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Assessing the Relationship between Economic Stability and Dynamic Employment Responses to Aggregate Shocks

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Abstract

Previous studies have identified a significant drop in the volatility of the U.S. GDP and other measures of aggregate activity since the mid-1980s. Yet uncertainty remains as to whether the reduced size and frequency of macroeconomic shocks, or the economy's reduced responses to shocks, are producing aggregate economic stability. To investigate this issue, this paper looks at the changes in aggregate employment responses to shocks. Using an interrelated factor demand model, this paper finds that the monthly employment elasticity to unanticipated demand shocks has declined by more than 80% in the manufacturing industry since 1984 in comparison with the elasticity during prior decades. Similarly, the work-hour elasticity to unanticipated demand shocks declined by more than 60%. At the same time, the paper does not find any observable change in the pattern of inventory adjustment, except in its responses to future demand. Using vector autoregressions (VARs), the paper also finds that the dynamic responses of employment to some measures of aggregate economic shocks, such as oil shocks and monetary policy shocks, are smaller and less volatile since 1984. This result holds for both manufacturing at monthly frequency and aggregate employment series at monthly and quarterly frequencies.

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1. Introduction

Over the past 20 years, the volatility of U.S. real GDP growth and other macroeconomic variables has been far milder than in preceding decades. The reduction in volatility, in turn, has reduced the frequency, length, and magnitude of recessions. While many economists have recognized this change, there is no consensus regarding the causes of this newfound macroeconomic stability (often called the "great moderation"). In particular, whether the stability arises from a reduction in the volatility of shock processes or from reduced responses to shocks via a structural change in the economy is unclear.

To investigate this issue, this paper focuses on aggregate employment responses to shocks. If the reduction in volatility is caused entirely by fewer and smaller macroeconomic shocks without any changes in adjustment mechanism, employment responses to macroeconomic shocks should remain unchanged. If, however, structural change is partly responsible for the reduced volatility in macroeconomic variables, the employment response to these shocks should be affected and should be smaller over the past 20 years.[1] Accordingly, an evaluation of the dynamic employment responses to various disturbances to the economy allows us to see if the economy has become more resilient as a result of structural changes.

[1] Note that these two causes are not necessarily distinct concepts. For example, changes in macroeconomic shock processes (i.e., reduced variance or persistence) may trigger a different pattern of production adjustment. Ramey and Vine (2006) show the reduced persistence of sales shocks can lower employment volatility, as producers use work-hour and inventory adjustment more intensively relative to employment to meet temporary fluctuations in demand. In this paper, I make a simple distinction by assuming that any systematic changes in employment, work-hour, or inventory adjustment mechanism are structural regardless of how they may be triggered by the changes in shock processes. The investigation into how they may be related will be left for the future.

This exercise has important implications for policymakers, who need to determine appropriate policy responses when aggregate shocks hit the economy. Monetary and fiscal policies are often used to smooth out fluctuations in economic activity and to alleviate the negative impact of recessions. The effectiveness of the policies often depends on the timing of their implementation, which in turn depends on policymakers' understanding of how the economy may handle unfavorable macroeconomic shocks.

This paper finds that employment and work-hour responses to shocks have been smaller over the last 20 years than those from the 1960s through the mid-1980s. The elasticity of monthly employment and work hours with respect to an unpredicted demand shock fell by more than 80% and 60%, respectively, in the manufacturing industry. Furthermore, vector autoregression (VAR) analysis shows that the dynamic responses of employment growth with respect to oil price and monetary policy shocks to the economy are smaller and less volatile since 1984 compared to preceding decades. This result is robust for both manufacturing and aggregate employment series.

Kim and Nelson (1999) and McConnell and Parez-Quiros (2000) independently find a break in U.S. GDP growth rate volatility in the first quarter of 1984. Similarly, Stock and Watson (2002) identify the structural break in the conditional variance of four-quarter GDP growth at the second quarter of 1983, with a 67% confidence interval for the structural break from the fourth quarter of 1982 to the third quarter of 1985. Furthermore, 40% of the 168 aggregate series examined have structural breaks that fall between 1983 and 1985. This paper does not further scrutinize the suggested break dates. Although it is unlikely that a break in economic activity can be assigned to a single date, the paper takes the date as given and focuses on the question of the causes of employment stability.

Although several explanations have emerged, substantial uncertainty remains as to what caused the observed reduction in aggregate volatility.[2] Leading explanations include the "good practice" hypothesis, driven by technological innovation and inventory management; the "good policy" hypothesis, linking better monetary policies to macroeconomic outcome; the "good luck" hypothesis, which emphasizes the reduced size and frequency of macroeconomic shocks; and the "financial innovations" hypothesis, characterized by smoothed consumption, and housing and business fixed investment.

McConnell and Parez-Quiros (2000) and Kahn, McConnell, and Parez-Quiros (2002) suggest that technological innovations have helped firms to better predict and prepare for the changes in demand conditions and consequently reduce inventory volatility. Furthermore, they claim that a smaller inventory adjustment has led to a reduction in output volatility.[3] Clarida, Gali, and Gertler (2000) argue that improved use of monetary policy by the Federal Reserve to control inflation contributed to the stabilization of aggregate output.[4] In contrast, Ahmed, Levin, and Wilson (2002) and Stock and Watson (2002) suggest that much of the reduction in aggregate volatility is

[2] An excellent literature review is provided by Cecchetti, Flores-Lagunes, and Krause (2006).
[3] Their theoretical explanation is tied to output inventories based on the observation that the volatility of output fell by more than the volatility of final sales. However, Herrera and Pesavento (2005) show that much of the reduction in inventory volatility arises from input inventory such as materials and supplies, instead of output inventory.
[4] However, Ahmed, Levin, and Wilson (2002) and Stock and Watson (2002) argue that improved monetary policy alone is insufficient to explain the observed stability in output. For example, Stock and Watson (2002) estimate that improved monetary policy can account for 10-25% of the reduction in aggregate economic volatility.

caused by a reduction in the size of shocks.[5] Dynan, Elmendorf, and Sichel (2006) show that financial innovations enhanced individuals' ability to borrow and that this in turn smoothed consumption, housing and business fixed investment, and hence aggregate volatility.

This paper does not assess each of these hypotheses but instead examines macroeconomic stability from another angle by looking at the dynamics of employment responses to shocks. By doing so, it aims to shed further light on shock versus structural change hypotheses. The paper uses two methods for the investigation. The first is the interrelated factor demand model suggested by Topel (1982), which allows us to estimate the scope of employment elasticity to unanticipated demand shocks. Since the model requires shipment data and performs more robustly using monthly frequency to capture demand shock processes, this exercise was applied only to the manufacturing industry because of limitations on data availability. The second method used is vector autoregressions (VARs). VAR analysis allows us to capture the dynamic employment responses to some measures of macroeconomic disturbances. This exercise was performed for both the manufacturing series at a monthly frequency and the aggregate employment series at monthly and quarterly frequencies. Both methods indicate that employment sensitivity to shock variables has been smaller since 1984 than in preceding decades.

[5] Stock and Watson (2002) discuss the reduction in monetary, fiscal, productivity, oil price, and other commodity price shocks. The volatility of the real oil price is higher in the post-1984 sample. Accordingly, their conclusion about an oil price shock is based on a Hamilton measure, which considers major supply disruptions as oil shocks.

While it is beyond the scope of this paper, an important question concerns the theoretical underpinning of this result. One could argue that the reduced aggregate sensitivity of employment to shocks arises from changes in microeconomic behavior at the firm level. For example, greater wage flexibility at the firm level may lead to reduced employment sensitivity to shocks. Although validation of this hypothesis would likely require a firm-level data set and data on total labor compensation, simple exercises performed in this paper do not find an increased flexibility in aggregate hourly earnings. Another possible explanation relates to labor adjustment costs: higher costs can reduce firms' employment responses to shocks. Similarly, nonconvex adjustment costs may cause employment volatility to interact nonlinearly with the variance of shocks.[6] Further empirical investigations of these possibilities would require firm-level data.

Alternatively, one might argue that reduced aggregate employment responses to shocks come from greater heterogeneity in firms' responses to shocks and the resulting reduction in covariance across firms' activities. If this were the case, firm-level and aggregate volatility might not move in the same direction.[7] Although studies have given conflicting evidence, the most comprehensive research using the Census Bureau's Longitudinal Business Database (LBD), which covers all U.S. firms with paid

[6] For instance, hiring or firing costs may prevent employers from making positive hiring or firing decisions for small enough shocks.

[7] Based on the evidence of a rise in firm-level volatility among publicly traded firms, Philippon (2003) suggests a model in which greater competition generates higher firm-level volatility while price flexibility reduces aggregate volatility. Comin and Mulani (2005) conjecture that an increased investment in firm-specific R&D combined with a reduced investment in common technology can explain higher firm-level volatility and lower aggregate volatility.

employees, shows that average firm-level volatility, in terms of the employment growth rate, declined between 1978 and 2001.[8]

This paper proceeds as follows. Section 2 provides a description of the interrelated factor demand model and discusses the results, which characterize employment, work hours, and inventory responses to unpredicted and predicted demand shocks. Section 3 provides the specifications used for VARs and the results, describing the changes in the dynamic employment growth responses to aggregate shocks such as oil price and monetary policy shocks. Section 4 concludes and identifies areas for additional investigation.

