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THE DISPERSION OF WAGES OVER THE BUSINESS CYCLE

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ABSTRACT

THE DISPERSION OF WAGES OVER THE BUSINESS CYCLE

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A number of studies have examined the effect of the business cycle on the dispersion of interindustry wages. However, the time-series models used in these analyses often lack appropriate labor quality measures to control for changes in the composition of the labor force. Other studies have used micro data to examine changes in wage dispersion over the cycle, but most have not accounted for the fact that industry wage premia and returns to human capital characteristics may vary over time.

This research uses both aggregate and micro-level data to examine the cyclicality of wage dispersion. Time-series models are used to examine interindustry dispersion for both one-digit SIC industries and two-digit SIC manufacturing industries. These models incorporate time-series properties that have not been taken into account in previous work. The results show little responsiveness to changes in cyclical activity. At the one-digit level, increases in the prime age male unemployment rate are associated with a higher

variance of interindustry wages. Unlike previous authors I find no relationship between the variance and the unemployment rate at the two-digit level.

The analysis then turns to a cross-section examination of the dispersion of individual wages, based on data from a series of May Current Population Surveys (CPS) chosen at cyclical peaks and troughs. Unlike time-series models, the cross-section analysis allows for detailed labor quality controls. Changes in the variance of the natural logarithm of wages are decomposed into the proportion attributable to changes in worker characteristics and the proportion attributable to changes in the return to worker characteristics.

The cross-section results show that a significant portion of the change in dispersion is indeed accounted for by the omitted labor quality variables. The estimates of the relationship between wage dispersion and the unemployment rate are generally positive and larger for manufacturing than in the total sample. The cyclical sensitivity of nonwhites and females is relatively large.

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INTRODUCTION

In recent years, a number of studies have examined the flexibility of the interindustry wage structure, noting trends in--as well as the cyclical performance of--the dispersion of wages across industries. This topic is important to economists because, in the competitive model of the labor market, wages play the central role in resource allocation across industries, determining the flow of labor resources to their most efficient use. Contrary to the competitive model, however, there appear to be persistent wage differentials across industries that are unaffected by labor market conditions.[1]

In the presence of these persistent differentials, labor market adjustment as predicted by the competitive model is unlikely to occur. Macroeconomists in the Keynesian tradition have argued that nominal wages are not

[1]Competitive models of the labor market allow for wage differentials at times. When the assumption of labor homogeneity is relaxed, wage differentials may exist because of the varying productivity of workers. Differentials may also arise due to differences in working conditions across firms. If conditions are unpleasant or unsafe, the firm may have to pay a compensating differential to attract enough workers to produce. A number of writers have documented persistent interindustry differentials; however, most conclude that these competitive sources of differentials are not enough to explain the interindustry wage structure.

flexible, as the competitive model assumes. They have argued that nominal wages are downwardly rigid, inhibiting the free adjustment of wage rates in the labor market. In a similar vein, other writers have speculated that under certain institutional settings real wages may be downwardly rigid if workers form rational expectations of inflation rates. Wage flexibility is reduced in both cases, and the consequence is unemployment. To examine wage flexibility, several authors have looked at the relationship between the dispersion of wages and the business cycle.

Economists are also interested in wage dispersion as a measure of economic opportunity. If the business cycle affects the dispersion of wages, income inequality may also vary over the cycle. And the cyclical effect may not be the same for all groups in the population.

A number of studies have examined the effect of the business cycle on the dispersion of interindustry wages. However, the time-series models used in these analyses often lack appropriate labor quality measures to control for changes in the composition of the labor force over the business cycle. Other studies have used micro data to examine changes in wages and wage dispersion over the cycle, but most have not accounted for the fact that industry wage premia and returns to human capital characteristics may vary over time.

This research uses both aggregate and micro-level data to examine the cyclicality of wage dispersion. Time-series models are used to examine interindustry dispersion for both one-digit SIC industries and two-digit SIC manufacturing industries. The time-series models are first differenced because augmented Dickey-Fuller tests cannot reject the presence of a unit root in the variance of the natural logarithm of wages at both the one-digit and the two-digit manufacturing level. As noted earlier, these time-series properties have not been taken into account in previous work.

The analysis then turns to a cross-section examination of the dispersion of individual wages, based on data from a series of May Current Population Surveys (CPS) chosen at cyclical peaks and troughs. Unlike time-series models, the cross-section analysis allows for detailed labor quality controls. Furthermore, the time-series models (like previous studies of this subject) presume that the return to human capital characteristics is constant over time. This cross-section analysis does not include that assumption. Changes in the variance of the natural logarithm of wages are decomposed into the change attributable to worker characteristics and the change in the return to worker characteristics. The latter is based on estimated wage equations corresponding to peaks and troughs of recent business cycles. Because the coefficients of the models are not constrained to be the same over time, the estimated parameters are used to calculate the changes in dispersion due to these structural changes in the wage equation.

Chapter 1 provides a review of the literature on interindustry wage dispersion. Chapter 2 develops a basic model of the labor market and explores the implications of the model for the cyclicality of dispersion. Chapter 3 presents time-series evidence on interindustry dispersion by one-digit and two-digit SIC industries. Unfortunately, time-series evidence is limited by the fact that it is very aggregated and lacks appropriate labor quality controls. Although considerable attention is devoted to that shortcoming, explicit quality controls are necessary for a more conclusive analysis. Therefore, Chapter 4 presents results based on an analysis cross-sectional data from May Current Population Surveys to extend the analysis. Chapter 5 concludes the study with a summary and an examination of the implications of the results.

CHAPTER 1

Wage Flexibility over the Business Cycle

Introduction

Wage flexibility may be measured in a number of ways. Typically, economists have used some measure of wage dispersion as an indication of wage responsiveness. Wachter (1970) uses the coefficient of variation of interindustry wages; Bell and Freeman (1985) use the standard deviation of the natural logarithm of interindustry wages; Montgomery and Stockton (1987) choose the variance. All of these metrics are natural measures of wage dispersion, but they have shortcomings as indicators of labor market flexibility. As an OECD (1985) report points out, the responsiveness of the interindustry wage structure must be measured along several dimensions. The authors suggest that the appropriate dimensions include a changing dispersion of wages, changes in the relative wage rankings and/or relative wages among industries, and a higher (lower) growth rate of relative wages among expanding (contracting) industries, (OECD (1985), p. 84).

To judge the flexibility of the wage structure on only one of these criteria might yield misleading results. For example, it is possible for the dispersion of wages to remain relatively stable in the presence of volatile industry rankings. Or, as in the case of the United States since 1970, the dispersion of wages has risen according to almost all available measures.[2] However, Montgomery and Stockton (1987) and Krueger and Summers (1987) document the stability of the U.S. interindustry wage structure in terms of industry rankings. Hence, the assessment by Bell and Freeman (1985) that the U.S. wage structure is flexible might be called into question when one considers the high correlation between industry wage rankings year after year.

Bell and Freeman note a 35 percent increase in the standard deviation of wages in the industries they examine, leading to their assessment. However, the industry rankings have remained stable over time. A juxtaposition of the Bell and Freeman results with those from the OECD (1985) provides a more complete picture. The OECD authors test the stability of the wage structure in a number of countries by regressing the wage structure in a series of years on a base year. For the U.S. 1975 was the base year, and regressions were performed in this manner from 1976 through 1982. Using the coefficient of determination as a measure of stability, they found that the U.S. wage structure is highly stable.

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[2]OECD (1985), Montgomery and Stockton (1987), Bell and Freeman (1985), and Lawrence and Lawrence (1985) each provide estimates of approximately a 35% increase in dispersion between 1970 and the early 1980's, even though they each compute dispersion over somewhat different industries.

The coefficient monotonically declined over time but was always greater than 0.97, a high correlation between wage structures separated by as much as seven years.

As for the third criterion, Lawrence and Lawrence (1985) examine the relationship between employment growth in high-wage industries and wage changes. They note that the correlation between 1970 wage levels and wage changes between 1970 and 1984 was a statistically significant 0.37. Further, they note that the decade of the 1970's brought a 30 and 15 percent increase in wages to steel workers and automobile employees, respectively--both are above average increases for this time period.

While some of these studies address the issue of cyclical variation of the wage structure, their primary emphasis is to explain the secular increase in dispersion since 1970. An early study of cyclical variation in interindustry wages is the well-known paper by Wachter (1970). He addressed two issues in this paper: he acknowledged the persistence of interindustry wage differentials, and he used a supply-side analysis of the labor market to address the cyclicality of wage dispersion.

Wachter does not actually explore causes of persistent wage differentials across industries. The extent of his analysis on this issue is to briefly survey the literature that cites heterogeneous skills and market structure as possible sources of these differentials. In exploring his first claim that differences in product and labor markets among industries cause inequalities for given skill levels, he says that differentials have been present for too long to be considered a random disturbance from the competitive ideal. He notes that these inequalities, in part, reflect differences in productivity among workers, but that the differentials cannot be explained solely by these factors (Wachter (1970), p. 75).

Two of the noncompetitive elements he stresses are the industry unionization rate and the industry's ability to pay. His analysis, however, does not attempt to sort out or confirm these theories. They are simply captured as the constant term in a dispersion equation where he uses the coefficient of variation of interindustry wages as the dependent variable.

Wachter examines the issue of labor heterogeneity in more detail, however. Using a constructed skill mix variable, Wachter finds a positive, statistically significant relationship between labor quality and the wage rate. He argues, however, that one industry is primarily the source of this relationship; to examine the sensitivity of his results, he performs his statistical analysis with and without the confounding industry. He finds similar qualitative results. Consequently, he argues that labor heterogeneity is not the source of interindustry dispersion or its cyclical behavior.

To provide a basis for his statistical analysis of cyclical variation, Wachter discusses the effects of the business cycle on the supply of labor to each industry, differentiating between high and low-wage industries. He assumes that high-wage industries hire from a queue created by this positive wage differential. Low-wage industries must attract the necessary number of workers by responding to cyclical conditions. Since, according to Wachter's model, labor supply to the industry is a function of the industry's relative wage as well as aggregate demand, low-wage industries will raise their wages during periods of high aggregate demand to attract a sufficient number of workers. In slack periods, they lower wages, and the differential increases. From this framework, Wachter predicts that wage dispersion increases during a recession and declines during a recovery.

To test this hypothesis, Wachter regresses the coefficient of variation of two-digit SIC manufacturing industries on a constant term and Almon lags of the inflation rate and the inverse of the aggregate unemployment rate.[3] He determines that inflation increases dispersion, but the effect is small with a long-run elasticity of 0.09. The unemployment rate increases dispersion also, with a long-run elasticity of 0.25. The positive and significant elasticity provides statistical support for his view of wage determination.

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[3]The dispersion measure is not weighted by employment in each industry, giving small industries a disproportionate influence.

While Wachter's statistical results match his expectations, his statistical analysis does not reveal much about the dynamics of wage adjustment in the labor market. While his discussion provides a rationale for the cyclical effect he finds statistically, it is hardly a confirmation of the dynamic adjustment he suggests.

In an attempt to examine labor market adjustment when moving from a slack to a tight economy, Okun (1973) suggests that a process he terms "cyclical upgrading" occurs. His view is based on a dual labor market approach, and the premise underlying his analysis is that prime-age males have a stronger attachment to the labor force than other demographic groups such as females or young workers. He notes that the simplest view of labor market adjustment suggests that industries experiencing the largest employment growth would be expected to experience the largest wage increases during an upturn in economic activity; consequently, one would expect wage differentials across industries to widen. Yet, citing the Wachter paper along with others, Okun notes that both skill differentials and wage differentials tend to narrow in a high-pressure economy. Okun, unlike Wachter, argues that a major part of wage adjustment occurs due to the change in the skill composition of the labor force.

Okun suggests a process of adjustment during an economic recovery where prime-age males leave low-paying sectors to enter high-wage industries. They are replaced in the low-wage sector by young workers or women. This gain in male employment is most substantial in high-wage manufacturing, transportation, construction, and mining jobs. The evidence that Okun presents suggests that perhaps Wachter underestimates the consequences of ignoring the changing skill composition of the labor force in analyzing dispersion (Okun (1973), p. 216).

At least two subsequent studies, as a by-product of their examination of the secular increase in dispersion, have examined the cyclicality of wage dispersion. Bell and Freeman note that the cyclicality of dispersion accounts for very little of the wage variability observed since 1970.[4] In a simple regression of the standard deviation of the logarithm of industry wages on real GNP and a time trend, they do not find a statistically significant cyclical effect. Hence, they look to productivity shocks at the industry level to explain the evolution of the interindustry wage structure as an alternative to the competitive model of the labor market.

Montgomery and Stockton (1987) construct a neoclassical model of the labor market in an attempt to explain the increase in the dispersion of wages. Using a model that incorporates technological progress, labor heterogeneity, and exogenously supplied capital, they find that most of the

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[4]Note that the combination of industries examined by Bell and Freeman is somewhat different than those examined by the previous authors.

change in dispersion may be accounted for by microeconomic factors.[5] To account for labor heterogeneity, they use the Gollop-Jorgenson labor quality indexes to develop a measure of the dispersion of labor skills; the inclusion of this measure highlights the role of skill differentials in wage determination across industries. Along with the labor quality controls, Montgomery and Stockton include capital (or capital-labor ratios), expected income, and a nonlinear time trend. The time trend is an attempt to incorporate technological progress. While they note the statistical significance of the trend and the theoretical interpretation associated with it, they caution against a literal interpretation of technological progress. Omitted factors correlated with the trend could easily be picked up in the estimation of such trends or factors other than technological progress could account for any observed trend.

