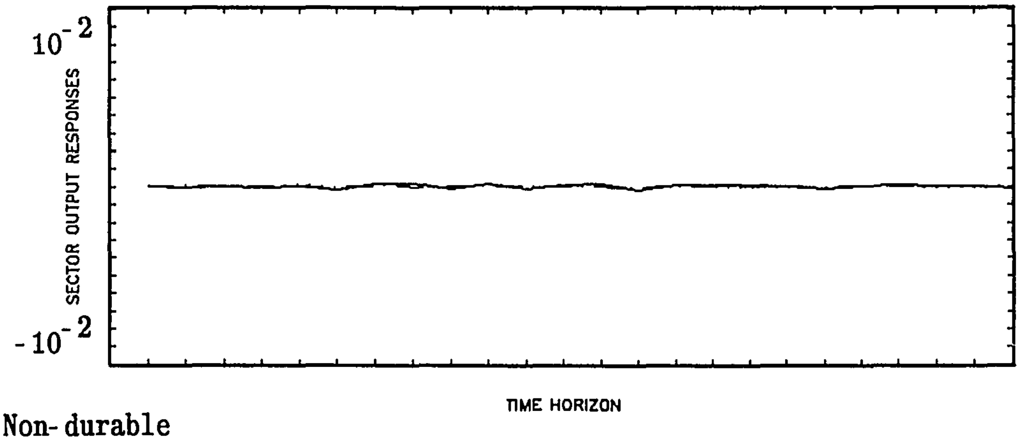
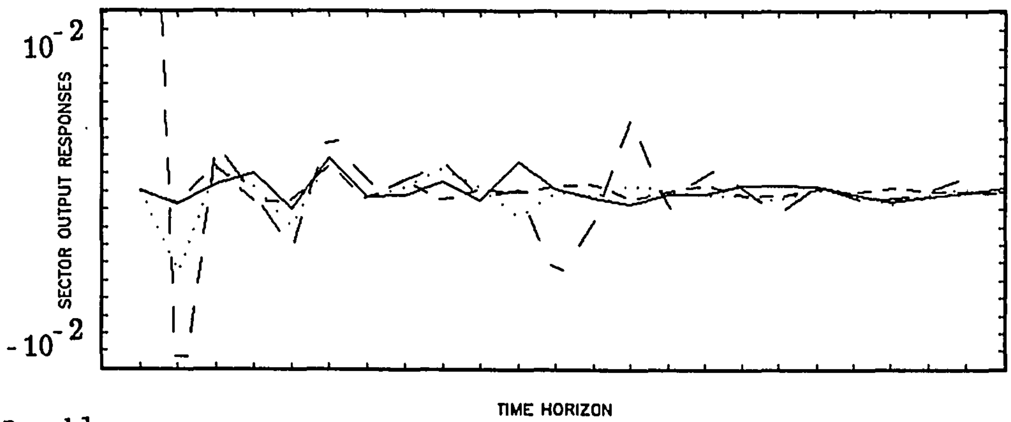


Figure 5-7. Output responses to the Othermin sector shock

Mining



Non-durable



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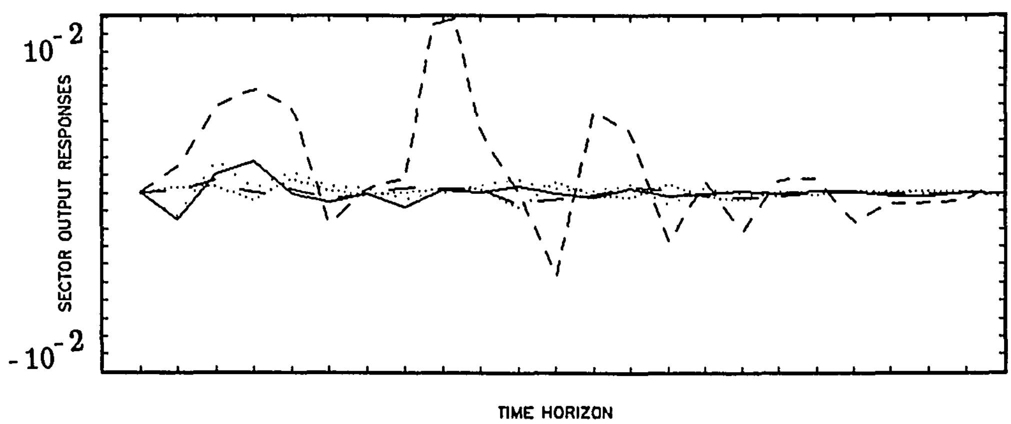


