Employment comovements at the sectoral level over the business cycle*

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Abstract

This paper extends the technique suggested by den Haan (2000) to investigate contemporaneous as well as lead and lag correlations among economic data for a range of forecast horizons. The technique provides a richer picture of the economic dynamics generating the data and allows one to investigate which variables lead or lag others, and whether the lead or lag pattern is short term or long term in nature. The technique is applied to monthly sectoral level employment data for the U.S. and shows that among the ten industrial sectors followed by the U.S. Bureau of Labor Statistics, six tend to lead the other four. These six have high correlations indicating that the structural shocks generating the data movements are mostly in common. Among the four lagging industries, some lag by longer intervals than others and some have low correlations with the leading industries. These low correlations may indicate that these industries are partially influenced by structural shocks beyond those generating the six leading industries, but they also may indicate that lagging sectors feature a different transmission mechanism of shocks.

JEL Classification: E32, E37

Keywords: Business cycle, sectoral employment comovement, leading and lagging sectors, forecast errors

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1 Introduction

Modern studies of the business cycle tend to focus on aggregated structures for the economy. Typically statistical analysis uses aggregated data of economic performance and models are built to capture the cyclical performance of these aggregate variables.[1] However, it is well known, at least at an anecdotal level, that the sectoral performance over the business cycle differs between sectors.[2] Some recent papers, such as Long and Plosser (1987), Clark (1998), Christiano and Fitzgerald (1998), Hornstein (2000), DiCecio (2009), and Foerster, Sarte and Watson (2011), have begun to address sectoral performance, but so far measurements for comovement among the economic sectors are relatively sparse and somewhat limited to industrial sectors. Part of the reason for the sparse measurement is no doubt due to the scarcity of data at the sectoral level. But another likely culprit is that the techniques for measuring comovement also need to be developed. This paper contributes to our understanding of sectoral comovement in two important ways. The first contribution is methodological, and shows a way to measure comovement in an intuitive and useful graphical format. The second contribution is to apply this technique to sectoral employment data for the U.S. economy and assess the degree of comovement among these sectors.

The methodological contribution extends a technique developed in den Haan (2000) for measuring contemporaneous comovement. In den Haan (2000) a new methodology, using forecast errors from unrestricted VARs, was developed for assessing the comovement of economic variables. The focus in den Haan (2000) was on contemporaneous comovements of the economic variables. Here we show how to extend this technique to look at, not only the contemporaneous comovements, but also lead and lag comovements in a straightforward manner. Such lead and lag analysis is familiar to readers of the Real Business Cycle literature, where it is routinely pre-

[1] These modern macroeconomic models owe much of their existence to the seminal work on Real Business Cycles by Kydland and Prescott (1982). Such models typically require simplicity somewhere in their formulation in order to remain manageable in dynamic settings and aggregation is the most popular approach to achieving manageability.

[2] The idea of differences in sectoral behavior has been around since work by Pigou (1929).

sented for describing stylized facts of aggregate data.[3] Furthermore, we decompose the lead and lag relationships so as to assess whether the leads or lags are due to short term or long term components of the data. We also suggest a graphical analysis for displaying these comovements which allows one to understand in an intuitive way how to interpret the results and whether these comovements are short term or long term in nature. This provides a more complete description of the data over the business cycle and will be useful as economists start extending dynamic models to include sectoral disaggregation.

We show employment in six industries, including Manufacturing, Construction, Leisure & Hospitality, Trade, Transportation & Utilities, Financial Activities, and Professional & Business Services, move together and do not appear to lead each other over the business cycle.[4] The correlations among this group are high, indicating that they share common structural shocks and a similar transmission channel of shocks. This group also appears to lead the other four industries, including Information Services, Natural Resources & Mining, Education & Health Services and Government, but lead patterns are not homogenous. Employment in these lagging sectors is relatively important since they account for 35% of total non-agricultural employment in the U.S. economy.

All six leading industries clearly anticipate Information Services with leads of about six months. These six industries also have high correlation values with Information Services, indicating that they mostly share the same structural shocks with each other. In addition, these six industries lead Natural Resources & Mining and Government at even longer leads of up to two years but the correlations are somewhat lower. These lower correlations may indicate that other structural shocks are driving

[3] See, for example, Prescott (1986) and Cooley and Prescott (1995).

[4] The data used in this paper came from the U.S. Bureau of Labor Statistics and was obtained from the FRED data base maintained by the St. Louis Federal Reserve Bank. The paper refers to the various sectors by using the names given by the Bureau of Labor Statistics to each sector with the exception of referring to Total Manufacturing as simply Manufacturing. We also use the ampersand, &, when it is part of the name given to a sector by the Bureau of Labor Statistics. In order to be clear when we are referring to a particular industrial sector, the paper uses a convention of capitalizing the name of the sector.

Natural Resources & Mining and Government beyond the structural shocks driving the group of six leading industries, but they may also show that shock transmission patterns in these lagging industries are different. Finally, three industries, including Construction, Leisure & Hospitality, Trade, Transportation & Utilities, lead Education & Health Services at up to two years. The correlations are also low in this case. In addition, the lagging industries display a range of important characteristics. For instance, the lead of Manufacturing over Natural Resources & Mining sets in quickly with short term forecast horizons, while the lead of Manufacturing over Information occurs at long term forecast horizons. Indeed, the extension of uncovering alternative comovement patterns depending on whether these are due to short term or long term components of the data helps to provide additional stylized facts, which are ignored by using a standard approach for analyzing comovement. These new empirical findings on the correlation structure might be helpful in designing a modelling strategy. For instance, significant short term dynamics might be the result of short-run wage rigidities in some sectors, as suggested by DiCecio (2009), that disappear in the long-run, whereas large long-run employment correlations between two sectors might be the result of forces affecting long-run growth.[5]

The paper has been organized as follows. In section 2, we begin by assessing the business cycle performance of the sectoral labor markets using two popular methods. The first is to simply plot the data over time with business cycle turning points designated by the NBER marked, and the second is to use the Hodrick-Prescott filter to isolate the cyclical component of the data and then to use these filtered data to measure intertemporal cross correlations using methods popularized in the Real Business Cycle literature.[6] Section 3 begins by describing our improved methodology

[5]Our objective here is to provide new summary statistics useful for developing better sectorial models of the economy. Some work, such as Clark (1998), Christiano and Fitzgerald (1998), Hornstein (2000), DiCecio (2009), Yedid-Levi (2009) and Foerster, Sarte and Watson (2011) have built models that match the general level of comovement recognized by the Business Cycle Dating Committee of the National Bureau of Economic Research. But these models to not capture the results that we find that some industries tend to be laggards and even among the leaders, some seem to have different transmission mechanisms from each other.

[6]Stock and Watson (1999) also use this lead and lag analysis to assess numerous data series comovements over the business cycle using log differenced data. A related approach is used in

for investigating lead, lag and contemporaneous comovements of variables over the business cycle based on den Haan's (2000) forecast error approach. This technique is then applied to the sectoral labor market data. In Section 4 we investigate the robustness of the results by considering a few alternative applications of the procedures described in Section 3. Section 5 then summarizes our empirical results and offers suggestions on how to make use of these results.

2 Traditional approaches to investigating business cycle comovements

In this section we evaluate the lead, lag and comovements of data using a few popular techniques commonly applied in the macroeconomics literature. The purpose of this data assessment using existing techniques is not to advocate these particular techniques. Instead, it is simply to show what these techniques tell us about business cycle movements, so that they can later be contrasted with the results from our methodology.

For our analysis we use payroll employment data at the sectoral level from January 1969 to May 2008 which is tabulated by the U.S. Bureau of Labor Statistics. The sectoral employment data was chosen because employment is one of the more commonly recognized measures of economic performance and because it is collected at a monthly frequency, which makes it better suited for assessing leading and lagging sectors over the course of the cycle.[7] To evaluate the cyclical properties of the data,

Christiano and Fitzgerald (1998) who detrend using the band pass filter described in Christiano and Fitzgerald (2003).

[7] Another popular measure of economic performance is output, but unfortunately there is no source that is useful for our purposes. Although aggregate GDP is computed at a quarterly frequency by the U.S. Commerce Department, sectoral output is only computed at an annual frequency. Alternative series on industrial production are computed at a monthly frequency by the Federal Reserve Bank. Unfortunately, this data tends to emphasize Manufacturing, Business Equipment, Mining and Electric & Gas Utilities and leaves out many other important service industries. This missing service sector component is particularly important in part, because the service sectors have grown to such a large percentage of GDP, but also because our results below show that some of these service sectors are part of the group of sectors which lag the rest of the economy. Given these constraints, we regard the employment data as more suitable. Later in section 4, we present some results using the manufacturing production data.

we first isolated the business cycle component from the time series by applying the filter described in Hodrick and Prescott (1997). This filter is widely used in the business cycle literature and is designed to extract frequencies between 2 and 8 years from the raw data.[8]

Figure 1 plots the industry level data series along with various business cycle turning points which have been designated by the NBER. This style of analysis dates back to the important work of Burns and Mitchell (1946). The figure contains four diagrams which plot only a subset of industries at a time in order to provide good resolution for the individual industries. The figure illustrates a number of important stylized facts on payroll employment fluctuations. First, observe that the level of employment associated with the goods producing sectors, Manufacturing, Construction and Natural Resources & Mining, which is plotted in Figure 1.A, fluctuates much more than the service providing sectoral employment displayed in the rest of the figures. Second, Figure 1.A. shows that, Manufacturing and Construction employment move together with Construction displaying larger fluctuations than Manufacturing employment, while Natural Resources & Mining employment follows a quite different pattern. Third, Figures 1.B and 1.C. show that fluctuations in the service providing sectors are procyclical while the Government sector is less procyclical. Figure 1.D plots Information Services by itself and shows an unusual data point in August of 1983. Aside from this one observation, the rest of the series has similar business cycle patterns as the other series.[9] Finally, the troughs for the business cycle employment in all sectors lag behind the end of the recession periods as dated by the NBER.

[8] This analysis was also carried out using the band pass filter advocated by Christiano and Fitzgerald (2003) with largely the same results. These results can be obtained from the authors upon request. Another alternative used in Stock and Watson (1999) is to take logarithmic differences of the data to focus on the growth rates of unit root processes. As is well known (Canova, 1998, pp. 489-490), first-difference detrending implies cycles of short length, which emphasize high-frequency data dynamics.

[9] This unusual data point in August 1983 is likely a miscode, but it could be because of employment changes arising from the break up of AT&T. However, regardless of its origin, since this is the way the data is reported, we did not want to change it. In all of the results reported below we used the data exactly as reported. As a check, we also ran the calculations using a value of 2213, which was the average of the series one month before and one month after that date, and found qualitatively the same results.

Another standard way to assess comovements among the various sectors is presented in Table 1 which shows the contemporaneous cross-correlations between sectors using the Hodrick-Prescott filtered data with a smoothing parameter value of 14,400. Table 1 shows that Manufacturing, Construction, Trade, Transportation & Utilities, Professional & Business Services and Leisure & Hospitality are highly correlated with each other yielding correlations with each other of 0.70 or higher. Information Services and Education & Health Services are more modestly correlated with the other sectors with correlations around 0.5 or lower while Natural Resources & Mining and Government are the least correlated with correlations often near zero and sometimes negative. On the other hand, Financial Activities has somewhat mixed correlations. It is moderately correlated with Construction, with a correlation of 0.61, and mildly correlated with other sectors, with correlations ranging from 0.08 to 0.41.

