ESSAYS ON SECTORAL SHIFTS OF LABOR DEMAND: MEASUREMENTS AND EFFECTS ON THE INCIDENCE AND THE DURATION OF UNEMPLOYMENT

A Dissertation

by

YANGGYU BYUN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2007

Major Subject: Economics

ESSAYS ON SECTORAL SHIFTS OF LABOR DEMAND: MEASUREMENTS AND EFFECTS ON THE INCIDENCE AND THE DURATION OF UNEMPLOYMENT

A Dissertation

by

YANGGYU BYUN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Hae-shin Hwang
Committee Members,	Dennis W. Jansen
	Li Gan
	David Bessler
Head of Department,	Amy Glass

August 2007

Major Subject: Economics

ABSTRACT

Essays on Sectoral Shifts of Labor Demand:

Measurements and Effects

on the Incidence and the Duration of Unemployment. (August 2007)

Yanggyu Byun, B.S., Seoul National University;

M.S., Seoul National University;

M.A., University of Rochester

Chair of Advisory Committee: Dr. Hae-shin Hwang

Sectoral shifts of labor demand can have significant effects on aggregate rate and duration of unemployment, and this is known as sectoral shifts hypothesis. To measure the sectoral shifts, past studies use David M. Lilien's dispersion measure which represents the effect of the changes in the distribution of sectoral shocks on aggregate rates of layoffs. This dissertation proposes an improved measure of sectoral shifts and tests the sectoral shifts hypothesis. It shows that, when the distribution of sectoral shocks is asymmetric, dispersion alone is not sufficient to capture the effect of the changes in distribution and, the skewness of the distribution can have a significant role in the approximation of aggregate rates of layoffs. Empirical results show a significant effect of the skewness measure on the aggregate rate of unemployment. The results also lend a strong support for the sectoral shifts hypothesis in Lilien type and Abraham-Katz type models, which contrasts with the rejection of the hypothesis in previous studies of the Abraham-Katz type models.

One concern about these empirical results is that the classical measures of dispersion and skewness are very sensitive to the presence of outliers and consequently the test of the hypothesis can be distorted by this presence. Strong evidence exists for the presence of outliers in the distribution of estimated sectoral shocks. Various robust measures of dispersion and skewness are computed. The sectoral shifts hypothesis is still strongly supported when the robust measures are used. This reinforces the empirical findings under the classical measures.

When the mobility of workers across sectors is limited because of frictions in the labor market, workers who become unemployed due to sectoral shifts of labor demand will experience a longer duration of unemployment because of the time associated with switching sectors. Therefore, for a given rate of unemployment, a higher proportion of these workers will increase the average duration of unemployment. Empirical results show that sectoral shifts have a statistically greater effect on the average duration of unemployment than cyclical fluctuations. Sectoral shifts help explain unusual upward trends in the duration of unemployment in the 1990s.

To my family

ACKNOWLEDGMENTS

I am indebted to my advisor Hae-shin Hwang for his insightful guidance and patience. I would also like to thank Dennis Jansen, Li Gan, Qi Li, David Bessler, and Joon Y. Park for their valuable suggestions. I am grateful to Gianluigi Pelloni and Wolfgang Polasek for their hospitality and helpful comments during my presentation at the inaugural conference "*Small Open Economies at a Globalized World*" at University of Bologna, Rimini, Italy. Valuable suggestions were received from workshop participants at Texas A&M University; Korea Economic Research Institute; KDI School of Public Policy and Management; Korea Institute for Industrial Economics and Trade; Korea Labor Institute; and Pusan National University. I would like to acknowledge the Department of Economics and the Private Enterprise Research Center at Texas A&M University for their financial support, and Ms. Diana Vance for her excellent editorial assistance.

Special thanks are reserved for my wife, Hojeong. She was always there whenever I needed her. Thanks to my two lovely kids, Rachel Subin and Jayden Sunbin, for revitalizing my life everyday. Lastly, I appreciate the endless support and love of my parents and my brother who are responsible for getting me where I am today. I love you all.

TABLE OF CONTENTS

LIST OF TABLES

TABLE Page

LIST OF FIGURES

FIGURE Page

CHAPTER I

INTRODUCTION

Sectoral shifts of labor demand are defined as the reallocation of labor resulting from compositional shifts in the structure of labor demand across sectors. These shifts of labor demand are caused by sectoral shocks which are independent of the fluctuations in aggregate demand. Sectoral shocks that shift labor demand from declining to expanding sectors produce laid-off workers who must go through the job search process to be employed again in a different sector. We would expect that most of the workers who lost their jobs in declining sectors would eventually find new jobs in growing sectors. However, this process is likely to be protracted due to the time associated with job search, creation of new jobs in expanding sectors and reallocation and retraining of workers. Thus, sectoral shifts of labor demand typically involves prolonged unemployment spells before employment across sectors adjusts fully to new patterns of labor demand.

The main objective of this dissertation is to propose a better measure of the sectoral shifts of labor demand and to investigate its effect on aggregate unemployment rate and average duration of unemployment. The sectoral shifts hypothesis of Lilien (1982) asserts that labor reallocation resulting from sectoral shifts of labor demand can generate significant fluctuations in aggregate unemployment that are not directly related to the fluctuations in aggregate demand.

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. Lilien's empirical results show that the sectoral reallocation in-

---

This dissertation follows the style of *American Economic Review*.

deed has a significant effect on the aggregate unemployment rate with a substantive magnitude. He also shows that the variation in natural rate of unemployment generated by sectoral reallocation explains "over half" of the variation of the aggregate unemployment rate.

Abraham and Katz (1984) argue that Lilien's empirical measure of dispersion can be correlated with the aggregate unemployment rate even in the absence of sectoral shifts. They argue that all monetary and non-monetary aggregate effects on employment growth rates must be "purged" in the estimation of the dispersion measure. Their empirical results contradict Lilien's results: when both aggregate monetary and non-monetary effects are eliminated, their measure of dispersion has no significant long-run effect on the unemployment rate and the fluctuations in the natural rate of unemployment are much smaller than Lilien's findings.

Past studies following Lilien (1982) and Abraham and Katz (1984) have accepted the dispersion of sectoral shocks as a suitable measure of the sectoral shifts and focused on the refinements of its estimation. In chapter II, I consider a more fundamental question in the measurement of sectoral shifts: Can dispersion measure alone adequately capture the effect of changes in the distribution of sectoral shocks on aggregate layoffs? The answer to this question clearly depends on the shape of the distribution of sectoral shocks. Dispersion alone is not sufficient when the distribution is asymmetric because a change in the shape of the distribution can have a significant effect on aggregate layoffs even when there is no change in the level of dispersion. Additional measures, such as skewness and kurtosis coefficients can provide an improvement in the approximation of the effect of the distribution function on the aggregate layoffs.

Lilien type and Abraham and Katz type empirical models are estimated for the sample period of 1955-2003. As expected, the dispersion measure has a positive effect and the skewness measure has a negative effect on the unemployment rate. Estimation results strongly support the sectoral shifts hypothesis with extremely small p-values in both types of models. A close examination of the results reveals that the lack of support for the sectoral shifts hypothesis in Abraham and Katz's (1984) study is partly due to the omission of the effect of skewness. The results also show that the natural rate of unemployment fluctuates more closely with the actual unemployment rate compared to Abraham and Katz's result of a relatively flat natural rate.

Many studies, including chapter II of this dissertation, have found strong evidence supporting sectoral shifts 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 of labor demand on aggregate unemployment rates. It is well known that classical measures of moments are very sensitive to the presence of outliers. Consequently, the test of sectoral shifts hypothesis based on the estimates of classical measures of dispersion and skewness can be distorted by the presence of outliers. Chapter III examines the presence of outliers in the estimated sectoral shocks and tests the sectoral shifts hypothesis based on alternative robust measures of the dispersion and skewness. Using various methods of outlier detection, I find strong evidence for the presence of outliers in cross sectional distributions of sectoral shocks.

I also 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 of dispersion and skewness are quite different from the classical measures in terms of their magnitude. However, a closer investigation reveals that both classical and robust measures show similar trends over time. All robust measures used in chapter III strongly support the sectoral shifts 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 parts of distribution and hence is not a good measure for detecting changes in skewness. Empirical results in chapter III reinforce the conclusion of chapter II.

There are two channels through which sectoral shifts of labor demand affect the aggregate unemployment rate: effect on the incidence of unemployment and effect on the duration of unemployment. In chapter IV, I analyze the effect of sectoral shifts on the average duration of unemployment. The duration of unemployment spells has been highly correlated with the unemployment rate over business cycles, but this historical relationship was changed in the early 1990s. The duration of unemployment did not follow the sharp decline in the unemployment rate during the 1990s. The duration has remained substantially longer than what the historical relationship would have predicted.

The average duration, published by the Bureau of Labor Statistics, can be considered as a weighted average of unemployment duration of two types of workers: workers who are adversely affected by the sectoral shifts and workers who are unemployed due to cyclical changes in aggregate demand. Upon being laid off, the former will experience longer unemployment duration than the latter because of the time associated with switching sectors. Therefore, holding the aggregate unemployment rate constant, an increase in the proportion of unemployed workers due to sectoral shifts will increase the average duration of unemployment in the economy. By allowing differential effects on the average duration of these two groups of workers, I investigate whether sectoral shifts of labor demand can help explain unusual movement of unemployment duration in the 1990s.

An alternative hypothesis about unemployment duration is the increase in the pace of technical progress proposed by Baumol and Wolff (1998). They argue that faster technical progress increases the frequency at which workers must retrain to keep up with the technical progress. This will shift labor demand away from low-skilled workers whose retraining cost is relatively higher than that of high-skilled workers, making it harder for the low-skilled worker to be reemployed. Consequently, the resulting increase in the share of low-skilled workers in the unemployment pool will raise average unemployment duration. I also investigate this hypothesis in comparison with the sectoral shifts hypothesis.

In chapter IV, I find that sectoral shifts of labor demand have a statistically greater effect on unemployment duration than cyclical fluctuations of aggregate demand. Their effect also lasts longer than cyclical factors. This is consistent with the underlying prediction of the sectoral shifts hypothesis. In addition, the effect of technical progress on unemployment duration is statistically significant. Both factors, sectoral shifts and technical progress, help explain the unusual movement of unemployment duration in the 1990s. However, there are remaining changes in the unemployment duration that these two factors cannot explain. When controls for the effects of demographic factors are considered, the effects of both factors depend on the choice of demographic variables, which implies a possible significant explanatory power of the demographic variables.

CHAPTER II

MEASUREMENTS OF SECTORAL SHIFTS: DISPERSION AND SKEWNESS

A. Introduction

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. Lilien's empirical results show that the sectoral reallocation has indeed a significant effect on the aggregate unemployment rate with a substantive magnitude. He also shows that the natural rate of unemployment generated by sectoral reallocation fluctuates substantially and it tracks the movements of the aggregate unemployment rate reasonably well. The variation of the natural rate explains "over half" of the variation of the aggregate unemployment rate.

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 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) pointed out, unemployment from sectoral reallocation of labor demand affects the wage inflation process differently from cyclical unemployment, and the unemployment rate is not an accurate measure of general labor market conditions when there are sectoral reallocations. 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. She demonstrated that the stability test of the Phillips curve leads to a wrong conclusion if the effect of sectoral shifts is omitted. In more recent studies, Rissman (2003), Groshen and Potter (2003), Aaronson et al. (2004), and Groshen et al. (2004) investigated 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[1].

Lilien's sectoral shift hypothesis is based on the empirical implication of the Lucas and Prescott (1974) model which shows the existence of a steady state aggregate unemployment in an economy where different markets are subject to idiosyncratic stochastic demand shocks and workers leave low-wage markets for high-wage markets. This process of labor reallocation "tends to be slow and typically involves significant unemployment before labor adjusts fully to new patterns of employment demand" (Lilien (1982), p.785). This frictional unemployment exists even in the absence of aggregate shocks, and its level depends on the size of aggregate layoffs which is determined by the *distribution* of sectoral shocks.

Lilien approximates the effect of the distribution on aggregate layoffs by a linear function of the mean and dispersion of employment growth rates across industries. Lilien assumes an identical mean for all industries. Since the mean represents the effect of aggregate monetary and non-monetary shocks on each industry's employment growth rate, Lilien's assumption of identical mean implies that aggregate shocks have the same effect on all industries. Abraham and Katz (1984) point out that this as-

[1]The idea of sectoral shifts hypothesis has also been used in recent studies to introduce persistent unemployment in a real business cycle model (Mikhail et al. (2003)), to study the macroeconomic effects of reallocation shocks in European countries (Panagiotidis et al. (2004)), to examine the natural rate of unemployment in relation to state-level labor market conditions (Wall and Zoëga (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 U.K. (Robson (2006)).

sumption is empirically untenable and show that, when industries differ in their sensitivity to aggregate shocks, Lilien's empirical measure of dispersion can be correlated with the aggregate unemployment rate even in the absence of sectoral shifts. They argue that all monetary and non-monetary aggregate effects on employment growth rates must be "purged" in the estimation of the dispersion measure. Their empirical results contradict Lilien's results: when both aggregate monetary and non-monetary effects are eliminated, their measure of dispersion has no significant long-run effect on the unemployment rate and the fluctuations in the natural rate of unemployment are much smaller than Lilien's findings.

Past studies have accepted the dispersion of sectoral shocks as a suitable measure of the sectoral shifts and focused on the refinements of its estimation to overcome the "observational equivalence" problem that Abraham and Katz raised. In this paper, we consider a more fundamental question in the measurement of sectoral shifts: Can dispersion measure alone adequately capture the effect of changes in the distribution of sectoral shocks on aggregate layoff rates? The answer to this question clearly depends on the shape of the distribution. Dispersion is sufficient when the sectoral shocks have a symmetric location-scale distribution such as a normal distribution. However, dispersion alone is not sufficient when the distribution is asymmetric because a change in the shape of the distribution can have a significant effect on aggregate layoff rates even when there is no change in the level of dispersion. Additional measures such as skewness and kurtosis coefficients can provide an improvement in the approximation of the effect of the distribution function on the aggregate layoff rates.

We show the importance of skewness and kurtosis by extending Lilien's example of a mean preserving spread to a mean-variance preserving transformation, or a mean-variance-skewness preserving transformation of an underlying discrete distribution. We also demonstrate through numerical simulations that the linear approximation of aggregate layoff rates can be improved substantially when skewness is included in addition to dispersion. The improvement measured by the changes in mean squared errors ranges from 55% to 93%.

There is a wide range of empirical model specifications in the literature and the results of the hypothesis test seem to depend on the model specifications. To examine the robustness of the effect of the skewness measure, empirical models in past studies are classified into two types: Lilien type and Abraham and Katz type. The Lilien-type models tend to support the sectoral shifts hypothesis and the natural rate of unemployment generated by the models tracks the aggregate unemployment rate reasonably well, but it has been criticized for an insufficient purging of aggregate non-monetary shocks in the estimation of dispersion. The Abraham and Katz type (AK type hereafter) models tend to reject the hypothesis and generate relatively flat natural rates of unemployment. The purging method employed in the AK type models is also criticized by Mills et al. (1995) and Gallipoli and Pelloni (2001, 2005) as an *ad hoc* method and for its tendency to "over-purge" the effects of aggregate non-monetary shocks[2].

The Lilien type and AK type empirical models are estimated for the sample period of 1955-1982 for comparability with the Abraham and Katz results and also for a longer sample period of 1955-2003. As expected, the dispersion measure has a positive effect and the skewness measure has a negative effect on the unemployment rate. Our estimation results strongly support the sectoral shifts hypothesis with

[2]Numerous studies attempted to construct a better measure of the sectoral shocks: Loungani (1986) estimated the unobservable aggregate non-monetary shocks by using common factor analysis; Loungani et al. (1990) and Brainard and Cutler (1993) suggested a dispersion of sectoral stock prices instead of sectoral employment; Rissman (1997) used Kalman filter; and Neelin (1987) decomposed Lilien's measure into parts explained and unexplained by aggregate activity. See Gallipoli and Pelloni (2001, 2005) for their extensive survey on this subject.

extremely small p-values in both types of models. A close examination of our results reveals that the lack of support for the sectoral shifts hypothesis in Abraham and Katz's (1984) study is partly due to omission of the effect of skewness. Our results also show that the natural rate of unemployment fluctuates more closely with the actual unemployment rate compared to Abraham and Katz's result of a relatively flat natural rate. This difference is more pronounced since the 1980s, suggesting an increased importance of skewness.

The paper is organized as follows. In Section B, Lilien's theoretical model that links the dispersion measure and aggregate layoff rates is briefly reviewed, and two numerical examples are presented to illustrate the importance of skewness in the linear approximation of aggregate layoff rates. In Section C, Lilien type and AK type empirical models are specified. We provide a theoretical basis for Abraham and Katz's estimator of unobservable aggregate non-monetary shocks in their purging equation by showing that it can be interpreted as a special case of a regression estimator of an unobservable variable subject to certain linear restrictions. We also show that the regression estimator without the restriction is the first principal component of the linear regression residuals. Empirical results on the test of sectoral shifts hypothesis and the natural rate of unemployment are presented in Section D, and Section E concludes the paper.

B. Lilien's Model and Effects of Higher Moments on Aggregate Layoff Rates

Lilien's (1982) empirical relationship between the aggregate unemployment rate and his measure of sectoral shifts is based on the flow identity of the change in the unemployment rate. The flow out of unemployment is assumed to be determined by a fixed fraction of the last period's unemployment and a distributed lag function of unanticipated monetary shocks. The flow into unemployment consists of two components: aggregate layoffs and non-layoffs (quits and new entrants)

The key feature of Lilien's model is his specification of the *aggregate* layoff function as a function of his measure of sectoral shifts. The aggregate layoff rate is derived from hiring and layoff decisions of individual firms. The net hiring rate h_{tj} of a typical firm in industry j is divided into two components, $h_{tj} = H_t + \epsilon_{tj}$, where H_t is the aggregate hiring rate, which is determined by the factors that affect all firms, and ϵ_{tj} is the idiosyncratic component which represents the factors that are specific to individual firms in industry j. Lilien assumes

(i) ϵ_{tj} is distributed as $f(\epsilon_{tj} \mid \theta_t)$ with mean zero and *time-varying* distribution parameters θ_t,

(ii) the layoff rate of an individual firm is defined by $\ell_{tj} = \max(0, -h_{tj})$ and

(iii) the aggregate layoff rate L_t is equal to the average layoff rate of firms which experience layoffs.

Under these assumptions he derives the aggregate layoff rate as the negative of the censored mean of net hiring rates:

$$\begin{aligned} L_t = E(\ell_{tj} \mid H_t) &= P(h_{tj} < 0) E(-h_{tj} \mid h_{tj} \leq 0) \\ &= -F(-H_t \mid \theta_t)[H_t + E(\epsilon_{tj} \mid \epsilon_{tj} \leq -H_t)] = L(H_t, \theta_t) \end{aligned}$$

where F is the cumulative distribution function of ϵ_{tj}. Lilien measures sectoral shifts by the distribution parameters θ_t of sectoral shocks, which affect the aggregate unemployment rate through their effects on the aggregate layoff rate[3].

For empirical applications, the aggregate layoff function is approximated by a *linear* function of (H_t, θ_t) or by a linear function of (H_t, H_t^2, θ_t). Lilien includes only the dispersion parameter σ_t of the distribution function. His simple example of a mean preserving spread provides a powerful motivation for the dispersion measure. His example compares two economies: An economy where employment grows at 2 percent in all firms, and an economy where employment in half of the firms grows at 8 percent and employment in the remaining half of the firms grows at -4 percent. Both economies have identical aggregate employment growth rates of 2 percent, but the latter economy will experience far more layoffs than the economy with a zero dispersion.

The dispersion measure captures an important property of a distribution function and it may be sufficient to approximate the aggregate layoff rate for a symmetric location-scale distribution such as a normal distribution. However, the dispersion measure alone is not sufficient to capture the effects of changes in distribution on aggregate layoff rates for asymmetric distributions. This can be shown by extending Lilien's example of the symmetric mean preserving spread to asymmetric distributions via a mean-variance preserving transformation and mean-variance-skewness preserving transformation[4]. Table 2-1 presents a few discrete densities, their first four centered moments and aggregate layoff rates. sk and kt denote the skewness and kurtosis coefficients, respectively.

---

[3]Lilien argues that "the process of adjustment to sectoral shifts tends to be slow and typically involves significant unemployment before labor adjusts fully to new patterns of employment demand." A change in its distribution affects the duration of the unemployment spell and thereby the aggregate unemployment rate.

[4]See Menezes et al. (1980) and Menezes and Wang (2004) for the details of the transformation.

TABLE 2-1 Effects of Skewness and Kurtosis on Aggregate Layoff Rates

	h_t								moments				layoff rate
	-10	-7	-4	-1	2	5	8	14	μ	σ	sk	kt	
f_1					1				2	-	-	-	-
f_2			$\frac{4}{8}$				$\frac{4}{8}$		2	6	0	1	2.00
f_3	$\frac{1}{8}$		$\frac{1}{8}$		$\frac{3}{8}$		$\frac{3}{8}$		2	6	-0.75	2.5	1.75
f_4	$\frac{1}{8}$				$\frac{6}{8}$			$\frac{1}{8}$	2	6	0	4	1.25
f_5			$\frac{3}{8}$		$\frac{3}{8}$		$\frac{1}{8}$	$\frac{1}{8}$	2	6	0.75	2.5	1.50
f_6		$\frac{1}{8}$	$\frac{1}{8}$	$\frac{2}{8}$		$\frac{1}{8}$	$\frac{3}{8}$		2	5.61	-0.23	1.51	1.625

The first two rows (f_1 and f_2) are the distributions in Lilien's example. Density f_3 is a mean-variance preserving transformation of f_2, and f_4 is a mean-variance-skewness preserving transformation of f_2. Densities f_2 through f_5 have identical means and variances, and yet they generate different aggregate layoff rates. The difference between f_2 and f_4 highlights the role of the kurtosis as they have identical first three moments. The difference between f_3 and f_5 highlights the role of the direction of skewness in determining aggregate layoff rates as the only difference between them is the sign of the skewness coefficient. The last row f_6 has a smaller variance than other distributions, but it generates a higher aggregate layoff rate than distribution f_4 or f_5, contradicting Lilien assertion that a wider dispersion will generate more layoffs.

These examples clearly indicate that changes in dispersion alone may not be sufficient to capture the variations in aggregate layoff rates, and that skewness and kurtosis can be important factors. To measure the quantitative magnitudes of the explanatory powers of the skewness and kurtosis in the approximation of the aggregate layoff rates L_t, we conducted numerical experiments by using the distribution function of Johnson's hyperbolic sine transformation, $\sinh(X)$, of a normal random variable, $X \sim N(\mu, \sigma^2)$. This distribution is unimodal and has a wide range of skewness and kurtosis. The location and scale parameters of the underlying normal distribution become the shape parameters of $Y = \sinh(X)$, which has the density function

$$f(y; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2(y^2+1)}} \exp\left\{ -\frac{(\sinh^{-1} y - \mu)^2}{2\sigma^2} \right\}.$$

The mean of the distribution is $\mu_y = [\exp(\sigma^2)]^{1/2} \sinh(\mu)$. When sectoral shocks $\epsilon = Y - \mu_y$ have this distribution function, it is straightforward showing that the aggregate layoff rate is given by

$$L = -F(\mu_y - H)\,[H + E(Y \mid Y \leq \mu_y - H) - \mu_y] = -F(c)\,[E(Y \mid Y \leq c) - c]$$

where

$$F(c) = \Phi\left(\frac{\sinh^{-1}(c) - \mu}{\sigma}\right)$$
$$E(Y \mid Y \leq c) = \frac{1}{2}\left(\exp^{\mu+\sigma^2/2} \frac{\Phi(b-\sigma)}{\Phi(b)} - exp^{-\mu+\sigma^2/2} \frac{\Phi(b+\sigma)}{\Phi(b)}\right)$$

and $c = \mu_y - H$, $b = \left[\sinh^{-1}(c) - \mu\right]/\sigma$, and Φ is the cumulative distribution function of standard normal.

We conducted two experiments. For a given value of parameter σ^2, we compute the aggregate layoff rates L for n equally spaced values of μ in the range of $[-0.5, 0.5]$, and then estimate the linear regression model of L on three different sets of regressors:$\{H, SD\}$, $\{H, SD, SK\}$ and $\{H, SD, SK, KT\}$ where SD is the standard deviation, SK is the skewness coefficient and KT is the kurtosis coefficient of the idiosyncratic shock. A similar experiment is conducted with a given parameter μ and

n equally spaced values of σ^2 in the range of $[0.1, 1.0]$. The value of the aggregate hiring rate H is set at 2 for both cases.

The true and predicted aggregate layoff rates by the linear regression estimates are shown on the left panel of Figure 2-1 for the first experiments with three values of σ^2, and on the right panel for the second experiments with three values of μ. The horizontal axis represents the values of skewness coefficients. Figure 2-1 clearly indicates the significant explanatory power of the skewness coefficient in the approximation of aggregate layoff rates. The kurtosis coefficient plays a very minimal role in our experiments. Improvement in the accuracy of approximation due to the skewness coefficient is substantial: the mean squared error is reduced by 55% to 93% compared to the case of regression on H, SD. The least improvement of 55% occurs in the first case of the left panel, but the aggregate layoff rates are extremely small in this case. Although these results are based on a specific distribution function, they clearly indicate a significant potential gain from introducing the skewness coefficient in the linear approximation of the aggregate layoff function.

C. 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 aggregate monetary and non-monetary effects on the employment growth rate of each industry.

There is a wide range of specifications for these equations and differences in

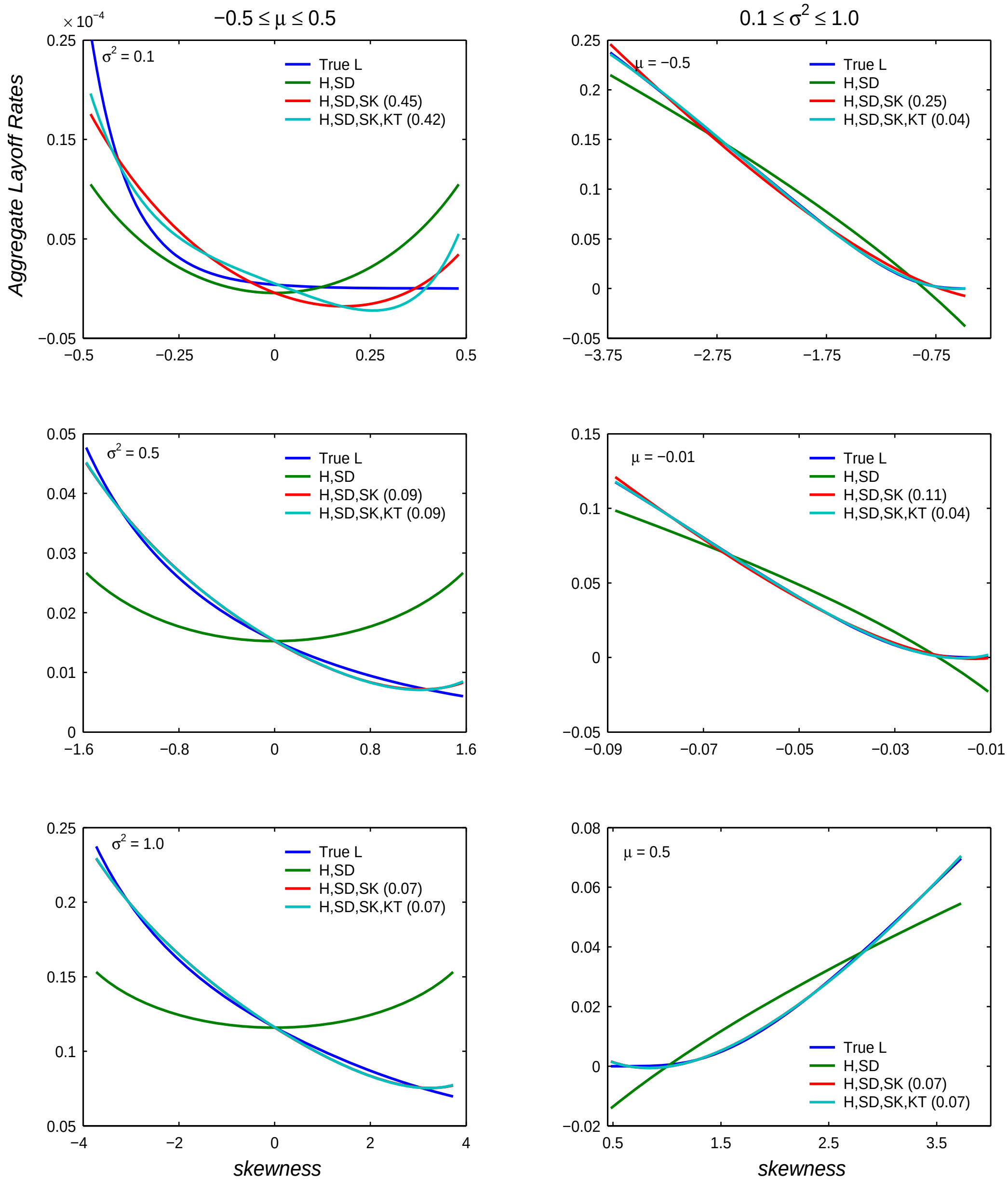


FIGURE 2-1 Effects of Skewness and Kurtosis on Estimation of Aggregate Layoff Rates

Notes: Numbers in parentheses are ratios of MSE to the MSE of the (H,SD) regression which approximates the aggregate layoff rate by only mean and dispersion.

the conclusion about the sectoral shifts hypothesis seem to be partly due to the differences in the model specifications. To examine the robustness of the effect of the skewness measure in different specifications of the empirical models, we classify the specifications in previous studies into two types. The first type follows and extends Lilien's earlier study and the second type is an extension of the Abraham and Katz model. This classification is based on the fact that a serious doubt about sectoral shifts hypothesis was first raised by the Abraham and Katz study, and their model and its variation include an estimate of unobservable aggregate non-monetary shocks while the Lilien type empirical models do not.