While these factors seem to primarily explain wage dispersion in the Montgomery and Stockton analysis, the authors also explore the impact of macroeconomic variables. They repeat several of their regressions including macroeconomic measures such as the prime-age male unemployment rate and the inflation rate.[6] They

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[5]They examine the dispersion of wages across two-digit manufacturing industries from 1948 to 1981.

[6]The prime-age male unemployment rate refers to males from 25 to 54 years old. It is a better cyclical measure than the aggregate unemployment rate, which lags current cyclical activity.

consistently found no role for inflation (expected or unexpected) as a source of wage variability, but they find a positive, statistically significant impact for the unemployment rate: during recessions (booms) dispersion increases (decreases). However, the explanatory power of the unemployment rate is small relative to the microeconomic factors according to Montgomery and Stockton.

Their findings stand in contrast to the results of a new literature that finds significant inflationary effects on wage adjustment across industries. Hamermesh (1986), Drazen and Hamermesh (1986), Fackler and Holland (1989), and Allen (1986) all focus on the effects of inflation on labor market adjustment. Hamermesh (1986) develops a model of the dispersion of wage changes across industries based on the Keynesian concept of downwardly rigid nominal wages. The model demonstrates that, with downward nominal wage rigidity, wage change dispersion should increase with increases in inflation. If real rather than nominal wages are downwardly rigid, only unexpected inflation should have the effect of increasing dispersion.

To test this model, Hamermesh obtains maximum likelihood estimates of the effects of expected and unanticipated inflation on wage change dispersion.[7] He

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[7]The dependent variables in this analysis is the variance of wage changes across one-digit industries (1965-1981) and two-digit manufacturing (1955-1981). He uses a number of measures of anticipated inflation: The Livingston Survey, the Survey Research Center survey of households, and an ARMA forecast.

finds no consistent effect for expected inflation, and contrary to the Keynesian analysis he finds that the dispersion of wage changes across industries is reduced by unexpected inflation. Drazen and Hamermesh (1986) find similar results using Israeli data. Hamermesh suggests that implicit indexation may be the source of this unexpected finding, but Fackler and Holland (1989) present evidence disputing that suggestion. At any rate, these results suggest a responsiveness of interindustry wage changes to the rate of change in prices, unlike the Montgomery and Stockton results.

Montgomery and Stockton note that their results account for microeconomic factors, while the inflation studies ignore those characteristics for the most part. Their suggestion implies that the impact of inflation is a statistical relic rather than a real phenomenon, resulting from the omission of labor quality variables from the analysis.

Several recent papers have dealt with the issue of wage cyclicality, and their findings bear upon this research. Several authors (Bils (1985), Keane et. al. (1989), and Blank (1989, 1990), for example) have revisited the question of how wages vary over they cycle. Bils notes that the variety of results presented in the debate over the cyclicality of wages is clouded by aggregation bias in many of the previous studies. He attempts to remedy this shortcoming by using micro panel data. Keane et. al. note that Bils estimates may be biased, however, since he eliminates those that fall from the sample over the cycle. They find that selectivity is important to in the cyclicality of real manufacturing wages, but like Bils, they found that wages are slightly procyclical. In a related vein, Shaw finds that real wages are much more sensitive to persistent sectorial shocks than to temporary cyclical shocks.

Blank (1989) disaggregates the effect of the business cycle on the distribution of income. Here she finds that both wages and hours show evidence of cyclicality, although hours seem more cyclically sensitive. Blank (1990) investigates wage cyclicality in the 1970's. She focuses further attention on the issue of worker selection over the cycle as well as the cyclicality of returns to worker skills. She finds that wages are affected by movement between broad sectors but that selectivity is not an important statistical issue since their is no statistical correlation between wage determination and sectorial choice. She also finds cyclicality in the returns to worker characteristics.

The Interindustry Wage Structure

A rather large literature has recently re-emerged examining the interindustry wage structure. The studies attempt to explain certain stylized facts of the labor market: of particular interest to these writers is the persistence of wage differentials and the stability of the interindustry wage structure over time and across countries. The persistence of these differentials has been noted by writers such as Katz and Summers (1989), Krueger and Summers (1987), Dickens and Katz (1987), and Murphy and Topel (1987).

As noted earlier, the stability of industry wage rankings is well known. Krueger and Summers (1987) document other regularities as well. They estimate industry wage differentials from Current Population Survey data (1984) and find that the differentials are basically unaffected by the inclusion of explicit labor quality controls, although they concede that unobserved labor quality might account for the differentials. Katz and Summers (1989), however, examine this issue further, concluding that unobserved labor quality is not the source of interindustry differentials. They argue that, contrary to the findings of Murphy and Topel (1987), the evidence is not consistent with this explanation. If education and experience are correlated with unobserved ability, high-wage industries would hire a disproportionately large number of these workers. That is not the case. They also show that gains (losses) to workers entering (leaving) an industry are equal to the industry differential, which is unlikely if unobserved labor quality accounts for industry wage differentials.

Krueger and Summers (1987) and Katz and Summers (1989) also show that the interindustry wage structure across industrialized countries is similar. They present evidence of a large positive correlation between industry wages across countries, and they speculate that certain regularities may lead to this occurrence.

Furthermore, certain characteristics seem to be correlated with the industry rankings. One interesting and somewhat mystifying phenomenon is that high-wage industries pay high wages to all occupations within the industry. Krueger and Summers argue that profitable industries share some of these rents with workers. Katz and Summers, upon further examination, argue that workers reap most of the rents.

Dickens and Katz (1987) examine other correlates of interindustry wage differences such as industry product market concentration, plant size, and unionization. They note that such determinants are important, but they argue the structural relationship between the differentials and these factors is not well established. These papers, as a group, suggest that efficiency wage models of labor market adjustment may be appropriate, though there is no structural evidence to support any particular version of these models.

An implication of the work on interindustry wage differentials is that the interindustry wage structure is relatively rigid and unresponsive to changes in aggregate demand. Some of the papers conjecture that the labor market may be more appropriately viewed as a dual labor market with a rigid high-wage sector and a relatively flexible low-wage sector. There is no real evidence to exclusively support that view, nor is it crucial to the analysis of interindustry wage differentials presented in these papers.

The fixed wage structure implies a different sort of labor market adjustment than the competitive model--or the dual approach described by Wachter. In this framework, the industry simply adjusts the quantity of employment to labor market conditions.[8] With a fixed interindustry wage structure, involuntary unemployment exists. Katz and Summers (1989) argue that in the case of a rigid wage structure, economic welfare may be increased by encouraging employment in high-wage industries. They suggest the possibility of subsidies to high-wage industries as a welfare-augmenting policy.[9] This also suggests that some benefits of countercyclical policy may be ignored in fighting recessions. If high-wage industries lose proportionally more employment in a downturn, then the cost of a recession is greater than in the competitive view of the labor market. The rents accruing to high-wage workers

[8]Hamermesh (1989) examines employment adjustment by seven plants of an unnamed firm and finds that the plants alter their workforces in response to rather large shocks but maintain steady employment for smaller shocks. Employment at the industry level appears to adjust to at the margin, however, due to the aggregation of responses from heterogeneous firms.

[9]The authors note that distributional and collateral costs may offset the desirability of this policy.

are best viewed as real losses to the economy during a downturn.[10]

Conclusion

The dispersion of wages over the business cycle may be measured in a number of ways. Most studies reviewed here use some measure of variability, such as the variance or standard deviation of wages across industries, but the rankings of industries are also a component of flexibility. The U.S. wage structure has demonstrated significant flexibility in terms of wage dispersion, with variability increasing by 35 percent from 1970 to 1982. However, the ranking of industries by wages is stable, changing little over the period of the 1970's. In fact, there is a significant, positive correlation between the level of wages and wage changes. So the picture of U.S. wage flexibility is not so clear as the dispersion literature might suggest.

In fact, the labor literature has long provided evidence for persistent wage differentials. Some authors suggest that the differentials do not support the competitive view of labor market adjustment, and they advocate policies based on this view of market adjustment.

To examine the flexibility of wages over the business cycle, the next chapter presents a simple model of wage

[10]Katz and Summers (1989) address this argument in detail in the context of international trade and industrial policy.

dispersion and several resulting hypotheses to be tested empirically.

CHAPTER 2

A Model of the Cyclicality of Dispersion

Introduction

In order to analyze the flexibility of interindustry wages, a simple model of the labor market provides a useful point of departure. The following model examines the effect of the business cycle on the short run determination of wages by industry. Labor market flexibility across industries in response to cyclical fluctuations may then be measured by computing the variance of the natural logarithm of the wage rate across industries.

The simplest form of the model analyzes labor market flexibility by assuming that workers have homogeneous skills with constant labor demand and supply elasticities across industries. A second assumption of the model is that the labor market in each industry clears in each time period. Aggregate demand affects the labor market through the product market since labor is a derived demand. This model counterfactually predicts that dispersion increases with cyclical upswings.

To provide a more complete picture, the assumptions of homogenous labor skills and market clearing are relaxed to extend the implications of the analysis. The relaxation of these assumptions allows alternatives to price flexibility for labor market adjustment. A variety of scenarios are developed under these assumptions to examine interindustry behavior. These models show that the cyclically changing skill composition offsets the direct effects of the cycle on interindustry dispersion. Further, the assumption of downward wage rigidity implies asymmetry in the dispersion of wages over the cycle.

An Equilibrium Model of the Labor Market

Since the focus of this work is on labor market flexibility and the existence of persistent interindustry wage differentials, I begin my analysis with an examination of wage determination in each industry. To simplify the analysis, I assume that labor is homogeneous in ability, so that one worker may fill a position as productively as another in a firm. Let the demand for labor be given by

$$L_{it}^{d} = d_i + \alpha(w_{it} - p_{it}) \tag{2.1}$$

where L^{d}_{it} is the quantity of labor demanded, α is the labor demand elasticity, w_{it} is the nominal wage rate, and p_{it} is the product price.[1] According to this equation, the sole determinant of labor demand in the industry is the value of

[1] L^{d}_{it}, w_{it}, and p_{it} are the natural logarithms of the actual values. All the variables in this chapter are stated in natural logarithms unless otherwise noted.

the worker's marginal contribution to the firm, the real wage from the industry's perspective.[2]

Labor supply in the industry is given by

$$L^{S}_{it} = s_i + \beta(w_{it} - P_t) \tag{2.2}$$

where L^{s}_{it} is the quantity of labor supplied, ß is the labor supply elasticity, and P_t is the expected price level. Equilibrium in the labor market of each industry is given where labor demand and supply are equated in each industry in each time period. Then,

$$w_{it} = \frac{s_i - d_i}{\alpha - \beta} + \frac{\alpha}{\alpha - \beta} p_{it} - \frac{\beta}{\alpha - \beta} P_t \ . \tag{2.3}$$

In this model, the nominal industry wage rate is an increasing function of the product price and of the expected price level. I assume that individuals form rational expectations of the aggregate price level so that expected

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[2]In this and subsequent equations, the price elasticity is constrained to be equal across industries. While this assumption is restrictive, I have no information about differences in responsiveness by industry. While a richer specification is desirable, it is not necessary to model the impact of cyclical activity on wage dispersion.

real wages are the determinant of labor supply.[3] The expected aggregate price level does not vary by industry.

The price, p_{it}, for an industry is formed in the product market. To close the model, it is necessary to describe equilibrium price determination in the industry. Let demand in the product market be given by

$$(2.4) \qquad Q^d_{it} = a_{1i}+a_2p_{it}+a_{3i}D_t$$

Q^d_{it} is the quantity of the product demanded, a_2 is the product price elasticity that is assumed to be constant across industries, p_{it} is the price of the product, a_{3i} is the elasticity of demand with respect to aggregate shocks, and D_t is a measure of real aggregate demand.

Supply is given by

$$(2.5) \qquad Q^s_{it} = b_{1i}+b_2p_{it}$$

where the quantity supplied of the industry's product is a function of the price. b_2 is the supply price elasticity, common to all industries in this analysis. In equilibrium, the product price is

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[3]Notice that the equation can be written as

$$(2.3') \qquad w_{it} = \frac{s_i-d_i}{\alpha-\beta}+\frac{1}{\alpha-\beta}(\alpha p_{it}-\beta P_t)$$

where the nominal industry wage is determined by a weighted average of the industry price and the expected price level. The constant term captures the industry-specific productive characteristics and noncompetitive elements that are time invariant.

$$p_{it} = \frac{b_{1i}-a_{1i}}{a_2-b_2} - \frac{a_{3i}}{a_2-b_2} D_t \ .$$

Substituting the product price into the reduced form wage equation (2.3) yields,

(2.6) $$w_{it} = c_0 + c_1 D_t + c_2 P_t$$

where

$$c_0 = \frac{s_i - d_i}{\alpha-\beta} + \frac{\alpha}{\alpha-\beta}\left(\frac{b_{1i}-a_{1i}}{a_2-b_2}\right) \ ,$$

$$c_1 = \left(\frac{\alpha}{\alpha-\beta}\right)\left(\frac{a_{3i}}{a_2-b_2}\right) > 0,$$

and

$$c_2 = -\frac{\beta}{\alpha-\beta} > 0.$$

Equation (2.6) gives the equilibrium industry wage rate in terms of the expected price level and aggregate demand. To examine labor market wage flexibility over the business cycle, it is natural to compute the variance of the natural logarithm of the wage rate, which states the variance as a function of the exogenous variables. This relationship is given by

(2.7) $$\sigma^2_{w_{it}} = \tau_0 + \tau_1 D_t^2 \ ,$$

where

$$\tau_0 = \frac{1}{(\alpha-\beta)^2}(\sigma^2_{s_i}+\sigma^2_{d_i}) + \frac{\alpha^2}{[(\alpha-\beta)(a_2-b_2)]^2}(\sigma^2_{b_{1i}}+\sigma^2_{a_{1i}})$$

and

$$\tau_1 = \frac{\alpha^2\sigma^2_{a_{31}}}{[(\alpha-\beta)(a_2-b_2)]^2} > 0 .$$

From this formulation, τ_1 is clearly positive, and the derivative of the variance with respect to the aggregate demand measure is greater than zero. These parameters are functions of labor and product market elasticities, the dispersion of sector-specific nonvarying parameters, and the variance of industry responses to cyclical shocks.

