노 동 정 책 연 구
2010. 제10권 제2호 pp.1~33

연구논문

Test of Sectoral Shifts Hypothesis Based on Robust Measures of Dispersion and Skewness

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Sectoral shifts hypothesis states that sectoral reallocation of labor demand has a significant effect on the fluctuation of unemployment rate even in the absence of aggregate shocks. Many studies have found strong evidence supporting the hypothesis. In those studies, classical measures of dispersion and skewness of the cross-sectional distribution of estimated sectoral shocks have been used to represent the effect of sectoral shifts on aggregate unemployment rates. However, it is well known that classical measures of moments are strongly affected by the presence of outliers. Consequently, the test of sectoral shifts hypothesis can be distorted by the presence of a few outliers. This paper examines the presence of outliers in the sectoral shocks estimated from the U.S. industrial data, and tests the sectoral shifts hypothesis based on alternative robust measures of the dispersion and skewness. We find strong evidence of the presence of outliers. However, it turns out that sectoral shifts hypothesis is still strongly supported when robust measures of dispersion and skewness are used as a measure of sectoral shifts. We also find that even in the absence of aggregate shocks the natural rate of unemployment fluctuates significantly over time due to sectoral shifts.

Keywords : sectoral shifts, sectoral shocks, robust measures of dispersion and skewness, natural rate of unemployment

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논문접수일: 2010년 5월 6일, 심사의뢰일: 2010년 5월 7일, 심사완료일: 2010년 6월 9일
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Ⅰ. Introduction

Sectoral shift is defined as the reallocation of labor demand across industries holding aggregate labor demand constant. When there is a sectoral shock that shifts labor demand from a declining industry to an expanding industry, the former industry lays off workers, and those workers will go through a job search process to find new jobs in the expanding industry. Because of the time associated with the search process, sectoral shift is expected to raise the aggregate unemployment rate. This is called the sectoral shifts hypothesis.

The seminal paper by Lilien (1982) presents a very simple and intuitive example that demonstrates a positive relationship between average layoff rate and dispersion of the distribution of sectoral shocks. Since Lilien (1982), a large number of studies on the sectoral shifts hypothesis employ the *classical* measure of cross-sectional dispersion of sectoral shocks to represent the effect of sectoral shifts of labor demand on aggregate unemployment rates. In a recent paper, Byun and Hwang (2006) argue that classical measure of dispersion alone is not enough for capturing sectoral shifts of labor demand, and that in addition to dispersion, classical measure of skewness also should be used when testing the sectoral shifts hypothesis. They empirically show that, when measured by dispersion and skewness, sectoral shifts have a significant effect on the aggregate unemployment rate.

It is well known that classical measures of moments are very sensitive to the presence of outliers. Consequently, tests of sectoral shifts hypothesis based on the estimates of classical measures of dispersion and skewness may be distorted by outliers in the estimates of sectoral shocks. By applying various methods of detecting outliers on cross-sectional distribution of sectoral shocks estimated from the U.S. industrial employment data, we find strong evidence for the presence of outliers for a large number of periods.

We then compute various robust measures of dispersion and skewness of the distribution of sectoral shocks, and use them in place of classical measures to test the sectoral shifts hypothesis. Robust measures are quite different from the classical measures in terms of their magnitude. However, the use of robust measures does not alter the result of testing the sectoral shifts hypothesis. All robust measures of sectoral shifts strongly support the hypothesis. The only exception is the case where medcouple is used as a robust measure of skewness. However, the medcouple, in the way it is constructed, is less likely to properly reflect any changes in the tail part of distribution and hence is not a good measure for detecting changes in skewness.

This chapter is organized as follows. In section II, we present a brief literature review regarding sectoral shifts hypothesis and the main objectives of this paper. In section III, we discuss classical and robust measures of dispersion and skewness, and deals with outlier detection methods. Section IV explains empirical models of testing sectoral shifts hypothesis. In section Ⅴ, empirical results from detection of outliers and test of sectoral shift hypothesis are presented, and the conclusion follows in section VI.

Ⅱ. Literature Review and Main Objectives

The sectoral shifts hypothesis of Lilien (1982) asserts that labor reallocation resulting from compositional shifts in the structure of labor demand across industries can generate significant fluctuations in aggregate unemployment that are not directly related to the fluctuations in aggregate demand. Based on his simple and intuitive example, Lilien approximates aggregate layoffs resulting from the sectoral shifts of labor demand by a linear function of the mean and dispersion of employment growth rates across industries. His empirical results show that the sectoral reallocation indeed has a significant effect on the aggregate unemployment rate with a substantive magnitude.

However, Abraham and Katz (1984) argue that all aggregate shocks on employment growth rates must be "purged" in the estimation of the dispersion measure. Their empirical results contradict Lilien's results: when aggregate shocks are eliminated according to their method, their measure of dispersion has no significant long-run effect on the unemployment rate. However, many studies have criticized their method for the tendency of 'over-purging[2]'.

Since Lilien (1982) and Abraham and Katz (1984), all past studies have accepted the dispersion of sectoral shocks as a suitable measure of sectoral shifts and focused on how to purge aggregate shocks. These works can be classified into two types: Lilien type and Abraham and Katz type depending on their purging methods. The empirical results of the past studies have differed due to the difference in purging methods, and debates on sectoral shifts hypothesis have lasted until Byun and Hwang (2006). In their paper, Byun and Hwang (2006) argue that dispersion measure alone is not enough to adequately capture the effect of changes in the distribution of sectoral shocks on aggregate unemployment rate. They empirically show that skewness measure in addition to the dispersion measure has a statistically significant effect on aggregate unemployment in both types of models. They also show that sectoral shifts hypothesis is strongly supported in both types of models regardless of the choice of purging methods. Since their work, many studies have focused on how to incorporate an important aspect of the nature of sectoral shocks: their asymmetry.

The sectoral shifts hypothesis has significant implications on macroeconomic issues. The hypothesis suggests a limited effectiveness of aggregate demand management policy in moderating unemployment fluctuations because a

2) When 'over-purging' is applied on sectoral employment growth rates, parts of sectoral shocks are removed as well as aggregate shocks. Thus, Abraham and Katz's method tends to under-estimate sectoral shocks.

significant portion of the unemployment is independent of aggregate demand shocks. The hypothesis also suggests a caution in the specification of the Phillips curve. As Rissman (1993) points out, unemployment from sectoral reallocation of labor demand affects the wage inflation process differently from the cyclical unemployment, and the unemployment rate is not an accurate measure of general labor market conditions when there is a sectoral reallocation. Therefore, changes in the natural rate of unemployment from sectoral reallocation must be taken into account in the computation of the unemployment gap as a measure of inflationary pressure in the study of the Phillips curve.