So far this analysis only shows how the sectors tend to comove, but does not offer anything informative about which sectors may lead or lag others. A more informative assessment of this type of correlation is presented in Table 2 which uses a format popularized by Prescott (1986) for assessing business cycle comovements.[10] To use the Prescott presentation, a base series needs to be chosen which is used to compare against the other series. We choose Manufacturing employment as our base series in part because our results described below show it to be one of the leading sectors of the economy and thus it provides a useful benchmark for discussion.[11]

[10] Stock and Watson (1999) also use this approach with disaggregated data. An alternative approach for lead and lag analysis is to use VAR methods as in Fuhrer and Moore (1995). In contrast to the VAR approach suggested in this paper, the VAR approach followed by Fuhrer and Moore (1995) requires that all variables included in the VAR to be covariance stationary. So detrending of non-stationary variables is required prior to computing their comovement under Fuhrer and Moore's approach. Space considerations kept us from including that analysis here, but sample assessments using this approach can be obtained from the authors on request.

[11] Prescott (1986) choose GDP as the base series.

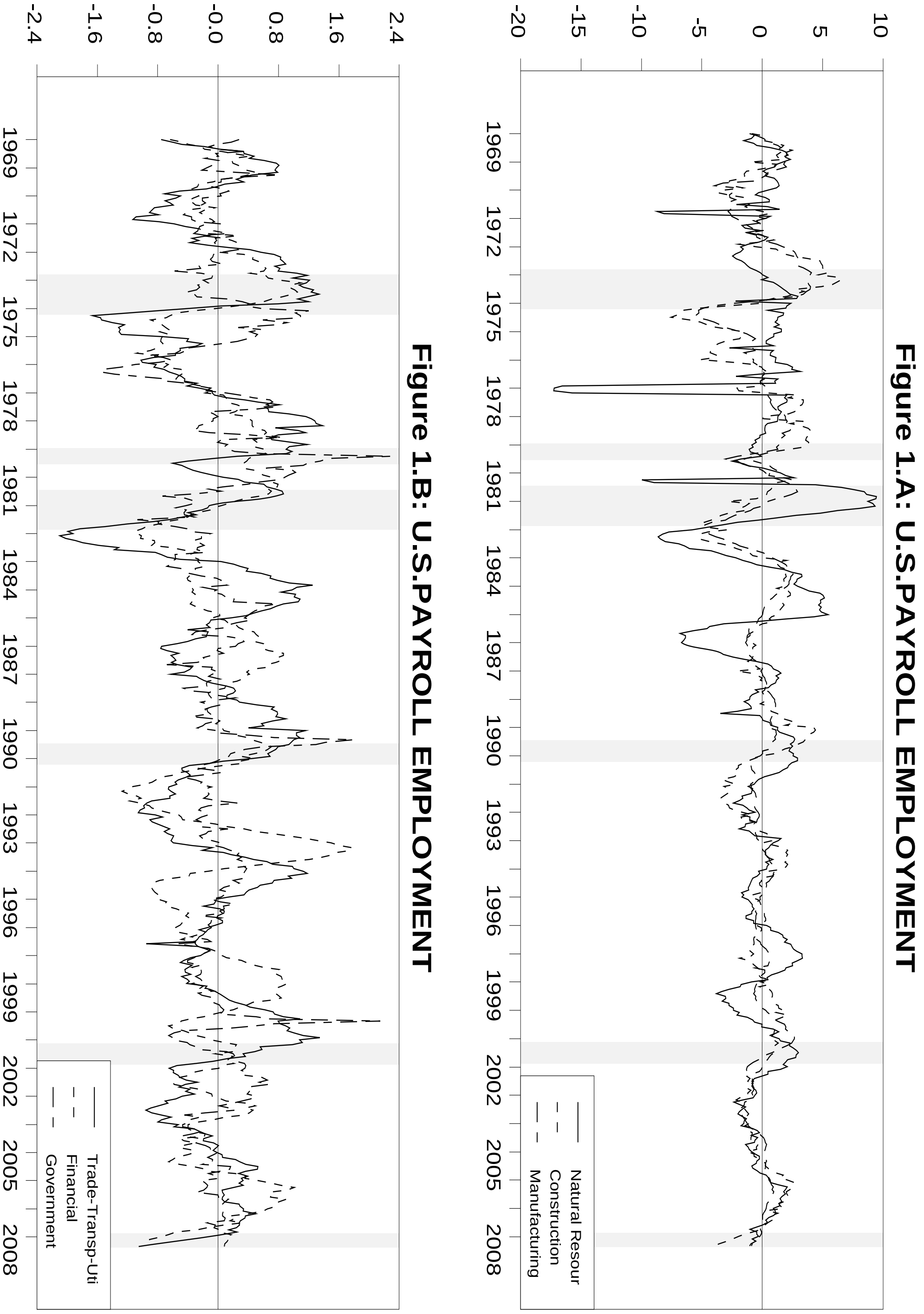

Figure 1: Sectoral Employment Fluctuations

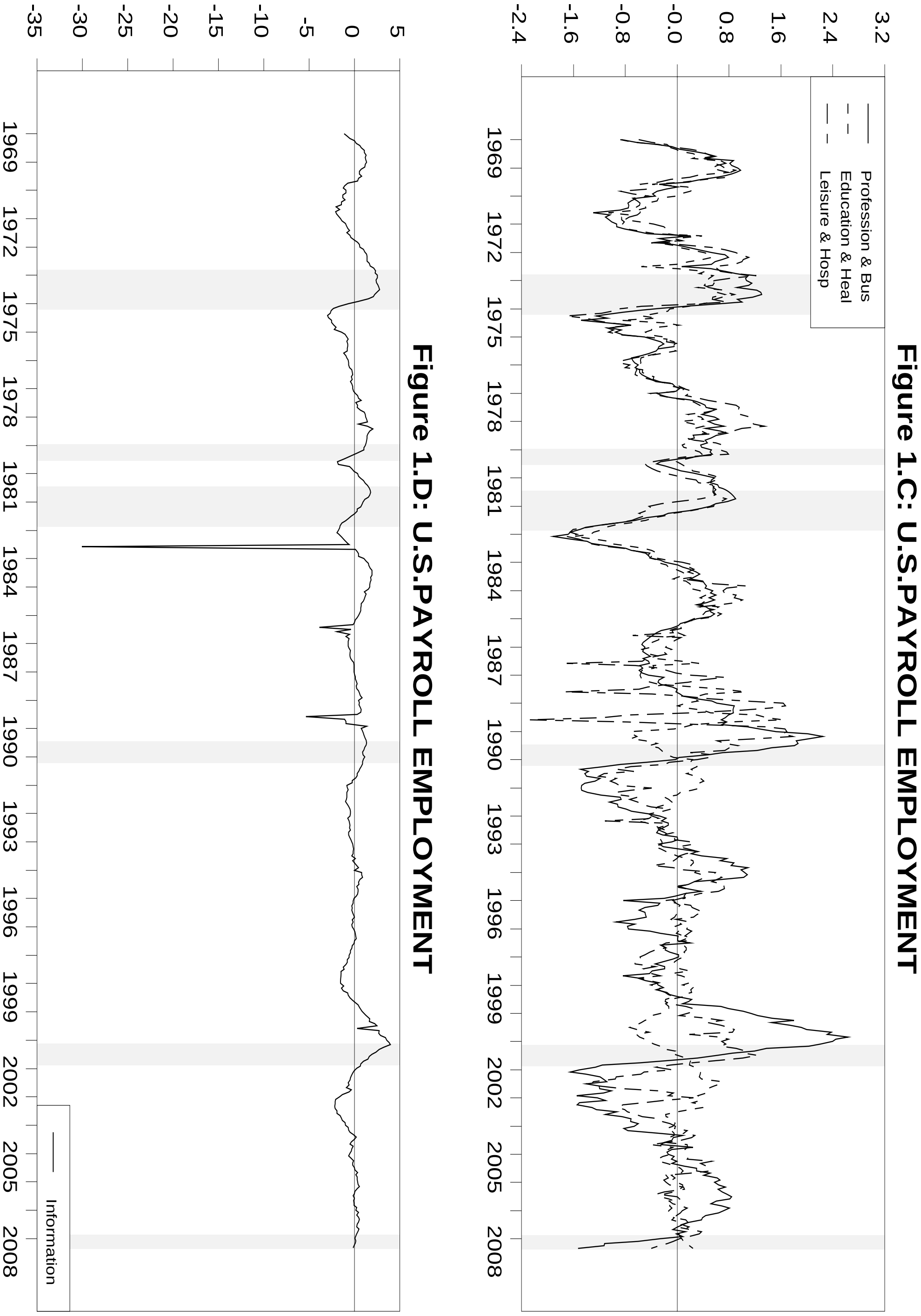

Figure 1 (*continued*): Sectoral Employment Fluctuations

Table 1. Contemporaneous cross-correlations between sectors
Filtered monthly U.S. data 1969:1-2008:5

Variable	M	C	NRM	TTU	IS	FA	PBS	EHS	LH	G
M	1.0									
C	0.79	1.0								
NRM	0.26	0.18	1.0							
TTU	0.86	0.82	0.28	1.0						
IS	0.57	0.46	0.27	0.58	1.0					
FA	0.41	0.61	0.08	0.39	0.19	1.0				
PBS	0.75	0.72	0.26	0.85	0.50	0.42	1.0			
EHS	0.50	0.38	0.30	0.52	0.24	0.28	0.26	1.0		
LH	0.73	0.70	0.17	0.80	0.50	0.32	0.73	0.26	1.0	
G	-0.09	0.12	-0.01	0.15	0.00	0.13	0.12	0.20	0.13	1.0

Abbreviations: NRM - Natural Resources & Mining; C - Construction; M - Manufacturing; TTU- Trade, Transportation & Utilities; IS-Information Services; FA- Financial Activities; PBS -Professional & Business Services; EHS -Education & Health Services; LH - Leisure & Hospitality; G- Government

Column 1 of Table 2 confirms quantitatively some of the conclusions drawn from Figure 1. In particular, it shows that Manufacturing, Construction, Natural Resources & Mining and Information Services have the highest levels of variation. On the other hand, Trade, Transportation & Utilities, Financial Activities, Professional & Business Services and Leisure & Hospitality are more modestly variable while Education & Health Services and Government have relatively low variation. Column 2 normalizes the standard deviations by dividing by the standard deviation for the Manufacturing sector and shows the relative variation across the sectors in a different form.

Following Prescott (1986), the other columns show the correlations of Manufacturing with leads and lags of the other sectors. One way to read the table is to look across a single row. The first such correlation (column 3) shows the correlation of the series with a six period lead relative to Manufacturing while the next three columns show the correlation of the series with a four, two and then one period lead relative to Manufacturing, respectively. After that, the contemporaneous correlation is presented and then correlations of the series at one, two, four and then six period lags relative to Manufacturing are presented.

In the table, the highest correlation in any given row is highlighted by writing the correlation in bold.[12] This highest correlation is useful for assessing the relative lead and lag situation for Manufacturing. So for instance, the high contemporaneous correlation of Manufacturing with Construction, Professional & Business Services and Leisure & Hospitality suggests that these four sectors tend to move together and are leading the rest of the economy. Next, the high correlation of Manufacturing at a one period lead with Trade, Transportation & Utilities, Information Services and Financial Activities suggests that Manufacturing leads these sectors by one month. Education & Health Services, Natural Resources & Mining and Government come next with highest correlations indicating Manufacturing leads these sectors by two months, four months and six months respectively.[13]

3 Forecast error comovements over the business cycle

In this section we investigate the data comovements by extending methods developed by den Haan (2000). This section has been broken into four subsections. In the first subsection we describe our extension of the den Haan method and spell out how we use this extension to investigate leading and lagging properties of the employment data over the business cycle. The next two subsections then apply this methodology to the employment data and conclusions are reached about which industrial sectors

[12] Some of the highest correlations appear to be equal to others with the two decimal place accuracy given in the table, but are higher if additional decimal places are considered. The additional decimal places are not reported to keep the table's width narrow enough to fit on a page.