According to this model, an increase in aggregate demand increases interindustry dispersion. Industries that are very responsive to aggregate demand experience positive shifts in their labor demand curves when aggregate demand rises due to the rise in product price. Wages in these sectors rise to attract labor from other industries. Changes in the expected price level should have no effect across sectors since expectations are formed in the same manner for all workers. Hence, the variance across industries is zero.

In the frictionless world of the perfectly competitive model, these differentials would exist only for a short period of time because labor would be immediately reallocated to the high-wage sectors. Labor supply in the low wage sectors of the economy would shift upward, forcing wage rates to rise in order to attract enough labor to produce at the profit-maximizing level. Wages would continue to rise in the low wage sectors (and of course, wages would decline in the high wage sector as labor entered) until no interindustry differential existed. All wage differentials would be eliminated in a short period of time, except for those that were compensating differentials.

The Heterogeneity of Labor

In a somewhat more complex world where actors face dynamic instead of purely static choices, economic actors may not respond as quickly as the competitive model assumes. Firms and workers may invest in human capital specific to the firm or industry. Since this training is most effectively gained on the job, productivity increases by undertaking this investment. Both the worker and the employer have an incentive to make the investment, but specific human capital is immobile. As a consequence, neither actor is willing to undertake the investment alone; therefore, both share the cost of investing in specific human capital so that neither side bears the complete loss in the event of a job separation.[4] As Oi (1962) points out, this type of investment introduces a degree of fixity into the analysis.

Due to this fixity, firms may be less likely to release labor during a downturn. Workers also take into account the joint investment in analyzing the net benefits of moving from current employment to a new job. Instead of simply responding to a wage differential, the worker must evaluate the expected net benefit of a job change. For the worker who has invested to a significant degree in specific human capital, larger differentials are required for this calculus to move the worker to scrap the previous investment. During an upswing, the firm is slower to take on additional workers since training is required for the worker to be as productive as desired. In short, the demand is less sensitive to changes in aggregate demand as a result of their use of specific human capital in the production process.

The result of this joint investment in specific human capital is reduced mobility across sectors due to wage differentials. Consequently, differentials are likely to persist for a longer period of time than the simplest competitive framework would imply. Even if the investment by the firm and the worker do not add to the productive

[4]Becker (1975) details the choices of the actors and analyzes the decision to invest in human capital, general or specific.

ability of the employee, the search and recruitment costs for each party reduce the mobility of labor across sectors to some degree.

Specific human capital has another effect besides the reduced mobility of labor across sectors. It also implies that workers have different productivities due to differences in skills. These differences undoubtedly account for some of the dispersion across industries. Workers may be more productive as a result of superior innate ability, specific training, or general training such as formal education. Differences in labor quality should naturally result in a dispersion of wages both within and between sectors. As industries form to use generally skilled or unskilled workers to produce output, the wage rate paid should reflect the skill differences. Skilled workers are able to attract a higher wage rate than those who have not undertaken investment in human capital. Workers would never undertake such an investment if the expected net benefit was not at least as great as their next best alternative. If some industries consistently use higher quality labor, permanent differentials across industries exist.

The business cycle may then affect wage dispersion across industries by altering the skill mix of the economy. When rigidities are introduced into the framework discussed above, unemployment occurs.[5] As fewer workers are needed during a recession, those who have invested little are the first to be dismissed since both they and the firm have incurred a relatively small loss should they decide to leave the industry. Since jobs in other sectors either pay less or require some investment in specific human capital (assuming jobs are available in such a sector), the worker must decide to either wait until the current industry rehires or to search for employment in another sector. The worker may remain unemployed for some time if many other sectors are rather rigid as well. The alternative may be to take employment in a low-wage industry.

The effect of this behavior is not clear a priori. If workers leave the sectors that are relatively unresponsive to wage changes during downturns to become unemployed, the dispersion of wages may decrease. The remaining workers would be more homogeneous, reducing the differential associated with human capital differences. A stylized fact of business cycle analysis is that relatively unskilled workers are the first to lose their jobs during a downturn. This is particularly evident in the manufacturing sector.[6]

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[5]In the discussion thus far, unemployment may be viewed as voluntary since workers decide not to change sectors in anticipation of being rehired in the sector with which they are currently affiliated. Labor markets still clear in this analysis, but the responsiveness of the sector to aggregate demand is reduced.

[6]See Bils (1985) for a summary of the basic stylized facts of aggregate wage performance over the business cycle.

Of course, all these workers will not remain unemployed. Some move to industries that rely less on skilled labor--especially those with specific skills. The laid-off workers may enter these industries, increasing the supply of labor to these sectors. Wages are depressed as a result, increasing the dispersion of wages. Unlike the simple competitive model, the heterogeneity of labor skills allows wage dispersion to increase during a recession as aggregate demand declines. The stylized facts of the labor market over the business cycle are consistent with such a decline.

To incorporate this analysis into the simple model developed above, assume that skill (S_{it}) increases both the demand for and supply of labor. Interindustry dispersion can then be described as

$$\sigma^2_{w_{it}} = \tau_0+\tau_1 D^2_t+\tau_2\sigma^2_{S_{it}} , \tag{2.8}$$

where interindustry dispersion is also determined by the skill distribution of the labor force.[7] If the skill distribution is unaffected by the business cycle, interindustry dispersion is altered only by the cyclical measure and the marginal impact of a shock is the same as in equation 2.7. If, however, the dispersion of skills is a function of cyclical activity as described above, then

$$\frac{\delta\sigma^2_{w_{it}}}{\delta D_t} = 2\tau_1 D_t + \tau_2 \frac{\delta\sigma^2_{S_{it}}}{\delta D_t}$$

where $\delta\sigma^2_{Sit}/\delta D_t < 0$. If labor quality varies inversely with the cycle, then the overall impact of the cycle on dispersion is ambiguous, a priori.

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[7]It is plausible to think of the demand for workers to increase as skill rises since worker productivity increases. One might also think of increasing skills as increasing labor supply since the worker has an investment in these skills that he must recoup. However, these assumptions are not necessary for the following to hold:

$$\tau_2 = \frac{(\theta-\mu)^2}{(\alpha-\beta)^2} > 0$$

where θ is the supply-side coefficient of skill and μ is the coefficient of skill in the labor demand equation. τ_0 and τ_1 are the same as above.

Disequilibrium in the Labor Market

The human capital story provides a rationale for the reduced responsiveness of an industry's labor market to aggregate demand. Both the workers and the firms have an incentive to protect investments in human capital. Any worker who does not leave the sector to look for work elsewhere is voluntarily out of the market, waiting for an increase in aggregate demand to draw him back. However, macroeconomists in the Keynesian tradition have argued that wages do not adjust to changes in aggregate demand. In such a case, the adjustment described above would understate the quantity adjustment in the labor market that occurs from changes in aggregate demand.

The Keynesian assumption of downward nominal wage rigidity leads to an asymmetry in the cyclical movements of the variance of interindustry wages over the cycle. When the economy is expanding, the equilibrium model derived describes the determination of the industry wage rate by Equation 2.6. But downward nominal rigidity means that the current wage remains unchanged if aggregate demand declines. So the model becomes

$$w_{it} = c_0 + c_1 D_t + c_2 P_t \quad if \quad (1-L)D_t \geq 0$$

$$= w_{i,t-1} \quad if \quad (1-L)D_t < 0 \;,$$

where $(1-L)D_t = D_t - D_{t-1}$.

Under such a regime (and allowing for labor heterogeneity), the variance of interindustry wages is

$$(2.10) \qquad \sigma^2_{w_{it}} = \tau_0+\tau_1 D_t^2+\tau_2\sigma^2_{S_{it}} \ \ if\ (1-L)D_t \geq 0$$

$$= \sigma^2_{w_{i,t-1}}+\tau_2\sigma^2_{S_{it}} \ \ if\ (1-L)D_t < 0\ .$$

Under these assumptions, the behavior of interindustry dispersion depends on the cycle itself. The response is asymmetric, producing a testable hypothesis about the behavior of dispersion over the cycle.[8] The effect of growth in aggregate demand is ambiguous, but a recession will reduce dispersion by decreasing the dispersion of skills across industries: that is,

$$\frac{\delta\sigma^2_{w_{it}}}{\delta D_t} = \frac{\delta\sigma^2_{S_{it}}}{\delta D_t} < 0,$$

when the economy is in recession.[9]

Another possible model of disequilibrium is based on empirical evidence about the labor market without a strong foundation in theory. As noted in chapter 1, persistent differentials have been noted across industries, and those differentials appear to change with relative productivity

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[8]This assumes the same behavior for all industries. The empirical viability of the assumption is explored in Chapter 3.

[9]The derivative is not defined at $(1-L)D_t = 0$ since the function is discontinuous at that point. The derivative is only valid when $(1-L)D_t < 0$. When $(1-L)D_t > 0$, the effect is the same as the symmetric case.

changes across industries rather than cyclical factors. Such a view of the labor market suggests that wages do not adjust to market conditions. Instead, labor would be reallocated across sectors during a recession, or workers become involuntarily unemployed.

To motivate this analysis, assume that all wages are downwardly rigid. When aggregate demand declines, the industry is unable to lower wages. Instead, the firms in the industry use fewer workers. If all industries experience such rigidity and are affected by a downturn to the same degree, then the distribution of wages is unaffected; the unemployment rate merely increases and there is no visible relationship between wage dispersion and the business cycle.

If all industries are not equally responsive to a downturn (perhaps because of the varying use of specific human capital in production), then wage dispersion can change with the cycle, not because of wage flexibility, but because of a change in the industrial composition of the workforce.[10] Those industries that retain relatively more labor receive a larger weight during a recession; hence, even if wages are completely rigid for all industries, dispersion could change simply because relatively high wage

[10]Bils (1985) addresses the importance of aggregation bias in examining the cyclicality of mean wages over the business cycle.

and low wage industries react differently to the change in aggregate demand.

Several writers have recently suggested that wage rigidity may be a profit maximizing choice on the firm's part. The analysis may be appropriate to the industry if firms choose similar technology in production. The implicit contract literature has attempted to explain wage rigidity as a risksharing proposition between the firm and workers. More recently, the efficiency wage literature has attempted to provide possible reasons that firms would pay above the competitive market wage and why wages would not clear the market in such an industry.

If some industries choose to forgo flexibility and others do not, then a recession means that the effects on dispersion are more severe than implied by the specific human capital story. In this case, workers become involuntarily unemployed, willing to work at the industry wage but unable to do so. The worker becomes unemployed or moves to a flexible-wage sector. Wages in this industry are depressed by a decrease in aggregate demand since the marginal revenue product of labor decline and the supply of labor to the industry decrease. The dispersion of wages increases due to the downturn, unlike the decrease experienced in the flexible market case. Wage rigidity results in quantity adjustment as the primary method of reallocation in the labor market.

The human capital analysis is congruent with the wage rigidity explanation. Since unskilled workers are primarily the workers affected in a cyclical downturn, firms implicitly alter the skill composition of the workforce over the cycle.

Implications

The method of labor market adjustment is more than a question of passing interest to economists. The properties of the competitive model are well known to economists, and the welfare characteristics are well established. If wages are not free to adjust to shocks, however, the efficiency of the market may be improved through governmental policy. Katz and Summers (1989) discuss welfare-augmenting policies in the presence of wage differentials in the context of trade policy. They suggest that under conditions of persistent wage differentials, the government may increase economic welfare by encouraging the expansion of high-wage industries --perhaps by subsidizing industries.

While the wisdom of such policy is still suspect when one considers the collateral costs and distributional effects of the policy, their analysis also has implications for government countercyclical policy. If wages are flexible to adjust to aggregate market conditions, workers who choose not to work are making a free, utility-maximizing choice. Unemployment may be considered voluntary; the worker has simply chosen not to take employment at the current market wage rate. When wages rise, the worker returns to a job. Even if the worker reports his labor market status as unemployed, he may simply be looking for work at or above his reservation wage rate.

If the wage rate in high-wage industries is rigid, giving rise to a persistent, positive differential, then unemployment from these industries may be viewed as involuntary to some degree. If the entire wage structure is rigid in the short run, it may be literally true that a worker willing to supply labor may be unable to find work. If as segmented labor market advocates claim, there is a secondary flexible-wage sector, the issue is fuzzier. Under either of these structures, however, the welfare analysis reviewed by Katz and Summers is applicable because the differentials present in either case provide a window of opportunity for government to expand welfare by encouraging employment in the high-wage industries.