2. Interrelated Factor Demand Model

Model

Topel's interrelated factor demand model captures the interdependence of decisions regarding the optimal levels of the following three variables: employment, work hours, and inventories. Given the initial values of these variables, the exogenous shock determines the desired level of each in this model. The exogenous shock here is the product demand, and the model distinguishes predicted and unpredicted components

[8] Studies using the database on publicly traded firms have found that firm-level volatility has increased while aggregate volatility has dropped. Comin and Philippon (2005) and Comin and Mulani (2006) show that firm-level volatility indicated by the growth rate of sales has increased over the past 50 years. Campbell, Lettau, Malkiel, and Xu (2001) use a capital asset pricing model (CAPM) and find that the role of idiosyncratic risk in explaining the total time-series volatility of stock returns has increased over the last couple of decades in the U.S., while market volatility has been stable over the same period. However, using the Longitudinal Business Database, Davis, Haltiwanger, Jarmin, and Miranda (2006) show that publicly held and private firms follow opposite trends in terms of employment volatility: while publicly traded firms exhibit a rising trend in employment volatility, privately held firms exhibit a declining trend. The overall volatility declines when using employment as a weight.

of product demand captured by the shipment series. More specifically, the following set of equations is used to investigate the interrelated factor demand decision rules:

$$L_t = \alpha_{10} + \alpha_{11} L_{t-1} + \alpha_{12} H_{t-1} + \alpha_{13} I_{t-1} + \sum_{\tau=0}^{T} \beta_{1\tau} \hat{q}_{t+\tau} + \lambda_1 q_t^{\,u} + trend + seasons, \tag{1}$$

$$H_t = \alpha_{20} + \alpha_{21} L_{t-1} + \alpha_{22} H_{t-1} + \alpha_{23} I_{t-1} + \sum_{\tau=0}^{T} \beta_{2\tau} \hat{q}_{t+\tau} + \lambda_2 q_t^{\,u} + trend + seasons, \tag{2}$$

$$I_t = \alpha_{30} + \alpha_{31} L_{t-1} + \alpha_{32} H_{t-1} + \alpha_{33} I_{t-1} + \sum_{\tau=0}^{T} \beta_{3\tau} \hat{q}_{t+\tau} + \lambda_3 q_t^{\,u} + trend + seasons. \tag{3}$$

L_t, H_t, and I_t refer to employment, work hours, and inventory in natural logarithms at time t. T is the planning horizon, $\hat{q}_t$ is the predicted component of demand while $q_t^{\,u}$ captures the unpredicted component (i.e., $q_t - \hat{q}_t$), and α, β, and λ are the impact elasticity coefficients to be estimated. Each regression includes a trend variable and seasonal dummies.

The following propositions are given by Topel: first, the speed-of-adjustment parameter (α_{jj} where *j=1, 2,* or *3*) is expected to increase (i.e., adjustment slows) as the labor adjustment costs increase or inventory costs decrease. These parameter values equal zero when inputs are freely variable and unity when they are fixed. Second, employment and work hours should respond positively to a rise in current unpredicted shocks while inventories should respond negatively. Responses of employment and work hours to current predicted demand are less certain as there may be smoothing incentives. A lower cost of inventories as well as higher labor adjustment costs increase both inventory and work-hour responses to current predicted or unpredicted shocks, whereas they reduce the employment responses to those shocks. Third, a rise in future expected shipments ($\sum_{\tau=0}^{T} \hat{q}_{t+\tau}$) should increase the demand for employment, work hours, and inventories.[9]

Next, it is assumed that expected monthly demand values depend only on the past values of shipments and not on the other endogenous variables. More specifically, the demand condition, characterized by the monthly series on log shipments, q_t, follows a seasonally differenced autoregressive integrated moving average (ARIMA) process of the following form:

$$A_a(L)(1-L)(1-L^{12})q_t = (1-\delta L^{12})M_m(L)u_t \qquad (4)$$

where L represents a lag operator, $A_a(L)$ and $M_m(L)$ are polynomials of orders a and m respectively in the lag operator, δ is a seasonal moving average parameter, and u_t is the white noise error term.

Following Topel (1982), an additional structure is imposed on the lead distributions of $\beta_{j\tau}$. Namely, I assume that they follow a third-order Almon polynomial, requiring the shortest planning horizon to be 4 months. I set the baseline planning horizon to 9 months, although assumed planning horizons of 6 or 12 months produce the same main results.

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[9] The expected τ-period ahead shipment at time *t* is given by $\hat{q}_{t+\tau} = E\left[q_{t+\tau} \mid u_{t-1,} u_{t-2,} \ldots \right]$.

Data and Results

Estimation based on the interrelated factor demand model uses monthly seasonally unadjusted series on shipments, employment, work hours, and inventories in the manufacturing industry from January 1958 through December 2005.[10] The data on shipments and inventories come from *Current Industrial Reports* published by the Census Bureau. Finished goods inventory series are used to investigate inventory adjustment, as other types of inventories such as materials and supplies or work-in-progress inventories are less effective substitutes for employment and work hours in response to demand shocks. Nonetheless, each regression includes lagged values of these inventories to control for other relevant input factors affecting the dynamics of employment, work hours, and finished goods inventories.[11] Nominal values of shipments and inventories are deflated using PPI for finished goods in the Producer Price Indexes provided by the Department of Labor's Bureau of Labor Statistics (BLS). The employment and work-hour series come from BLS's establishment survey.[12]

As discussed in Topel (1982), seasonally unadjusted series are preferred over seasonally adjusted series because "the transitory and highly predictable character of seasonal fluctuations makes them prime candidates for inventory smoothing and temporary layoffs."[13] However, as shown below, the use of seasonally adjusted data does

[10] The seasonally unadjusted series based on SIC classifications covers the period from January 1958 though March 2001 (when it was discontinued), while the same series based on NAICS covers the period from 1992. I spliced these two seasonally unadjusted series at March 2001.
[11] The original interrelated factor demand model proposes that we include a lagged value of other input factors or stocks such as materials on the right-hand side of each equation.
[12] Employment is defined as "employees on nonfarm payroll" and work hour is "average weekly hours of production of nonsupervisory workers on private nonfarm payroll."
[13] Footnote 16 in Topel (1982).

not change the main results; hence, it seems that much of the change comes from factors unrelated to seasonal adjustment.

Figure 1 shows shipments, employment, hours, and inventories (all in logs) from January 1958 to December 2005 for the manufacturing industry.[14] While the volume of real manufacturing shipments has increased over time, the employment series does not exhibit any obvious trend between 1970 and 2000 and follows a steady decline after 2001. Although all results shown cover the period after 2001, the elasticity estimates for the post-1984 sample are insensitive to the exclusion of data after 2001.[15]

To compare the changes in the dynamic responses to shock series, the sample series are split at March 1984, as most literature on aggregate volatility has identified the structural break in the aggregate GDP series during the first quarter of 1984. I take this date as given and use it for all equations, although as discussed below, Bai-Perron multiple structural break tests show that the suggested break date varies somewhat for each equation. Regardless, the main results are insensitive to the adjustment of break dates based on Bai-Perron tests, and will be discussed later. Finally, ordinary least squares (OLS) estimation of equations (1), (2), and (3) exhibits serial correlation in disturbance terms. Therefore, the Beach and MacKinnon maximum likelihood iterative procedure was used for all estimations to obtain consistent estimates of equations (1), (2), and (3).

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[14] The original shipment and inventory series are in millions of dollars, and the employment figure is in thousands.

[15] In other words, the difference in the elasticity estimates is not driven by the factors which have caused a steady decline of manufacturing employment after 2001.

Table 1 shows the estimates of an interrelated factor demand model using seasonally unadjusted series for the baseline case of a 9-month forecast horizon. The first, second, and third columns of the table show, respectively, the estimates of equations (1), (2), and (3). The standard errors are reported in parentheses, and the coefficients for future predicted demand are the sum of the coefficients for future months including the current month. In order to model the time-series process for demand, the best parsimonious specification that removed autocorrelation in the residuals was chosen based on the Akaike information criterion.[16] Although the results are not shown here, I fit two separate ARIMA models for the pre- and post-1984 samples to construct a demand shock series.[17] The standard error of the residuals (i.e., unpredicted component of shipments) falls by 9% during the post-1984 period, even though the standard deviation of the shipment series detrended by a Hodrick-Prescott filter increases by 6.5%.

Prior to 1984, employment responses to current unpredicted shocks were positive and statistically significant at the 1% level. However, the same coefficient is much smaller and insignificant after 1984. More specifically, the elasticity of employment with respect to unexpected demand shocks falls by 89%. Furthermore, these two coefficients are statistically different from each other. A similar change takes place for current predicted shocks although the elasticity estimates are smaller compared to current unpredicted shocks. One explanation for this result is that employment responses are smoothed out over time when demand shocks are predicted. Employment responses to

[16] I experimented with a number of specifications with both lags ranging from one to four.

[17] I used AR=4 and MA=4 for the pre-1984 period and AR=3 and MA=4 for the post-1984 period. Due to the lags involved in fitting the model, the pre-1984 sample series covers from June 1959 through March 1984 and the post-1984 sample series covers from April 1984 through December 2005.

future predicted shocks are significant in both periods, but smaller after 1984. Again, these estimates are statistically significantly different from each other. The higher persistence of the employment series also highlights slower employment adjustment during the second period.

As in the employment case, the elasticity of hours with respect to current unpredicted shocks drops significantly and the coefficient, which drops by 66%, turns insignificant after 1984. But unlike the employment case, the response of hours to current predicted shocks is insignificant for the pre-1984 period and turns negative and significant for the post-1984 sample.[18] A negative response can happen if much of the work-hour adjustment in response to current predicted shocks takes place just prior to the month of the shock. As for future predicted shocks, the coefficient becomes smaller during the second period, and the difference between the two is statistically significant.

For inventories, the coefficients are not statistically significant for either current demand shock for either period.[19] However, for future predicted shocks, the coefficient is negative and significant at the 1% level prior to 1984 and turns positive and insignificant after 1984. It is puzzling that inventory is relatively insensitive to current demand and responds negatively to future demand for the pre-1984 sample.[20] In general, we do not

[18] An upper limit on work hours or disutility of working overtime may create a smoothing incentive in response to current predicted shocks.

[19] This does not indicate that the model is inappropriate for capturing inventory responses to demand shocks. For example, when the same exercise is done using Japanese manufacturing data, we obtain significant coefficients with expected signs. The size of coefficients is also much larger. These results can be made available upon request.

[20] Since inventory stocks are valued at historical prices, deflating by PPI may lead to some measurement error depending upon the age composition of inventories. An attempt was made to overcome this problem by using seasonally adjusted real manufacturing monthly inventory data since 1967 taken from National Income and Product Accounts (NIPAs). However, the main results did not change.

find any observable change in the pattern of inventory adjustment before and after 1984, except in its responses to future predicted demand.[21]

Tables 2 and 3 show the estimates of the same model when the forecast horizons are set at 6 and 12 months, respectively. Overall, the results are similar to the 9-month forecast horizon case; the 12-month results in particular are essentially the same. For the 6-month case, the coefficients on current predicted shocks are insignificant for employment and work hours, but their size is similar to the 9-month case. The main difference is observed in the inventory adjustment for the 6-month forecast horizon case. Table 2 shows that the responses to current demand shocks are all negative and mostly significant. However, we still cannot determine if there has been a systematic change in inventory responses to current predicted shocks, as the coefficients are not statistically different from each other. As for the future predicted shock, the coefficient turns from negative to positive as before, but now they are both significant.[22]

Next, in order to examine the sensitivity of the results to the modeling of the demand process, I fitted one ARIMA specification for the entire series to model demand shocks instead of fitting two separate ARIMA specifications.[23] The main results are essentially unchanged, as shown in Table 4. The standard error of unpredicted current demand shocks falls by 13%, while the elasticity of employment with respect to unexpected demand shocks falls by 83% and the elasticity of hours falls by about 64%.