[13] Since Manufacturing, Construction, Leisure & Hospitality Services, and Professional & Business Services are highly contemporaneously correlated we concluded that they lead the other sectors. As a robustness check of this conclusion, it is possible to recompute the table with either of these sectors as the benchmark sector. Such a computation yields results that are analogous to the ones presented here for Manufacturing and in the interest of space are not presented. However, in the analysis which uses our new technique, we do describe the results for alternative benchmark industries. We also considered the possibility of using aggregate employment as a benchmark in the lead-lag analysis, but disregarded this because the contemporaneous correlations will be higher in this case by construction than those obtained using any leading sector as a benchmark sector. More important, these larger contemporaneous correlations may then induce a different bias in the lead-lag analysis depending on the relative importance of each sector on aggregate employment.

seem to lead and which seem to lag others over the course of the business cycle. In the first of these subsections, the focus is on the correlations of Manufacturing with the other industries. There a rather complete picture is provided. In the following subsection, a less complete picture is provided of the correlations of the other industries with each other. This less complete picture is intended to highlight the key results, without taking up too much space. Finally, the last subsection summarizes our findings and compares them to the findings using the traditional approach in Section 2.

Table 2. Cross-correlation coefficients with Manufacturing

Variable	σ_z	σ_z/σ	ρ_{z+6}	ρ_{z+4}	ρ_{z+2}	ρ_{z+1}	ρ_z	ρ_{z-1}	ρ_{z-2}	ρ_{z-4}	ρ_{z-6}
M	1.62	1.00	0.55	0.76	0.92	0.97	**1.00**	0.97	0.92	0.76	0.55
C	2.19	1.35	0.51	0.66	0.75	0.78	**0.79**	0.78	0.75	0.65	0.51
NRM	3.08	1.90	0.38	**0.38**	0.34	0.31	0.26	0.20	0.14	0.00	-0.13
TTU	0.70	0.43	0.62	0.76	0.85	**0.87**	0.86	0.83	0.76	0.62	0.42
IS	1.83	1.13	0.46	0.54	0.58	**0.58**	0.57	0.53	0.48	0.36	0.22
FA	0.57	0.35	0.32	0.37	0.41	**0.41**	0.41	0.39	0.37	0.30	0.21
PBS	0.82	0.50	0.50	0.63	0.73	0.75	**0.76**	0.74	0.70	0.58	0.42
EHS	0.42	0.26	0.45	0.51	**0.53**	0.52	0.50	0.46	0.42	0.29	0.14
LH	0.65	0.40	0.43	0.57	0.67	0.71	**0.73**	0.72	0.69	0.58	0.44
G	0.44	0.27	**0.12**	0.04	-0.03	-0.06	-0.09	-0.11	-0.11	-0.08	-0.03

Notes: σ_z denotes the standard deviation of variable z, σ_z/σ denotes the relative standard deviation of z with respect to Manufacturing. $\rho_{z\pm j}$ is the cross-correlation of the j- lead/lag with current Manufacturing. Bold characters highlight the highest cross-correlation coefficients.

3.1 Measuring comovement

In den Haan (2000) a new methodology for assessing the comovement of economic variables was developed.[14] The method makes use of forecast errors for assessing comovement and is attractive for several reasons. First, the method does not require any modelling assumptions, such as VAR ordering or structural assumptions on the error terms, to be applied. Second, it does not require that the data be detrended in

[14] In addition to den Haan (2000), other applications of this approach include den Haan and Sumner (2004) and María-Dolores and Vázquez (2008). Cassou and Vázquez (2010) show how to use the extension described in this paper to investigate the lead-lag comovement between output and inflation in the context of a New Keynesian model.

a specific way or that the variables in the model have identical orders of integration.[15] As forcefully argued by Canova (1998), different filters provide different business cycle statistics. Some of them (say first-differences) emphasize short-term movements of the data, the Hodrick-Prescott filter isolates business cycles movements lasting from 2 to 8 years, whereas linear detrending and multivariate detrending methods, such as the one suggested by King, Plosser, Stock and Watson (1991) based on a model of common stochastic trends, emphasize movements of longer duration. Our approach, based on forecast errors obtained at alternative forecast horizons allows one to analyze whether the correlation structure between two variables is driven by the short-term and/or the long-term components of the data in a systematic way, thus providing a more comprehensive view of dynamic comovement.

Another salient feature of the den Haan (2000) approach is the interpretation for the sources of fluctuations. As in typical VAR methods, the fluctuations in both the data and thus in the forecast errors originate from some underlying structural shocks which could be associated with the various variables in the model. However, the method does not need to identify which structural shocks play a role in any particular equation and can be left unspecified.[16] One simply envisions that all of the structural shocks play some role in each of the model variables and the comovements in the observed data are shaped by the importance of these structural shocks in the variables for which comovements are being investigated, but sorting out which of the structural shocks are important is not necessary.[17]

The focus in den Haan (2000) was on contemporaneous comovements of the economic variables, but for our investigation, we are interested in more than just that. Here we extend this methodology to look at not only the contemporaneous comove-

[15] Avoiding detrending of the data is useful because den Haan (2000, p. 5) argues that the negative correlation between output and prices often found in the data could be an artifact of common detrending procedures used to make the data stationary.

[16] Indeed, an important difference between the approach here and the one in Clark (1998) is that Clark uses methods to identify the sectoral and regional structural shocks.

[17] One limitation of this approach is that it does not provide standard impulse response functions which show the responses of each endogenous variable to alternative structural shocks. However, den Haan (2000) views this as a positive feature as he notes that such standard impulse response analysis requires an identification structure which is often the subject of some dispute.

ments, but also lead and lag comovements. Such lead and lag analysis is familiar to readers of the Real Business Cycle literature and was reviewed for our application in Section 2. As shown below, the lead and lag analysis of the forecast errors provides a broader format for describing the data comovements than the approach in Section 2 and leads to a more complete description of the nature of these comovements.

We begin by running a VAR of the form

$$X_t = \mu + Bt + Ct^2 + \sum_{l=1}^{L} A_l X_{t-l} + \varepsilon_t \tag{1}$$

where A_l is an $N \times N$ matrix of regression coefficients, μ, B, and C are N-vectors of constants, ε_t is an N-vector of innovations, and the total number of lags included is equal to L. The ε_t are assumed to be serially uncorrelated, but the components of the vector can be correlated with each other. As in the traditional analysis, we logged the data. For our application, $N = 10$, because there are ten sectors for which there is monthly employment data. Also, following popular forecasting practice, we let $L = 12$, so there is one full year worth of lags in the VAR.[18]

From this VAR, forecast errors can be computed for alternative forecast horizons. A particular N-vector of forecast errors can then be viewed as the cyclical component of X_t determined by a particular forecast horizon K. The forecast errors associated with short-term horizons would tend to be more highly influenced by the high-frequency components of the data whereas long-term forecast errors would tend to emphasize relatively more low-frequency components because the long-term forecast errors essentially rebuild the series minus the deterministic trend. Each of these forecast errors obtained from the different equations at various forecast horizons can then be used to compute contemporaneous correlations for the forecast errors from the different equations at various forecast horizons as in den Haan (2000).

In our analysis, we simply extend this approach by further using these forecast errors to compute cross correlations at various leads and lags, as in the Real Business Cycle style of analysis used in Section 2, to determine which variables lead and

[18] We also investigated a 24 lag VAR forecasting equation and found the results to be qualitatively the same as the 12 lag VAR.

lag the cycle. These calculations provide a more complete dynamic perspective of comovement than the alternative approaches suggested by the Real Business Cycle literature and den Haan (2000) by not only showing useful information about how the data comove both contemporaneously as well as at leads and lags, but also by showing how data comove at alternative forecast horizons. These alternative forecast horizons thus tell us if the lead and lag patterns are arising due to more short term or more long term components of the data. In the next subsection we show how this system of lead and lag correlations between forecast errors can be plotted against the forecast horizon to conveniently assess the business cycle properties of the data.

3.2 Correlations of Manufacturing with all other industries

In order to organize the results in a coherent form, this subsection provides an extensive set of diagrams illustrating the correlations of the various industries with Manufacturing. This set of diagrams is rather exhaustive and is provided for this one situation to illustrate the extent of the analysis that can be carried out using this empirical methodology. In the next subsection, a less exhaustive set of diagrams is presented for the correlations of the other industries with each other. In that presentation, diagrams which show somewhat different correlations are presented, while those that are similar to the ones from the manufacturing analysis are omitted and simply noted to have similar features.[19]

Figure 2 presents a set of six diagrams for the forecast error correlations between Manufacturing and Information Services.[20] One common element in all the diagrams is the contemporaneous correlation which is plotted at various forecast horizons in

[19] A complete set of diagrams can be obtained from the authors upon request.

[20] The length of forecast error series used to compute the lead-lag correlations in this and the remaining figures of the paper is 318. It is possible to use standard bootstrapping methods to find confidence bands around the correlation plots. Such confidence bands were generated using programs from den Haan's web site and showed sufficiently wide bands that the individual correlation plots were not significantly different from each other. However, as in Prescott (1986) and Stock and Watson (1999), we still interpret maximal correlations that are different from the contemporaneous correlation as indicating a lead or lag. Because the bands did not indicated significance, they are not provided here, but sample plots can be obtained from the authors upon request.

each diagram by a dashed line.[21] Each of the six diagrams then has a lead-lag pair in which a contemporaneous forecast error for Manufacturing is matched with a lead (thick solid line) or a lag (thin solid line) forecast error for Information Services. The upper left diagram has a lead-lag pair in which the correlations are for Information Services 24 months, or two years, ahead or behind Manufacturing, while the upper right diagram has a lead-lag pair corresponding to 18 months, the middle left diagram has a lead-lag pair corresponding to 12 months, the middle right has a lead-lag pair corresponding to 6 months, the lower left has a lead-lag pair corresponding to 3 months and the lower right has a lead-lag pair corresponding to 1 month. A useful comparison of these diagrams can be made with Table 2 above by noting that if one focuses on the lead lines and one moves upward through the diagrams (i.e. one moves through the diagrams with progressively longer leads), it is the same type of exercise as moving to the left of the contemporaneous column in Table 2, while if one focuses on the lag lines and one moves upward through the diagrams (i.e. moves through the diagrams with progressively longer lags), it is the same type of exercise as moving to the right of the contemporaneous column in Table 2.

Interpreting the diagrams borrows insights from both the Real Business Cycle approach and the den Haan (2000) approach. As in the Real Business Cycle approach, in places where the lead correlation is higher than the contemporaneous correlation, one would interpret Manufacturing as leading Information Services. Furthermore, as in den Haan (2000), the horizontal axis represents the forecast horizon and provides information about whether the correlation occurs in the short run or long run. Situations in which the lead line exceeds the contemporaneous line toward the right edge of the diagram would indicate that Manufacturing leads Information Services at longer forecast horizons. Because the Hodrick and Prescott filter is often set to isolate so called business cycle frequencies between 2 and 8 years, our diagrams have as their highest forecast horizon 96 months (i.e. 8 years). We use forecast horizons as low as 1 month, so the left side of the diagrams consist of short run correlations.

[21] This contemporaneous correlation plot is the one used by den Haan (2000) for his analysis.