While Katz and Summers focus on trade policy, the analysis has implications for countercyclical policy. When high-wage employment is decreased, economic welfare declines under such a regime. And if high-wage employment (such as durable goods in manufacturing) is particularly hurt by a recession, the social cost of a negative shock to aggregate demand is greater under the limited-flexibility model than is recognized by the flexible wage model.

For policymakers, such a consideration is important. In inflationary periods, activist policymakers would generally call for a decrease in aggregate demand. In analyzing the consequences to economic welfare, however, the associated costs of such a policy may differ considerably under these different views of labor market adjustment. The costs of a recession would be larger in the limited flexibility case, reducing the attractiveness of restricting aggregate demand as a means of slowing inflation.[11] The remainder of this research attempts to decipher which view of labor market adjustment is more appropriate by describing the links between cyclical activity and wage dispersion.

Conclusion

The competitive, flexible model of the labor market presented argues that wage dispersion in the short run would be unrelated to the business cycle if there were no frictions in the market. Given that some exist, however, the model demonstrates that under the assumptions of homogenous labor and flexible wages, short-lived wage

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[11]The macroeconomic literature in recent years has noted that countercyclical policy may be ineffective in manipulating economic activity. This is particularly true in models with flexible markets and economic actors who are endowed with Muthian rational expectations. Other models have noted that policy may be effective in the absence of the immediate adjustment of markets. This class of neo-Keynesian models would be congruent with the analysis of persistent wage differentials.

differentials would exist, and wage dispersion would increase during an increase in aggregate demand, stimulating labor mobility to high wage sectors. Conversely, a downturn would reduce dispersion since wage differentials would be smaller in high wage industries with the withering of aggregate stimulus.

The assumptions of wage flexibility and labor homogeneity are not innocuous, however. Skill differences are a source of wage differentials; if labor skills vary over the cycle, then a portion of the variance of wage over the cycle must result from labor heterogeneity, having an ambiguous affect on dispersion. When the model is extended to account for disequilibrium, wage dispersion does not behave symmetrically over the cycle.

Given well-documented interindustry wage differentials that persist over long periods of time, several authors have suggested that wages are not flexible in some industries while they are more flexible in others. Wage rigidity in some sectors could account for the stylized fact that wage dispersion increases during a cyclical downturn; these methods of labor market adjustment imply different social costs of economic downturns. In a cost-benefit analysis of countercyclical policy, these two models imply different returns to activist policy. The flexible wage structure leaves less room for governmental interference in the labor market.

CHAPTER 3

Time-Series Evidence on Interindustry Wage Dispersion

Introduction

Many of the studies that have examined labor market flexibility have used time-series data from one-digit industries or two-digit manufacturing industries as defined by the Standard Industrial Classification. In order to provide a basis for comparison to these studies, this chapter presents time-series evidence on the responsiveness of interindustry wage dispersion to the business cycle. The model described in chapter 2 provides the basis for the estimation.

The results of the estimation below show that the dispersion of wages across one-digit industries is sensitive to the business cycle, increasing as unemployment rises. The responsiveness, though statistically significant, is rather small. For two-digit manufacturing industries, there is no distinguishable impact of unemployment on the dispersion of wages. Furthermore, wage dispersion across both one-digit and two-digit SIC industries does not exhibit the asymmetric behavior predicted under the assumption of nominal wage rigidity--though some manufacturing industries exhibit such behavior.

To distinguish between the possible sources of labor market adjustment, I then present evidence on the responsiveness of industry employment and real wage rates to the business cycle. Real industry wage rates are not very sensitive to cyclical activity; industry employment responds considerably more than wages to cyclical shocks. However, the Wachter view that high-wage industries respond through employment changes and low-wage industries adapt by altering wages is not supported.

This chapter presents evidence not only on two-digit manufacturing industries but also on one-digit industries. The dispersion estimates are also dissected in order to obtain a picture of what happens across industries rather than rely solely on summary measures between dispersion measures and the unemployment rate. Furthermore, the estimates are generated from a model that utilizes the time-series properties of the data to correct for labor heterogeneity over the cycle.

Estimation

To statistically determine the effect of the business cycle on wage dispersion, it is necessary to estimate Equation 2.7 from Chapter 2,

$$\sigma^2_{w_{it}} = \tau_0+\tau_1 D^2_t+\epsilon_t.$$

This equation was derived under the assumption of homogenous labor, but as discussed, the business cycle is likely to alter the mix of labor skills used by each industry. Hence, it becomes necessary to include human capital variables to control for skill differences.[1] Unfortunately, labor quality controls do not exist at the industry level.[2] Some other method of estimation will be necessary to estimate the effect of the cycle on wage dispersion, controlling for labor quality.

Ideally, one should include observed worker characteristics in the regressions to account for the variance across industries. Equation 2.8 provides the relation between interindustry dispersion and these variables:

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[1]The typical controls would include years of schooling, experience, and the square of experience. When these variables are included in the wage equation, they control for human capital differences in the industry wage equation. When the variance of the wage rate is computed to get equation (2.8), the human capital controls become variances and covariances of schooling, experience and its square.

[2]Gollop and Jorgenson (1983) have developed a labor quality index for manufacturing industries. The indexes are computed annually from 1948 to 1978. Since the data in this analysis is monthly, the annual indexes are of little use. Below, I test the injury caused by not using the indexes on annual data.

$$\sigma^2_{w_{it}} = \tau_0+\tau_1 D^2_t+\tau_2\sigma^2_{S_{it}}+\epsilon_t \ ,$$

The greater the dispersion of education and experience across industries, the more dispersed wages should be.[3] Hence, an accurate statistical analysis must account for variation in these characteristics. Unfortunately, time-series data do not exist (generally) at the industry level to allow such controls to be included.[4] So it becomes necessary to ask under what circumstances estimation is valid without the inclusion of human capital variances and covariances.

They may be omitted if they are uncorrelated with the other regressors. No bias would be imparted in the results, though efficiency would be reduced. The variances and covariances of human capital characteristics may also be omitted under another circumstance. Assume that experience and its square, along with schooling (and any other human

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[3]Unobserved characteristics may also account for dispersion. Murphy and Topel (1986) note that this is a serious potential problem in analyzing the structure of interindustry wages, but Katz and Summers (1989) present evidence to the contrary and demonstrate shortcomings in the Murphy and Topel work.

[4]As noted in chapter 1, Montgomery and Stockton (1987) control for labor quality by using the Gollop and Jorgenson (1983) labor quality indexes. These are constructed under the assumption of homogeneity within broad demographic categories and are available only on an annual basis. They incorporate the assumption of intra-group homogeneity within broad demographic categories and are available only on an annual basis. The assumption of intra-group homogeneity, while necessary, is restrictive (Sedalek and Heckman, (1985)).

capital characteristic), may be viewed as stationary time-series processes. Then these variables display no trend and a constant variance. More generally, these variables may be trend stationary, displaying a trend with a constant variance around that trend. The relationship between the variance of wages and the business cycle may be estimated without bias from these omitted variables, then, by differencing the variables in equation 2.8.[5] With constant variances and covariances, the omitted human capital variables will impart no bias to the estimation of

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[5]Given the work of other researchers that shows that the variance of w_{it} has increased in recent years, one might expect that neither it, nor the human capital variables are stationary. The differenced model of Equation 2.8 is further justified, however, in order to avoid spurious regressions in tests of the cyclical hypothesis. Differencing removes the unconditional mean of the variables, and the spurious results that occur from regressing trending variables on one another are avoided. A final justification lies in the method of modeling technological change, which accounts for much of the secular increase in interindustry wage dispersion. Montgomery and Stockton (1987) use linear and quadratic time trends to model the evolution of technology. Although they do not claim that such a specification excludes other interpretations, they explicitly include time in the model to account for technological change. Their model may be viewed as a trend-stationary model. The differenced model in Equation 2.8 eliminates these trends also, but the implication is that the variance is subject to permanent shocks rather than smooth growth that occurs over time. If technological progress may be viewed as a permanent shock to the variance of w_{it}, then the differenced specification may be more appropriate than the trend-stationary model. See Plosser and Schwert (1977) for a discussion of the differenced model.

(3.1) $$(1-L)\sigma^2_{w_{it}} = \tau_1(1-L)D_t^2 + (1-L)\epsilon_t \ ,$$

where L is the lag operator indicating for a variable x_t that $L(x_t) = x_{t-1}$ and $(1-L)\epsilon_t$ is an MA(1) process with a unit root.[6] Assuming that τ_1 is constant over time, τ_1 may be interpreted as the marginal change in interindustry dispersion resulting from a small increase in the aggregate measure of economic activity. Note that the error term of this relationship will be first differenced also when one accounts for measurement error in the statistical estimation of this relationship. This creates a first-order moving average process with a unit root if the error term follows the typical assumptions of the classical regression model. Plosser and Schwert (1977) discuss the estimation of such a model.[7]

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[6]If the constant term in Equation 2.8 does not change over time, it will be differenced away. If there is drift in σ^2_{wit} over time, $(1-L)\tau_{0t}$ will not equal 0. This is a testable hypothesis. The constant term is never significantly different from zero in any of the estimated monthly equations reported below.

[7]According to the structure of the model in Equation 2.8, the error process in this equation is a MA(1) process with a unit root. In the estimates below, I present OLS estimates without the MA(1) because tests easily rejected the null hypothesis of a unit root. In no circumstance could I reject the hypothesis that the MA(1) parameter equals zero.

Data

To estimate this equation, I used average industry wages for one-digit SIC industries and two-digit SIC manufacturing industries, available on a monthly basis from Citibase.[8] Wage data are available for one-digit industries from 1964 while two-digit data are available from 1956.[9] Using this information, I compute the variance of the natural logarithm of industry wages by the following formula:

$$\sigma^2_{w_{it}} = \frac{\Sigma_i[(w_{it}-W_t)^2 E_{it}]}{N_t}$$

where W_t is the weighted average of the natural logarithm of wage rates across industries, E_{it} is industry employment at time t, and N_t is total employment in the sector at time t. The cyclical measure is also taken from Citibase. It is the prime-age male unemployment rate, which is a better measure of cyclical activity than the aggregate unemployment rate,

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[8]The one-digit industries include mining, construction, manufacturing, transportation, wholesale trade, retail trade, finance, and services. The two-digit industries are food, tobacco, textiles, apparel, lumber, furniture, paper, printing, chemicals, petroleum, rubber, leather, stone, primary metals, fabricated metals, machinery, electrical equipment, transportation, instruments, and miscellaneous manufacturing.

[9]Since the control variables begin in 1956, this is all that I can use. However, two-digit wage information is available from 1948.

although it moves opposite to aggregate demand, changing the expected sign of the estimated coefficients.[10]

While the method of estimation is chosen to eliminate the bias associated with omitting the variances and covariances of human capital variables, the hypothesis is not directly testable with this data. In a rather ad hoc attempt to capture this possible omission, I have included demographic variables to gauge possible change in labor quality. If labor quality differs systematically with demographic characteristics, they control for differences in labor quality over the business cycle. These variables, also taken from Citibase, are the percentage of those working who are (1) 16 to 19 years old, (2) female, (3) nonwhite, and (4) part-time for noneconomic reasons. Like the unemployment rate, the variables are squared and then first differenced as the derivation of the model requires.

As discussed in chapter 1, a significant literature has recently addressed the impact of inflation on the adjustment of the labor market. I use the annualized inflation rate computed from the consumer price index to measure inflation. To examine the effects of expected and unexpected inflation separately, I use an ARIMA (1,1,1) process to predict the

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[10]The prime-age male unemployment is computed for males 25 to 54 years old.

inflation rate and residuals from the process become unanticipated inflation.[11]

Results

Tables 3.1 and 3.2 report OLS results for one-digit and two-digit SIC industries, respectively. Although the error-term implied by the differenced equation is a MA(1) process with a unit root, tests for such a process reject that conclusion.[12] Hence, only OLS results are reported here. All the regressions in Table 3.1 show a positive, statistically significant relationship between the unemployment rate and the dispersion of wages across one-digit industries. This result concurs with the findings in the literature discussed in chapter 1. The dispersion of wages increases as the unemployment rate rises; this means that a decrease in aggregate demand increases dispersion.

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[11]An ARIMA (1,1,1) model was the simplest of several models that were used to predict the inflation, the results of less parsimonious models yielded substantially the same results.

[12]The test is described by Plosser and Schwert (1977). This result described here is not surprising. Many economic variables exhibit the time-series property of a unit root. The regressions would only have an non-invertible MA(1) process under classical assumptions about the error term. The fact that the MA(1) parameter is not different than zero after differencing suggests that the dependent variable is difference stationary--that is, the variance in the natural logarithm of interindustry wages contains a unit root. Augmented Dickey-Fuller tests for stationarity support that conclusion. The implication of nonstationarity is that interindustry dispersion is subject to shocks that persist over time--technological innovation, perhaps.

The standard neoclassical view of the labor market would either predict no relationship or an increase in dispersion over the cycle. So as most writers have noted, the results do not appear to concur with the standard view of labor market adjustment. Even after controlling for other factors that potentially affect dispersion, the relationship is still positive and significant.