In more recent studies, Rissman (2003), Groshen and Potter (2003), Aaronson et al.(2004), and Groshen et al.(2004) investigate the role of sectoral shifts of labor demand in explaining the differences of employment growth trends following the end of recessions, in particular, the jobless recovery after the 2001 recession[3]. Recent studies also employ the sectoral shifts as a research tool for the current financial crisis. Basu and Fernald (2009) recognize the possibility that sectoral reallocation of labor from shrinking sectors such as housing-related sectors and financial sector may cause potential output growth to slow down temporarily and the natural rate of unemployment to hike up. As Phelps (2008) has outlined, Based on sectoral imbalance interpretation, Valletta and Cleary (2008) examine current increase in unemployment. They find that sectoral imbalance caused by excessive expansion of some particular sectors is at the bottom of the current U.S. economic downturn, and this might

3) The idea of sectoral shifts hypothesis has also been used in recent studies to introduce persistent unemployment in the real business cycle model(Mikhail, Eberwein and Handa (2003)), to study the macroeconomic effects of reallocation shocks in European countries (Panagiotidis, Pelloni and Polasek (2003)), to examine natural rate of unemployment in relation to state-level labor market conditions(Wall and Zoega (2004)), and to examine the effect of sectoral shifts and employment specialization on the efficiency of the process with which unemployed workers are matched to available job vacancies in regional labor markets in the UK (Robson (2004)).

require substantial movement of labor across industries.

In summary, the sectoral shifts hypothesis has provided an alternative explanation of unemployment fluctuation since the seminal work of Lilien (1982). As Byun and Hwang (2006) argue, sectoral shifts of labor demand across industries can be adequately measured by dispersion and skewness of the distribution of sectoral shocks regardless of the purging methods. However, one criticism regarding this approach is that *classical* measures of dispersion and skewness, which have adopted in all previous studies, might be distorted due to the presence of outliers in the distribution of sectoral shocks. In response to this criticism, this paper aims to re-test the sectoral shifts hypothesis using various robust measures of dispersion and skewnesss in a setting that resembles the original work of Lilien (1982).

Ⅲ. Robust Measures of Dispersion and Skewness

An outlier is a sample value that lies an abnormal distance from the majority of the sample. Outliers can be caused by gross error such as mistakes in computation or choices of wrong models. However, this does not mean that analysts must remove all outliers before further analysis of the data because they may be correct. Therefore, analysts can do better by down-weighting outliers rather than just discarding them. In this section, We present alternative robust measures of dispersion and skewness, and discuss their properties.

Two most commonly used robust alternatives to the classical dispersion measure are based on the interquartile range and the median absolute deviation (MAD). Let $x = \{x_1, x_2, \cdots, x_n\}$ be a random sample of size n, and let Q_p be the p^{th} quantile of x. The dispersion measure based on the interquartile range is defined by

$$d_{iqr} = c_{iqr}(Q_{0.75} - Q_{0.25})$$

where $c_{iqr} = 1/(2\alpha)$ and $\alpha = \Phi^{-1}(0.75) \approx 0.67449$. The normalization factor c_{iqr} is to make d_{iqr} comparable to the classical standard deviation σ when the sample is from a normal $N(\mu, \sigma^2)$[4]. It should be noted that d_{iqr} does not reflect any information from outside of two quartiles. Therefore, its breakdown point is 25%[5].

The MAD is the median of the absolute distances between each data point and overall median of the data set, and the dispersion measure based on the MAD is then defined as

$$d_{mad} = c_{mad} med_i(|x_i - med_j(x_j)|)$$

where the normalization factor $c_{mad} = 1/\alpha \approx 1.4826$ is to make d_{mad} comparable to σ. The MAD has the best possible breakdown point of 50%.

The MAD statistic implicitly assumes a symmetric distribution as it measures the distance from a measure of central location (the median). Rousseeuw and Croux (1993) proposed two new statistics, S_n and Q_n, as alternatives to the MAD statistic. The dispersion measure based on S_n is defined by

$$d_{rcs} = c_{rcs} med_i(med_j(|x_i - x_j|))$$

where the outer median, med_i, is the median of n medians of $\{|x_i - x_j|, j = 1, 2, \cdots, n\}$. The correction factor $c_{rcs} = 1.1926$ is to reduce the small sample bias in the estimation of the standard deviation. The S_n statistic has a breakdown point of 50% and has better normal efficiency than the

4) If x is distributed as a normal $N(\mu, \sigma^2)$, then $MAD(x) = \alpha\sigma$ and $IQR(x) = 2\alpha\sigma$, where $\alpha = \Phi^{-1}(0.75)$.

5) The breakdown point of an estimator is defined as the proportion of arbitrarily large observations an estimator can handle before giving an arbitrarily large result.

MAD.

The dispersion measure based on Q_n is defined by

$$d_{rcq} = c_{rcq}\{|x_i - x_j|; i < j\}_{(k)}, \qquad k = \binom{h}{2}, \quad h = [n/2] + 1$$

where $c_{rcq} = 2.2219$ and $[n/2]$ is the integer part of $n/2$. This estimator is a constant times the k^{th} order statistic of the $n(n-1)/2$ distances between data points and has a breakdown point of 50%. It also has a significantly better normal efficiency than the d_{mad} and d_{rcs}, and does not depend on symmetry.

One of the robust measures of skewness is Hinkley’s (1975) generalization of Bowley’s (1920) coefficient of skewness, which is defined by

$$sk_h(p) = \frac{(Q_{1-p} - Q_{0.5}) - (Q_{0.5} - Q_p)}{(Q_{1-p} - Q_{0.5}) + (Q_{0.5} - Q_p)}, \quad 0 < p < 1/2$$

It takes a value in the interval $[-1,1]$ and has breakpoint of 12.5% when octile skewness($p = 1/8$) is used.[6].

Hinkley’s measure requires a choice of p and the measure may be sensitive to a particular choice. Furthermore, this measure is insensitive to the distribution in the tails outside the chosen quantiles. The skewness measure proposed by Groeneveld and Meeden (1984) overcomes this problem by taking probability-weighted averages of the numerator and denominator terms in Hinkley’s measure. It is defined by

$$sk_{gm} = \frac{\int_0^{\frac{1}{2}} \left(\left[F^{-1}(1-p) - Q_{0.5} \right] - \left[Q_{0.5} - F^{-1}(p) \right] \right) dp}{\int_0^{\frac{1}{2}} \left(\left[F^{-1}(1-p) - Q_{0.5} \right] + \left[Q_{0.5} - F^{-1}(p) \right] \right) dp}$$

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6) Aucremenne et al. (2004) used the de-standardized versions of Hinkley's measure in their study of inflation rate, i.e., they used only the numerator term of the Hinkley's measure with $p = 1/4$ and $p = 1/8$.

and takes a zero value for a symmetric distribution and a value in the interval $[-1,1]$ 7).

Brys et al. (2003) introduced the medcouple (MC) as a robust measure of skewness. Let the sample be sorted in ascending order: $x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)}$. The medcouple is defined by

$$sk_{mc} = med_{x_{(i)} \leq Q_{0.5} \leq x_{(j)}} h(x_{(i)}, x_{(j)})$$

where the kernel function is defined as8)

$$h(x_{(i)}, x_{(j)}) = \frac{(x_{(j)} - Q_{0.5}) - (Q_{0.5} - x_{(i)})}{(x_{(j)} - Q_{0.5}) + (Q_{0.5} - x_{(i)})}$$

for all $x_{(i)} \leq Q_{0.5} \leq x_{(j)}$. Since the value of the kernel function lies in the interval $(-1,1)$ for all $x_{(i)} \leq Q_{0.5} \leq x_{(j)}$, sk_{mc} takes a value in $(-1,1)$. Note that the kernel function is the same as Hinkley's measure of skewness except that Q_p and Q_{1-p} are replaced by order statistics $x_{(i)}$ and $x_{(j)}$. The sk_{mc} has breakdown point of 25%.