Figure 5-9. Output responses to the Chemicals sector shock

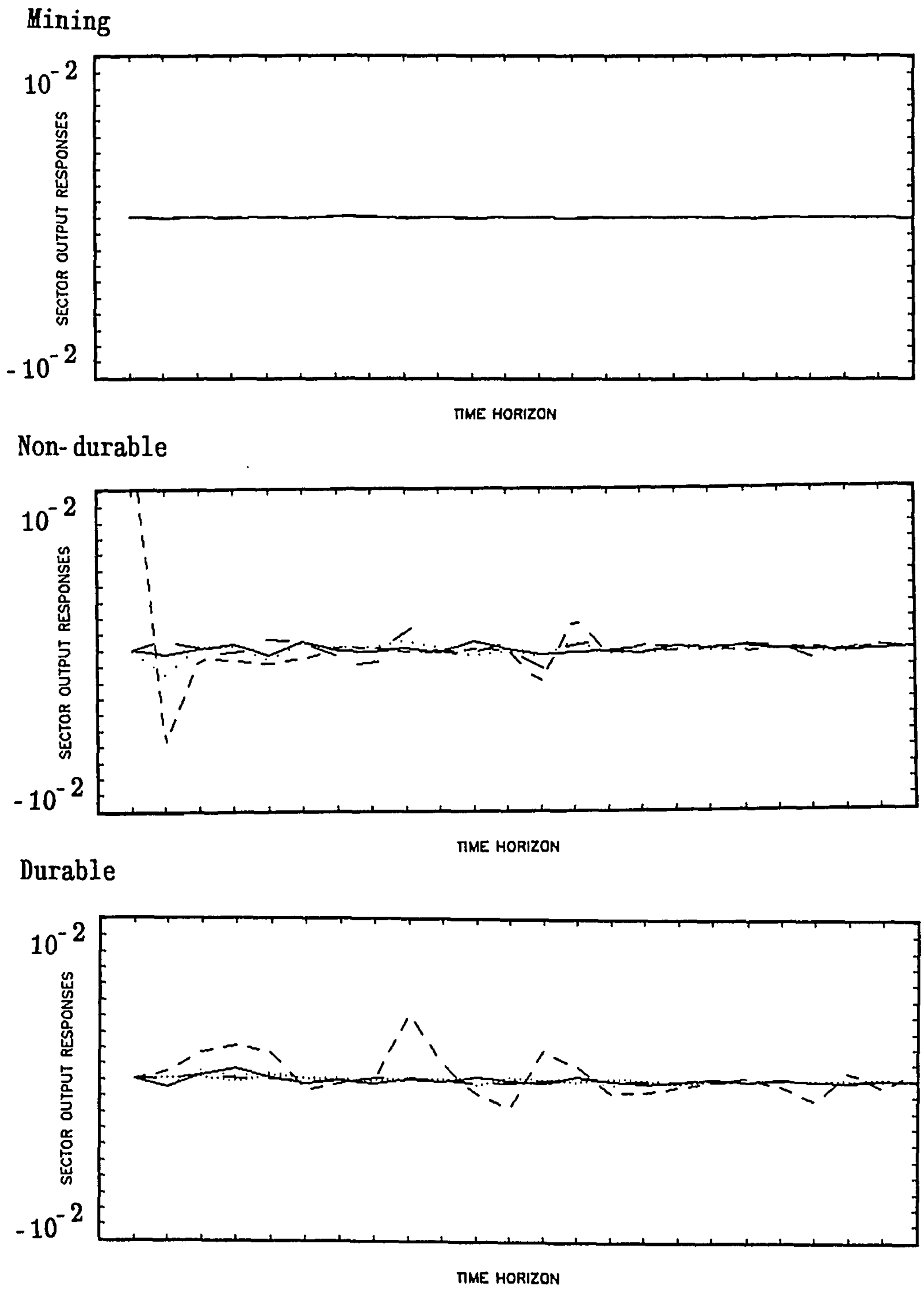
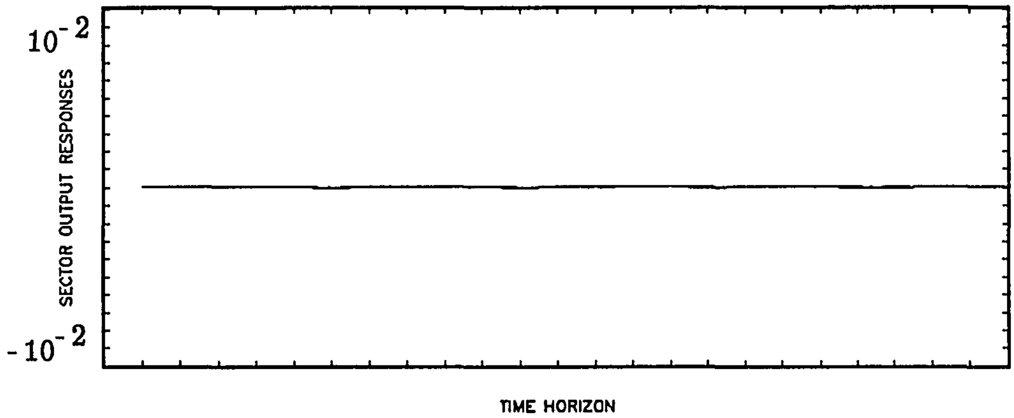
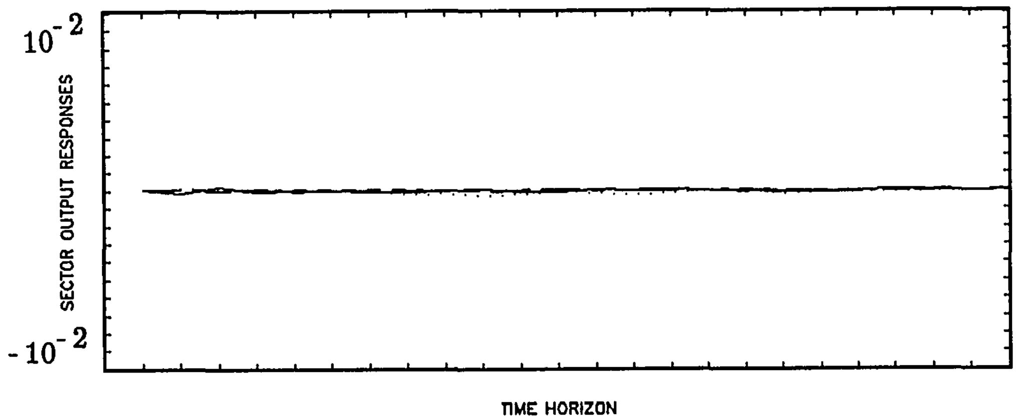


Figure 5-11. Output responses to the Paper sector shock

Mining



Non-durable



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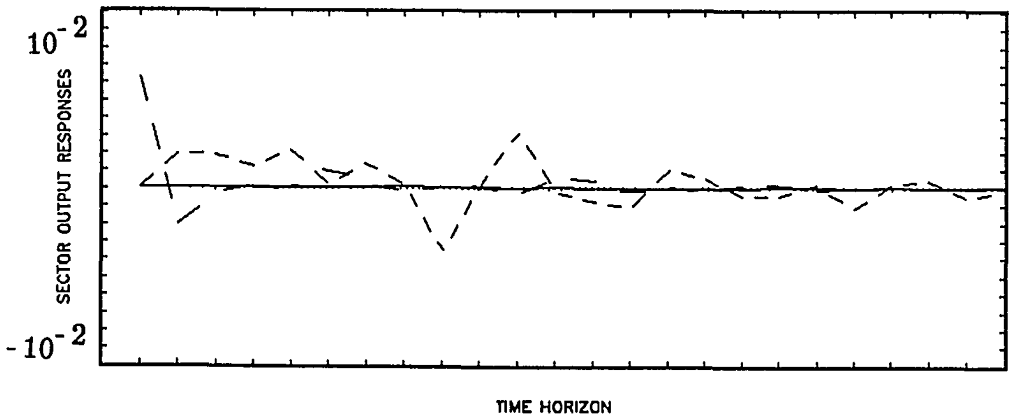