It is worth noting the effects of inflation in these results. Unlike the literature that finds significant effects of inflation, Table 3.1 does not show any statistically significant relationship between inflation and wage dispersion. When inflation is decomposed into expected and unexpected components, there is still no significant relationship between dispersion and either component, as Montgomery and Stockton (1987) find in their analysis.

Other controls included in columns 2-4 of Table 3.1 are the demographic controls. These variables do appear to exert a significant influence on dispersion. In columns 2 and 4, the youth measure (the percent of those working who are 16-19 years old) and the nonwhite variable (the percent of those working who are nonwhite) reduce the dispersion of wages. The results support Okun (1973) who argues that "secondary" workers move into the low-wage industries to replace adult males who are upgraded to high-wage industries.[13] He argues that low-wage industries are more flexible with respect to wages, so the increase in wages in these industries is necessary to attract these marginal workers. Unfortunately, the method of labor market adjustment is not clear from these results, even though Okun's and Wachter's analyses both predict the cyclical observed in these regressions. There are differences in their views that cannot be sorted out for the results presented in Tables 3.1 and 3.2. That issue will be addressed later in this chapter.[14]

Table 3.2 provides results for two-digit manufacturing industries. In these results, I cannot find any statistical relationship between the unemployment rate and wage dispersion. The result is robust to all specifications attempted. This outcome stands in contrast to the literature reviewed in Chapter 1. While Wachter (1970) and Montgomery and Stockton (1987) show a positive, statistically significant relationship between the unemployment rate and wage dispersion in two-digit manufacturing, I am unable to find such a result. The finding is closer in spirit to Montgomery and Stockton's

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[13]Okun refers to women, youth, and minority workers as secondary workers since they are the major participants in the "secondary labor market."

[14]Note that the demographic variables are transformed with the rest of the model. Therefore, they are also squared and differenced. I am assuming that the coefficient is constant over time, so the discussion proceeds in terms of levels of the variables instead of changes in the variables.

since the effect they find is very small, though significant.

Table 3.1 One-Digit Industries

Dependent Variable: Changes in the variance of log wages[1]

	1	2	3	4
Time Period	1964.02 1987.06	1964.02 1987.06	1977.02 1987.06	1964.02 1987.06
Changes in the square of				
Unemployment rate	2.11 (3.60)	1.88 (3.19)	1.50 (2.20)	1.88 (3.15)
inflation rate	-	-0.00 (-0.03)	-0.06 (-1.62)	-
expected inflation rate	-	-	-	0.03 (0.26)
unexpected inflation rate	-	-	-	0.01 (0.36)
net exports	-	-	-0.00 (-0.85)	-
% 16-19 years old	-	-2.16 (-2.94)	-1.07 (-0.80)	-2.18 (-2.95)
% female	-	0.12 (0.82)	-0.13 (-0.53)	0.13 (0.82)
% nonwhite	-	-2.14 (-2.76)	-0.87 (-0.82)	-2.15 (-2.77)
% voluntarily part time	-	-0.34 (-1.50)	0.03 (0.83)	-0.35 (-1.51)
adj R^2	0.04	0.08	0.03	0.08
D.W.	2.06	2.00	1.82	2.00
F-statistic	-	6.09	1.67	5.24

(t-statistics in parentheses.)
[1]Multiplied by 10^8.

Table 3.2 Two-digit Manufacturing Industries

Dependent Variable: Changes in the variance of log wages[1]

	1	2	3	4
Time Period	1956.02 1987.08	1956.02 1987.08	1956.02 1987.08	1977.02 1987.08
Changes in the square of				
Unemployment rate	-2.31	-10.18	-0.00	16.56
	(-0.12)	(-0.51)	(-0.00)	(0.60)
inflation rate	-	-1.09	-1.08	-0.12
		(-1.51)	(-1.51)	(-0.90)
overtime hours in mfg	-	-	129.04	119.14
			(2.71)	(1.45)
net exports	-	-	-	-0.00
				(-1.64)
% 16 - 19 years old	-	-14.47	-14.95	2.02
		(-0.55)	(-0.57)	(0.04)
% female	-	7.57	6.68	1.59
		(1.44)	(1.28)	(0.17)
% nonwhite	-	22.07	23.50	4.70
		(0.87)	(0.93)	(0.11)
% voluntarily part time	-	-8.44	-11.31	17.14
		(-1.05)	(-1.41)	(0.43)
adj R^2	-0.003	-0.001	0.016	-0.01
D.W.	2.16	2.15	2.18	2.31
F-statistic	-	0.96	2.04	0.79

(t-statistics in parentheses.)

[1]Multiplied by 10^6.

Table 3.2 (continued)

Dependent Variable: Changes in the variance of log wages[1]

	5	6
Time Period	1956.02 1987.08	1977.02 1987.08
Changes in the square of		
Unemployment rate	1.38 (0.07)	15.80 (0.56)
expected inflation rate	-0.17 (-0.24)	8.15 (1.37)
unexpected inflation rate	-1.28 (-1.20)	2.63 (-0.39)
overtime hours in mfg	129.05 (2.69)	125.81 (1.55)
net exports	-	-0.00 (-1.53)
% 16-19 years old	-16.46 (-0.63)	-11.45 (0.06)
% female	6.79 (1.29)	2.55 (0.27)
% nonwhite	20.09 (0.79)	-4.10 (-0.10)
% voluntarily part time	-11.36 (-1.41)	3.44 (0.21)
adj R^2	0.01	-0.01
D.W.	2.17	2.31
F-statistic	1.65	0.96

(t-statistics in parentheses.)
[1]Multiplied by 10^6.

This finding is not a complete surprise. If the interindustry wage structure is somewhat rigid (as suggested by the literature reviewed in Chapter 1), it is not surprising to find that manufacturing dispersion is not much affected by changes in aggregate demand. A rigid wage structure implies quantity rather than price adjustment. If quantity adjustment is the correct description of labor market adjustment, the reallocation of labor will not be limited to movements within manufacturing. Since the range of industries is more narrow, significant quantity adjustment may occur without reallocating within the manufacturing sector itself. Workers who lose their job during a recession either leave the work force, go to another manufacturing job, or move to a nonmanufacturing job. Since the scope for choice is greater when the focus on industries is more limited, it is not surprising to find little evidence of cyclicality in the two-digit manufacturing sector.

Conversely, the positive relationship between the unemployment rate and one-digit dispersion may be accounted for by the fact that all industries are accounted for (save agriculture). Whether quantity allocation, price allocation, or a combination is correct in describing market adjustment, the relationship is more likely to be observed in the broader context. While aggregate data are not sufficient to examine this behavior, below I present comparisons of industry wage and employment responses to the cycle in order to examine the validity of this argument.

Several writers have speculated that the OPEC oil embargo of the mid-1970's induced a structural change in the economy. This explanation is a possible source of the increased dispersion of the 1970's and 1980's, although dispersion began increasing as early as 1970. In order to examine the potential impact of the shift on the unemployment/dispersion relationship, I split the sample at the peak of the business cycle nearest the embargo, November 1973. Table 3.3 presents the results of this analysis before and after 1973.11 for one-digit industries. Before November, 1973, the effect of the business cycle was somewhat larger than after, though both are statistically significant at the conventional level.[15] The controls for labor quality also have more impact before 1973, with the youth and nonwhite variables showing statistical significance. However, a test for structural change at 1973.11 rejects the hypothesis at the 5 percent level. So for one-digit industries, the relationship does not appear to have been significantly affected by the embargo.

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[15]The difference between the means is statistically significant at the 5 percent level.

Table 3.3 One-Digit Industries

Dependent Variable: Changes in the variance of log wages[1]

Time Period	1 1964.02 1973.11	2 1973.12 1987.06	3 1964.02 1973.11	4 1973.12 1987.06
Changes in the square of				
Unemployment rate	5.42 (2.23)	1.78 (2.88)	5.32 (2.19)	1.85 (2.99)
inflation rate	0.01 (0.50)	-0.03 (-0.93)	-	-
expected inflation rate	-	-	-0.00 (-0.13)	0.01 (0.37)
unexpected inflation rate	-	-	0.04 (1.16)	-0.07 (-0.89)
% 16 - 19 years old	-3.10 (-3.31)	-0.53 (-0.44)	-3.08 (-3.30)	-0.48 (-0.40)
% female	0.33 (1.42)	0.06 (0.28)	0.33 (1.41)	0.05 (0.24)
% nonwhite	-3.95 (-3.26)	-0.71 (-0.71)	-3.87 (-3.19)	-0.79 (-0.79)
% voluntarily part time	-0.41 (-1.22)	-0.28 (-0.89)	-0.43 (-1.27)	-0.31 (-0.98)
adj R^2	0.18	0.04	0.18	0.04
D.W.	2.08	1.87	2.10	1.87
F-statistic	6.08	2.49	5.26	2.06

(t-statistics in parentheses.)
[1]Multiplied by 10^8.

Table 3.4 similar estimates for two-digit manufacturing industries, with similar conclusions. There is no evidence of structural change from the OPEC embargo at the two-digit manufacturing level. There is still no evidence of a cyclical relationship between aggregate demand and wage dispersion at this level, in either period.

These results strongly reject cyclicality at the two-digit level, but it is worth asking how sensitive dispersion is at the one-digit level to changes in the unemployment rate. To gain some insight into the economic significance of the relationship, I have calculated the elasticities of the dispersion measure with respect to the unemployment rate for one-digit industries.

Although these results cannot be directly compared to the results surveyed in Chapter 1, one may gain some insight as to the sensitivity implied by these results versus the results of previous writers. Table 3.5 presents the elasticities for each regression estimated in Tables 3.1 and 3.3, evaluated at the means of the variables. These elasticities range from 0.07 to 0.11, numbers that are far smaller than Wachter found for two-digit manufacturing -- 0.25. I have not computed the elasticities at the two-digit level because the coefficients are not statistically significant.

Table 3.4 Two-digit Manufacturing Industries

Dependent Variable: Changes in the variance of log wages[1]

	1	2	3	4
Time Period	1956.02 1973.11	1973.11 1987.08	1956.02 1973.11	1973.12 1987.08
Changes in the square of				
Unemployment rate	-41.60 (-1.23)	21.73 (0.84)	-40.63 (-1.19)	23.20 (0.90)
inflation rate	-1.17 (-1.30)	-0.96 (-0.78)	-	-
expected inflation rate	-	-	0.19 (0.21)	-0.61 (-0.49)
unexpected inflation rate	-	-	-1.13 (-0.98)	-2.19 (-0.73)
overtime hours in mfg	153.70 (2.04)	105.40 (1.62)	156.37 (2.06)	107.27 (1.64)
% 16 - 19 years old	-23.53 (-0.73)	-12.24 (-0.25)	-25.33 (-0.78)	-10.09 (-0.21)
% female	12.15 (1.71)	0.25 (0.03)	11.83 (1.67)	0.69 (0.08)
% nonwhite	29.82 (0.90)	9.96 (0.25)	27.59 (0.83)	5.51 (0.14)
% voluntarily part time	-23.15 (-2.15)	0.68 (0.05)	-22.69 (-2.10)	0.03 (0.01)
adj R^2	0.03	-0.02	0.03	-0.02
D.W.	2.12	2.21	2.12	2.21
F-statistic	2.26	0.53	1.82	0.50

(t-statistics in parentheses.)
[1]Multiplied by 10^6.

Table 3.5 Cyclical Responsiveness of Wage Dispersion

	Column[1]			
	1	2	3	4
Table 3.1	0.08	0.07	0.08	0.07
Table 3.3	0.07	0.10	0.07	0.11

[1]This table presents elasticities of the variance of interindustry wages with respect to the unemployment rate for columns 1-4 of tables 3.1 and 3.3. The elasticities are evaluated at the mean of the variables in each equation. No calculations are done for two-digit industries because the coefficient is not statistically different from zero in any specification.

Sensitivity to Omitted Variables

Even though I have attempted to control for changes in the skill composition of the workforce over time, there are no guarantees that the differenced specification or the employment composition variables will be adequate to do so. In order to get some idea of the sensitivity of the results reported in Tables 3.1-3.5, I rely on the model estimated by Montgomery and Stockton (1987).

These authors estimate a neoclassical model of wage dispersion where the variance in w_{it} depends on the dispersion of skill and capital across industries as well as the covariance of the two. They also include expected income and its square, dummies for the Korean Conflict and the Nixon price controls, and a quadratic in time where the linear term is also interacted with expected income. The dependent variable is the variance of the logarithm of wages across two-digit manufacturing industries from 1948-1981.[16]

I estimate a rough replication of their model with annual data that ranges from 1948 to 1978. Since their model contains explicit controls for labor quality, by re-estimating their model in differenced form, I can gain some insight into the sensitivity of my previous estimates to omitted labor quality.[17] These estimates are contained in Table 3.6.

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[16]Since I use monthly data to estimate my model, the Montgomery and Stockton estimates might be more appropriate since capital in the short run is generally considered fixed. Monthly data for capital in these industries is not available, however. The following empirical exercise is an attempt to determine the implications of omitting these variables.

[17]The estimates do not duplicate their results completely. The estimates in table 6 do not include the dummy variables they use for the Korean Conflict and for the Nixon price controls. And while I use the same technique to construct the skill index described in appendix A to their paper, my data are taken from the 1976 May CPS tape. Instead of tenure, I must use potential experience in my construction of the variable. And while Montgomery and Stockton report their results in capital intensive form, I use the variance of the capital stock and its covariance with the skill index. I was generally successful in replicating the sign and order of magnitude of their estimates when I estimated their model in levels, although I was not successful in every specification they report.

