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A REAL-TIME DATA SET FOR MACROECONOMISTS:
DOES THE DATA VINTAGE MATTER?

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A REAL-TIME DATA SET FOR MACROECONOMISTS: DOES THE DATA VINTAGE MATTER?

Abstract

This paper presents a real-time data set that can be used by economists for testing the robustness of published econometric results, for analyzing policy, and for forecasting. The data set consists of vintages, or snapshots, of the major macroeconomic data available at quarterly intervals in real time. The paper illustrates why such data may matter, explains the construction of the data set, examines the properties of several of the variables in the data set across vintages, and examines key empirical papers in macroeconomics, investigating their robustness to different vintages.

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I. INTRODUCTION

Macroeconomists use historical data for a variety of purposes: to test models, to analyze economic events, and to forecast. In many cases, however, the data that should be used in these studies are not the (final, revised) data available from government statistical agencies today, but rather the original, unrevised data available to economic agents who were around at the time. In other cases, the ability to verify published findings and to check the robustness of those findings to different data sets is an important test of the validity of the results.

These reasons motivated us to create a data set that gives snapshots of macroeconomic data available to an academic researcher, policymaker, or forecaster at any given date in the past. We refer to each data set corresponding to the information set at a particular date as a “vintage” and to the collection of such vintages as a “real-time data set.”

This paper explains the reasons for the construction of this data set, describes the data set, and provides some empirical demonstrations of cases when the vintage matters and when it doesn’t matter.

The type of analysis we perform in this paper is related to earlier literature. The most well-known study that compared results based on real-time data with later data was Diebold and Rudebusch (1991), who showed that the index of leading indicators does a much worse job of predicting future movements of output in real time than it does after the data are revised. Runkle (1998) has developed some ideas similar to those in this paper, using a real-time data set on real output to show how much vintage matters. There have been a number of attempts to examine how preliminary and incomplete data affect monetary policy, beginning with the seminal study of

Maravall and Pierce (1986), who showed that even though the revisions to measures of the money supply are large, monetary policy wouldn't have been much different if more accurate data had been known. Recently, a number of studies have analyzed similar issues in the context of Taylor's rule for setting monetary policy. These studies include: (1) Orphanides (1997), who showed that Taylor's rule doesn't fit nearly as well in real time as it does using revised data; (2) Ghysels, Swanson, and Callan (1998), who showed that, contrary to the results of Maravall and Pierce, if the Fed used a Taylor-type rule and based policy decisions on changes in the index of industrial production, policy would have improved significantly if policymakers waited for data to be revised, rather than reacting to newly released data; (3) Evans (1998), who found that the federal funds futures market does a better job of forecasting the federal funds rate than does a Taylor-type rule, using real-time data; (4) Orphanides (1998), who uses such policy rules to examine the impact of data uncertainty on the optimal rule; and (5) Rudebusch (1998b), who showed that although some research (which assumed that data don't get revised) suggests that the optimal coefficients in a Taylor-type rule are much bigger than Taylor originally suggested, data uncertainty potentially plays an important role in reducing the coefficients in the rule. Amato (1998) looks at the predictive power of M2 using real-time data. In addition, Rudebusch (1998a) questions the value of VAR estimates of monetary-policy shocks because they aren't based on real-time data.

Our goal is to provide a foundation for these types of studies and to provide benefits by allowing researchers to use a standard data set, rather than being forced to collect all the real-time data themselves for every different study. Section II of this paper describes the data set. In section III, we look at the properties of selected variables across vintages, to illustrate how much vintage matters for raw data. In section IV, we look more closely at real consumption data, examining the structure of the revisions. In section V, we look at some key empirical papers in macroeconomics and explore the degree to which vintage matters for their results. We draw conclusions from these results in section VI.

II. THE DATA SET

In a lengthy process over the past eight years, we have developed our real-time data set. It consists of a series of vintages of data, each corresponding to an economist's information set on the date of the vintage. For example, the February 1977 vintage of data contains information on GNP and all its components, as well as other macroeconomic variables, just as an economist would have viewed the data on February 15, 1977. There's one of these data sets for each quarter, beginning in November 1965, each containing information that was available on the 15th day of the middle month of the quarter.

Data in each vintage include nominal and real GNP (GDP after 1991); the components of real GNP/GDP, including total personal consumption expenditures, broken down into durables, nondurables, and services; business fixed investment; residential investment; the change in business inventories; government purchases (government consumption and government investment since 1996); exports and imports; the chain-weighted GDP price index (since 1996); the M1 and M2 measures of the money supply; total reserves at banks (adjusted for changes in reserve requirements); nonborrowed reserves; nonborrowed reserves plus extended credit; the adjusted monetary base (measures of reserves and the monetary base are from the Federal Reserve Board, not the St. Louis Fed); the civilian unemployment rate; the consumer price index

(CPI-U); the three-month T-bill interest rate; and the 10-year Treasury bond interest rate. The interest rates are included for completeness, even though they are never revised. The vintages are mostly complete; there are some missing data for the money stock variables and a lot of missing data for the monetary base and reserves variables. For additional descriptive information about the construction of the real-time data, see Croushore and Stark (1999). For complete notes on all the variables and any missing data, see the documentation files on our web page: www.phil.frb.org/page.asp?page=forecastreal.

III. DATA REVISIONS

How big are the revisions to the data? We don't have space here to describe the revisions to all the data, so we'll look at certain key variables, including nominal output, real output, real consumption spending, and the price level.

First, let's see how much vintage matters for the medium run, that is, five-year average growth rates. Table III.1 shows the annual average growth rate over five-year periods from 1949Q4 to 1994Q4 for data from vintages dated November 1975, 1980, 1985, 1991, 1995, and 1998. The first five of these vintages were chosen because they were the last vintages prior to a comprehensive revision of the national income and product accounts; the last vintage, November 1998, is the latest available data at the time this article was first written. For ease of exposition, we'll call these benchmark vintages. Each of the comprehensive revisions that were made after our benchmark vintage dates incorporated major changes to the data, including new source data and definitional changes. In addition, the base year was changed for real variables in January 1976 (from 1958 to 1972), in December 1985 (from 1972 to 1982), in late November 1991 (from

1982 to 1987), and in January 1996 (from 1987 to 1992), so some of the differences across the benchmark vintages we look at incorporate base-year changes, which affect real variables. In particular, since the base-year changes in 1976, 1985, and 1991 used the old fixed-weighted index methodology, the change of base year alters the timing of substitution bias; this bias is large for dates further away from the base year.

There are two other changes of note regarding the comprehensive revisions. First, the output variable (both real and nominal) is GNP before 1992, but GDP since then. Our data set is consistent with the "headline" variable, but users need to be aware of this change, since the differences between GNP and GDP are not random; they are persistent in sign. So some of the differences across vintages in nominal and real output arise because of this definitional change.[1] In the current exercise, keep in mind that differences in benchmark vintages before and after 1992 reflect this change.

The second major change in methodology comes from the switch to chain weighting in vintages beginning in 1996. This represented a significant change in how real variables were constructed, one that greatly reduces the substitution bias. In particular, the switch to chain weighting means that a change of base year (which is arbitrary under chain weighting) will have no effect on the growth rates of variables, whereas the growth rates changed significantly under the old fixed-weighting method.

Reading across the columns of Table III.1 shows how the five-year annual average growth rate has changed across benchmark vintages. Nominal output from the 1950s and 1960s

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[1] We could create a data set with all GNP data, but GNP data are no longer released at the same time as the headline number (GDP), so the timing in all the data sets would change.

wasn't revised too much, but the data from the 1970s and early 1980s show changes of as much as 0.5 percentage point across vintages. Real output is strongly affected by changes in benchmark vintage, especially when the base year is changed. The differences are, on average, much larger than they are for nominal output. Especially large changes show up in the November 1991 benchmark vintage (reflecting the base-year shift of December 1985) and the November 1998 benchmark vintage (reflecting the move to chain weighting). Shifts similar to those of real output, but in the opposite direction, show up in the data on the price level.[2] Finally, changes across benchmark vintages in growth rates for real consumption are usually in the same direction as changes in real output growth rates but of smaller magnitude.

To investigate these issues further, we examine plots (Figures III.1 to III.4) of the same data, where we show differences between the log levels of the variables, with the mean difference subtracted (since it reflects mainly base-year changes). Define the variable X(t,s) as the level of the data for time t in vintage s. The plots show, for each date t, the log [X(t,a)/X(t,b)] - m, where m is the mean of log[X(τ,a)/X(τ,b)] over the largest sample of τ contained in both vintages, and where b is a later vintage than a.[3]

In the figures, each column of plots represents a particular benchmark vintage (1 to 5). In each row, the data from a particular vintage (2 to 6) are subtracted from the data from the benchmark vintage in that column. The labels on each plot follow the structure Lz#, where L means the logarithm of the variable, z represents the variable (z=N for nominal output, z=Y for

[2] Note that the price level in the November 1998 vintage is the chain-weighted price index; in earlier vintages, it's the deflator. But the differences between the two concepts are trivial.

[3] Since we've removed the mean, we won't capture any mean shifts in variables, but those are illustrated in Table III.1.

real output, z=P for the price level, z=C for real consumption) and where # represents the benchmark vintage, with #=1 for the November 1975 vintage, #=2 for 1980, #=3 for 1985, #=4 for 1991, #=5 for 1995, and #=6 for 1998. Reading along the main diagonal of the plots reflects a comparison of adjacent benchmark vintages; the plots below the main diagonal reflect comparisons across more than one benchmark vintage. Each plot shows dates along the horizontal axis from 1947Q1 to 1998Q3. The last data point plotted is 1975Q3 in column 1, 1980Q3 in column 2, 1985Q3 in column 3, 1991Q3 in column 4, and 1995Q3 in column 5. The vertical axis in each plot runs from -0.08 to +0.08; these are demeaned log differences.

There are three major features to note about the plots: (1) trends; (2) spikes; and (3) persistent deviations from a linear trend. First, the dominant feature of the plots is the presence of trends. A downward tilt means that data from a later vintage were revised upward relative to earlier-vintage data, reflecting faster trend growth; similarly, an upward tilt means that later data points were revised downward relative to earlier data. Second, a spike in a plot means that data for a particular date or series of dates were revised significantly in one direction relative to other dates in the sample. The third source of difference in the plots is the presence of long-lived deviations from a linear trend (or, when no trend is evident, from zero), suggesting that there are low frequency differences between vintages. Unit root tests find some of the plots exhibiting stationarity, while others do not. Taken together, the plots point to cross-vintage differences at many frequencies, an observation we explore shortly in the frequency domain.

In Figure III.1, the most striking result is the downward spike in all the plots in the first column. This arose because the original estimates of nominal GNP (in vintage 1) in late 1974 through the third quarter of 1975 were too low. Data used in the comprehensive revision of

January 1976 raised nominal GNP substantially, especially in 1975Q3. But GNP for that date was also increased substantially in the annual revisions that occurred in July 1976 and July 1977. So the spike is attributable to a series of new source data over time that made a substantial difference in the level of nominal GNP over the course of several quarters.

In Figure III.2, the effects of substitution bias are apparent. You'll note that the real output series, especially moving from vintage 3 to vintage 4, is tilted upward. This arises because the fixed-weighted method using the 1982 base year greatly changes the relative pricing relationships between energy and other goods. Thus, even data from long before were affected in a strong way, leading to a tilt in the plot. But note that when we move from vintage 5 to vintage 6, chain weighting reverses that effect. Notice also that the movement from GNP to GDP (from vintage 4 to vintage 5) didn't cause much of a permanent effect in the log ratio, though some serial correlation is evident in the series.

Figure III.3 shows that the price level is affected quite a bit by vintage changes. As with real output, note the substantial tilt between vintages 3 and 4. The downward tilt shows the large change in relative prices over time reflected in the price index. This tilt was reversed when we moved to chain-weighting, as the lower right-hand plot between vintages 5 and 6 shows. Note that the net effect on long-ago data, shown in the lower left-hand plot between vintages 1 and 6, is relatively small.

Figure III.4 shows that real consumption revisions do not mirror real output revisions terribly closely, so it has its own unique differences across vintages. There are substantial tilts in the plots, but many of them reverse direction, which means there's more going on than substitution bias, as was the case for real output. The move to chain weighting, shown in the lower right-hand plot, shows up as a reversal of the tilt in earlier plots. In the plot showing the differences between vintages 2 and 3, we see that there was very little difference at all across the vintages for data between 1947 and 1968.

Spectral Analysis

Another method of looking at the revisions is to use spectral analysis.[4] The idea is to make a transformation into the frequency domain, allowing us to look at the spectrum to see where the main action is in the revisions. If the revisions are white noise, the spectrum will be flat. But spectra with peaks at different frequencies show that the revisions aren't white noise but follow patterns at the given frequencies.

To estimate the population spectrum, we use nonparametric (kernel) methods described by Hamilton (1994, pp. 165-7).[5] We'll show figures just for real consumption, though the spectral estimates for other real variables are similar.

We begin by estimating the spectrum of the ratio of the logarithms of real consumption across benchmark revisions (Figure III.5), using the same naming conventions used earlier. The estimates are neither surprising, nor terribly interesting, as they exhibit the typical spectral shape of macroeconomic data (Sargent, 1987, pp. 279-83), indicating that most of the power resides at low frequencies.

More interesting are the spectra of the revisions to quarterly growth rates of real consumption (Figure III.6). In some cases there's action at business-cycle frequencies

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[4] The present analysis is in the spirit of Sargent (1987, pp. 346-8), who showed that inferences drawn from VAR coefficients can be susceptible to measurement errors in the underlying data.

[5] In particular, we're using a kernel estimate with a tent-shaped window of width 9.

(frequencies between 0.2 and 0.8 correspond to business cycles, with periodicity ranging from roughly eight years for a frequency of 0.2, to two years for a frequency of 0.8), as in the lower middle graph (reflecting the revision from benchmark vintage November 1991 to November 1995). In other cases, most of the differences are seasonal, as in the lower left graph, at a frequency of 1.5, which corresponds to a periodicity of four quarters.

It is of some interest to examine the relationship of revisions across variables. In the frequency domain, this can be done by examining the squared coherences of the revisions. We show such coherences for real output growth revisions and real consumption growth revisions (Figure III.7). In most of the graphs, the coherence is high at business-cycle frequencies, but note that each different set of benchmark vintages seems to have slightly different coherence, perhaps because of the influence of definitional changes or particular changes in relative prices on the consumption component of output.

All these differences across vintages point to the fact that the data are revised substantially. If we look at quarterly log differences from one quarter to the next in the variables (Table III.2), we find that while most of the correlations across these vintages are above 0.9, the correlations aren't as high as one might expect, given that these are different measurements of data over the same period. Thus, growth rates from quarter to quarter can change substantially; they may even be large from one year to the next. To sharpen our focus on these issues, we now take a particular variable, real consumption, and run some additional tests to illustrate how much vintage matters for growth rates.

IV. PROPERTIES OF REAL CONSUMPTION DATA ACROSS VINTAGES

The examples given in the introduction were illustrative of the types of issues for which having a real-time data set may be important. But how much does it really matter? Are the differences between the real-time data and the final revised data trivial? Or do they matter economically?

To further investigate the degree to which having a real-time data set matters, we begin by looking at real consumption spending from the national income accounts.[6] We select three vintages, dated February 1986, November 1993, and February 1998, and plot the data on real consumption growth (quarterly, at annual rates) from 1947Q2 to 1985Q4 (Figure IV.1). There are substantial differences between the growth rates, especially in the 1950s. One important difference between the vintages is that the 1986 and 1993 vintage data sets use a fixed base year to calculate real consumption spending, whereas the 1998 vintage data set uses chain weighting. To demonstrate this more clearly, we plot the differences between the growth rates across each pair of vintages of the data (Figure IV.2). You can see that in some quarters the growth rates of consumption change nearly 5 percentage points, and differences of more than 2 percentage points are not uncommon. Moreover, in many instances, significant differences of the same sign persist for more than a quarter, and the variance of the differences in the growth rates appears to change over time. However, there's not as much difference between the February 1986 and November 1993 vintages as there is between either of those and the February 1998 chain-weighted vintage.