Figure 5-13. Output responses to the Wood sector shock

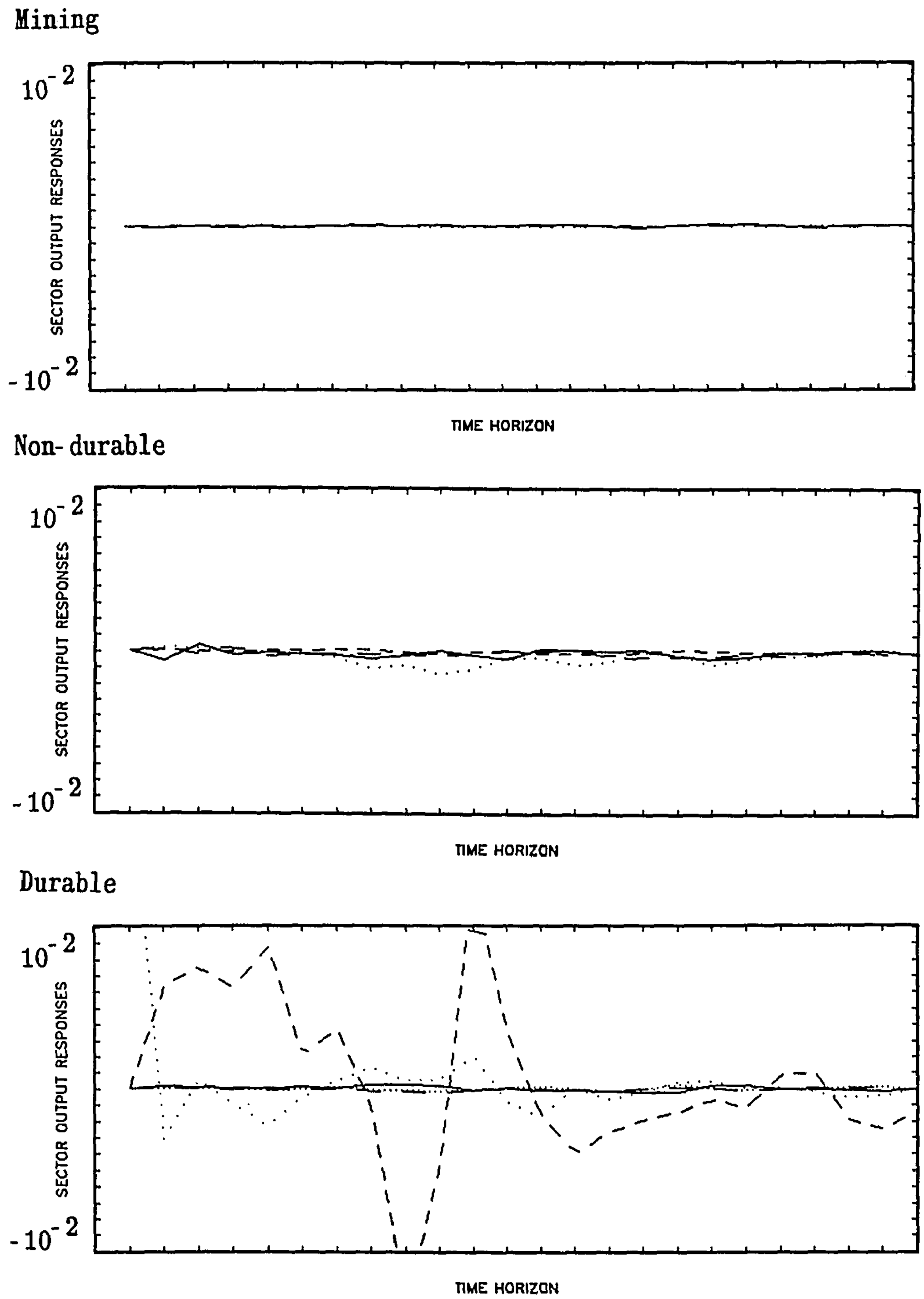


Figure 5-14. Output responses to the Basmetal sector shock

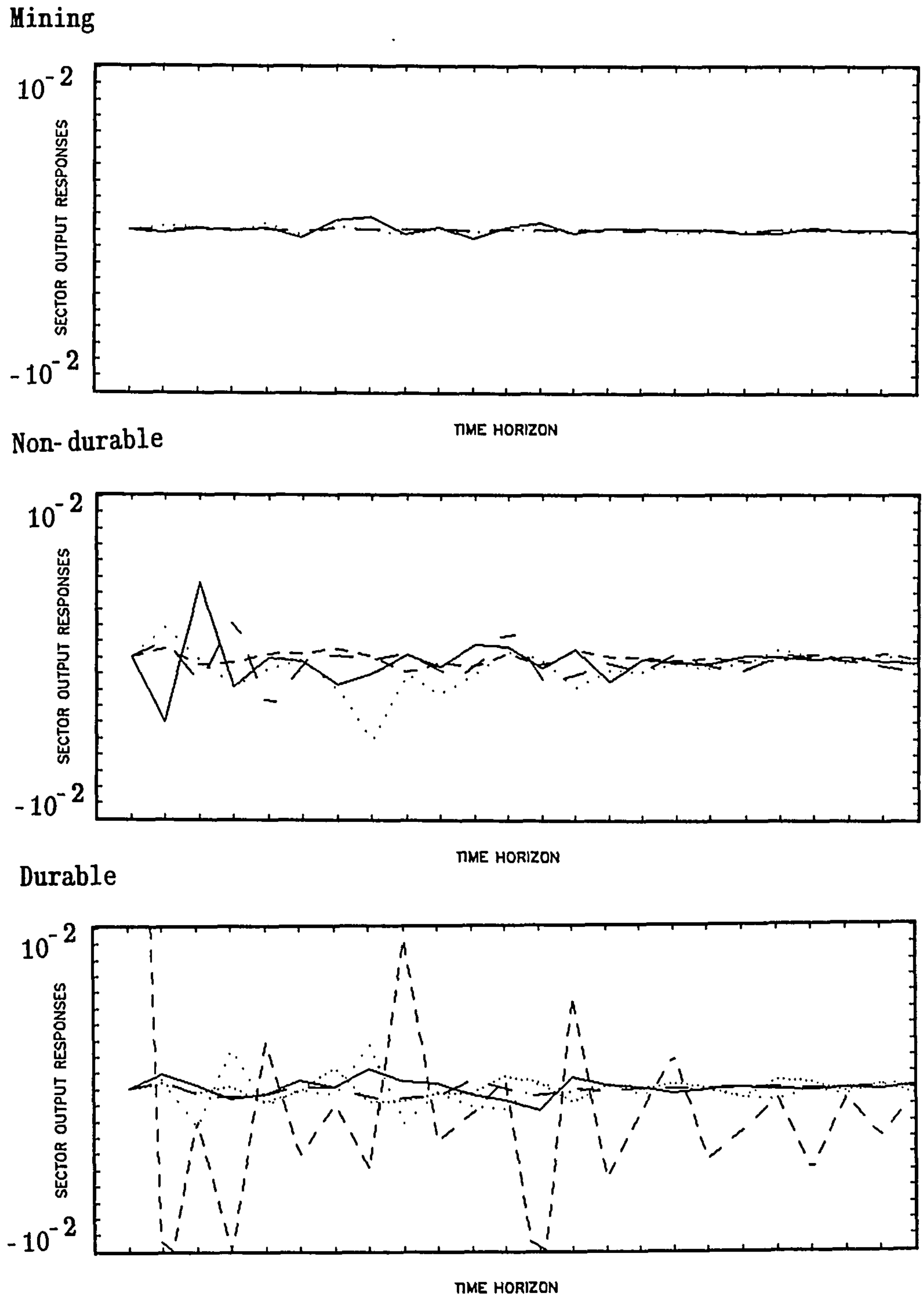
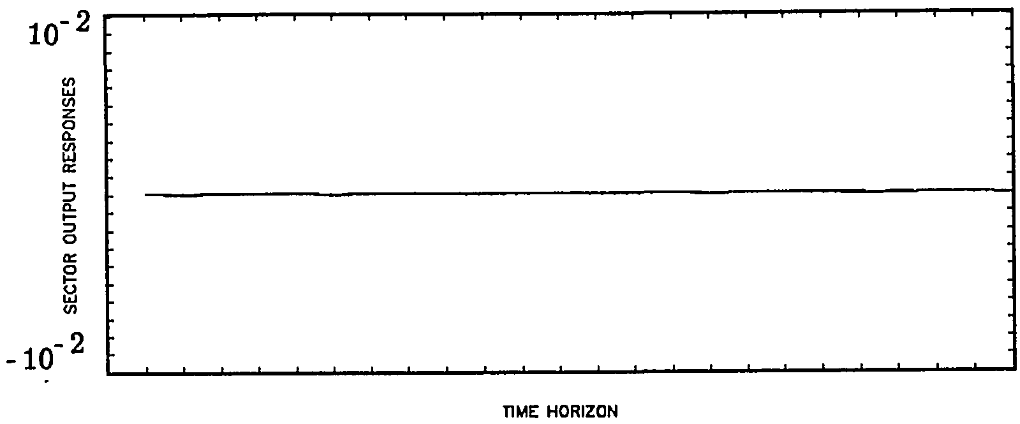
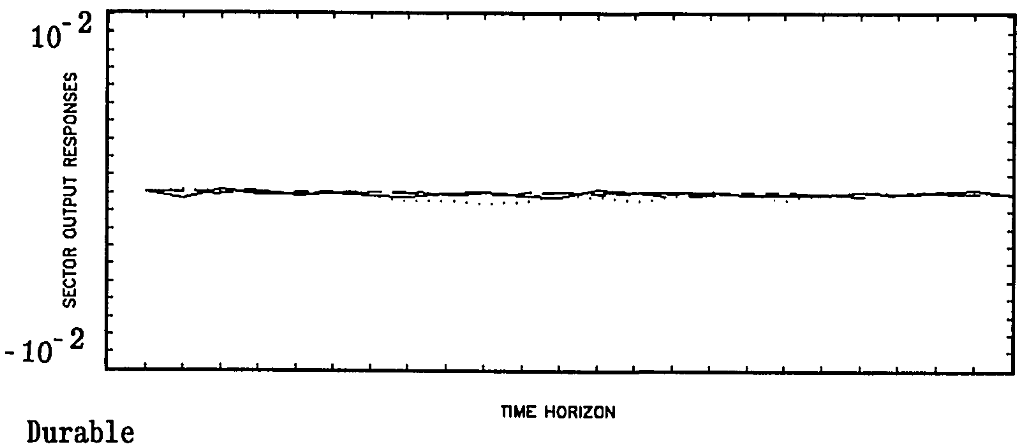


Figure 5-15. Output responses to the Fabmetal sector shock.

Mining



Non-durable



Durable

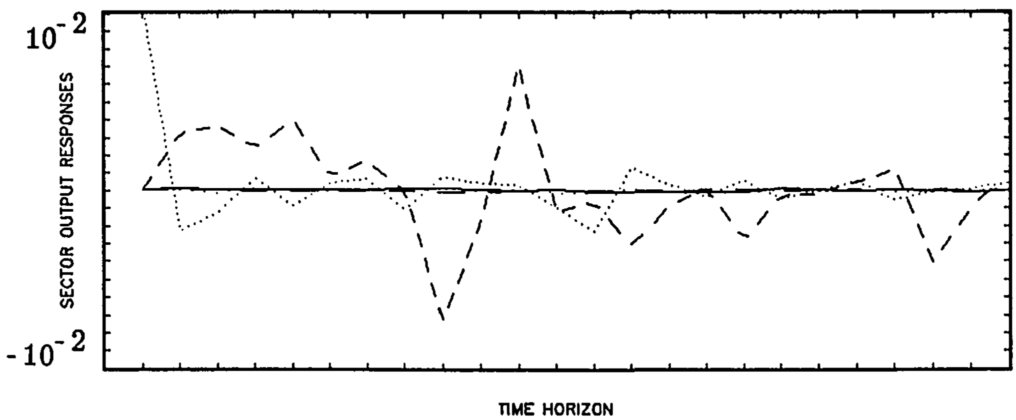


Figure 5-16. Output responses to the Otherman sector shock

6 SUMMARY AND CONCLUSIONS

This dissertation was written to examine the relative importance of aggregate and disaggregate shocks in explaining movements in Korean manufacturing output. The study uses a linear general equilibrium macroeconomic model of the business cycle, disaggregated by industry. The model is a special case of the multi-sector business cycle model developed by Long and Plosser (1983).