Most controversial in the literature of sectoral shifts hypothesis is the specification of the purging equation, and there is still no consensus about the proper specification. The purging equation estimates the sector specific shocks from a regression of the net hiring rates h_{tj} of industry j in period t on a set of regressors to 'purge' aggregate monetary and non-monetary effects in h_{tj}. Past studies have used a variety of purging regressors which may be classified into three groups: the aggregate net hiring rate H_t; a set of variables X_t that includes a time trend, unanticipated money growth rate DMR_t and anticipated money growth rate DMF_t; and an estimate of "unobservable" aggregate non-monetary shocks g_t:

$$h_{tj} = \alpha_j H_t + X_t \beta_j + \gamma_j g_t + \epsilon_{tj} \qquad t = 1, 2, \cdots, T \qquad j = 1, 2, \cdots, n$$

where ϵ_{tj} is the sectoral shock. Lilien's (1982) original model estimates the sectoral shocks by $\hat{\epsilon}_{tj} = h_{tj} - H_t$, i.e., he imposes restriction $\alpha_j = 1$ and $\beta_j = \gamma_j = 0$. This method has has been severely criticized[5] by Abraham and Katz (1984, 1986), and it is now generally accepted that Lilien's original model is insufficient to "purge" the aggregate effect. Models proposed by Abraham and Katz (1984), Loungani (1986) and Neelin (1987) have a restriction $\alpha_j = 0$, and Samson's (1990) model has restrictions $\alpha_j = 0$ and $\gamma_j = 0$[6]. The restriction $\alpha_j = 0$ can be interpreted as a time-invariant constant intercept term for each industry, while restriction $\alpha_j = 1$ can be interpreted as a model of time-varying intercepts for each industry and the difference between time varying intercepts of two industries is independent of time[7]. An unrestricted coefficient α_j allows a more general time varying intercept term.

Equations for the unemployment rate, the money growth rate and the net employment growth rate in the Lilien type model are specified as

---

[5]They showed that the dispersion of employment growth rates and the change in unemployment rate can be positively correlated even in the absence of sectoral shifts if "industries differ in their cyclical sensitivities and labor force adjustment costs are asymmetric such that an increase in employment costs more than a decline of equal magnitude (Abraham and Katz (1986), p.510)."

[6]Neelin's (1987) model of sectoral net hiring rates is the same as Abraham and Katz's (1984) first model, but she also estimates the dispersion of aggregate net hiring rates and includes it in the estimation of the aggregate unemployment rate. Loungani's (1986) model does not include the time trend and includes changes in oil prices in his second model. Samson's (1990) model does not include a time trend and includes the expected money growth rate.

[7]Let β_{1j} be the intercept coefficient in β_j. When $\alpha_j = 1$, the intercept is $c_{tj} = H_t + \beta_{1j}$ and the cross sectional difference $c_{tj} - c_{tk} = \beta_{1j} - \beta_{1k}$ is independent of time.

$$
\begin{aligned}
UR_t &= \alpha_0 + \alpha_1 t + \sum_{s=0}^{4} \beta_s \sigma_{t-s} + \sum_{s=0}^{4} \lambda_s sk_{t-s} + \sum_{s=0}^{8} \gamma_s DMR_{t-s} && \text{(2.1a)} \\
&\quad + \sum_{s=1}^{4} \delta_s UR_{t-s} + \eta_t \\
DM_t &= a_0 + \sum_{s=1}^{8} b_s DM_{t-s} + \sum_{s=0}^{3} c_s FEDV_{t-s} + \sum_{s=1}^{4} d_s UN_{t-s} + \xi_t && \text{(2.1b)} \\
h_{tj} &= a_{j0} + a_{j1} H_t + a_{j2} t + \sum_{s=0}^{4} b^r_{js} DMR_{t-s} + \sum_{s=0}^{4} b^f_{js} DMF_{t-s} && \text{(2.1c)} \\
&\quad + c_j h_{t-1,j} + \epsilon_{tj}
\end{aligned}
$$

where UR_t is the aggregate rate of unemployment, σ_t and sk_t are measures of dispersion and skewness, respectively, DMR_t is the estimate of unanticipated aggregate monetary shocks. In monetary equation (2.1b), $DM_t = \ln(M_t/M_{t-1})$ 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, 1991), and $UN_t = \ln(UR_t/1 - UR_t)$. The aggregate monetary shock DMR_t and the anticipated money growth rate DMF_t are estimated by the residual term $\hat{\xi}_t$ and the estimated mean $\hat{DM}_t$, respectively.

The unemployment equation (2.1a) is a quarterly version of Lilien's model except for the skewness variables. The monetary equation is a quarterly version of Barro's specification as used in Rissman (1993). Lilien (1982) used the annual version of Barro's specification. The purging equation (2.1c) is a generalized version of Samson's (1990) model. We do not impose Samson's restriction $a_{j1} = 1$ to allow for a more general time varying intercept term, and we add the time trend and a lagged dependent variable. The trend term is added for comparability with the Abraham and Katz specification of their purging equation. 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 (2.1a) which includes lagged unemployment rates as regressors[8]. As we will report later, 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 anticipated money growth rates, DMF_t, are often included because they can have a short-run effects as Samson (1990), Mills, Pelloni and Zervoyianni (1995, 1996, 1997), and Sakata (2002) argue.

The AK type model is a slight modification of the model that Abraham and Katz used:

$$\begin{aligned}
UR_t &= \alpha_0 + \hat{\alpha}_1 t + \sum_{s=0}^{8} \beta_s \sigma_{t-s} + \sum_{s=0}^{8} \lambda_s sk_{t-s} + \sum_{s=0}^{8} \gamma_s DMR_{t-s} + \nu_t \qquad (2.2a) \\
\nu_t &= \sum_{s=1}^{4} r_s \nu_{t-s} + \eta_t \\
DM_t &= a_0 + a_1 t + \sum_{s=1}^{4} b_s DM_{t-s} + \sum_{s=1}^{4} c_s TB_{t-s} + \xi_t \qquad (2.2b) \\
h_{tj} &= a_{j0} + a_{j1} g_t + a_{j2} t + \sum_{s=0}^{4} b^r_{js} \triangle DMR_{t-s} + \sum_{s=0}^{4} b^f_{js} \triangle DMF_{t-s} + \epsilon_{tj} \qquad (2.2c) \\
\epsilon_{tj} &= \rho_j \epsilon_{t-1,j} + u_{tj}
\end{aligned}$$

where TB_t is the interest rate on three month treasury bills, and g_t is an estimate of 'unobservable' aggregate non-monetary shocks. In the unemployment equation (2.2a), $\hat{\alpha}_1$ is predetermined from a linear detrending of UR_t on a constant and time. The purging equation (2.2c) is same as the purging equation in Abraham and Katz study except for the additional terms DMF_t, which are included for comparability with (2.1c).

Unemployment rate equation (2.1a) and (2.2a) of these two models differ in the detrending method and in the number of lag length for the dispersion and skewness

[8]Purging equations in Palley (1992) and Groenewold and Hagger (1998) also include a lagged dependent variable.

variables. More importantly, the Lilien type model includes a lagged dependent variable with serially independent disturbance term, while the AK type model does not include a lagged dependent variable, but assumes the fourth-order serial correlation in the disturbance term. The difference appears to play a significant role in determining the natural rate of unemployment.

Purging equations show some minor differences in the way the DMR_t enters the equation and the lagged dependent variable versus serial correlation in the error term. A major difference is whether it includes the aggregate net hiring rate H_t or an estimate of non-monetary shocks g_t. These specifications, however, can be interpreted as equivalent models if H_t is a linear function of monetary and non-monetary variables. Therefore, we may interpret that the aggregate non-monetary shocks are captured by H_t in equation (2.1c) and by the estimated g_t in (2.2c).

We use two alternative estimators of unobservable aggregate non-monetary shocks g_t. The first estimator is the one proposed by Abraham and Katz (1984). Let $\hat{e}_{tj}$ be the OLS residuals in (2.2c) for each industry subject to $a_{j1} = 0$. The Abraham and Katz estimator of g_t is a weighted average of $\hat{e}_{tj}$

$$\hat{g}_{ak,t} = \sum_{j=1}^{n} w_{tj} \hat{e}_{tj} \tag{2.3a}$$

where w_{tj} is the employment share of industry j in period t. This estimator has been used widely, but Gallipoli and Pelloni (2001) criticized it on the grounds that it is an *ad hoc* estimator and tends to 'over-purge' the effects of aggregate non-monetary shocks.

An alternative estimator of g_t is the element of the first principal component[9] of the least squares residuals $\hat{E} = (\hat{e}_1, \hat{e}_2, \cdots, \hat{e}_n)$,

$$\hat{g}_{pc,t} = \sum_{j=1}^{n} \hat{\gamma}_j \hat{e}_{tj} \tag{2.3b}$$

where $\hat{\gamma}_j$ is the j^{th} element of the normalized characteristic vector of $\hat{E}'\hat{E}$ corresponding to its largest characteristic root, i.e., $(\hat{E}'\hat{E} - \lambda I)\hat{\gamma}$. It is shown in the Appendix that this principal component estimator is a least squares estimator that minimizes the sum of the squared residuals

$$\min_{\beta_j, \gamma_j, g} \sum_{j=1}^{n} \left(h_j - X\beta_j - \gamma_j g\right)' \left(h_j - X\beta_j - \gamma_j g\right)$$

subject to a normalization restriction $\gamma'\gamma = 1$, where X denote the observation matrix of all other regressors except for g_t. It is also shown in the Appendix that the Abraham-Katz estimator of g_t in (2.3a) can be considered as a similar estimator with additional constraints $\gamma_j = 1$ for all j. In a recent paper, Coakley et al. (2002) also propose to use the principal component as an estimator of unobservable common factors in a panel data model in which the regressors are not identical across industries. However, their proposal is not based on an optimization procedure[10].

The sectoral shifts variables, dispersion and skewness, are estimated from the estimates of error terms in the purging equations. Let $\hat{\epsilon}_{tj}$ be the OLS residuals in

[9] Loungani (1986) estimated g_t by "a factor score using common factor analysis." He did not specify the set of variables from which the factor score is computed. If he used the set of Abraham and Katz's residual and used the principal factor analysis to compute the factor, then his estimator will be the first principal component. Several papers mentioned that Lilien (1983) used a time fixed effect for g_t. We were unable to locate the paper and do not know exactly how Lilien estimated g_t.

[10] They simply note that, under the normalization restriction $\gamma'\gamma = 1$, we can write $g = \sum \gamma_j \hat{e}_j + \zeta$. The first term is in the form of a principal component of $\hat{E}$, and this suggests measuring g by a principal component of $\hat{E}$. See Appendix for this argument.

(2.1c), and let $\tilde{\epsilon}_{tj}$ and $\tilde{u}_{tj}$ be the GLS estimates of the sectoral shock ϵ_{tj} and the innovation term u_{tj}, respectively, in (2.2c). Lilien type models estimate the cross sectional dispersion by a weighted average of squared $\hat{\epsilon}_{tj}$

$$\hat{\sigma}_t^2 = \sum_{j=1}^{n} w_{tj}\hat{\epsilon}_{tj}^2 \tag{2.4}$$

The weights are introduced to capture the differences in the number of firms across industries[11]. This estimator is used in Samson (1990), Mills et al. (1995), Rissman (2003), Aaronson et al. (2004), and Garonna and Sica (2000) among others.

Abraham and Katz (1984) and Loungani (1986) estimate the dispersion measure from the estimates of the *normalized* innovation term, $\tilde{u}_{tj}/\tilde{\theta}_{uj}$

$$\tilde{\sigma}_{ut}^2 = \sum_{j=1}^{n} w_{tj}\left(\frac{\tilde{u}_{tj}}{\tilde{\theta}_{uj}}\right)^2, \qquad \tilde{\theta}_{uj} = \left(\frac{1}{T}\sum_{t=1}^{T}\tilde{u}_{tj}^2\right)^{\frac{1}{2}} \tag{2.5a}$$

where $\tilde{\theta}_{uj}$ is an estimate of the scale parameter for industry j that does not change over time. The normalization is equivalent to the assumption of cross-sectional heteroscedasticity in the innovation term, $E(u_{tj}^2) = \theta_{uj}^2\sigma_t^2$, and their dispersion measure captures only the time-varying component σ_t of the standard deviation. Abraham and Katz (1984) justify the use of normalized residuals on the ground that the "normalized measure captures more of the variation in unemployment ... than does a non-normalized measure" (p.18). Loungani (1986) used the normalized residuals to "capture scale difference in variances" (p.537). Gallipoli and Pelloni (2005) criticize the use of normalization because it is based on the assumption that the variance of the purged sectoral shock is time-invariant, which contradicts the main idea of the sectoral shifts hypothesis that the distribution of sectoral shocks varies over time.

[11]Most studies used time varying weights w_{tj}, but Lilien's (1982) analysis of the manufacturing industry and Loungani (1986) used employment shares in a particular year as the weights.

However, our interpretation of the use of normalized residuals does not negate the essential idea of the sectoral shifts hypothesis that the variance of sectoral shock is time-varying.

It should be noted that Lilien's theory is concerned with the dispersion of net hiring rates h_{tj}, and hence, it is the dispersion of ϵ_{tj} that is of concern to Lilien's theory even if ϵ_{tj} is serially correlated. It is thus theoretically preferable to estimate the dispersion measure from its GLS estimate $\tilde{\epsilon}_{tj}$

$$\tilde{\sigma}_{\epsilon t}^2 = \sum_{j=1}^{n} w_{tj} \left(\frac{\tilde{\epsilon}_{tj}}{\tilde{\theta}_{\epsilon j}} \right)^2, \qquad \tilde{\theta}_{\epsilon j} = \left(\frac{1}{T} \sum_{t=1}^{T} \tilde{\epsilon}_{tj}^2 \right)^{\frac{1}{2}} \tag{2.5b}$$

The Lilien-type dispersion estimator in (2.4) uses non-normalized residuals. However, for comparability with the Abraham and Katz estimator, we use in this paper the normalized residuals for the Lilien type estimator

$$\hat{\sigma}_{\epsilon t}^2 = \sum_{j=1}^{n} w_{tj} \left(\frac{\hat{\epsilon}_{tj}}{\hat{\theta}_{\epsilon j}} \right)^2, \qquad \hat{\theta}_{\epsilon j} = \left(\frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_{tj}^2 \right)^{\frac{1}{2}} \tag{2.6}$$

The measure of the third moment to compute skewness is defined in a similar way. Allowing for scale differences in the third moment across industries such that $E(\eta_{tj}^3) = \tau_j^3 \mu_{3t}$, the time-varying component of the third moment is estimated by

$$\mu_{3t} = \sum_{j=1}^{n} w_{tj} \left(\frac{\eta_{tj}}{\tau_j} \right)^3, \qquad \tau_{tj} = \left(\frac{1}{T} \sum_{t=1}^{T} |\eta_{tj}|^3 \right)^{\frac{1}{3}} \tag{2.7}$$

where η_{tj} can be either $\hat{\epsilon}_{tj}$ or $\tilde{\epsilon}_{tj}$ or $\tilde{u}_{tj}$. The skewness measure is then estimated by $sk_t = \mu_{3t}/\sigma_t^3$. The scale parameter τ_j is estimated by using the absolute values of estimated residuals to avoid the cancellation of positive and negative residuals.

D. Empirical Analysis

1. Data

The quarterly data used in this paper is drawn from the Bureau of Labor Statistics (BLS) and the Federal Reserve Economic Data (FRED). Seasonally adjusted numbers of employees series are taken from the Current Employment Statistics (CES) survey of nonfarm payroll records from the BLS. With the release of Nonfarm Payroll series in May 2003, the CES underwent a complete industry reclassification from the 1987 Standard Industrial Classification System (SICS) to the 2002 North American Industry Classification System (NAICS). Historical time series were reconstructed as part of the NAICS conversion process, but most NAICS series still have a short history back to only 1990. In order to cover the sample period of Lilien and Abraham and Katz, this chapter draws employment data based on the SICS, which dates back farther and is available through the first quarter of 2003. The sample period in this paper covers the first quarter of 1955 through the first quarter of 2003[12].

The 30-industry classification is used in this paper. It matches the two-digit 1987 SIC code with detailed classification of the manufacturing sector. The seasonally adjusted unemployment rate of the civilian noninstitutional population is drawn from the Current Population Survey (CPS) of the BLS. Seasonally adjusted M1 money stock series and 3-month Treasury Bill secondary market rates are from FRED. The current federal government expenditure and the GDP deflator that are used in construction of the $FEDV$ variable are from FRED and various issues of Economic Report of the President.

[12] The actual sample period is not identical for all specifications because of differences in the number of lagged variables.

2. Test of Sectoral Shifts Hypothesis

As noted earlier, purging equations (2.1c) and (2.2c) are the extended versions of the Samson (1990) and Abraham and Katz (1984) models, respectively. We first conduct the specification tests of these extensions. We test the null hypotheses $a_{j1} = 1$, $a_{j2} = 0$ and $c_j = 0$ in (2.1c) individually as well as jointly for each industry. Each hypothesis is rejected at a 5% level of significance in 22 industries for $a_{j1} = 1$, in 8 industries for $a_{j2} = 0$, and in 21 industries for $c_j = 0$. The joint hypotheses are rejected at a 5% level in 27 industries with extremely small p-values. Although the hypothesis that the coefficient of the trend term is zero is not rejected in most of the 30 industries, the joint hypothesis $a_{j2} = 0$ for all j is strongly rejected with a p-value close to zero. The null hypothesis of zero coefficients, $b^f_{js} = 0$, for the current and lagged values of the DMF_t in the Abraham-Katz purging equation (2.2c) is rejected at 5% level in 24 industries regardless of the choice of aggregate non-monetary shocks. Therefore, we conclude that equations (2.1c) and (2.2c) are reasonable modifications of the models in previous studies.

Unemployment rate equations (2.1a) and (2.2a) are estimated and the long run effects of the dispersion and skewness measures are tested[13]. Table 2-2 presents the sum of the estimated coefficients of current and lagged dispersion measures and skewness measures, their estimated standard errors and p-values. For the AK type model, we consider both the Abraham and Katz estimator g_{ak} and principal component estimator g_{pc} of non-monetary shocks g_t. As expected, the dispersion measure has a positive effect and the skewness measure has a negative effect on the unemployment rate. As the distribution of sectoral shocks becomes more dispersed and more neg-

[13]The coefficient of time trend in (2.2a) was predetermined in Abraham-Katz study. We estimated (2.2a) treating the coefficient as a free parameter and the results were qualitatively the same as reported below.

TABLE 2-2 Estimates of Sectoral Shifts Variables
(1955Q1 $\sim$ 2003Q1)

Model	Variable	sum of coeffs	SD	p-value	joint p-value
Lilien	σ	0.289	0.113	0.012	0.000
	sk	-0.324	0.092	0.001	
AK(g_{ak})	σ	1.552	0.830	0.064	0.000
	sk	-1.644	0.516	0.002	
AK(g_{pc})	σ	1.952	0.772	0.013	0.000
	sk	-1.240	0.375	0.001	

Notes: Table 2-2 is based on the estimation results of (2.1a) and (2.2a). $AK(g_{ak})$ and $AK(g_{pc})$ represent AK type model with σ and sk computed using the Abraham and Katz estimator g_{ak} and principal component estimator g_{pc}, respectively. The dispersion and skewness measure for the AK type models are computed from (2.5b) and (2.7) with $\eta_{tj} = \tilde{\epsilon}_{tj}$

atively skewed, the aggregate unemployment rate increases. The null hypothesis of zero long-run effects of the dispersion and skewness measures are rejected individually as well as jointly with small p-values[14] in all three cases as reported in Table 2-2. The test of sectoral shifts hypothesis is the test of the joint hypothesis and it is supported strongly with extremely small p-values in all three cases. These results contrast sharply with the test result in Abraham and Katz's study, which included only the dispersion of sectoral shocks and rejected the sectoral shifts hypothesis.

Since our test results in AK type model contradict the results reported in past studies, we estimated several alternative specifications to the AK type model to examine the sensitivity of the test to model specifications. The results using the g_{ak}

[14]The largest p-value is 0.064 for the dispersion measure in the $AK(g_{ak})$ model.

estimator are reported in Table 2-3[15]. Alternative specifications of the model used

TABLE 2-3 Alternative Specifications of AK(g_{ak}) Model: p-values of Tests of Hypotheses

Sample Period	*DMF*		σ and sk			σ only
			σ & sk	σ	sk	
1955Q1 ∼ 2003Q1	included	ϵ_{tj}	0.001	0.064	0.002	0.017
		u_{tj}	0.014	0.197	0.014	0.198
	excluded	ϵ_{tj}	0.000	0.040	0.001	0.011
		u_{tj}	0.017	0.048	0.077	0.044
1955Q1 ∼ 1982Q1	included	ϵ_{tj}	0.000	0.032	0.001	0.079
		u_{tj}	0.021	0.098	0.031	0.180
	excluded	ϵ_{tj}	0.005	0.078	0.028	0.046
		u_{tj}	0.034	0.091	0.093	0.101

Notes: Column "σ" and "*sk*" show p-values from individual tests of zero long run effect of dispersion and skewness. Column "σ and *sk*" shows p-values from joint test of zero long run effect. Column "σ only" corresponds to the case where only dispersion measure is included in unemployment rate equation.

in Table 2-3 reflect four major differences between the Abraham and Katz's (1984) model and our model: (i) their model does not include the skewness measure in the unemployment rate equation, (ii) their sample period 1955Q1-1982Q1 is shorter than our sample period, (iii) their purging equation does not include the DMF_t variable,

[15]Test results with the principal component estimator g_{pc} are qualitatively the same as the results reported in Table 2-3. This indicates that alternative estimators of aggregate non-monetary shocks do not matter for the test of sectoral shifts hypothesis although g_{pc} is intuitively more appealing in the least squares sense than the Abraham-Katz estimator g_{ak}.

and (iv) they estimate the dispersion from the estimates of the innovation term u_{tj} while we use the estimates of sectoral shocks ϵ_{tj}.

The first column in Table 2-3 indicates the sample period, the second column indicates the inclusion or exclusion of the DMF in the purging equation, and the third column indicates whether the dispersion and skewness are estimated from $\tilde{\epsilon}_{tj}$ or $\tilde{u}_{tj}$. The remaining four columns show the p-values of the tests of the sectoral shifts hypothesis when the unemployment equation includes both the dispersion and skewness measures and when it includes only the dispersion measure. Abraham and Katz's original model is the case in the last row and the last column, and rejects the sectoral shifts hypothesis with a p-value of 0.101.

When both dispersion and skewness measures are included (the column under σ & sk), the hypothesis is strongly supported regardless of the sample period, inclusion or exclusion of DMF in the purging equation, and the choice of $\tilde{\epsilon}_{tj}$ or $\tilde{u}_{tj}$. The test results are sensitive to these factors when only the dispersion is included as a measure of the sectoral reallocation. For example, in the short sample period without DMF, the hypothesis is rejected or accepted depending on whether σ is computed from $\tilde{u}_{tj}$ or $\tilde{\epsilon}_{tj}$.

A close examination of the p-values in Table 2-3 reveals a clue to the source of Abraham and Katz's rejection of the hypothesis. The last column of the table shows that, when the skewness measure is not included, the dispersion measure based on $\tilde{u}_{tj}$ has higher p-values than the dispersion measure based on $\tilde{\epsilon}_{tj}$ in all cases. This observation indicates that Abraham and Katz's use of $\tilde{u}_{tj}$ in their computation of σ played a role in their rejection of the hypothesis. The exclusion of DMF in their study is not a source of their rejection of the hypothesis as the p-values are smaller when DMF is excluded from the purging equation. It is interesting to note that the p-values of σ between the equation with both σ and sk (fifth column) and the equation with

σ only (last column) are quite close when $\tilde{u}_{tj}$ is used to estimate σ. This implies that the skewness measure makes a net contribution to the failure to reject the hypothesis when it is included. These observations lead to a conclusion that the lack of support for the sectoral shifts hypothesis in the Abraham and Katz study is due to their use of $\tilde{u}_{tj}$ and because they did not consider the effects of skewness.

The effect of sectoral shifts variables in (2.1a) and (2.2a) are assumed to remain constant over the entire sample period. However, Davis (1987) and Mills et al. (1995) argue that the effect of sectoral shifts may vary with the stage of the business cycle because the duration of unemployment depends on the business cycle as workers adjust their job-search efforts to changes in the opportunity cost of unemployment. To examine such effects we also consider expanded version of (2.1a) and (2.2a) by including interaction terms of dispersion and skewness with a variable that measures the stage of business cycle. Mills et al. (1995) used a binary dummy variable, taking a value of 1 if the logarithm of real GNP is below its linear trend and zero otherwise. They also considered the difference between the trend and the logarithm of real GNP. In all three models reported in Table 2-2, inclusion of interaction terms has little effect on the estimates of long run effects of dispersion and skewness and their p-values, and the coefficients of these interaction terms are insignificant individually as well as jointly with very high p-values. Thus, we do not find any significant stage-of-the-cycle effects in our models.

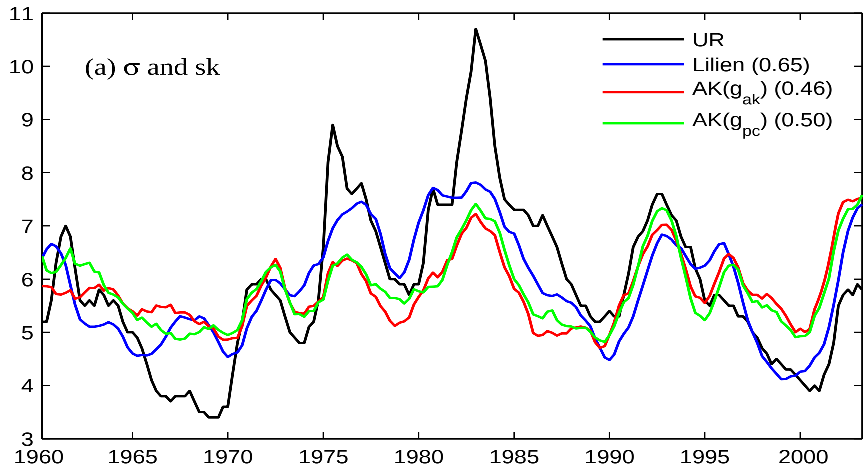
3. Natural Rates of Unemployment

Following Lilien and Abraham and Katz, the natural rates of unemployment (NRU) are computed from (2.1a) and (2.2a) as the rates that would have been observed if all monetary shocks and the disturbance terms had been zero. The upper panel in Figure 2-2 presents the NRU series of the models reported in Table 2-2 when both dispersion and skewness are included. A cursory inspection of the figure reveals that the NRU series of the Lilien type model trace the actual rates of unemployment (UR) more closely than the AK type model. Between the AK type models, the NRU with g_{pc} tends to trace UR slightly better than the NRU with g_{ak}, but the difference is quite small. These observations are also supported by the R^2 measures of the regression of UR on each NRU series.

The lower panel of Figure 2-2 shows the NRU series when only the dispersion measure is included. The NRU series of the Abraham and Katz original model ($AK(org)$) is also shown[16]. Each of theses series varies less than the corresponding series in the upper panel, i.e., the skewness effects tend to make the NRU series fluctuate more. As observed in past studies, the NRU series of the Lilien type model in this panel varies more significantly and tracks the actual rates of unemployment more closely than the Abraham and Katz models. There is not much difference among the AK type models though the $AK(g_{ak})$ and $AK(g_{pc})$ models have a slightly more variant NRU series than the *AK(org)* model.

To see the effects of the skewness more easily, Figure 2-3 presents the NRU series with and without the skewness measure in each model. A close examination of these series reveals that omission of the skewness effect on the NRU can lead to quite a different diagnosis of the source of labor market conditions. Lilien (1982) observed in his annual data model that "... between 1964 and 1969, monetary growth was above its expected level, which resulted in unemployment below the natural rate in late sixties" (p.792). Our estimate of the NRU series, based on σ only in the top panel of Figure 2-3, confirms his observation, and the estimate of the NRU series with the

[16]This is based on the estimates of Abraham and Katz model without the DMF in the purging equation over the longer sample period (1955Q1-2003Q1), which supports the sectoral shifts hypothesis with a p-value of 0.044. See Table 2-3.



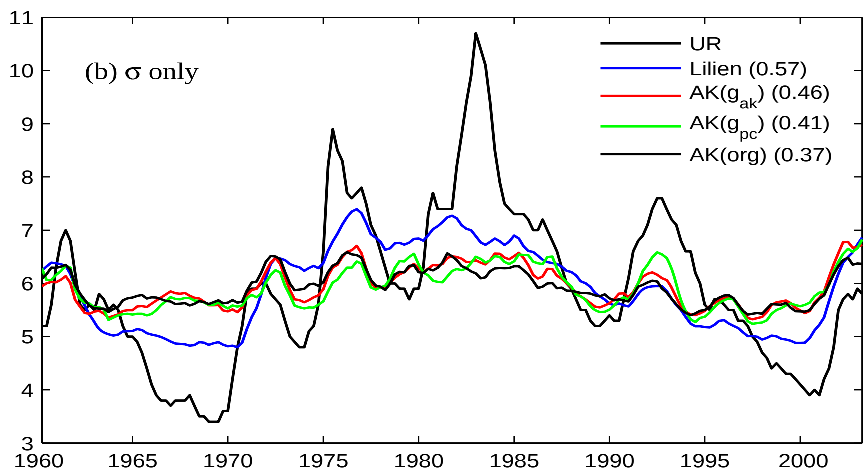


FIGURE 2-2 Natural Rate of Unemployment

Notes: *UR* is the actual rate of unemployment. *Lilien* shows the natural rate of unemployment from the Lilien type model. $AK(org)$ represents Abraham and Katz original model which includes only σ and is estimated for the longer sample period (1955Q1-2003Q1). It excludes *DMF* in the purging equation and estimates σ based on $\tilde{u}_{tj}$. For $AK(g_{ak})$ and $AK(g_{pc})$, see the notes in Table 2-2. Numbers in parentheses are the R^2 from the regression of the *UR* on each natural rate.

skewness measure also leads to the same conclusion, except for the very beginning of this period. Similar results hold for the period of 1977-1981, except that the NRU series with the skewness measure ascribes the fluctuation of the unemployment substantially more to the factors that affect the natural rate than the NRU series without the skewness effect.