Hosking (1990) introduced L-moments which are summary statistics for probability distributions and data samples. They provide measures of location, dispersion, skewness, kurtosis, and other aspects of the shape of probability distributions or data samples. They are particularly useful in identifying skewed distributions and their estimators are quite robust to the presence of outliers in the data.

L-moments are defined as a linear function of the expected order statistics

$$\ell_r = \frac{1}{r}\sum_{k=0}^{r-1}(-1)^k \binom{r-1}{k} E(X_{r-k:r}), \qquad r = 1, 2, \cdots$$

7) Note that the denominator of sk_{gm} can be considered as a measure of dispersion. If the denominator term is replaced with the classical dispersion measure, it becomes Pearson's coeffifients of skewness $sk_p = 3(mean - meadian)/\sigma$.

8) In the special case of $x_{(i)} = x_{(j)} = Q_{0.5}$, the kernel function $h(x_{(i)}, x_{(j)})$ takes a value $+1$ if $i > j$, 0 if $i = j$, and -1 if $i < j$.

where $E(X_{j:r})$ is the expectation of the j^{th} order statistic in a sample of size r drawn from the distribution of $F(x)$. These moments can also be expressed as linear functions of the weighted probability moments introduced by Greenwood et al. (1979)

$$\ell_r = \frac{1}{r}\sum_{k=0}^{r-1}(-1)^{r-k-1}\binom{r-1}{k}\binom{r+k-1}{k}\beta_k, \qquad r = 1, 2, \cdots$$

where β_k is the probability weighted moment

$$\beta_k = \int x\,[F(x)]^k dF(x)$$

We will use ℓ_2 as a robust measure of dispersion:

$$d_{lm} = \ell_2 = 2\beta_1 - \beta_0$$

Hosking (1990) shows that *L*-moment ratios $\tau_r = \ell_r/\ell_2,\ \ r = 3, 4, \cdots$ are bounded in $(-1, 1)$, and proposes to use τ_3 as a measure of skewness. We will follow his suggestion and use

$$sk_{lm} = \tau_3 = \ell_3/\ell_2$$

as a robust measure of skewness. Note that this is dimensionless quantities, independent of the units of measurement of the data.

L-moments and *L*-moment ratios can be estimated from the estimators b_k of the probability weighted moments β_k,

$$b_0 = \frac{1}{n}\sum_{j=1}^{n} x_{(j)}$$
$$b_k = \frac{1}{n}\sum_{j=k+1}^{n}\frac{(j-1)(j-2)\cdots(j-k)}{(n-1)(n-2)\cdots(n-k)}x_{(j)}$$

where $x_{(j)}$ is the j^{th} order statistic of a sample sorted in ascending order.

As mentioned earlier, we need to identify outliers in estimated sectoral shocks. We will adopt various methods of detecting outliers commonly

〈Table 1〉 Various Outlier Identifiers

Identifiers	formula	characteristics
Boxplot Identifier Tuckey(1971)	$[Q_{0.25}-cIQR,\ Q_{0.75}+cIQR]$ $c=1.5$	• Uses 1st and 3rd quartiles as reference points • tends to classify too many data points as outliers when the distribution is skewed
VH Identifier Vandervieren & Hubert(2004)	$[Q_{0.25}-c_1IQR,\ Q_{0.75}+c_3IQR]$ $c_1=1.5e^{\alpha_1 MC},\ c_3=1.5e^{\alpha_3 MC}$ $MC=medcouple$	• uses medcouple to determine the length of whiskers • gives better identification when the distribution is skewed
Carling Identifier Carling(2000)	$[Q_{0.5}-cIQR,\ Q_{0.5}+cIQR]$ $c=2$ or 3	• uses median instead of quartiles
Hampel Identifier Davies & Gather(1993)	$[Q_{0.5}-cd_{mad},\ Q_{0.5}+cd_{mad}]$ $c=2$ or 3	• uses MAD dispersion estimator for whisker
RRT Identifier Rousseeuw et al.(1999)	$[Q_{0.5}-c(Q_{0.5}-Q_{0.25}),$ $Q_{0.5}+c(Q_{0.75}-Q_{0.5})]$ $c=3$ or 4	• adopts different whisker lengths depending on the degree of skewness

suggested in the literature, and their characteristics are summarized in <Table 1>.

Ⅳ. Specification of Empirical Models

Empirical estimation and tests of the sectoral shifts hypothesis involve specification of three equations: (i) the unemployment rate equation from which the significance of the sectoral shifts variables are tested and the natural rates of unemployment are computed, (ii) the monetary equation from which the anticipated and unanticipated aggregate monetary shocks are estimated, and

(iii) the purging equation from which the sectoral shifts variables are estimated after purging the cyclical effects. The model tested in this paper is a comprehensive version of the model in Lilien (1982) and its variations. It might be possible to extend the equation (ii) to reflect advances in measuring monetary shocks. However, the main purpose of this paper is to identify the significance of robust dispersion and skewness measures in an econometric approach as akin as possible to those of Lilien (1982). Therefore, we adopt the same econometric methodology for the equation (ii) as in Lilien (1982).

The unemployment rate equation is specified as

$$UR_t = \alpha_0 + \alpha_1 t + \sum_{s=0}^{4} \beta_s \sigma_{t-s} + \sum_{s=0}^{4} \lambda_s sk_{t-s} + \sum_{s=0}^{8} \gamma_s DMR_{t-s} + \sum_{s=1}^{4} \delta_s UR_{t-s} + \eta_t \tag{1}$$

where UR_t is the aggregate rate of unemployment, σ_t and sk_t are measures of dispersion and skewness of sectoral shocks, respectively. DMR_t is the estimate of unanticipated monetary aggregate shocks and η_t is assumed to be an i.i.d. disturbance term with a zero mean and a finite variance.

The monetary equation is a quarterly version of Barro's (1977) equation

$$DM_t = \alpha_0 + \sum_{s=1}^{8} b_s DM_{t-s} + \sum_{s=0}^{3} c_s FEDV_{t-s} + \sum_{s=1}^{4} d_s UN_{t-s} + e_t \tag{2}$$

where $DM_t = \ln(M_t / M_{t-1})$ is the growth rate of $M1$. $FEDV_t$ is the real federal government expenditure in excess of its normal level as defined in Barro (1977 and 1991), and $UN_t = \ln(UR_t / (1 - UR_t))$. The unanticipated aggregate monetary shock DMR_t is estimated by the residual term in equation (2).

Sectoral shocks are estimated from the net hiring rates h_{tj} of industry j in time t after 'purging' aggregate monetary effects in h_{tj}. The purging equation is specified as

$$h_{tj} = a_{j0} + a_{j1} H_t + a_{j2} t + \sum_{s=0}^{4} b_{js}^{r} DMR_{t-s} + \sum_{s=0}^{4} b_{js}^{f} DMF_{t-s} + c_j h_{t-1,j} + \epsilon_{tj} \tag{3}$$

where H_t is the aggregate net hiring rate, and DMF_t is the anticipated money growth rate which is the estimated mean $\widehat{DM}_t$ from equation (2). ϵ_{tj} is assumed to be an i.i.d. random disturbance term. The lagged dependent variable is included partly for the autoregressive nature of the net hiring rate and partly for consistency with the aggregate unemployment rate equation in (1), which includes lagged unemployment rates as regressors. Note that the restrictions $a_{j1} = 1$, $a_{j2} = 0$ and $c_j = 0$ are strongly rejected individually for most industries and strongly rejected jointly for all industries.