These short term correlations are typically close to, but not equal to, zero because of noise. If there were no noise, then these correlations would be equal to zero because the forecast errors from different information sets are uncorrelated up until where the forecast horizons start to share common unknown elements.[22]

To be more concrete about the actual results, lets start by walking through the middle right diagram in Figure 2. The fact that the contemporaneous correlation is highest at the short-term forecast horizons indicates there is no evidence that Manufacturing leads Information Services at a six month lead for these forecast horizons. The fact that all three correlations are relatively low for the short-term forecast horizons indicates that noise dominates these correlations. As one moves to the right of the diagram, we see that the six month lead crosses the contemporaneous correlation around a forecast horizon of 42 months. This indicates that for longer forecast horizons, Manufacturing leads Information Services by about six months. Once one understands how to interpret this middle right diagram, the others fall into place relatively easily. To summarize the main points of these diagrams, we see that Manufacturing leads Information at longer forecast horizons for leads up to about six months, but for shorter horizons Manufacturing no longer leads Information Services. This comovement pattern is likely to be the result of a larger share of high-skilled, technical-skilled workers in Information Services (mostly, telecommunication, radio and television broadcasting, and publishing activities), which may require a longer job screening process when jobs are posted during expansions and a sluggish layoff reaction in recessions due to a labor hoarding effect (i.e. it is profitable not laying off unneeded workers during recessions to ensure that skilled workers are available in the initial stages of expansion).[23] The fact that the leads show up at long-term forecast

[22] At this point, it is also possible to illustrate one of the methodological differences between this paper and the important work by Long and Plosser (1987). They also looked at forecast errors. However, they only looked at one step ahead forecast errors and did not look at lead and lag correlations. Their comovement statistic is roughly equivalent to the first correlation displayed on the left edge of the contemporaneous correlation line in our diagram.

[23] Blankenau and Cassou (2009) document that Information Services as well as Education & Health Services, discussed below, have a higher skilled labor percentage than Manufacturing, where skilled labor is defined as workers with college degrees.

horizons (i.e. low frequency components of the data) is consistent with the idea that technical progress and human capital are among the main determinants of long-run growth.

Figures 3-6 present correlation diagrams between Manufacturing and the other eight sectors. In order to save space, for these industry combinations, we have reduced the number of lead-lag combinations from six to three, by eliminating the 24 month, the 18 month and the 1 month diagrams. Figures 3-6, still present six diagrams each, but now these figures display three diagrams for the comovement of Manufacturing with two of the sectors with each column of diagrams representing the three diagrams for a particular sector.

Because the pattern for displaying the results is the same as in Figure 2, interpreting the results is fairly straightforward. These diagrams show that a group of five industries, including Construction, Trade, Transportation & Utilities, Financial Activities, Professional & Business Services and Leisure & Hospitality tend to move with Manufacturing and none leads or lags Manufacturing. On the other hand, Manufacturing does lead Natural Resources & Mining up to one year. The lead occurs at the medium-term forecast horizons while there is no lead at the short forecast horizons where noise dominates the forecast errors. This lead likely occurs because Manufacturing uses natural resources, so when Manufacturing picks up, demand for Natural Resources & Mining sector soon follows.

Manufacturing also leads Education & Health Services up to two quarters at long-term forecast horizons. This type of comovement is also likely to be the result of a larger share of high-skilled workers in Education & Health Services (among others, professors, medical doctors, teachers, nurses), explained by a longer job screening process and the presence of a labor hoarding effect in the Education & Health Services. The fact that the leads show up at long-term forecast horizons is also consistent with the idea that education and health services are among the main engines of long-run growth.

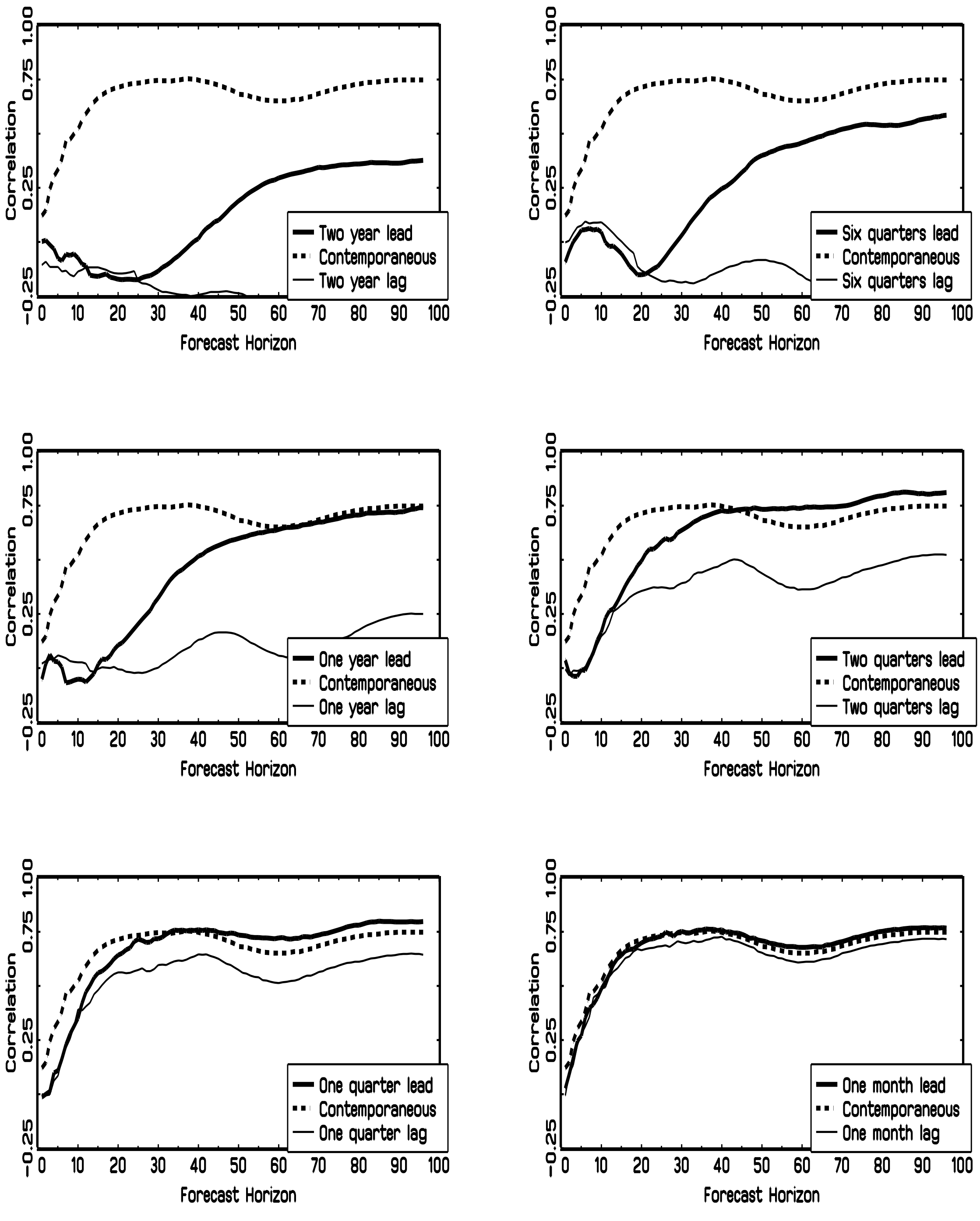

Figure 2: Comovement between Manufacturing and Information

Manufacturing also leads Government employment not only at one year leads shown here, but also up to two year leads. These long leads of Manufacturing over Government employment is also related to a larger share of high-skilled workers in Government employment, but it may be explained also in part by government decision lags resulting from budget approval after -long- political debates.

It is also worth noting that the correlations of Manufacturing employment are somewhat lower with Natural Resources & Mining, Financial Activities, Education & Health Services and Government than they are with other sectors. This may indicate that the structural shocks that move Manufacturing are somewhat different than those moving these other sectors thus resulting in lower correlations, but it may also a consequence of different transmission mechanism of shocks due to other factors such as different union membership rates across sectors. High union membership rates is a good proxy of high union power, which may induce a small and sluggish reaction of Government sector employment to shocks. According to the U.S. Bureau of Labor Statistics in 2010 the union membership rate for public sector workers (36.2%) was five times higher than the rate for private sector workers (6.9%). Within the public sector, local government workers had the highest union membership rate (42.3%).

3.3 Correlations among the other industries

Figures analogous to those in Figures 2-6 were generated with each of the other sectors substituting for Manufacturing as the reference industry. Here we only summarize the results and provide a few examples that are noteworthy.[24]

[24] It may be useful to note, that because of the symmetry with regard to the leads and lags, Figures 2-6 also show how the plots would look when other industries are the reference. So for example Figure 2 shows how the plots would look when Information Services is the reference industry and correlations with Manufacturing are plotted. The only difference is that the line representing the lead (lag) correlation in Figure 2 would now represent the lag (lead) correlation when Information Services is the reference industry.

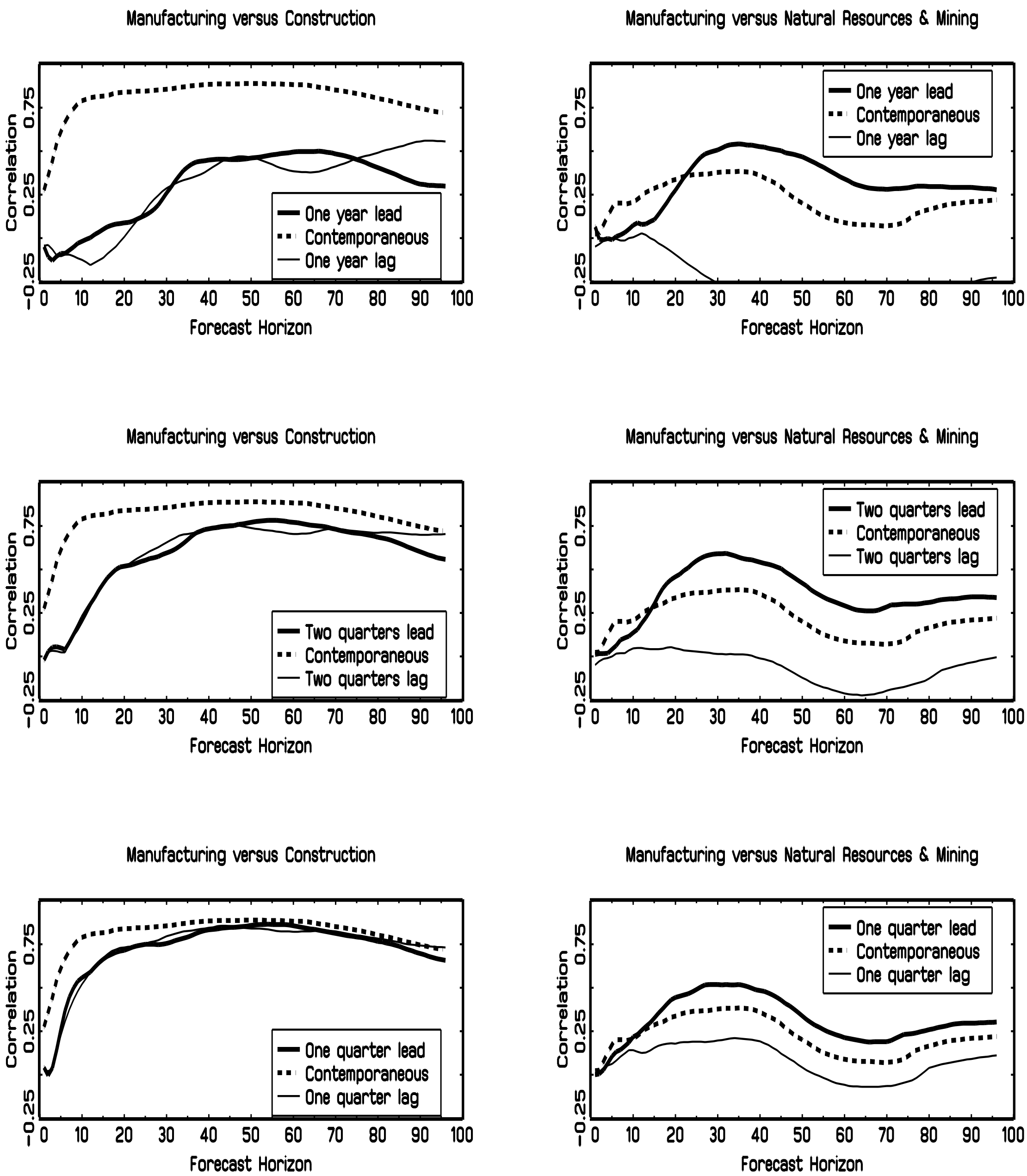

Figure 3: Manufacturing Comovement with Construction and Natural Resources & Mining