[21] In addition, unlike the employment case, note that the coefficients on lagged dependent variables display lower persistence for both work hours and inventories.

[22] The change in the coefficient for future predicted shocks suggests that shipment lags were reduced and/or firms were able to better prepare for the future increase in demand via inventory management after 1984. However, the evidence is still rather weak given that the post-1984 coefficient on future predicted demand is insignificant in most cases.

[23] I used AR=4 and MA=3. Due to the lags involved in fitting the model, the sample series covers from June 1959 through December 2005.

In Table 5, the same exercise was done using seasonally adjusted series in order to evaluate the role of seasonality in generating the differences.[24] The standard error of unpredicted current demand shocks falls by 18% while the employment elasticity to current unpredicted shocks drops by 82%. Overall, seasonality seems to play almost no role in explaining reduced sensitivity of employment and hours to shocks. Finally, although not shown here, the main results were robust to the use of new order series instead of shipments to capture demand shocks.[25]

Bai-Perron multiple structural break tests suggest the following structural break dates for each equation: September 1983 for the employment equation, January 1982 for the work-hour equation, and December 1981 and April 1986 for the inventory equation.[26] The number of structural breaks is chosen by Bayesian information criteria (BIC). Although not presented here, dividing the sample series at the suggested structural break dates for each equation does not significantly alter the estimates.

Reduced responses of employment and work hours raise the possibility of more flexible wage responses to shocks after 1984. To investigate this possibility, the same regression was run using hourly earnings as a dependent variable while controlling for lagged values of all variables used in other regressions. The data on average hourly earnings in the manufacturing industry come from BLS's establishment survey. Nominal figures are again deflated using the Producer Price Index (PPI) for finished goods. The

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[24] The ARIMA specification used for both pre- and post-1984 periods is AR=3 and MA=3. Due to the lags involved in fitting the model, the sample series covers from May 1959 through December 2005.

[25] Employment and work-hour responses to current unpredicted shocks are slightly smaller for the pre-1984 sample when using new order series. The results are available upon request.

[26] In contrast, the Andrews-Ploberger structural break test identifies a single break date of each coefficient instead of multiple breaks of an entire equation. The following structural break dates are suggested for the coefficients on current unpredicted shocks: August 1975 for employment, April 1998 for work hours, and May 1996 for inventories.

results for both seasonally unadjusted and adjusted series are shown in Table 6. In both cases, we do not find evidence for a more flexible wage adjustment to aggregate shocks after 1984. In particular, the elasticity for current unpredicted shocks has dropped by half for both series. However, a more robust test would require a firm-level data set.[27] Note also that the flexibility of other labor compensation such as bonuses and benefits needs to be investigated for a more complete analysis.[28]

3. VAR Analysis

VAR Specifications

Vector autoregressions are used to investigate the dynamic responses of employment with respect to various aggregate shocks to the economy. Here, the aggregate shock measures are the real oil price, the aggregate price level, and the federal funds rate. The latter are used to capture monetary policy shocks where the rise in the rates corresponds to monetary tightening.

In order to recover structural innovations, I use a standard Cholesky decomposition by assuming the following order of the contemporaneous correlations between structural innovations: real oil price, aggregate price level, fed funds rate, and

[27] Davis and Haltiwanger (1990) show that idiosyncratic shocks play a larger role than aggregate or sector-specific shocks in driving aggregate job flows in the manufacturing industry. Accordingly, it may be theoretically possible that wage has become more flexible to idiosyncratic shocks at the firm level and exhibits less sensitivity at the aggregate level. Alternatively, it may be possible that wage flexibility for individual workers has reduced wage-productivity mismatches that get corrected in response to aggregate shocks, thereby reducing wage sensitivity at the aggregate level. Further empirical analysis using a micro-level data set would enable us to formulate a more appropriate theoretical framework.

[28] Average hourly earnings do not capture labor costs entirely as they exclude retroactive payments and irregular bonuses, employee benefits (i.e., fringe and medical), and the employer's share of payroll taxes. While the Employment Cost Index (ECI) provides a broader measure of labor cost, the ECI is published only quarterly and its total compensation series covers from 1981. The ECI also corrects for the wage changes associated with the compositional changes of labor force across occupations and industries.

employment. I took the first difference of all variables in logs in order to use growth rates rather than levels (except the fed funds rates, for which simple difference was taken). This ensures stationarity for all variables.[29] While the fed funds rates are nominal, impulse response functions of employment remain essentially unchanged when I use inflation-adjusted real fed funds rates.[30]

More formally, let $Y_t = [DOIL_t, DP_t, DFUNDS_t, DEMP_t]$, where each variable reflects the series discussed above, and represent Y_t in linear moving average (MA) form in terms of structural innovations $\varepsilon_t = [\varepsilon_{ot}, \varepsilon_{pt}, \varepsilon_{ft}, \varepsilon_{et}]$. That is,

$$Y_t = B(L)\varepsilon_t, \quad B(0) = B_0. \qquad (5)$$

$B(L)$ denotes an infinite-order matrix lag polynomial, and the upper triangular components of B_0 matrix are zero due to my identification restriction.

The real oil price is placed first in the Cholesky decomposition as it is probably the most exogenous of the four measures and therefore least likely to be contemporaneously affected by various shocks to the economy.[31] The aggregate price level is placed second as the shock to the real oil price immediately affects the aggregate price by construction, while price adjustment should lag in response to other types of shocks to the economy if prices are sticky. The fed funds rate is placed before employment since, as discussed in Bernanke and Blinder (1992), monetary policy in general reacts to economic conditions with some lag due to the time it takes for the

[29] Note that impulse response functions of employment remain unchanged when the aggregate price level is double differenced or when the fed funds rates are not differenced.
[30] Personal consumption expenditure chain-type price indexes were used to adjust for annual rate of inflation.
[31] Granger causality tests for the oil price equation show that other variables (except inflation rate) have little power in predicting the movement of the oil price growth rate.

relevant data to become available. Employment is placed at the end as most economic shocks are likely result in some immediate impact on employment. The extent of responsiveness should be partly determined by the size of labor adjustment costs.

These identification restrictions are probably more appropriate for monthly than quarterly series. However, for both monthly and quarterly VARs, impulse response functions are largely insensitive to changes in the ordering of variables in the Cholesky decomposition.

Data and Results

The VAR exercises use the manufacturing employment series at a monthly frequency and aggregate nonfarm employment series at both monthly and quarterly frequencies. The employment data are taken from BLS's establishment survey. The monthly oil price series is the price for West Texas Intermediate (domestic spot prices) deflated by the PPI.[32] As a measure of the aggregate price level, personal consumption expenditure chain-type price indexes are used for the monthly VARs and GDP chain-type price indexes for the quarterly VARs.[33] For other variables, I constructed quarterly series by taking an average for each quarter. All series are seasonally adjusted with the exception of the federal funds rates. Figures 2 and 3 show, respectively, the series used

[32] More specifically, the original series was seasonally adjusted using the X-12 ARIMA process and deflated by the seasonally adjusted PPI for all commodities.
[33] Monthly personal consumption expenditure chain-type price indexes come from *Personal Income and Outlays*, and quarterly GDP chain-type price indexes come from *GDP Press Release*, both provided by the Department of Commerce's Bureau of Economic Analysis (BEA).

for monthly and quarterly VARs. The series are again split in March 1984 to compare the responses before and after that date.[34]

Hamilton (1996) argues that oil price changes that are reversed quickly do not affect the economy, and that a reduction in oil price does not stimulate the economy to the same extent that an increase in oil price stifles the economy. Accordingly, I ran VARs using the Hamilton oil price measure, which considers only major positive price changes relevant to the economy.[35] Although these results are not presented, the main results did not change.

Figures 4 and 5 show, respectively, the impulse response functions of monthly manufacturing employment before and after March 1984 with respect to one unit increase in each structural innovation (i.e., orthogonalized innovation). The variances of structural innovations are normalized to one. The number of lags for VARs was set equal to 12 to cover the entire year.[36] The dotted lines show the error bands equivalent to a two-standard-deviation confidence interval, constructed using Monte Carlo integration as suggested by Sims and Zha (1999). The figures indicate that dynamic employment responses to each structural innovation and the corresponding error bands are, in general, larger before 1984, suggesting that there was much greater uncertainty in terms of forecasting employment responses to each of these shocks.

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[34] Although the real oil price remained rather steady prior to the first oil shock, excluding the period before 1973 does not change the main results. Also, note that the volatility of real oil price growth is higher after 1984 even though extremely large spikes such as the one observed in 1973 are absent.

[35] The measure takes the higher of (i) zero and (ii) the difference between the real oil price for month t and the maximum real oil price during the preceding 12 months. This filters out the price changes that offset each other within a year.

[36] First the optimal number of lags was chosen based on the Akaike information criterion for the number of lags between 1 and 20 for the entire sample period. When this number was less than the number to cover the entire year (i.e., 12 for the monthly VARs), the latter was used.

Figure 6 shows the same impulse response functions displayed in the previous two figures, but I put pre- and post-1984 impulse response functions together to facilitate the comparison for each shock. The solid line shows the pre-1984 impulse response functions, and the dashed line shows those for the post-1984 period. Figure 6 shows that the oil price shock negatively affects the employment growth rate and raises volatility before 1984, while the response is much milder after 1984. Similarly, the aggregate price shock leads to higher volatility in monthly employment growth prior to 1984. Furthermore, the monetary shock causes an initial rise followed by a longer period of negative growth in employment before 1984, while it does not seem to affect the employment growth rate significantly after 1984.[37]

Employment growth responses to a unit shock to the structural innovation of employment equation do not provide much of a meaningful interpretation. Since the variances of structural innovations are normalized to one, the first period response in the impulse response functions is the standard error of the reduced form innovations.

I also implemented the same VARs using annual growth rates instead of month-to-month growth rates.[38] The number of lags is set equal to 15 based on the Akaike information criterion. Figure 7 shows the results. Here again we observe higher volatility in the responses of manufacturing employment growth rates to each of the structural shocks. One notable feature is that the impact of an oil price shock has a more persistent negative impact on employment after 1984.