The dispersion and skewness measures that represent the sectoral shifts of labor demand are computed from normalized residuals, $x_{tj} \equiv \widehat{\epsilon_{tj}}/\widehat{\theta}_j$, where $\widehat{\theta}_j$ is an estimate of the scale parameter for industry j that does not change over time, and is given by $\widehat{\theta}_j = \left(1/T\sum_{t=1}^{T}\widehat{\epsilon_{tj}^2}\right)^{1/2}$. This normalizations are used in many previous researches including Abraham and Katz (1984), Loungani (1986) and Byun and Hwang (2006). As pointed out by Byun and Hwang (2006), the normalization by the scale parameter is equivalent to the assumption of cross sectional heteroscedasticity in the sectoral shock, $E(\epsilon_{tj}^2) = \theta_j^2 + \sigma_t^2$, and the dispersion measure captures only the time varying component σ_t, of the standard deviation. The classical measure of dispersion that has been used in past studies is specified as $\widehat{\sigma_t^2} = \sum_{j=1}^{n} w_{tj}\left(\widehat{\epsilon_{tj}}/\widehat{\theta}_j\right)^2$ where w_{tj} is the employment share of industry j in period t. This can be interpreted as the classical measure of dispersion of the transformed variable $e_{tj} \equiv \sqrt{nw_{tj}}\,\widehat{\epsilon_{tj}}/\widehat{\theta}_j$, which is assumed to have a zero mean. The computation of classical measures of skewness, the computation of robust measures of dispersion and skewness, and outlier detections are all based on this transformed variable e_{tj}.

V. Empirical Results

Seasonally adjusted numbers of employees series of all industries are taken from the Current Employment Statistics survey of nonfarm payroll records from the Bureau of Labor Statistics. In order to obtain a longer sample period which covers the study of Lilien, this chapter uses a 30-industry classification based on the 1987 SICS code with a detailed classification of the manufacturing sector[9]. It covers the first quarter of 1955 through the first quarter of 2003[10]. Other quarterly data series such as unemployment rate and M1 money stock series are drawn mainly from the Bureau of Labor Statistics (BLS), the Federal Reserve Economic Data (FRED) and various issues of Economic Report of the President.

<Table 2> above shows means and standard deviations of the variables used in empirical analysis. Aggregate employment has grown by 0.50% every quarter on average for the sample period of the first quarter of 1955 through

9) Nonfarm 30-industry classification includes mining and logging; construction; transportation and public utilities; wholesale trade; retail trade; finance, insurance, and real estate; services; federal government; state government; local government; and 20 detailed manufacturing sectors which contains lumber and wood products,; furniture and fixtures; stone, clay, and glass products; primary metal industries; fabricated metal products; industrial machinery and equipment; electrical and electronic equipment; transportation equipment; instruments and related products; miscellaneous manufacturing industries; food and kindred products; tobacco products; textile mill products; apparel and other textile products; paper and allied products; printing and publishing; chemicals and allied products; petroleum and coal products; rubber and miscellaneous plastics products; and leather and leather products.

10) With the release of May 2003 data, the CES Nonfarm Payroll series underwent a complete industry reclassification. Historical time series have a short time span back to only 1990. In order to cover the sample period of Lilien, this paper draws data based on the SICS classification which dates back farther and is available through the first quarter of 2003.

〈Table 2〉 Basic Statistics

variable	mean	s.d.	variable	mean	s.d.
total employment growth	0.50	0.60	Retail trade	0.59	0.59
sectoral emp. growth			Finance, insurance	0.65	0.47
mining	−0.17	3.00	Services	1.00	0.43
construction	0.45	1.69	Federal government	0.11	1.83
Lumber, wood	−0.01	2.04	State government	0.76	0.66
Furniture, fixtures	0.19	1.79	Local government	0.71	0.55
Stone, clay, glass	0.01	1.47			
Primary metal	−0.38	3.52	**Unemployment rate (UR)**	5.83	1.48
Fabricated metal	0.08	1.67	**Money growth (DM)**	1.17	1.13
Industrial machinery	0.12	1.86	**Gov. expenditure (FEDV)**	3.63	2.17
Electric, electronic eq.	0.15	1.86			
Transportation eq.	−0.05	2.46			
Instruments	0.19	1.37	**Dispersion**		
Misc. manufacturing	−0.03	1.31	$d_{classical}$	0.940	0.335
Food	−0.04	0.52	d_{iqr}	0.508	0.203
Tobacco	−0.57	2.19	d_{mad}	0.488	0.196
Textile mill	−0.48	1.46	d_{rcs}	0.538	0.210
Apparel, other textile	−0.45	1.45	d_{rcq}	0.663	0.246
Paper	0.06	0.89	d_{lm}	0.463	0.155
Printing, publishing	0.28	0.66			
Chemicals	0.15	0.71	**Skewness**		
Petroleum, coal	−0.33	2.41	$sk_{classical}$	0.029	1.615
Rubber, plastics	0.46	1.98	$sk_h(1/8)$	−0.114	0.246
Leather	-1.03	1.71	sk_{gm}	−0.005	0.232
Transportation, utilities	0.26	0.93	sk_{mc}	−0.011	0.209
Wholesale trade	0.43	0.60	sk_{lm}	−0.001	0.204

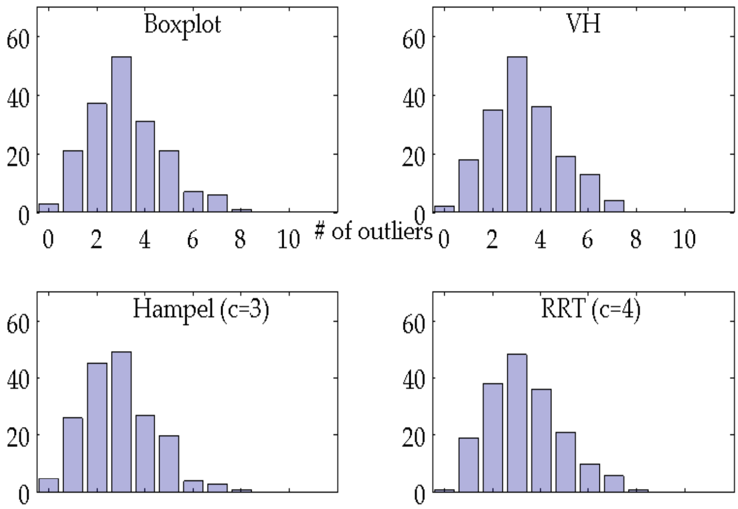
Note : 1) Growth rates are computed by log difference multiplied by 100.
2) See footnote 9 for full industry names, and section III for the names and properties of dispersion and skewness measures.

the first quarter of 2003. However, sectoral employment growth varies industry by industry. Employment of 11 sectors out of 30 have declined on average and quarterly employment growth rates range from -1.03% of leather and leather product sector to 1.00% of service sector. On average for the sample period, about 2.4 million workers found new jobs while 0.7 million workers lost their jobs annually. Roughly estimating, this means that about 3.1 million workers were relocated among sectors every year, and accounts for more than 3.5% of total employment. This allows us to speculate that there have been considerable labor reallocation among sectors.