A slightly different way of looking at the data is to compare how the data change between when they are first released and later versions. Because we collect the data in mid-quarter, the

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[6] We don't examine real output, as Runkle (1998) did, because the switch from GNP to GDP in 1992 led to systematic differences, which may affect some of the tests we perform later.

first time an additional observation appears in the data set for a particular quarter, it is the version of the data known as the "advance" release. We can track the value of the observation from its advance value to its latest (most recent) value. One reason for doing this is to see the extent to which the revisions are characterized as containing news or reducing noise, as suggested by Mankiw, Runkle, and Shapiro (1984) and Mankiw and Shapiro (1986). The idea is that if the revisions are characterized as containing news, subsequent releases of the data for that date contain new information that was not available in the earlier releases. As a result, the advance release is an efficient estimate of later data. This implies that the revision to the data is correlated with the revised data but not with the earlier data. It also implies that the variance of the data should increase as we look at later and later vintages, since an optimal forecast is smoother than the data. On the other hand, if data are characterized as reducing noise, subsequent releases of the data just eliminate noise in the earlier release, so the earlier release is the true value plus measurement error that gets reduced over time. In this case, the revision should be uncorrelated with the revised data, but correlated with the advance data. In addition, the variance of the data should decline as it is further revised. In running tests for news and noise, Mankiw and Shapiro found that the revisions to real GNP data from 1976 to 1982 were best characterized as containing news, while Mankiw, Runkle, and Shapiro found that the revisions to money were best characterized as reducing noise.

To formalize this, we use the following notation. Let X(t, s) represent the data for date t as of vintage s. Then a revision of the data from vintage i to vintage j (where j > i) is $e(t, i, j) \equiv X(t, j) - X(t, i)$. For example, e(93Q4, Feb. '94, Feb. '95) ≡ X(93Q4, Feb. '95) - X(93Q4, Feb. '94). To say that a revision is characterized as containing news means that the revision is uncorrelated (orthogonal) to earlier vintage data, so that e(t, i, j) $\perp$ X(t, i). To say that a revision is characterized as reducing noise means that the revision is uncorrelated with later vintage data, so that e(t, i, j) $\perp$ X(t, j).

We begin by looking at four different data sets, each consisting of quarterly growth rates of real consumption. One data set (labeled initial) consists of the growth rate each quarter as shown in the advance release made available one month after the end of a quarter, which is X(t, t+1), where t+1 refers to the vintage 1 quarter after date t. The second (labeled 1-year-later estimate) consists of the growth rate for a quarter based on a data set with a vintage one year after the initial vintage or five quarters after date t, X(t, t+5); the third (3-year-later estimate) is based on a vintage three years after the initial vintage or 13 quarters after date t, X(t, t+13). The fourth data set (latest) consists of the November 1998 vintage of data, X(t, Nov. 1998).

A time-series plot of the four-quarter moving average of real consumption growth rates from these four different data sets shows that although the qualitative movements of the different series are similar, growth rates across the series can vary by significant amounts—as much as two percentage points (Figure IV.3).

It's also instructive to examine the corresponding *revisions* to the data from the initial release to 1 year later, from 1 year to 3 years later, and from 3 years later to the latest data (Figure IV.4). Revisions to the four-quarter growth rates are often quite large from one of our data sets to the next, with many revisions exceeding 1 percentage point. The standard deviation of all the revisions is in the neighborhood of one-half of a percentage point. In going from the initial release to the final data, the revisions to the annual growth rates are even larger, with a standard deviation of 0.8 percentage point (Figure IV.5).

Are the revisions to real consumption data best characterized as containing news or reducing noise? To find out, we run tests like those of Mankiw and Shapiro. First, we examine the standard deviation of the real consumption growth rates from the four different data sets in Table IV.1. If the revisions contain news, the standard deviation should increase from initial, to 1-year, to 3-year, to latest data sets; if the revisions reduce noise, the standard deviation should decline as we move down the rows from initial to latest. As the table shows, the standard deviation rises from initial to 1 year, then falls in each successive series. So, the initial to 1-year revision contains news, while the 1-year to 3-year and 3-year to latest revisions reduce noise.

Next, we examine the correlation between the revisions and the growth rates (Table IV.2). Consistent with the earlier result, only the initial to 1-year revision can be characterized as containing news because it is correlated with later data and uncorrelated with earlier data. The other five revisions can be characterized as reducing noise because they are correlated with some earlier data and uncorrelated with later data. Overall, one could argue that revisions to the initial consumption data contain news and that subsequent revisions simply reduce noise.

These results suggest that revisions to the data can be substantial, so they could potentially influence the outcomes of research studies. The extent to which they do so is our next subject.

V. DOES VINTAGE MATTER FOR KEY MACROECONOMIC RESULTS?

It's clear that the vintage of the data makes a difference for growth rates in different periods, but does it matter for empirical work? We now take a number of empirical exercises from the economic literature, rerun them with differing vintages of data, and see how much the vintage matters. We examine empirical work by Kydland and Prescott (1990), Hall (1978), Beveridge and Nelson (1981), and Blanchard and Quah (1989).

Kydland and Prescott (1990)

Kydland and Prescott examine the correlation of real GNP with lags and leads of itself and other variables. They filter the data with an HP filter, then calculate the cross correlations. They use data from a 1990 vintage; we compare our results for data vintages from February 1990, February 1994, and February 1998 to their results (Table V.1) for output autocorrelations and cross-correlations between real GNP and the price deflator, real consumption, and M2. As the table shows, although there are some quantitative differences, the qualitative pattern is quite similar across all the vintages. A plot of the HP-filtered cyclical data from the three vintages shows little difference across vintages (Figure V.1). The biggest differences across vintages are on the order of one percentage point and occur only in the 1950s (Figure V.2). Trend real output growth also behaves similarly across vintages, though the four-quarter average of trend output growth can differ as much as 0.5 percentage point at times (Figure V.3). Part of the differences across vintages for real output could be attributable to the switch between GNP and GDP that occurred between the 1990 and 1994 vintages. So it's useful to also examine other variables, for which the revision pattern may be different. Figure V.4 shows results for real consumption, showing much smaller revisions between the 1990 and 1994 vintages. Altogether, however, since the purpose of Kydland and Prescott's research was to establish general business-cycle facts, it's hard to conclude that the data vintage matters.

Hall (1978)

Hall found evidence supporting the life-cycle/permanent-income hypothesis using data on U.S. consumption spending. Although Hall's results have been challenged and modified in a variety of ways, in such papers as those by Flavin (1981) and Deaton (1987), an even more fundamental question is: are Hall's empirical results robust to different data sets? That is, would we get significantly different outcomes depending on what vintage of data we used?

Hall's original data set included observations on consumption from 1948Q1 to 1977Q1, so we assume that he had data of vintage May 1977. Hall begins by testing to see if consumption can be predicted from its own past values. Under the pure life-cycle/permanent-income hypothesis, only the first lagged value of consumption should help predict current consumption. Hall regresses consumption on four lags of consumption, testing to see if the last three lags are jointly zero.[7] His original result is shown in the first line of Table V.2. In the table, the coefficient estimates are given, with standard errors in parentheses. The column labeled s shows the standard error of estimate; DW is the Durbin-Watson statistic; and F is the value of the F-statistic testing the hypothesis that the coefficients on the second, third, and fourth lags of consumption are jointly zero, with the p-value for the test shown in parentheses. The F-test shows that you can't reject the hypothesis at the 5 percent level.

Using our real-time data set with consumption data from the May 1977 vintage, we are able to replicate Hall's results fairly closely, as the second line of the table shows. Our replication confirms Hall's finding that the coefficients on the second, third, and fourth lagged terms are jointly zero.

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[7] The variable used is real consumption of nondurables and services divided by the population.

However, when we rerun the test on the same sample period (1948Q1 to 1977Q1) using vintage data from February 1998, the coefficients change dramatically, and the F-test now rejects the hypothesis that the second-through-fourth lagged consumption terms are jointly zero. The p-value for the test is only .02, so we reject the hypothesis at the 5 percent level.

Further, when we update the sample to include data through 1997, we reject the hypothesis even more convincingly. Again, the coefficient estimates change dramatically, and the F-statistic rises to 8.1, with a p-value of less than 0.005.

Further investigation shows that, beginning with Hall's vintage data, as we use data from later and later vintages, the p-value of the F-test declines (not changing the sample dates, just using later vintages of data). But the p-value remains above .05 until the shift to chain-weighting occurs.

These results mean that Hall's original hypothesis—that only the first lag of consumption matters in determining contemporaneous consumption—is not well supported by the data. Hall's test was legitimate, but his empirical result does not stand the test of time, either in terms of revisions to the data or in terms of additional data.

Beveridge and Nelson (1981)

In their classic 1981 paper, Beveridge and Nelson introduced a procedure for decomposing a time series into permanent and transitory components, in which both components were stochastic. The methodology depends only on past data, but revisions to the data could well make the vintage of the data matter. The question we pose is: does a change in the vintage of the data set make a significant difference to how a time series is decomposed?

We apply the Beveridge-Nelson procedure to data on real output and compare the results across vintages. We begin by assuming that their data, which included GNP data through 1977Q1, were the data available in May 1977. We run their procedure first on the May 1977 data set, again on the data set of May 1987, and again on the data set from August 1997, to compare the decomposition of data vintages a decade apart, but covering the same sample period (1947Q2 to 1977Q1). The original Beveridge-Nelson paper includes a decomposition of real GNP but doesn't indicate the time-series process used. Based on our implementation of Box-Jenkins methods, and comparing our results to those of Beveridge and Nelson, we think they used an ARIMA(1,1,2) process for real GNP, so we use that as well.[8]

The results show that the transitory components (Figure V.5) are not affected very much by the vintage of the data set. As the figure shows, the lower frequency movements of the transitory components are similar in all three vintages of the data. There are a few periods in which the transitory component differs in magnitude, such as in 1950, 1957, and 1968. But, overall, the vintage of the data set doesn't matter very much, at least at lower frequencies.

Repeating this exercise for other variables, such as real consumption shown in Figure V.6, shows similar patterns to that of real output, with the main differences across vintages coming when the data spike up or down.

Blanchard and Quah (1989)

Blanchard and Quah use a structural VAR in output and unemployment to define supply disturbances as shocks that have a permanent effect on output, and demand disturbances as

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[8] Similarly, an ARIMA(1,1,2) process is used by Blanchard and Fischer (1989), page 16, in their general characterization of the business-cycle facts.

shocks that have a temporary effect on output. They examine U.S. data from 1950 to 1987, calculating impulse responses and variance decompositions based on a VAR model in output and unemployment. We examine how changes in the vintage of the data affect the decomposition of shocks into supply disturbances versus demand disturbances, how the impulse responses change across data vintages, and how the cumulative effects of demand and supply shocks vary with the data vintage.

We compare Blanchard and Quah's results to ours using the February 1988 version of our data set, then comparing those results in turn to our November 1993 data set and our February 1998 data set. First, using our February 1988 data set, we are able to replicate the results of Blanchard and Quah fairly precisely. The impulse responses to supply and demand shocks (not shown) are quite similar to those found by Blanchard and Quah, both qualitatively and quantitatively.[9]

When we look at the decomposition of shocks into demand and supply shocks for the three different vintages of the data (Figure V.7), we notice there are substantial differences across data vintages. The differences are particularly noticeable for demand shocks, as many of the local peaks and troughs are largest in magnitude when using the '88 vintage data and smallest in magnitude when using the '98 vintage data. However, demand shocks are temporary, so these differences in magnitude don't seem to matter as much when we look at the cumulative effect of the shocks (Figure V.8). As this figure shows, even the fairly small differences across vintages in

---

[9] To measure the unemployment rate, Blanchard and Quah use the seasonally adjusted rate for males, age 20 and over. Because this rate does not appear in our data set, we substitute the total civilian rate of unemployment for the Blanchard/Quah measure. On the basis of our replication using the February '88 vintage, this substitution has little effect on the results.

the measured supply shocks have a large impact on the cumulative effect on output and unemployment.

The other way in which the method of Blanchard and Quah is often used is to establish stylized facts about how economic variables respond to shocks. These are generally shown in figures that illustrate the impulse responses to a shock. Using the Blanchard and Quah method, and the same three vintages of data used above, we calculate the impulse responses for demand and supply shocks (Figure V.9). Note that the impulse responses are very sensitive to vintage, especially for demand shocks. The response of output or unemployment to a demand shock is sometimes as much as five times as large, using 1998 data, than when using 1988 data. So the vintage of the data set seems to matter quite significantly for impulse responses. Why this is so is difficult to determine, but the estimated variance-covariance matrix shows a much different variance of the structural shocks, along with a substantially different parameter estimate of the coefficient on output in the unemployment equation. This occurs despite the fact that differences in the data don't seem large. This suggests that there may be something about the procedure for estimating a structural VAR that makes it very sensitive to small changes in the data.

Can we be more precise? As noted above, in examining the estimated coefficients of the structural VAR representation, we notice particularly large differences in the estimated coefficient on contemporaneous output growth in the structural unemployment equation as we move from vintages February '88 and November '93 to February '98. The coefficient estimate is 4.62 in the February '88 data, 2.45 in the November '93 data, and 0.63 in the February '98 data, with output growth measured in log first differences and the unemployment rate expressed as a percent, rather than in percentage points.

In a recent paper, Sarte (1997) shows that standard structural VAR instrumental variables (IV) techniques—which use structural shock estimates as instruments—can fail over certain ranges of the parameter space. The key condition for such a failure is a low pairwise correlation between the instrument/structural shock and the variable instrumented. In estimating the model, we employ the standard IV approach and use the estimated structural shock attached to the output equation as an instrument for contemporaneous output growth in the unemployment equation. We then checked Sarte's key condition for IV failure by computing for each vintage the correlation coefficient between the output-equation structural shock and output growth. For vintages February '88 and November '93, those correlations border on zero: 0.04 and 0.08, respectively. Such low correlations call into question the usefulness of structural shocks as instruments and, by implication, the just-identified structural VAR methodology. Indeed, a reasonable conclusion is that the SVAR is unidentified empirically in the first two vintages. In contrast, the pairwise correlation in the February '98 data rises significantly, to 0.23, suggesting a higher possibility that the model is identified empirically.

We view these results as an extension of Sarte's. Sarte showed that alternative identification schemes, holding constant the data vintage, may fail empirically. Our results indicate that a given identification scheme may fail empirically in some vintages but not in others. On the basis of these results, structural VAR users may wish to check their results for robustness along the lines suggested by Sarte and across different vintages of data.

VI. CONCLUSIONS

This paper reports on the structure of data revisions and on how such revisions can lead to somewhat different results for major studies in macroeconomics. It is somewhat reassuring that for many of the studies we examine, the results are generally robust, at least qualitatively, for different vintages of the data. But in some cases, the empirical results are quite sensitive to the exact vintage of the data.

What can we conclude from these results? In practice, economists run thousands of empirical exercises each day, some of which get reported in academic journals and influence economists' thoughts about the structure of the economy. Our exercise is really one in the spirit of checking such results for robustness and can thus be used to confirm some results in the literature, such as those of Kydland and Prescott. But when empirical results are sensitive to the vintage of the data, economists should be more cautious about accepting those particular results or perhaps about accepting the empirical methods that led to those results. If an empirical method is robust to data vintage, as in the case of Kydland and Prescott, an empirical researcher can have more confidence that the method itself is sound and not overly sensitive to minor variations in the data. But if the empirical method is one that leads to very different results for minor variations in the data, a researcher should be skeptical. Or, certainly, further research is needed to establish the validity of the research method.

Our hope is that the real-time data set presented in this paper and available on our web site will serve as a standard for macroeconomic researchers.