On the other hand, the two estimates of the NRU series suggest different assessments of the monetary policy for the period of 1988-1991. The NRU series with σ only suggests that the cumulative effects[17] of monetary policy were expansionary and kept unemployment below the natural rate. However, the NRU series with the skewness effect suggests that the cumulative effects of monetary policy were not expansionary enough and consequently, unemployment remained above the natural rate. The implication of the two series is reversed for the period of 1995- 1997. For the period of jobless recovery after the 2001 recession, both estimates of the NRU series attribute the rise in unemployment to the rise in the natural rate, and imply that the effect of unexpected money growth kept unemployment below the natural rate.

There is much less difference between the estimates of the NRU series with and without the skewness effect in the AK type models. Lilien's observation about the late sixties still holds for both estimates. However, there is no significant conflict of assessment of the monetary effects between the two estimates, though the $AK(g_{ak})$ and $AK(g_{pc})$ models show a small difference in the assessment in the late seventies and eighties.

Although both the Lilien and AK type models support the sectoral shifts hypothesis, they show sizable differences in their estimates of the NRU series. The source of

[17]Lilien's unemployment equation has lagged unemployment rate as a regressor and hence, the effect of DMR on NRU in any period is the cumulative effect of all past effects of DMR.

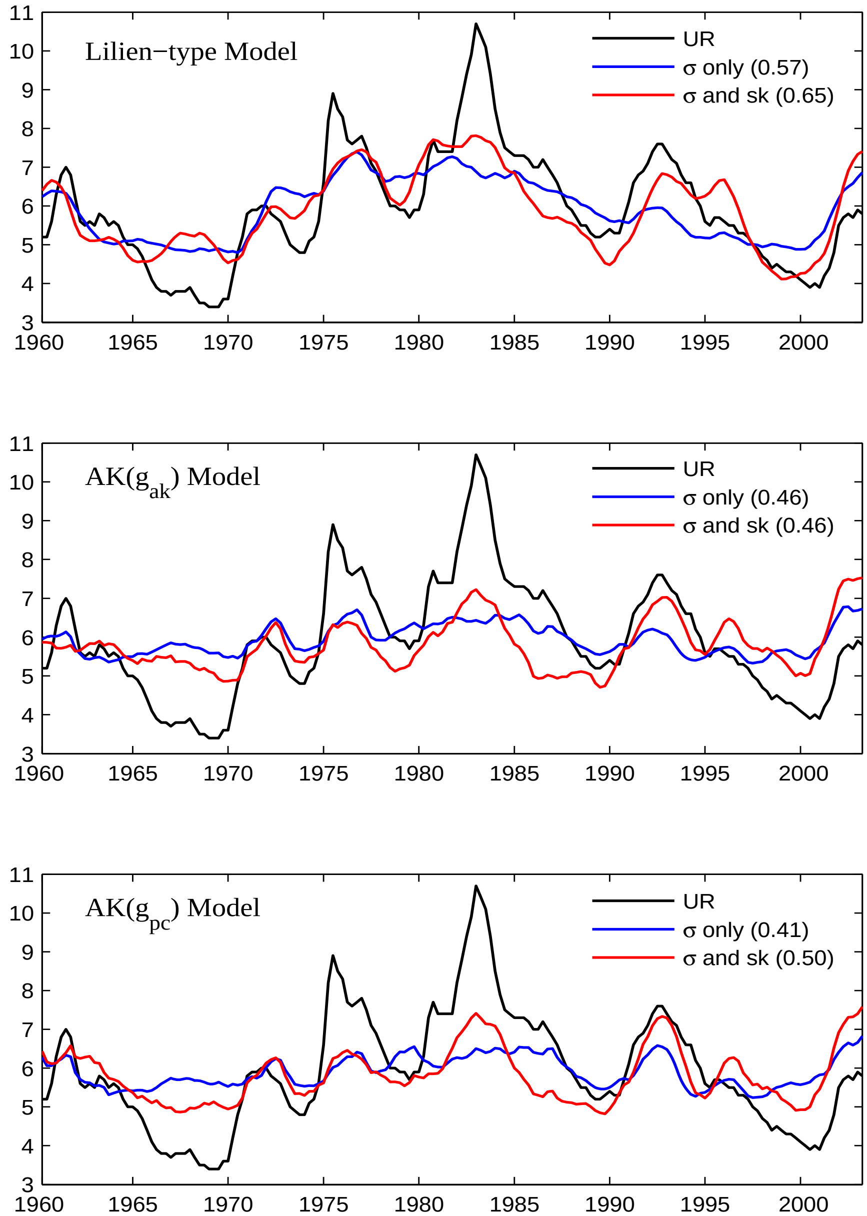


FIGURE 2-3 Natural Rate of Unemployment: Effects of Skewness in Each Model

these variations is not the differences in the estimators of the dispersion and skewness measures. The estimates of the NRU series in the AK type model were not affected much when we used the estimates of the dispersion and skewness measures from the Lilien type models in the Abraham-Katz unemployment equation. The discrepancy seems to lie in the difference in the structure of the unemployment rate equation.

E. Conclusion

The sectoral shifts hypothesis has important macroeconomic implications. 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 unemployment fluctuations, and an analysis of the inflation process must take the effects of sectoral reallocation into account in the measure of inflationary pressure. Lilien (1982) derived the relationship between the sectoral reallocation of labor demand and the aggregate unemployment rate through the effect of reallocation on the aggregate layoff rate. He measured the latter by the dispersion of net employment growth rates across industries. There are two types of empirical models in past studies that use cross-sectional dispersion as the measure of sectoral shifts: the Lilien type and the AK type empirical models. The former supports the hypothesis and the latter rejects it.

We demonstrated that the measurement of sectoral shifts by dispersion alone is not sufficient for asymmetric distributions and the skewness of the sectoral shocks can substantially improve the measurement of sectoral shifts. One of the hotly debated issues in the test of the sectoral shifts hypothesis is how to purge aggregate monetary and non-monetary shocks. The Lilien type models that purge only the aggregate monetary shocks tend to support the hypothesis, while the AK type models, which purge both aggregate monetary and non-monetary shocks, tend to reject the hypothesis. The estimators of aggregate non-monetary shocks g_t in the latter models have been criticized as an *ad hoc* procedure, but we showed that they can be interpreted as regression estimators of an unobservable variable.

Following Abraham and Katz, we assumed cross-sectional heteroscedasticity in the sectoral shocks and compute the dispersion and skewness measures from the "normalized" sectoral shocks. This procedure captures only the time-varying component of dispersion and skewness. The Lilien type model and AK type model are estimated by using the U.S. quarterly data for a short sample period that is comparable to the study of Abraham and Katz (1984) and for a longer sample period. Our estimation results show that the skewness measure has a statistically significant effect on aggregate unemployment in both types of models, and the sectoral shifts hypothesis is strongly supported by both types of models regardless of the choice of purging methods. Our estimation results also indicate that the lack of support for the hypothesis in the Abraham-Katz study is due to the omission of the skewness measure and due to their use of dispersion of the innovation terms in serially correlated sectoral shocks instead of the dispersion of the sectoral shocks themselves.

The natural rates of unemployment estimated from these models show more fluctuations than the relatively flat natural rates of unemployment reported in the Abraham and Katz study. Although both types of models support the sectoral shifts hypothesis, there is a sizable difference in the natural rates of unemployment generated by these models. The skewness measure has a significant effect on the natural rates of unemployment in the Lilien type model, but does not have as much effect in the AK type model. The natural rates of unemployment computed with and without the skewness measure in the Lilien type model can lead to conflicting assessments of the source of the labor market condition.

CHAPTER III

TEST OF SECTORAL SHIFTS HYPOTHESIS BASED ON ROBUST MEASURES OF DISPERSION AND SKEWNESS

A. 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) starts with the positive relationship between layoffs and aggregate unemployment rate based on job search. The key element in Lilien's analysis is the relationship between the average layoff rate and the distribution of sectoral shocks. Lilien 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) show that the classical measure of skewness of the distribution also has a significant effect on the aggregate unemployment rate. Dispersion and skewness measures for each period are typically computed from the cross-sectional residuals of 'purging' regression equations of net employment growth rates on monetary and aggregate non-monetary shocks.

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. I use various methods of detecting outliers and find evidence for their presence in cross sectional distribution of sectoral shocks for a large number of periods.

I also 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, a closer investigation reveals that both classical and robust measures show similar trends over time. Therefore, 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 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 B, I discuss classical and robust measures of dispersion and skewness. Section C deals with outlier detection methods, and section D explains empirical models of testing sectoral shifts hypothesis. In section 5, empirical results from detection of outliers and test of sectoral shift hypothesis are presented, and the conclusion follows.

B. Classical and Robust Measures of Dispersion and Skewness

It is well known that classical measures of dispersion and skewness are very sensitive to the presence of outliers. 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, I present alternative robust measures of dispersion and skewness, and discuss their properties.

Two most commonly used robust alternatives to the classical standard deviation are dispersion measures based on the interquartile range and the median absolute deviation (MAD). The MAD in particular is a very robust estimator. Let $x = \{x_1, x_2, \cdots, x_n\}$ be the 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 $N(\mu, \sigma^2)$[1]. It should be noted that d_{iqr} does not reflect any information from outside of two quartiles. Therefore, its breakdown point is 25%[2].

The MAD is the median of the absolute distances between each data point and

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

[2] 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.

overall median of the data set

$$MAD(x_i) = med_i\left(|x_i - med_j(x_j)|\right)$$

where the inner median, $med_j(x_j)$, is the median of n observations and the outer median, med_i, is the median of the n absolute values of the deviations about the overall median. The dispersion measure based on the MAD is defined by

$$d_{mad} = c_{mad} MAD(x_i)$$

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 which is 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 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 MAD.

The Q_n measure of Rousseeuw and Croux is defined by

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

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. This estimator 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 skewness measures is Hinkley's (1975) generalization of Bowley's (1920) coefficient of skewness, which is defined by

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

which takes a value in the interval $[-1, 1]$. The quartile skewness with $p = 1/4$ is Bowley's measure. The quartile skewness has breakdown point of 25% and is less sensitive to outliers than the octile skewness ($p = 1/8$) whose breakdown point is 12.5%, but the latter uses more information from the tails of the distribution and can be more useful in detecting asymmetry[3].

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

$$\begin{aligned} sk_{gm} &= \frac{\int_0^{\frac{1}{2}} \left([F^{-1}(1-p) - Q_{0.5}] - [Q_{0.5} - F^{-1}(p)] \right) dp}{\int_0^{\frac{1}{2}} \left([F^{-1}(1-p) - Q_{0.5}] + [Q_{0.5} - F^{-1}(p)] \right) dp} \\ &= \frac{\mu - Q_{0.5}}{E|X - Q_{0.5}|} \end{aligned}$$

This measure takes a zero value for a symmetric distribution and takes a value in the interval $[-1, 1]$[4]. This estimator can be estimated by using the sample mean $\bar{x}$ for μ and the sample mean of $|x_i - Q_{0.5}|$ for the denominator.

[3]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 $p = 1/8$.

[4]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 coefficients of skewness $sk_p = 3(\text{mean} - \text{median})/\sigma$.

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

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

where the kernel function is defined as[5]

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

for all $x_{(i)} \leq Q_{0.5} \leq x_{(j)}$. Note that, if either $x_{(i)}$ or $x_{(j)}$ coincides with the median, then $h(x_{(i)}, x_{(j)}) = 1$ for all $x_{(j)} \geq x_{(i)} = Q_{0.5}$, and $h(x_{(i)}, x_{(j)}) = -1$ for all $x_{(i)} \leq x_{(j)} = Q_{0.5}$. If there are more than one data point which coincide with the median such that $x_{(j)} = x_{(i)} = Q_{0.5}$, then the kernel function is defined as $h(x_{(i)}, x_{(j)}) = +1$ if $i > j$, $h(x_{(i)}, x_{(j)}) = -1$ if $i < j$, and $h(x_{(i)}, x_{(j)}) = 0$ if $i = j$. Thus, if m number of data points coincide with the median, the kernel function takes m number of zero values and $m(m-1)/2$ number of $+1$ and -1, respectively. 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. L-moments can characterize a wider range of distributions than the classical moments because the existence of L-moments requires the existence of only the first order moment. They are particularly useful in identifying skewed distributions and their estimators are more robust to the presence of

[5]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 $i < j$.

outliers in the data. They also provide measures of location, dispersion, skewness, kurtosis, and other aspects of the shape of probability distributions or data samples.

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

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

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

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

The first four L-moments can thus be written as

$$\ell_1 = \beta_0, \qquad \ell_2 = 2\beta_1 - \beta_0, \qquad \ell_3 = 6\beta_2 - 6\beta_1 + \beta_0$$

where the coefficients are those of the shifted Legendre polynomials. $\ell_1$is the sample mean, a measure of location. The second L-moment ℓ_2 is (a multiple of) Gini's mean difference statistic, a measure of the dispersion of the data values about their mean. We will use ℓ_2 as a robust measure of dispersion:

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

By dividing the higher-order L-moments by the dispersion measure, we obtain L-moment ratios,

$$\tau_r = \ell_r/\ell_2, \qquad r = 3, 4, \cdots$$

These are dimensionless quantities, independent of the units of measurement of the data. Hosking shows that τ_r for $r \geq 3$ are bounded in $(-1, 1)$, and proposes to use τ_3 as a measure of skewness, which is called the L-skewness. This is a robust measure of skewness which will be used in later analysis:

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

L-moments and L-moment ratios are 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.

C. Detection of Outliers

One of the most widely used identifiers is Tuckey's (1971, 1977) boxplot identifier which uses the first and third quartiles as reference points and determines the length of the whisker by a constant multiple of the interquartile range (IQR):

$$\textit{Boxplot identifier}: \quad [Q_{0.25} - cIQR,\, Q_{0.75} + cIQR], \quad c = 1.5$$

Samples outside of this interval are considered as outliers. The boxplot rule is based only on the measures of location and dispersion, and hence, it tends to classify too many data points as outliers when the underlying distribution is skewed. Vandervieren and Hubert (2004) modified Tuckey's boxplot by introducing a robust measure of skewness in the determination of whiskers

$$\textit{VH identifier}: \quad [Q_{0.25} - c_1 IQR,\, Q_{0.75} + c_3 IQR]$$

$$c_1 = 1.5e^{\alpha_1 MC},\ c_3 = 1.5e^{\alpha_3 MC}$$

where MC is the medcouple measure of skewness. $\alpha_1 = -3.5$ and $\alpha_3 = 4$ when $MC \geq 0$ and $\alpha_1 = -4$ and $\alpha_3 = 3.5$ when $MC \leq 0$. When the distribution is skewed to the right, $MC \geq 0$ and the boundary values of the interval are greater than those of the standard boxplot. This gives a better identification of outliers for skewed distribution.

Carling (2000) proposed the use of median $Q_{0.5}$ instead of quartiles $Q_{0.25}$ and $Q_{0.75}$ as the reference point and to use the IQR for the whisker length

$$\textit{Carling identifier}: \quad [Q_{0.5-}cIQR,\ Q_{0.5} + cIQR], \qquad c = 2 \text{ or } 3$$

This identifier is also called the *median rule.* When the dispersion estimator d_{mad} from the MAD is used instead of the IQR, it is called the Hampel identifier (Davies and Gather (1993))

$$\textit{Hampel identifier}: \quad [Q_{0.5} - cd_{mad},\ Q_{0.5} + cd_{mad}], \qquad c = 2 \text{ or } 3^6$$

Rousseeuw et al. (1999) proposed the bagplot which is a bivariate generalization of the boxplot, and defined the univariate fences as

$$\textit{RRT identifier}: \quad [Q_{0.5} - c(Q_{0.5} - Q_{0.25}),\ Q_{0.5} + c(Q_{0.75} - Q_{0.5})], \quad c = 3 \text{ or } 4$$

Aucremenne et al. (2004)[7] called this identifier the *asymmetric boxplot rule* and used $c = 3$, while Rousseeuw et al. (1999) used $c = 4$.

---

[6]Other choices of the values of c have been used in the literature such as c=3.5 in Sabade and Walker (2002).

[7]They defined the fences of the standard boxplot rule as $[Q_{0.5} - 1.5IQR,\ Q_{0.5} + 1.5IQR]$, but this definition is not consistent with the conventional definition that is widely used in the literature.

Note that the *Carling identifier* and the *Hampel identifier* have the same length of upper and lower whiskers from the median, but the *RRT identifier* has different lengths of whiskers and they depend on the terms that appear in Hinkley's measure of skewness.

D. 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.

The unemployment rate equation is specified as

$$UR_t = \alpha_0 + \alpha_1 t + \sum_{s=0}^{4} \beta_s \sigma_{t-s} + \sum_{s=0}^{4} \lambda_s sk_{t-s} + \sum_{s=0}^{8} \gamma_s DMR_{t-s} + \sum_{s=1}^{4} \delta_s UR_{t-s} + \eta_t \tag{3.1}$$

where UR_t is the aggregate rate of unemployment, σ_t and sk_t are measures of dispersion and skewness, 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

$$DM_t = a_0 + \sum_{s=1}^{8} b_s DM_{t-s} + \sum_{s=0}^{3} c_s FEDV_{t-s} + \sum_{s=1}^{4} d_s UN_{t-s} + e_t \tag{3.2}$$

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 $UN_t = \ln(UR_t/(1 - UR_t))$.

Sectoral shocks are estimated from the net hiring rates h_{tj} after 'purging' aggregate monetary effects in h_{tj}. The purging equation is specified as

$$h_{tj} = a_{j0} + a_{j1}H_t + a_{j2}t + \sum_{s=0}^{4} b_{js}^{r} DMR_{t-s} + \sum_{s=0}^{4} b_{js}^{f} DMF_{t-s} + c_j h_{t-1,j} + \epsilon_{tj} \qquad (3.3)$$

where H_t is the aggregate net hiring rate, and DMR_t and DMF_t are the unanticipated aggregate monetary shock and the anticipated money growth rate, respectively. 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 (3.1), which includes lagged unemployment rates as regressors. 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, $x_{tj} \equiv \hat{\epsilon}_{tj}/\hat{\theta}_j$, where $\hat{\theta}_j$ is an estimate of the scale parameter for industry j that does not change over time, and it is given by

$$\hat{\theta}_j = \left(\frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_{tj}^2 \right)^{1/2}$$

The normalized residuals are used in Abraham and Katz (1984), Loungani (1986) and Byun and Hwang (2006)[8]. As pointed out by Byun and Hwang (2006), the normalization by the scale parameter is equivalent to the assumption of cross sectional

[8]Lilien type models set $\hat{\theta}_j = 1$.

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

$$\hat{\sigma}_t^2 = \sum_{j=1}^{n} w_{tj}\left(\frac{\hat{\epsilon}_{tj}}{\hat{\theta}_j}\right)^2$$

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 $e_{tj} \equiv \sqrt{nw_{tj}}\hat{\epsilon}_{tj}/\hat{\theta}_j$, which is assumed to have a zero mean. The computation of classical measures of skewness[9], the computation of robust measures of dispersion and skewness, and outlier detections are all based on this transformed variable e_{tj}.

E. Empirical Results

The quarterly data used in this paper is drawn from the Bureau of Labor Statistics (BLS) and the Federal Reserve Economic Data (FRED). Seasonally adjusted numbers of employees series are taken from the Current Employment Statistics (CES) survey of nonfarm payroll records from the BLS. 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. It covers the first quarter of 1955 through the first quarter of 2003. Seasonally adjusted unemployment rate of civilian noninstitutional population is drawn from the Current Population Survey (CPS) of the BLS. Seasonally adjusted M1 money stock series and 3-month Treasury Bill secondary market rates are from FRED. The current

[9] This estimator of the classical skewness is slightly different from the estimator used in Byun and Hwang (2006) which used a different normalization for the skewness under the assumption of $E(\hat{\epsilon}_{tj}^3) = \tau_j^3\mu_{3t}$. The empirical results are very similar. I use the same normalization for both dispersion and skewness in this chapter for simplicity in the computation of robust measures.

federal government expenditure and the GDP deflator that are used in construction of the *FEDV* variable are from FRED and various issues of Economic Report of the President.

1. Outlier Detection

The purging equations in (3.3) 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 described in section C are presented in Figure 3-1. All identifiers indicate the presence of outliers. The mode of number of outliers in each period varies across identifiers, ranging from 3 to 5. The proportion of periods in which the actual number of outliers is greater than the mode ranges from 31% by *Hampel 3 identifier*[10] to 52% by *Carling identifier*. Based on the number of outliers detected for each period and the number of periods with a consequential existence of outliers, I conclude that there exist outliers in the cross-sectional distribution of sectoral shocks.

I am also concerned about the extent to which each outlier deviates from whiskers because some outliers with a significant degree of deviation can distort the computation of classical measures of dispersion and skewness. Figure 3-2 shows maximum and minimum outliers, if they exist, for each identifier over the sample period. It also shows the median of e_{tj} and upper and lower whiskers. Visual inspection reveals that the degree of outlying is quite considerable. 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 also quite consequential. From Figures 3-1 and 3-2, I conclude that despite the differences among

[10] *Hampel 3 identifier* implies that c=3 is used.

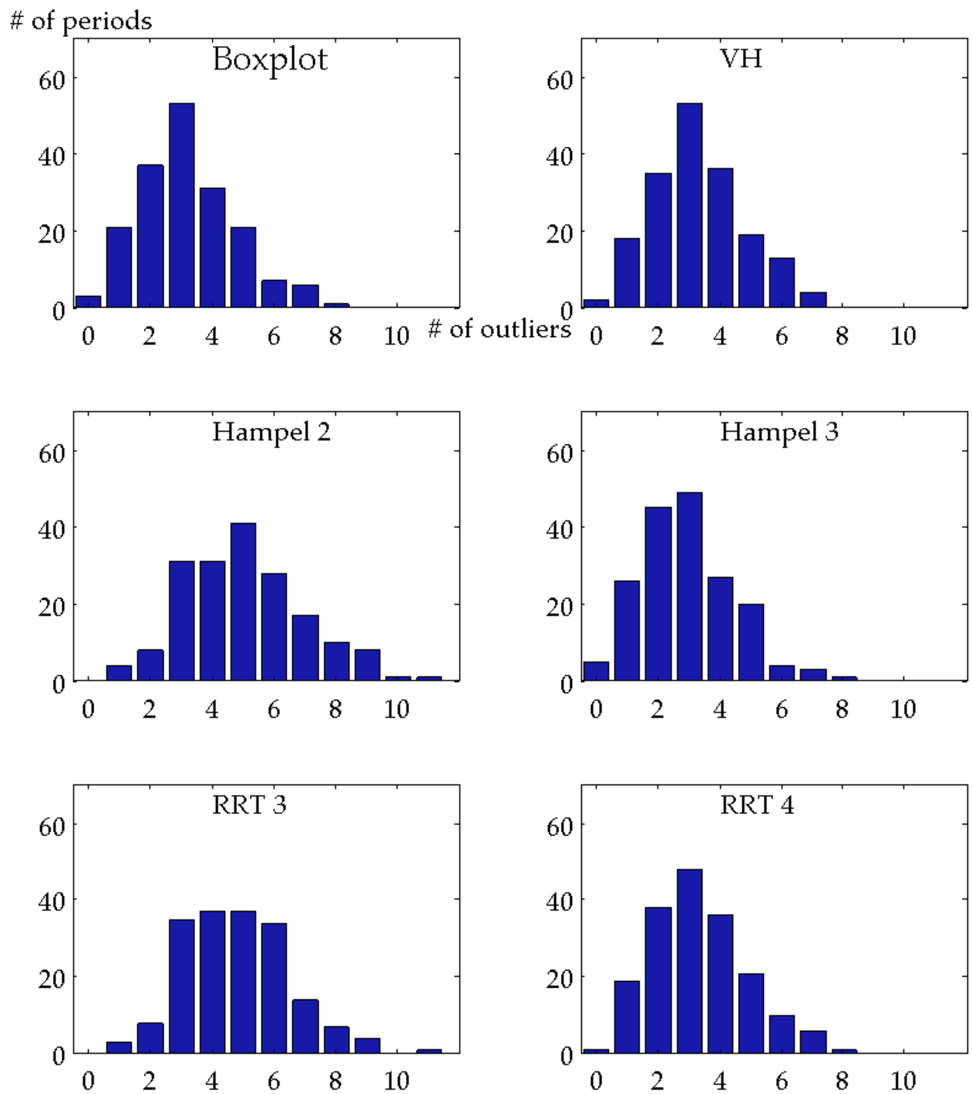


FIGURE 3-1 Distribution of Number of Outliers

Notes: The horizontal axis represents the number of outliers out of 30 industries detected by each identifier, and the vertical axis represents the number of periods with corresponding number of outliers out of 180 observations. The result, when the *Carling identifier* is used, is quite similar to the *Hampel 3* case and is not reported here.

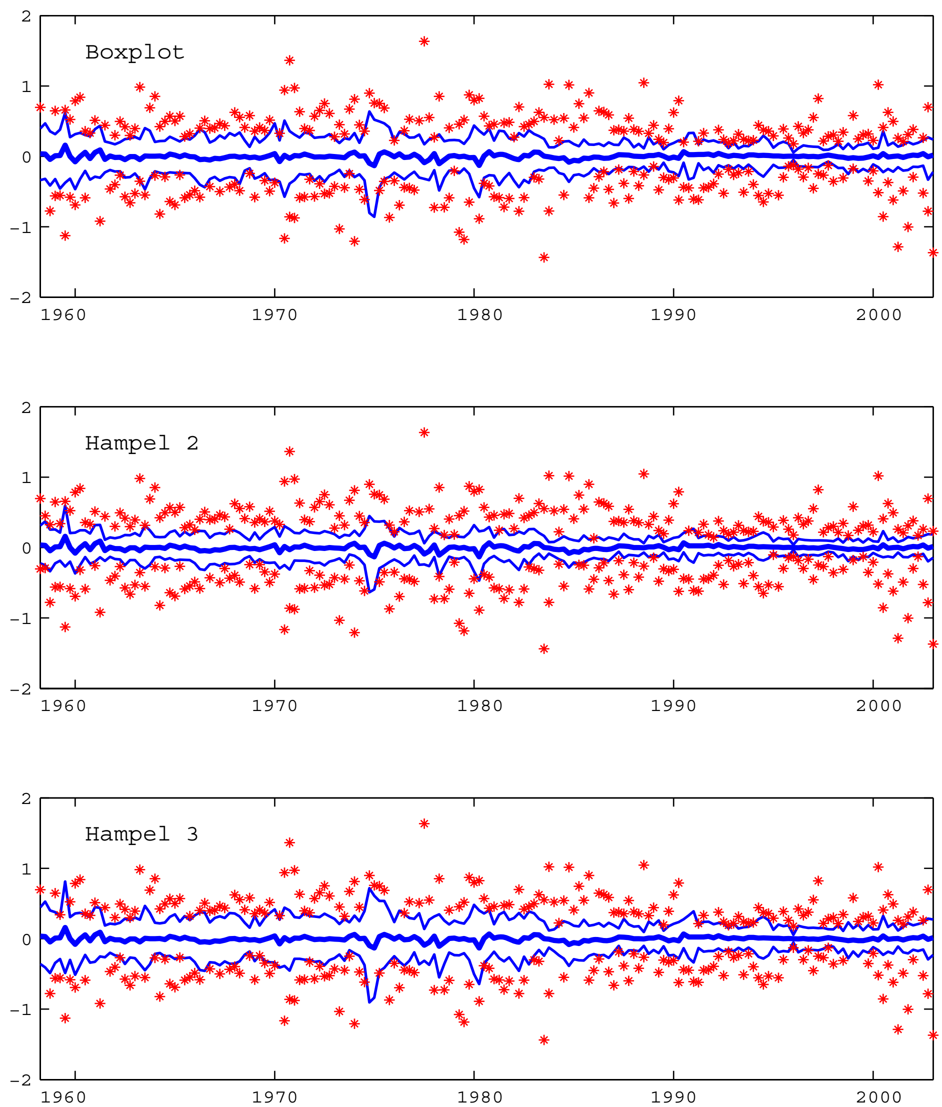


FIGURE 3-2 Degree of Outlying

Notes: 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.