1. Outlier Detection

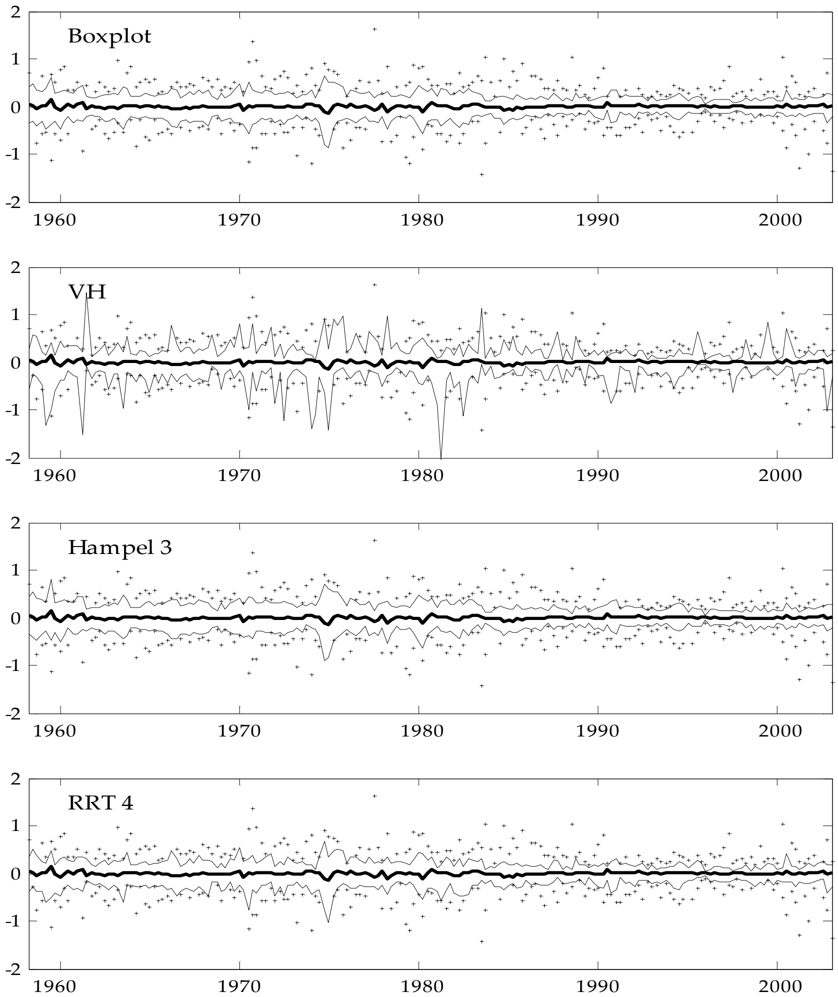
The purging equation (3) is estimated, and the quartiles of the cross sectional values of e_{tj} are computed for each period to be used in outlier detection. The number of periods in which outliers are identified by the methods in <Table 1> are presented in [Figure 1]. All identifiers indicate the presence of outliers. The mode of number of outliers in each period varies across identifiers,

〔Fig. 1〕 Distribution of Number of Outliers



Note : Horizontal axis represents number of outliers out of 30 industries detected by each identifier, and vertical axis represents the number of periods with corresponding number of outliers out of 180 periods. The result of Carling Identifier is almost identical to that of Hampel Identifier, and is not reprted here.

〔Fig. 2〕 Degree of Outlying



Note : Thin and bold lines represent upper, lower whisker and median of residuals, respectively. Asterisks represent maximum or minimum outliers of each period, if they exist.

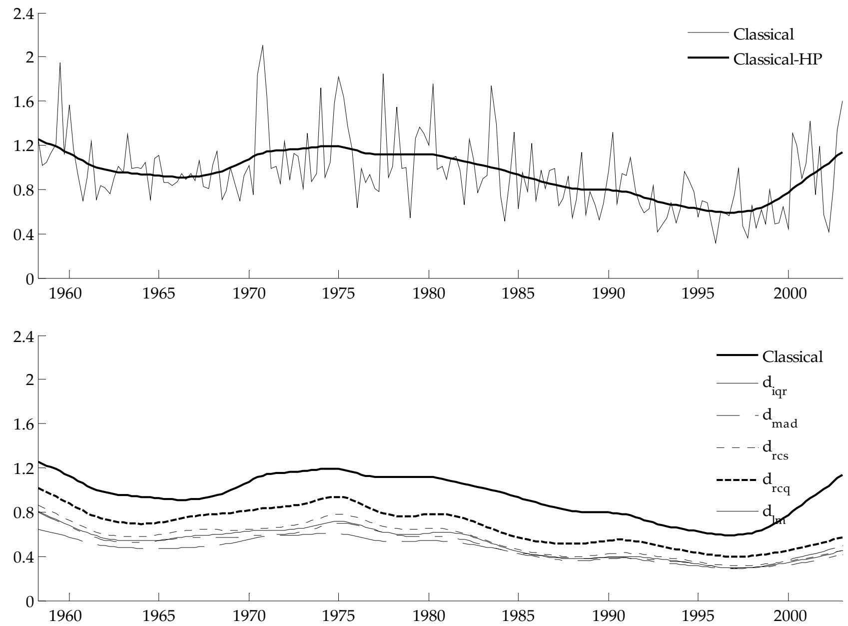
ranging from 3 to 5 out of 30 industries. The proportion of periods in which the actual number of outliers is greater than the mode ranges from 31% to 52%. Based on this, we conclude that there exist outliers in the cross-sectional distribution of sectoral shocks.

We are also concerned about the extent to which each outlier deviates from whiskers because a few outliers with a significant degree of deviation can distort the computation of classical measures. [Figure 2] shows maximum and minimum outliers, if they exist, for each identifier over the sample period. The average distance of maximum (minimum) outliers from the median is almost three times the distance of upper (lower) whisker from the median. This shows that the degree of outlying is quite consequential. From [Figure 1] and [Figure 2], we conclude that outliers do exist and the degree of outlying is considerable. This casts concerns on the estimated dispersion and skewness by classical method.

2. Robust Measure of Dispersion and Skewness

Classical and robust measures of dispersion of sectoral shocks are depicted in [Figures 3]. The upper panel shows a classical measure of dispersion and