Table 3.6 Two-digit Manufacturing Industries

Dependent Variable: Changes in the variance of log wages

Annual data 1949 - 1978	1	2	3	4
Constant	-	0.00 (1.74)	-	0.01 (2.49)
variance in skill	0.17 (0.55)	-0.12 (-0.34)	0.11 (0.35)	-0.19 (-0.64)
variance in capital	0.00 (0.55)	-0.00 (-0.05)	-0.00 (-1.23)	-0.00 (-0.66)
covariance of skill & capital	0.00 (0.29)	0.00 (0.09)	-0.00 (-0.17)	-0.00 (-0.51)
unemployment rate	0.00 (0.51)	0.00 (0.55)	0.00 (0.52)	0.00 (1.36)
inflation rate	-0.00 (-2.28)	-0.00 (-1.91)	-0.00 (-1.59)	-0.00 (-2.80)
expected income	-	-	-0.00 (-0.82)	-0.00 (-2.64)
square of expected income	-	-	8.6E-08 (2.05)	2.5E-07 (3.27)
adj R^2	-0.04	0.04	0.21	0.35
D.W.	1.24	1.08	1.46	2.01
F-statistic	0.73	1.24	2.25	3.25

(t-statistics in parentheses.)

In differenced form the estimates are sensitive to specification, but in no case is the variance of skill or its covariance with capital statistically significant. For all the regressions in the table, F-tests cannot reject the null hypothesis that differences in the variance of skill, capital, and the covariance of skill have no effect. From this evidence, it seems reasonable to conclude that there is no serious damage done in Tables 3.1-5 by omitting the skill indexes. The differenced form seems to adequately handle the problem. Like the monthly two-digit results presented in Tables 3.2 and 3.4, the unemployment rate does not have a significant impact. In contrast to those results, however, the constant term is significant.[18] And other variables that Montgomery and Stockton include seem to account for much of the variation. In particular, expected income and its square are important determinants in these results. Note that unlike the Montgomery and Stockton results or the results presented in Tables 3.1-3.4, the inflation rate causes a statistically significant reduction in dispersion; this result is similar to those of Hamermesh (1986) and other writers discussed in Chapter 1.

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[18]The MA(1) process with a unit root is still rejected in this specification.

The Adjustment of the Labor Market

The results presented above provide evidence consistent with a few possible explanations of labor market adjustment to the cycle. Is the positive correlation between unemployment and one-digit dispersion solid evidence of the Wachter version of dual labor markets, one high-wage and inflexible and another low-wage and flexible? Or is the result more consistent with a rigid interindustry wage structure which relies almost exclusively on quantity adjustment? And would the two-digit result imply a rigid manufacturing wage structure, or is it in line with rapid market adjustment in the neoclassical framework? The only way to gain more conclusive evidence is to examine the impact of the cycle on an industry-by-industry basis.

In order to estimate the impact of aggregate demand on the industry wage rate, I estimate the reduced form industry wage equation, Equation 2.6, from chapter 2:

$$w_{it} = c_0+c_1D_t+c_2P_t$$

where c_0 and c_1 are parameters to be estimated, and c_2 is restricted to 1. The cyclical measure is again the prime-age male unemployment rate, and w_{it} is the natural logarithm of the nominal wage for the industry. This equation is first differenced to induce stationary and reduce spurious correlation by regressing trending variables on one another. Also, omitted variable bias is reduced since the correlation of first differences is usually less than of levels of the variables. I have, however, included the first differences of the demographic variables to control for changing labor force composition since it is not likely that labor is homogeneous and unchanging over the cycle. I have also included the inflation rate to see if the rate of price increase has an effect at the level of the individual industry. The results are presented in Tables 3.7 and 3.8.

While the magnitudes are small, several industries at both the one- and two-digit level exhibit some cyclical sensitivity.[19] A comparison of these industry results with the dispersion estimates suggests that industry responses at the one-digit level vary enough to account for some of the observed relationship between dispersion and the unemployment rate. At the two-digit level, however, sensitivity is small and relatively homogeneous across industries, accounting for no observed relationship between wage dispersion and the unemployment rate.

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[19]See Tables 3.7 and 3.8.

Table 3.7 Real Wage Estimates, One-Digit

Sample: 1964.02--1987.06
Dependent Variable: natural logarithm of the industry wage rate[1]

Industry	Unemployment[2]	Inflation[2]	Adj. R^2
Mining	0.0029 (0.77)	-0.0002 (0.93)	0.021
Construction	0.0002 (0.07)	-0.0004 (2.26)	0.026
Manufacturing	-0.0027 (1.61)	-0.0004 (5.02)	0.087
Transportation	-0.0039 (2.02)	-0.0004 (3.74)	0.037
Wholesale Trade	-0.0045 (2.83)	-0.0004 (5.23)	0.097
Retail Trade	-0.0039 (1.75)	-0.0003 (2.53)	0.021
Finance	-0.0049 (2.17)	-0.0003 (3.12)	0.028
Service	-0.0033 (1.61)	-0.0004 (4.16)	0.050

[1]Control variables are not shown. They are
(1) percent of the workforce 16 to 19 years old,
(2) percent of the workforce that is nonwhite,
(3) percent of the workforce that is female, and
(4) percent of the workforce employed part-time. The absolute value of t-statistics are show in parentheses.

[2]All variables are first differenced.

Table 3.8 Real Wage Estimates, Two-Digit

Sample: 1956.02--1987.08
Dependent Variable: natural logarithm of the industry wage rate[1]

Industry	Unemployment[2]	Inflation[2]	Adj. R^2
Food	-0.0006 (0.38)	-0.0004 (3.97)	0.040
Tobacco	0.0028 (0.35)	-0.0010 (2.28)	0.004
Textiles	-0.0029 (1.65)	-0.0004 (3.90)	0.036
Apparel	-0.0046 (2.43)	0.0000 (0.03)	0.004
Lumber and Wood	-0.0033 (1.43)	-0.0001 (1.04)	-0.001
Furniture and Fixtures	-0.0043 (2.98)	-0.0001 (1.52)	0.018
Paper and Allied Products	-0.0014 (1.03)	-0.0004 (5.61)	0.073
Print and Publishing	-0.0028 (2.30)	-0.0004 (5.80)	0.077
Chemical and Allied	-0.0001 (0.08)	-0.0003 (4.33)	0.059
Petroleum and Coal	-0.0024 (0.90)	-0.0004 (2.72)	0.022
Rubber and Misc. Plastics	-0.0014 (0.63)	-0.0004 (3.07)	0.011
Leather	-0.0035 (2.22)	-0.0001 (0.96)	0.003
Stone, Clay, and Glass	-0.0032 (2.53)	-0.0003 (4.02)	0.050

Table 3.8 (continued)

Industry	Unemployment[2]	Inflation[2]	Adj. R^2
Primary Metal	-0.0078 (3.61)	-0.0005 (4.20)	0.081
Fabricated Metal	-0.0041 (2.66)	-0.0003 (3.85)	0.040
Machinery (except electric)	-0.0037 (2.84)	-0.0004 (5.09)	0.068
Electric Equip.	-0.0014 (1.06)	-0.0003 (4.49)	0.043
Transportation Equip.	-0.0053 (2.14)	-0.0003 (2.54)	0.012
Instruments	-0.0026 (2.09)	-0.0004 (6.09)	0.090
Misc. Mfg.	-0.0037 (2.38)	-0.0003 (4.02)	0.042

[1]Control variables are not shown. They are
(1) percent of the workforce 16 to 19 years old,
(2) percent of the workforce that is nonwhite,
(3) percent of the workforce that is female, and
(4) percent of the workforce employed part-time. The absolute value of t-statistics are show in parentheses.

[2]All variables are first differenced.

While the real wage estimates provide some support for wage flexibility in response to cyclical activity, the responses are quite small. They do not rule out the rigid wage structure hypothesis since many of the industries show no responsiveness to the cycle.

To examine this further, I estimated the reduced form Equation 2.6, solved for employment instead of wages. Tables 3.9 and 3.10 contain these results for one-digit and two-digit manufacturing industries respectively, where the natural logarithm of industry employment is the dependent variable in each equation. The results are quite interesting. All the industry employment regressions show a negative elasticity with respect to the unemployment rate.[20] The elasticities vary widely, ranging between 0 and -0.15 for two-digit manufacturing industries. For one-digit industries, the range is narrower, 0 to -0.06. This result also argues against the Wachter hypothesis in favor of the fixed industry wage structure. A cyclical shock seems to cause quantity adjustments with little movement in prices.

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[20]There may be endogeneity in using the prime-age male unemployment rate as the measure of the cycle since the measure should be correlated to some degree with the error term of each equation. However, the problem is less serious than it first appears since each industry alone does not have an overwhelming impact on the on the unemployment rate. Two stage least squares and OLS estimates generally yielded similar results although the TSLS elasticities were not different from zero in some cases. Generally, signs and magnitudes did not change; hence, only OLS results are reported.

In fact these results show that one-digit high-wage industries have no less wage flexibility than low-wage industries, contrary to the dual labor market view. Table 3.9 shows the nominal one-digit wage rate as of June 1987, the estimated employment elasticity with respect to the unemployment rate, and the estimated wage elasticity with respect to the unemployment rate. The correlation between the nominal wage and the real wage elasticity is 0.61.[21] The positive correlation indicates that high-wage industries exhibit more wage responsiveness over the cycle. Since the estimates of the wage elasticity are not precise (e.g., many of the estimated coefficients were not statistically different than zero), the correlation of the two may not be such a good measure. The rank correlation might be more useful since the numbers themselves are subject to question. The rank correlation does not alter the picture--it is 0.57, but the relationship is not statistically significant. Hence, there seems to be no discernable relationship between high-wage industries and wage flexibility.

For two-digit manufacturing industries the numbers (shown in Table 3.10) are lower but still positive. The correlation coefficient is 0.29 and the rank correlation is

[21]When the correlation is weighted by industry employment, the correlation is 0.5.

0.26, and neither of these numbers are statistically different than zero.[22]

For one-digit industries, the correlation between wages and employment elasticities is negative and not statistically significant. The same is true for the two-digit results until the sample is weighted by employment. The weighted correlation between industry wages and the employment elasticity is -0.51 and is statistically different than zero.

Table 3.9 Wage and Employment Flexibility, One-Digit

Industry	Wage	Employment Elasticity	Wage Elasticity
Mining	12.44	-0.005	0.011
Construction	12.61	-0.058	0.001
Manufacturing	9.45	-0.058	-0.001
Transportation	11.91	-0.028	-0.016
Wholesale	9.57	-0.012	-0.019
Retail	6.08	-0.021	-0.016
Finance	8.68	-0.006	-0.020
Service	8.35	-0.008	-0.014

The wage rate is the nominal average wage for each industry as of June, 1987. The employment elasticity is the elasticity of industry employment with respect to the unemployment rate. The wage elasticity is the elasticity of the real industry wage with respect to the unemployment rate.

[22]When weighted by employment, the sign reverses, and the correlation is -0.09. It is still not statistically different that zero, however.

Table 3.10 Wage and Employment Flexibility, Two-Digit

	Wage	Employment Elasticity	Wage Elasticity
Food	8.91	-0.013	-0.002
Tobacco	15.57	-0.001	0.011
Textiles	7.15	-0.042	-0.011
Apparel	5.91	-0.038	-0.019
Lumber	8.44	-0.070	-0.014
Furniture	7.66	-0.034	-0.018
Paper	11.41	-0.027	-0.006
Printing	10.19	-0.014	-0.011
Chemicals	12.27	-0.027	-0.001
Petroleum	14.43	-0.055	-0.010
Rubber	8.87	-0.065	-0.006
Leather	6.04	-0.044	-0.014
Stone	10.29	-0.063	-0.013
Primary Metal	11.97	-0.113	-0.032
Fabricated	10.00	-0.091	-0.017
Machinery	10.76	-0.058	-0.015
Electric Equip.	9.84	-0.082	0.006
Transportation	12.88	-0.159	-0.022
Instruments	9.70	-0.048	-0.011
Miscellaneous	7.74	-0.040	-0.015

The wage rate is the nominal average wage for each industry as of June 1987. The employment elasticity is the elasticity of employment with respect to the unemployment rate. The wage elasticity is the elasticity of the real industry wage with respect to the unemployment rate.

Wage Rigidity and Symmetry over the Cycle

In Chapter 2, I discussed the implications of assuming that the labor market clears in every period. If unemployment is not correctly viewed as voluntary, the assumption clearly leads to a misspecified model. If the Keynesian description of wage adjustment is correct, the dispersion of wage would be described by Equation 2.10:

$$\sigma^2_{w_{it}} = \tau_0+\tau_1 D_t^2+\tau_2\sigma^2_{S_{it}} \quad if \; (1-L)D_t \geq 0$$

$$= \sigma^2_{w_{i,t-1}}+\tau_2\sigma^2_{S_{it}} \quad if \; (1-L)D_t < 0.$$

Dispersion would behave asymmetrically over the cycle if industry wage rates were downwardly rigid.