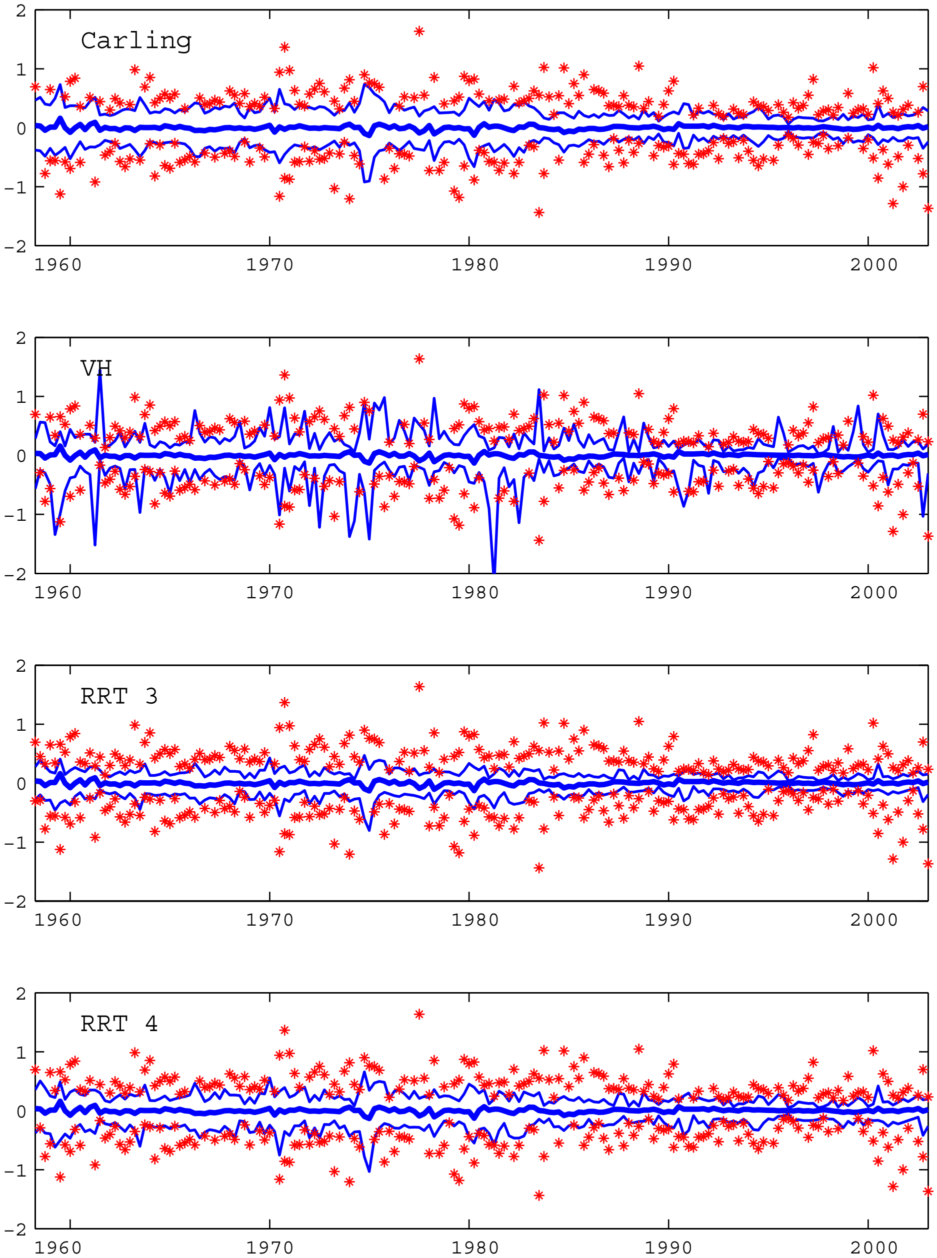


FIGURE 3-2 Continued

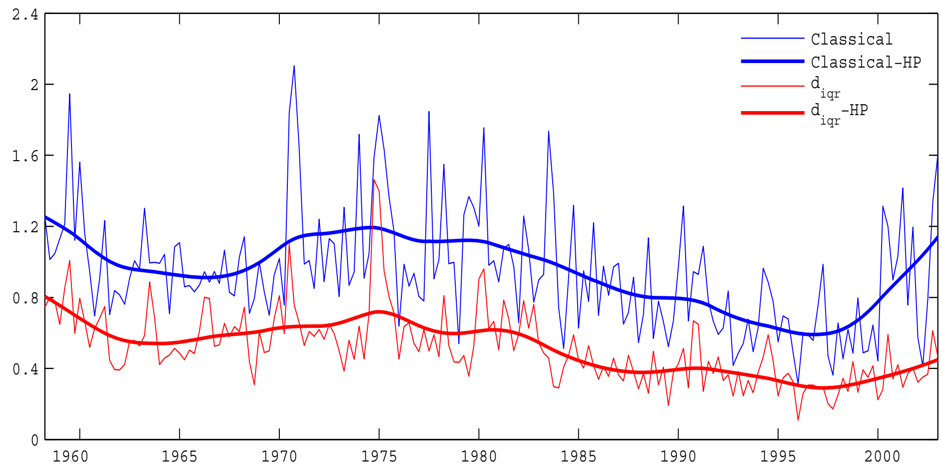
identifiers, outliers do exist and the degree of outlying is considerable. This casts concerns on the estimated dispersion and skewness by the classical method.

2. Robust Measure of Dispersion and Skewness

Classical and robust measures of dispersion and skewness of sectoral shocks are depicted in Figures 3-3 through 3-5. The upper panel of Figure 3-3 shows a classical measure of dispersion and d_{iqr}. The robust measure d_{iqr} is much smaller than the classical measure. In order to visually show trends of these measures, we also draw lines of dispersion measures smoothed by Hodrick-Prescott (HP) filter. Even though the robust measure d_{iqr} of dispersion is quite a bit smaller than the classical measure, the HP-filtered d_{iqr} shows trends similar to that of the classical measure. Moreover, in the lower panel where HP-filtered lines of the remaining robust measures of dispersion are drawn, we find a similar observation. Robust measures of dispersion are smaller than the classical measure, but they show trends similar to that of the classical measure.

When actual values of robust measures are compared, we find some differences among robust measures of dispersion. The table below Figure 3-3 reports R^2 from the regression of classical measure of dispersion on a constant and each robust measure. d_{lm} stands out among robust measures in terms of R^2. d_{lm}'s R^2 is about 0.91 and significantly higher than those of other robust measures. In summary, robust measures of dispersion show trends over time similar to that of classical measure of dispersion. In terms of their linear association with the classical measure, there is a significant difference among robust measures of dispersion.

Figure 3-4 shows classical and robust measures of skewness. We also find that robust measures of skewness are much smaller than the classical measure. This is because the robust measures, by their definition, are to lie between -1 and 1. Accordingly, their variation over time is much smaller. In order to easily compare the trend



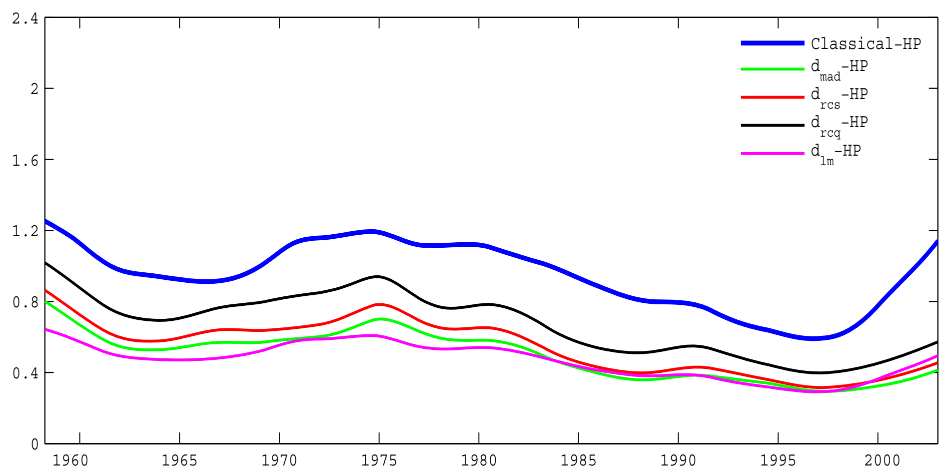


FIGURE 3-3 Classical and Robust Measures of Dispersion

Notes: "-HP" represents each measure smoothed by HP-filter. The table below shows R^2 from the regression of classical measure on a constant and each robust measure.

	d_{iqr}	d_{mad}	d_{rcs}	d_{rcq}	d_{lm}
R^2	0.40	0.34	0.40	0.43	0.91

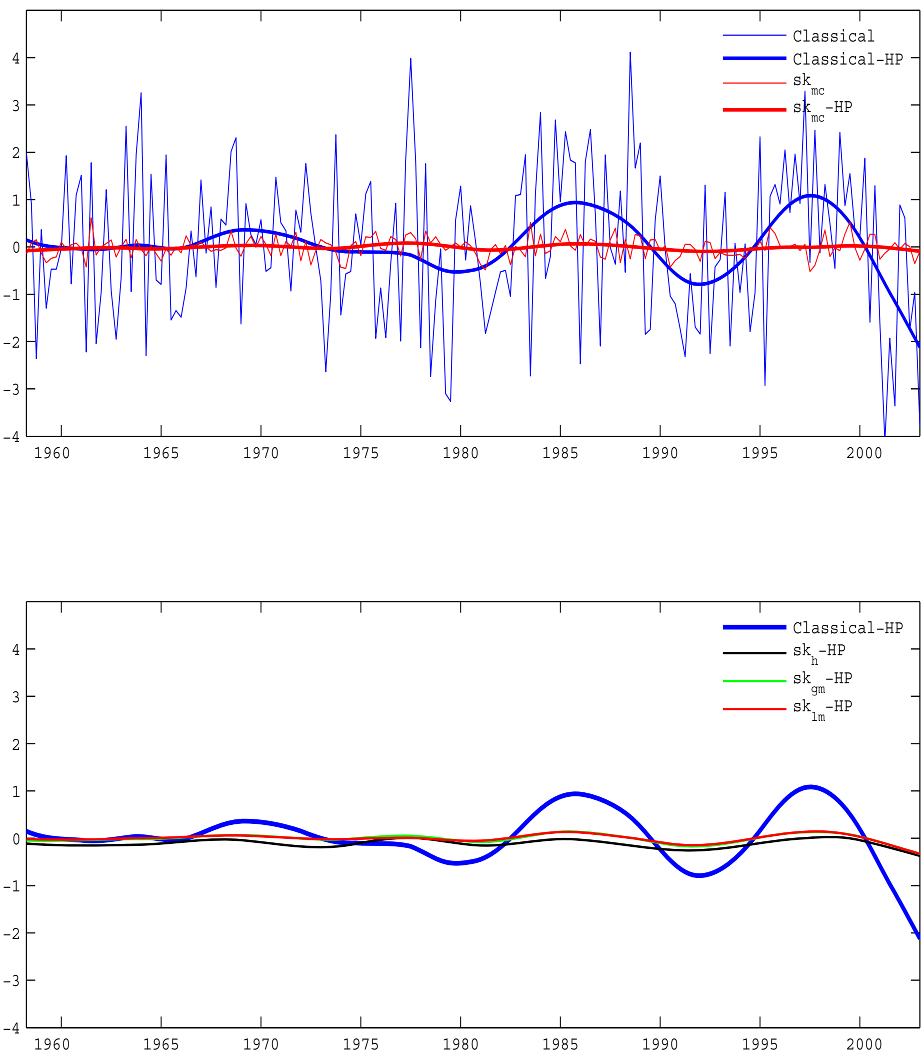


FIGURE 3-4 Classical and Robust Measures of Skewness

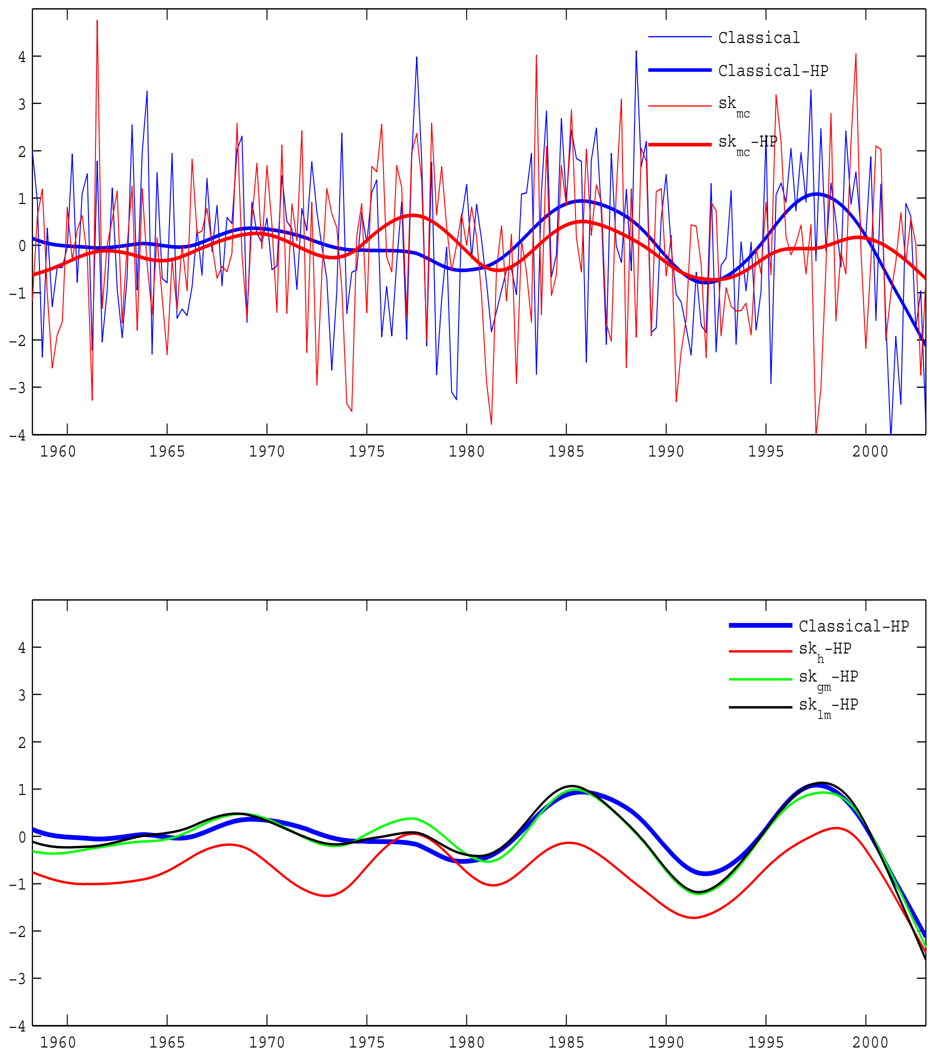


FIGURE 3-5 Classical and Robust Measures of Skewness: Re-scaled

Notes: The table below shows R^2 from the regression of classical measure on a constant and each robust measure.

	sk_h	sk_{gm}	sk_{mc}	sk_{lm}
R^2	0.18	0.65	0.07	0.84

over time of these measures, we rescale the robust measures of skewness by multiplying a constant so that they have the same variance as the classical measure. When used in the unemployment rate equation, this rescaling only changes the coefficient size and does not alter the significance of the coefficients. The result is shown in Figure 3-5. 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, showing high R^2 of 0.84 and 0.65, respectively. sk_h is much smaller than other robust measures of skewness, but it shows trends somewhat similar to the classical measure[11]. On the other hand, sk_{mc} shows a different trend. It has a significantly low R^2 of 0.07 and shows no signs of intensifying fluctuations in the second half of the period. As mentioned in the previous section, sk_{mc} is quite robust to the presence of outliers, with a breakdown point of 25%. On the other hand, this implies that sk_{mc} is incapable of detecting small changes in skewness. We conclude that, depending on the choice of robust measure, robust measures of skewness show trends somewhat different from those of the classical measure, and that the associations with classical measure vary across different robust measures.

In Figure 3-6, we reproduce Figures 3-4 and 3-5 using the LOESS method of smoothing to check the robustness of our observation 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 initial fitted value is computed at each data point using weighted least squares and

[11]We use octile skewness $sk_h(\frac{1}{8})$ in our analysis, which has breakdown point of 12.5%. This measure is more capable of detecting small changes in skewness than sk_{mc}. However, it is less robust to the presence of outliers. The quartile skewness $sk_h(\frac{1}{4})$, which has the same breakdown point as sk_{mc}, shares quite similar properties with sk_{mc} in terms of its robustness to the presence of outliers and its capability of detecting changes in skewness.

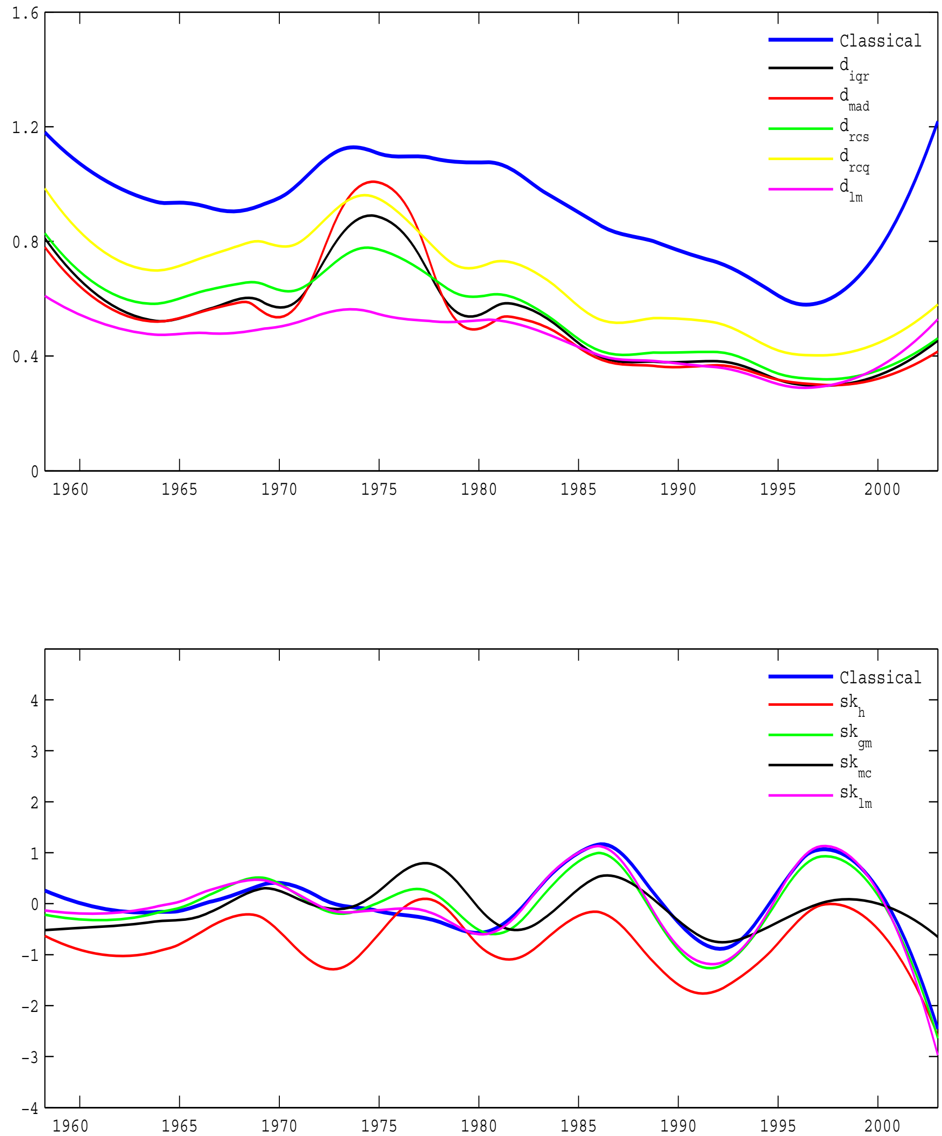


FIGURE 3-6 Classical and Robust Measures of Dispersion and Skewness: LOESS Method

the computations of new weights and new fitted values are repeated several times. New weights are based on the size of the residual from previous estimations, that is, giving more weight to the data points with small residuals and less weight to the data points with large residuals. This iterated procedure, including the initial fitting computation, is referred to robust locally weighted regression and is used to eliminate the effect of outliers distorting the smoothed points. See Appendix and Cleveland (1993) for a detailed explanation on LOESS method.

The result is in accordance with what we observe in previous Figures. Robust measures of dispersion show trends similar to that of the classical measure. The only exception is the spike found in d_{iqr} and d_{mad} around 1975, which we do not observe in HP-filtered trends in previous Figures. This difference stems from the property of the HP filter that penalizes the variations in the growth rate of the trend component. The actual values of dispersion rose sharply around 1975. However, the penalty in the HP filter controls these increases, so that the trend lines in Figure 3-4 are smoother than those in Figure 3-6. The robust measures of skewness also show similar results. The trends in sk_{gm} and sk_{lm} behave quite similarly to the classical measure, while the trend in sk_{mc} is somewhat different from that in the classical measure. As noted before, sk_{mc} does not show any intensifying fluctuations in trend in the latter half of the sample period.

From Figures 3-3 through 3-6, I find that though actual values of robust measures of dispersion are somewhat different from the classical measure, they show trends over time quite similar to those of classical measure of dispersion. Among robust measures, L-moments, d_{lm}, is most similar to the classical measure. For the case of skewness, while sk_{mc} shows different trends from the classical measure, sk_{gm}, sk_{mc} and sk_{lm} show trends similar to that of classical measure. Especially, robust measures of dispersion and skewness based on L-moments show the most resemblance with the classical measures. In the following section, I will test the sectoral shifts hypothesis using different measures of dispersion and skewness, and investigate the effect of using robust measures on the test.

3. Test of Sectoral Shifts Hypothesis

In this section, the long-run effect of sectoral shifts on the aggregate unemployment rate is tested. The unemployment rate equation (3.1) is estimated and the long-run effects of the dispersion and skewness measures are tested using robust measures along with classical measure. Table 3-1 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'. 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. 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 of dispersion and skewness are used, we also find strong evidences supporting the sectoral shifts hypothesis. The null hypothesis of zero long-run effects of the dispersion and skewness measures are jointly rejected at a 5% significance level in most of the cases. However, note that sk_{mc} has the highest p-values among robust measures of skewness. Moreover, when it is used with robust measures of dispersion d_{mad}, d_{rcs} or d_{rcq}, the p-value of the joint tests is higher than 0.05. We suspect that sk_{mc} is least capable of detecting skewness even though it is

TABLE 3-1 p-values from Tests of Sectoral Shifts Hypothesis

dispersion	skewness	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

Notes: 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.

robust to the presence of outliers.

Looking at the individual p-values of dispersion and skewness, I find that the high p-values of the joint tests are contributable to the insignificance of sk_{mc}. Robust measures of dispersion are all significant with the highest p-value of 0.053. Robust measures of skewness are also significant except sk_{mc}. These may be due to different breakdown values of robust measures. The breakdown value represents the maximum proportion of outliers that has no influence on the computation of robust measures (Rousseeuw and Leroy (1987); Brys et al. (2003)). The sk_{mc} has a breakdown value of 25%, which implies that it does not change even when 25% of the observations are outliers. Thus, sk_{mc} is more unlikely to reflect the information from the tail part of distribution, and more unlikely to reflect changes in the skewness of the underlying distribution. Moreover, the breakdown values of d_{mad}, d_{rcs} and d_{rcq} are 50%. When these measures are used with sk_{mc} in the test of sectoral shifts hypothesis, they might not adequately reflect changes in dispersion and skewness. However, note that in all cases we reject the zero long run joint effect of dispersion and skewness at a 10% significance level.

Robust measures of dispersion and skewness are different from the classical measures in terms of their magnitudes, but they are similar to the classical measure in terms of their trends over time, except for sk_{mc}. No matter which robust measures are used in the unemployment rate equation, it turns out that they all support the sectoral shifts hypothesis.

4. Natural Rates of Unemployment

In previous section, I find strong evidence supporting the sectoral shifts hypothesis using robust measures of dispersion and skewness of sectoral shocks. In this section, I will examine the effect of using robust measures on the size of coefficients of dispersion and skewness in the unemployment rate equation. As mentioned in the previous section, classical measure and robust measures are different in their scale. Thus, it is not possible to directly compare the size of the coefficients. One way of comparing the effect of dispersion and skewness on the unemployment rate is to compute the natural unemployment rates as defined by Lilien (1982) based on different robust measures.

The natural rates of unemployment (NRU) are computed from (3.1) as the rates that would have been observed if all monetary shocks and the disturbance terms had been zero. Figures 3-7 and 3-8 show the NRU based on robust measures along with the NRU based on classical measure. In each panel of Figure 3-7, 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[12]. In Figure 3-8, we fix the robust measure of dispersion at d_{iqr}, d_{rcq} and d_{lm}, respectively, and compute NRU with various robust measures of skewness.

Using robust measures of dispersion and skewness does not show any significant changes in the NRU compared to the NRU based on classical measures. One noticeable change is that the NRU tracks the actual rate of unemployment more closely during the 1974-1980 period when robust measures are used. In order to quantify any differences in the NRUs, I report R^2 from the regression of actual unemployment rate on a constant and each NRU in Table 3-2. As observed in Figures 3-7 and 3-8, 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 rates of unemployment explained by the variation of the NRU is quite similar regardless of the choice of sectoral shifts measures.

---

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

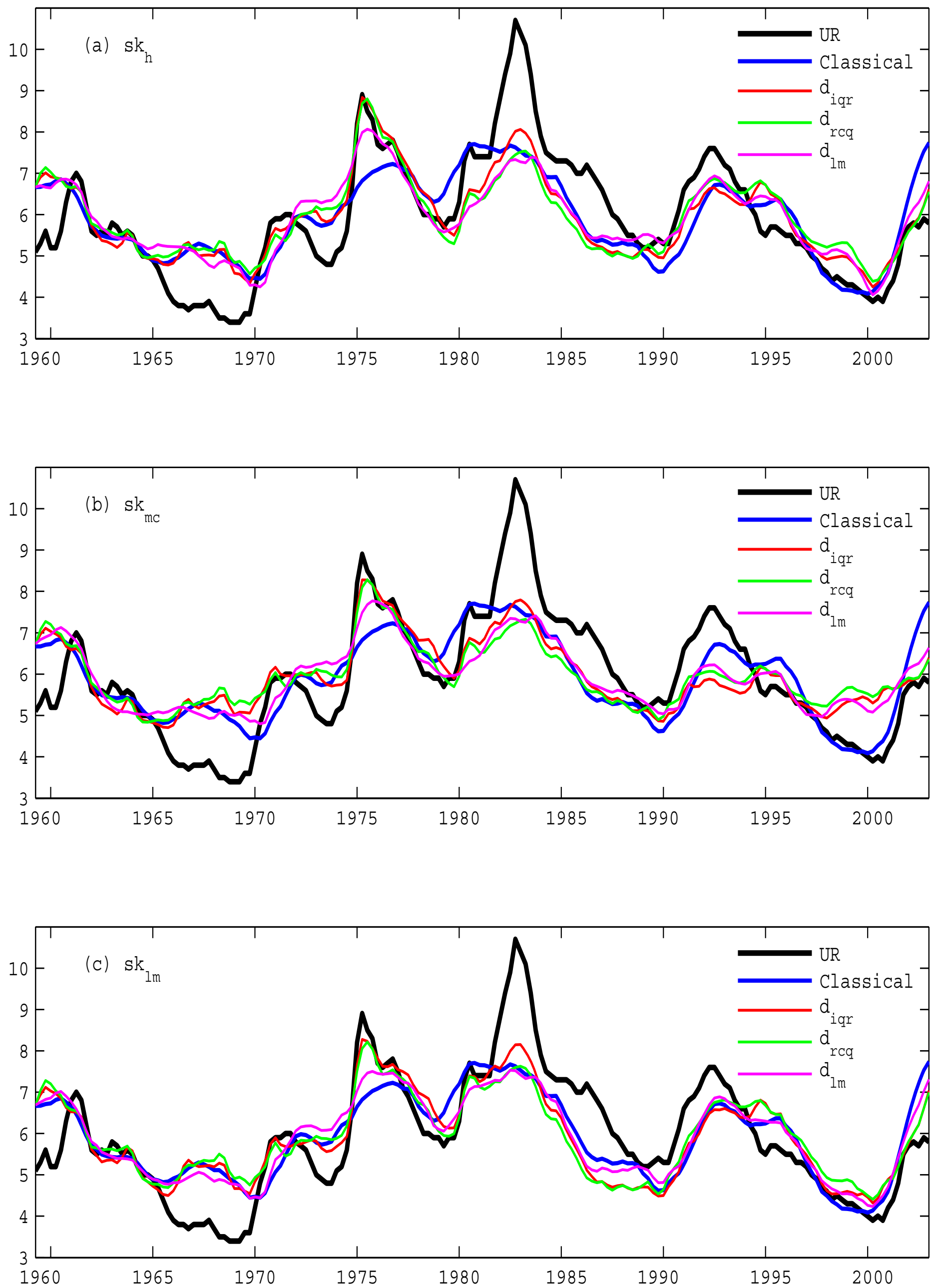


FIGURE 3-7 Natural Rate of Unemployment for given Robust Measures of Skewness

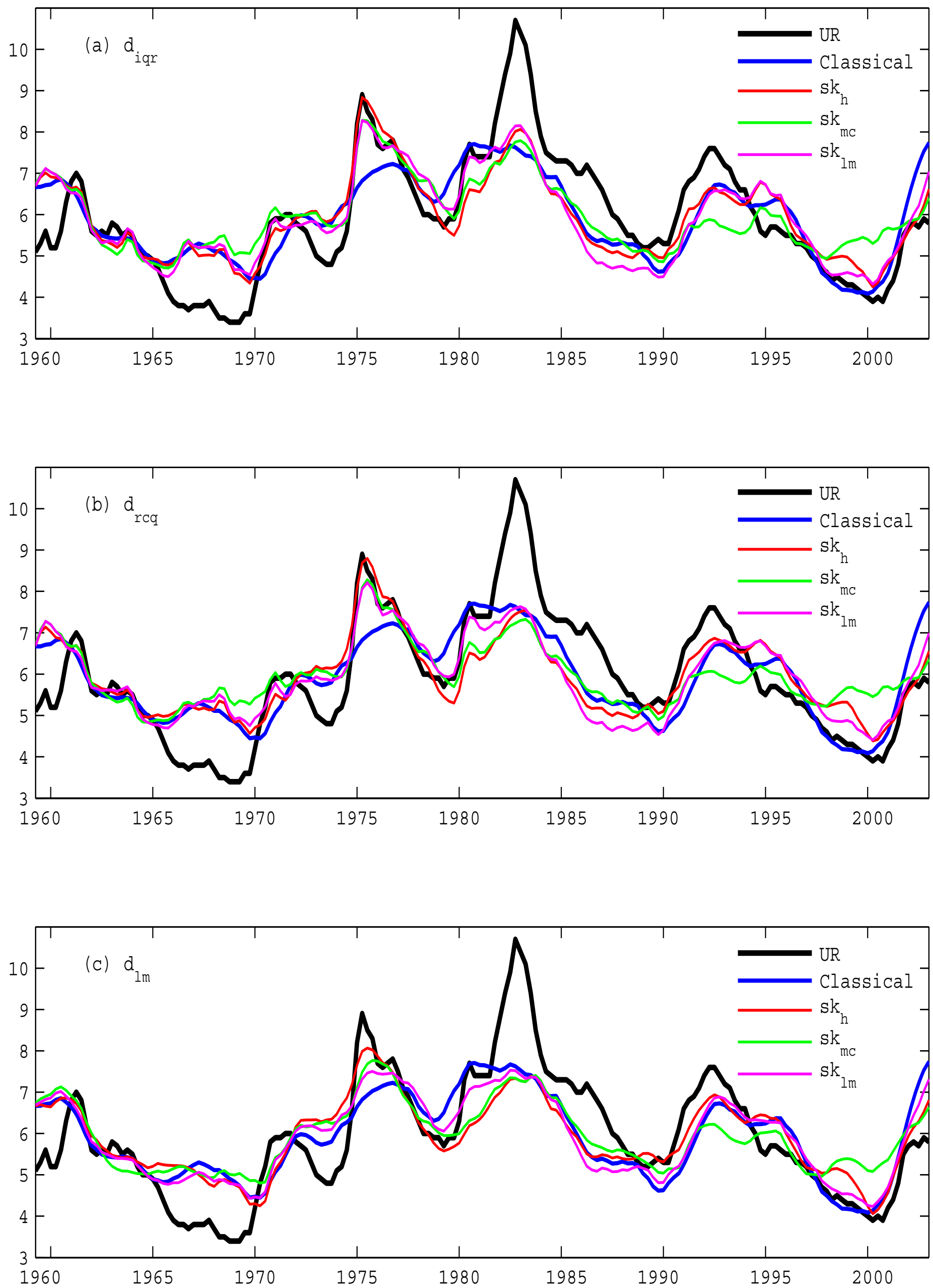


FIGURE 3-8 Natural Rate of Unemployment for given Robust Measures of Dispersion

TABLE 3-2 R^2 from Regressions of Actual Rate of Unemployment on Natural Rate of Unemployment

			skewness			
	R^2	CLS	sk_h	sk_{gm}	sk_{mc}	sk_{lm}
	CLS	0.60				
dispersion	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

In Table 3-3, I report modified Kendall's τ[13], which measures the strength of the tendency of UR and NRU to move in the same direction. In general, the tendency of moving in the same direction becomes slightly stronger when robust measures are used except for the case of sk_{mc}. However, the difference is not significant. We believe that sk_{mc} does not fully reflect the changes in skewness, especially in the latter half of the sample period, due to its breakdown value property.