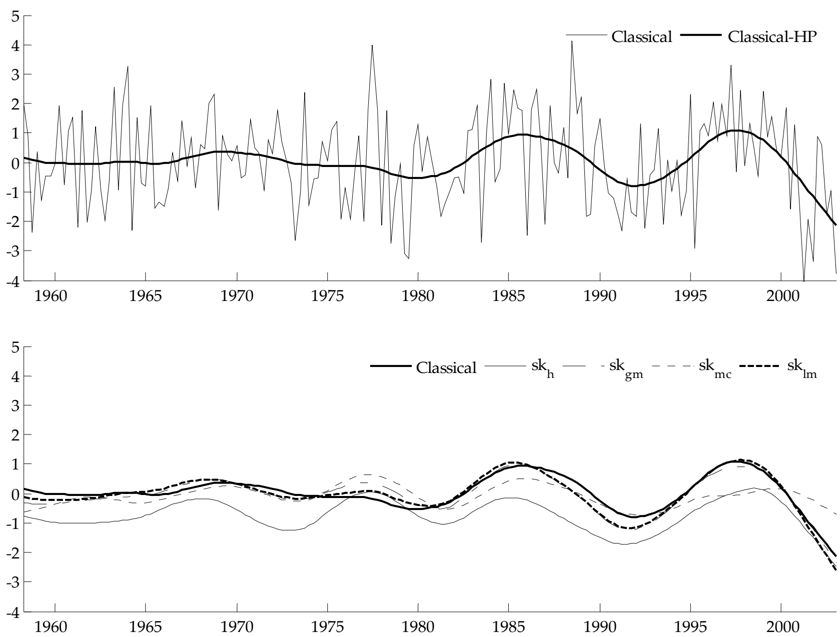
〔Fig. 3〕 Classical and Robust Measures of Dispersion



its HP filtered series. The dispersion of sectoral shocks has been declining since mid 1970s, but showed a sharp increase in the late 1990s and early 2000s. In order to visually compare the trends of robust measures, we draw HP filtered robust measures rather than actual measures of dispersion in the lower panel[11]. Even though the robust measures of dispersion are smaller than the classical measure, they show trends similar to that of the classical measure.

[Figure 4] shows classical measure of skewness, its HP-filtered series and HP-filtered[12] robust measures of skewness. We also find that robust measures

〔Fig. 4〕 Classical and Robust Measures of Skewness



11) HP-filtered series are used only for visual comparisons. Regressions in the latter part of the paper use actual values of robust measures.

12) We also use the LOESS method of smoothing to check the robustness of our observations to the choice of smoothing methods. The LOESS method employs the concept of iterated weighted least squares, a technique of robust estimation (Beaton and Tukey(1974); Andrews(1974)). The result is in accordance with HP filtering cases and available upon request. See Cleveland(1993, 1994) for a detailed explanation on LOESS method.

of skewness are much smaller than the classical measure. This is because the robust measures, by their definition, are set to lie between -1 and 1. Accordingly, their variation over time is much smaller.

To easily compare the trend over time of these measures, in [Figure 4] we rescale the robust measures of skewness by multiplying a constant so that they have the same variance as the classical measure. Classical measure of skewness varies over time with the variation intensified in the latter half of the sample period. Among robust measures of skewness, we find that sk_{gm} and sk_{lm} show trends similar to that of the classical measure. Even though sk_h is much smaller than other robust measures of skewness, it also shows trends similar to the classical measure[13]. On the other hand, sk_{mc} shows no signs of intensifying fluctuations in the second half of the sample period. As mentioned earlier, sk_{mc} is quite robust to the presence of outliers, with a breakdown point of 25%. However, this implies that sk_{mc} is incapable of detecting small meaningful changes in skewness.

Based on [Figure 3] and [Figure 4], we conclude that though actual values of robust measures are somewhat different from the classical measure, they show trends over time quite similar to that of classical measure. In the following section, we will test the sectoral shifts hypothesis using different measures of dispersion and skewness, and investigate the effect of sectoral shifts on the fluctuation of unemployment rate.

3. Test of Sectoral Shifts Hypothesis

In this section, the unemployment rate equation (1) is estimated and the long-run effects of sectoral shifts are tested using robust measures along with

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13) We use octile skewness $sk_h(1/8)$ in our analysis, which has breakdown point of 12.5%. This measure is more capable of detecting small changes in skewness than sk_{mc}.

classical measure. <Table 3> presents the p-value from the test of zero long-run effect of dispersion and skewness on aggregate unemployment rates. Note that the test of sectoral shifts hypothesis is the joint test of long-run effect of dispersion and skewness, which is represented under the column of 'σ &sk'.

〈Table 3〉 p-values from Tests of Sectoral Shifts Hypothesis

dispersion measure	skewness measure	σ	sk	σ & sk
CLS	CLS	0.009	0.003	0.000
d_{iqr}	sk_h	0.002	0.004	0.001
	sk_{gm}	0.005	0.007	0.001
	sk_{mc}	0.011	0.284	0.026
	sk_{lm}	0.006	0.004	0.001
d_{mad}	sk_h	0.005	0.007	0.002
	sk_{gm}	0.012	0.008	0.003
	sk_{mc}	0.028	0.370	0.068
	sk_{lm}	0.014	0.004	0.002
d_{rcs}	sk_h	0.015	0.005	0.003
	sk_{gm}	0.035	0.008	0.004
	sk_{mc}	0.053	0.275	0.091
	sk_{lm}	0.039	0.005	0.003
d_{rcq}	sk_h	0.014	0.005	0.002
	sk_{gm}	0.027	0.009	0.003
	sk_{mc}	0.038	0.226	0.057
	sk_{lm}	0.029	0.007	0.003
d_{lm}	sk_h	0.007	0.007	0.001
	sk_{gm}	0.006	0.008	0.001
	sk_{mc}	0.008	0.091	0.008
	sk_{lm}	0.006	0.010	0.001

Note : Numbers are p-values from testing zero long-run effects of dispersion and skewness. CLS stands for the classical measure. The columns under σ and sk represent individual test of long run zero effect of dispersion and skewness, respectively. The column under σ & sk corresponds to joint test of zero long run effect of dispersion and skewness.

On the unemployment rate, the dispersion measure has a positive effect and the skewness measure has a negative effect. As the distribution of sectoral shocks becomes more dispersed and more negatively skewed, the aggregate unemployment rate increases. This perfectly coincides with basic intuition of the sectoral shifts hypothesis that increased labor reallocation among industries raises unemployment rate.

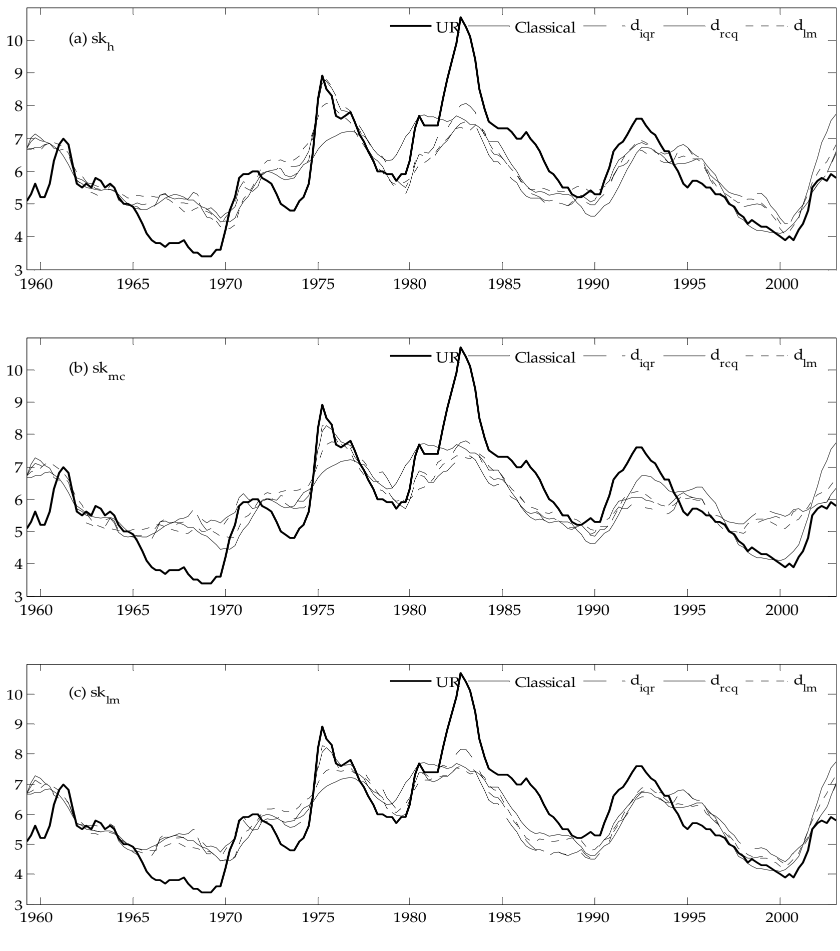
In the case of classical measures, the hypothesis that the dispersion and skewness measures of sectoral shocks have zero long-run effects is strongly rejected individually as well as jointly. Thus, sectoral shifts of labor demand have a significant effect on the aggregate unemployment rate.