The first question addressed was whether aggregate shocks cause sectoral business cycles or sector-specific shocks cause aggregate business cycles. A trivariate VAR model was proposed to examine this question. Statistical tests indicated that twelve monthly lags were appropriate for the trivariate VAR with differenced data. The results indicated that aggregate output Granger causes sectoral output for most mining and durable manufacturing industries but aggregate shocks do not in general Granger cause sectoral output in non-durable manufacturing. Each sector in durable manufacturing has a strong production or trade linkage with other sectors in the economy. Sectoral output in mining industry has the strongest causal link to aggregate output. Forecasting error variance decompositions (FEVD) showed that aggregate shocks play a more important role in sectoral output variation in durable manufacturing relative to other sectors.

The second question refers to the number of common shocks in the economy. In this study we are interested in the dimensionality of common shocks in explaining twelve sectoral output growth rates. Factor analysis which decomposes a set of random variables into hypothetical unobserved common factors and a set of unique factors was employed to answer the second question. The results of the factor analysis (reported in Chapter 5) indicate that one common factor (or shock) model is appropriate and the common factor explains 5 to 34 percent of the variation in sectoral output.

The third question refers to the relative importance of aggregate and disaggregate shocks in explaining sectoral output growth rates. Three types of shocks are assumed to exist: aggregate, industry-specific and sector-specific shocks. A restricted vector autoregressive (VAR) multi-sector model is estimated by seemingly unrelated regression method. The residuals from the restricted VAR model are used to identify various shocks. The error components model is employed to decompose those shocks, using a method of moments estimation technique. These are used to identify the responses coefficients and variances of the various shocks. Sectoral shocks are by far and the most important source of sectoral output fluctuations. The durable goods manufacturing sectors are more responsive to the aggregate shock than are other sectors. The relative importance of aggregate and disaggregate shocks can be measured by FEVD. All three types of shocks play a significant role in all level of output fluctuations but the dominant influence comes from the sector-specific shocks.

This study empirically examined whether real business cycle theory, which claims that disaggregate disturbances play a very important role in business cycles, is consistent with fluctuations in the Korean economy. Technology shocks to individual sectors (or sector-specific shocks) seem to generate business cycles in Korean economy not aggregate shocks to the overall economy. The findings are supportive of the "weak" version of real business cycle theory. Some possible extensions of this study include cross-country analysis of business cycle and the source of various shocks. The role of world common shocks and country-specific shocks in explaining variation of country output growth could be examined in the context of this study. It is also interesting to study the possible source of various shocks in the economy, i.e., whether shocks are supply-driven or demand-driven. Finally, it would be useful to add sectoral relative price to sectoral output as indicators of sectoral economic activity. This would allow an examination of whether shocks are absorbed through sectoral output or sectoral prices.

Debreu, G. 1954. Valuation Equilibrium and Pareto Optimum. Proceedings of the National Academy of Sciences of the U.S. 38:886-893.

Dellas, H. 1986. A Real Model of the World Business. *Journal of International Money and Finances* 5:381-394.

Dickey, D. A. and W. A. Fuller. 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association* 74:427-31.

Dickey, D. A. and W. A. Fuller. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* 49:1057-1072.

Doan, T. A. 1989. *User's Manual of RATS* (Version 3.11). VAR Econometrics, Inc., Evanston.

Dollar, D. and K. Sokoloff. 1990. Pattern of Productivity Growth in South Korean Manufacturing Industries, 1963-1979. *Journal of Development Economics* 33:309-327.

Durlauf, S. N. 1989. Output Persistence, Economic Structure, and the Choice of Stabilization Policy. *Brookings Papers on Economic Activity* 2:69-116.

Engle, R. F. and C. W. J. Granger. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55:251-276.

Engle, R. F. and B. S. Yoo. 1987. Forecasting and Testing in Cointegrated Systems. *Journal of Econometrics* 35:143-159.

Fair, R. 1988. Sources of Economic Fluctuations in the United States. *Quarterly Journal of Economics* 103:313-332.

Frisch, R. 1933. Propagation Problems and Impulses Problems in Dynamic Economics. Pages 171-205 *in Economic Essays in Honour of Gustav Cassel*. Allen & Unwin, London.

Fuller, W. A. 1976. *Introduction to Statistical Time Series*. Wiley, New York.

Granger, C. W. J. 1969. Investing Causal Relations by Econometric Models and Cross-Spectral Models. *Econometrica* 37:424-438.

Granger, C. W. J. 1986. Developments in the Study of Cointegrated Economic Variables, *Oxford Bulletin of Economics and Statistics*

48:213-228.

Granger, C. W. J. and W. K. Newbold. 1974. Spurious Regressions in Econometrics. *Journal of Econometrics* 2:111-120.

Haberler, G. 1963. *Prosperity and Depression.* 4th ed. Atheneum, New York.

Harvey, A. C. 1981. *The Econometric Analysis of Time Series.* Phillip Allan, Oxford.

Harvey, A. C. 1989. *Forecasting, Structural Time Series Models and the Kalman Filter.* Cambridge University Press, Cambridge.

Hawtrey, R. G. 1923. *Monetary Reconstruction.* Longman Group, London.

Hayek, F. A. 1933. *Monetary Theory and the Trade Cycle.* Cape, London.

Huffman, W., and J. Lothian. 1984. The Gold Standard and the Transmission of Business Cycles,1833-1932: Pages 455-511 *in* Bordo M. and Schwartz, A., eds. *A Retrospective on the Classical Gold Standard.* The University of Chicago Press.

Kim, J., and C. W. Mueller. 1978. *Introduction to Factor Analysis: what it is and how to do it.* Sage Publications, Beverly Hills.

Kim, J., and C. W. Mueller. 1978. *Factor analysis: statistical methods and practical issues.* Sage Publications, Beverly Hills.

Kim, J., and W. Enders. 1991. Real and Monetary Causes of Real Exchange Rate Movements in the Pacific Rim. *Southern Journal of Economics* 57:1061-1070.

Kim, K. 1988. *Equilibrium Business Cycle Theory in Historical Perspective.* Cambridge University Press.