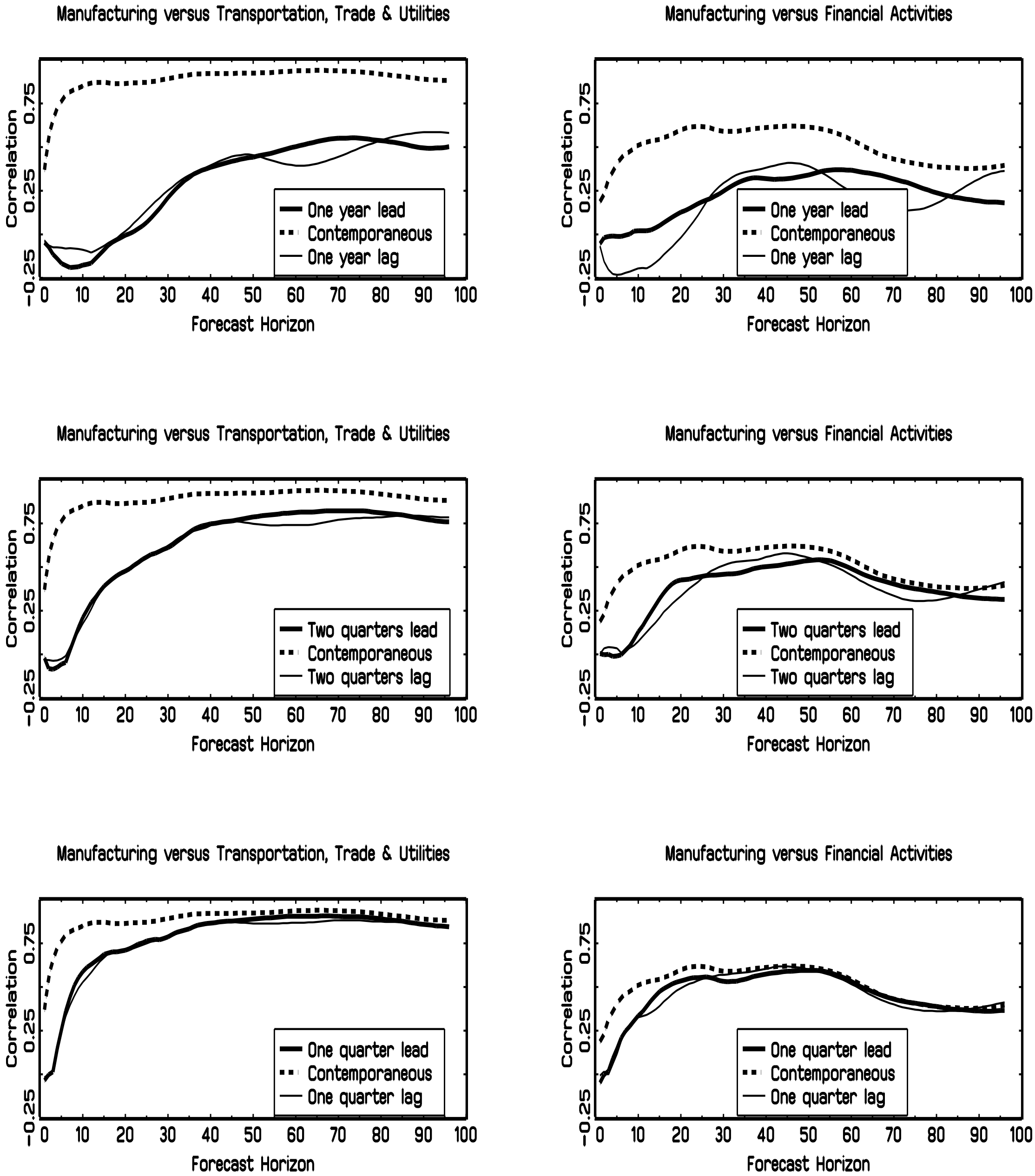

Figure 4: Manufacturing Comovement with Trade, Transportation & Utilities and Financial Activities

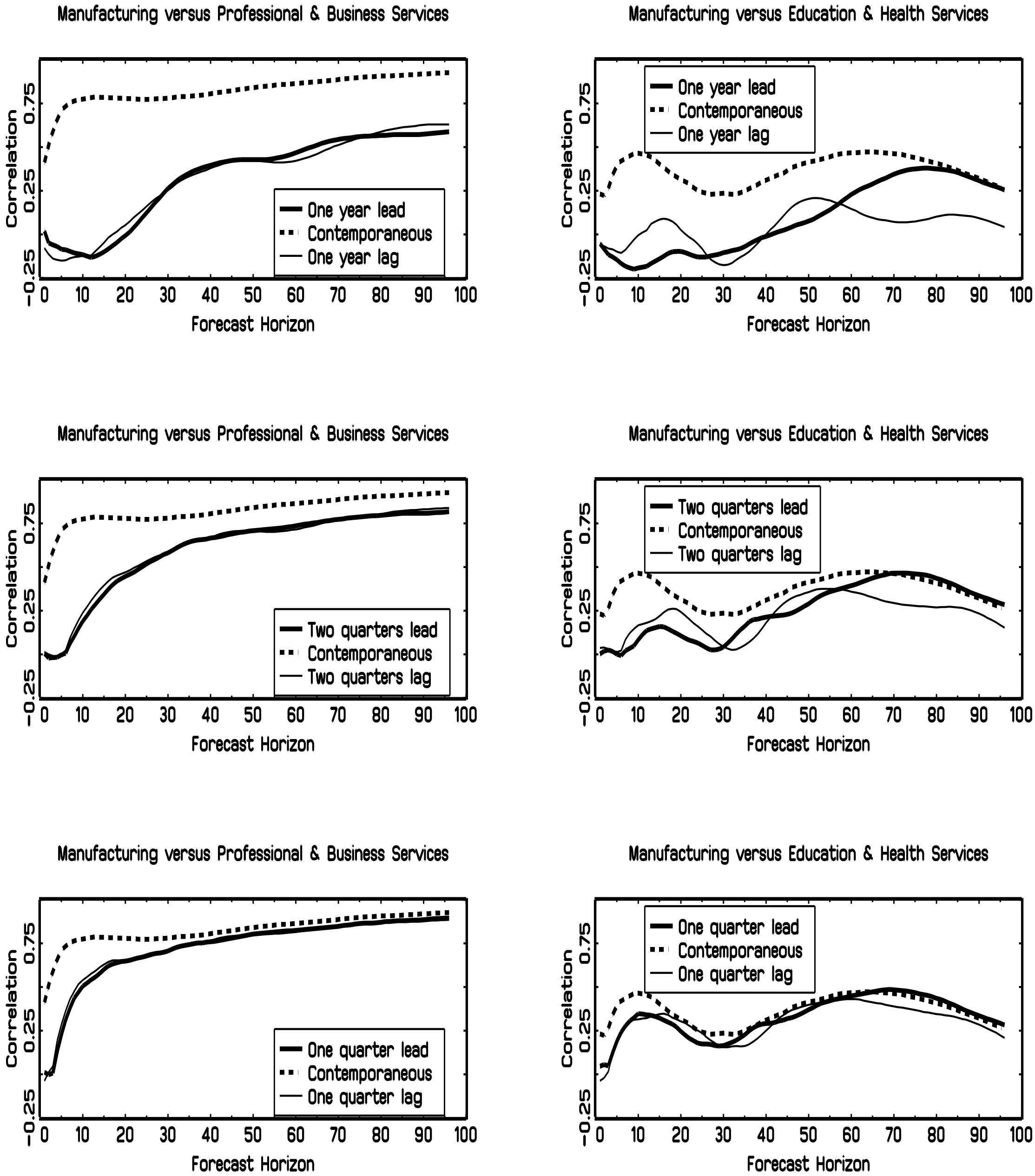

Figure 5: Manufacturing Comovement with Professional & Business Services and Education & Health Services