When robust measures are used, the null hypothesis of zero long run effects are jointly rejected at a 5% significance level in most of the cases. However, when sk_{mc}, Brys et al.(2003)'s robust measure of skewness based on medcouple, is used with other dispersion measures such as d_{mad}, d_{rcs} or d_{rcq}, the p-value of the joint tests is higher than 0.05. Looking at the individual p-values of dispersion and skewness, robust measures of dispersion are all significant with the highest p-value of 0.053 and measures of skewness are also significant except sk_{mc}. This leads us to the conclusion that the high p-values of the joint tests with sk_{mc} are contributable to the insignificance of sk_{mc}. This stems from the property that sk_{mc} is most unlikely to reflect the information from the tail part of distribution. However, note that in all cases we reject the zero long run joint effect of dispersion and skewness at a 10% significance level.

4. Natural Rates of Unemployment

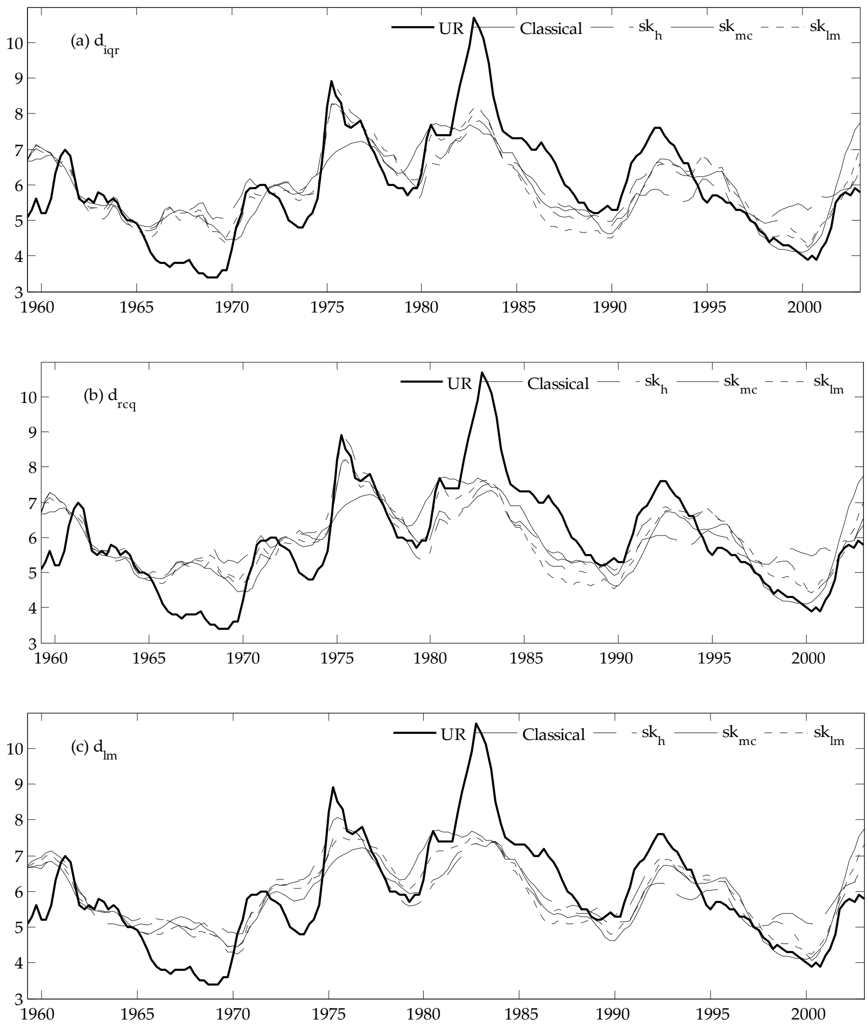
In this section, we will quantify the effect of sectoral shifts on unemployment rate(UR). As mentioned in the previous section, classical and robust measures are different in their scales. Thus, it is not possible to directly compare the size of the coefficients. One way of quantifying the effect of sectoral shifts on UR is to compute the natural rate of unemployment(NRU) defined as the rates that would have been observed if all monetary shocks and the disturbance terms had been zero by Lilien (1982). In each panel of [Figure 5], we fix the robust measure of skewness at sk_h, sk_{mc} and sk_{lm}, respectively, and compute the NRU with various robust measures of dispersion[14]. In

〔Fig. 5〕 Natural Rate of Unemployment (I)



14) The case of sk_{gm} is quite similar to sk_h and is not reported here due to limited space.

〔Fig. 6〕 Natural Rate of Unemployment (II)



[Figure 6], we do the opposite.

Using robust measures of dispersion and skewness does not show any significant changes in the NRU compared to the case of classical measures. One noticeable change is that the NRU tracks the actual UR more closely during the 1974-1980 period when robust measures are used. In order to quantify any differences in the NRUs, we report R^2 from the regression of actual UR on a constant and each NRU in <Table 4>. As observed in [Figure 5] and [Figure 6], there is no significant differences in R^2's across different choices of classical and robust measures. Thus, the proportion of the variation in the actual UR explained by the variation of the NRU is quite similar regardless of the choice of sectoral shifts measures.

Another difference we observe is that the NRU is relatively flat during the 1997-2002 period when sk_{mc} is used. However, we do not see this when other measures of skewness are used. As mentioned earlier, we believe that the difference stems from the property that sk_{mc} is least likely to capture small changes in the tail part of sectoral shock distribution.

To measure the association between UR and NRU in a different way, we modify Kendall's τ and report its values in <Table 5>. The modified Kendall's τ[15] measures the strength of the tendency of UR and NRU to move in the same direction over two adjacent periods. A cursory inspection of the table reveals that modified Kendall's τ is greater than 1/3 in most cases, which means that UR and NRU are twice as likely to be concordant than discordant. Thus, UR and NRU generally move in the same direction, which confirms

〈Table 4〉 R^2 Linear Association between UR & NRU

		skewness				
		CLS	sk_h	sk_{gm}	sk_{mc}	sk_{lm}
dispersion	CLS	0.60				
	d_{iqr}		0.68	0.64	0.59	0.63
	d_{mad}		0.61	0.56	0.49	0.55
	d_{rcs}		0.57	0.53	0.49	0.52
	d_{rcq}		0.58	0.56	0.51	0.56
	d_{lm}		0.64	0.64	0.61	0.63

15) See Appendix for details about the modification we made on the original Kendall's τ.