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. Thus, we believe that the difference stems from the breakdown value property of sk_{mc}, which has been explained in the previous section.

In this section, we have investigated the effect of using robust measures in terms

[13]See Appendix for details about the modification I made on original Kendall's τ.

TABLE 3-3 Modified Kendall's τ between Actual and Natural Rate of Unemployment

			skewness			
	Kendall's τ	CLS	sk_h	sk_{gm}	sk_{mc}	sk_{lm}
	CLS	0.37				
dispersion	d_{iqr}		0.50	0.46	0.38	0.42
	d_{mad}		0.39	0.34	0.33	0.37
	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

of the size of the effect of dispersion and skewness on the unemployment rate. Despite some minor differences, using robust measures of dispersion and skewness does not alter the effect of sectoral shifts on the unemployment rate. The minor differences are closely related to the use of sk_{mc} which has a relatively high breakdown value and thus is less likely to reflect changes in skewness.

F. Conclusion

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's 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 also has a significant effect on the aggregate unemployment rate.

However, classical measures of dispersion and skewness are sensitive to the presence of outliers, and consequently, tests of sectoral shifts hypothesis based on the estimates of classical measures may be distorted by outliers in the estimates of sectoral shocks.

In this chapter, the presence of outliers are discovered by various methods of outlier detection. It also computes various robust measures of dispersion and skewness of the distribution of sectoral shocks. 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. Estimated natural rates of unemployment based on robust measures of dispersion and skewness are quite similar to those based on classical measure. The only case where some noticeable differences are observed is the case where sk_{mc}, a skewness measure based on medcouple, is used as a robust measure of skewness. However, we argue that due to its breakdown value of 25% this measure is less likely to adequately reflect any changes in the distribution from the tail part, and is not appropriate to capture changes in the skewness of the distribution of sectoral shocks, even though it is robust to the presence of outliers.

CHAPTER IV

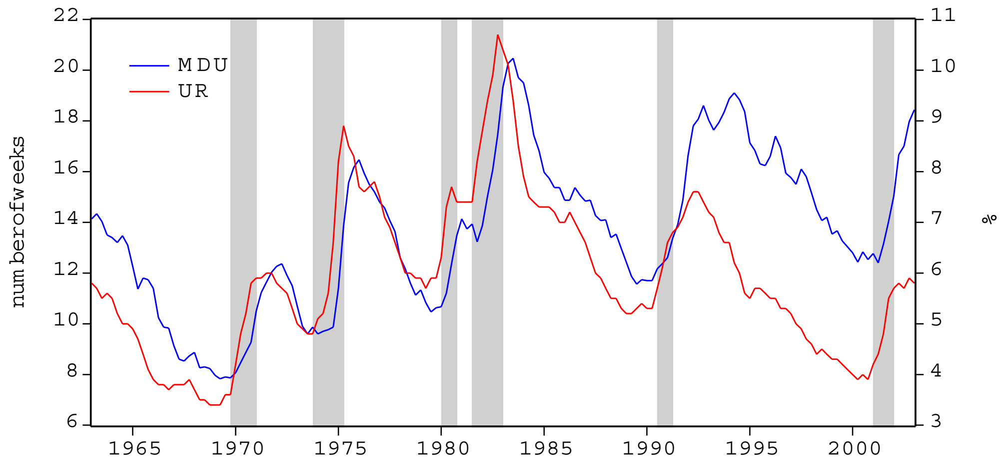
EFFECTS OF SECTORAL SHIFTS ON AVERAGE DURATION OF UNEMPLOYMENT

A. Introduction

The duration of unemployment spells has been highly correlated with the unemployment rate over business cycles, but this historical relationship changed in the early 1990s. The duration of unemployment did not follow the sharp decline in the unemployment rate during the 1990s. The duration has remained substantially longer than what the historical relation would have predicted, and consequently, the ratio of the unemployment duration to the unemployment rate has remained higher than the historical average. The high ratio is on the upward trend line that started after the end of the 1982 recession. The ratio shows a large increase in the early 1990s and remains high during the remaining 1990s.

Figure 4-1 shows the aggregate unemployment rate and mean duration of unemployment in progress over the sample period of 1963Q1 to 2003Q1 on two different scales. Shaded areas are recession periods defined by the business cycle dating committee of the National Bureau of Economic Research. Both the unemployment rate and duration show cyclical patterns with the duration lagging the unemployment rate by 1 to 2 quarters. The mean duration tracks the unemployment rate quite well up until the early 1990s, but their stable linear relationship has changed since then. The duration remained high during the recovery period of the 1991 recession, raising its ratio to the unemployment rate.

In this chapter, I investigate the effect of sectoral shifts of labor demand on the average duration of unemployment. The average duration published by the Bureau of



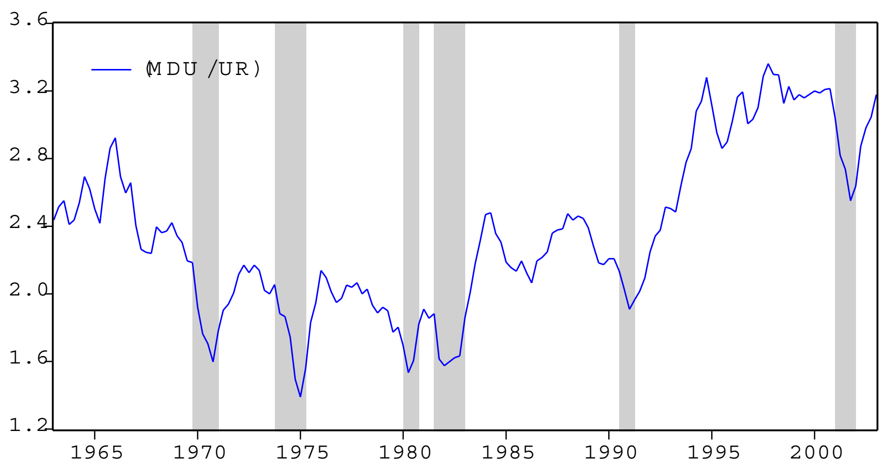


FIGURE 4-1 Relationship between Mean Duration and Unemployment Rate

MDU: mean duration of unemployment
UR: aggregate unemployment rate

Labor Statistics can be considered as a weighted average of unemployment duration of two types of workers: workers who are adversely affected by the sectoral shifts and workers who are unemployed due to cyclical changes in aggregate demand. Upon being laid off, the former will experience longer unemployment duration than the latter because of the time associated with switching sectors. Therefore, holding the aggregate unemployment rate constant, an increase in the proportion of unemployed workers due to sectoral shifts of labor demand will increase the average duration of unemployment in the economy. By allowing differential effects on the average duration of these two groups of workers, we investigate whether sectoral shifts of labor demand can help explain the unusual movement of unemployment duration in the 1990s.

An alternative hypothesis about unemployment duration is the increase in the pace of technical progress proposed by Baumol and Wolff (1998). They argue that faster technical progress increases the frequency at which workers must retrain to keep up with the technical progress. This will shift labor demand away from low-skilled workers whose retraining cost is relatively higher than that of high-skilled workers, making it harder for low-skilled worker to be reemployed. Consequently, the resulting increase in the share of low-skilled workers in the unemployment pool will raise the average unemployment duration. I also investigate this hypothesis in comparison with the sectoral shifts hypothesis.

I find that sectoral shifts of labor demand have a statistically greater effect on unemployment duration than cyclical fluctuations of aggregate demand. Their effect also lasts longer than cyclical factors. In addition, the effect of technical progress on unemployment duration is statistically significant. Both factors, sectoral shifts and technical progress, help explain the unusual movement of unemployment duration in the 1990s. However, there are remaining changes in the unemployment duration that these two factors cannot explain. When a control for the effects of demographic factors are considered, the effects of both factors depend on the choice of demographic variables, implying the significant explanatory power of these demographic variables.

The results from studies of unemployment duration, including this chapter, have important implications for welfare analysis and policy design for the economy. As Abraham and Shimer (2001) explain, "Welfare is lower when unemployment duration is longer, holding other things constant (p. 368)," when risk-averse workers are subject to uninsurable labor-income risk. Therefore, analysis of unemployment duration provides a better welfare assessment of an economy. As Solow (1970) and Blanchard and Diamond (1994) argue, for a given unemployment rate, differences in unemployment duration may imply different wage inflation pressure because workers who have been unemployed for a long period of time are more willing to endure wage cuts to be employed. Therefore, investigating unemployment duration is important for the analysis of wage inflation pressures. Understanding patterns of unemployment duration over time also has implications on the design of labor market policies. As Valletta (1998) argues, countercyclical unemployment duration calls for the use of a policy of unemployment insurance for reducing cyclical fluctuations in the unemployment rate, while the secular trend in the duration justifies the use of long-term labor market policies, such as subsidies, for retraining and relocating workers.

This chapter is organized as follows. Section B investigates the effect of sectoral shifts of labor demand on unemployment duration using quarterly data. Section C analyzes the effects of sectoral shifts and technical progress using two sets of demographic variables: the employment share of different age groups used in Baumol and Wolff (1998) and the increase in female workers' labor force attachment in Abraham and Shimer (2002). Section D presents the conclusion.

B. Sectoral Shifts of Labor Demand and Average Duration of Unemployment

The source of the upward trend in the unemployment duration relative to the unemployment rate and the cause of the changes in their historical relation since the 1990s have been investigated in many recent studies. Explanations suggested in these studies are changes in demographic and institutional factors such as the increase in the incidence of permanent job loss examined by Valletta (1998, 2005), the increase in female workers' labor force attachment discussed by Abraham and Shimer (2002) and Valletta (2005), the changes in non-participation rates of prime-age male workers proposed by Juhn et al. (2002), and the changes in unemployment benefits considered by LaLive et al. (2006) and Van Ours and Vodopivec (2006). Other explanations range from the technological changes in Baumol and Wolff (1998), adverse shifts in labor demand for low skilled workers in Juhn et al. (2002), an increase of within-group wage inequality in Mukoyama and Şahin (2005), a combination of more efficient search and improved sorting mechanisms in Mochado et al. (2006), and a fall in the rate of job turnover in Campbell and Duca (2007).

In this section we analyze the effect of sectoral shifts of labor demand across industries on the average duration of unemployment. Sectoral shifts of labor demand across industries can cause significant fluctuations in the unemployment rate that are not directly related to the fluctuations in aggregate demand. There are two channels through which sectoral shifts affect the aggregate unemployment rate: effect on the incidence of unemployment and effect on the duration of unemployment. It has been argued that the latter effect plays a more important role. For example, Loungani and Rogerson (1989) find that the correlation between the unemployment rate and the duration of movers is 0.65 while the correlation of the unemployment rate and the number of movers is only 0.26. In a more recent paper, Shin and Shin (2001) report that the unemployment duration of intersectoral movers is, on average, 1.4 times longer than the duration experienced by movers within sectors. They also find from the PSID data over the sample period of 1986-1996 a strong evidence of a significant contribution of sectoral shocks to unemployment fluctuations and the contributions are mainly due to a longer duration of intersectoral movers[1].

Since sectoral shifts of labor demand imply intersectoral moves for workers who lost their jobs and their unemployment duration is expected to be longer than those who are affected by temporal aggregate shocks, sectoral shifts of labor demand will increase the proportion of unemployed workers with a longer duration of unemployment. This is the hypothesis that Brainard and Cutler (1993) and Loungani and Trehan (1997) test in their studies. They use the dispersion of stock returns across industries, i.e., the weighted standard deviation of industry stock returns, as a measure of sectoral shifts, and examine the effect of sectoral shifts index on the unemployment rate of four different durations, 0 to 4 weeks, 5 to 14 weeks, and spells that are 27 weeks or longer. They find that sectoral shifts play a very significant role in the determination of the long-duration unemployment rate, but not the short-duration unemployment rate[2].

Loungani and Trehan (1997) argue that the increase in the measure of sectoral shifts can explain the high proportion of workers with long unemployment duration

[1] They find in the annual data that the correlation coefficient of the aggregate unemployment rate with the number of intersectoral movers is 0.07, while its correlation with the duration-based measure of intersectoral movers is 0.81.

[2] Brainard and Cutler (1993) find that the effect of sectoral shifts index on short-term unemployment (0-4 weeks) is statistically insignificant and it is highly significant for all durations exceeding four weeks. On the other hand, Lilien's (1982) dispersion measure of sectoral shifts from the distribution of employment growth rates is significant only in explaining short-term unemployment. They interpret this as evidence that their measure from the stock returns is the proper measure for a reallocation due to sectoral shifts and Lilien's measure reflects aggregate changes.

since 1993, but they do not examine the effect of sectoral shifts on the average unemployment duration of all unemployed workers, nor on the average unemployment duration in each group of different duration. It is likely that sectoral shifts affect not only the proportion of unemployed workers in each group, but also their average unemployment duration. Our analysis of the effect of sectoral shifts on average unemployment duration will include both effects.

These studies use the dispersion of the rate of stock return or the dispersion of employment growth rates across industries as the measure of sectoral shifts. However, Byun and Hwang (2006) demonstrate in a recent paper that dispersion measure alone cannot adequately capture the effect of sectoral shifts when the distribution of sectoral shocks is asymmetric, and propose to use the skewness as well as the dispersion of the distribution to measure the sectoral shifts. The sectoral shifts hypothesis is generally supported in most empirical studies which use Lilien's (1982) dispersion measure, and the support is even stronger when both the dispersion and the skewness are used as measures of sectoral shifts. Inclusion of skewness also makes the effect of sectoral shifts significant in the Abraham and Katz (1984) model which rejects the hypothesis when only the dispersion is used as the measure of sectoral shifts.

Lilien constructs a measure of the natural rate of unemployment, which is a measure of unemployment induced by sectoral shifts, holding the effects of monetary and other variables constant. Lilien shows that the natural rates can explain "over half" of the variation of the unemployment rate, and the explanatory power of natural rates increases to 65% when skewness is also used as a measure of sectoral shifts. The explanatory power is a little lower in the Abraham and Katz model, but it is still in the range of 46% to 50%. We use the natural rates of unemployment as a measure of sectoral shifts in our analysis of the effects of sectoral shifts on the average duration of unemployment, while Brainard and Cutler (1993) and Loungani and Trehan (1997) use their dispersion measure as one of the explanatory variables.

The natural rate of unemployment as a measure of sectoral shifts of labor demand is related to other measures that have been used in the literature. Baumol and Wolff (1998) emphasize the shift in labor demand from low-skilled workers to high-skilled workers as a result of technical progress and analyze the effect of measures of technical progress on the average duration of unemployment. Such shifts of labor demand will be partly captured by Lilien's measure unless shifts from low-skilled to high-skilled workers are limited within the industry. Valletta (1998, 2005) finds the increase in incidence of permanent job loss as the major source for the upward trend in unemployment duration and changes in the historical relationship between unemployment duration and unemployment rate[3]. He also finds that the increasing incidence of permanent job loss plays a more significant role than the increase in female workers' labor force attachment. Incidence of permanent job loss may be caused by either aggregate shocks or sectoral shocks, but as argued among many including Orr (1997) and Glasmeier and Salant (2006), permanent job loss represents a long-term trend in the composition of labor demand, such as persistent industrial restructuring on the labor force. In this sense, permanent job loss in Valletta (2005) represents structural change in the labor market of an economy, and sectoral shocks are more likely the source of permanent job loss as the aggregate cyclical shocks are usually temporary. Therefore, the major part of Valletta's measure is expected to be captured by Lilien's measure of sectoral shifts.

Mukoyama and Şahin (2005) show that demographic and institutional changes can explain only a small fraction of the observed increase in the average duration of

[3]Valletta (2005) analyzes the changes in the shares of unemployment incidence by reason, and the effects of the unemployment rate, time trend, and seasonal dummies on expected completed durations of various demographic groups and groups with different reasons for unemployment incidence.

unemployment. Citing the well known result in job search models that an increase in the dispersion of wage distribution can have a large effect on the job search length, they argue that the increase in the wage dispersion in recent years can be a major source for the increase in unemployment duration. They show by using a calibrated job search model that more than 70% of the increase in the duration of unemployment can be explained by an increase in the dispersion of wage distribution. They cite the recent increase in embodied technological progress (Violante (2002)) as the source of the increase in wage dispersion. Since sectoral shifts of labor demand will affect the distribution of wage rates across sectors, Lilien's dispersion measure of sectoral shifts can also explain the increase wage dispersion and hence, the increase in average duration of unemployment.

The natural rate of unemployment is estimated from an unemployment rate equation

$$UR_t = \alpha_0 + \alpha_1 t + \sum_{s=0}^{q} \beta_s \sigma_{t-s} + \sum_{s=0}^{q} \lambda_s sk_{t-s} + \sum_{s=0}^{p} \gamma_s DMR_{t-s} + \delta\, UR_{t-1} + \eta_t \qquad (4.1)$$
$$\eta_t = \sum_{s=1}^{r} \rho_s \eta_{t-s}$$

where UR_t is the aggregate unemployment rate, σ_t and sk_t are the estimates of dispersion and skewness of the distribution of sectoral shocks, and DMR_t is the estimate of unexpected monetary shocks. Lilien (1982) includes the lagged unemployment rate ($\delta \neq 0$) and assumes no serial correlation ($\rho_s = 0$), while Abraham and Katz (1984) do not include the lagged unemployment rate ($\delta = 0$) and assume a serial correlation ($\rho_s \neq 0$)[4]. The natural rate of unemployment is computed as the predicted value under the assumption of zero values of monetary shocks DMR_t for all periods.

[4]Abraham and Katz (1984) detrend the unemployment rate first so that α_1 is predetermined. However, the results are very similar regardless of pre-detrending.

The monetary shock DMR_t is measured by the six variable VAR model used in Christiano et al. (1996). It measures the underlying shocks to the monetary policy variable (nonborrowed reserves) recovered from the disturbances of their benchmark VAR model of output, price level, commodity prices, nonborrowed reserves, the federal funds rate and total reserves. The underlying assumption is that monetary authority determines the level of nonborrowed reserves from current information about output and price level, and that the policy shocks have no contemporaneous effect on the variables included in the information set. Anticipated changes in monetary policy, DMF_t, is measured by the fitted values of the monetary policy variable from the VAR model.

Dispersion and skewness of sectoral shocks are estimated from a purging equation which eliminates the monetary and non-monetary effects on the employment growth rate

$$h_{tj} = \alpha_{j0} + \alpha_{j1} g_t + \alpha_{j2} t + \sum_{s=0}^{n} b_{js}^{r} \triangle DMR_{t-s} + \sum_{s=0}^{n} b_{js}^{f} \triangle DMF_{t-s} + \epsilon_{tj} \tag{4.2}$$

$$\epsilon_{tj} = \rho_j \epsilon_{t-1,j} + u_{tj}$$

where h_{tj} is the net hiring rate of industry j in period t and g_t represents the unobservable aggregate nonmonetary shocks. Two alternative estimators of g_t are considered. The first estimator is the estimator proposed by Abraham and Katz. Let $\hat{e}_{tj}$ be the OLS residuals in (4.2) for each industry subject to $\alpha_{j1} = 0$. The Abraham-Katz estimator[5] of g_t is a weighted average of $\hat{e}_{tj}$

$$\hat{g}_{ak,t} = \sum_{j=1}^{n} w_{tj} \hat{e}_{tj} \tag{4.3}$$

[5] This estimator has been criticized by Gallipoli and Pelloni (2001, 2005) on the ground that it is an *ad hoc* estimator and tends to “over-purge” the effects of aggregate non-monetary shocks.

where w_{tj} is the employment share of industry j in period t. An alternative estimator of g_t is the element of the first principal component of the least squares residuals $\hat{E} = (\hat{e}_1, \hat{e}_2, \cdots, \hat{e}_n)$, $\hat{e}_j = (\hat{e}_{1j}, \hat{e}_{2j}, \cdots, \hat{e}_{Tj})'$, $j = 1, 2, \cdots, n$:

$$\hat{g}_{pc,t} = \sum_{j=1}^{n} \hat{\gamma}_j \hat{e}_{tj} \tag{4.4}$$

where $\hat{\gamma}_j$ is the j^{th} element of the normalized characteristic vector of $\hat{E}'\hat{E}$ corresponding to its largest characteristic root. It is shown in Byun and Hwang (2006) that this principal component estimator is a solution to the least squares estimator of g_t that minimizes the sum of the squared residuals.

Dispersion and skewness of the distribution of sectoral shocks are estimated from the normalized residual terms of the purging equation. Let $\hat{\epsilon}_{tj}$ be the GLS estimator of ϵ_{tj} after g_t is substituted by $\hat{g}_t$ if $\alpha_{j1} \neq 0$. The dispersion measure is computed from the normalized residuals by

$$\hat{\sigma}_t^2 = \sum_{j=1}^{n} w_{tj} \left(\frac{\hat{\epsilon}_{tj}}{\hat{\theta}_{\epsilon j}} \right)^2, \qquad \hat{\theta}_{\epsilon j} = \left(\frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_{tj}^2 \right)^{\frac{1}{2}}$$

where $\hat{\theta}_{\epsilon j}$ is an estimate of the scale parameter for industry j that does not change over time. The measure of the third moment to compute the skewness is defined in a similar way. Allowing for scale differences in the third moment across industries, the time-varying component of the third moment is estimated by

$$\hat{\mu}_{3t} = \sum_{j=1}^{n} w_{tj} \left(\frac{\hat{\epsilon}_{tj}}{\hat{\tau}_j} \right)^3, \qquad \hat{\tau}_{tj} = \left(\frac{1}{T} \sum_{t=1}^{T} |\hat{\epsilon}_{tj}|^3 \right)^{\frac{1}{3}}$$

and the skewness measure is then estimated by $hatsk_t = \hat{\mu}_{3t}/\hat{\sigma}_t^3$. The scale parameter is estimated by using the absolute values of estimated residuals to avoid the cancellation of positive and negative residuals.

Variables used to construct measures of sectoral shifts are drawn from the Bureau of Labor Statistics (BLS) and the Federal Reserve Economic Data (FRED). Seasonally adjusted numbers of employee series are taken from the Current Employment Statistics (CES) survey of nonfarm payroll records of the BLS. This chapter uses a 30-industry classification based on the 1987 SICS code with detailed classification of the manufacturing sector. Seasonally adjusted unemployment rate of the civilian noninstitutional population is drawn from the Current Population Survey (CPS) of the BLS. Real GDP, the GDP deflator, the consumer price index and monetary policy variables used to construct unanticipated monetary policy shocks are from the FRED.

For the empirical analysis of the effect of sectoral shifts, the natural logarithm of mean duration of unemployment ($\ln(MDU_t)$) is specified as

$$\ln(MDU_t) = \alpha + \beta_1 NUR_t + \beta_2 NUR_{t-1} + \theta_1 CUR_t + \theta_2 CUR_{t-1} + \sum_i \gamma_i DEM_{ti} + \eta_t \tag{4.5}$$

where NUR_t and NUR_{t-1} are the current and lagged natural rate of unemployment, and CUR_t and CUR_{t-1} are the cyclical component of the unemployment rate ($CUR_t = UR_t - NUR_t$). DEM_{ti} denotes a set of demographic variables. As will be shown in the next section, this equation is equivalent to the best fitting specification of Baumol and Wolff (1998) except that I use the natural rate as a measure of shifts of labor demand. The natural logarithm of MDU_t is used as the dependent variable because of the problems[6] associated with measuring unemployment duration in-progress. It is

[6] As an estimate of unemployment duration, the duration-in-progress data series has an upward bias because individuals with longer unemployment spells are more likely to be unemployed at the time of survey and thus more likely to be included in the computation of the average duration. Moreover, this series will underrepresent short durations of unemployment because individuals who are unemployed only between surveys will not be included. On the other hand, this series also has a downward bias because the length of duration-in-progress is right-censored at the time of the survey.

also consistent with the job search framework with exponentially distributed hazard rate out of unemployment. I use the demographic variables in Baumol-Wolff study: the percentage of total employees in age groups 16-19, 20-24 and the percentage of total employees who are men in the age group 25-54. They argue that an increase in the share of young workers may reduce average unemployment duration due to the transitory nature of teenage employment. The share of prime-aged workers may increase the duration of unemployment because of their strong attachment to the labor force.

The estimation equation (4.5) allows differential effects on the mean duration of the workers who lost their jobs due to sectoral shifts of labor demand and the workers who lost their jobs due to cyclical changes in labor demand. Note that, if both groups of unemployed workers have an identical effect on the mean duration (i.e., $\beta_i = \theta_i$), then the mean duration will be a linear function of only the aggregate unemployment rates and demographic variables. This interpretation is particularly useful in capturing the results of the micro data analysis which show that intersectoral movers have longer unemployment duration.

Equation (4.5) is estimated by using quarterly data over the sample period 1963Q1 - 2003Q1, and the results are presented in Table 4-1. The third column in Table 4-1 shows the results with restrictions that the natural rate and cyclical rate of unemployment have the same effect ($\beta_i = \theta_i$) on the MDU, and the last column includes only the demographic variables as explanatory variables. All estimated coefficients are highly significant, except for the coefficient Emp(16-19) in the second and third columns and the coefficient of Emp(25-54) in the last column.

The natural rate and cyclical rate of unemployment have a negative effect on the mean duration in the short run, but they have a positive long run effect. An increase in the natural or cyclical unemployment rate implies an increased inflow of

TABLE 4-1 Estimation of ln(MDU): Sectoral Shifts versus Cyclical Fluctuations (1963Q1 ∼ 2003Q1)

Variables	Estimated Coefficients (1)	(2)	(3)
C	4.648	4.190	1.923
	(0.000)	(0.000)	(0.000)
NUR	-0.195	-0.122	
	(0.001)	(0.000)	
NUR_{-1}	0.348	0.264	
	(0.000)	(0.000)	
CUR	-0.060	-0.122	
	(0.024)	(0.000)	
CUR_{-1}	0.187	0.264	
	(0.000)	(0.000)	
Emp(16-19)	0.004	-0.004	-0.226
	(0.769)	(0.764)	(0.000)
Emp(20-24)	-0.113	-0.100	0.118
	(0.000)	(0.000)	(0.000)
Emp(25-54)	-0.042	-0.032	0.019
	(0.000)	(0.000)	(0.092)
$\overline{R}^2$	0.904	0.895	0.599
$log\ L$	196.25	188.08	81.18

Notes: Numbers in parentheses are the p-values of coefficient estimates.

newly unemployed workers. As they are initially counted as workers with short term duration, the average duration falls. As expected from the micro data analysis, the natural rate of unemployment has a greater long run marginal effect than the cyclical rate of unemployment. Evaluated at the sample mean of 13.60 weeks for the mean duration, the natural rate increases the mean duration by slightly more than two weeks while the cyclical rate increases the mean duration by about 1.7 weeks in the long run. Therefore, a change in the composition of unemployment from cyclical to natural, holding the total unemployment rate constant, increases the mean duration by about 0.35 weeks. When the equality of the effects of natural and cyclical rates of unemployment is imposed, a one percent increase in the unemployment rate (either natural or cyclical) increases the mean duration by 1.9 weeks in the long run. These results are summarized in Table 4-2.

Table 4-3 presents the tests of the hypotheses about the differential effects of the natural and cyclical rate of unemployment. The null hypotheses H_1 and H_2 test whether NUR and CUR have the same short term effect in each period, and H_3 is a joint test of their equality in both periods. The null hypothesis H_4 tests the equality of long term effects of NUR and CUR. All null hypotheses of equality of short term effects are strongly rejected in both equations. The equality of long term effects is rejected at a 10% significance level, but not rejected at a 5% significance level. This indicates that although the natural and cyclical rate of unemployment have significantly different effects in the current and lagged period, the difference in the sum of the effect over two periods becomes less significant.