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[37] The initial positive spike in employment for the pre-1984 VAR is unobserved if we place employment series before the fed funds rates in Cholesky decomposition.

[38] Again, for the fed funds rate, a simple difference over a year is taken instead of the log difference.

Figures 8 and 9 show the impulse response functions of monthly aggregate nonfarm employment growth rates before and after March 1984, with respect to one unit increase in each structural innovation.[39] The main results are similar to the analysis of manufacturing industry: employment responses are more pronounced and error bands are bigger for the pre-1984 sample. Figure 10 combines the two periods to facilitate the comparison. Again, the solid line corresponds to pre-1984 impulse response functions and the dashed line corresponds to post-1984 functions. Figure 11 uses an annual growth rate instead of a one-month growth rate.[40] In both cases, the aggregate employment responses to each of the shocks are similar to the manufacturing case.

Figure 12 shows the impulse response functions of aggregate employment growth rates at a quarterly frequency.[41] All variables except aggregate price are averaged across months for each quarter. Quarterly series on a GDP deflator were used to construct a quarterly inflation measure. Obviously, quarterly impulse response functions exhibit smoother responses than monthly ones due to time aggregation. By and large, the results for aggregate quarterly series confirm the results obtained from the monthly aggregate series. Figure 13 uses an annual instead of a quarterly growth rate.[42] The main difference compared to the monthly case given by Figure 11 seems to be that the volatility of employment growth does not fall as much after 1984 in response to oil price and aggregate price shocks.

[39] Again, the selected number of lags is 12 for both periods.
[40] The number of lags is set equal to 15 based on the Akaike information criterion (AIC).
[41] The number of lags equals 5 based on AIC.
[42] The number of lags equals 6 based on AIC.

Figures 14 and 15, respectively, show the same monthly and quarterly VARs using the real average hourly earnings growth rate instead of aggregate employment growth rate.[43] For the monthly VARs, real hourly earnings growth is almost equally responsive to each of the shocks. For the quarterly VARs, it is equally or more responsive before 1984. Again, these exercises do not find evidence of an increased flexibility in aggregate hourly earnings. However, as mentioned previously, a more robust test would require a firm-level analysis and an examination of the flexibility in other compensation such as benefits.[44]

Tables 7 and 8 show, respectively, the results of variance decomposition for the monthly manufacturing and aggregate employment series. For the manufacturing case, the fraction of the forecast variance explained by the two price measures declined while that of the fed funds rate remained more or less the same after 1984. Aggregate employment, however, exhibits an opposite pattern. Although it is not clear what explains the difference, the increase in the influence of sector-specific shocks affecting manufacturing employment may partially account for it. Note that in both cases, the oil price, the aggregate price level, and the fed funds rate play a small role in explaining overall employment forecast variance. Consequently, a large fraction of the disturbances driving employment series fluctuations remains to be identified.[45]

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[43] The data on real average hourly earnings for the total private sector are from BLS's establishment survey.

[44] The Employment Cost Index (ECI) was preferred, but was not used for the quarterly VARs due to its short coverage before 1984.

[45] An instrument for demand shocks may be needed to better explain the overall dynamics of employment growth rates. Demand shocks were not used for the VARs as the identification requires us to impose more structure. This topic will be left for future research.

Stock and Watson (2002) find that shocks, not the propagation mechanism, drive the dynamics of the four-quarter GDP growth rate volatility. In order to evaluate the role of the post-1984 error structure in reducing volatility, the estimated lag coefficients from the pre-1984 period and the post-1984 error covariance matrix of reduced form innovations were used to forecast the post-1984 sample standard deviations. Likewise, to evaluate the relative importance of the post-1984 propagation mechanism in reducing the volatility, the pre-1984 error covariance matrix of reduced form innovations and the post-1984 lag coefficients were used to estimate the post-1984 sample standard deviations.

The results are shown in Table 9.[46] The last two columns of the table show the hypothetical standard deviations of the variables implied by the above-mentioned combinations of lag coefficients and error covariance matrices of the reduced form innovations. The table shows that imposing the post-1984 reduced form error covariance structure explains much of the variation in employment series—74% of the reduction for monthly manufacturing employment series and 85% for monthly aggregate employment series. At the same time, imposing the post-1984 coefficients fails to reduce the implied standard deviation of employment. In other words, the results are consistent with Stock and Watson (2002) as the changes in the lag coefficients play a small role in explaining the reduced volatility.[47]

Even though these exercises may lead one to conclude that shocks are more important than the propagation mechanism, I caution against dismissing the structural change argument. As variance decomposition tables show, the oil price, the aggregate

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[46] Note that the sample standard deviation of real oil price growth rate is higher in the post-1984 period since oil prices were very stable between 1958 and 1973.

[47] I thank Stock and Watson for providing the RATS code on their website.

price level, and the fed funds rate play relatively small roles in explaining the overall variation of employment: the larger part is attributed to unidentified shocks. Accordingly, the decrease in shocks may appear to be more important than the reduced responses to the oil price and the fed funds rate. However, one must be cautious in interpreting this result as smaller unidentified shocks may actually be the manifestation of favorable structural changes.[48] While the model is far from complete, investigation of employment responses to these shocks should elucidate the hypothesis as to how employment may respond to other unidentified shocks.

4. Conclusion

The U.S. economy has demonstrated a substantial decline in volatility since the mid-1980s. An interesting question is whether changes in the shock processes are entirely responsible for the increased stability, or whether structural changes that increased the resilience of the economy to shocks are partly responsible for the increased stability. To investigate this question, this paper analyzed employment responses to various shocks to the economy and found that these responses have been smaller since the mid-1980s than from the 1960s through the mid-1980s. The results suggest that some structural changes may have been partly responsible for the increased stability.

Using Topel's interrelated factor demand model, this paper finds that the monthly employment elasticity to unpredicted demand shocks has decreased by more than 80% in the manufacturing industry. Similarly, work-hour elasticity to unpredicted demand

[48] For example, a better financial environment that leads to smaller adverse effects from financial shocks could show up as smaller employment shocks. I owe this point to Ufuk Demiroglu.

shocks fell by more than 60%. Employment responses to current predicted demand shocks also declined but by a smaller amount, perhaps due to a smoothing effect. Both employment and work-hour responsiveness to future predicted demand fell. Inventory responses to current demand shocks are insignificant in most cases, and even when significant, the coefficients are not significantly different from each other. For future demand, the inventory coefficient turns from negative to positive, but only the negative ones are significant. Overall, the paper does not find any observable change in inventory adjustment after 1984, except in its responses to future predicted demand.

VARs were used to investigate the dynamic employment responses to aggregate shocks for the manufacturing series at monthly frequency and for the aggregate series at monthly and quarterly frequencies. Impulse response functions show that both the size and volatility of dynamic employment growth responses to the oil price, the aggregate price level, and monetary policy shocks have decreased since the mid-1980s, but variance decomposition exercises reveal that the role of these shocks in explaining the forecasting variance is small. An instrument for demand shocks may be needed to better explain the overall dynamics.

Finally, an interesting question involves the theoretical underpinnings of the reduced employment sensitivity to shocks. One possibility is that wage flexibility has led to reduced employment volatility. Although simple exercises done in this paper do not find evidence of increased flexibility in aggregate hourly earnings, a more robust analysis would require a micro analysis using a firm-level data set with an examination of total compensation flexibility including benefits. Alternatively, flexibility within firms may have increased at other margins of adjustment. For instance, a model with financial innovations that give firms more financial flexibility may explain the observed results. It is also possible that nonconvex labor adjustment costs generate a disproportional reduction in employment sensitivity when the size of shocks is smaller. Further theoretical and empirical research in this area would help us better understand the stability of the U.S. economy.

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Figures and Tables

Figure 1: Manufacturing Monthly Shipments, Employment, Work Hours, and Inventories (in logs) from January 1958 to December 2005