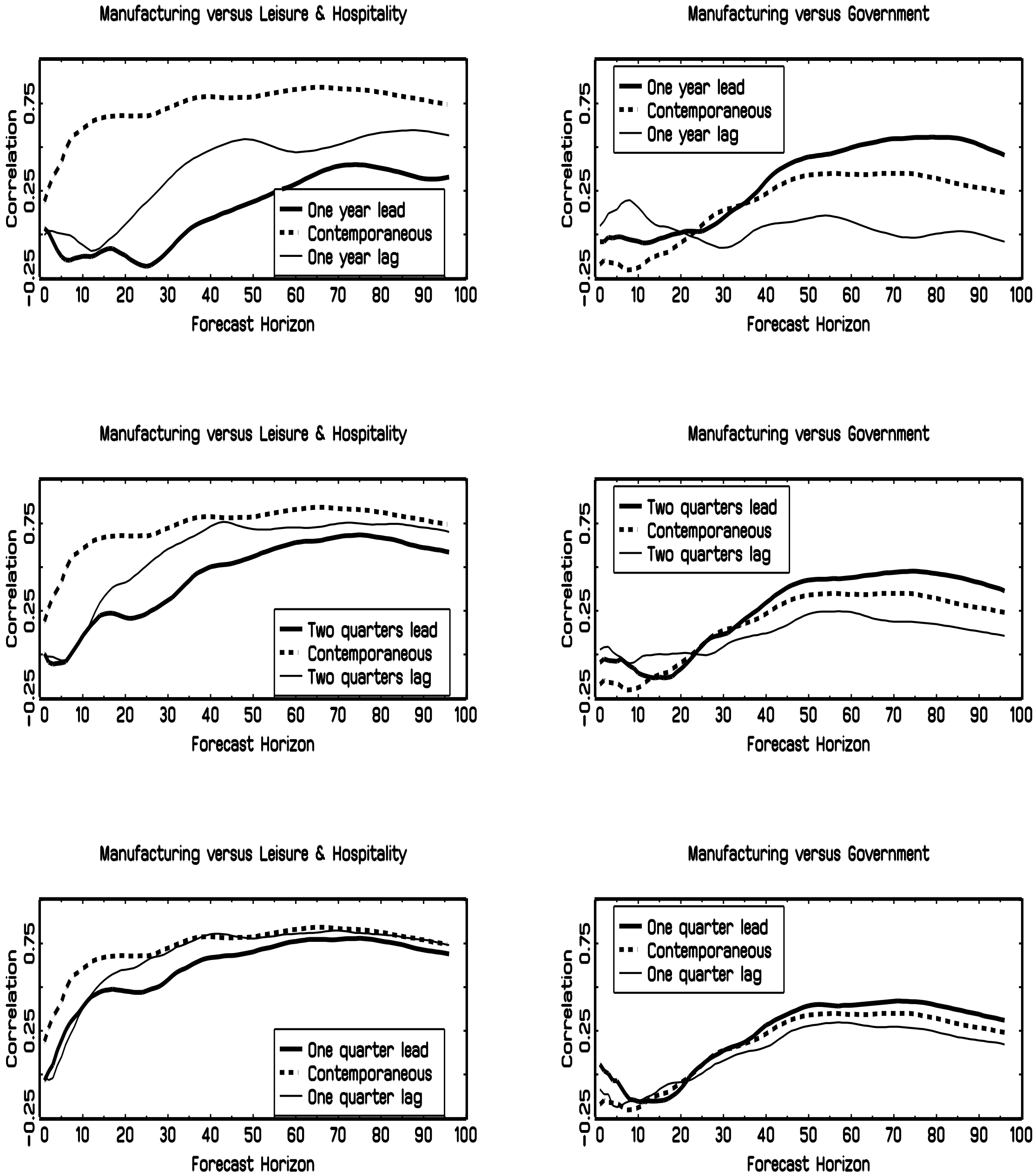

Figure 6: Manufacturing Comovement with Leisure & Hospitality and Government

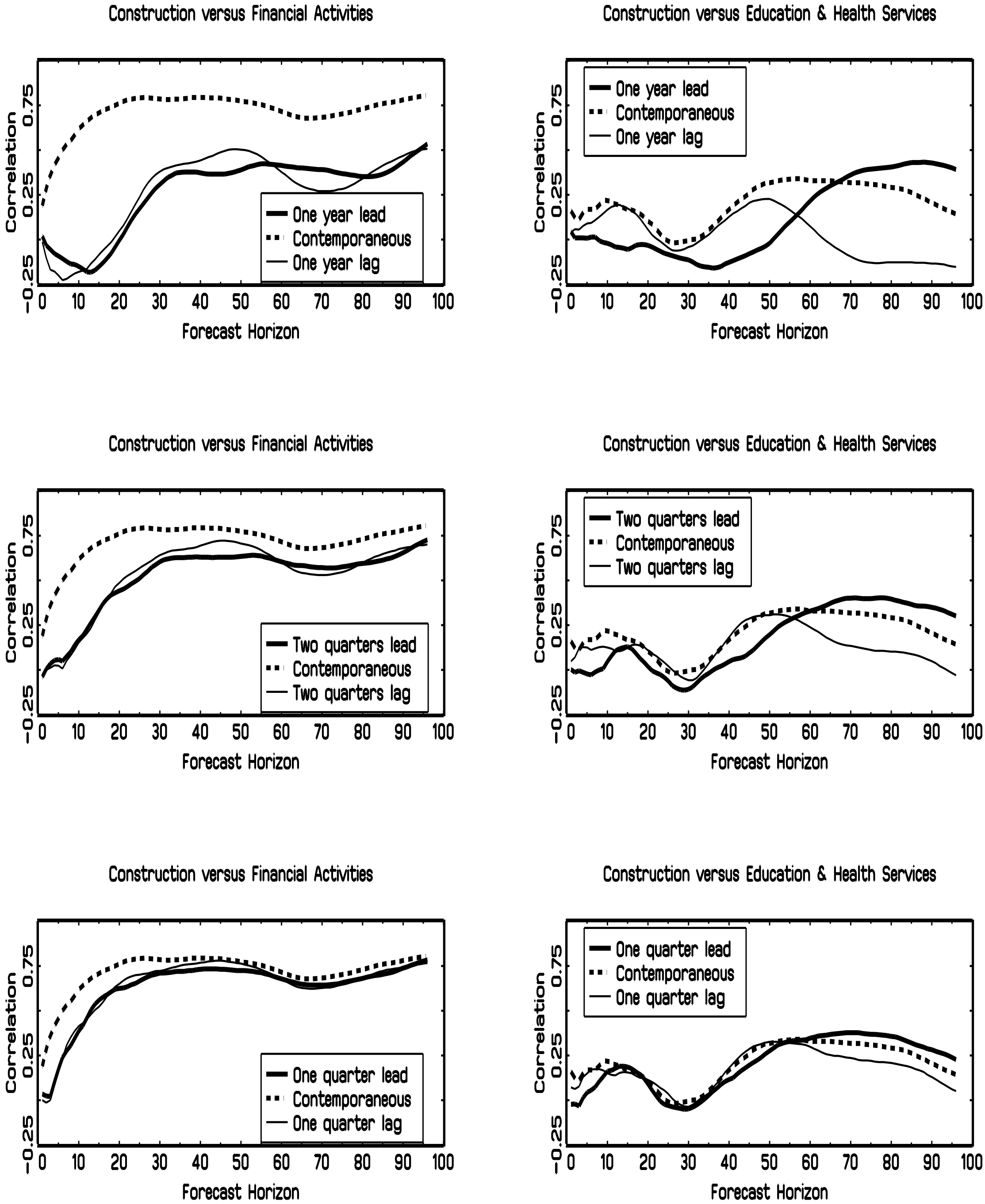

Figure 7: Construction Comovement with Financial Activities and Education & Health Services

When Construction was used as the reference industry, most of the plots were almost identical to those when Manufacturing was the reference. Figure 7 highlights two differences. The three diagrams to the left plot the correlations with Financial Activities. As these diagrams show, Construction has a larger correlation value with Financial Activities at the long-term forecast horizons than Manufacturing does. This comes as no surprise since Financial Activities includes the real estate sector. Moreover, this larger correlation seems reasonable because much of Construction is home construction which typically require purchasers to take out mortgages. Another difference is highlighted in the three diagrams to the right in Figure 7 which plot correlations between Construction and Education & Health Services. These diagrams show low correlations as we saw in Figure 5, but they also show that Construction leads Education & Health Services more than Manufacturing did. This is perhaps because when new housing subdivisions are built, new schools and other health and educational facilities also need to be built.

When Leisure & Hospitality and Trade, Transportation & Utilities were used as the reference industry the plots were almost identical to those when Construction was the reference industry and were mostly the same as those when Manufacturing was the reference. The main difference from when Manufacturing was the reference is that these industries were more highly correlated with Financial Activities and tended to lead Education & Health Services in the same way that Construction did. On the other hand, when Professional & Business Services was used as the reference, the diagrams where more like those for Manufacturing than Construction with lower correlations with Financial Activities and no leading indications for Education & Health Services.

3.4 Summary and comparison to traditional approaches

We can summarize our findings as follows. Six industries, including Manufacturing, Construction, Leisure & Hospitality, Trade, Transportation & Utilities, Financial Activities, and Professional & Business Services, move together and do not appear to lead each other over the business cycle, but seem to lead the other four industries to some extent. All six industries clearly lead Information Services with leads of about six months with high levels of correlation. In addition, all six industries lead Natural Resources & Mining and Government at even longer leads of up to two years, but the correlations are somewhat lower, indicating the presence of different transmission channels of shocks and the presence of other structural shocks impacting Natural Resources & Mining and Government too. Finally, three industries, including Construction, Leisure & Hospitality, Trade, Transportation & Utilities, lead Education & Health Services at up to two years. Here the correlations are also low indicating again that different transmission channels and shocks are driving Education & Health Services.

It is also useful to compare the results using this approach with those using the methods of Section 2. First, it is useful to note there is a lot of similarities between the two approaches. Both techniques found that Natural Resources & Mining, Education & Health Services and Government were lagging sectors and that the correlations with those sectors were relatively low. However, there are also important differences. For instance, the methods of Section 2 found that Manufacturing, Construction, Leisure & Hospitality seemed to lead Trade, Transportation & Utilities, Financial Activities and Information Services while our approach found that only Information Services lagged within this group. Second, the methods in Section 2 only found leads versus Information Services of 2 months, while we found the leads were up to six months and for the other three industries were up to two years. Third, the methods of Section 2 only provide an aggregate measure of the various business cycle frequency correlations, while our approach provides a dynamic perspective by reporting leads and lag correlations for alternative forecast horizons. Thus we saw, for instance, that while Manufacturing tends to lead Information Services, this lead occurs at longer-term forecast horizons and that there is no tendency for Manufacturing to lead at short-term forecast horizons (i.e. up to 42-month forecast horizons).

One can also compare the results here to those in Christiano and Fitzgerald (1998) who had a similarly motivated paper. There are two key differences between this study and theirs. First, our data is more disaggregated at the service level, while theirs is more disaggregated at the goods producing level. Second, our analysis computes lead and lag correlations.[25] One advantage of our methodology is that it is specifically designed to go beyond simple contemporaneous comovement analysis which their method focused on. Furthermore, the advantage of our data set is that the disaggregation of the service sector allows for the detection of lags for some of these sectors which their aggregated service sector data could not detect. We believe that a careful understanding of the service sector dynamics is particularly important because this sector has shown a steady increase in its percentage of U.S. GDP.

4 Robustness and suggestions for application

In this section, we describe a few experiments we conducted in order to investigate the robustness of the results described in Section 3. These experiments taught us a few application ideas which we also describe here.

4.1 Variable choice for the forecast VAR

In the forecast VAR used in Section 3, we included all ten sectors for the economy. This seemed like a natural choice since it brings into the forecast equation all the information that the data for these ten sectors contain. The first robustness experiment we conducted was to reduce the forecasting VAR down to just a bivariate system containing the two variables which we wanted to use for calculating comovements. The results for this experiment were largely unchanged. Not only did we

[25] Other less consequential differences are that the analysis here uses a multivariate approach based on forecast errors while theirs uses a univariate band-pass filter. Moreover, our analysis uses employment data while theirs uses hours worked. One may use the band-pass filter to obtain similar information as our approach based on VAR forecast errors. For instance, one may use the band-pass filter to isolate selected short-, medium- and long-term cyclical components of the data and then analyze whether the comovement properties of pairs of variables change with the definition of the cyclical component.

find the same lead and lag structures as in the ten variable VAR, but the shapes and the magnitudes for the correlation plots were largely the same. We conjecture that the reason for the similar results is that the number of structural shocks which are generating the dynamics in the data are few and are largely contained in any of these bivariate VAR systems. Thus adding the other eight sectors did not add any new structural shocks and did not improve the forecasting performance. What this suggests is that simple VARs may be sufficient for applying this procedure.[26]

A second experiment was to add two nominal variables to the two variables in the bivariate forecasting system to see if this combination might yield a better forecasting system. The two variables we added were the inflation rate and the federal funds rate. One might interpret these additions as including some monetary policy variables into the forecasting system. This experiment resulted in virtually no difference in the correlation plots. Again, the shapes and the magnitudes for the correlation plots were largely the same. We interpret this result as showing that the structural shocks present in the nominal variables which we introduced had little effect on the two labor employment variables and thus did nothing to improve the forecasts and alter the correlation plots. Again, this experiment suggests that simple VARs may be sufficient for applying the procedure.

4.2 Alternative subsamples of the data

Another set of robustness experiments was to investigate how the results might differ over different subsamples. For this investigation we have two noteworthy results.

The first result centers on the stability of the results in large system VAR forecast equations. In exploring alternative subsamples, we ran the experiments in Section 3 with the ten variable forecast equation over a number of subsamples and found some stability issues. So for instance, if we dropped say 50 data points at either the beginning or the end of the sample period, similar results arose. But, if we

[26] Den Haan (2000) also found that bivariate VARs yielded similar results to multivariate VARs in his contemporaneous forecast error analysis.

dropped say 100 data points at either the beginning or the end of the sample period, some differences in the correlation patterns arose. At first we thought this indicated a robustness problem for this methodology. But, next we conducted the same experiment with both the bivariate VAR systems and the four variable VAR systems with the nominal components. In these later two forecasting models the results were robust to the different subsamples. We believe that the lack of robustness for the ten variable VAR was arising because the large number of parameters in the VAR system reduced the forecasting performance when the sample size was small. Based on this insight, and the fact that we found from our earlier robustness experiments that the simple bivariate VAR proved to be sufficient for applying this procedure, we feel simple VARs not only can be sufficient, but may yield more stable results in small data series.

The second result in our subsample experiments centers on whether the so called, "great moderation," changed the nature of the business cycle.[27] The idea for the great moderation is that beginning sometime in the early 1980s, the conduct of monetary policy in the U.S. seemed to result in much longer boom periods and much shallower bust periods. So to investigate whether the correlation patterns changed during this period, we focused the subsample to begin at a number of dates in the early 1980s and run to the end of the sample. As one would expect from the previous paragraph, the ten variable system showed differences in the different subsamples. However, the results of the bivariate and four variable models showed largely the same correlation patterns as described in Section 3. Because of our stability concerns with the large variable forecasting equations when the time series become short, we believe the smaller system results are more reliable for this exercise. The smaller system results indicate that the so called great moderation period is not different in at least this one dimension of the business cycle.