Table III.1
Average Growth Rates Over Five Years
For Benchmark Vintages
Annualized percentage points

Vintage Year: Period	'75	'80	'85	'91	'95	'98
			Nominal Output			
49Q4 to 54Q4	7.9	7.9	7.9	8.1	8.0	8.0
54Q4 to 59Q4	5.6	5.6	5.7	5.7	5.7	5.7
59Q4 to 64Q4	5.6	5.5	5.6	5.6	5.7	5.6
64Q4 to 69Q4	8.0	8.1	8.2	8.3	8.2	8.2
69Q4 to 74Q4	8.6	8.8	8.9	9.1	9.0	9.1
74Q4 to 79Q4	NA	11.1	11.2	11.3	11.4	11.4
79Q4 to 84Q4	NA	NA	8.5	8.2	8.5	8.6
84Q4 to 89Q4	NA	NA	NA	6.5	6.7	6.7
89Q4 to 94Q4	NA	NA	NA	NA	5.2	5.1
			Real Output			
49Q4 to 54Q4	5.2	5.1	5.1	5.5	5.5	5.3
54Q4 to 59Q4	2.9	3.0	3.0	2.7	2.7	3.2
59Q4 to 64Q4	4.1	4.0	4.0	3.9	4.0	4.2
64Q4 to 69Q4	4.3	4.0	4.1	4.0	4.0	4.4
69Q4 to 74Q4	2.1	2.2	2.5	2.1	2.3	2.6
74Q4 to 79Q4	NA	3.7	3.9	3.5	3.4	3.9
79Q4 to 84Q4	NA	NA	2.2	2.0	1.9	2.2
84Q4 to 89Q4	NA	NA	NA	3.2	3.0	3.2
89Q4 to 94Q4	NA	NA	NA	NA	2.3	1.9
			Prices			
49Q4 to 54Q4	2.6	2.7	2.7	2.5	2.4	2.6
54Q4 to 59Q4	2.6	2.6	2.6	2.9	2.9	2.4
59Q4 to 64Q4	1.4	1.5	1.5	1.6	1.6	1.3
64Q4 to 69Q4	3.6	3.9	3.9	4.1	4.1	3.7
69Q4 to 74Q4	6.3	6.5	6.2	6.8	6.5	6.3
74Q4 to 79Q4	NA	7.1	7.0	7.5	7.7	7.2
79Q4 to 84Q4	NA	NA	6.1	6.1	6.4	6.2
84Q4 to 89Q4	NA	NA	NA	3.3	3.6	3.4
89Q4 to 94Q4	NA	NA	NA	NA	2.9	3.1

Vintage Year:	‘75	‘80	‘85	‘91	‘95	‘98
Period						
			Real Consumption			
49Q4 to 54Q4	3.6	3.3	3.3	3.7	3.9	3.8
54Q4 to 59Q4	3.4	3.3	3.3	3.3	3.4	3.5
59Q4 to 64Q4	4.1	3.8	3.8	3.7	3.8	4.0
64Q4 to 69Q4	4.5	4.3	4.4	4.4	4.5	4.8
69Q4 to 74Q4	2.3	2.6	2.6	2.5	2.6	2.8
74Q4 to 79Q4	NA	4.4	4.4	3.9	3.9	4.1
79Q4 to 84Q4	NA	NA	2.8	2.5	2.5	2.6
84Q4 to 89Q4	NA	NA	NA	3.2	3.1	3.4
89Q4 to 94Q4	NA	NA	NA	NA	2.3	2.1

Table III.2
Contemporaneous Correlations Across Benchmark Vintages
Quarterly changes in logarithms of variables

Vintage Year:	‘75	‘80	‘85	‘91	‘95	‘98
			Real Output			
‘75	1.00					
‘80	0.97	1.00				
‘85	0.97	0.99	1.00			
‘91	0.92	0.95	0.96	1.00		
‘95	0.91	0.94	0.95	0.97	1.00	
‘98	0.92	0.92	0.94	0.94	0.95	1.00
			Real Consumption			
‘75	1.00					
‘80	0.96	1.00				
‘85	0.96	0.99	1.00			
‘91	0.94	0.97	0.98	1.00		
‘95	0.94	0.96	0.97	0.98	1.00	
‘98	0.96	0.96	0.97	0.97	0.97	1.00
			Prices			
‘75	1.00					
‘80	0.94	1.00				
‘85	0.94	0.99	1.00			
‘91	0.87	0.96	0.96	1.00		
‘95	0.85	0.94	0.95	0.95	1.00	
‘98	0.94	0.93	0.93	0.90	0.90	1.00
			Nominal Output			
‘75	1.00					
‘80	0.98	1.00				
‘85	0.98	0.99	1.00			
‘91	0.96	0.98	0.98	1.00		
‘95	0.96	0.97	0.98	0.99	1.00	
‘98	0.95	0.97	0.98	0.99	0.99	1.00

Table IV.1
Standard Deviations of Real Consumption Growth Rates
1965Q3 to 1995Q3
In percentage points

Data Set	Standard Deviation
Initial Release	3.40
1-Year Later	3.57
3-Years Later	3.17
Latest	3.10

Table IV.2
Correlations of Revisions with Growth Rates
Consumption Data
1965Q3 to 1995Q3

Revisions/Data Set	Initial	1-Year	3-Year	Final
Initial to 1-Year	-0.02	0.30*	0.27*	0.20*
	(0.18)	(3.45)	(3.02)	(2.25)
1-Year to 3-Year	-0.44†	-0.48†	-0.15	-0.14
	(5.37)	(5.98)	(1.69)	(1.56)
3-Year to Final	-0.16	-0.22†	-0.23†	0.11
	(1.79)	(2.45)	(2.58)	(1.18)
Initial to 3-Year	-0.37†	-0.17	0.08	0.04
	(4.39)	(1.84)	(0.82)	(0.40)
1-Year to Final	-0.43†	-0.50†	-0.26?	-0.04
	(5.21)	(6.25)	(2.95)	(0.40)
Initial to Final	-0.42†	-0.28?	-0.08	0.10
	(5.08)	(3.16)	(0.83)	(1.06)

Absolute values of t-statistics are in parentheses below each correlation coefficient.
An asterisk (*) means there's a significant (at the 5% level) correlation between the revision and the later data, implying "news."
A dagger (†) means there's a significant (at the 5% level) correlation between the revision and the earlier data, implying "noise."
A question mark (?) means there's a significant correlation that doesn't fit easily into the news/noise dichotomy.

Table V.1
Kydland-Prescott Cross-Correlations

		Cross Correlation of Real GNP/GDP With										
Vintage	Variable x	x(t-5)	x(t-4)	x(t-3)	x(t-2)	x(t-1)	x(t)	x(t+1)	x(t+2)	x(t+3)	x(t+4)	x(t+5)
KP 1990	Real GNP/GDP	-0.03	0.15	0.38	0.63	0.85						
Feb. 1990		-0.03	0.15	0.37	0.62	0.85						
Feb. 1994		-0.02	0.15	0.36	0.61	0.84						
Feb. 1998		-0.09	0.11	0.34	0.60	0.84						
KP 1990	GNP/GDP deflator	-0.50	-0.61	-0.68	-0.69	-0.64	-0.55	-0.43	-0.31	-0.17	-0.04	0.09
Feb. 1990		-0.49	-0.60	-0.67	-0.69	-0.64	-0.56	-0.43	-0.31	-0.18	-0.05	0.08
Feb. 1994		-0.51	-0.60	-0.66	-0.66	-0.59	-0.48	-0.36	-0.26	-0.15	-0.05	0.07
Feb. 1998		-0.35	-0.49	-0.60	-0.68	-0.70	-0.66	-0.55	-0.40	-0.22	-0.04	0.12
KP 1990	Real Consumption	0.25	0.41	0.56	0.71	0.81	0.82	0.66	0.45	0.21	-0.02	-0.21
Feb. 1990		0.24	0.40	0.55	0.70	0.80	0.82	0.65	0.44	0.21	-0.02	-0.21
Feb. 1994		0.18	0.35	0.53	0.71	0.84	0.87	0.70	0.48	0.25	0.02	-0.17
Feb. 1998		0.12	0.31	0.50	0.69	0.84	0.88	0.71	0.48	0.23	-0.02	-0.20
KP 1990	M2	0.48	0.60	0.67	0.68	0.61	0.46	0.26	0.05	-0.15	-0.33	-0.46
Feb. 1990		0.46	0.57	0.64	0.66	0.60	0.46	0.25	0.05	-0.14	-0.31	-0.42
Feb. 1994		0.44	0.57	0.65	0.69	0.64	0.50	0.29	0.08	-0.10	-0.28	-0.41
Feb. 1998		0.44	0.58	0.66	0.69	0.63	0.48	0.27	0.07	-0.12	-0.28	-0.40

Table V.2
Hall's Tests on Consumption

Regression 1: $c_t = \hat{a}_0 + \hat{a}_1 c_{t-1} + \hat{a}_2 c_{t-2} + \hat{a}_3 c_{t-3} + \hat{a}_4 c_{t-4} + e_t$

	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	$\hat{a}_3$	$\hat{a}_4$	R^2	s	DW	F
Sample 1948Q1 to 1977Q1									
Hall's results	8.2	1.130	-0.040	0.030	-0.113	.9988	14.5	1.96	1.7
	(8.3)	(0.092)	(0.142)	(0.142)	(0.093)				(0.17)
Replication	-8.122	1.130	-0.024	-0.004	-0.095	.9988	14.7	1.97	1.7
vintage May '77	(8.489)	(0.092)	(0.142)	(0.143)	(0.094)				(0.17)
Replication	-9.859	1.102	0.166	-0.256	-0.007	.9988	57.5	2.00	3.5
vintage Feb. '98	(27.498)	(0.093)	(0.138)	(0.137)	(0.094)				(0.02)
Sample 1948Q1 to 1997Q4									
Vintage Feb. '98	15.589	1.153	0.163	-0.011	-0.157	.9997	57.0	1.97	8.1
	(14.296)	(0.070)	(0.108)	(0.108)	(0.070)				(0.00)

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Figure III.1
Log Nominal Output Ratios (Demeaned)
Vertical Axis: -0.08 to 0.08
Horizontal Axis: 1947Q I to 1997Q4

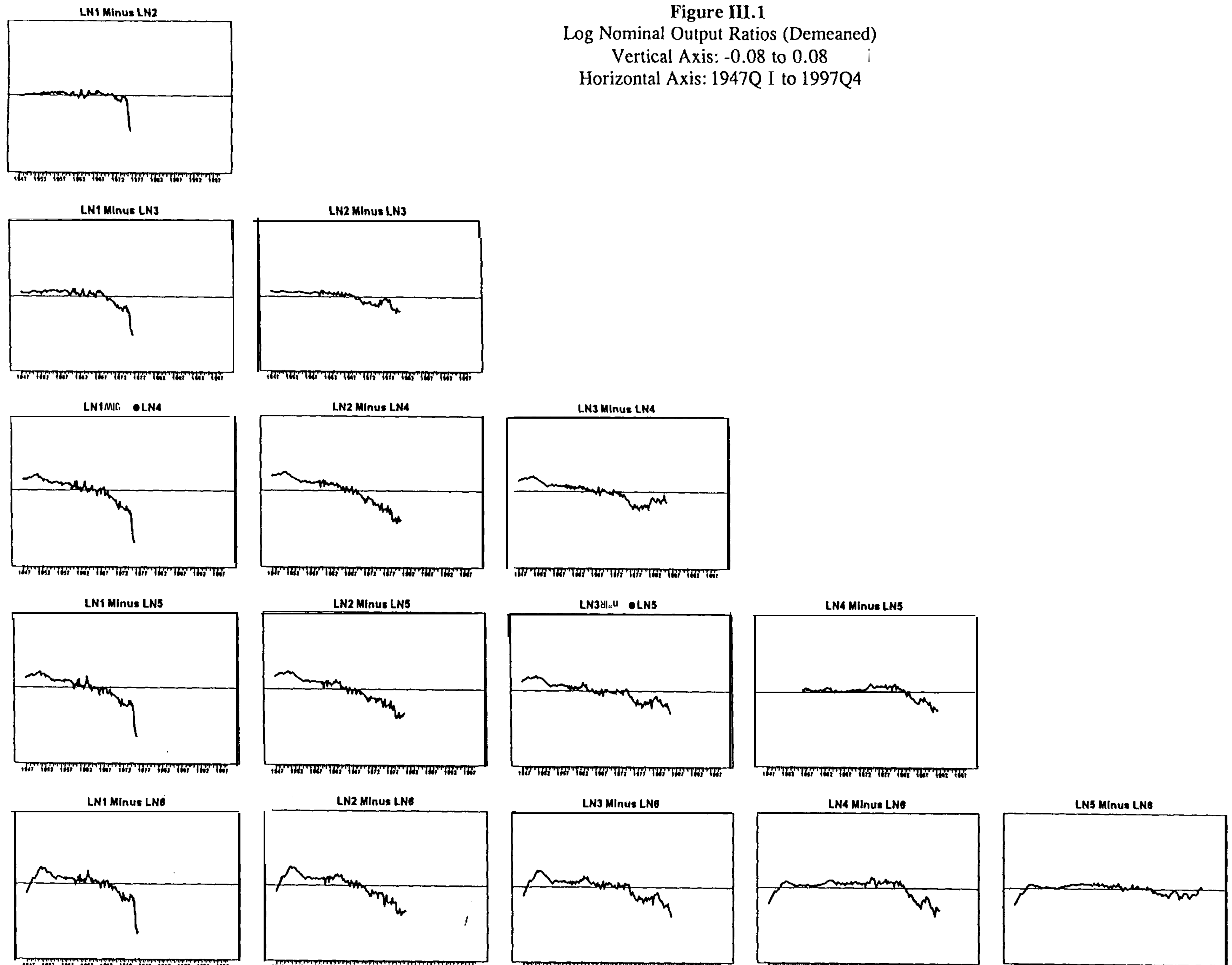
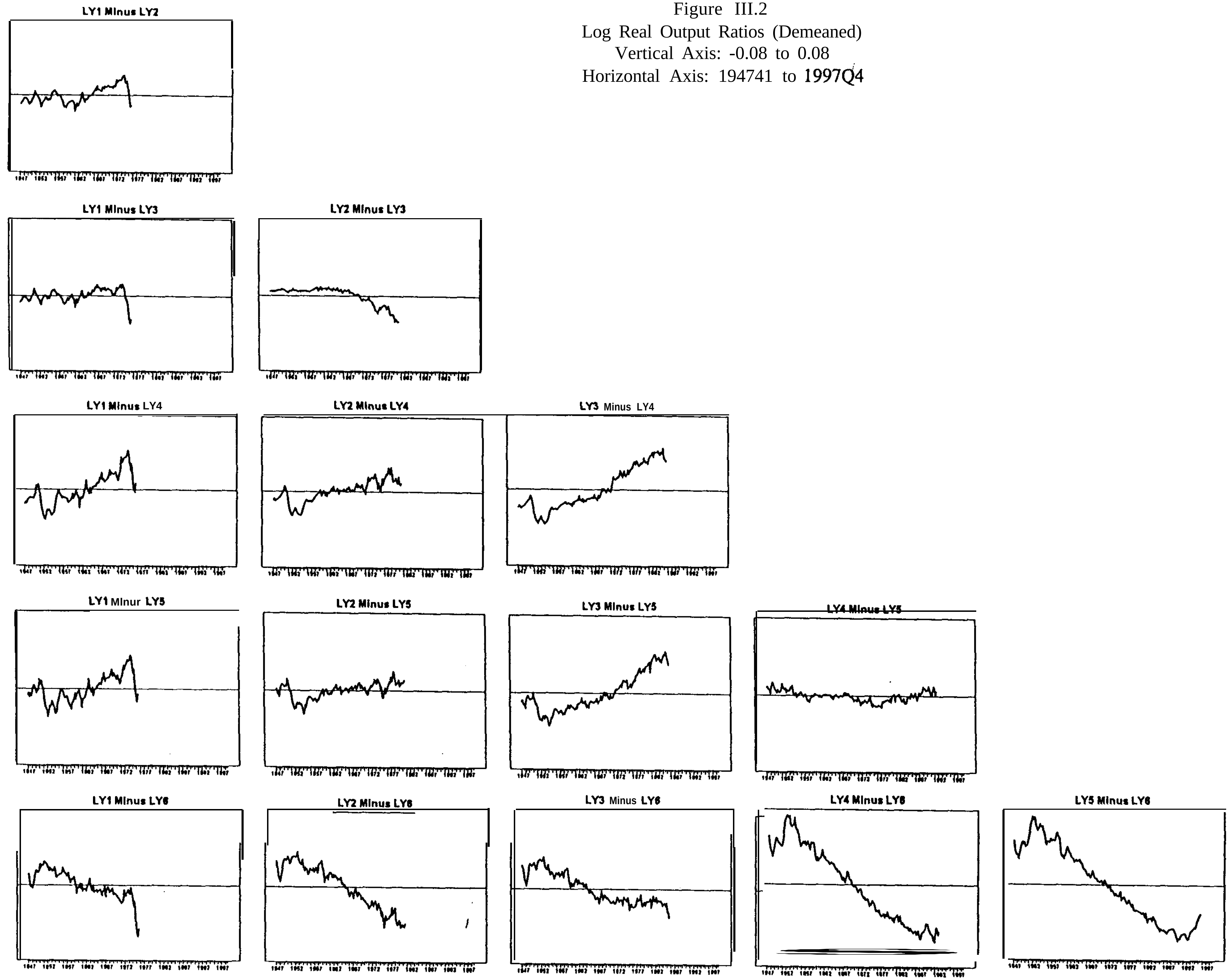