To examine how well each specification in Table 4-1 traces the mean duration of unemployment, we plot the in-sample fitted values in Figure 4-2. Demographic variables alone explain the general movements of mean duration surprisingly well. Fitted values of equation (4.5) with or without restriction $\beta_i = \theta_i$ trace the actual

TABLE 4-2 Short-Term and Long-Term Marginal Effects on *MDU*: Sectoral Shifts versus Cyclical Fluctuations

(1963Q1 ∼ 2003Q1)

Term	Variables	Marginal Effect	
Short Term	NUR	-2.651	
		(0.000)	
	NUR_{-1}	4.737	
		(0.000)	
	CUR	-0.813	
		(0.024)	
	CUR_{-1}	2.547	
		(0.000)	
	UR		-1.653
			(0.000)
	UR_{-1}		3.594
			(0.000)
Long Term	NUR	2.087	
		(0.000)	
	CUR	1.733	
		(0.000)	
	UR		1.941
			(0.000)

Notes: Numbers in parentheses are the p-values of coefficient estimates. Coefficients are converted into number of weeks using a sample mean of 13.60 weeks for the mean duration.

TABLE 4-3 Test Statistics of Hypotheses: Sectoral Shifts versus Cyclical Fluctuations (1963Q1 $\sim$ 2003Q1)

Null Hypothesis	Statistics
H_1 : Identical Effects of NUR and CUR	12.585 (0.001)
H_2 : Identical Effects of NUR_{-1} and CUR_{-1}	16.024 (0.000)
H_3 : Joint Test of H_1 and H_2	8.175 (0.000)
H_4 : Identical Long Term Effects of NUR and CUR	3.376 (0.068)

Notes: Numbers are statistics from hypothesis testing with p-values in parenthesis.

MDU very closely, almost completely filling the gap that is not explained by the demographic factors. There is practically no difference between the fitted values of column (1) and (2) for all periods except for a slight difference in the late 1990s. This is due to a less significant difference in the long run effects of the natural and the cyclical rate of unemployment.

C. Technical Progress and Female Workers' Labor Force Attachment

In this section I consider Baumol and Wolff's (1998) technical progress hypothesis and Abraham and Shimer's (2002) hypothesis of changes in female workers' labor force attachment as a source of the changes in the relation between the average duration of unemployment and the unemployment rate. Because of the limitation of data

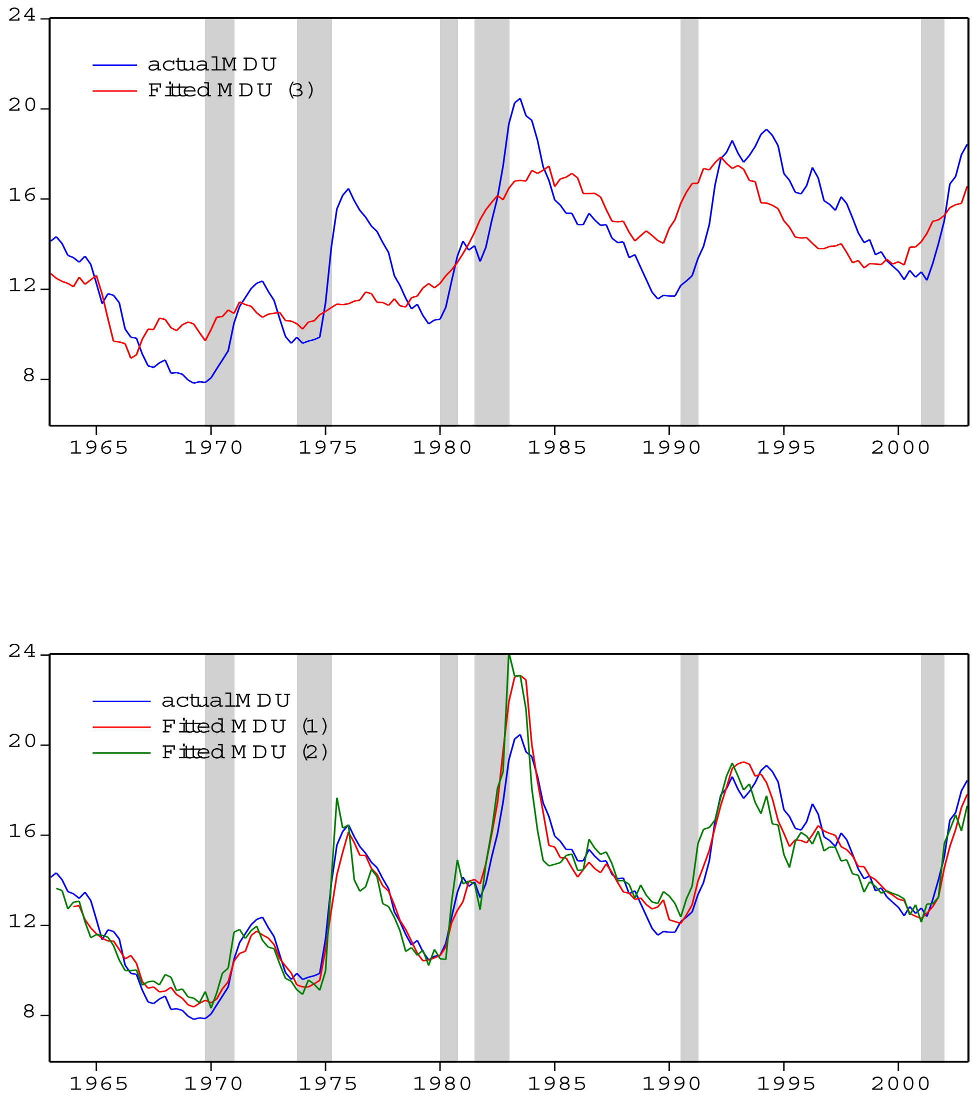


FIGURE 4-2 Comparison of Fitted Mean Durations of Unemployment

Fitted MDU (1): including all variables
Fitted MDU (2): including all variables with restriction $\beta_i = \theta_i$
Fitted MDU (3): including only demographic variables

availability these two hypotheses are analyzed with annual data, and the results are compared with the annual version of the sectoral shifts hypothesis that is discussed in the previous section.

Baumol and Wolff (1998) argue that, in addition to the changes in demographic and institutional factors, the pace of technical progress has a significant effect on the natural rate of unemployment and the average duration of unemployment. An increase in the pace of innovation will require a more frequent retraining of workers. Since the cost of retraining is relatively higher for less-skilled workers, the demand for labor shifts from less-skilled workers to more-educated workers. Less-skilled workers will be more likely to lose their job and it will take them longer than before to find another one. The increase in the rate of technology change thus raises the share of jobless persons whose duration of unemployment is relatively long, and hence, it increases the average duration of unemployment.

Since the pace of innovation is not directly observable, they use five alternative indices to measure the technological progress: the growth rate of total factor productivity ($GTFP$), the ratio of research and development (R&D) expenditures to gross domestic product (GDP), the number of full-time equivalent scientists and engineers engaged in R&D per 1,000 employees, investment in new equipment and machinery per full-time equivalent employee ($FTEE$), and investment in office, computing, and accounting equipment (OCA) per $FTEE$. They regress the logarithm of average duration of unemployment on technological, institutional and demographic variables by using the aggregate time-series data for the U.S., covering the period 1950-1995. Their results show significant effects of technological variables ($GTFP$ and OCA) and demographic variables on the average duration, but the institutional factors are not statistically significant. I will use the $GTFP$ and OCA as measures of technical progress and their demographic variables that are already used in the previous section.

Abraham and Shimer (2001, 2002) argue that an increase in labor force attachment of female workers is a major factor[7] for the rise in unemployment duration relative to the unemployment rate in the 1980s and 1990s. This conclusion is based on the analysis of the effects of changes in transition rates of workers across labor market states (employment, unemployment, and not-in-the-labor-force). They conclude that declining exit rates of employed female workers from the labor force plays a quantitatively important role in explaining both the decrease in the unemployment rate and the increase in the unemployment duration of female workers.

Abraham and Shimer use the Markov chain model of the distribution of workers across three labor market states with transition rate λ_{ij} from state i to state j. Let e, u and n denote the fraction of the population that is employed, unemployed and not in the labor force, respectively. The steady-state distribution of workers is

$$e = k\left(\lambda_{nu}\lambda_{ue} + \lambda_{un}\lambda_{ne} + \lambda_{ue}\lambda_{ne}\right)$$

$$u = k\left(\lambda_{ne}\lambda_{eu} + \lambda_{en}\lambda_{nu} + \lambda_{eu}\lambda_{nu}\right)$$

$$n = k\left(\lambda_{ue}\lambda_{en} + \lambda_{eu}\lambda_{un} + \lambda_{en}\lambda_{un}\right)$$

where k is a proportionality constant that makes $e+u+n = 1$. They estimate the transition rates from the CPS data, and compute the "implied steady-state unemployment rate" by $u/(e+u)$ from the steady-state distribution of workers. This unemployment rate tracks the actual unemployment rate of female workers very closely. This im-

[7]Abraham and Shimer also found two other sources for the increase in unemployment duration relative to the unemployment rate: an increase of about half a week in mean unemployment duration due to the 1994 Current Population Survey redesign, another half-week increase over the 1980-2000 period due to the aging of the baby boom generation. But these two sources did not play a major role in the increased unemployment duration.

plies that the Markov chain model with estimated transition rates is suitable for the analysis of the unemployment rate and unemployment duration of female workers.

The implied steady-state unemployment rates reflect changes in all transition rates. To identify the transition rates that explain the secular variation in aggregate and the short-term unemployment rates of female workers, they conduct three experiments, allowing for time-variation in transition rates only between (i) employment and unemployment (λ_{eu} and λ_{ue}), (ii) unemployment and not in the labor force (λ_{un} and λ_{nu}), and (iii) employment and not in the labor force (λ_{en} and λ_{ne}), holding other transition rates constant at their 1979 levels. Comparing the resulting time series of unemployment rates with the all-flow unemployment rates (the implied unemployment rate when all transition rates are time-varying), they find that changes in λ_{eu} and λ_{ue} are important factors in short-run variations of the unemployment rate, but changes in λ_{un} and λ_{nu} do not play a significant role. They find that changes in transition rates λ_{en} and λ_{ne}, the exit rate λ_{en} in particular, contribute significantly to the secular decrease in the unemployment rate, the short-term unemployment rate[8] in particular, of female workers. They interpret the changes in λ_{en} and λ_{ne} as the changes in female workers' labor force attachment.

Abraham and Shimer claim that the increase in labor force attachment of female workers, in particular the declining exit rate λ_{en} of employed female workers from the labor force, can also explain the increase in their unemployment duration. However, they do not analyze how well the Markov chain model with their estimated transition rates can explain the changes in unemployment duration of female workers, nor the effects of changes in labor force attachment of female workers on their unemployment

[8] Abraham and Shimer compute the short-term unemployment rate by $(\lambda_{ue} + \lambda_{un})(u/(e+u))$ because, in the steady-state, the fraction of workers exiting the unemployment pool in each period equals the fraction of workers who are in their first period of unemployment.

duration. They simply note that the increase in labor force attachment may also raise unemployment duration by reducing the pool of workers who chronically transition from unemployment to not-in-the-labor-force. They also allude to the observation of a sharp drop in the short-term unemployment rate and a sustained high level in very long-term unemployment rates of female workers.

To examine the implication of the Markov chain model of Abraham and Shimer on the average unemployment duration of female workers, we replicate their experimental procedure for two cases. In the first case, all transitions rates are allowed to be time-variant to determine how well the Markov chain model explains the average unemployment duration. In the second case, to analyze the effects of the changes in labor force attachment, only the transition rates that reflect the changes in the labor force attachment are allowed to be time-variant, holding other transition rates constant at their 1979 level. For the second case, in addition to the transition rates λ_{en} and λ_{ne} that Abraham and Shimer used, we also include the exit rate of unemployed workers from the labor force (λ_{un}) for two reasons. A stronger labor force attachment tends to make workers stay unemployed rather than dropping out of the labor force. Furthermore, the average unemployment duration in a steady state depends only on the exit rates (λ_{un} and λ_{ue}) from unemployment, and hence, the average unemployment duration stays constant in any experiment if both λ_{un} and λ_{ue} are held constant. Since the Markov chain is memoryless, the probability that a worker will end the unemployment spell in n periods is $\lambda_{uu}^{n-1}(1-\lambda_{uu})$, where $\lambda_{uu} = (1-\lambda_{ue}-\lambda_{un}$. Therefore, the mean duration of unemployment (MDU) in every steady state is given by

$$MDU = \sum_{n=1}^{\infty} n\lambda_{uu}^{n-1}(1-\lambda_{uu}) = \frac{1}{1-\lambda_{uu}}$$

Figure 4-3 shows the unemployment rate and short-term unemployment rate of female workers over the period of 1976-2000, the sample period that Abraham and Shimer used in their study. Each panel in Figure 4-3 shows the experimental results computed from the Markov chain model for three cases: (i) all transition rates are time variant (all-flows), (ii) only λ_{en} and λ_{ne} are time variant, the Abraham-Shimer case of changes in labor force attachment, and (iii) only λ_{en}, λ_{ne} and λ_{un} are time variant, an extended measure of labor force attachment.

The implied unemployment rate with all time-variant transition rates tracks the actual unemployment rate very closely. It also tracks the fluctuations of the short-term unemployment rate quite well with a relatively constant difference in levels. There is not much difference between the case (ii) and (iii). Both series reflecting the changes in labor force attachment capture the secular decline in actual unemployment rates very well, though they explain the secular decline in short-term rates better. Abraham and Shimer show that over half of the trend decline in the actual short-term unemployment rate is explained by the changes in labor force attachment.

The Markov chain model does not explain the unemployment duration as well as it explains the unemployment rate. The "all-flows" implied unemployment duration in the top panel of Figure 4-4 matches the fluctuation of the actual unemployment duration relatively well before 1990, but there is a wider gap between the actual and implied unemployment duration in the 1990s. As noted earlier, the mean duration of unemployment is constant when only the Abraham and Shimer's measure of labor force attachment of female workers (λ_{en} and λ_{ne}) are time varying. For the extended measure of attachment (λ_{en}, λ_{ne} and λ_{un}), the implied unemployment duration[9] tends to reflect the direction of changes in the actual duration, but the magnitude seems to be too small to explain the fluctuation of the mean duration of unemployment.

[9]The implied unemployment duration is computed by $m/(1-\lambda_{uu})$, where $m = 4.5$ is the number of weeks in each period.

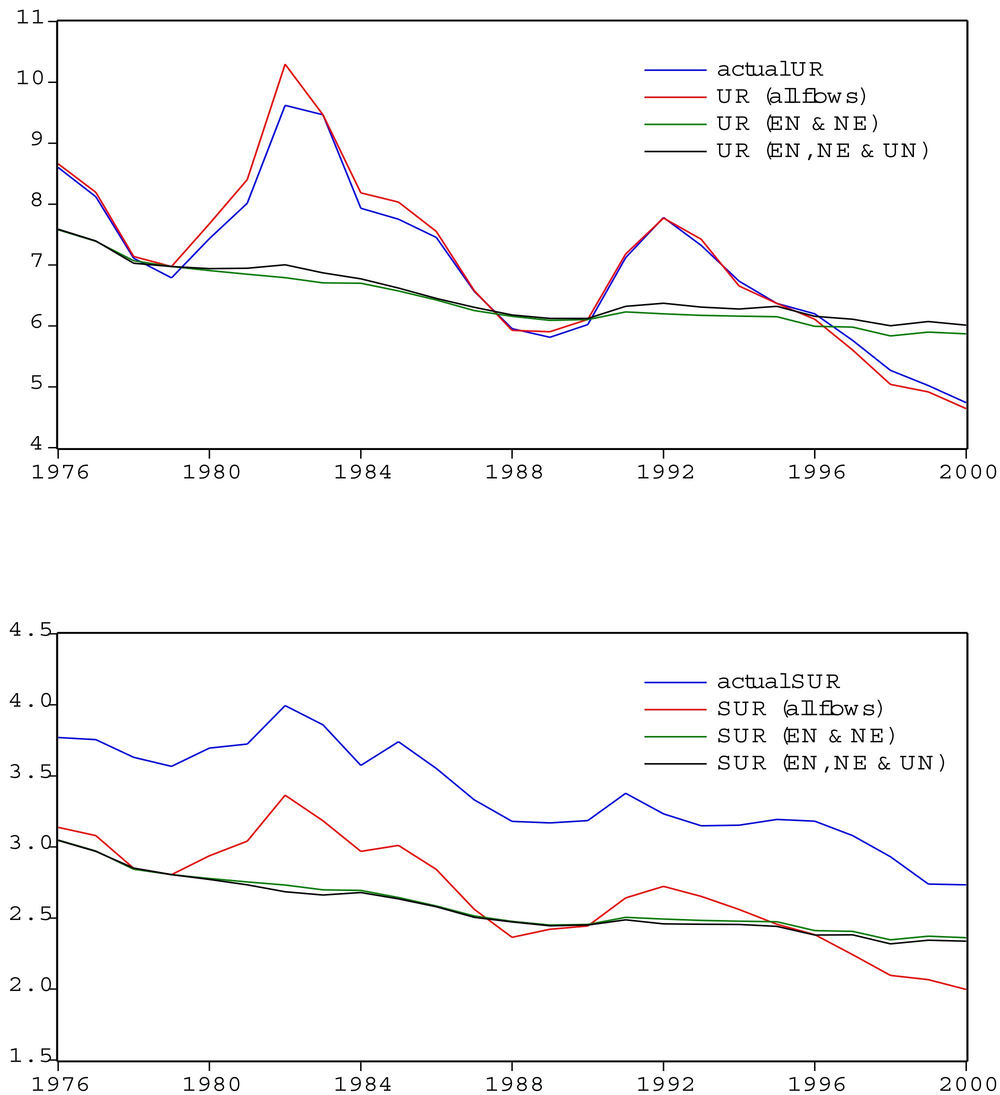


FIGURE 4-3 Implied Aggregate and Short-Term Unemployment Rate from Abraham and Shimer's Markov Chain Model of Female Workers

UR, SUR: implied unemployment rate and short-term unemployment rate, respectively.
(all flows) : All transition rates are time-varying.
(EN & NE) : λ_{en} and λ_{ne} are time-varying.
(EN, NE & UN) : λ_{en}, λ_{ne} and λ_{un} are time-varying.

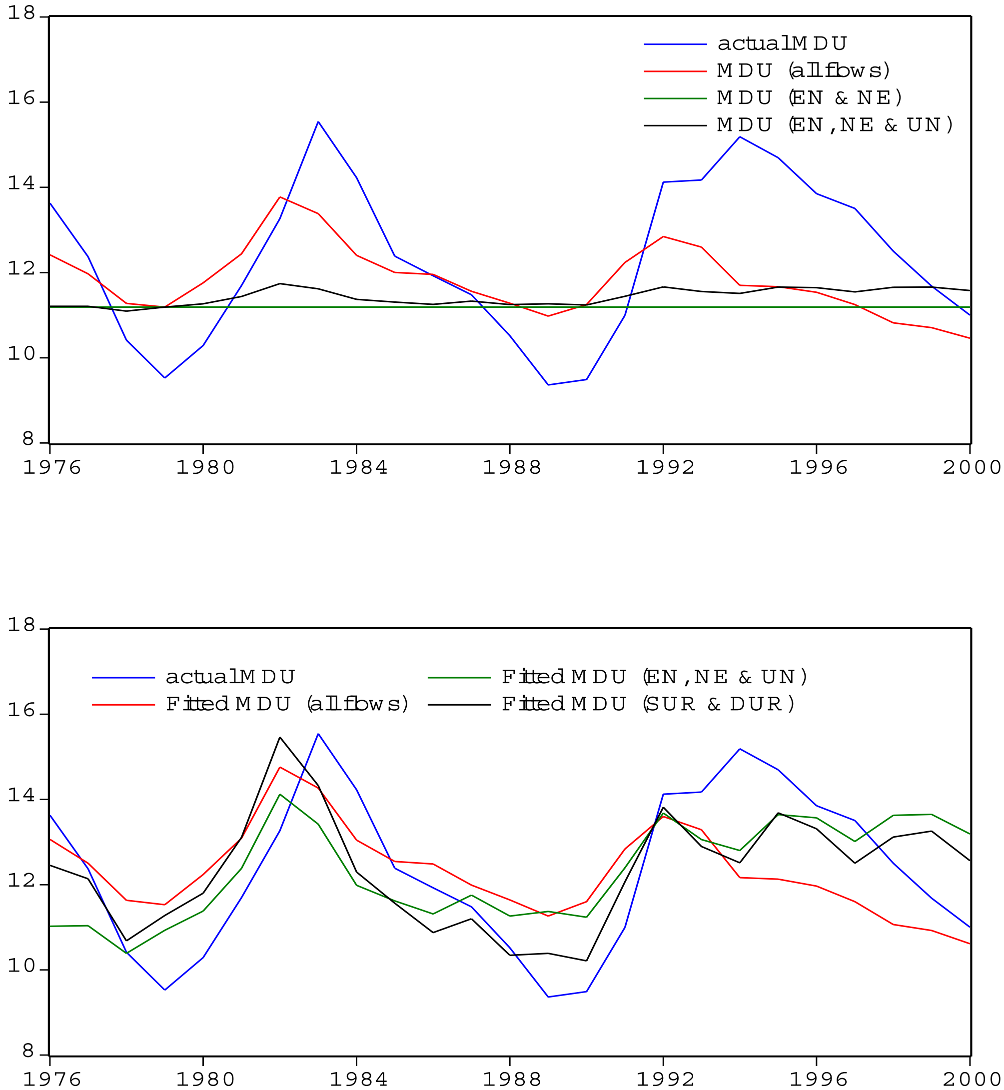


FIGURE 4-4 Implied Mean Duration of Unemployment from Abraham and Shimer's Markov Chain Model of Female Workers

Fitted values from a regression of actual MDU on:
Fitted MDU(all flows) : on implied MDU(all flows)
Fitted MDU(EN, NE & UN) : on implied MDU(EN, NE & UN)
Fitted MDU(SUR & DUR) : on implied SUR(EN, NE & UN) and MDU(EN, NE & UN)

However, the implied duration of "all-flows" or of the extended attachment measure explains the actual mean duration quite well in the least-squares sense. The bottom panel in Figure 4-4 shows the fitted values from the regression of actual MDU (a) on the implied MDU(all-flows), (b) on the implied $MDU(\lambda_{en}, \lambda_{ne}, \lambda_{un})$, and (c) on both the implied short-term unemployment rate $SUR(\lambda_{en}, \lambda_{ne}, \lambda_{un})$ and the implied $MDU(\lambda_{en}, \lambda_{ne}, \lambda_{un})$. All fitted values trace the actual values quite well. In particular, the implied $SUR(\lambda_{en}, \lambda_{ne}, \lambda_{un})$ and the implied $MDU(\lambda_{en}, \lambda_{ne}, \lambda_{un})$ together explain the mean unemployment duration of female workers quite well. Therefore, in our analysis of annual data below, changes in the labor force attachment of female workers are measured by the short-term unemployment rate and the mean duration of unemployment when the transition rates, $(\lambda_{en}, \lambda_{ne}, \lambda_{un})$, are time varying while other transition rates being held constant. The transition rates between labor market states are constructed from matched basic CPS, which is available only from 1976[10].

I use a modified version of the Baumol-Wolff model that they find best fit in their study[11]:

$$\ln(MDU_t) = \alpha + \delta_1 GTFP_t + \delta_2 OCA_t + \theta_1 UR_t + \theta_2 UR_{t-1} + \sum_i \gamma_i DEM_{ti} + \eta_t \tag{4.6}$$

where $GTFP_t$ and OCA_t are their measures of the shift in labor demand from less-skilled to highly-skilled workers. They include the aggregate unemployment rate

[10]We are grateful to Robert Shimer who generously provided for the estimates of transition rates.

[11]This is equation (6) in their Table 5, which has the best fit among other specifications. In addition to demographic variables, Baumol and Wolff (1998) control for the effect of institutional factors such as the percentage of labor force covered by union and minimum wage that may affect unemployment duration. They find that both factors are insignificant when they are used with the pace of technical progress variable.

UR_{t-i} to represent the overall labor market condition: a higher unemployment rate lowers the probability of finding a job and prolongs the unemployment duration. Their model includes only the current unemployment rate UR_t, but our study includes the lagged unemployment rate UR_{t-1} to capture the carry-over effect from the previous period.

The five year running average of the growth rate of total factor productivity ($GTFP_t$) is computed from a Cobb-Douglas production function of gross domestic product as a function of full-time equivalent employee (FTEE), private fixed nonresidential asset and average income share of labor. The investment in office, computing and accounting equipment (OCA_t) per 100 FTEE includes the investment in computers and peripheral equipment, software, communication equipment, photocopy and office and accounting equipment. Being complementary to the total factor productivity, OCA captures the new technology embodied in information processing capital, which plays an important role in the propagation of new technology. The FTEE variable is drawn from the National Income and Product tables of the Bureau of Economic Analysis (BEA).

Equation (4.5) that I use to analyze the effect of sectoral shifts of labor demand using quarterly data can be rewritten in a form that is comparable to (4.6):

$$\ln(MDU_t) = \alpha + \beta_1 NUR_t + \beta_2 NUR_t + \theta_1 CUR_t + \theta_2 CUR_{t-1} + \sum_i \gamma_i DEM_{ti} + \eta_t \tag{4.7}$$

$$= \alpha + (\beta_1 - \theta_1) NUR_t + (\beta_2 - \theta_2) NUR_t + \theta_1 UR_t + \theta_2 UR_{t-1}$$

$$+ \sum_i \gamma_i DEM_{ti} + \eta_t$$

Thus, Baumol and Wolff measure the shift of labor demand across skill levels by $GTFP_t$ and OCA_t, while our approach measures the shifts of labor demand across industries by the current and lagged natural rate of unemployment.

Regression results of (4.6) and (4.7) are presented in Table 4-4 for two sets of demographic variables: Baumol-Wolff and Abraham-Shimer. Table 4-5 shows the marginal effects of the major variables of interest on the mean duration of unemployment. Both the $GTFP$ and the OCA of the Baumol and Wolff model in column (1) are highly significant. Table 4-5 shows that a one percent increase in the $GTFP$ raises the mean duration of unemployment by about one-tenth of a week, and a \$1000 increase in the OCA per worker increases the mean duration by about eight-tenths of a week.

Coefficients of NUR_t and NUR_{t-1} in column (2) are statistically insignificant, which implies that the difference between the marginal effects of the natural rate and cyclical rate in each period are statistically insignificant. A joint test of the equalities also indicates insignificant difference with p-values of 0.110. However, equality of the long-run effects of the natural rate and cyclical rate[12] is rejected with p-value of 0.048. Table 4-5 shows that a one percent increase in the NUR and the CUR, respectively, increases the MDU by almost three weeks and a little more than two weeks in the long run. Column (3) in Table 4-4 indicates that the Baumol and Wolff's demographic variables alone have a high explanatory power, explaining almost 60% of the variations in $ln(MDU)$.

The marginal effects of technical progress variables and current sectoral shifts variables are sensitive to the choice of demographic variables. For example, the marginal effect of the OCA becomes insignificant in equation (4) when Abraham and Shimer's demographic variables are used. Since equation (1) and (2) in Table 4-4 are different from (4) and (5) in terms of sample period as well as the choice

[12] This is the test that the sum of the coefficients of NUR_t and NUR_{t-1} is zero.

TABLE 4-4 Estimation of $\ln(MDU)$: Pace of Technical Progress

Variables	Baumol-Wolff (1)	(2)	(3)	Abraham-Shimer (4)	(5)	(6)
C	2.865 (0.002)	4.224 (0.000)	1.799 (0.092)	-0.688 (0.883)	-2.996 (0.066)	-4.926 (0.038)
$GTFP$	0.008 (0.034)			0.014 (0.033)		
OCA	0.056 (0.011)			0.009 (0.822)		
NUR		0.037 (0.085)			-0.009 (0.797)	
NUR_{-1}		0.017 (0.439)			-0.016 (0.620)	
UR	0.080 (0.000)	0.060 (0.002)		-0.002 (0.955)	-0.028 (0.293)	
UR_{-1}	0.104 (0.000)	0.100 (0.000)		0.107 (0.000)	0.137 (0.000)	
Emp(16-19)	0.043 (0.072)	0.060 (0.020)	-0.230 (0.000)			
Emp(20-24)	-0.107 (0.001)	-0.165 (0.000)	0.123 (0.001)			
Emp(25-54)	-0.011 (0.488)	-0.034 (0.009)	0.021 (0.354)			
$SUR(\lambda_{en}, \lambda_{ne}, \lambda_{un})$				-0.319 (0.018)	-0.216 (0.185)	0.255 (0.148)
$MDU(\lambda_{en}, \lambda_{ne}, \lambda_{un})$				0.302 (0.115)	0.496 (0.000)	0.608 (0.002)
$\overline{R}^2$	0.960	0.951	0.592	0.851	0.811	0.311
$log\ L$	68.57	64.60	21.86	37.69	34.72	16.05

Notes: Numbers in parentheses are the p-values of coefficient estimates. Sample periods are 1963-2002 for (1)∼(3), and 1976-2000 for (4)∼(6).

TABLE 4-5 Short-Term and Long-Term Marginal Effects on MDU: Sectoral Shifts, Cyclical Fluctuations and Pace of Technical Progress

Term	Variables	Marginal Effect (2)	(5)
Short Term	NUR	1.309	-0.501
		(0.000)	(0.203)
	NUR_{-1}	1.590	1.648
		(0.000)	(0.000)
	CUR	0.814	-0.379
		(0.000)	(0.000)
	CUR_{-1}	1.357	1.859
		(0.002)	(0.000)
Long Term	NUR	2.899	1.147
		(0.000)	(0.003)
	CUR	2.171	1.480
		(0.000)	(0.001)
$GTFP$		0.109	0.186
		(0.034)	(0.033)
OCA		0.760	0.128
		(0.011)	(0.822)

Notes: Numbers in parentheses are the p-values of coefficient estimates. Coefficients are converted into number of weeks using sample mean of 13.57 weeks for the mean duration. Sample periods are 1963-2002 for (2) and 1976-2000 for (5).

of demographic variables, we repeat the estimation of equation (1) and (2) for the shorter sample period of the equations (4) and (5)[13]. It turns out that the *OCA* is also insignificant in equation (1) estimated for the short sample period. Thus, it is uncertain whether the explanatory power of the *OCA* depends on the choice of sample periods or the choice of demographic variables. The current *NUR* also becomes insignificant when Abraham and Shimer's demographic variables are used (See Table 4-5). Since it is significant in equation (2) estimated for the same sample period as in (5), the explanatory power of the current *NUR* depends on the choice of demographic variables. One possible explanation is that the demographic variables, in particular, $SUR(\lambda_{en}, \lambda_{ne}, \lambda_{un})$ is picking up some of the effect of the *NUR*.