King, R, C. Plosser and S. Rebelo. 1988. Production, Growth and Business Cycles I. The Basic Neoclassical Model. *Journal of monetary Economics* 21:195-232.

King, R., C. Plosser, J. Stock, and M. Watson. 1987. Stochastic Trends and Economic Fluctuations. NBER Working Paper no. 2229. Cambridge.

Krieger, R. 1989. Sectoral and Aggregate Shocks to Industrial Output in Germany, Japan and Canada. Federal Reserve Board. Finance and Economics Discussion Series no. 75, Washington, D.C.

Post-War Years. *Journal of Economic Dynamics and Controls* 14:523-551.

Norrbin, S. C., and D. E. Schlagenhauf. 1991. The Importance of Sectoral and Aggregate Shocks in Business Cycles. *Economic Inquiry* 24:317-335.

Phillips, P. C. B. 1986. Understanding Spurious Regressions in Econometrics. *Journal of Econometrics* 33:311-340.

Phillips, P. C. B., and P. Perron. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75:335-346.

Pigou, A. C. 1927. *Industrial Fluctuations*. Macmillan, New York.

Plosser, C. I. 1989. Understanding Real Business Cycles. *Journal of Economic Perspectives* 3:51-77.

Prescott, E. C., and R. E. Lucas. 1972. A note on Price Systems in Infinite Dimensional source. *International Economic Review* 13: 416-422.

Romer, C. D. 1991. The Cyclical Behavior of Individual Production Series, 1889-1984. *Quarterly Journal of Economics* 106:1-31.

Sargent, T. J. 1987. *Dynamic Macroeconomic Theory*. Harvard University Press.

Schumpeter, J. A. 1939. *Business Cycles*. McGraw-Hill, New York.

Shapiro, M. D., and M. W. Watson. 1988. Sources of Business Cycle Fluctuations. *NBER Macroeconomics Annual* 3:111-148.

Shiller, R. J. 1987. Ultimate Sources of Aggregate Variability. *American Economic Review Proceedings* 77:87-92.

Sims, C. A. 1972. Money, Income and Causality. *American Economic Review* 62:540-552.

Sims, C. A. 1980. Macroeconomics and Reality. *Econometrica* 48:1-48.

Sims, C. A. 1986. Are Forecasting Models Usable for Policy Analysis? *Quarterly Review*. Federal Reserve Bank of Minneapolis (Winter):2-16.

Stock, J. and M. Watson. 1988. Variable Trends in Economic Time Series. *Journal of Economic Perspectives* 2:147-174.

Stockman, A. C. 1988. Sectoral and National Aggregate Disturbances to Industrial Output in Seven European Countries. *Journal of Monetary Economics* 21:387-409.
Todd, R. M. 1990. Vector Autoregression Evidence on Monetarism: Another Look at the Robustness Debate. Quarterly Review. Federal Reserve Bank of Minneapolis (Spring):19-37.

United Nations. 1988. *National Accounts Statistics: Main Aggregates and Detailed Tables*, Part I.

Watson, M. W. 1986. Univariate Detrending Methods with Stochastic Trends. *Journal of Monetary Economics* 18:49-75.

Wicksell, K. 1935. *Lectures on Political Economy*. Macmillan, New York.

APPENDIX A DERIVATION OF DECISION RULES IN SECTION 3.1

The way how to solve the problem given in section 3.1 can be described in the following manner. The conjectured solution can be given by

$$V(S_t) = \phi_1 \ln Y_{1t} + \phi_2 \ln Y_{2t} + \phi_3 \ln Y_{3t} + J(\lambda_t) + K \qquad \text{(A-1)}$$

Shifting (A-1) one time period forward and substituting (3-2) - (3-4) into it yields

$$\begin{aligned} V(S_{t+1}) &= \phi_1 \ln Y_{1t+1} + \phi_2 \ln Y_{2t+1} + \phi_3 \ln Y_{3t+1} + J(\lambda_{t+1}) + K \\ &= \phi_1(\ln\lambda_{1t+1} + b_1 \ln L_{1t} + \alpha_{11}\ln X_{11t} + \alpha_{21}\ln X_{21t} + \alpha_{31}\ln X_{31t}) \\ &\quad + \phi_2(\ln\lambda_{2t+1} + b_2 \ln L_{2t} + \alpha_{12}\ln X_{12t} + \alpha_{22}\ln X_{22t} + \alpha_{32}\ln X_{32t}) \\ &\quad + \phi_3(\ln\lambda_{3t+1} + b_3 \ln L_{3t} + \alpha_{13}\ln X_{13t} + \alpha_{23}\ln X_{23t} + \alpha_{33}\ln X_{33t}) \\ &\quad + J(\lambda_{t+1}) + K \qquad \text{(A-2)} \end{aligned}$$

Taking conditional expectation on both sides of (A-2) gives

$$\begin{aligned} E[V(S_{t+1})|S_t] &= \phi_1(b_1 \ln L_{1t} + \alpha_{11}\ln X_{11t} + \alpha_{21}\ln X_{21t} + \alpha_{31}\ln X_{31t}) \\ &\quad + \phi_2(b_2 \ln L_{2t} + \alpha_{12}\ln X_{12t} + \alpha_{22}\ln X_{22t} + \alpha_{32}\ln X_{32t}) \\ &\quad + \phi_3(b_3 \ln L_{3t} + \alpha_{13}\ln X_{13t} + \alpha_{23}\ln X_{23t} + \alpha_{33}\ln X_{33t}) \\ &\quad + E[J(\lambda_{t+1})|\lambda_t] + K \qquad \text{(A-3)} \end{aligned}$$

since $E(\ln\lambda_{it+1}|\lambda_{it}) = E(\ln\lambda_{it+1})$ (by i.i.d)

$$X_{21t}: \frac{\phi_2}{C_{2t}+X_{21t}+X_{22t}+X_{23t}} = \frac{\beta\phi_1 a_{21}}{X_{21t}} \quad \text{(A-11)}$$

$$X_{22t}: \frac{\phi_2}{C_{2t}+X_{21t}+X_{22t}+X_{23t}} = \frac{\beta\phi_2 a_{22}}{X_{22t}} \quad \text{(A-12)}$$

$$X_{23t}: \frac{\phi_2}{C_{2t}+X_{21t}+X_{22t}+X_{23t}} = \frac{\beta\phi_3 a_{23}}{X_{23t}} \quad \text{(A-13)}$$