[27] Of course the current recession may make economists rethink this characterization. But regardless of whether this occurs, the exercise here contributes to the debate over whether the great moderation does have different business cycle characteristics.

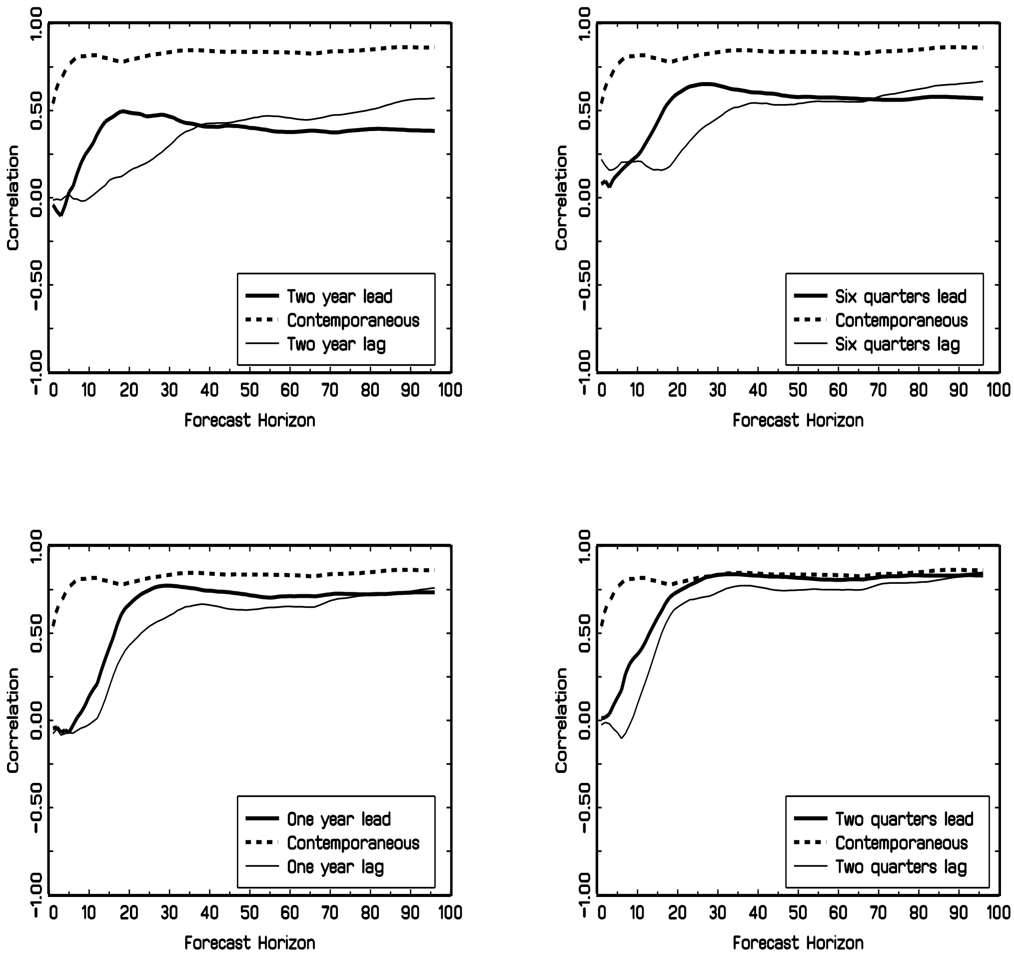

Figure 8: Comovement between Manufacturing Production and Manufacturing Employment

4.3 Industrial production data

As we noted in Section 2, we choose to use employment data for our analysis in part because of its availability at a monthly frequency. It would be interesting to know if our lead and lag results are robust for output data since output is also regarded as one of the central data concepts for business cycle analysis. Unfortunately, there is no output data at the sectoral level and monthly frequency to conduct this experiment.

The only output measure that comes close to these two criteria is the industrial production series compiled by the Federal Reserve Bank which is measured at the monthly frequency, but has a focus on non-service oriented industries like manufacturing. However, an alternative business cycle hypothesis that can be investigated using the limited industrial production data is whether output leads employment.

To investigate this question, we focused on the manufacturing sector and used the Industrial Production for Manufactured Goods and the Manufacturing Employment series. The industrial production series are not quite as long as the employment series, so the time interval for this experiment only runs from January 1972 to May 2008. For the forecast VAR, we followed our own advice and stuck to a bivariate system consisting of just these two series and again we used logged data. The results of this experiment are provided in Figure 8 for lead and lag calculations of two years, one and a half years, one year and half a year. This figure shows neither leads nor lags of output over employment.

5 Conclusions

This paper contributes to our ability to understand sectoral comovements in two ways. The first contribution is methodological. We show how to extend the technique in den Haan (2000) to investigate lead and lag correlations over a range of forecast horizons and provide a useful graphical plotting format for interpreting the results. This extension, not only provides important information about which data may lead or lag others, but it also shows how long the lead or lag is and whether it is a short run or long run relationship. For instance, significant short term dynamics might be the result of nominal rigidities in some sectors that disappear in the long-run, whereas large long-run employment correlations between two sectors might be the result of forces such as labor hoarding affecting long-run growth. These empirical findings on the correlation structure may thus be potentially useful in designing modelling strategies.

The second contribution is an application of this technique to sectoral employment data for the U.S. economy. This analysis assesses which industries lead or lag others and whether the lead is a short run or long run relationship. It was shown that, among the ten industrial sectors followed by the U.S. Bureau of Labor Statistics, six tend to lead the other four. These six have high correlations indicating that (i) the structural shocks generating the data movements are mostly in common, and (ii) they share a similar channel for shock transmission. Among the four lagging industries, some lag by longer intervals than others and some have low correlations with the leading industries. These lead and lag results showing that some industries do lead others are new and illustrate the value of the methodology introduced here.

Although not used in this paper, these contributions may be useful for a variety of other applications. For instance, by showing the leading and lagging variables, the methodology may be useful as a preliminary analysis in determining VAR orderings or other structural shock identification strategies. In addition, the empirical evidence may be useful to theoretical researchers who are introducing multisectoral structures into business cycle models.

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Appendix (Not intended for publication)

A.1 - Introduction

This appendix includes some additional analysis that was mentioned in the text but was not included in the final draft of the paper in order to keep the length down. This analysis includes four additional exercises. First, as noted in the discussion of the traditional lead and lag analysis, it is possible to generate Tables 1 and 2 using a band pass filter like the one suggested by Christiano and Fitzgerald (2003). Such tables are presented in Section A.2 below. Second, also as noted in the discussion of the traditional lead and lag analysis, another method for investigating leads and lags was suggested by Fuhrer and Moore (1995). In Section A.3, we present Figure A.1 which shows plots of a Fuhrer and Moore (1995) type lead and lag graph. Third, it was also noted in the text that it is possible to draw bootstrapped confidence intervals for the lead and lag correlations. In Section A.4, we present Figure A.2 which shows this supplementary exercise for some of the lead plots from Figure 2 in the text. Finally, it was also noted in the paper that one might question whether a lag of 12 months in the forecast equation is sufficient to provide uncorrelated forecast errors. To investigate this, we ran a 24 lag forecast equation. Section A.5 presents Figure A.3 which shows the results for this exercise along with confidence interval plots.

A.2 - Tables 1 and 2 using the band pass filter

Tables A.1 and A.2 present the contemporaneous cross-correlations between sectors and the lead and lag analysis in the Prescott (1986) style using data that was filtered using a band pass filter as described in Christiano and Fitzgerald (2003) which focused on frequencies of 18-96 months. As these tables show, the results presented in the paper are robust to this alternative detrending procedure.

Table A.1 Contemporaneous cross-correlations between sectors
BP Filtered monthly U.S. data 1969:1-2008:5

Variable	M	C.	NRM	TTU	IS	FA	PBS	EHS	LH	G
M	1.0									
C	0.87	1.0								
NRM	0.14	-0.04	1.0							
TTU	0.86	0.92	0.12	1.0						
IS	0.86	0.81	0.24	0.90	1.0					
FA	0.49	0.70	-0.14	0.52	0.48	1.0				
PBS	0.77	0.76	0.13	0.86	0.81	0.51	1.0			
EHS	0.45	0.49	0.23	0.55	0.47	0.42	0.22	1.0		
LH	0.77	0.88	-0.03	0.93	0.83	0.54	0.77	0.56	1.0	
G	0.20	0.49	-0.02	0.51	0.40	0.54	0.36	0.63	0.55	1.0

Band-pass filtered data selecting frequencies at 18-96 months.
Abbreviations: NRM - Natural Resources & Mining; C - Construction;
M - Manufacturing; TTU- Trade, Transportation & Utilities; IS -Information Services; FA- Financial Activities; PBS -Professional & Business Services;
EHS - Education & Health Services; LH - Leisure & Hospitality; G - Government

Table A.2. Cross-correlation coefficients with Manufacturing (Band-pass filter)											
(Band-pass filter isolating cycles lasting between 18 months and 8 years)											
Variable	σ_z	σ_z/σ	ρ_{z+6}	ρ_{z+4}	ρ_{z+2}	ρ_{z+1}	ρ_z	ρ_{z-1}	ρ_{z-2}	ρ_{z-4}	ρ_{z-6}
NRM	3.33	1.41	**0.40**	0.34	0.25	0.20	0.14	0.07	0.00	-0.14	-0.28
C	3.69	1.56	0.68	0.78	0.85	0.87	**0.87**	0.87	0.85	0.79	0.69
T	2.37	1.00	0.72	0.87	0.97	0.99	**1.00**	0.99	0.97	0.87	0.72
TTU	1.13	0.48	0.74	0.83	0.88	**0.88**	0.88	0.86	0.82	0.72	0.59
IS	1.92	0.81	0.80	0.87	**0.89**	0.89	0.86	0.83	0.78	0.65	0.49
FA	1.04	0.44	0.47	0.51	**0.52**	0.52	0.51	0.49	0.47	0.42	0.35
PBS	1.25	0.53	0.64	0.72	0.77	**0.78**	0.77	0.76	0.73	0.65	0.53
EHS	0.63	0.27	0.56	**0.56**	0.54	0.51	0.48	0.44	0.38	0.26	0.12
LH	0.99	0.42	0.60	0.70	0.77	0.79	**0.80**	0.79	0.78	0.72	0.62
G	0.67	0.28	**0.43**	0.36	0.29	0.26	0.22	0.19	0.16	0.11	0.06

Notes: σ_z denotes the standard deviation of variable z, σ_z/σ denotes the relative standard deviation of z with respect to Manufacturing. $\rho_{z\pm j}$ is the cross-correlation of the j- lead/lag with current Manufacturing. Bold characters highlight the highest cross-correlation coefficients.

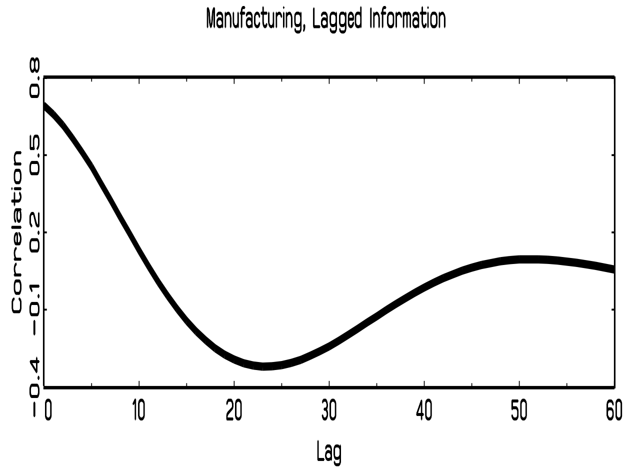
A.3 - Lead and lag analysis using Fuhrer and Moore's (1995) approach

Now consider a lead and lag analysis using the Fuhrer and Moore (1995) method. Figure A.1 shows the comovement between Manufacturing and Information Services obtained by computing the second moments associated with a covariance-stationary bivariate VAR(12) as described in Hamilton (1994, pp. 264-266) and used by Fuhrer and Moore (1995) to analyze the comovement between output and inflation. In particular, the lower graph shows that Manufacturing leads Information Services by 2 to 3 months. This is consistent with the 1- to 2-month lead reported in Tables 2 and A.2 which was found using the Prescott (1986) method.