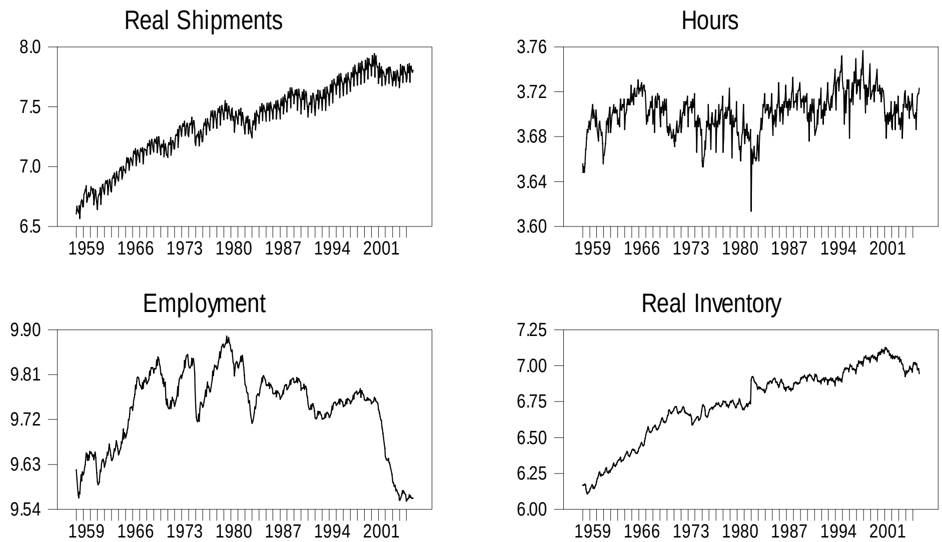
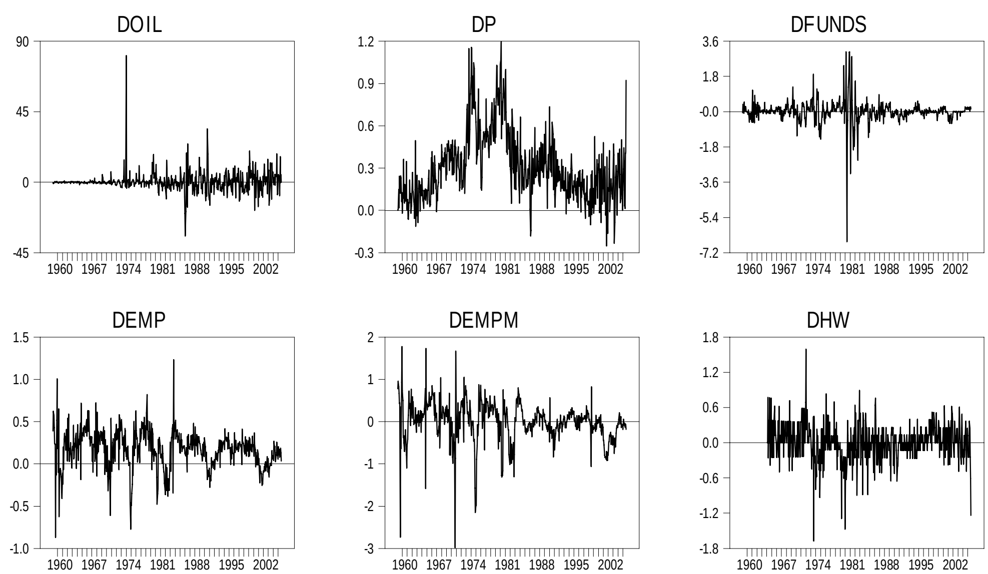
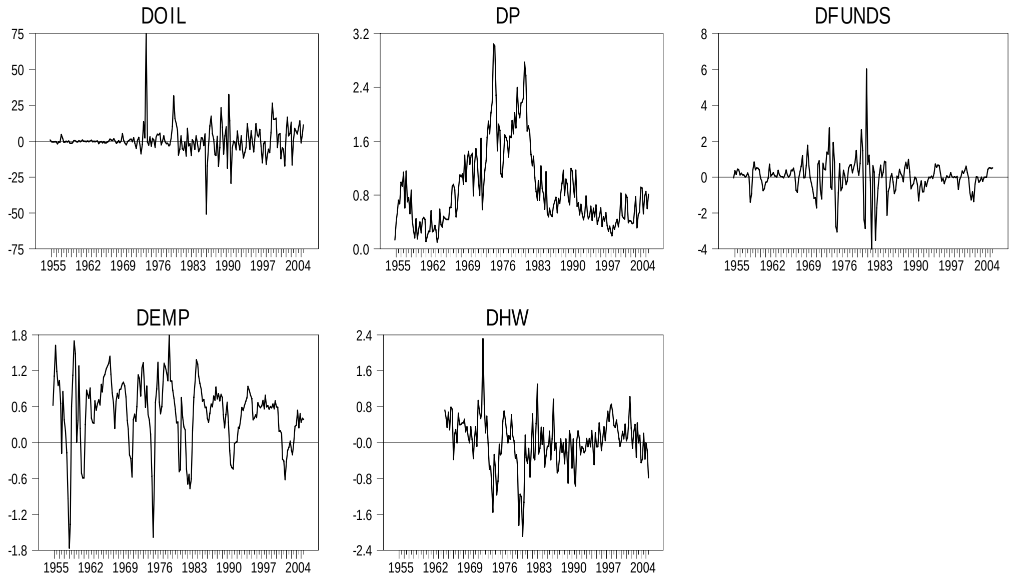


Figure 2: Monthly Series Used for VARs from February 1959 to September 2005



Note: Real oil price growth rate (DOIL), inflation rate (DP), change in the fed funds rates (DFUNDS), total nonfarm employment growth rate (DEMP), manufacturing employment growth rate (DEMPM), and total private real hourly earnings growth rate (DHW).

Figure 3: Quarterly Series Used for VARs from 1954:Q4 to 2005:Q3



Note: Real oil price growth rate (DOIL), inflation rate (DP), change in the fed funds rates (DFUNDS), total nonfarm employment growth rate (DEMP), and real hourly earnings growth rate (DHW).

Figure 4: Impulse Response Functions of Manufacturing Employment, Monthly Series from February 1960 to March 1984

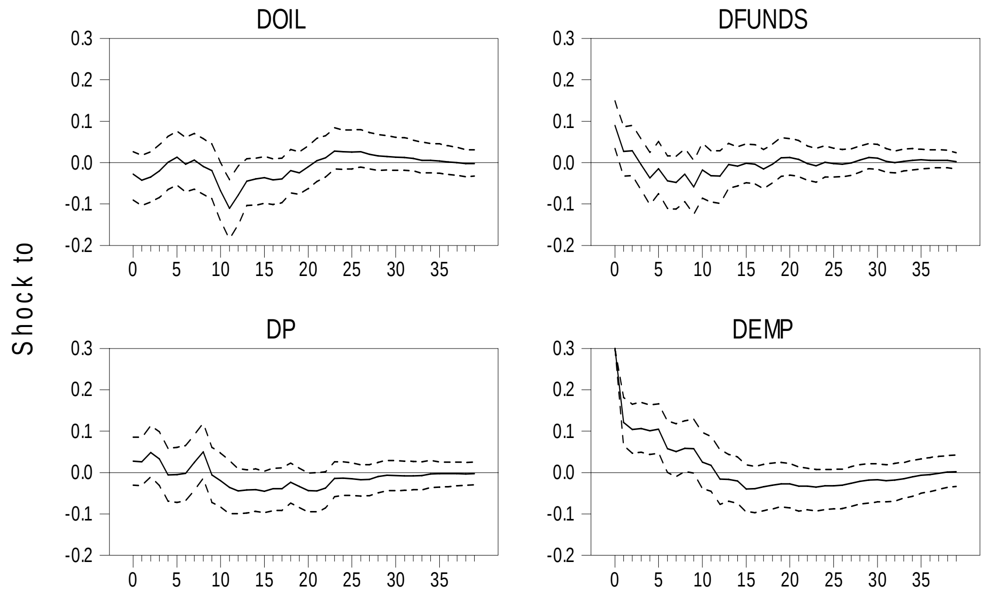


Figure 5: Impulse Response Functions of Manufacturing Employment, Monthly Series from April 1984 to September 2005

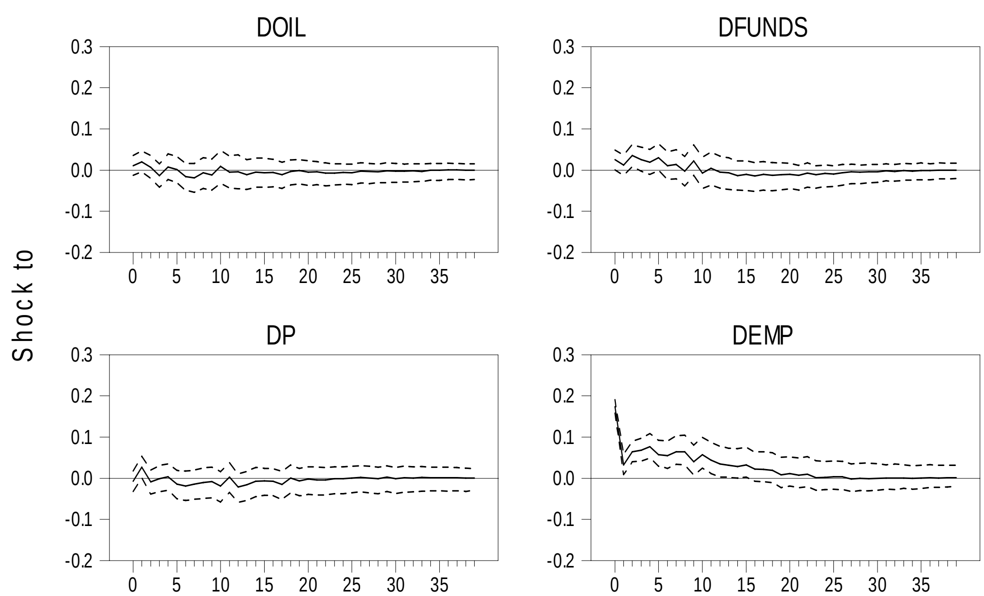


Figure 6: Impulse Response Functions of Manufacturing Employment, Monthly Series

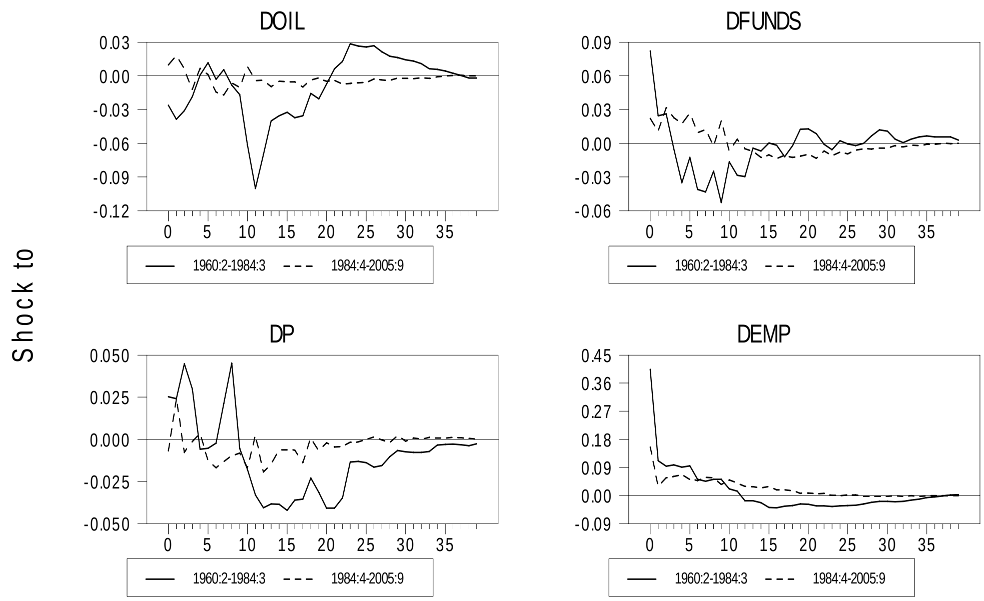


Figure 7: Impulse Response Functions of Manufacturing Employment, 12-Month Growth