To test the proposition, I estimated this model. This equation is simply a switching regression with a known switching point. To test for asymmetry, I included a dummy variable equal to one when the unemployment rate rises (corresponding to $(1-L)D_t < 0$) and interacted the dummy with the unemployment measure. The test for asymmetry was an F-test of the joint significance of the two variables--or a t-test of the statistical significance of the interaction term.[23]

F-tests (or the t-tests) could not reject the null hypothesis of symmetry over the cycle. Neither model demonstrated different behavior during booms and recessions. It is possible, however, that this test is too crude to pick up asymmetry even if it exists. If industry cyclical responses differ, it is possible that each industry demonstrates asymmetric behavior that is masked by looking at dispersion alone. Hence, I performed the same test for each industry individually.

One-digit industries do not behave asymmetrically, with the exception of manufacturing. Nominal manufacturing wage estimates reject the null hypothesis of symmetry, but real wages do not--even for manufacturing. The Keynesian model is rejected at this level.

Two-digit manufacturing industries demonstrate more variety that the one-digit industries. The null hypothesis of symmetry over the cycle (that is, that the dummy and interaction are not significantly different from zero) is rejected in four of the twenty manufacturing industries for

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[23]Joint significance of the dummy and the interaction term would imply that the mean dispersion changes during a downturn and the impact of the cycle is different when unemployment is rising and falling. The t-test for the significance of the interaction term examines the differential response to the unemployment rate alone.

both nominal and real wages.[24] In this instance, some disequilibrium behavior is masked by considering the interindustry variance without examining the components.

Conclusion

This chapter provides time-series estimates of the effect of the business cycle on wage dispersion across one-digit SIC and two-digit SIC manufacturing industries, where the cyclical measure is the prime-age male unemployment rate. At the two-digit level I could find no evidence of a cyclical relationship, unlike previous research. Since differencing removes much of the variation, this approach is rather conservative but avoids spurious results from regressing unrelated trending variables on one another. One-digit industries show a significant increase in dispersion when aggregate demand declines, though the elasticity with respect to the unemployment rate (evaluated at the mean) is rather small. The source of the cyclical effect appears to be changes in the relative employment weights rather than wage flexibility.

Other controls exert some influence. The demographic variables are at times significant, supporting Okun's cyclical upgrading hypothesis. The monthly time-series did

[24]Those four industries are food and kindred products, electrical equipment, instruments and related products, and miscellaneous manufacturing.

not show an inflationary effect, but the replication of Montgomery and Stockton's work does show a decrease in dispersion due to inflation. These replicated results from annual data are much more sensitive to specification than the monthly data.

The use of the differenced model in this work is a specific attempt to eliminate the effects of omitted variables: there are no good labor quality controls, and labor quality is almost certain to vary over the cycle. These results are conditional on the assumption of the stationarity of the human capital variables. This hypothesis is not testable, and to a degree, limits the confidence one can place in these results. Chapter 4 will attempt to address this shortcoming.

In examining the dynamics of labor market adjustment, these results seem to suggest a rather fixed wage structure that, at least in the short run, relies on quantity reallocation across industries over the cycle rather than wage adjustment to allocate labor flows. One cannot tell from these results if one-digit dispersion shows some cyclical sensitivity due to a reweighting of the industries over the cycle as industries change relative sizes or a change in the quality of the labor force due to the cycle. Even though the differenced estimation was chosen to alleviate that difficulty, the assumptions required are stringent and nontestable. In order to explore this issue further, Chapter 4 presents results from cross-section data from various years of the May Current Population Survey.

CHAPTER 4

A Cross-Sectional Analysis of Wage Dispersion

Introduction

Unfortunately, time-series data on the dispersion of interindustry wages can provide only limited information about wage dispersion over the business cycle. Even if the problems noted earlier did not exist, these data could only provide information about dispersion across industries. That information is important, but economists also have broader interests that should be addressed. For example, how does economic opportunity vary over the cycle for males versus females or whites versus nonwhites? Time-series data to perform such analyses are not available, but cross-sectional data may be used for such purposes. Large data sets provide a large number of observations on earnings, hours, and wages for individuals along with more appropriate controls for human capital characteristics. While problems are present in these data also, such information makes possible a different research strategy to analyze some of the relevant issues.

The chief advantage granted by these large data sets is the availability of detailed human capital controls. The time-series work in chapter 3 relies on stationarity to difference away human capital variables. Unfortunately, economic data are rarely stationary without detrending or differencing, so the assumption is difficult to accept. And since the information is not available at the industry level, the hypothesis is not directly testable. Other work, such as Montgomery and Stockton (1987), has used labor quality controls developed by Gollop and Jorgenson (1983) to control for differences in human capital. As Heckman and Sedlacek (1985) point out, however, Gollop and Jorgenson develop their measure with the assumption that labor within a particular demographic group or industry is relatively homogeneous. That assumption is probably not a good one, as the Heckman-Sedlacek results indicate. Consequently, little work has been done that adequately controls for human capital differences.

To provide such an analysis requires a disaggregated look at dispersion. This chapter presents estimates from cross-section data to conduct such an analysis. The May Current Population Surveys (CPS) for selected years provide information on race, sex, industry, wages, earnings, and hours worked along with other information to control for differences in individual earnings. The chosen years roughly correspond to peaks and troughs in the business cycle. By examining dispersion at peaks versus troughs over relatively short periods of time, this cross-sectional analysis will provide further insight into the changes in dispersion caused by the business cycle.[1]

Research Strategy

To examine the dispersion of wages while accounting for human capital characteristics, I will attempt to decompose the source of the variance. A standard technique for such a decomposition can be found in Freeman (1980). Freeman uses the technique to decompose the variance in the natural logarithm of wages into explained and unexplained variation to examine the effects of unions on the dispersion of wages. This analysis will use that variance decomposition in order to examine the cyclical dispersion of wages.

Suppose that wages are represented by the following equation:

$$\ln(w)_s = \beta_{0s}+\Sigma_i\beta_{is}X_{is}+\epsilon_s \tag{4.1}$$

Let s = 1,2 represent two possible states of the world, the trough of a recession or the peak of a business cycle. β_0

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[1]Blank (1989, 1990) uses micro data from the Panel Survey of Income Dynamics (PSID) to decompose the distribution of income and examine the cyclical responsiveness of each. She also uses these data to examine the effect of changes in GNP on the wage rate. She regresses the measures of interest, constructed from the micro data, on the percentage change in GNP to compute an elasticity. The focus in this research is to decompose the variance of log wages into the variances and covariances of worker characteristics, the estimated coefficients corresponding to those characteristics, and the residual variance in order to determine the routes by which the business cycle affects dispersion.

is a constant term and X_i, i= 1,...,n are human capital variables included in the earnings function to control for individual differences in earning potential. ϵ is the error term, which is lognormally distributed. As shown earlier, the variance of the natural log of the wage rate is

$$(4.2) \qquad \sigma^2_{\ln(w)} = \sigma^2 + \Sigma_i \beta_i^2 \sigma^2_{X_i} + \Sigma_{i \neq j} \beta_i \beta_j \sigma_{X_i X_j} \text{ ,}$$

where σ^2 is the variance of the error term, σ^2_{Xi} is the variance of the human capital characteristic i, and σ_{XiXj} is the covariance of any two human capital characteristics i and j, given a state of the world.

Freeman provides a decomposition for this framework which he uses in his analysis of the effect of unions on dispersion. This decomposition allows changes in the dependent variable to be broken into differences in characteristics, differences in returns to characteristics, and differences in the unexplained variation in the equation. For the present analysis, differences in variation resulting from differences in the covariances of human capital characteristics may be represented as follows:

$$(4.3) \qquad \Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti} X_{tj}} - \sigma_{X_{t-1,i} X_{t-1,j}}) \text{ ;}$$

t represents the current turning point of the business cycle and t-1 represents the previous turning point. This expression is the sum of the differences in the variances of the human capital characteristics at the peak and the trough of the cycle (or vice versa), weighted by the estimated coefficients of the earnings equation. There is no a priori reason to choose either the peak or the trough estimates to use as weights for the variances and covariances. Since the estimates are not sensitive to the choice of the base year, I have performed the calculations using the earliest year in the comparison of each turning point.

Cyclical differences in the variance may also arise because the return to human capital characteristics differs from peak to trough. If returns differ, the portion of the variance attributable to alternative earnings functions is given by the following expression:

$$(4.4) \qquad \Sigma_i(\beta^2_{ti}-\beta^2_{t-1,i})\sigma^2_{X_i}+\Sigma_i\Sigma_j(\beta_{ti}\beta_{tj}-\beta_{t-1,i}\beta_{t-1,j})\sigma_{X_iX_j} ,$$

where the differences in estimated coefficients are weighted by the appropriate variances and covariances of the explanatory variables. Again I used the earliest year of each pairwise comparison since the results are not sensitive to the base year chosen.

Finally, the residual variance represents the variance in the natural log of the wage rate controlling for the human capital characteristics included in the earnings regression. If the variables determine the wage rate, one could then attribute these differences in the residual variance to the business cycle. This residual dispersion is given by the square of the estimated standard error of the regression.

These quantities, taken together, may provide useful information about the cyclicality of wage dispersion in addition to the time-series estimates obtained in Chapter 3. Expression 4.3 gives the portion of dispersion accounted for by changes in the variance and covariances of human capital characteristics. Expression 4.4 gives the portion accounted for by changes in the regression coefficients--these may be interpreted as differences in the returns to individual characteristics between peaks and troughs of the cycle. Differences in the residual variance reflect the impact of the cycle after controlling for individual characteristics and changes in their returns over the cycle.

Dooley and Gottschalk (1984) used March CPS data to form a time series which they used to examine the cyclicality of the variance of the natural logarithm of wage rates, controlling for education, potential experience, part-time status, and a time trend. The approach described above differs from theirs in a number of ways. First, the derivation above suggests that dispersion is a function of the variances and covariances of the exogenous variables. Secondly, the composition of the labor force changes over the business cycle through layoffs and changes in labor force participation. In the Dooley and Gottschalk paper, this is picked up by the coefficient measuring the impact of the unemployment rate on dispersion, controlling for the human capital variables. The decomposition above, however, allows one to see the effects of the cycle on dispersion by breaking the effects into their component parts. Not only can the variances and covariances changes over the peak and trough of the cycle, so can the regression coefficients.[2]

The Data

As noted earlier, the May CPS tapes contain information that is useful in analyzing the dispersion of wages over the business cycle. My strategy here is to choose the surveys conducted near the peaks and troughs of the most recent complete business cycles in order to form the decomposition described above.

My goal is to choose CPS cross sections to match economic peaks and troughs. I selected 1974, 1975, 1980, and 1983. The 1974 survey reflects the peak of 1973.IV, and the 1975 tape corresponds to the 1975.I trough. The 1980 tape corresponds to the 1979.IV peak, and 1983 reflects the 1982.IV trough.[3] Unfortunately, the May surveys cannot correspond to the cyclical turning points precisely, so I have attempted to select the surveys as judiciously as possible to reflect the cycle and improve the accuracy of the analysis. The most difficult choice is for the short recession of 1980. After the credit controls imposed by the

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[2]Note that Dooley and Gottschalk allow the coefficient of experience to vary over time, but the other coefficients are restricted to remain constant.

[3]The business cycles are defined by the National Bureau for Economic Research.

Federal Reserve in 1979, the economy experienced a short, dramatic slowdown. From the peak in 1979.IV, the slide lasted only until 1980.II with the next peak happening in 1981.II. Since some of the survey questions for wages, hours, and earnings are retrospective, I have chosen the tapes for the year following the turning point; and I have ignored the minirecession of 1980, focusing on the turning points in 1979 and 1982. I also included data from the 1985 May CPS, which is two years into the expansion following the 1982 trough.

The sample I use for this analysis includes all private and government workers in the sample, excluding all self-employed, private household, and agriculturally employed workers. I also eliminated those workers who did not report weekly hours and earnings. The data set includes individuals who report both usual weekly earnings and hours in order to compute of a wage rate for that person. The wage attributed to each individual in this set is simply their usual weekly earnings divided by usual weekly hours.[4]

In order to estimate the wage equations for the decomposition described above, I need information on the

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[4]The May CPS includes reported wage rates for individuals paid on an hourly basis. To restrict estimation to this group limits the sample size available, and the sample cannot be considered random since these workers are likely to differ considerably from the sample at large. I did estimate the wage equations using the reported wage for hourly workers and the calculated wage for the rest of the sample. The results differed little; the results reported here are those using only the calculated wage for the entire sample.

schooling and work experience of each person in the sample. The CPS contains each individual's age and schooling, but actual work experience is not contained in the survey. Hence, I compute potential experience for each person by subtracting 6 and the number of years in school from the individual's age. I also calculate the square of experience in order to estimate the quadratic form of the earnings function.

Results

The results of the decomposition are given in Tables 4.1 and 4.2. Table 4.1 gives the decomposition for estimates based on the full sample in each of the years corresponding to peaks and troughs of the business cycle. In this analysis, the decomposition is based on a wage equation that regresses the natural logarithm of the real wage rate (deflated by the CPI) on years of schooling, experience, experience squared, dummies for race and sex, and a group of industry dummy variables for major industry affiliation as defined in the 1970 Census classification.[5]

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[5]The dummies are included for construction, durable manufacturing, nondurable manufacturing, railroads, retail trade, finance, business and repair, personal services (except household), entertainment and recreation, medical (except hospitals), hospitals, welfare and religious, education, other professional services, forestry and fisheries, and public administration. As stated before, agriculture, private household workers, and those who have never worked are eliminated form the sample. The remaining industries are included in the intercept term. These are

Table 4.1 gives the results of the decomposition described above based on the estimated wage equations in each of the sample years. These results may be viewed, rather crudely however, as counterparts to the one-digit time series results presented in Chapter 3.