When Abraham and Shimer's variables are used, the long-term effect of the *NUR* becomes much smaller (from about three weeks to a little more than one week). Note that this decrease in the long-run effect is almost solely from a large decrease in the effect of the current *NUR* (from statistically significant 1.309 to statistically not different from zero). Since the long-term effect of the *NUR* is still significant and about 2.846 weeks in the shorter sample period[14], its effect depends on the choice of demographic variables. Again, this implies that Abraham and Shimer's demographic variables may pick up some of the effects of *NUR*.

To examine how well each specification in Table 4-4 traces the mean duration of unemployment, we plot the in-sample fitted values in Figures 4-5 through 4-7. As shown in Figure 4-5, demographic variables alone explain the general movements of mean duration quite well in annual data. Baumol and Wolff's demographic variables

[13] Estimation results are not reported here.

[14] When equation (2) is estimated for the Abraham and Shimer's sample period, the sum of the coefficients on the current and lagged *NUR* and CUR is 0.191 and statistically different from zero with a p-value of 0.000. This implies that, evaluated at the sample mean 14.90 of *MDU*, the long-term effect of *NUR* is 2.846 weeks.

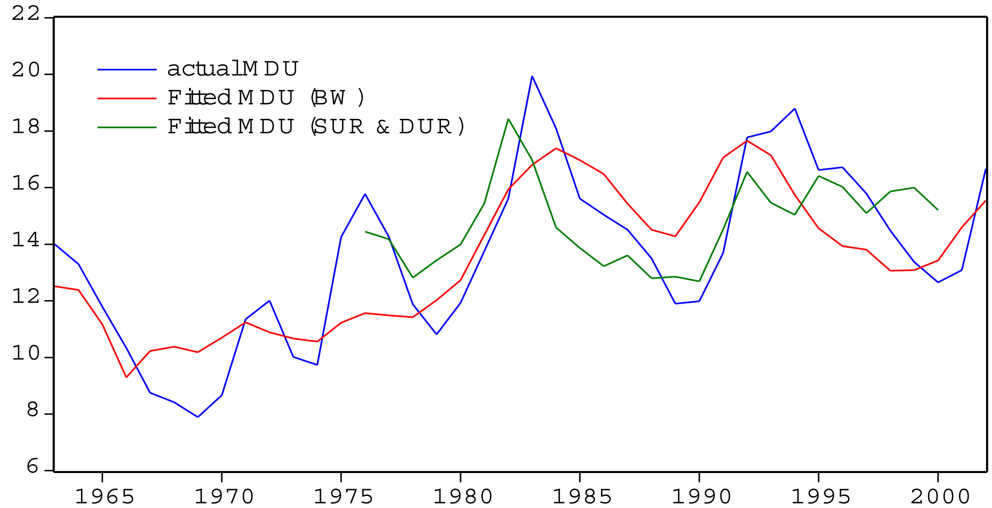
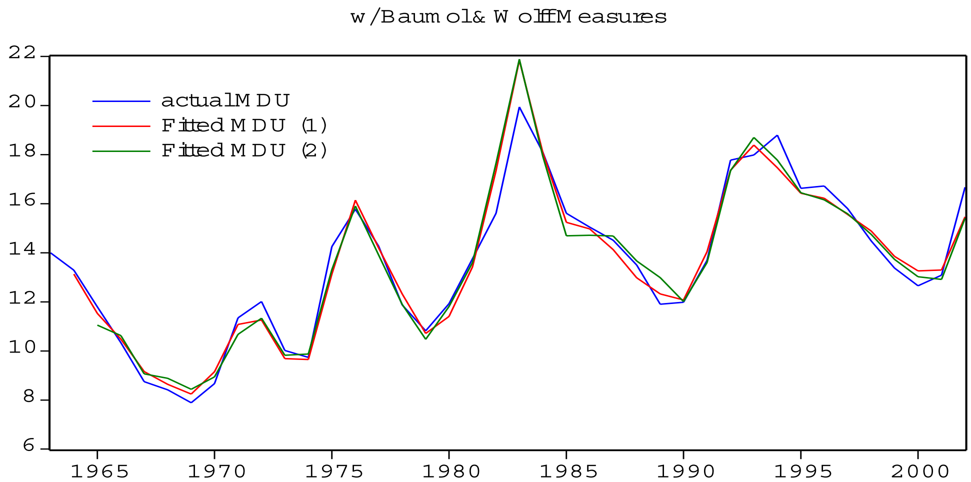


FIGURE 4-5 Fitted Mean Duration of Unemployment: Demographic Variables Only

Fitted MDU(BW) : Only Baumol and Wolff's demographic variables are included
Fitted MDU(AS) : Only Abraham and Shimer's demographic variables are included.

alone explain about 60% of the variation in mean duration of unemployment, which is comparable to the analysis of quarterly data. Abraham and Shimer's demographic variables explain about 30% of the variation in mean duration. This is also comparable to Baumol and Wolff's demographic variables because they show about the same explanatory power in the same short sample period. Figures 4-6 and 4-7 compare fitted values of mean duration of unemployment from equation (1), (2), (4) and (5). With either Baumol and Wolff's or Abraham and Shimer's demographic variables, there is no difference in fitted values between equation (1) of the technical progress hypothesis and (2) of the sectoral shifts hypothesis, except for a slight difference in the mid-1990s. Figure 4-7 shows that both equations fit slightly better, in particular in the 1990s, under Baumol and Wolff's demographic variables, but again, virtually, there is no difference.

Since there seems to be no difference between fitted values of (1), (2), (3) and (4),



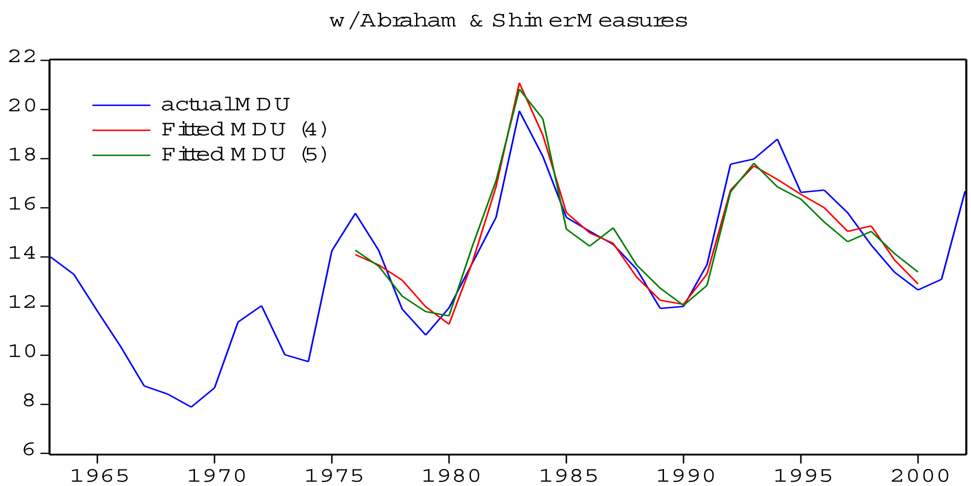
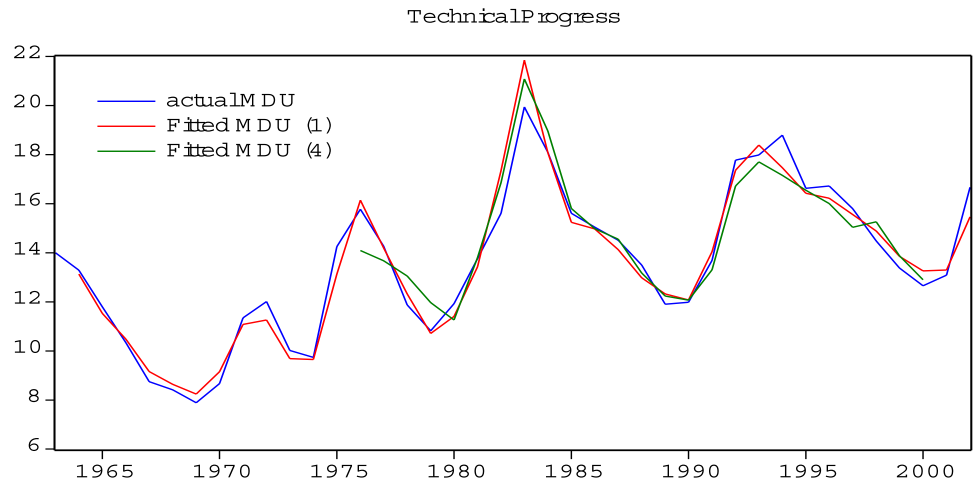


FIGURE 4-6 Comparison of Fitted Mean Durations of Unemployment: Sectoral Shifts versus Technical Progress

Fitted MDU(1) : Technical Progress under Baumol-Wolff Demographic Variables ((1) in Table 4)
Fitted MDU(2) : Sectoral Shifts under Baumol-Wolff Demographic Variables ((2) in Table 4)
Fitted MDU(4) : Technical Progress under Abraham-Shimer Demographic Variables ((4) in Table 4)
Fitted MDU(5) : Sectoral Shifts under Abraham-Shimer Demographic Variables ((5) in Table 4)



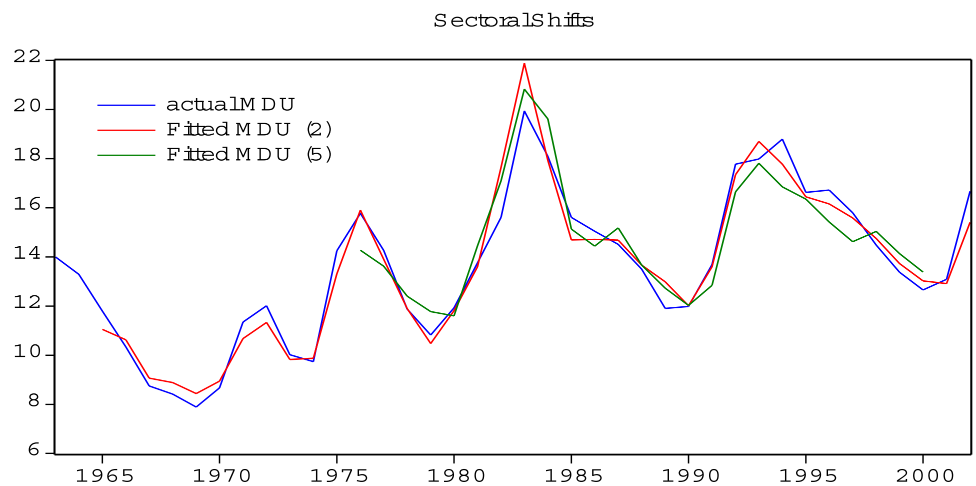


FIGURE 4-7 Comparison of Fitted Mean Durations of Unemployment: Baumol and Wolff versus Abraham and Shimer

Fitted MDU(1) : Technical Progress under Baumol-Wolff Demographic Variables ((1) in Table 4)
Fitted MDU(2) : Sectoral Shifts under Baumol-Wolff Demographic Variables ((2) in Table 4)
Fitted MDU(4) : Technical Progress under Abraham-Shimer Demographic Variables ((4) in Table 4)
Fitted MDU(5) : Sectoral Shifts under Abraham-Shimer Demographic Variables ((5) in Table 4)

I isolate the contributions of sectoral shifts and technical progress to unemployment duration in each specification. Figure 4-8 compares the contribution of sectoral shifts and technical progress. The figure reveals two interesting observations. As we have already noted above, the *NUR* has a much larger effect than the technical progress variables under Baumol and Wolff's demographic variables. The difference, however, becomes much smaller when Abraham and Shimer's variables are used. This indicates that Abraham and Shimer's demographic variables pick up some of the effects of the *NUR*. Secondly, the combined effect of the *GTFP* and the *OCA* stays quite stable at about one week over the entire sample period and its level is not affected by the choice of demographic variables.

D. Conclusion

Recent studies have investigated the source of the upward trend in the unemployment duration relative to the unemployment rate and the cause of changes in their historical relationship since the 1990s. This chapter proposes and investigates a source of such changes: the sectoral shifts of labor demand. When the mobility of workers across industries is limited due to frictions in the labor market, workers unemployed due to sectoral shifts of labor demand will experience a longer duration of unemployment because of the time-consuming feature of switching sectors. Therefore, a higher proportion of these workers relative to those unemployed due to cyclical fluctuations will increase the mean duration of unemployment of the economy even when the aggregate unemployment rate is constant.

By allowing differential effects of sectoral shifts and cyclical fluctuation on mean duration of unemployment, this chapter finds evidence supporting the claim from the analysis of quarterly data from 1963Q1 to 2003Q1. Sectoral shifts of labor demand

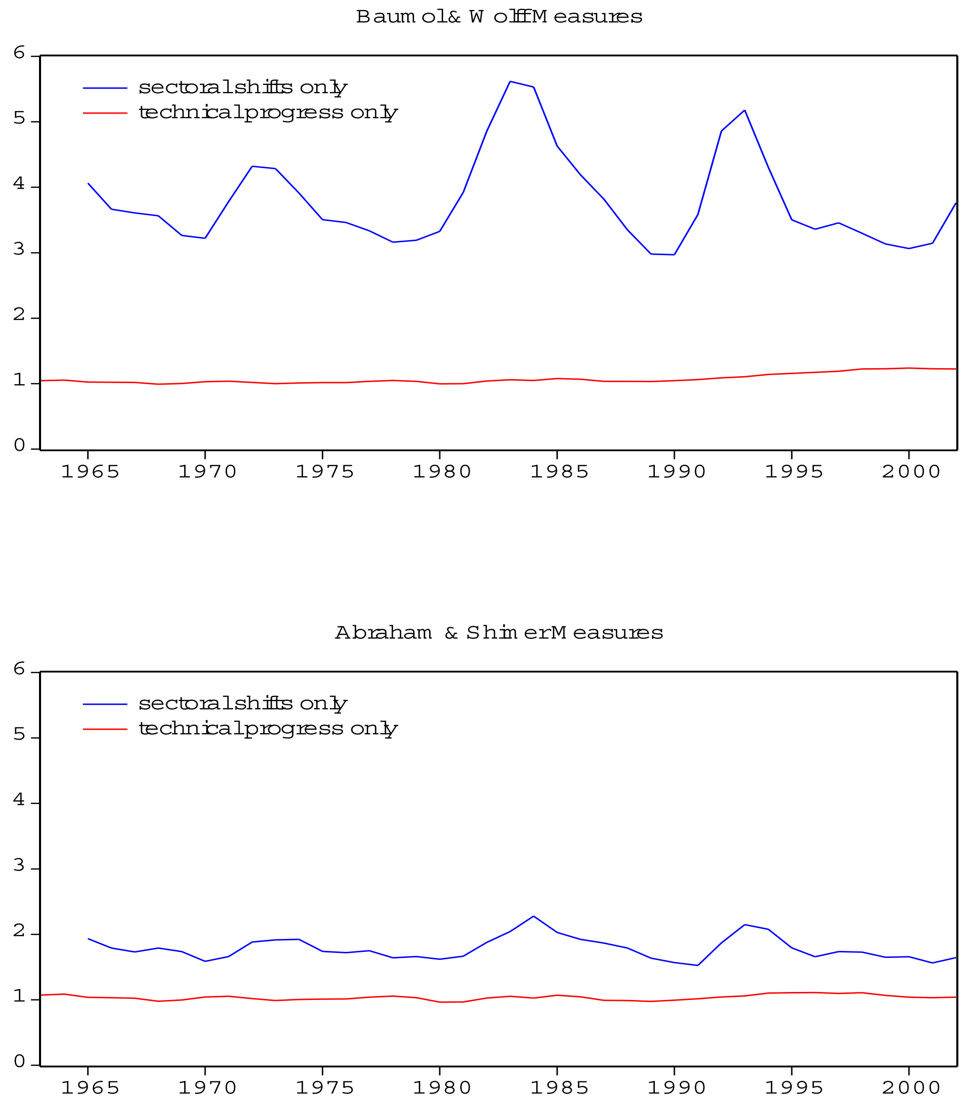


FIGURE 4-8 Contribution of Sectoral Shifts and Technical Progress

have a greater effect on the mean duration of unemployment which is statistically different from the effect of cyclical fluctuations. In addition, past sectoral shifts of labor demand have a significantly greater effect on the mean duration than past cyclical fluctuations, which implies that the effect of sectoral shifts on unemployment duration lasts longer than the cyclical component. Empirical evidence in this chapter supports one of the implications of the sectoral shifts hypothesis that sectoral shifts of labor demand affect aggregate unemployment rate not only by generating a higher incidence of unemployment but also by generating longer durations of unemployment. The sectoral shifts measured by the natural rate of unemployment help explain the unusual movement of unemployment duration in the 1990s, but there still remain changes in the unemployment duration that sectoral shifts cannot explain.

Empirical analysis also investigates alternative measures of shifts of labor demand, the pace of technical progress of Baumol and Wolff (1998). Similar to the role of sectoral shifts of labor demand, the pace of technical progress also plays a significant role in determining the mean duration of unemployment. However, the effects of both depend on the choice of demographic variables which control for the effect of changes in demographic composition of labor force and female workers' labor force attachment.

CHAPTER V

CONCLUSION

This dissertation has investigated measurements of sectoral shifts of labor demand, and their effects on the incidence and the duration of unemployment. The sectoral shifts of labor demand in the literature are defined as the reallocation of labor demand across sectors, holding the aggregate labor demand constant. They can generate significant fluctuations in aggregate unemployment that are not directly related to the fluctuations in aggregate demand. This is known as sectoral shifts hypothesis proposed by Lilien (1982). The sectoral shifts hypothesis has important macroeconomic implications. 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 unemployment fluctuations, and labor market policies that aim to ease the transition of workers across sectors will deserve more attention.

Lilien (1982) derived the relationship between the sectoral reallocation of labor demand and the aggregate unemployment rate through the effect of reallocation on the aggregate layoff rate. He measured the latter by the dispersion of net employment growth rates across sectors. There are two types of empirical models in past studies that use cross-sectional dispersion as the measure of sectoral shifts: Lilien type and AK type empirical models. The Lilien type models that purge only the aggregate monetary shocks from employment growth rates tend to support the hypothesis, while the AK type models, which purge both aggregate monetary and non-monetary shocks, tend to reject the hypothesis.

Chapter II of this dissertation investigates the pertinence of Lilien's dispersion measure that has been adopted in past studies. It is demonstrated that the measurement of sectoral shifts by dispersion alone is not sufficient for asymmetric distributions and that the skewness of the sectoral shocks can substantially improve the measurement of sectoral shifts

The Lilien type model and AK type model using dispersion and skewness as measures of sectoral shifts are estimated for the U.S. economy. Estimation results show that the skewness measure has a statistically significant effect on aggregate unemployment in both types of models and that the sectoral shifts hypothesis is strongly supported by both types of models regardless of the choice of purging methods. The estimation results also indicate that the lack of support for the hypothesis in the Abraham and Katz's (1984) study is mainly due to the omission of the skewness as a measure of sectoral shifts.

The natural rates of unemployment estimated from these models show more fluctuations than the relatively flat natural rates of unemployment reported in the Abraham and Katz (1984). Although both types of models support the sectoral shifts hypothesis, there is a sizable difference in the natural rates of unemployment generated by these models. The differences is not between the estimates of dispersion and skewness but rather the difference in the structure of the unemployment equation.

Past studies and chapter II of this dissertation use classical measures of dispersion and skewness as measures of sectoral shifts of labor demand. However, these classical measures are sensitive to the presence of outliers, and consequently, tests of sectoral shifts hypothesis based on the estimates of classical measures may be distorted by the presence of outliers in the estimates of sectoral shocks. In chapter III, the presence of outliers is discovered by various methods of outlier detection. Various robust measures of dispersion and skewness of the distribution of sectoral shocks are also computed. They are somewhat different from the classical measures in terms of their magnitude but show similar trends over time. It turns out that the sectoral shifts hypothesis is strongly supported in all cases. It is also found that estimated natural rates of unemployment based on robust measures are quite similar to those based on classical measure. These findings reinforce the empirical results of chapter II.

Chapter IV proposes and investigates a source of upward trend in unemployment duration relative to aggregate unemployment rate in the 1990s: the sectoral shifts of labor demand. When the mobility of workers across sectors is limited due to friction in the labor market, workers unemployed due to sectoral shifts of labor demand will experience a longer duration of unemployment because of the time-consuming feature of switching sectors. Therefore, even for a given aggregate unemployment rate, a higher proportion of these workers relative to those unemployed due to cyclical fluctuations will increase the mean duration of unemployment of the economy.

By allowing differential effects of sectoral shifts and cyclical fluctuation on mean duration of unemployment, this chapter finds evidence supporting the role of sectoral shifts in the increase of unemployment duration. Sectoral shifts of labor demand have a statistically greater effect on the mean duration of unemployment than cyclical fluctuations. In addition, past sectoral shifts of labor demand have a significantly greater effect on the mean duration than past cyclical fluctuations. This implies that the effect of sectoral shifts on unemployment duration lasts longer than the cyclical component, which is consistent with the prediction of the sectoral shifts hypothesis. Empirical evidence in this paper supports another implication of the sectoral shifts hypothesis that sectoral shifts of labor demand affect aggregate unemployment rate, not only by generating a higher incidence of unemployment but also by generating longer durations of unemployment.

Empirical analysis of chapter IV also investigates alternative measure of shifts of labor demand, the pace of technical progress proposed by Baumol and Wolff (1998). Similar to the role of sectoral shifts of labor demand, the pace of technical progress also plays a significant role in determining the mean duration of unemployment by shifting labor demand away from low-skilled workers, whose retraining cost is relatively high. Both factors, sectoral shifts of labor demand and the pace of technical progress, help explain unusual movement of unemployment duration in the 1990s.

Some comments should be made to conclude this dissertation. First, there is a variety of ways to model monetary shocks and unemployment rate. In this dissertation, the main focus is on the purging equation and the estimation of sectoral shocks. Therefore, I borrowed the specifications of the money growth equation and unemployment equation from past studies. Current advancements in the research of estimating monetary shocks and modeling unemployment determination can be applied to the study of this dissertation. Secondly, due to the need for long sample period and the limitation of data availability, the sample period in this dissertation covers only up to the first quarter of 2003. It would be interesting to include more recent data because the adjustment of the labor market after the most recent recession would probably have lasted well past the first quarter of 2003. Lastly, studies in this dissertation are only concerned with sector affiliation of workers. For example, a janitor who moves from manufacturing to a service sector would be counted as having sectoral shifts of labor demand. However, it is expected that he or she will experience a much shorter job search process than, for instance, a production worker who experiences the same change in his or her sector affiliation. Therefore, it would be useful, if possible, to consider another dimension such as occupation switch in the research of sectoral shifts of labor demand.

REFERENCES

Aaronson, Daniel; Rissman, Ellen R. and Sullivan, Daniel G. "Can Sectoral Reallocation Explain the Jobless Recovery?" *Federal Reserve Bank of Chicago Economic Perspectives*, 2004, (2Q), pp. 36–49.

Abraham, Katherine G. and Katz, Lawrence F. "Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?" National Bureau of Economic Research (Cambridge, MA) Working Paper No. w1410, July 1984.

Abraham, Katherine G. and Katz, Lawrence F. "Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?" *Journal of Political Economy*, 1986, *94* (3), pp. 507–522.

Abraham, Katherine G. and Shimer, Robert "Changes in Unemployment Duration and Labor-Force Attachment." National Bureau of Economic Research (Cambridge, MA) Working Paper No. w8513, October 2001.

Abraham, Katherine G. and Shimer, Robert "Changes in Unemployment Duration and Labor-Force Attachment." in Alan B. Kruger and Robert M. Solow, eds., *The Roaring Nineties: Can Full Employment Be Sustained?*, New York, NY: The Russell Sage Foundation, 2002, pp. 367–420.

Andrews, David F. "A Robust Method for Multiple Linear Regression." *Technometrics*, 1974, *16*, pp. 523–531.

Aucremenne, Luc; Brys, Guy; Hubert, Mia; Rousseeuw, Peter J. and Struyf, Anja "A Study of Belgian Inflation, Relative Prices and Nominal Rigidities using New Robust Measures of Skewness and Tail Weight," in M. Hubert;

G. Pison; M. Struyf and S. Van Aelst, eds., *Theory and Applications of Recent Robust Methods,* Boston, MA: Birkhäuser Verlag, 2004, pp. 13–26.

Barro, Robert J. "Unanticipated Money Growth and Unemployment in the United States." *American Economic Review*, 1977, *67*(2), pp. 101–115.

Barro, Robert J. *Macroeconomic Policy.* Cambridge, MA: Harvard University Press, 1991.

Baumol, William J. and Wolff, Edward N. "Speed of Technical Progress and Length of the Average Interjob Period." Jerome Levy Economics Institute of Bard College (Blithewood, NY) Working Paper 237, May 1998.

Beaton, Albert E. and Tukey, John W. "The Fitting of Power Series, Meaning Polynomials, Illustrated on Band-Spectroscopic Data." *Technometrics*, 1974, *14*, pp. 147–185.

Blanchard, Olivier J. and Diamond, Peter "Ranking, Unemployment Duration, and Wages." *Review of Economic Studies*, 1994, *61*, pp. 417–434.

Bowley, Arthur L. *Elements of Statistics*, New York, NY: Charles Scribner's Sons, 1920.

Brainard, S. Lael and Cutler, David M. "Sectoral Shifts and Cyclical Unemployment Reconsidered." *Quarterly Journal of Economics*, 1993, *108*(1), pp. 219–243.

Brys, Guy; Hubert, Mia and Struyf, Anja "A Comparison of Some New Measures of Skewness," in R. Dutter; P. Filzmoser; U. Gather and P. J. Rousseeuw, eds., *Developments in Robust Statistics: International Conference on Robust Statistics.* New York, NY: Physica Verlag, 2003, pp. 97-112.

Byun, Yanggyu and Hwang, Hae-shin "Measurements of Sectoral Shifts: Dispersion and Skewness." Working Paper, Department of Economics, Texas A&M University, 2006.

Campbell, Carl M. and Duca, John V. "The Impact of Evolving Labor Practices and Demographics on U.S. Inflation and Unemployment." Federal Reserve Bank of Dallas (Dallas, TX) Working Paper 0702, February 2007.

Carling, Kenneth "Resistant Outlier Rules and the Non-Gaussian Case." *Computational Statistics and Data Analysis*, 2000, *33*, pp. 249–258.

Christiano, Lawrence J.; Eichenbaum, Martin and Evans, Charles "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds." *Review of Economics and Statistics*, 1996, *78*, pp. 16–34.

Cleveland, William S. *Visualizing Data.* Summit, NJ: Hobart Press, 1993.

Cleveland, William S. *The Elements of Graphing Data.* Summit, NJ: Hobart Press, 1994.

Coakley, Jerry; Fuertes, Ana-Maria and Smith, Ron "A Principal Components Approach to Cross-Section Dependence in Panels." Working Paper, Department of Economics, Birkbeck College, University of London, 2002.

Davies, Laurie and Gather, Ursula "The Identification of Multiple Outliers." *Journal of American Statistical Association*, 1993, *88*, pp. 782–801.

Davis, Steven J. "Fluctuations in the Pace of Labor Reallocation." *Carnegie-Rochester Conference Series on Public Policy*, 1987, *27*, pp. 335–402.

Fan, Jianqing and Gijbels, Irene *Local Polynomial Modelling and Its Applications.* New York, NY: Chapman & Hall, 1996.

Gallipoli, Giovanni and Pelloni, Gianluigi "Macroeconomic Effects of Employment Reallocation Shocks: A Review and an Appraisal from an Applied Perspective." Working Paper 15, School of Economics, Free University of Bozen - Bolzano, 2001.

Gallipoli, Giovanni and Pelloni, Gianluigi "Aggregate Shocks vs Reallocation Shocks: an Appraisal of the Applied Literature." Working Paper, Institute for Fiscal Studies, 2005.

Garonna, Paolo and Sica, Francesca G.M. "Intersectoral Labour Reallocations and Unemployment in Italy." *Labour Economics*, 2000, *7*, pp. 711–728.

Glasmeier, Amy and Salant, Priscilla "Low-Skill Workers in Rural America Face Permanent Job Loss." *Carsey Institute Policy Brief*, 2006, *2*, pp. 1–7.

Greenwood, J.A.; Landwehr, Jurate M.; Matalas, N.C. and Wallis, John R. "Probability Weighted Moments: Definition and Relation to Parameters of Several Distributions Expressible in Inverse Form." *Water Resources Research*, 1979, *15*(5), pp. 1049–1054.

Groeneveld, Richard A. and Meeden, Glen "Measuring Skewness and Kurtosis." *The Statistician*, 1984, *33*, pp. 391–399.

Groenewold, Nicolaas and Hagger, A.J. "The Natural Unemployment Rate in Australia Since the Seventies." *Economic Record*, 1998, *74*, pp. 24–35.

Groshen, Erica and Potter, Simon "Has Structural Change Contributed to a Jobless Recovery?" *Current Issues in Economics and Finance*, 2003, *9*(8), pp. 1–7.

Groshen, Erika; Potter, Simon and Sela, Rebecca Paul "Was the 2001 Recession Different in the Labor Market? Comparing Measures." Working Paper, Federal Reserve Bank of New York, 2004.

Hinkley, David V. "On Power Transformations to Symmetry." *Biometrika*, 1975, *62*, pp. 101–111.