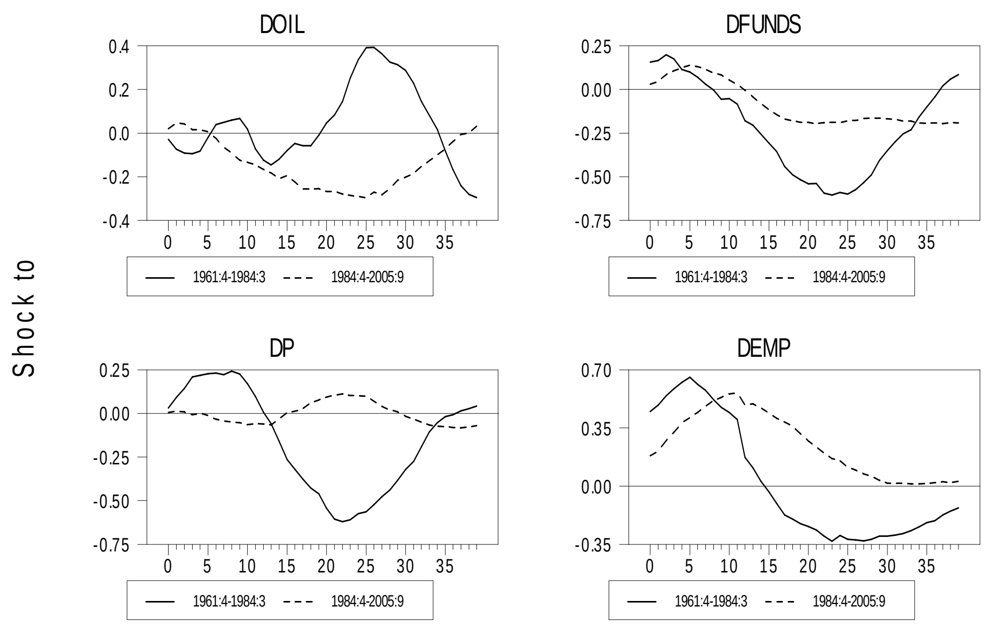


Figure 8: Impulse Response Functions of Aggregate Employment, Monthly Series from February 1960 to March 1984

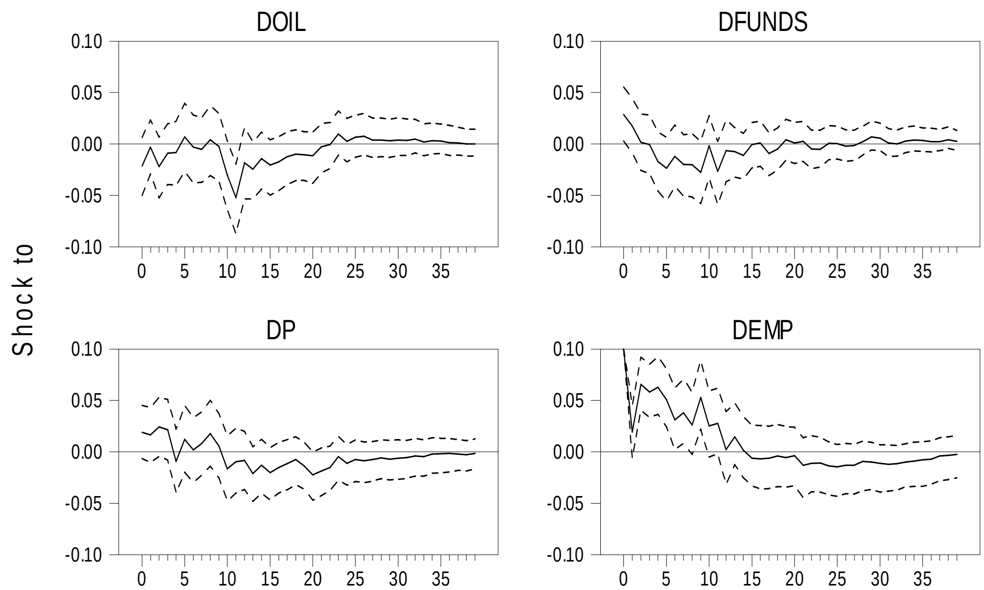


Figure 9: Impulse Response Functions of Aggregate Employment, Monthly Series from April 1984 to September 2005