$$X_{31t}: \frac{\phi_3}{C_{3t}+X_{31t}+X_{32t}+X_{33t}} = \frac{\beta\phi_1 a_{31}}{X_{31t}} \quad \text{(A-14)}$$

$$X_{32t}: \frac{\phi_3}{C_{3t}+X_{31t}+X_{32t}+X_{33t}} = \frac{\beta\phi_2 a_{32}}{X_{32t}} \quad \text{(A-15)}$$

$$X_{33t}: \frac{\phi_3}{C_{3t}+X_{31t}+X_{32t}+X_{33t}} = \frac{\beta\phi_3 a_{33}}{X_{33t}} \quad \text{(A-16)}$$

$$L_{1t}: \frac{\phi_0}{H - L_{1t} - L_{2t} - L_{3t}} = \frac{\beta\phi_1 b_1}{L_{1t}} \quad \text{(A-17)}$$

$$L_{2t}: \frac{\phi_0}{H - L_{1t} - L_{2t} - L_{3t}} = \frac{\beta\phi_2 b_2}{L_{2t}} \quad \text{(A-18)}$$

$$L_{3t}: \frac{\phi_0}{H - L_{1t} - L_{2t} - L_{3t}} = \frac{\beta\phi_3 b_3}{L_{3t}} \quad \text{(A-19)}$$

Equation (A-17) - (A-19) simultaneously determine the following labor input decisions:

$$L_{1t}^{*} = \frac{\beta\phi_1 b_1}{\theta_0+\beta(\phi_1 b_1+\phi_2 b_2+\phi_3 b_3)} H \quad \text{(A-20)}$$

$$L_{2t}^{*} = \frac{\beta\phi_2 b_2}{\theta_0+\beta(\phi_1 b_1+\phi_2 b_2+\phi_3 b_3)} H \quad \text{(A-21)}$$

$$L_{3t}^{*} = \frac{\beta\phi_3 b_3}{\theta_0+\beta(\phi_1 b_1+\phi_2 b_2+\phi_3 b_3)} H \quad \text{(A-22)}$$

Equation (A-5), (A-8), (A-9), (A-10) and (3-6) simultaneously determine the following consumption and input decisions:

$$C_{1t}^{*} = \frac{\theta_1}{\theta_1+\beta(\phi_1 a_{11}+\phi_2 a_{12}+\phi_3 a_{13})} Y_{1t} \qquad \text{(A-23)}$$

$$X_{11t}^{*} = \frac{\beta\phi_1 a_{11}}{\theta_1+\beta(\phi_1 a_{11}+\phi_2 a_{12}+\phi_3 a_{13})} Y_{1t} \qquad \text{(A-24)}$$

$$X_{12t}^{*} = \frac{\beta\phi_2 a_{12}}{\theta_1+\beta(\phi_1 a_{11}+\phi_2 a_{12}+\phi_3 a_{13})} Y_{1t} \qquad \text{(A-25)}$$

$$X_{13t}^{*} = \frac{\beta\phi_3 a_{13}}{\theta_1+\beta(\phi_1 a_{11}+\phi_2 a_{12}+\phi_3 a_{13})} Y_{1t} \qquad \text{(A-26)}$$

Equation (A-6), (A-11), (A-12), (A-13) and (3-7) simultaneously determine the following consumption and input decisions:

$$C_{2t}^{*} = \frac{\theta_2}{\theta_2+\beta(\phi_1 a_{21}+\phi_2 a_{22}+\phi_3 a_{23})} Y_{2t} \qquad \text{(A-27)}$$

$$X_{21t}^{*} = \frac{\beta\phi_1 a_{21}}{\theta_2+\beta(\phi_1 a_{21}+\phi_2 a_{22}+\phi_3 a_{23})} Y_{2t} \qquad \text{(A-28)}$$

$$X_{22t}^{*} = \frac{\beta\phi_2 a_{22}}{\theta_2+\beta(\phi_1 a_{21}+\phi_2 a_{22}+\phi_3 a_{23})} Y_{2t} \qquad \text{(A-29)}$$

$$X_{23t}^{*} = \frac{\beta\phi_3 a_{23}}{\theta_2+\beta(\phi_1 a_{21}+\phi_2 a_{22}+\phi_3 a_{23})} Y_{2t} \qquad \text{(A-30)}$$

Equation (A-7), (A-14), (A-15), (A-16) and (3-8) simultaneously determine the following consumption and input decisions:

$$C_{3t}^{*} = \frac{\theta_3}{\theta_3+\beta(\phi_1 a_{31}+\phi_2 a_{32}+\phi_3 a_{33})} Y_{3t} \qquad \text{(A-31)}$$

$$X_{31t}^{*} = \frac{\beta\phi_1 a_{31}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \tag{A-32}$$

$$X_{32t}^{*} = \frac{\beta\phi_2 a_{32}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \tag{A-33}$$

$$X_{33t}^{*} = \frac{\beta\phi_3 a_{33}}{\theta_3 + \beta(\phi_1 a_{31} + \phi_2 a_{32} + \phi_3 a_{33})} Y_{3t} \tag{A-34}$$

From (A-5) we have the following equilibrium condition:

$$\phi_1 C_{1t} = \theta_1 C_{1t} + \theta_1 X_{11t} + \theta_1 X_{12t} + \theta_1 X_{13t} \tag{A-35}$$

Substituting optimal decisions into equation (A-35) and rearranging the terms yields

$$\phi_1 = \theta_1 + \beta(\phi_1 \alpha_{11} + \phi_2 \alpha_{12} + \phi_3 a_{13}) \tag{A-36}$$

From (A-6) we have the following equilibrium condition:

$$\phi_1 C_{2t} = \theta_2 C_{2t} + \theta_2 X_{21t} + \theta_2 X_{22t} + \theta_2 X_{23t} \tag{A-37}$$

Substituting optimal decisions into equation (A-37) and rearranging the terms yields

$$\phi_2 = \theta_2 + \beta(\phi_1 \alpha_{21} + \phi_2 \alpha_{22} + \phi_3 a_{23}) \tag{A-38}$$

Similarly we have the following equilibrium condition from (A-7)

$$\phi_3 C_{3t} = \theta_3 C_{3t} + \theta_3 X_{31t} + \theta_3 X_{32t} + \theta_3 X_{33t} \qquad \text{(A-39)}$$

By the same procedure we have the following equation:

$$\phi_3 = \theta_3 + \beta(\phi_1 \alpha_{31} + \phi_2 \alpha_{32} + \phi_3 \alpha_{33}) \qquad \text{(A-40)}$$

Equation (A-36), (A-38) and (A-40) simultaneously determine ϕ_1, ϕ_2 and ϕ_3 in terms of parameters.