Figure III.2
Log Real Output Ratios (Demeaned)
Vertical Axis: -0.08 to 0.08
Horizontal Axis: 194741 to 1997Q4



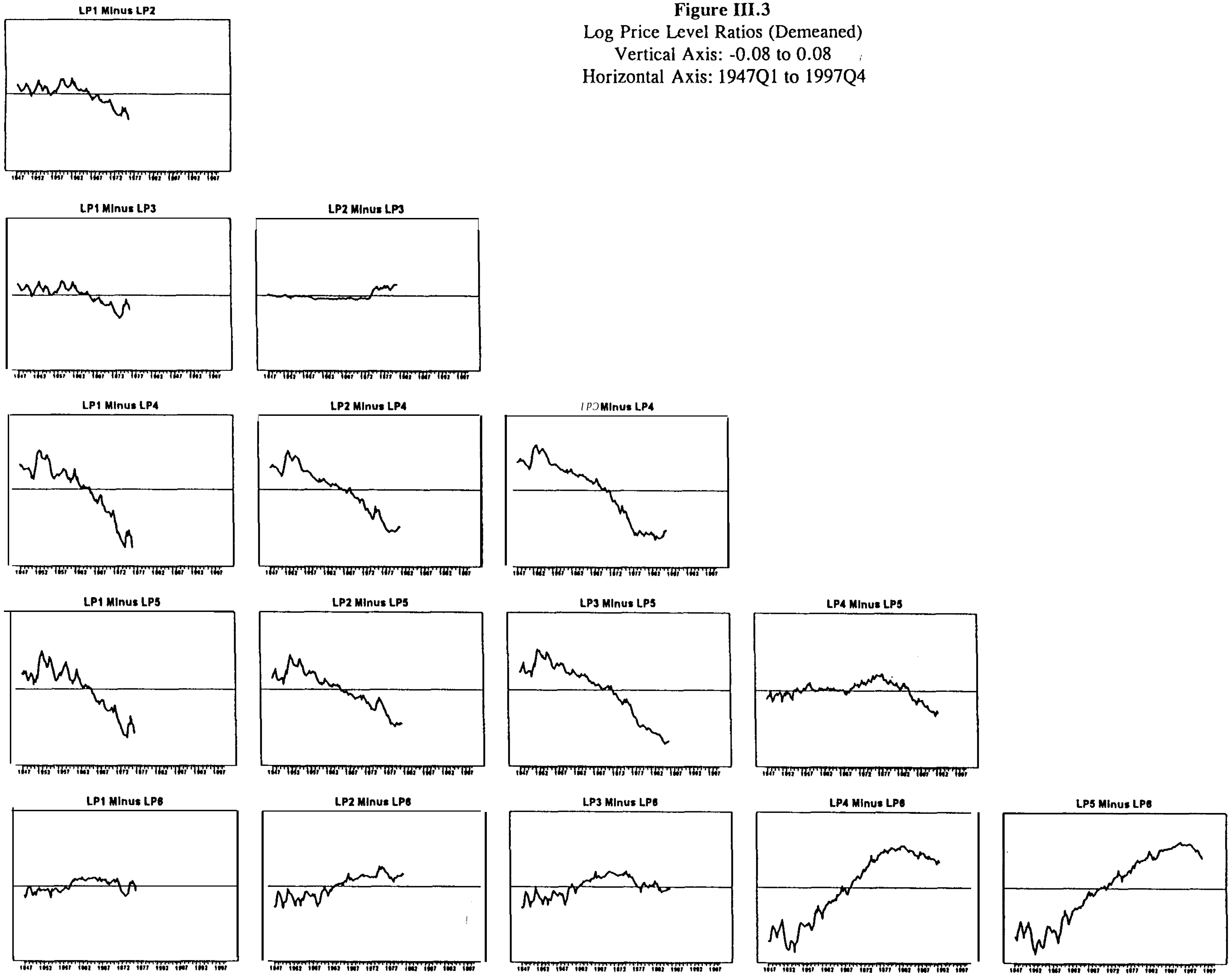


Figure III.3
Log Price Level Ratios (Demeaned)
Vertical Axis: -0.08 to 0.08
Horizontal Axis: 1947Q1 to 1997Q4

Figure III.4
Log Real PCE Ratios (Demeaned)
Vertical Axis: -0.08 to 0.08
Horizontal Axis: 1947Q1 to 1997Q4