Hosking, Jonathan R.M. "L-Moments: Analysis and Estimation of Distributions Using Linear Combinations of Order Statistics." *Journal of the Royal Statistical Society* Series B, 1990, *52*, pp. 105–124.

Juhn, Chinhui; Murphy, Kevin M. and Topel, Robert H. "Current Unemployment, Historically Contemplated." *Brookings Papers on Economic Activity*, 2002, *1*, pp. 79–116.

LaLive, Rafael; Van Ours, Jan and Zweimüller, Josef "How Changes in Financial Incentives Affect the Duration of Unemployment." *Review of Economic Studies*, 2006, *73*, pp. 1009–1038.

Lilien, David M. "Sectoral Shifts and Cyclical Unemployment." *Journal of Political Economy*, 1982, *90*(4), pp. 777–793.

Lilien, David M. "A Sectoral Model of the Business Cycle." Working Paper 8231, Department of Economics, University of Southern California, 1983.

Loungani, Prakash "Oil Price Shocks and the Dispersion Hypothesis." *Review of Economics and Statistics*, 1986, *68*(3), pp. 536–539.

Loungani, Prakash and Rogerson, Richard "Cyclical Fluctuations and Sectoral Reallocation: Evidence from the PSID." *Journal of Monetary Economics*, 1989, *23*, pp. 259–273.

Loungani, Prakash; Rush, Mark and Tave, William "Stock Market Dispersion and Unemployment." *Journal of Monetary Economics*, 1990, *25*, pp. 367–388.

Loungani, Prakash and Trehan, Bharat "Explaining Unemployment: Sectoral vs. Aggregate Shocks." *Federal Reserve Bank of San Francisco Economic Review*, 1997, *1*, pp. 3–15.

Lucas, Robert E. Jr. and Prescott, Edward C. "Equilibrium Search and Unemployment." *Journal of Economic Theory*, 1974, *7*, pp. 188–209.

Menezes, Carmen F. and Wang, X. Henry "Increasing Outer Risk." Working Paper, Department of Economics, University of Missouri-Columbia, 2004.

Menezes, Carmen F.; Geiss, C. and Tressler, John "Increasing Downside Risk." *American Economic Review*, 1980, *70*, pp. 921–932.

Mikhail, Ossama; Eberwein, Curtis and Handa, Jagdish "Can Sectoral Shift Generate Persistent Unemployment in Real Business Cycle Models?" Working Paper, Department of Economics, University of Central Florida, 2003

Mills, Terence C.; Pelloni, Gianluigi and Zervoyianni, Athina "Unemployment Fluctuations in the United States: Further Tests of the Sectoral-Shifts Hypothesis." *Review of Economics and Statistics*, 1995, *77*(2), pp. 294–304.

Mills, Terence C.; Pelloni, Gianluigi and Zervoyianni, Athina "Cyclical Unemployment and Sectoral Shifts: Further Tests of the Lilien Hypothesis for the UK." *Economics Letters*, 1996, *52*, pp. 55–60.

Mills, Terence C.; Pelloni, Gianluigi and Zervoyianni, Athina "Unemployment Fluctuations in the UK: 1958-92." *Applied Economics Letters*, 1997, *3*, pp. 253–255.

Mochado, José A. F.; Portugal, Pedro and Guimarães, Juliana "U.S. Unemployment Duration: Has Long Become Longer or Short Become Shorter?" Banco del Portugal (Lisboa, Portugal) Working Paper 13, June 2006.

Mukoyama, Toshihiko and Şahin, Ayşegül "Why Did the Average Duration of Unemployment Become So Much Longer?" Federal Reserve Bank of New York (New York, NY) Staff Report No. 194, November 2005.

Neelin, Janet "Sectoral Shifts and Canadian Unemployment." *Review of Economics and Statistics*, 1987, *69*(4), pp. 718–723.

Orr, James "Industrial Restructuring in the New York Metropolitan Area." *Federal Reserve Bank of New York Economic Policy Review*, February 1997, pp. 61–74.

Palley, Thomas "Sectoral Shifts and Cyclical Unemployment: A Reconsideration." *Economic Inquiry*, 1992, *30*(1), pp. 117–133.

Panagiotidis, Theodore; Pelloni, Gianluigi and Polasek, Wolfgang "Macroeconomic Effects of Reallocation Shocks: A Generalised Impulse Response Function Analysis for Three European Countries." Center for Household, Income, Labor and Demographic Economics (Torino, Italy) Working Paper No. 02, 2004.

Rissman, Ellen R. "Wage Growth and Sectoral Shifts." *Journal of Monetary Economics*, 1993, *31*, pp. 395–416.

Rissman, Ellen R. "Measuring Labor Market Turbulence." *Federal Reserve Bank of Chicago Economic Perspectives*, 1997, *21*(3), pp. 2–14.

Rissman, Ellen R. "Can Sectoral Labor Reallocation Explain the Jobless Recovery?" Federal Reserve Bank of Chicago (Chicago, IL) Chicago Fed Letter No. 197, December 2003.

Robson, Martin "Sectoral Shifts, Employment Specialization and the Efficiency of Matching: an Analysis Using UK Regional Data." *Regional Studies* 2006, *40*(7), pp. 743–754.

Rousseeuw, Peter J. and Leroy, A. *Robust Regression and Outlier Detection.* New York, NY: John Wiley, 1987.

Rousseeuw, Peter J. and Croux, Christopher "Alternatives to the Median Absolute Deviation." *Journal of the American Statistical Association*, 1993, *88*(424), pp. 1273–1283.

Rousseeuw, Peter J.; Ruts, Ida and Tukey, John W. "The Bagplot: a Bivariate Boxplot." *The American Statistician*, 1999, *53*, pp. 382–387.

Sabade, Sagar S. and Walker, Duncan M., "Evaluation of Effectiveness of Median of Absolute Deviations Outlier Rejection-Based IDQQ Testing for Burn-In Reduction," in "Proceedings of the 20th IEEE VLSI Test Symposium," Washington, DC, USA: IEEE Computer Society, 2002, pp. 81–86.

Sakata, Kei "Sectoral Shifts and Cyclical Unemployment in Japan." *Journal of Japanese and International Economies*, 2002, *16*, pp. 227–252.

Samson, Lucie "Sectoral Shifts and Aggregate Unemployment: Additional Empirical Evidence." *Applied Economics*, 1990, *22*, pp. 331–346.

Shin, Donggyun and Shin, Kwanho "Inter- and Intra-Sectoral Movement of Labor and Unemployment Rate." Working Paper, Department of Economics, Korea University, 2001.

Solow, Robert, "Comment on George L. Perry, Changing Labor Markets and Inflation," *Brookings Papers on Economic Activity*, 1970, (3), pp. 411–448.

Tukey, John W. *Exploratory Data Analysis.* Ann Arbor, MI: University Microfilms, 1971.

Tukey, John W. *Exploratory Data Analysis.* Reading, MA: Addison-Wesley, 1977.

Valletta, Robert G. "Changes in the Structure and Duration of U.S. Unemployment, 19671998." *Federal Reserve Bank of San Francisco Economic Review*, 1998, (3), pp. 29–40.

Valletta, Robert G. "Rising Unemployment Duration in the United States: Casues and Consequences." Working Paper, Federal Reserve Bank of San Francisco, 2005.

Van Ours, Jan and Vodopivec, Milan "How Shortening the Potential Duration of Unemployment Benefit Affects the Duration of Unemployment: Evidence from a Natural Experiment." *Journal of Labor Economics*, 2006, *24*(2), pp. 351–378.

Vandervieren, Ellen and Hubert, Mia "An Adjusted Boxplot for Skewed Distributions," in J. Antoch, ed., *COMPSTAT: Proceedings in Computational Statistics.* Heidelberg: Physica-Verlag, 2004, pp. 1933–1940.

Violante, Giovanni L. "Technological Acceleration, Skill Transferability, and the Rise in Residual Inequality." *Quarterly Journal of Economics*, 2002, *117*, pp. 297–338.

Wall, Howard and Zoëga, Gylfi, "U.S. Regional Business Cycles and the Natural Rate of Unemployment." *Federal Reserve Bank of St. Louis Review*, 2004, 86(1), pp. 23–31.

APPENDIX A

LEAST SQUARES ESTIMATION OF EQUATIONS WITH AN UNOBSERVABLE COMMON REGRESSOR

Consider a system of linear equations

$$y_j = X\beta_j + g\gamma_j + \epsilon_j \qquad j = 1, 2, \cdots, n \tag{A.1}$$

where X is a $T \times K$ matrix of K observable regressors and g is a $T \times 1$ vector of an unobservable regressor. Since regressors are common to all equations, the seemingly unrelated regression estimators of parameters are identical to the least squares estimator of each equation if g is observable. Let $Y = (y_1, y_2, \cdots, y_n)$, $B = (\beta_1, \beta_2, \cdots, \beta_n)$ and $E = (\epsilon_1, \epsilon_2, \cdots, \epsilon_n)$. Let $\hat{B}$ and $\hat{E}$ be least squares estimators of B and E subject to restrictions $\gamma_j = 0$. That is,

$$\hat{B} = (X'X)^{-1}X'Y, \qquad \hat{E} = \left[I - X(X'X)^{-1}X'Y\right]Y \equiv QY$$

We write (A.1) for all equations as

$$y = (I_n \otimes X)\beta + (\gamma \otimes I_T)g + \epsilon \equiv Z_1\beta + Z_2 g + \epsilon \tag{A.2}$$

where $y = vec(Y)$, $\beta = vec(B)$, $\epsilon = vec(E)$ and $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_n)'$. We wish to estimate parameters β and γ and the unobservable regressor g by minimizing the sum of squared residuals subject to the identifying normalization restriction $\gamma'\gamma = 1$.

$$\min_{\beta,\gamma,g} (y - Z_1\beta - Z_2 g)'(y - Z_1\beta - Z_2 g)$$
$$\text{subject to } \gamma'\gamma = 1$$

The estimator β is given by

$$\widetilde{\beta}_j = (Z_1'Z_1)^{-1}Z_1'(y - Z_2 g) = \widehat{\beta} - \left[\gamma \otimes (X'X)^{-1}X'\right] g \tag{A.3}$$

where $\widehat{\beta} = vec(\hat{B})$. It is easy to show that the normal equations for g are given by $(Z_2'A_1Z_2)g = Z_2'A_1y$, where $A_1 = I - Z_1(Z_1'Z_1)^{-1}Z_1'$. It is straightforward to show $A_1 = I_n \otimes Q$, and $Z_2'A_1Z_2 = \gamma'\gamma \otimes Q = Q$ due to the restriction $\gamma'\gamma = 1$. Therefore, the normal equation for g can be written as

$$Qg = (\gamma)' \otimes Q)y \tag{A.4}$$

Though the linear system in (A.4) does not have a unique solution for g because Q is singular, it is a consistent system and has a solution

$$\widetilde{g} = Q^{-}\widehat{E}\gamma + (I_T - Q^{-}Q)g_0 \tag{A.5}$$

where Q^{-} is the generalized inverse of Q and g_0 is any vector. It is well known that the generalized inverse of an idempotent matrix is itself. Therefore, we can rewrite (A.5) as

$$\widetilde{g} = Q(\gamma' \otimes Q)y + (I_T - Q)g_0 = (\gamma' \otimes Q)y + (I_T - Q)g_0 \tag{A.6}$$

Substituting $\widetilde{g}$ into (A.3), we can show by using the relationship $X'Q = 0$ that

$$\widetilde{\beta} = \hat{\beta} - \left[\gamma \otimes (X'X)^{-1}X'\right] g_0 \tag{A.7}$$

Substitution of (A.6) and (A.7) into (A.2) gives

$$\begin{aligned}
\widetilde{\epsilon} &= y - Z_1\widetilde{\beta} - Z_2\widetilde{g} \qquad (A.8)\\
&= y - \left[I_n \otimes (I_T - Q)\right] y + \left[\gamma \otimes (I_T - Q)\right] g_0 - \left[\gamma\gamma' \otimes Q\right] y - \left[\gamma \otimes (I_T - Q)\right] g_0\\
&= (I_n \otimes Q)y - (\gamma\gamma' \otimes Q)y
\end{aligned}$$

This in turn gives

$$\begin{aligned}\tilde{\epsilon}'\tilde{\epsilon} &= y'(I_n \otimes Q)y - [y'(\gamma \otimes Q)]\,[(\gamma' \otimes Q)y] \\ &= y'(I_n \otimes Q)y - \gamma'\hat{E}'\hat{E}\gamma\end{aligned}$$

where the last equality is due to the relationship

$$(\gamma' \otimes Q)y = (\gamma' \otimes Q)vec(Y) = vec(QY\gamma) = \hat{E}\gamma$$

Minimization of $\tilde{\epsilon}'\tilde{\epsilon}$ with respect to γ subject to the normalization restriction $\gamma'\gamma = 1$ is thus equivalent to maximization of $\gamma'\hat{E}'\hat{E}\gamma$ subject to $\gamma'\gamma = 1$. From the Lagrange equation

$$\mathcal{L} = \gamma'\hat{E}'\hat{E}\gamma + \lambda(1 - \gamma'\gamma)$$

we can derive the first order condition

$$\hat{E}'\hat{E}\tilde{\gamma} - \lambda\tilde{\gamma} = (\hat{E}'\hat{E} - \lambda I)\tilde{\gamma} = 0$$

Thus, $\tilde{\gamma}$ is the normalized characteristic vector of $\hat{E}'\hat{E}$ corresponding to its largest characteristic root λ because the first order condition indicates $\lambda = \tilde{\gamma}'\hat{E}'\hat{E}\tilde{\gamma}$. Substitution of $\tilde{\gamma}$ into (A.6)-(A.8) gives the estimators

$$\begin{aligned}\tilde{g} &= (\tilde{\gamma}' \otimes Q)y + (I_T - Q)g_0 = \hat{E}\tilde{\gamma} + X(X'X)^{-1}g_0 \\ \tilde{\beta} &= \hat{\beta} - \left[\gamma \otimes (X'X)^{-1}X'\right]g_0 \\ \tilde{\epsilon} &= (I_n \otimes Q)y - (\tilde{\gamma}\tilde{\gamma}' \otimes Q)y = vec(\hat{E}) - vec(\hat{E}\tilde{\gamma}\tilde{\gamma}')\end{aligned}$$

If we choose $g_0 = 0$, $\tilde{g}$ is the first principal component of OLS residuals $\hat{E}$ and the estimator $\tilde{\beta}$ is the OLS estimator with restriction $\gamma = 0$. Note that the residual estimator does not depend on the choice of g_0, and it can be written in a matrix form as $\tilde{E} = \hat{E} - \hat{E}\tilde{\gamma}\tilde{\gamma}'$.

Abraham and Katz (1984) estimate the unobservable aggregate non-monetary shocks by the weighted means of the least squares residuals $\hat{\eta}_{tj}$ which is estimated from regression equations

$$y_{tj} = X_t\beta_j + \eta_{tj} \qquad t = 1, 2, \cdots, T, \quad j = 1, 2, \cdots, n$$

This procedure implicitly assumes time-varying means of η_{tj} and we can write it explicitly as

$$y_{tj} = X_t\beta_j + g_t + \epsilon_{tj} \qquad t = 1, 2, \cdots, T, \quad j = 1, 2, \cdots, n$$

where g_t is the mean of η_{tj} in period t and it represents the aggregate non-monetary effect. This system of equations is same as (A.1) with restrictions $\gamma_j = 1$ for all j. Let γ be an n-dimensional vector of ones. Then, the normal equations for g becomes $Z_2'A_1Z_2 = nQz = Z_2'A_1y$ because $Z_2'A_1Z_2 = \gamma'\gamma \otimes Q = nQ$. Therefore, the estimator of g in (A.6) becomes

$$\tilde{g} = \frac{1}{n}\left[(\gamma' \otimes Q)y + (I_T - Q)g_0\right] = \frac{1}{n}\sum_{j=1}^{n}\hat{\epsilon}_j - \frac{1}{n}(I_T - Q)g_0$$

where $\hat{\epsilon}_j$ is the least squares residual vector of the regression equation of industry j, $y_j = X\beta_j + \epsilon_j$. If we choose $g_0 = 0$, this estimator becomes

$$\tilde{g} = \frac{1}{n}\sum_{j=1}^{n} Qy_j = \frac{1}{n}\sum_{j=1}^{n}\hat{\epsilon}_j$$

which is similar to the Abraham and Katz estimator except for the weights.

The Abraham and Katz estimator uses employment share weights w_{tj} in the place of the uniform weights $1/n$. Their weighting system will arise in this derivation if the number of firms varies across industries. we may capture the differences in the number of firms by assigning weights n_{tj}/n_t, where n_{tj} and n_t denote total number of firms in industry j and in the whole economy in period t respectively, to the dependent variable y_j and replace y_j with $(n_{tj}/n_t)y_j$. Then the estimator of g becomes

$$\tilde{g} = \frac{1}{n}\sum_{j=1}^{n} Q\left(\frac{n_{tj}}{n_t}y_j\right) = \frac{1}{n}\sum_{j=1}^{n}\hat{\epsilon}_j$$

In a recent paper, Coakley et al. (2002) also propose to use the principal component as an estimator of unobserved common factors in a panel data model. However, their motivation is quite different from the least squares method described above. The system of equation in (A.2) can be written as

$$Y = XB + g\gamma' + E = X(B + d\gamma') + (g - Xd)\gamma' + E = X\Theta + U$$

where Xd is the mean function of g in a regression relationship $g = Xd + \xi$. Post-multiplying γ to U and imposing the normalization restriction $\gamma'\gamma = 1$, we have

$$U\gamma = (g - Xd)\gamma'\gamma + E\gamma = g - Xd + E\gamma$$

Ignoring the last two terms, they recognize that g can be approximated by $g = U\gamma = \sum_{j=1}^{n}\gamma_j u_j$, which is the form of principal component.

APPENDIX B

LOESS FIT

The LOESS method is based on the idea that any function can be well-approximated in a small neighborhood by a low-degree polynomial function. It fits a locally weighted low-degree polynomial regression for each data point in the sample. The polynomial is fit using weighted least squares, giving more weight to points near the data point of interest and less weight to points further away. This procedure is iterated m times, giving smaller weights to observations with larger residuals. Specifically, I start with the weighted regression minimizing the weighted sum of squared residuals

$$W = \sum_{i=1}^{[\alpha N]} w_i(y_i - a - \beta_1 z_i - \beta_2 z_i^2 - \cdots - \beta_k z_i^k)$$

where z_i is the time variable and $[\alpha N]$ is $100 \times \alpha\%$ of the total sample size, truncated to an integer. We choose $\alpha = 0.2$ and $k = 2$. I use a *tricube* weight, a traditional weight function used in the LOESS method. Let $\triangle_i(z) = |z - z_i|$ and $\triangle_{(q)}(z)$ be q^{th} smallest distance among $\triangle_i(z)$. The *tricube* weight, w_i is defined as

$$w_i = \begin{cases} \left(1 - \left|\frac{\triangle_i(z)}{(\triangle_{([\alpha N])}(z))}\right|^3\right)^3 & \text{for } \left|\frac{\triangle_i(z)}{(\triangle_{([\alpha N])}(z))}\right| < 1 \\ 0 & \text{otherwise} \end{cases}$$

We repeat this procedure with updated weights $w_i r_i$ where r_i is the *bisquare* weight function. Let the residuals from the first estimation be $\hat{\epsilon}_i$. Then, r_i is defined as

$r_i = B(\hat{\epsilon}_i; 6m)$ where

$$m = med(|\hat{\epsilon}_i|)$$

$$B(a;b) = \begin{cases} \left(1 - \left(\frac{a}{b}\right)^2\right)^2 & \text{for } \left|\frac{a}{b}\right| < 1 \\ 0 & \text{otherwise} \end{cases}$$

For details on LOESS, see Cleveland (1994), Fan and Gijbels (1996) and Cleveland's web page at http://cm.bell-labs.com/cm/ms/departments/sia/wsc/.

APPENDIX C

MODIFIED KENDALL'S $\boldsymbol{\tau}$

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

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

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 $(1+\tau)/(1-\tau)$.

APPENDIX D

ESTIMATION RESULTS OF THE ABRAHAM AND KATZ MODELS

Estimations in Tables 4-1 through 4-5 are repeated using two alternative natural rates of unemployment. They are $NUR(\hat{g}_{ak})$ and $NUR(\hat{g}_{pc})$, the natural rate of unemployment from the Abraham and Katz model under non-monetary aggregate shock estimators $\hat{g}_{ak}$ and $\hat{g}_{pc}$, respectively.

Tables D-1 through D-3 show estimation results of quarterly data. All results are qualitatively identical to those reported in section 2. All estimated coefficients are highly significant regardless of the natural rate of unemployment used, except for the coefficient *Emp*(16-19). The natural rate and cyclical rate of unemployment have negative effects on the mean duration in the initial period, but they have positive long-term effects. The natural rate of unemployment has a greater long-run marginal effect than the cyclical rate of unemployment. The differential long-term effects between natural and cyclical unemployment rates become somewhat smaller compared to Table 4-2. In particular, when the $NUR(\hat{g}_{ak})$ is used, the difference is only about 0.15 week and insignificant. However, note that the differential is still significant at a 10% significance level under the $NUR(\hat{g}_{pc})$ which builds on a less strict assumption than the $NUR(\hat{g}_{pc})$. All null hypotheses of equality of short-term effects are strongly rejected in both equations in Table D-3. The equality of long-term effects is rejected at 10% significance level in $NUR(\hat{g}_{pc})$ case, which indicates that the effects of the natural and cyclical unemployment rates over longer periods becomes less distinct.

Tables D-4 and D-5 present estimation results of annual data. Coefficients of the NUR_t and NUR_{t-1} in columns $(2)'$ through $(5)''$ are statistically insignificant, which implies that the difference between the marginal effects of the natural rate and

TABLE D-1 Estimation of $\ln(MDU)$: Sectoral Shifts versus Cyclical Fluctuations under Alternative Natural Rates of Unemployment

(1963Q1 $\sim$ 2003Q1)

Variables	Estimated Coefficients	
	$(1)'$	$(1)''$
	$NUR(\hat{g}_{ak})$	$NUR(\hat{g}_{pc})$
C	4.237	4.181
	(0.000)	(0.000)
NUR	-0.219	-0.219
	(0.000)	(0.000)
NUR_{-1}	0.368	0.373
	(0.000)	(0.000)
CUR	-0.090	-0.084
	(0.000)	(0.000)
CUR_{-1}	0.229	0.218
	(0.000)	(0.000)
Emp(16-19)	-0.005	-0.008
	(0.752)	(0.575)
Emp(20-24)	-0.101	-0.097
	(0.000)	(0.000)
Emp(25-54)	-0.033	-0.033
	(0.000)	(0.000)
$\overline{R}^2$	0.900	0.906
$log\ L$	193.57	198.27

Notes: Numbers in parentheses are the p-values of coefficient estimates.

TABLE D-2 Short-Term and Long-Term Marginal Effects on MDU: Sectoral Shifts versus Cyclical Fluctuations under Alternative Natural Rates of Unemployment

Term	Variables	Marginal Effect $(1)'$ $NUR(\hat{g}_{ak})$	$(1)''$ $NUR(\hat{g}_{pc})$
Short Term	NUR	-2.974	-2.982
		(0.000)	(0.000)
	NUR_{-1}	5.005	5.006
		(0.000)	(0.000)
	CUR	-1.230	-1.114
		(0.000)	(0.000)
	CUR_{-1}	3.110	2.960
		(0.000)	(0.000)
Long Term	NUR	2.032	2.083
		(0.000)	(0.000)
	CUR	1.881	1.823
		(0.000)	(0.000)

Notes: Numbers in parentheses are the p-values of coefficient estimates. Coefficients are converted into number of weeks using a sample mean of 13.60 weeks for the mean duration.

TABLE D-3 Test Statistics of Hypotheses: Sectoral Shifts versus Cyclical Fluctuations under Alternative Natural Rates of Unemployment

(1963Q1 $\sim$ 2003Q1)

Null Hypothesis	Statistics (1)′ $NUR(\hat{g}_{ak})$	Statistics (1)″ $NUR(\hat{g}_{pc})$
H_1 : Identical Effects of NUR and CUR	9.371 (0.003)	15.359 (0.000)
H_2 : Identical Effects of NUR_{-1} and CUR_{-1}	10.668 (0.001)	19.651 (0.000)
H_3 : Joint Test of H_1 and H_2	5.400 (0.005)	10.331 (0.000)
H_4 : Identical Long Term Effects of NUR and CUR	0.953 (0.331)	3.299 (0.071)

Notes: Numbers are statistics from hypothesis testing with p-values in parenthesis.

TABLE D-4 Estimation of $\ln(MDU)$: Controlling for Demographic Effects

Variables	Baumol-Wolff $(2)'$ $NUR(\hat{g}_{ak})$	Baumol-Wolff $(2)''$ $NUR(\hat{g}_{pc})$	Abraham-Shimer $(5)'$ $NUR(\hat{g}_{ak})$	Abraham-Shimer $(5)''$ $NUR(\hat{g}_{pc})$
C	5.173	5.764	-2.516	-2.832
	(0.000)	(0.000)	(0.072)	(0.064)
NUR	0.001	-0.007	-0.071	-0.024
	(0.957)	(0.709)	(0.132)	(0.609)
NUR_{-1}	-0.008	0.035	-0.052	0.021
	(0.717)	(0.090)	(0.389)	(0.622)
UR	0.085	0.089	0.035	-0.017
	(0.000)	(0.000)	(0.392)	(0.625)
UR_{-1}	0.116	0.100	0.151	0.115
	(0.000)	(0.000)	(0.001)	(0.005)
Emp(16-19)	0.076	0.090		
	(0.006)	(0.001)		
Emp(20-24)	-0.179	-0.193		
	(0.000)	(0.000)		
Emp(25-54)	-0.054	-0.071		
	(0.001)	(0.000)		
$SUR(\lambda_{en}, \lambda_{ne}, \lambda_{un})$			-0.449	-0.249
			(0.017)	(0.191)
$MDU(\lambda_{en}, \lambda_{ne}, \lambda_{un})$			0.513	0.484
			(0.000)	(0.001)
$\overline{R}^2$	0.947	0.953	0.840	0.811
$log\ L$	61.17	63.28	36.80	34.70

Notes: Numbers in parentheses are the p-values of coefficient estimates. Sample periods are 1963-2002 for $(2)'$ and $(2)''$, and 1976-2000 for $(5)'$ and $(5)''$

TABLE D-5 Short-Term and Long-Term Marginal Effects on MDU: Sectoral Shifts versus Cyclical Fluctuations under Alternative Demographic Variables

Term	Variables	Marginal Effect $(2)'$ $NUR(\hat{g}_{ak})$	$(2)''$ $NUR(\hat{g}_{pc})$	$(5)'$ $NUR(\hat{g}_{ak})$	$(5)''$ $NUR(\hat{g}_{pc})$
Short Term	NUR	1.165 (0.000)	1.116 (0.000)	-0.540 (0.207)	-0.612 (0.143)
	NUR_{-1}	1.457 (0.000)	1.837 (0.000)	1.472 (0.008)	2.026 (0.000)
	CUR	1.151 (0.000)	1.124 (0.000)	0.520 (0.392)	-0.260 (0.625)
	CUR_{-1}	1.568 (0.000)	1.362 (0.001)	2.247 (0.001)	1.710 (0.005)
Long Term	NUR	2.622 (0.000)	2.952 (0.000)	0.848 (0.014)	1.288 (0.000)
	CUR	2.719 (0.000)	2.576 (0.000)	2.520 (0.003)	1.321 (0.034)

Notes: Numbers in parentheses are the p-values of coefficient estimates. Coefficients are converted into number of weeks using sample mean duration of 13.57 weeks for $(2)'$ and $(2)''$, and 14.90 weeks for $(5)'$ and $(5)''$. Sample periods are 1963-2002 for $(2)'$ and $(2)''$, and 1976-2000 for $(5)'$ and $(5)''$

cyclical rate in each period are statistically insignificant. A joint test of the equalities also indicates an insignificant difference. The long-term effects of both the *NUR* and the *CUR* are statistically different from zero, but their magnitudes are quite similar.

As in the case with Lilien type natural rates of unemployment, current *NUR* also becomes insignificant in the case of column $(5)'$ and $(5)''$. Since it is significant in columns $(2)'$ and $(2)''$ estimated for the sample period of 1976-2000, the explanatory power of the current *NUR* depends on the choice of demographic variables. The long-term effect of the *NUR* becomes much smaller when Abraham and Shimer's demographic variables are used. Note that this decrease in the long-run effect is solely from a large decrease in the effect of the current *NUR*. Since the long-term effect of the *NUR* is still significant and about 2.594 weeks in column $(2)'$ and 3.154 weeks in column $(2)''$ for the shorter sample period, its effect depends on the choice of demographic variables. Again, this implies that the Abraham and Shimer's demographic variables may pick up some of the effects of the *NUR*.

The use of the $NUR(\hat{g}_{ak})$ or the $NUR(\hat{g}_{pc})$ does not alter the conclusions about the effect of sectoral shifts of labor demand on the mean duration of unemployment in the analysis of quarterly data. Sectoral shifts of labor demand have significant effects on the mean duration of unemployment, which are statistically different from those of cyclical fluctuations. In the analysis of annual data, the long-term effects of sectoral shifts of labor demand are still statistically significant, but there is no statistically significant difference between the long-term effects of sectoral shifts and cyclical fluctuation.

VITA

Yanggyu Byun received his Bachelor of Science degree in economics from Seoul National University in 1988. He received his Master of Science degree and Master of Arts degree in economics from Seoul National University and University of Rochester in 1992 and 1997, respectively. He received his Ph.D. in Economics from Texas A&M University in August of 2007. His fields of specialization are Macroeconomics, Labor Economics, and Econometrics. Yanggyu Byun can be reached at Korea Economic Research Institute, FKI Building, 28-1, Yoido-dong, Yeongdungpo-ku, Seoul, 150-756, Korea, or by email at econbyun@hotmail.com.