APPENDIX B IMPULSE AND PROPAGATION MECHANISM

This appendix shows how "exterior impulses" are "propagated" through time and across sectors in the case of three sectors. From the equation (3-16) in Section 3.1 we have the following linear system of stochastic difference equations if the disturbances are decomposed into common aggregate shock and sector-specific shocks. Assume that coefficients are time-invariant.

$$y_{1t} = \alpha_{11}y_{1t-1} + \alpha_{21}y_{2t-1} + \alpha_{31}y_{3t-1} + f_1c_t + e_{1t}$$
$$y_{2t} = \alpha_{12}y_{1t-1} + \alpha_{22}y_{2t-1} + \alpha_{32}y_{3t-1} + f_2c_t + e_{2t}$$
$$y_{3t} = \alpha_{13}y_{1t-1} + \alpha_{23}y_{2t-1} + \alpha_{33}y_{3t-1} + f_3c_t + e_{3t}$$

where, the coefficients $(\alpha_{11},\ldots.\alpha_{33})$ represent the propagation mechanism while the coefficients, $(f_1,..f_3)$, represent the sectoral output responses to the aggregate impulse.

A positive shock in sector i may result from either aggregate shock or sector i-specific shock. Therefore we can trace out how a shock in one sector is propagated across sectors.

(Case 1) Suppose there is a positive sector-specific shock (Δ_1) in sector 1 at time t. Then the shock is transmitted across sectors and time in the following way:

sector\time	t	t+1	t+2
Δy_1	Δ_1	$a_{11}\Delta_1$	$(a_{11}^2+ a_{21}a_{12}+ a_{31}a_{13})\Delta_1$
Δy_2	-	$a_{12}\Delta_1$	$(a_{12}a_{11}+ a_{22}a_{12}+ a_{32}a_{13})\Delta_1$
Δy_3	-	$a_{13}\Delta_1$	$(a_{13}a_{11}+ a_{23}a_{12}+ a_{33}a_{13})\Delta_1$

Note that it takes one time period for sector-specific shocks to propagate across sectors.

(Case 2) Suppose there is a positive aggregate shock (Δ_c). Then the shock is transmitted across sectors and time in the following way:

sector\time	t	t+1	t+2
Δy_1	$f_1\Delta_c$	$(a_{11}f_1+ a_{21}f_2+ a_{31}f_3)\Delta_c$	$a_{11}\Delta^1_{t+1}+ a_{21}\Delta^2_{t+1}+ a_{31}\Delta^3_{t+1}$
Δy_2	$f_2\Delta_c$	$(a_{12}f_1+ a_{22}f_2+ a_{32}f_3)\Delta_c$	$a_{12}\Delta^1_{t+1}+ a_{22}\Delta^2_{t+1}+ a_{32}\Delta^3_{t+1}$
Δy_3	$f_3\Delta_c$	$(a_{13}f_1+ a_{23}f_2+ a_{33}f_3)\Delta_c$	$a_{13}\Delta^1_{t+1}+ a_{23}\Delta^2_{t+1}+ a_{33}\Delta^3_{t+1}$

where, $\Delta^1_{t+1}\equiv(a_{11}f_1+a_{21}f_2+a_{31}f_3)\Delta_c$, $\Delta^2_{t+1}\equiv(a_{12}f_1+a_{22}f_2+a_{32}f_3)\Delta_c$, and $\Delta^3_{t+1}\equiv(a_{13}f_1+a_{23}f_2+a_{33}f_3)\Delta_c$.

Note that the aggregate shock is propagated across sectors immediately.

The procedure is to choose simultaneously a parameter vector which minimizes the distance between the actual sample covariance matrix and the predicted covariance matrix given the model and the parameter estimates.

The system is over-identified (under-identified) if the number of equations is greater (smaller) than the number of parameters to be estimated (f_1, f_2, f_3, f_4, σ^2_c, σ^2_{e1}, σ^2_{e2}, σ^3_{e4} and σ^3_{e3}) and the system is just-identified if the number of equations is equal to the number of parameters to be estimated. In this case, there are 10 equations and 9 parameters so that the system is over-identified.

APPENDIX D INDUSTRY AND ITS WEIGHT

There are sixteen monthly industrial production series from 1970:1 to 1990:12. The industry acronyms are defined as follows:

Total:	Total industrial production
Mining:	Mining industry
Non-durable:	Non-durable manufacturing industry
Durable:	Durable manufacturing industry
Coal(COAL):	Coal mining
Ore(METL):	Metal ore mining
Othermin(OMIN):	Other mining
Food(FBT):	Food, beverages and tobacco
Chemicals(CPRP):	Chemicals and petroleum, coal, rubber, and plastic products
Textiles(TWL):	Textiles, wearing apparel and leather
Paper(PPP):	Paper and paper products, printing and publishing
Glass(NMMP):	Non-metallic products
Wood(WAF):	Wood and wood products including furniture
Basmetal(BMET):	Basic metal
Fabmetal(FMME):	Fabricated metal products, machinery and equipment
Otherman(OMAN):	Other manufacturing

Two types of weight reported in the next table: one is the share of sectoral output out of the total output (w_i) and the other is the share of sectoral output out of its industry output (w_i^I).

Industry	Sector	w_i	w_i^I
Mining	Coal	.01931	.65859
	Metal ore	.00155	.05287
	Other mining	.00846	.28854
(Total)			1.0
Non-Durable	Food	.10413	.21032
	Chemicals	.17679	.35709
	Textiles	.16935	.34206
	Paper	.04482	.09053
(Total)			1.0
Durable	Glass	.03826	.09338
	Wood	.01485	.03624
	Basic metal	.05324	.12994
	Fabricated metal	.2835	.6919
	Otherman	.01989	.04854
(Total)			1.0
(Sub-total)		.93415	
Excluded Electricity		.06585	
(Total)		1.0	