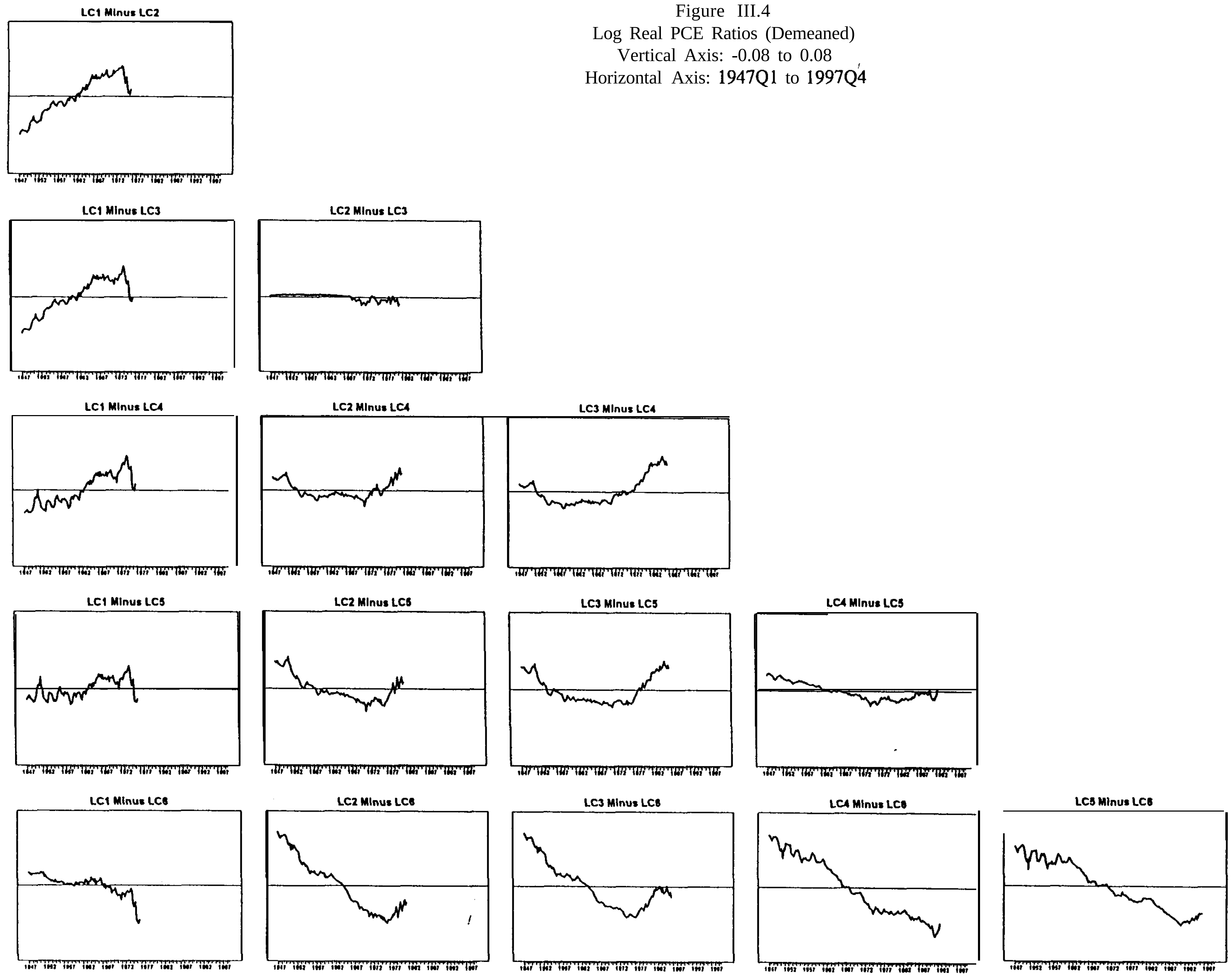


Figure III.5

Nonparametric Spectral Density Function Estimates, Log PCE Ratios

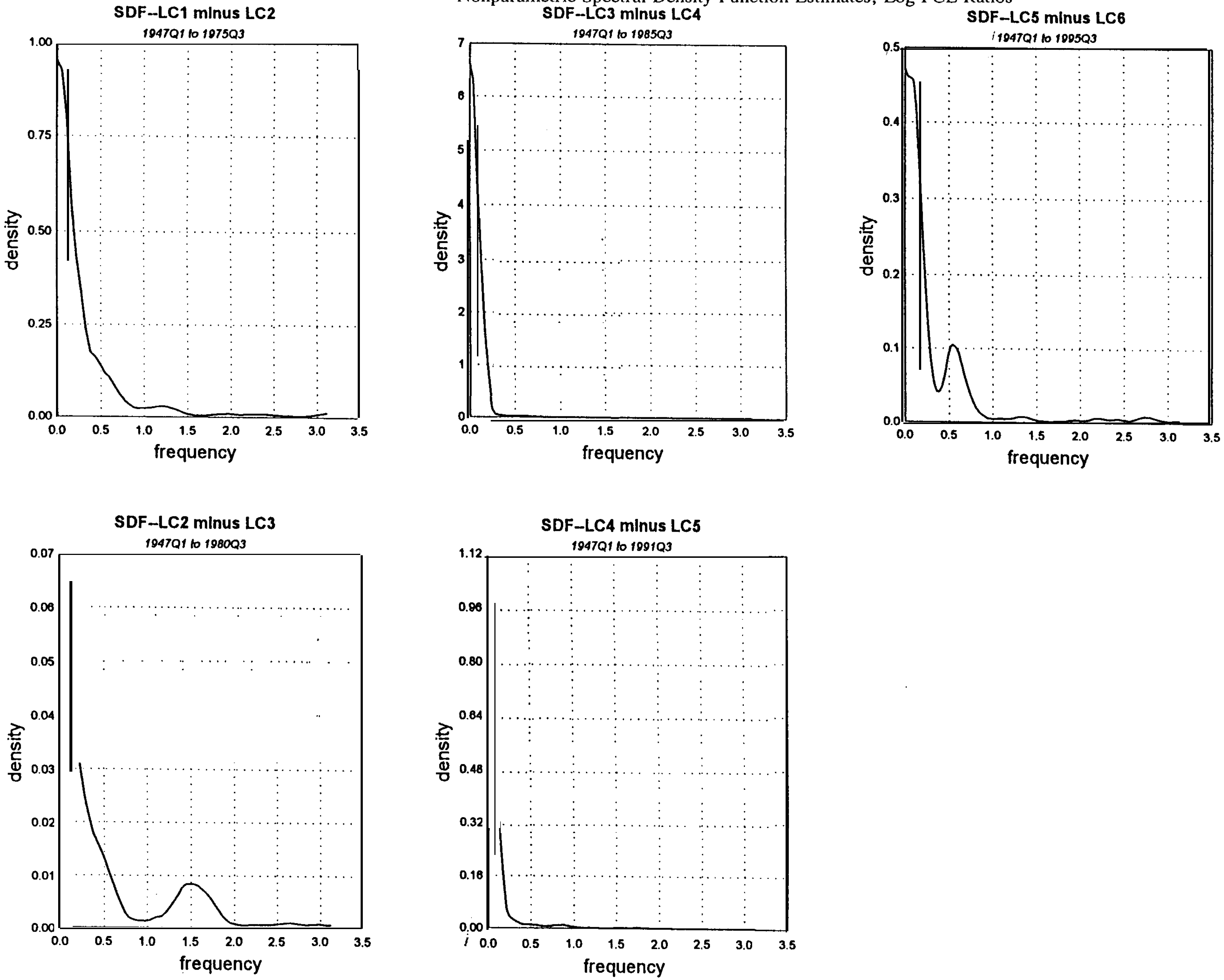


Figure III.6

Nonparametric Spectral Density Function Estimates, Delta Log PCE Ratios

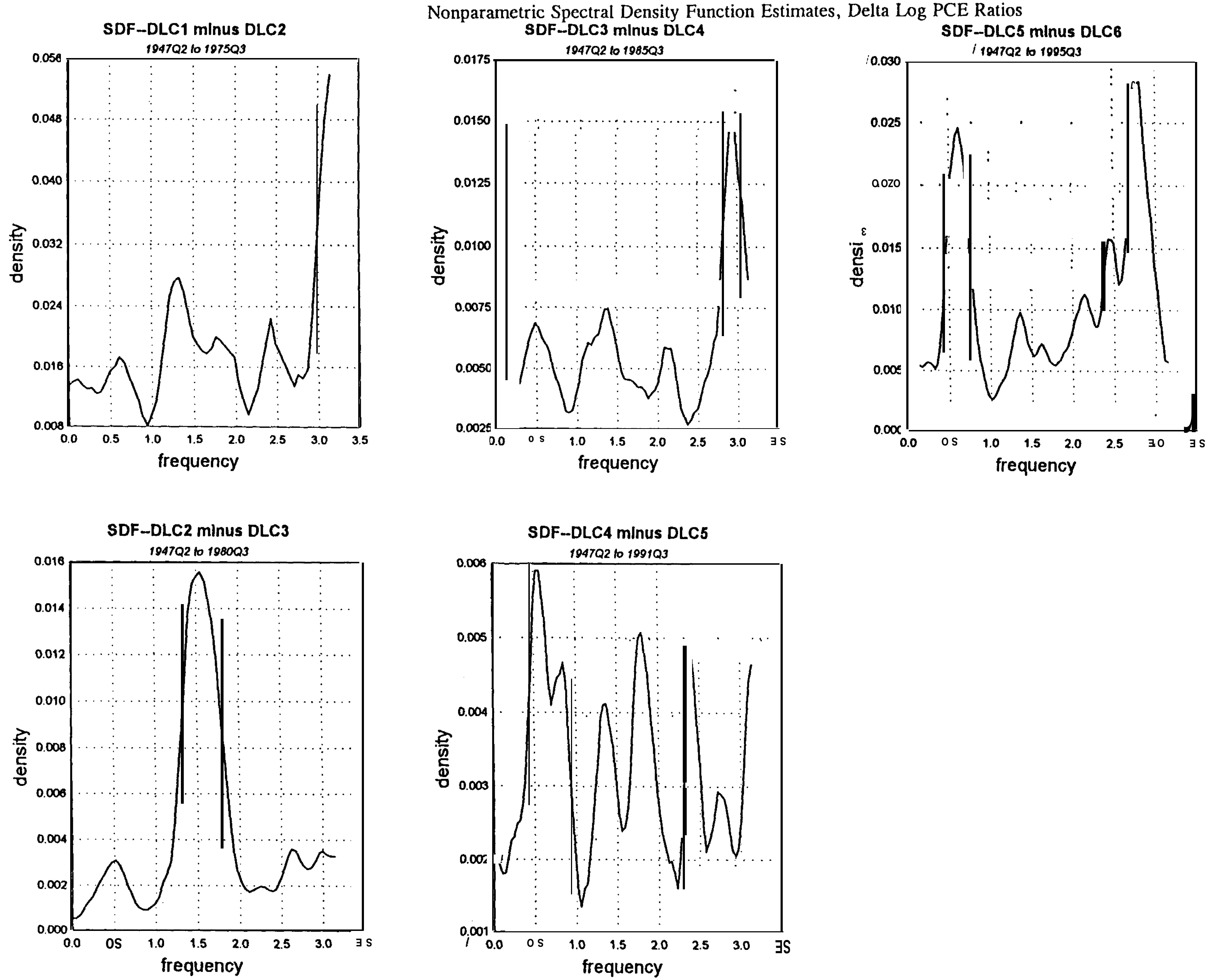


Figure III.7

Estimated Squared Coherences, Delta Log Real Output & Delta Log Real PCE

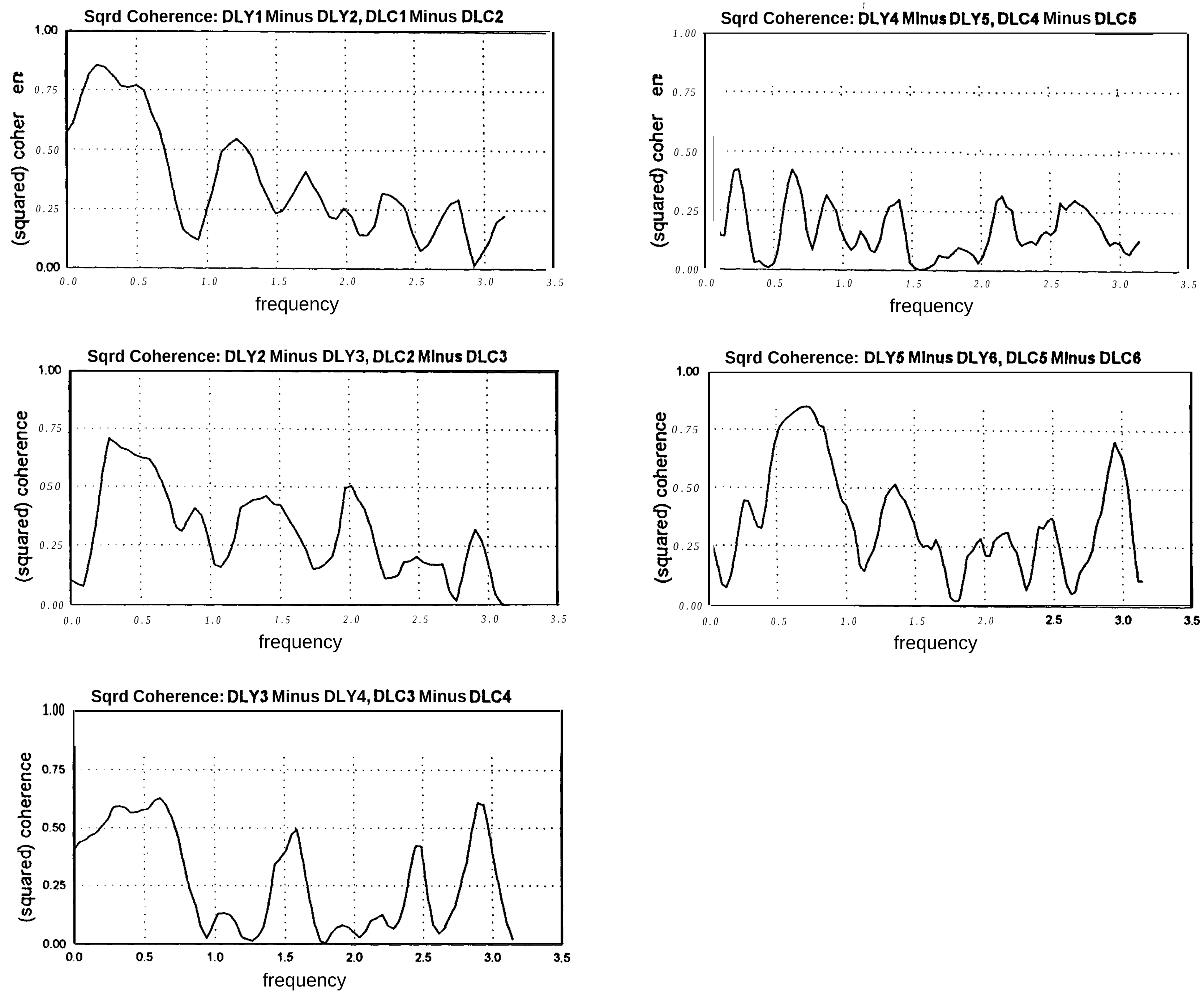


Figure IV.1

Annualized Quarter-Over-Quarter Real PCE Growth Rates

1947Q2 to 1985Q4

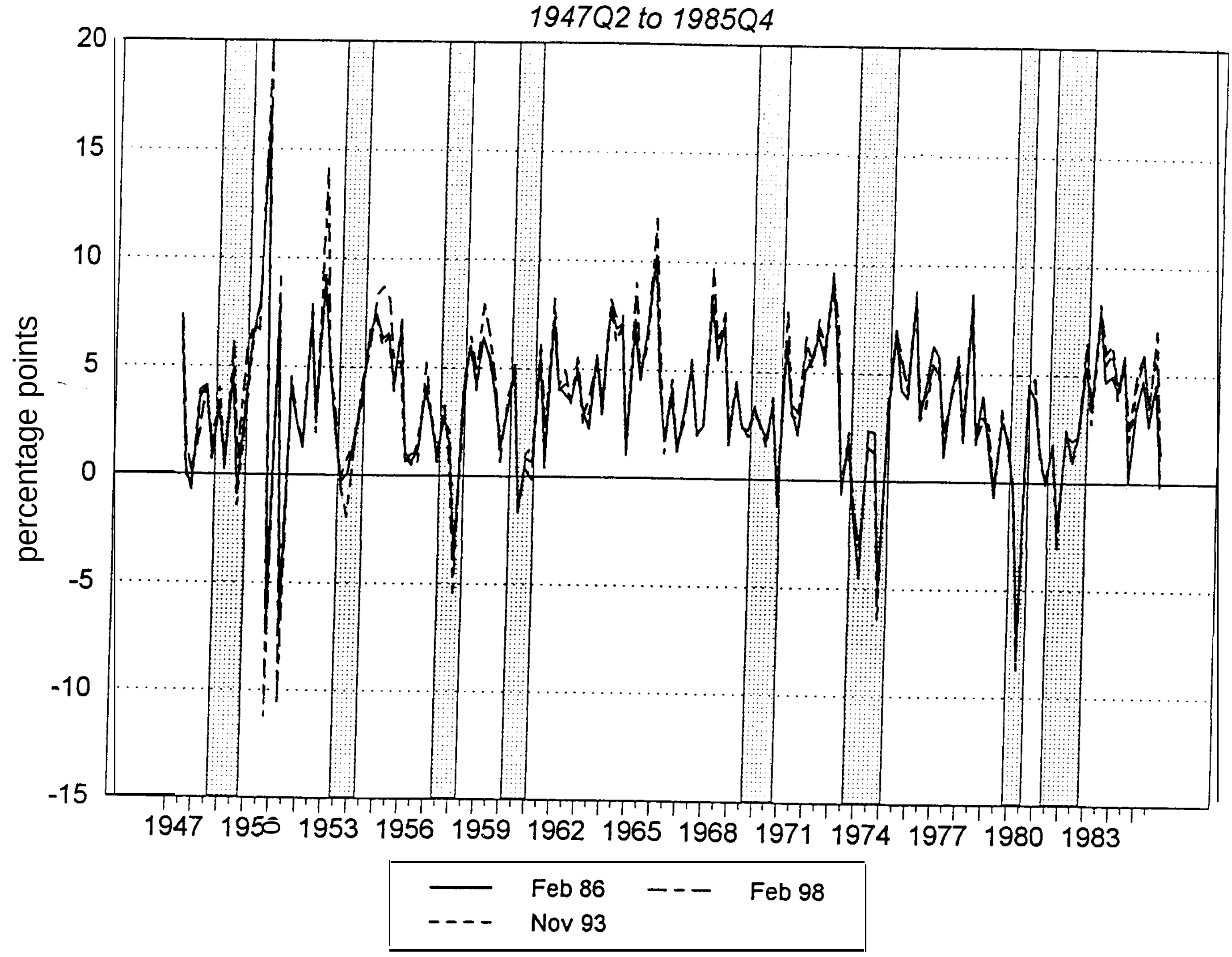
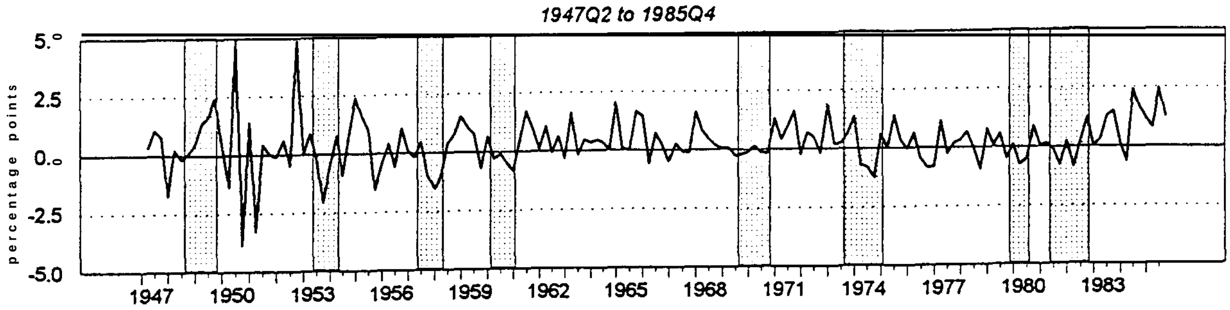


Figure IV.2

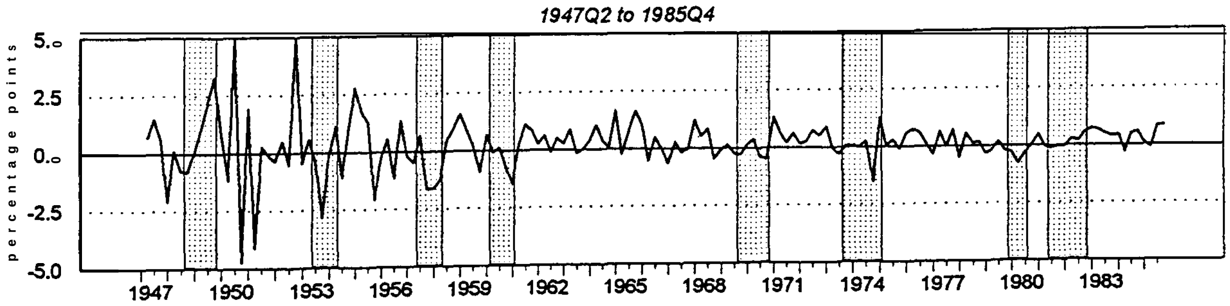
Annualized Real PCE Growth Differences: Feb 98 Minus Feb 86