To connect this methodology with our new methodology, one can compare these graphs with the graphs in Figure 2 as follows. If one focuses on the lead lines in Figure 2 and one moves upward through the diagrams (i.e. one moves through the diagrams with progressively longer leads), it is the same type of exercise as moving from the origin to the right in the lower diagram of Figure A.1, while if one focuses on the lag lines in Figure 2 and one moves upward through the diagrams (i.e. moves through the diagrams with progressively longer lags), it is the same type of exercise as moving from the origin to the right in the upper graph in Figure A.1.

To be more concrete about the connection between the two approaches, consider the middle right diagram in Figure 2. Notice that the lead plot in essence decomposes the single six month correlation value in the lower diagram of Figure A.1, the lag plot in essence decomposes the single six month quarter correlation value in the upper diagram in Figure A.1, and the contemporaneous correlation plot in essence decomposes the contemporaneous correlation value which is the left edge value of both the upper and lower diagrams in Figure A.1.

As we noted in the paper, our method shows a somewhat longer lead of manufacturing over information, with a six month lead, than the Prescott (1986) approach or the Fuhrer and Moore (1995) approach. This is not too surprising because these other methods required that the data be detrended and as noted in Canova (1998), some detrending methods tend to emphasize the shorter term frequencies. What our method shows is that if we do not detrend and keep longer term frequencies, we find somewhat longer leads for this pair of industries.



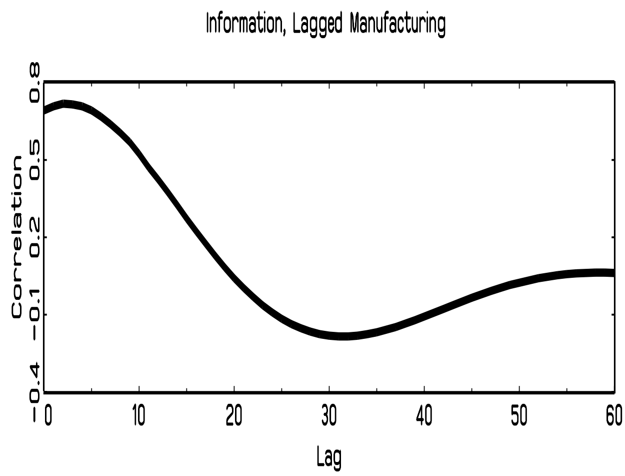


Figure A.1: Comovement between Manufacturing and Information Services using a covariance stationary VAR

A.4 - Confidence bands

Figure A.2 shows the confidence bands associated with the contemporaneous and lead comovements between Manufacturing and Information Services which were displayed in Figure 2. This figure breaks apart some of the individual diagrams in Figure 2, so that only one plot is shown in each of the sub-figures. In particular, each of the sub-figures include either a contemporaneous or a lead plot from Figure 2 along with a 95% confidence intervals around the plot. The confidence bands where generated using a bootstrap method. As Figure A.2 shows, the confidence bands are quite wide and that the individual lead lines are not significantly different from the contemporaneous line. As we noted in the text, we still think that it is possible to interpret the leads and lags as we did in the paper in spite of the lack of statistical significance. Such an interpretation is consistent with the methods used by Prescott (1986), Fuhrer and Moore (1995) and numerous others.

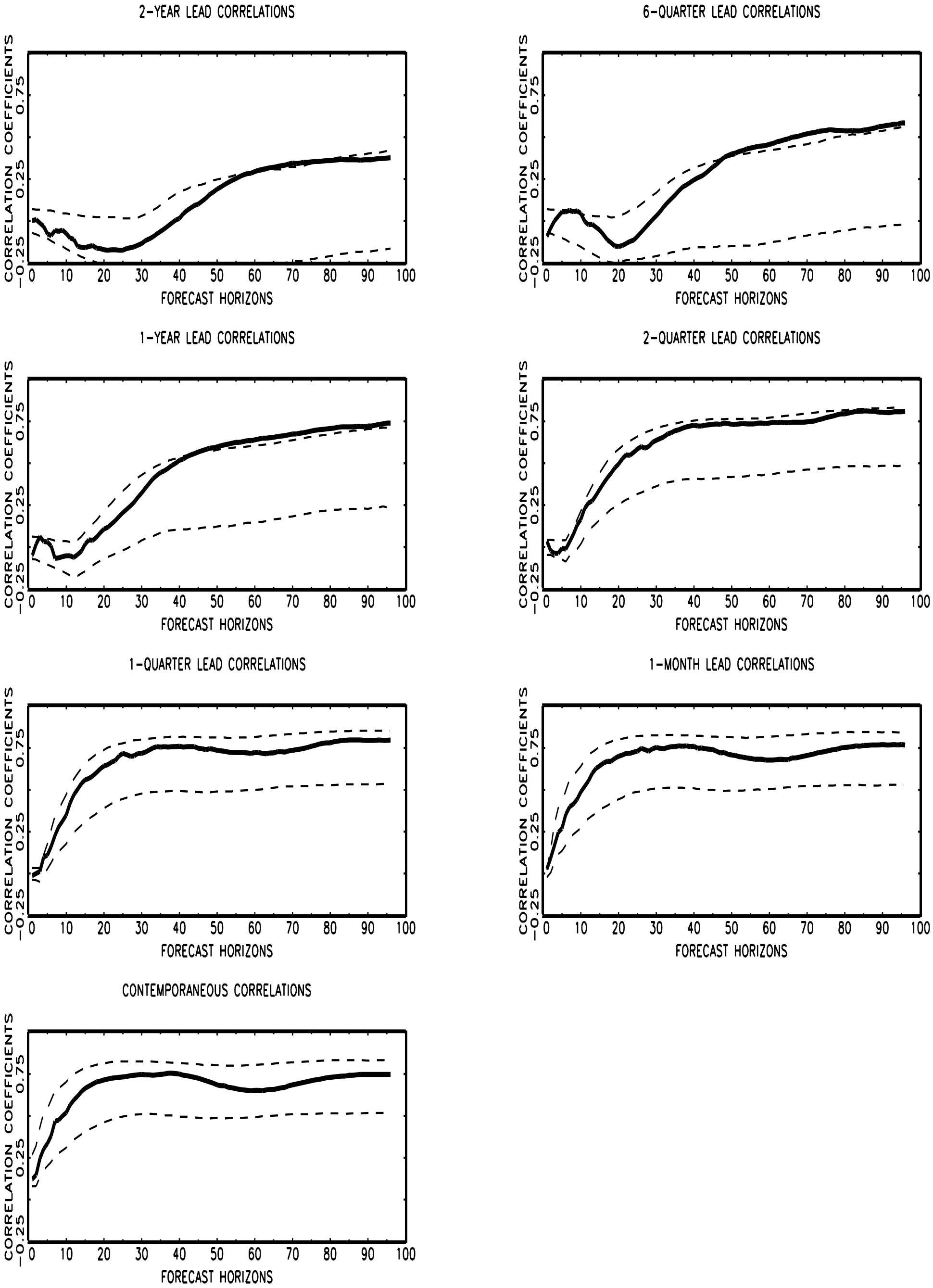


Figure A.2: Comovement between Manufacturing and Information Services (Confidence Bands)

A.5 - 24 lag forecast equation

Finally, Figure A.3 shows a last robustness exercise where we used 24 lags in the forecast equation. This equation also shows the confidence bands, although that is not what we are interested in here. What these graphs show is that when a larger number of lags are included in the forecast equation, there is no noticeable difference in the lead and lag analysis.

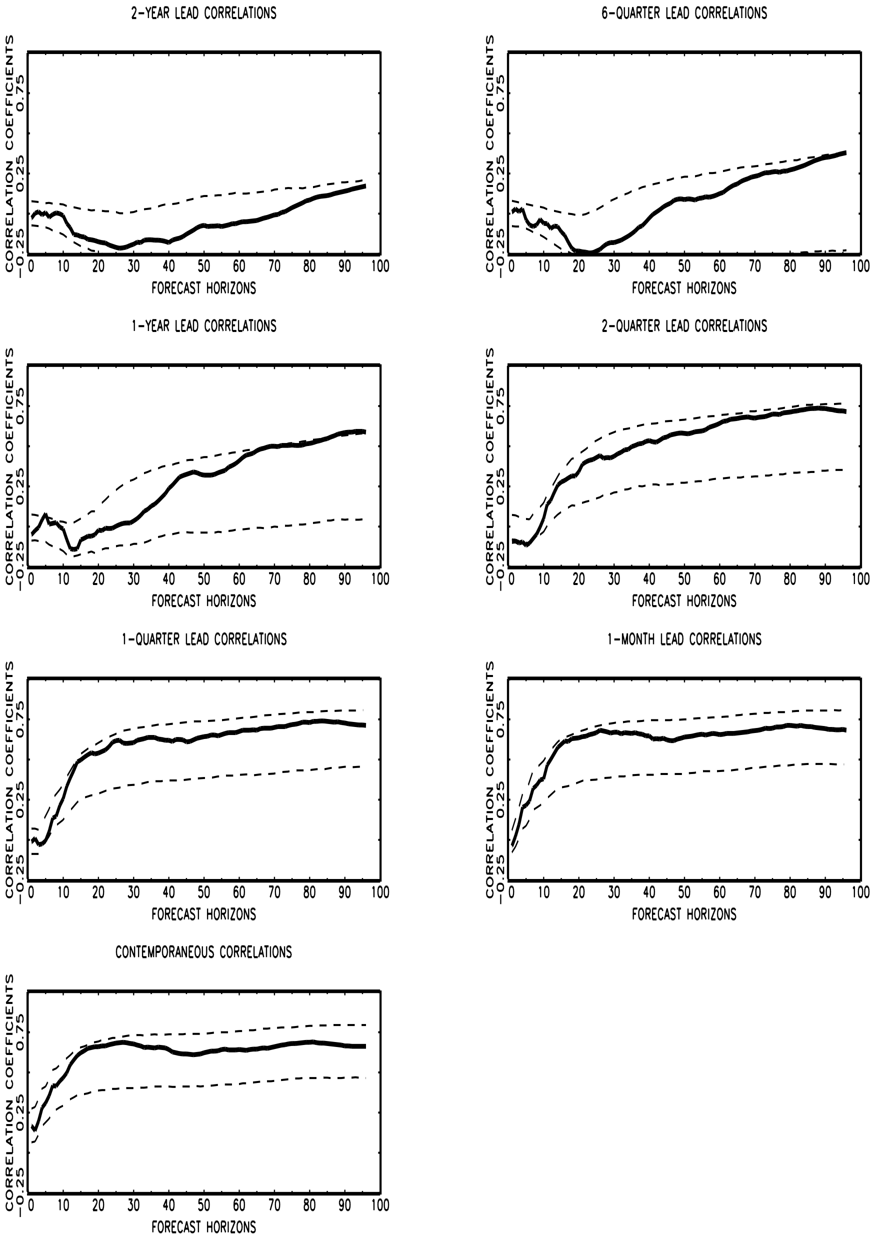


Figure A.3: Comovement between Manufacturing and Information Services (Confidence Bands) using a VAR(24)