〈Table 5〉 Modified Kendall's τ between Actual and Natural Rate of Unemployment

		skewness				
		CLS	sk_h	sk_{gm}	sk_{mc}	sk_{lm}
	CLS	0.37				
	d_{iqr}		0.50	0.46	0.38	0.42
	d_{mad}		0.39	0.34	0.33	0.37
dispersion	d_{rcs}		0.38	0.37	0.26	0.32
	d_{rcq}		0.35	0.38	0.34	0.39
	d_{lm}		0.46	0.41	0.34	0.43

again the results in <Table 4>.

In this section, we have investigated the effect of sectoral shifts on UR using various robust measures. The most important observation in this exercise is that 49-68% of total variation in UR can be explained by NRU. This implies that almost 2/3 of the variation in UR is due to sectoral shifts of labor demand. Therefore, even in the absence of aggregate shocks, UR fluctuates over time because of sectoral shifts of labor demand across industries.

VI. Conclusion

The sectoral shifts hypothesis has important macroeconomic implications. For example, if the hypothesis is true, and if the effects of the sectoral shifts are sufficiently large, conventional aggregate demand management policies will have a limited effect on moderating UR fluctuations. As we have seen, NRU is fluctuating over time more than it was known to be. This finding implies that an analysis of the inflation process must take into account the effects of sectoral reallocation on NRU when measuring inflationary pressure by the deviation of UR from NRU.

Lilien (1982) empirically shows that the unemployment rate varies over time due to sectoral shocks even in the absence of aggregate shocks and that its level depends on the size of aggregate layoffs, which is determined by the distribution of sectoral shocks. Lilien' dispersion measure of sectoral shifts of labor demand represents the effect of the changes in the cross-sectional distribution of sectoral shocks on aggregate layoff rates. In a recent paper, Byun and Hwang (2006) showed that the classical measure of skewness of the distribution should also be used as an additional measure of sectoral shifts, and that sectoral shifts has a significant effect on the aggregate unemployment rate. However, classical measures of dispersion and skewness are known to be quite sensitive to the presence of outliers, and consequently, it is the main concern of the paper that tests of sectoral shifts hypothesis based on the estimates of classical measures in previous studies may be distorted by the presence of outliers in the estimates of sectoral shocks.

In this paper, we find strong evidence for the presence of outliers in the distribution of sectoral shocks. Based on the evidence, we also compute various robust measures of dispersion and skewness of the distribution of sectoral shocks. Those computed robust measures of dispersion and skewness are somewhat different from the classical measures in terms of their magnitude and trends over time. However, it turns out that they all support the sectoral shifts hypothesis. It implies that sectoral shifts measured by dispersion and skewness of the distribution of sectoral shocks have significant effect on the determination of unemployment rate even without the presence of aggregate shocks. Based on the inspection of NRU, we find that a significant portion in UR fluctuation can be explained by sectoral shifts of labor demand in the post-war U.S. economy.

Finally, we are fully aware that a future version of this paper must take into account some econometric methodological advances. For example, the monetary shock can be measured by various VAR models such as Christiano et al. (1996). We may also adopt a more advanced version of UR equation. However, the main purpose of this paper is to re-test sectoral shifts hypothesis based on robust measures of dispersion and skewness in a setting which is as akin as possible to the original one in Lilien (1982). Therefore, we would like to keep the current model intact for now to serve the main purpose of the paper.

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〈APPENDIX〉

Modified Kendall's τ

The original Kendall's τ measures strength of association of two rankings. Suppose we have pairs of bivariate observations (X_t, Y_t) and (X_s, Y_s) with $t = s = 1, 2, \cdots, T$. A pair is concordant (discordant) if $(X_s - X_t)$ and $(Y_s - Y_t)$ have the same (opposite) sign. Kendall's τ is defined as the difference in the number of concordant pairs and the discordant pairs divided by total number of pairs $T(T-1)/2$. In the original Kendall's τ , concordance and discordance are measured for all possible pairs. However, for our analysis, it is more relevant to measure the concordance and discordance of adjacent pairs only because we are interested in the changes of X and Y over two consecutive periods. Thus, we modify Kendall's τ as

$$\tau = \frac{\sum_{t=1}^{T-1} sgn(X_t - X_{t+1}) sgn(Y_t - Y_{t+1})}{\left[(T_0 - T_X)(T_0 - T_Y)\right]^{\frac{1}{2}}}$$

where $sgn(z) = -1$ if $z < 0$, $sgn(z) = 0$ if $z = 0$ and $sgn(z) = 1$ if $z > 0$. $T_0 = (T-1)$ is total number of pairs, and T_X and T_Y are numbers of tied pairs in group X and Y, respectively. Thus, our modified Kendall's τ measures the strength of tendency of X and Y to change in the same direction over two adjacent periods. The modified Kendall's τ has simple interpretation. For example, with $\tau = 1/3$, two sets of observations (X_t, Y_t) and (X_{t+1}, Y_{t+1}) are twice as likely to be concordant than discordant. More generally, in a population with Kendall correlation coefficient τ, the odds ratio of the concordant to discordant observations equals $(1+\tau)/(1-\tau)$.

abstract

강건왜도 및 강건분산을 이용한 부문간 노동이동가설의 검증

변양규·전주영

'부문간 노동이동 가설(Sectoral Shifts Hypothesis)'에 의하면 경제 전체에 대한 충격이 없는 경우라도 산업간 노동이동에 의해 실업률이 크게 변동할 수 있다. Lilien(1982)을 포함한 모든 과거 연구들은 우선 각 산업의 순고용률(net hiring rate)에서 경기변동의 영향을 제거한 부문별 충격 분포(sectoral shock distribution)를 추정하고 이로부터 전통적인 방식의 분산 및 왜도(classical measures of dispersion and skewness)를 계산하여 부문간 노동이동의 정도를 파악하였다. 그러나 이러한 분산 및 왜도는 이상치(outlier)에 대해 상당히 민감하게 반응하며 그 결과 '부문간 노동이동 가설'에 대한 검증 역시 이상치에 의해 왜곡될 수 있다는 지적이 있다. 본 연구의 결과에 의하면 우선 부문별 충격의 분포에는 상당한 정도의 이상치가 존재하는 것으로 나타났으며 그 결과 전통적 방식에 의해 계산된 분산 및 왜도를 이용할 경우 검증 결과가 왜곡될 가능성이 있는 것으로 추정된다. 이러한 결과에 근거해 본 연구는 다양한 형태의 강건분산 및 강건왜도(robust measures of dispersion and skewness)를 활용하여 미국의 1955년 이후 노동시장에 대한 '부문간 노동이동 가설'을 검증하였다. 검증 결과에 의하면 강건분산 및 강건왜도로 측정된 부문간 노동이동은 여전히 실업률 결정에 상당히 유의한 영향을 미치는 것으로 나타났다. 특히 실업률 변동 중 부문간 노동이동으로 설명되는 자연실업률 부분이 49~68%나 됨에 따라 기존 총수요 관리정책을 통한 실업률 안정화정책의 역할은 상당히 제한적이며 오히려 부문간 노동이동을 원활히 하는 정책이 실업률 안정화에 효과적일 수 있다는 함의를 얻을 수 있다.

핵심용어 : 부문간 노동이동, 부문별 충격, 강건분산, 강건왜도, 자연실업률