1947Q2 to 1985Q4



Annualized Real PCE Growth Differences: Feb 98 Minus Nov 93

1947Q2 to 1985Q4



Annualized Real PCE Growth Differences: Nov 93 Minus Feb 86

1947Q2 to 1985Q4

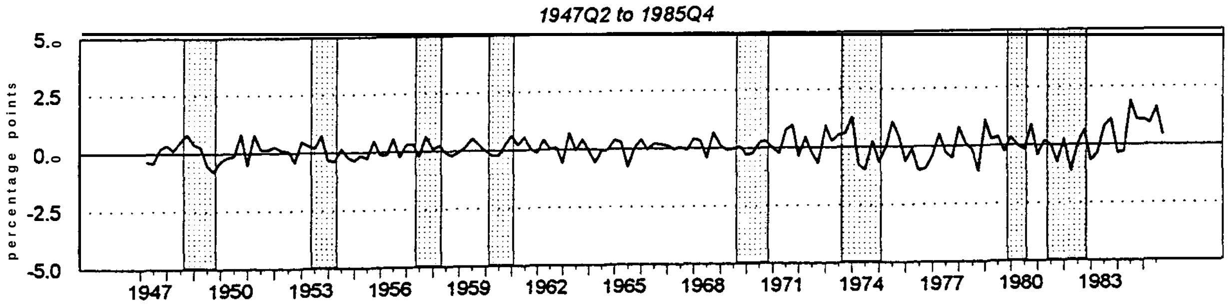


Figure IV.3

Real Consumption Growth Rates

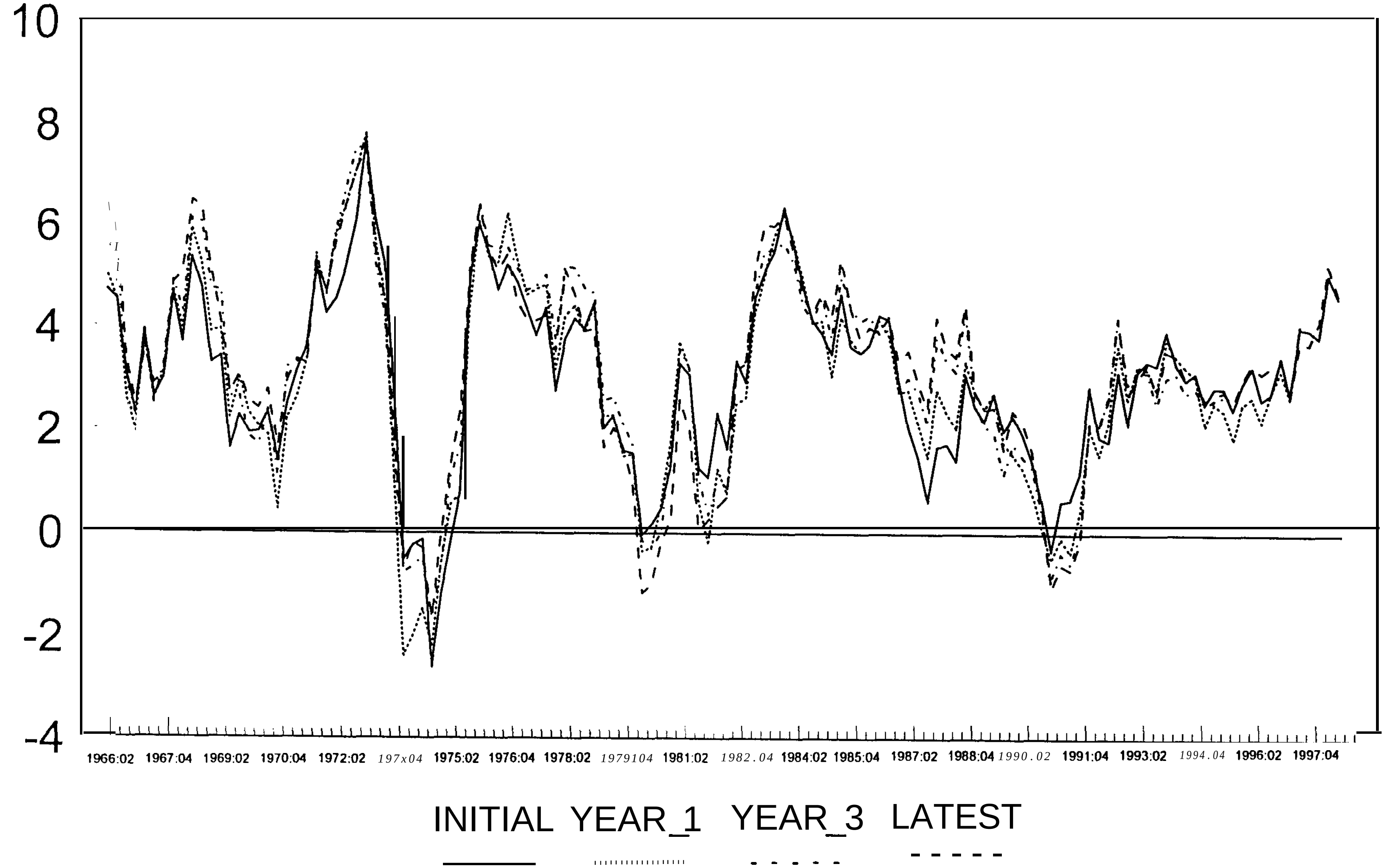
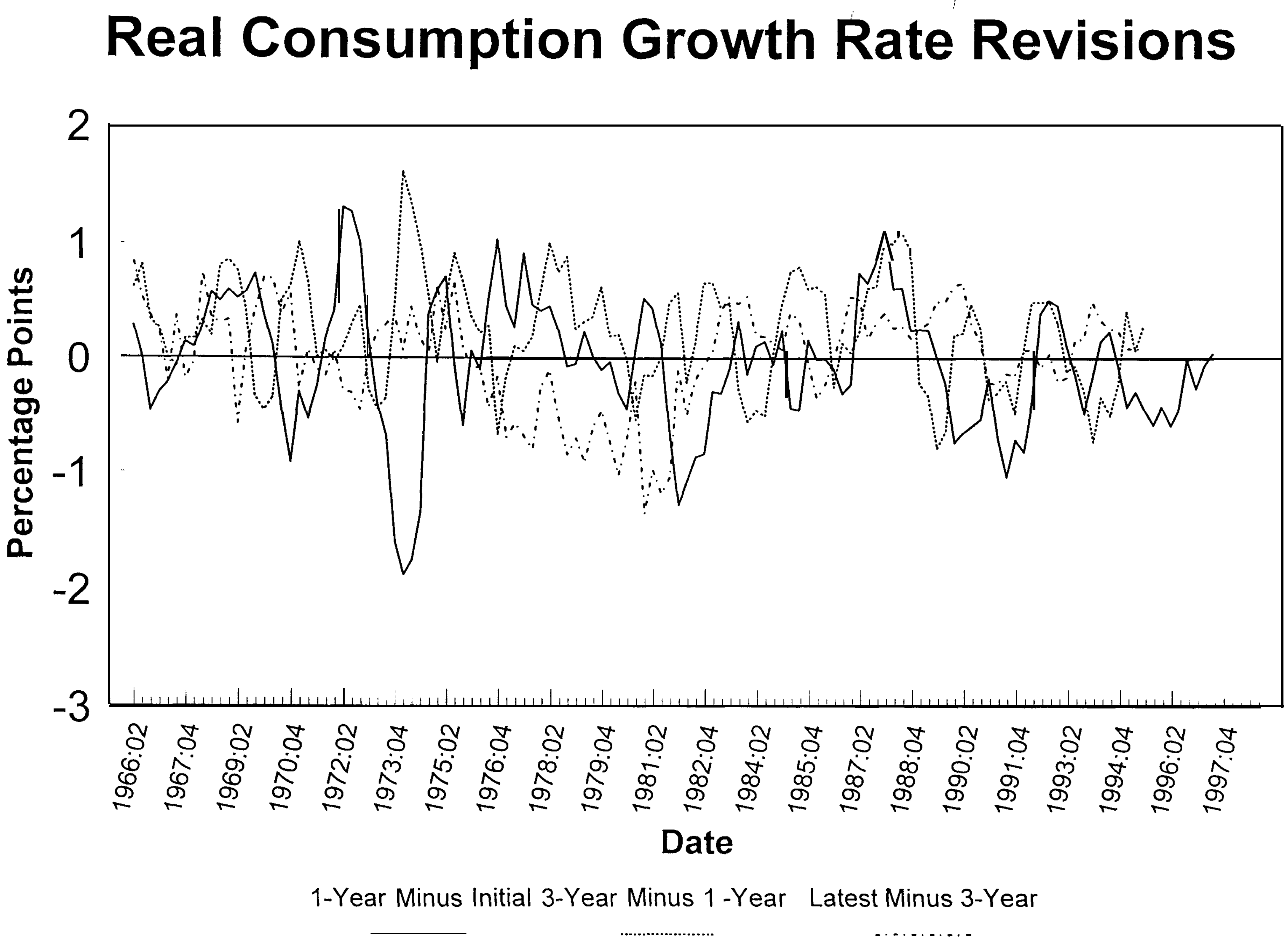


Figure IV.4



Real Consumption Growth Rate Revisions
2
1
0
-1
-2
-3
Percentage Points
1966:02
1967:04
1969:02
1970:04
1972:02
1973:04
1975:02
1976:04
1978:02
1979:04
1981:02
1982:04
1984:02
1985:04
1987:02
1988:04
1990:02
1991:04
1993:02
1994:04
1996:02
1997:04
Date
1-Year Minus Initial
3-Year Minus 1 -Year
Latest Minus 3-Year

Figure IV.5

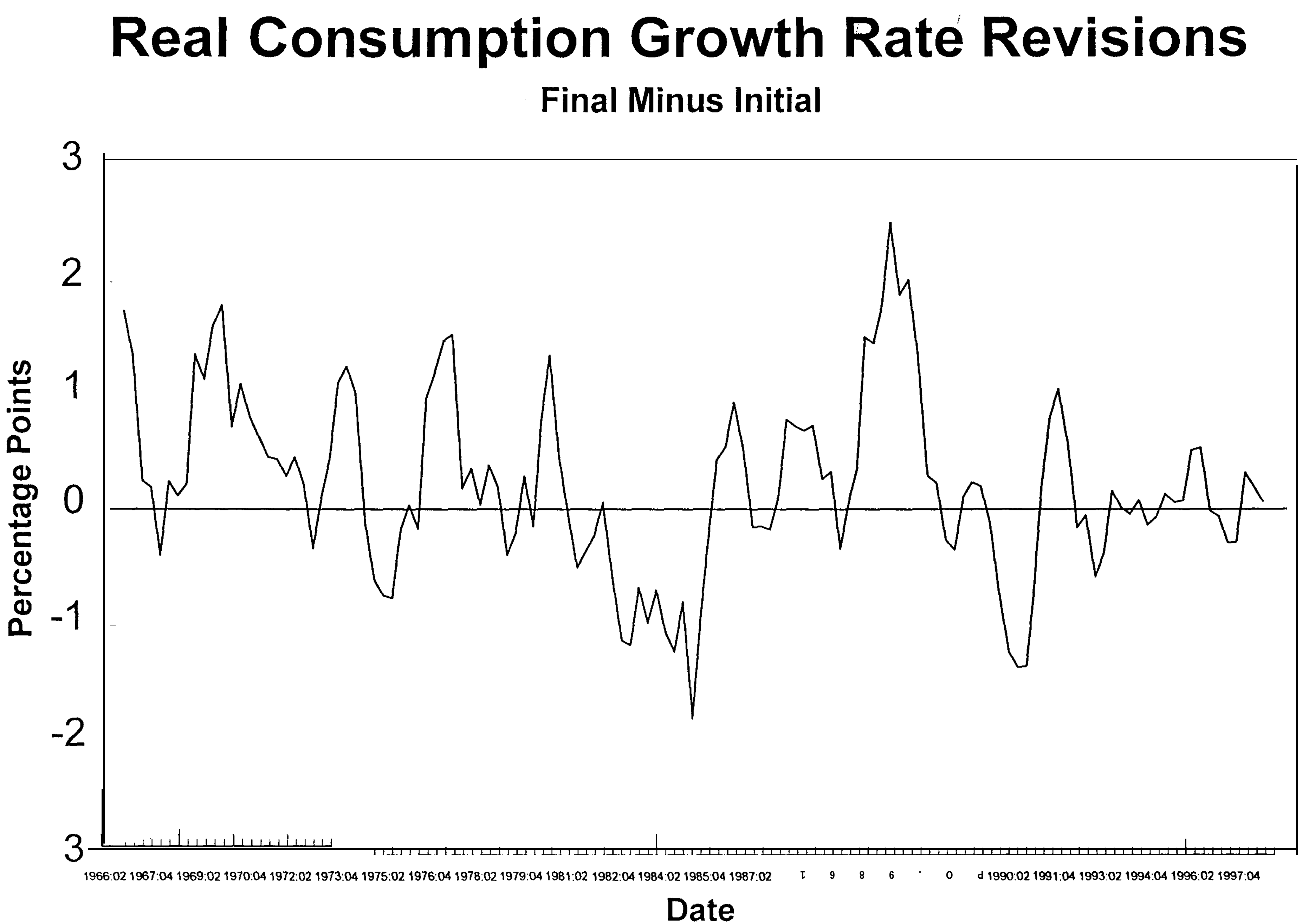
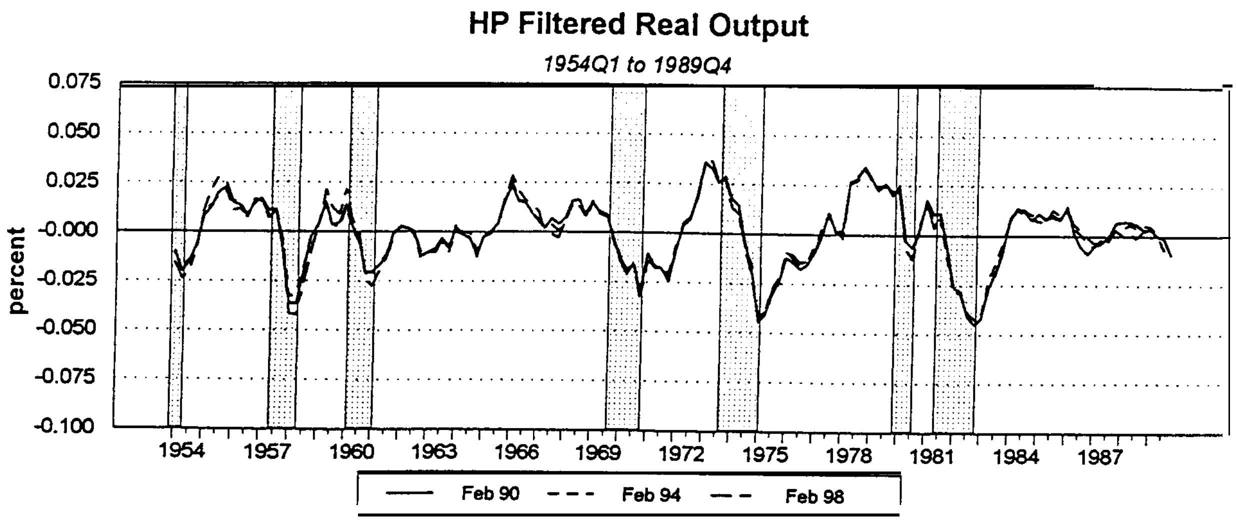

Real Consumption Growth Rate Revisions
Final Minus Initial
Percentage Points
3
2
1
0
-1
-2
3
1966:02 1967:04 1969:02 1970:04 1972:02 1973:04 1975:02 1976:04 1978:02 1979:04 1981:02 1982:04 1984:02 1985:04 1987:02
1990:02 1991:04 1993:02 1994:04 1996:02 1997:04
Date

Figure V.1


HP Filtered Real Output
1954Q1 to 1989Q4
0.075
0.050
0.025
-0.000
-0.025
-0.050
-0.075
-0.100
percent
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
Feb 90
Feb 94
Feb 98

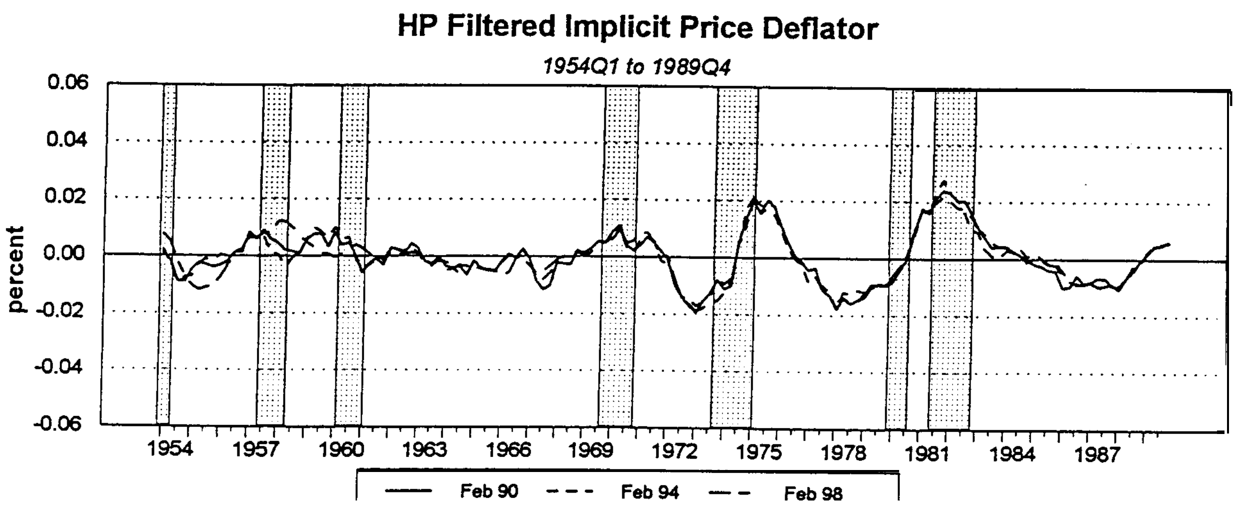

HP Filtered Implicit Price Deflator
1954Q1 to 1989Q4
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
percent
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
Feb 90
Feb 94
Feb 98

Figure V.2

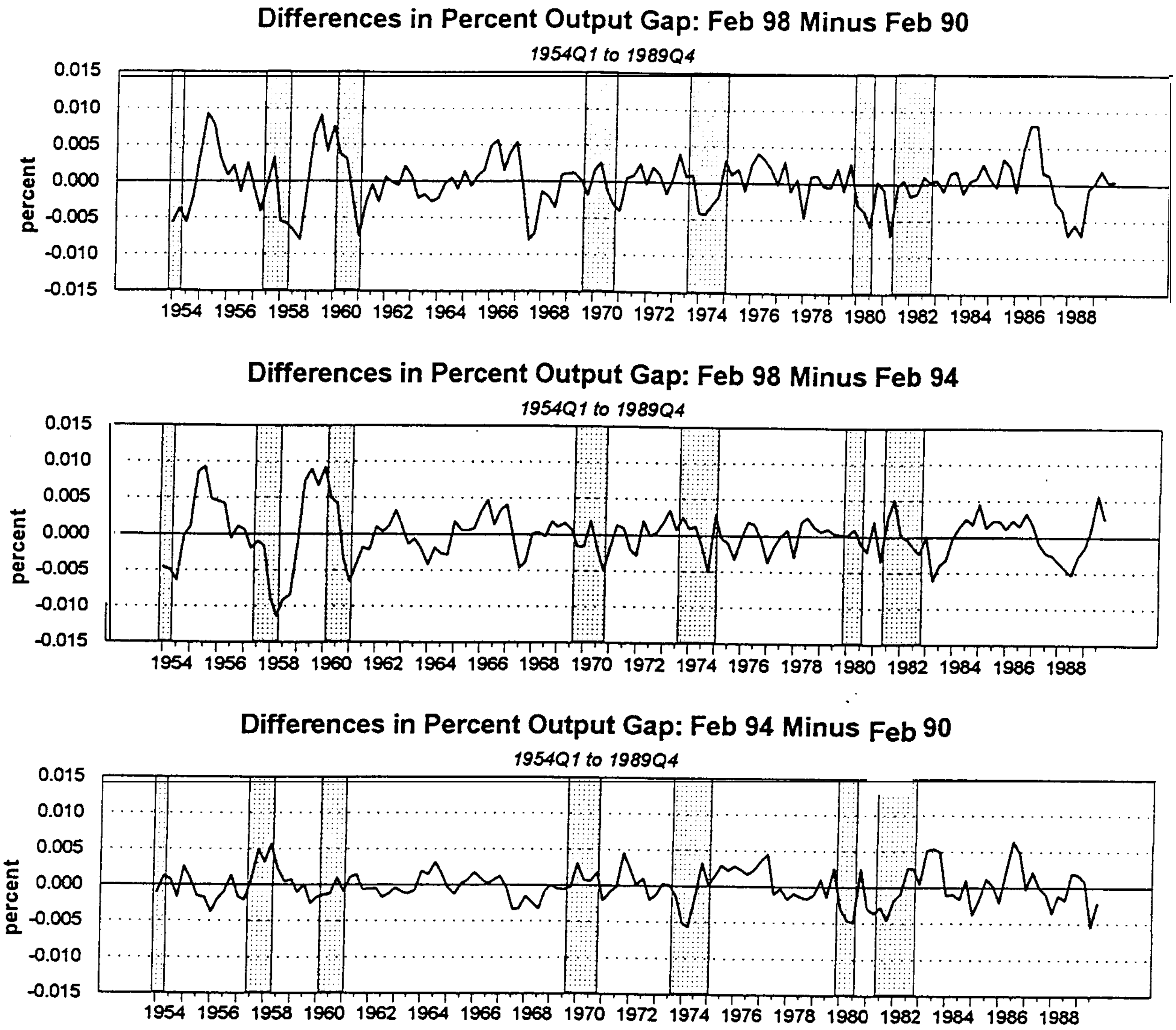

Differences in Percent Output Gap: Feb 98 Minus Feb 90
1954Q1 to 1989Q4
percent
0.015
0.010
0.005
0.000
-0.005
-0.010
-0.015
1954 1956 1958 1960 1962 1964 1966 1968 1970 1972 1974 1976 1978 1980 1982 1984 1986 1988
Differences in Percent Output Gap: Feb 98 Minus Feb 94
1954Q1 to 1989Q4
percent
0.015
0.010
0.005
0.000
-0.005
-0.010
-0.015
1954 1956 1958 1960 1962 1964 1966 1968 1970 1972 1974 1976 1978 1980 1982 1984 1986 1988
Differences in Percent Output Gap: Feb 94 Minus Feb 90
1954Q1 to 1989Q4
percent
0.015
0.010
0.005
0.000
-0.005
-0.010
-0.015
1954 1956 1958 1960 1962 1964 1966 1968 1970 1972 1974 1976 1978 1980 1982 1984 1986 1988