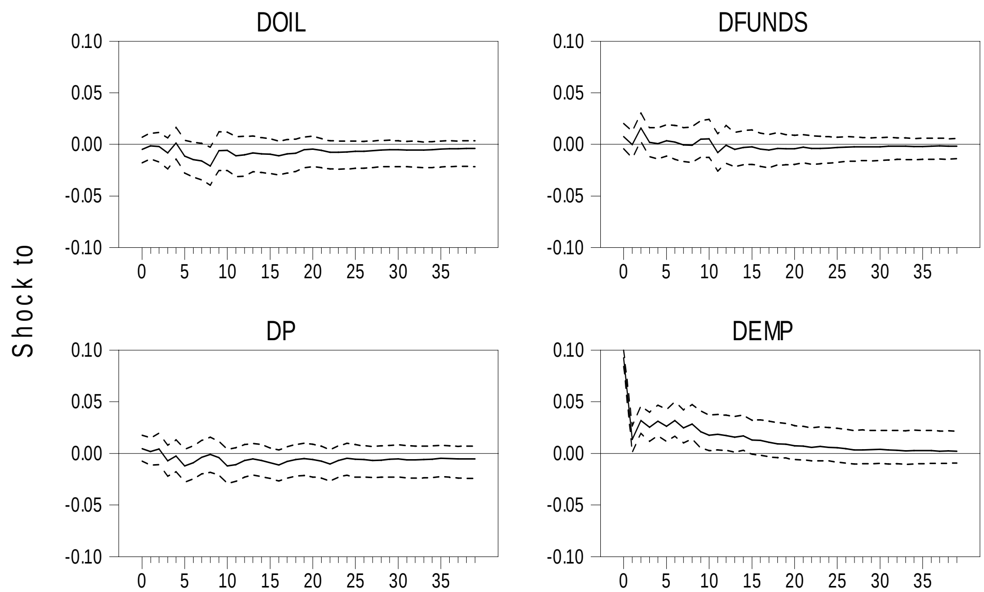


Figure 10: Impulse Response Functions of Aggregate Employment, Monthly Series

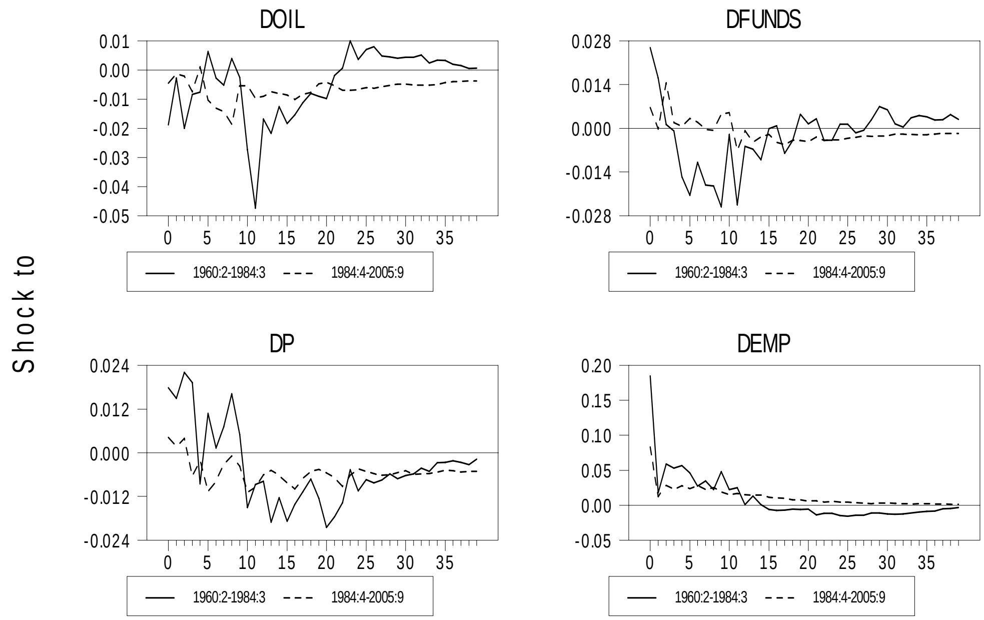


Figure 11: Impulse Response Functions of Aggregate Employment, 12-Month Growth

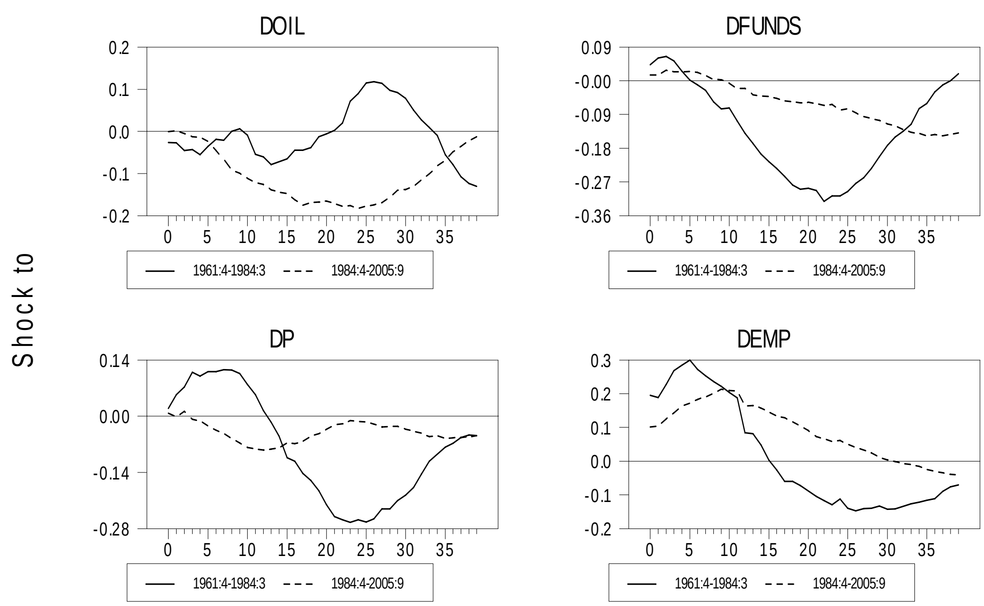


Figure 12: Impulse Response Functions of Aggregate Employment, Quarterly Series

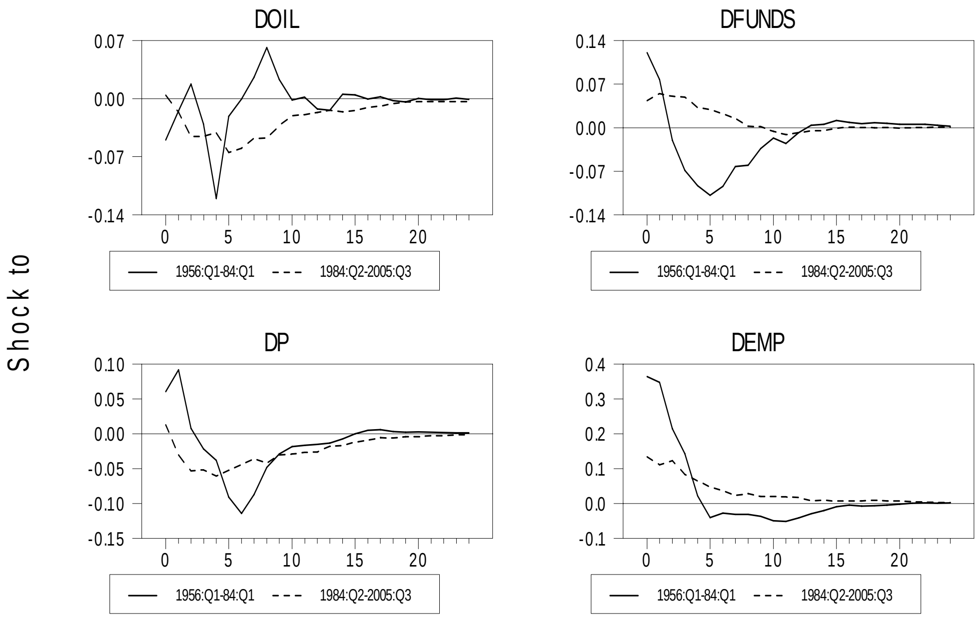


Figure 13: Impulse Response Functions of Aggregate Employment, 4-Quarter Growth

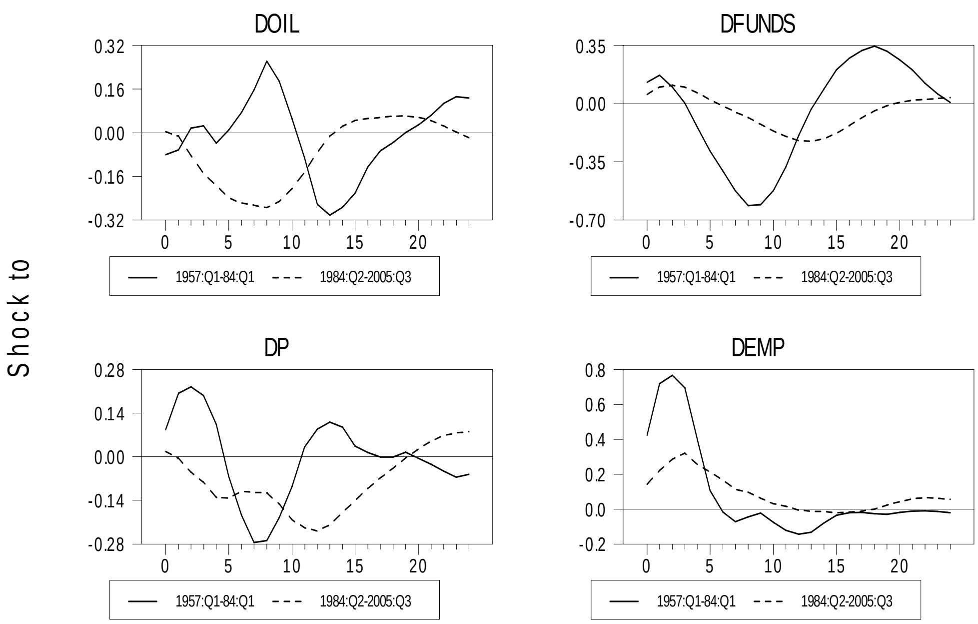


Figure 14: Impulse Response Functions of Real Hourly Earnings, Monthly Series

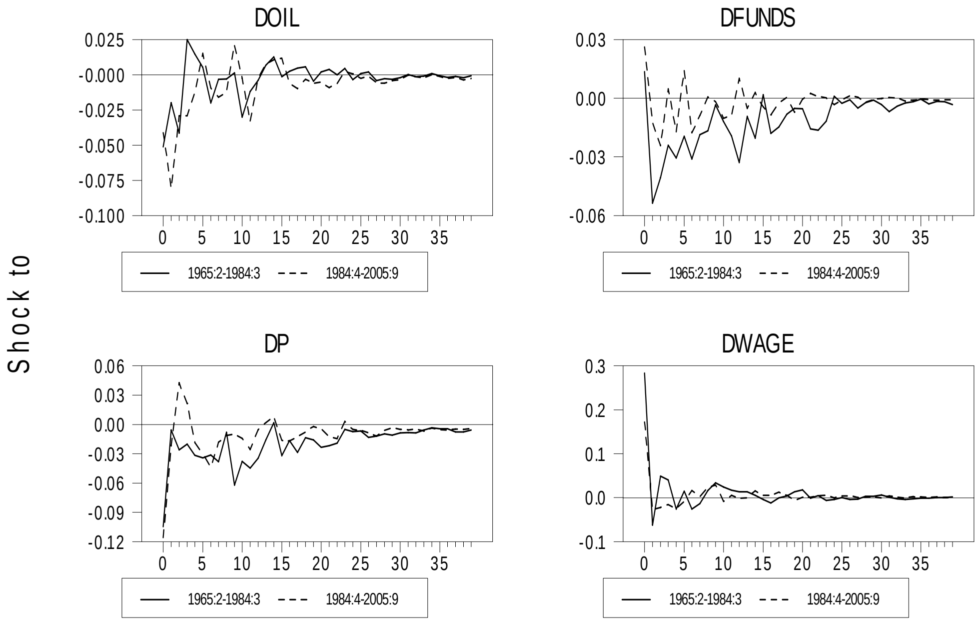


Figure 15: Impulse Response Functions of Real Hourly Earnings, Quarterly Series

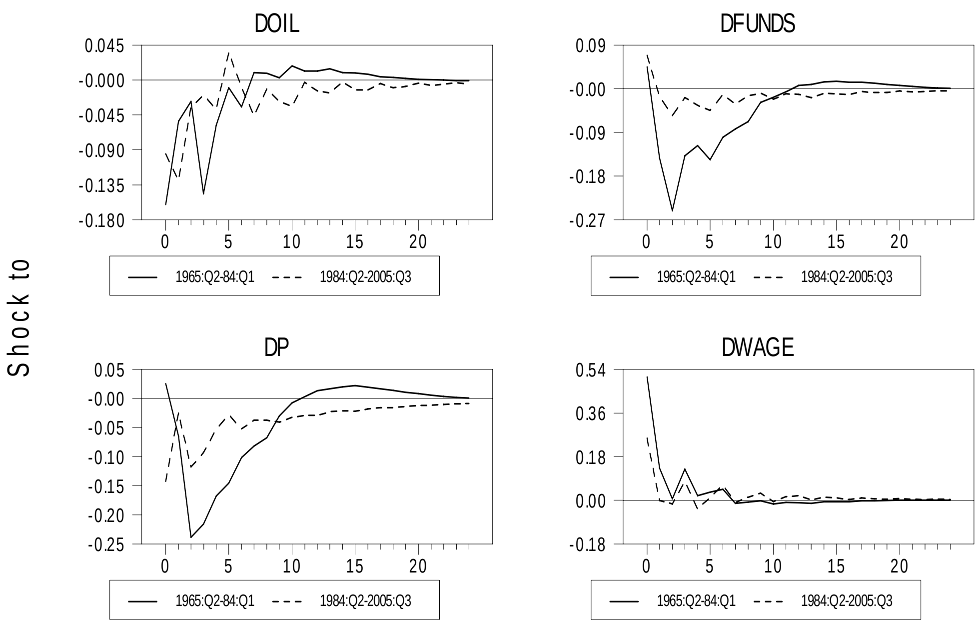


Table 1: Estimates of Interrelated Factor Demand Model Using Seasonally Unadjusted Series and Separate ARIMA Models, 9-month forecast horizon, 1959-2005

	(1)		(2)		(3)	
	Employment		Hours		Inventories	
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:						
Current unpredicted	0.096***	0.011	0.094***	0.032	0.002	-0.015
	(0.018)	(0.009)	(0.032)	(0.029)	(0.050)	(0.037)
Current predicted	0.037***	-0.009	0.025	-0.040*	-0.030	0.034
	(0.013)	(0.009)	(0.017)	(0.024)	(0.033)	(0.033)
Future predicted	0.104***	0.027***	0.079***	0.043***	-0.094***	0.037
	(0.012)	(0.007)	(0.015)	(0.015)	(0.030)	(0.023)
Lagged Dep. Variables:						
Employment	0.844***	0.983***	-0.060**	0.084***	0.127**	0.078*
	(0.020)	(0.013)	(0.024)	(0.029)	(0.051)	(0.046)
Hours	0.051	0.044*	0.712***	0.627***	0.140	-0.136*
	(0.033)	(0.021)	(0.043)	(0.053)	(0.086)	(0.077)
Inventories	-0.056***	-0.044***	-0.027**	-0.057**	0.992***	0.862***
	(0.011)	(0.008)	(0.013)	(0.017)	(0.029)	(0.027)
Other Lagged Variables:						
Material and supply	-0.043***	0.019**	-0.035***	-0.012	0.027	0.051
inventories	(0.008)	(0.09)	(0.009)	(0.021)	(0.020)	(0.033)
Work-in-progress	0.048***	-0.004	0.021*	-0.015*	-0.017	-0.033***
inventories	(0.010)	(0.004)	(0.012)	(0.008)	(0.026)	(0.013)
Number of obs.	289	252	289	252	289	252
R-squared	0.997	0.999	0.835	0.847	0.996	0.992
Breusch-Godfrey Test	0.839	0.766	0.096	0.245	0.853	0.820

Note: I impose an Almon-type restriction that the distribution of the coefficients on the predicted future shipments is assumed to be polynomial of the third degree. Therefore, the shortest possible period of prediction is 4 months. Here, the coefficient on future predicted shipments is the sum of the coefficients on the 9-month forecast, including the current month. Each regression includes seasonal dummies and a trend variable. Beach and MacKinnon maximum likelihood iterative procedure was used to obtain consistent estimates in the presence of autocorrelated disturbances. The Breusch-Godfrey Test shows the significance level of the test statistic for autocorrelation based on χ^2 distribution. The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 2: Estimates of Interrelated Factor Demand Model Using Seasonally Unadjusted Series and Separate ARIMA Models, 6-month forecast horizon, 1959-2005