Figure V.3

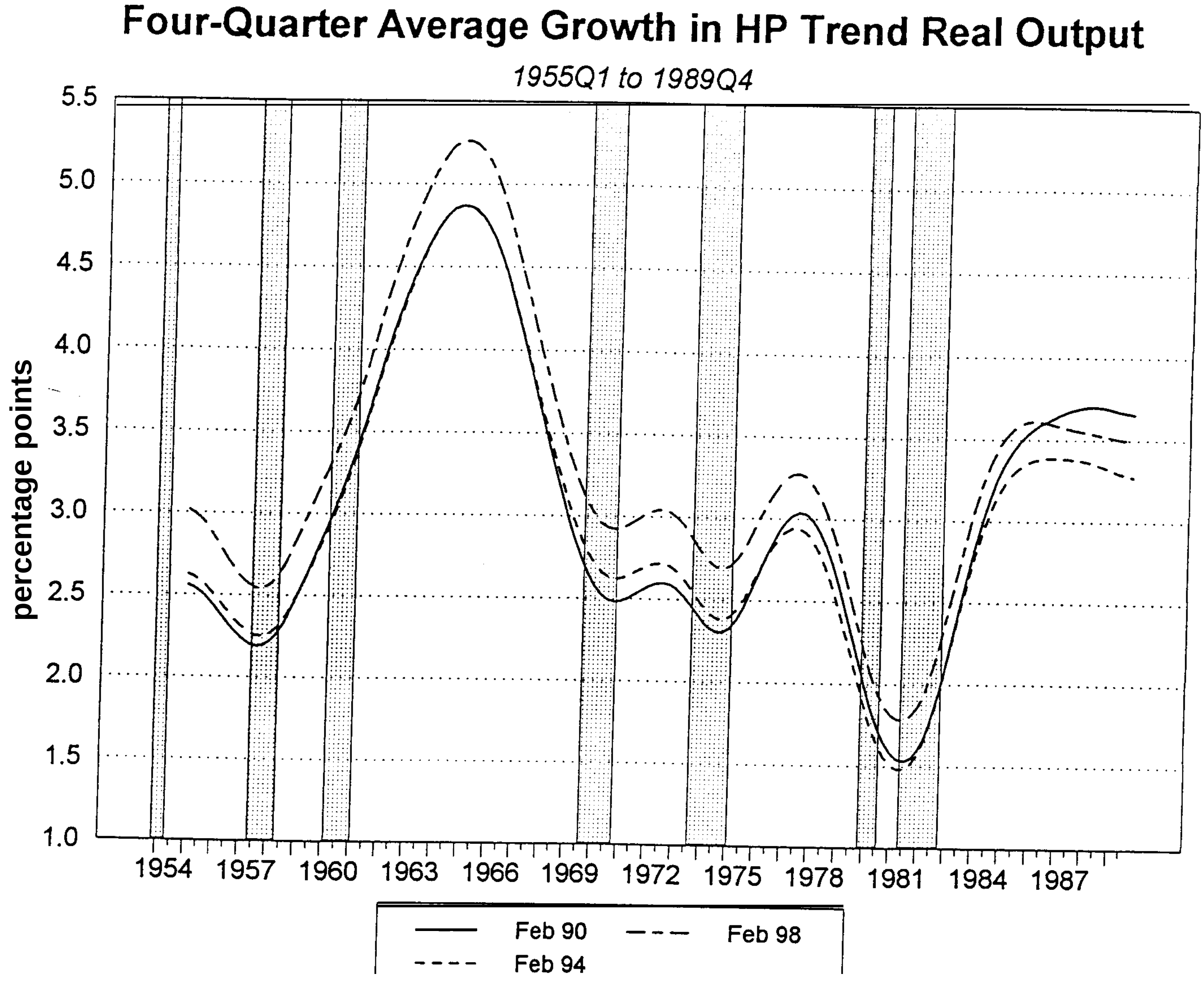
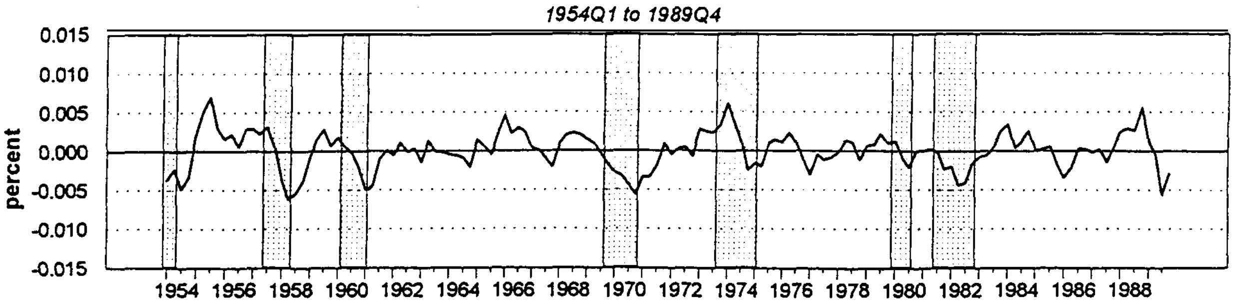

Four-Quarter Average Growth in HP Trend Real Output
1955Q1 to 1989Q4
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
percentage points
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
Feb 90
Feb 98
Feb 94

Figure V.4

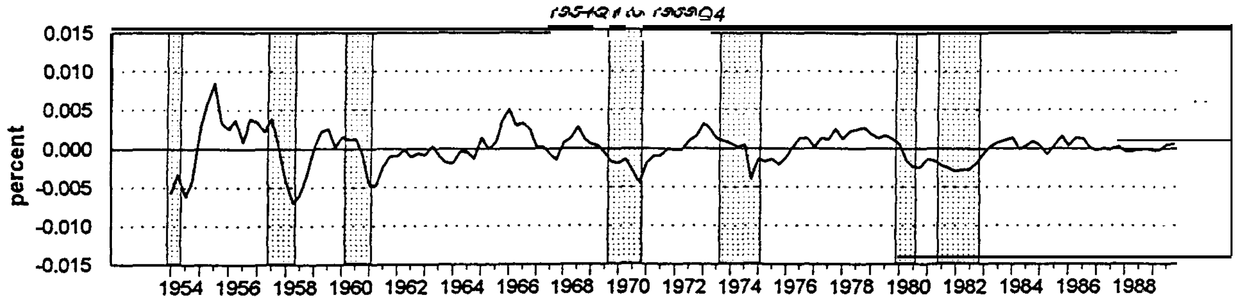
Differences in Percent PCE Gap: Feb 98 Minus Feb 90

1954Q1 to 1989Q4



Differences in Percent PCE Gap: Feb 98 Minus Feb 94

1954Q1 to 1989Q4



Differences in Percent PCE Gap: Feb 94 Minus Feb 90

1954Q1 to 1989Q4

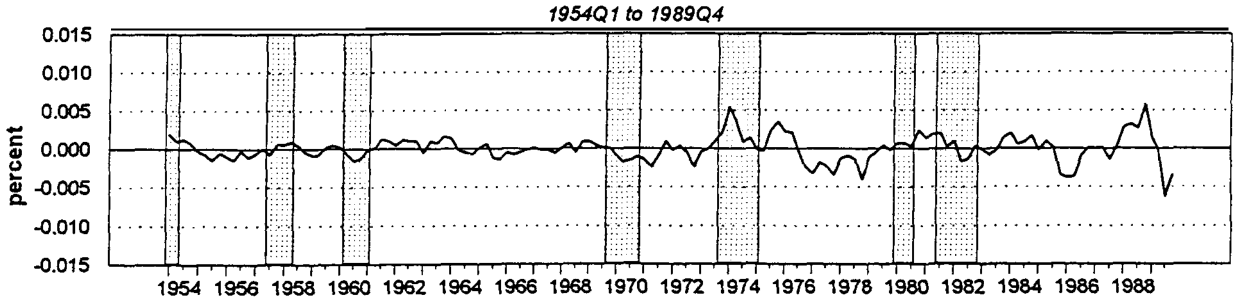
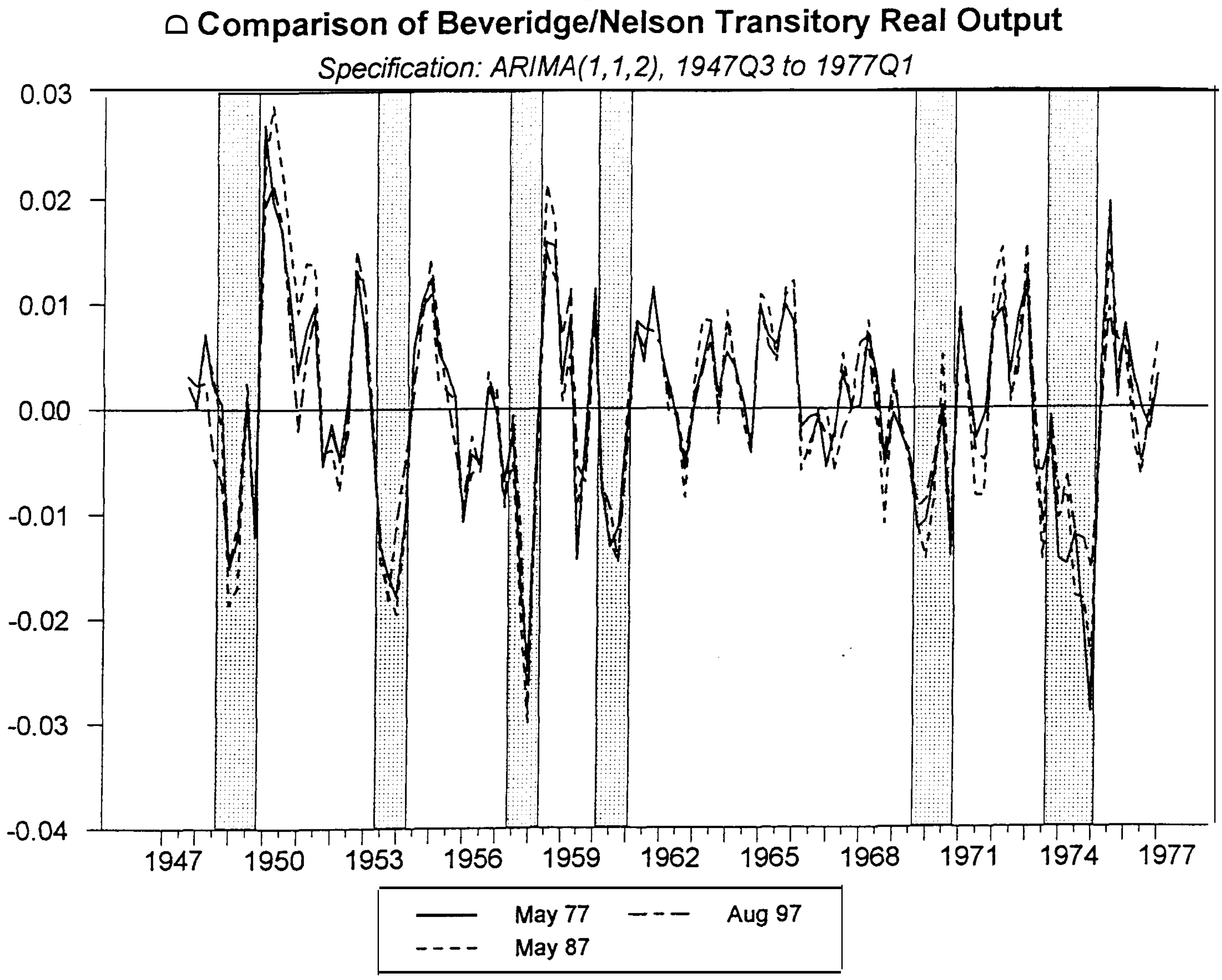


Figure V.5



Comparison of Beveridge/Nelson Transitory Real Output
Specification: ARIMA(1,1,2), 1947Q3 to 1977Q1
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
-0.04
1947
1950
1953
1956
1959
1962
1965
1968
1971
1974
1977
May 77
Aug 97
May 87