	(1) Employment		(2) Hours		(3) Inventories	
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:						
Current unpredicted	0.089***	0.011	0.115***	0.022	-0.097	-0.090**
	(0.022)	(0.010)	(0.041)	(0.033)	(0.061)	(0.038)
Current predicted	0.025	-0.010	0.044	-0.055	-0.139***	-0.094**
	(0.019)	(0.011)	(0.030)	(0.033)	(0.051)	(0.041)
Future predicted	0.102***	0.029***	0.081***	0.040***	-0.104***	0.045*
	(0.012)	(0.006)	(0.015)	(0.014)	(0.030)	(0.023)
Lagged Dep. Variables:						
Employment	0.852***	0.981***	-0.071***	0.088***	0.134***	0.077*
	(0.018)	(0.013)	(0.023)	(0.028)	(0.048)	(0.045)
Hours	0.046	0.042	0.723***	0.639***	0.164*	-0.173***
	(0.032)	(0.020)	(0.042)	(0.052)	(0.084)	(0.074)
Inventories	-0.057***	-0.042***	-0.028**	-0.053***	0.991***	0.873***
	(0.011)	(0.008)	(0.013)	(0.017)	(0.029)	(0.027)
Other Lagged Variables:						
Material and supply	-0.041***	0.018*	-0.037***	-0.016	0.027	0.043
inventories	(0.007)	(0.009)	(0.009)	(0.020)	(0.019)	(0.033)
Work-in-progress	0.046***	-0.004	0.023**	-0.014*	-0.015	-0.030**
inventories	(0.010)	(0.004)	(0.012)	(0.007)	(0.025)	(0.013)
Number of obs.	292	255	292	255	292	255
R-squared	0.997	0.999	0.834	0.848	0.996	0.992
Breusch-Godfrey Test	0.880	0.788	0.084	0.248	0.865	0.904

Note: The coefficient on future predicted shipments is the sum of the coefficients on the 6-month forecast, including the current month. The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 3: Estimates of Interrelated Factor Demand Model Using Seasonally Unadjusted Series and Separate ARIMA Models, 12-month forecast horizon, 1959-2005

	(1)		(2)		(3)	
	Employment		Hours		Inventories	
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:						
Current unpredicted	0.097***	0.018*	0.096***	-0.017	-0.010	-0.004
	(0.017)	(0.009)	(0.029)	(0.028)	(0.047)	(0.036)
Current predicted	0.035***	-0.002	0.028**	-0.037**	-0.039	0.042*
	(0.010)	(0.007)	(0.012)	(0.017)	(0.026)	(0.025)
Future predicted	0.104***	0.026***	0.080***	0.055***	-0.096***	0.026
	(0.011)	(0.007)	(0.014)	(0.015)	(0.030)	(0.024)
Lagged Dep. Variables:						
Employment	0.848***	0.987***	-0.051**	0.075**	0.115**	0.085*
	(0.020)	(0.013)	(0.024)	(0.029)	(0.053)	(0.046)
Hours	0.050	0.045**	0.699***	0.610***	0.156*	-0.096
	(0.034)	(0.021)	(0.044)	(0.053)	(0.089)	(0.077)
Inventories	-0.061***	-0.045***	-0.027*	-0.055***	1.002***	0.870***
	(0.012)	(0.008)	(0.014)	(0.017)	(0.031)	(0.027)
Other Lagged Variables:						
Material and supply	-0.044***	0.017*	-0.035***	-0.014	0.029	0.046
inventories	(0.008)	(0.009)	(0.009)	(0.020)	(0.020)	(0.033)
Work-in-progress	0.049***	-0.005	0.018	-0.012	-0.019	-0.033*
inventories	(0.010)	(0.004)	(0.012)	(0.008)	(0.026)	(0.012)
Number of obs.	286	249	286	249	286	249
R-squared	0.997	0.999	0.838	0.853	0.996	0.992
Breusch-Godfrey Test	0.827	0.762	0.109	0.234	0.829	0.853

Note: The coefficient on future predicted shipments is the sum of the coefficients on the 12-month forecast, including the current month. The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 4: Estimates of Interrelated Factor Demand Model Using Seasonally Unadjusted Series and Same ARIMA Model, 9-month forecast horizon, 1959-2005

	(1)		(2)		(3)	
	Employment		Hours		Inventories	
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:						
Current unpredicted	0.092***	0.016*	0.095***	0.034	0.008	0.023
	(0.018)	(0.009)	(0.030)	(0.029)	(0.049)	(0.034)
Current predicted	0.032**	-0.003	0.026	-0.032	-0.025	0.038
	(0.013)	(0.008)	(0.017)	(0.021)	(0.034)	(0.030)
Future predicted	0.101***	0.026***	0.072***	0.047***	-0.097***	0.024
	(0.012)	(0.007)	(0.015)	(0.015)	(0.031)	(0.024)
Lagged Dep. Variables:						
Employment	0.848***	0.981***	-0.070***	0.079***	0.130**	0.079*
	(0.019)	(0.013)	(0.023)	(0.029)	(0.050)	(0.046)
Hours	0.054*	0.051**	0.762***	0.634***	0.137*	-0.117
	(0.030)	(0.021)	(0.038)	(0.054)	(0.079)	(0.078)
Inventories	-0.057***	-0.044***	-0.028**	-0.060***	0.989***	0.865***
	(0.011)	(0.008)	(0.013)	(0.018)	(0.029)	(0.028)
Other Lagged Variables:						
Material and supply	-0.041***	0.020**	-0.035***	-0.012	0.028	0.059*
inventories	(0.008)	(0.009)	(0.009)	(0.021)	(0.020)	(0.033)
Work-in-progress	0.047***	-0.004	0.024**	-0.014*	-0.016	-0.035***
inventories	(0.010)	(0.004)	(0.012)	(0.008)	(0.025)	(0.013)
Number of obs.	298	252	298	252	298	252
R-squared	0.997	0.999	0.833	0.846	0.996	0.992
Breusch-Godfrey Test	0.827	0.690	0.072	0.252	0.887	0.828

Note: The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 5: Estimates of Interrelated Factor Demand Model Using Seasonally Adjusted Series and Separate ARIMA Models, 9-month forecast horizon, 1959-2005

	(1)		(2)		(3)	
	Employment		Hours		Inventories	
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:						
Current unpredicted	0.093***	0.018*	0.090***	-0.035	0.004	0.031
	(0.018)	(0.010)	(0.030)	(0.029)	(0.050)	(0.040)
Current predicted	0.030**	0.003	0.022	-0.057***	-0.042	0.052
	(0.015)	(0.009)	(0.018)	(0.021)	(0.039)	(0.035)
Future predicted	0.104***	0.034***	0.071***	0.065***	-0.095***	0.011
	(0.011)	(0.007)	(0.014)	(0.015)	(0.030)	(0.027)
Lagged Dep. Variables:						
Employment	0.859***	0.986***	-0.066***	0.079***	0.130**	0.062
	(0.019)	(0.012)	(0.022)	(0.024)	(0.050)	(0.044)
Hours	0.020	0.036	0.764***	0.633***	0.129	-0.065
	(0.032)	(0.024)	(0.039)	(0.053)	(0.085)	(0.089)
Inventories	-0.053***	-0.032***	-0.024**	-0.026	1.002***	0.872***
	(0.011)	(0.007)	(0.012)	(0.015)	(0.027)	(0.027)
Other Lagged Variables:						
Material and supply	-0.043***	0.006	-0.032***	-0.043**	0.029	0.063*
inventories	(0.007)	(0.009)	(0.008)	(0.018)	(0.019)	(0.034)
Work-in-progress	0.042***	-0.004	0.021**	-0.008	-0.023	-0.030***
inventories	(0.009)	(0.003)	(0.011)	(0.006)	(0.024)	(0.012)
Number of obs.	290	252	290	252	290	252
R-squared	0.997	0.999	0.839	0.869	0.997	0.994
Breusch-Godfrey Test	0.775	0.674	0.146	0.462	0.924	0.817

Note: The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 6: Estimates of Wage Responses, 9-month forecast horizon, 1959-2005

	(1)		(2)	
	Hourly Earnings, Unseasonally Adjusted Series		Hourly Earnings, Seasonally Adjusted Series	
	Pre-1984	Post-1984	Pre-1984	Post-1984
Demand:				
Current unpredicted	0.084***	0.047*	0.105***	0.048
	(0.026)	(0.025)	(0.025)	(0.029)
Current predicted	0.008	-0.042*	0.012	-0.069***
	(0.018)	(0.023)	(0.020)	(0.026)
Future predicted	0.056***	0.008	0.043**	0.019
	(0.020)	(0.028)	(0.020)	(0.027)
Lagged Dep. Variables:				
Hourly earnings	0.919***	0.939***	0.926***	0.948***
	(0.020)	(0.031)	(0.018)	(0.023)
Number of obs.	289	252	290	252
R-squared	0.996	0.995	0.997	0.996
Breusch-Godfrey Test	0.724	0.874	0.721	0.889

Note: The coefficient on future predicted shipments is the sum of the coefficients on the 9-month forecast, including the current month. A separate ARIMA model was used to capture the demand shock processes for each period. Other variables included in the regressions are lagged value of employment, hours, inventories, material and supply inventories, and work-in-progress inventories. The standard errors are reported in parentheses. *, **, and *** show the significance level at 10%, 5%, and 1%, respectively.

Table 7: Variance Decomposition for Monthly Manufacturing Employment

Horizon		% of forecast variance explained by: Oil price	Aggregate price	Fed funds rate	Employment
1960-1984					
	1	0.40	0.37	3.95	95.28
	12	6.66	3.04	6.56	83.74
	24	10.08	7.56	6.18	76.18
	∞	10.84	8.10	6.09	74.97
1984-2005					
	1	0.35	0.07	1.99	97.59
	12	2.16	2.59	6.42	88.83
	24	2.51	3.67	7.76	86.06
	∞	2.69	3.68	8.12	85.51

Table 8: Variance Decomposition for Monthly Aggregate Employment

Horizon		% of forecast variance explained by: Oil price	Aggregate price	Fed funds rate	Employment
1960-1984					
	1	1.00	0.90	1.87	96.23
	12	6.44	3.60	5.90	84.07
	24	8.82	6.84	5.89	78.45
	∞	8.83	7.52	5.89	77.77
1984-2005					
	1	0.25	0.29	0.54	98.92
	12	6.63	3.19	2.68	87.50
	24	8.77	6.10	2.90	82.22
	∞	11.21	11.37	3.16	74.26

Table 9: Implied Standard Deviations from Subsample VARs

Employment growth rates	Standard deviation implied by the VARs			
	1958-1984	1984-2005	Coef: pre-84 Error: post-84	Coef: post-84 Error: pre-84
Monthly manufacturing	0.57	0.26	0.34	0.67
Monthly aggregate	0.27	0.14	0.16	0.28