Figure V.6

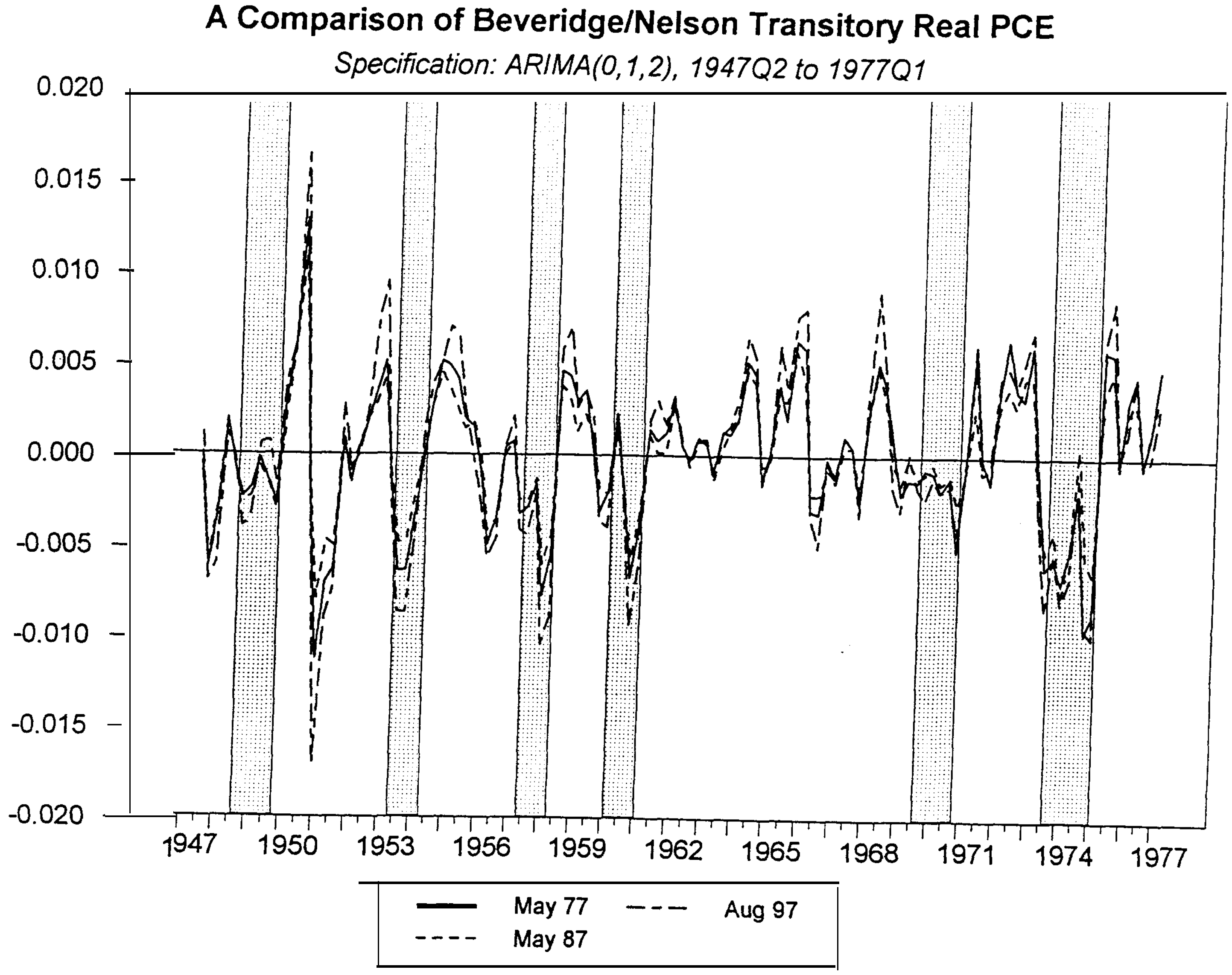
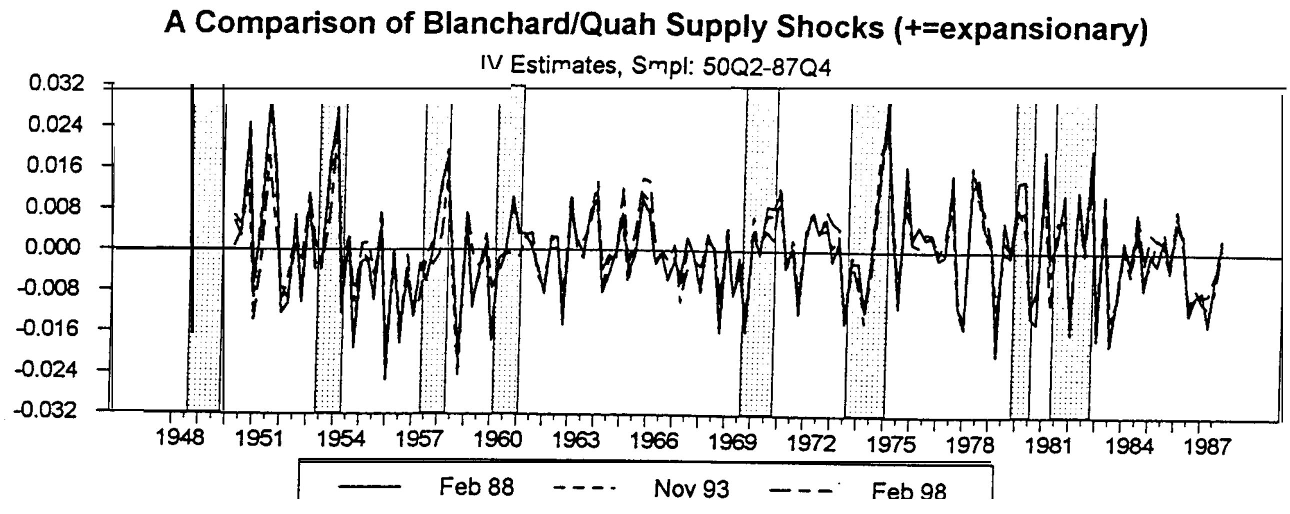

A Comparison of Beveridge/Nelson Transitory Real PCE
Specification: ARIMA(0,1,2), 1947Q2 to 1977Q1
0.020
0.015
0.010
0.005
0.000
-0.005
-0.010
-0.015
-0.020
1947
1950
1953
1956
1959
1962
1965
1968
1971
1974
1977
May 77
Aug 97
May 87

Figure V.7


A Comparison of Blanchard/Quah Supply Shocks (+=expansionary)
IV Estimates, Smpl: 50Q2-87Q4
0.032
0.024
0.016
0.008
0.000
-0.008
-0.016
-0.024
-0.032
1948
1951
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
Feb 88
Nov 93
Feb 98

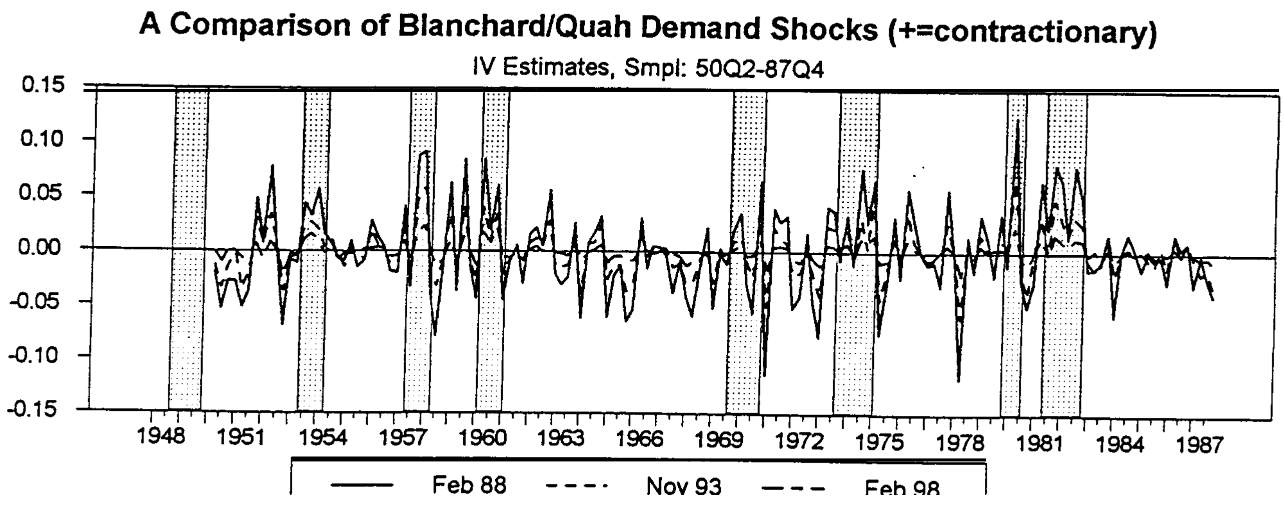

A Comparison of Blanchard/Quah Demand Shocks (+=contractionary)
IV Estimates, Smpl: 50Q2-87Q4
0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
1948
1951
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
Feb 88
Nov 93
Feb 98

Figure V.8

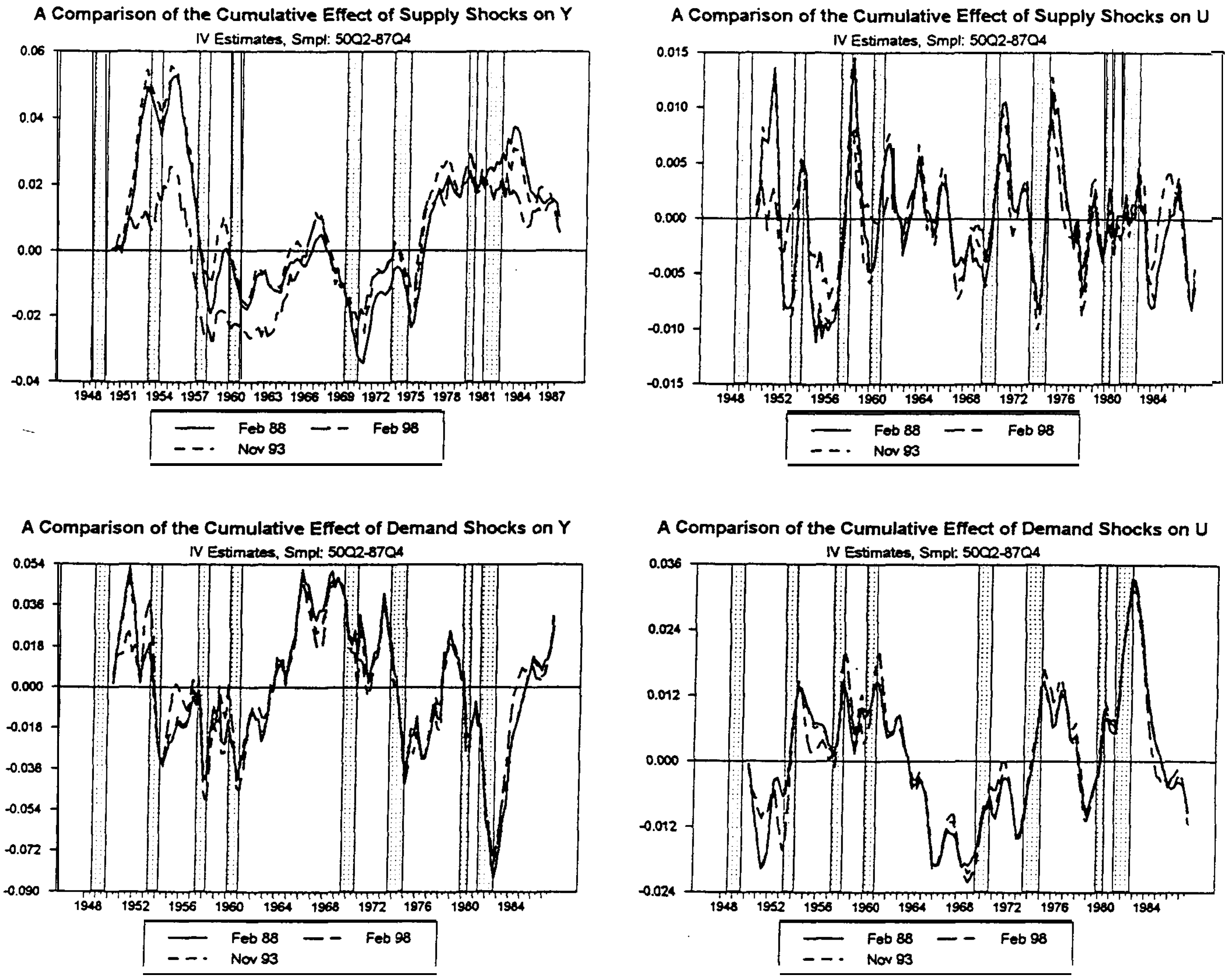
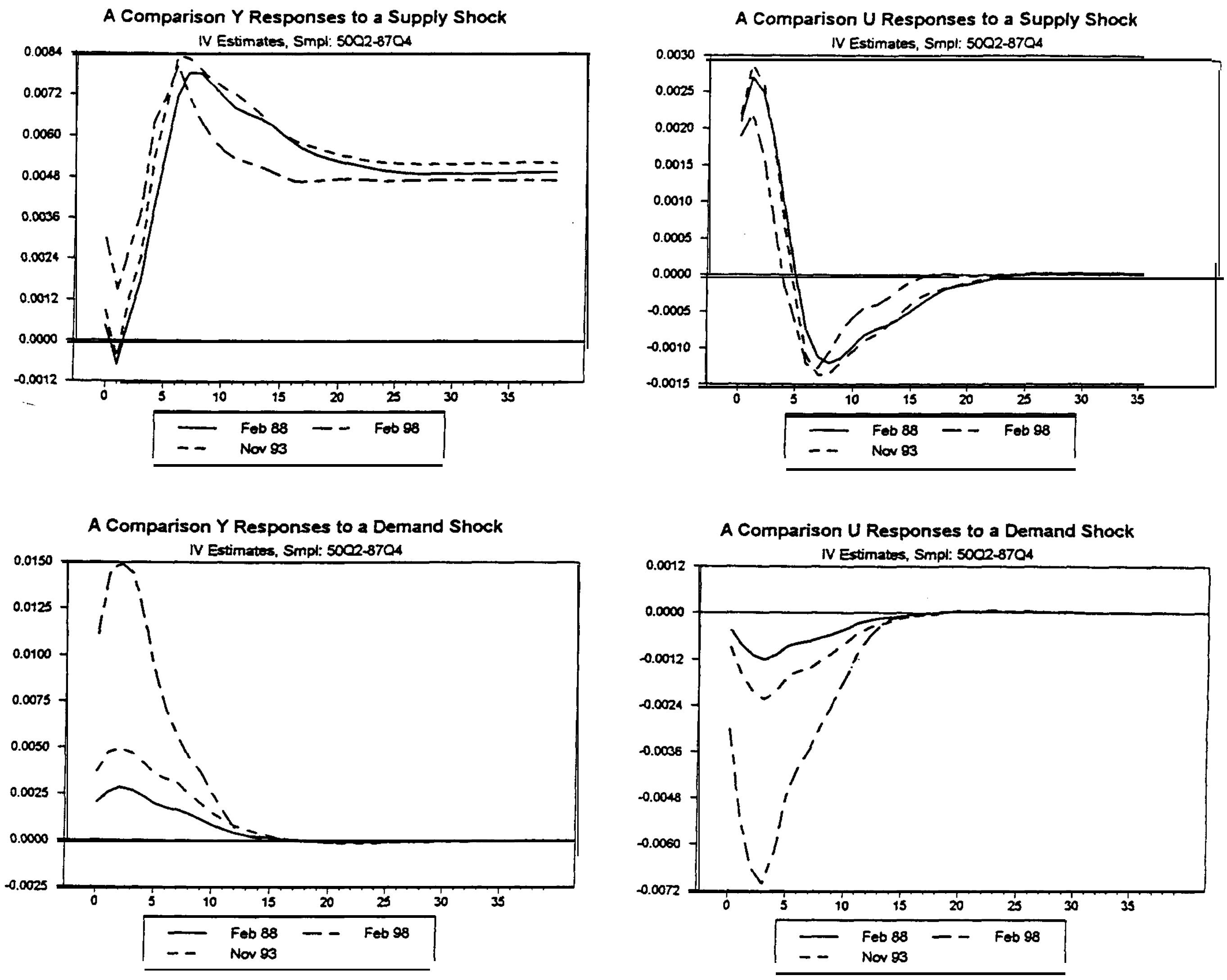

A Comparison of the Cumulative Effect of Supply Shocks on Y
IV Estimates, Smpl: 50Q2-87Q4
Feb 88
Feb 98
Nov 93
A Comparison of the Cumulative Effect of Supply Shocks on U
IV Estimates, Smpl: 50Q2-87Q4
Feb 88
Feb 98
Nov 93
A Comparison of the Cumulative Effect of Demand Shocks on Y
IV Estimates, Smpl: 50Q2-87Q4
Feb 88
Feb 98
Nov 93
A Comparison of the Cumulative Effect of Demand Shocks on U
IV Estimates, Smpl: 50Q2-87Q4
Feb 88
Feb 98
Nov 93

Figure V.9


A Comparison Y Responses to a Supply Shock
IV Estimates, Smpl: 50Q2-87Q4
0.0084
0.0072
0.0060
0.0048
0.0036
0.0024
0.0012
0.0000
-0.0012
0 5 10 15 20 25 30 35
Feb 88
Feb 98
Nov 93
A Comparison U Responses to a Supply Shock
IV Estimates, Smpl: 50Q2-87Q4
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
-0.0005
-0.0010
-0.0015
0 5 10 15 20 25 30 35
Feb 88
Feb 98
Nov 93
A Comparison Y Responses to a Demand Shock
IV Estimates, Smpl: 50Q2-87Q4
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
-0.0025
0 5 10 15 20 25 30 35
Feb 88
Feb 98
Nov 93
A Comparison U Responses to a Demand Shock
IV Estimates, Smpl: 50Q2-87Q4
0.0012
0.0000
-0.0012
-0.0024
-0.0036
-0.0048
-0.0060
-0.0072
0 5 10 15 20 25 30 35
Feb 88
Feb 98
Nov 93