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mining, other transportation, other utilities, and wholesale trade. The constant includes these industries since mining was chosen arbitrarily as the base industry for comparison; the other industry definitions were altered in the 1983 and 1985 CPS, disallowing comparison over the entire 1974-1985 period.

Table 4.1 Decomposition, Full Sample

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances (human capital only)	-0.013 (-0.005)	0.011 (0.003)	-0.003 (-0.001)	-0.002 (-0.001)
Differences[3] in coefficients (human capital only)	-0.014 (0.000)	-0.000 (-0.008)	0.009 (-0.003)	0.009 (0.006)
Differences in residual variance	-0.017	-0.014	0.018	0.006
Actual difference in variance	-0.038	-0.009	0.025	0.015

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{x_{ti}} - \sigma^2_{x_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{x_{ti}x_{tj}} - \sigma_{x_{t-1,i}x_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{x_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{x_i x_j}$$

Table 4.2 Decomposition, Manufacturing

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances (human capital only)	0.001 (0.001)	0.002 (0.002)	0.002 (0.009)	-0.015 (-0.017)
Differences[3] in coefficients (human capital only)	0.005 (0.004)	0.001 (-0.001)	0.034 (0.026)	-0.015 (-0.015)
Differences in residual variance	-0.007	0.011	0.035	-0.032
Actual difference in variance	-0.002	0.011	0.080	-0.060

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{x_{ti}} - \sigma^2_{x_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{x_{ti} x_{tj}} - \sigma_{x_{t-1,i} x_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{x_i} + \Sigma_I \Sigma_J (\beta_{ti} \beta_{tj} - \beta_{t-1,i} \beta_{t-1,j}) \sigma_{x_i x_j}$$

Table 4.2 does a similar analysis for manufacturing workers in each of the sample years in order to compare cross-section evidence to the two-digit times-series results. A similar wage equation is estimated for manufacturing workers to perform this decomposition; while the controls include schooling, experience, experience squared, and race and sex dummies, this equation includes industry dummies for affiliation with two-digit manufacturing industries that closely correspond to those used in the time-series data.[6] The decomposition presented in these tables shows the portion of the change in the variance between peaks and troughs of the business cycle that may be attributed to changes in the variance and covariances of worker characteristics, changes due to differences in the coefficients of these characteristics in each year, and changes in the residual variance.[7] Changes in the residual variance may be viewed as the effect of the business cycle on dispersion, although some caution must be exercised in doing so.

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[6]The industry dummies are lumber, furniture, stone (clay and glass), primary metals, fabricated metals, machinery, electrical equipment, automobiles, aircraft, other transportation, miscellaneous, food, tobacco, textiles, apparel, paper, printing, chemicals, and petroleum. The constant includes leather (and not specified manufacturing), rubber and plastics, instruments, and ordnance.

[7]Note that this decomposition is only an approximation, so the three elements may not add up to the total change in the variance in the natural logarithm of wages. Rounding error and the interaction of differences in the covariances and coefficients account for the remainder.

Recall that the time-series evidence presented in Chapter 3 relied on the presumed stationarity of the characteristics of workers to remove the influence of these variables from the dispersion equations. The decomposition presented in Table 4.1 demonstrates the importance of changes in labor quality over the business cycle. When examining the change in the variation of the natural logarithm of wages attributable to changes in worker characteristics (the first line of Table 4.1), it is clear that the changing variation in worker characteristics causes a significant portion of the altered dispersion. This portion of the change in dispersion accounts for as little as 13 percent of the total change at times and is actually larger than the total change in dispersion at other times. Nor is the direction of the change consistent: only in 1974 to 1975 did the change in the covariances move in the same direction as the total change in the variance. One cannot interpret this as the countercyclical adjustment of labor quality, however, since too few data points exist to examine the correlation between the cycle and the portion of the change in dispersion attributable to the covariances of human capital characteristics. The information does show that the change is substantial and highlights the potential bias existing in the time-series estimation presented in Chapter 3.

From the arguments presented in Chapter 2 and the evidence of Chapter 3, one would expect that much of the change in dispersion that occurs would result from a reallocation of workers across industries and not from the changes in the returns to industry affiliation. As a consequence, the bulk of the change attributable to the covariances should come from the variances and covariances of industry dummies. In order to examine that proposition, I have shown the portion of the change in characteristic covariances due to non-industry factors, the human capital characteristics. These numbers are given in parentheses. Human capital covariances alone account for 27 to 50 percent of the total change from worker characteristics, leaving the bulk attributable to changes in industry covariances. This result seems consistent with the quantity adjustment hypothesis.[8]

According to the quantity adjustment idea, little of the change over the cycle should come from the change in the industry differentials experienced by workers since the interindustry wage structure is relatively stable over time. In the decomposition shown in Table 4.1, the second row shows the change in dispersion that results from changes in the estimated coefficients of the wage equation. The

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[8]This fact is derived by looking at the portion of the variance attributed to industry affiliation, controlling for other characteristics and changes in the estimated coefficients of the wage equation. In short, by looking at the change in the variances and covariances of the industry dummies and weighting by the estimated regression coefficients, I conclude that one-half to three-quarters of the change in the variance is accounted for by industry affiliation.

industry dummies measure the industry differential; the decomposition can then be used to determine the change in dispersion that results from changes in the relative wage structure. In the second row of Table 4.1, the change in dispersion attributable human capital coefficients is shown.[9] The change attributable to changes is industry wage premia is the difference between the total coefficient effect and the human capital coefficient effect.

The industry effect is substantial, ranging from 20 to more than 100 percent of the total change in dispersion. This fact does not negate the quantity adjustment hypothesis, however. Except for the 1974-1975 period, differences in coefficients served to increase wage dispersion. This result is no surprise given the positive correlation between wage levels and wage changes noted by Lawrence and Lawrence (1985) and mentioned in Chapter 2. This correlation suggests that the wage structure, while quite stable in terms of industry wage rankings, is changing with increasing wage premia to high-wage industries. This evidence is also consistent with the Bell and Freeman findings that sector-specific productivity shocks, not the business cycle, are the major source of increased dispersion since 1970. There is too little information here to sort out the cyclical impact versus the secular trend, but the

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[9]The estimated wage equations do not account for selection bias, and part of the change in coefficients from peak to trough may be due to changes in unobserved characteristics correlated with the variables in the model.

body of available research suggests that the relatively large portion of the change in dispersion is best interpreted as noncyclical. The time-series results provide little support for wage sensitivity to the business cycle. However, no clear judgement may be made from these cross-section results alone.

The unexplained variation, the square of the standard error of the equation, is the last component of the total change in dispersion to analyze. If the residual variance is viewed as the dispersion of wages controlling for human capital and industry affiliation, observed changes in the adjusted dispersion measure between cyclical peaks and troughs might be attributed to the business cycle. These differences are given in the third row of Table 4.1. These differences do not display the clear cyclical pattern found in the time-series estimates in Chapter 3 as well as the literature. According to these estimates, dispersion decreased during the downturn between 1974 and 1975. Time-series estimates, however, lead one to expect an increase in dispersion. And during the upswing between 1983 and 1985, dispersion increased contrary to expectations.[10]

One must exercise caution in interpreting the change in the unexplained variation as a pure cyclical effect. Other factors such as inflation, international trade, and

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[10]F-tests for the equality of the explained variation in each adjacent year reject equality at the 5 percent level as do tests for the equality of the unexplained variation.

industry-specific productivity shocks are ignored in these estimates since their impact occurs over time.[11] Given that the time-series results show a small cyclical impact on wage dispersion, the cyclical impact captured here may be overshadowed by these other factors. And these factors will also affect the portion of the decomposition that shows the change in dispersion attributable to changes in the covariances of human capital characteristics and changes in the returns to these characteristics. Hence, to interpret the change in the residual variance as a cyclical effect involves some peril.

A particular difficulty in interpreting these results is the secular increase in dispersion noted in several of the papers discussed in Chapter 1. The cross sections do not provide enough data points to extract a trend and accurately estimate a cyclical impact. As a consequence, the trend is subsumed in these results. Since a secular increase has been documented by most accounts in Chapter 1 (though not all), increases in dispersion appear too large, and decreases are understated. As a rough-and-ready method of calculating the trend, I calculated the increase from peak to peak (1974 to 1980) and from trough to trough (1975 to 1983).[12] I then took the average of these changes as the

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[11]A bright spot in the analysis, however, is that inflation and international trade do not have a statistically significant impact in the time-series results.

[12]I do not use 1985 in computing the trend since it is only two years into the recovery rather than at a cyclical peak.

trend in dispersion. Table 4.3 shows the variances, both adjusted and unadjusted, before and after detrending.[13]

Table 4.3 Variance of Wages

YEAR	1974	1975	1980	1983	1985
			Full Sample		
Total variance	0.337	0.299	0.290	0.315	0.331
(detrended)	(0.337)	(0.302)	(0.307)	(0.341)	(0.362)
Adjusted variance	0.193	0.176	0.163	0.181	0.187
(detrended)	(0.193)	(0.179)	(0.176)	(0.201)	(0.211)
			Manufacturing		
Total variance	0.223	0.222	0.233	0.314	0.254
(detrended)	(0.223)	(0.215)	(0.194)	(0.255)	(0.182)
Adjusted variance	0.129	0.121	0.132	0.167	0.135
(detrended)	(0.129)	(0.118)	(0.115)	(0.141)	(0.104)

In order to compare the cross section results to the time series estimates, it is useful to look at the cyclical responsiveness implied by these results. Since too few observations are available for time-series analysis, I have computed the simple arc elasticity for each peak-to-trough

[13]Note that the trend in the total sample is decreasing 0.002 per year; manufacturing shows an increase of 0.007 per year. The decrease in the total sample, while in conflict with the industry results of most of the studies surveyed in Chapter 1, in consistent with the results reported by Krueger and Summers who also use micro-level data from the CPS.

(or trough-to-peak) comparison by dividing the percentage change in the dispersion measure by the percentage change in the prime-age male unemployment rate over the corresponding time period. The results for the total sample and for manufacturing are given in Table 4.4. I have shown the elasticity implied before and after detrending and before and after adjusting for worker characteristics in order to highlight the impact of these alterations.

Table 4.4 Arc Elasticities

	total variance	detrended total variance	adjusted variance	detrended adjusted variance
		Total sample		
1974-1975	-0.142	-0.131	-0.111	-0.096
1975-1980	0.229	0.134	0.581	0.095
1980-1983	0.173	0.218	0.217	0.276
1983-1985	-0.161	-0.204	-0.106	-0.169
		Manufacturing		
1974-1975	-0.010	-0.047	-0.073	-0.104
1975-1980	-0.387	0.750	-0.673	0.310
1980-1983	0.679	0.618	0.519	0.441
1983-1985	0.627	0.942	0.624	0.899

The first column of Table 4.4 shows the elasticity before controlling for human capital characteristics and industry affiliation. The elasticities are small, and they do not provide a clear picture of cyclical sensitivity.

These estimates range form -0.16 to 0.23 compared to time-series estimates of 0.06 to 0.11. As noted in Chapter 3, however, the omission of human capital characteristics may bias the results. The third column of Table 4.4 shows the elasticities after controlling for these factors. The range widens, -0.111 to 0.581. The upper end of this range is five to six times as large as the time-series estimates, which examine industry averages instead of individual data.

The fourth column of Table 4.4 is the most important of these results. It contains the detrended estimates of dispersion, controlling for individual characteristics. After removing the secular trend, the range of the elasticities is reduced (-0.17 to 0.28), and the mean of the estimates is 0.03 in the total sample, a number not unlike the corresponding time-series estimates. It is important that this comparison not be taken too literally, however, because the dispersion measured in Chapter 3 is across industries; the cyclical effect shown here controls for industry affiliation. Given that the industry definitions are broad, however, there is much room for quantity and price reallocation within these broad industries to account for the cyclical sensitivity.

Table 4.2 provides the results of this decomposition for the manufacturing sector. Like the total sample, the proportion of the change in the total variance accounted for by the covariances and coefficients is substantial. It is interesting to note, however, that most of the changes are attributable to differences in the covariances and coefficients of the human capital variables, not from industry affiliation. Quantity reallocation as measured by the variance and covariances of the industries within the manufacturing sector is less important than the changes in labor quality, measured by potential experience and education.

The portion of the change in dispersion attributable to changes in the industry coefficients (which may be interpreted as wage premia), however, is remarkably small, which lends additional support to the quantity adjustment approach. Almost all of the change in coefficients is accounted for by the human capital variables. The interindustry wage structure is relatively fixed over the cycle.

Finally, the fourth column of Table 4.4 shows the elasticity of dispersion over the business cycle among manufacturing workers. The range here is significantly wider than in the total sample, -0.10 to 0.90. The average of these estimates is 0.39. While the time-series results for the full sample were comparable to the cross-section results above, the results are considerably different here. There was no significant impact of the cycle on the dispersion of wages in the manufacturing sector, but the elasticities here are surprisingly large. A direct comparison is difficult here, however. While F-tests of the equality of the residual variances reject the hypothesis in each pairwise analysis, the 0.39 elasticity is estimated imprecisely, and one should not have great confidence in the number as a point estimate of the cyclical elasticity.[14] Given that the range of the estimates is rather broad, the cyclical sensitivity may be illusory.

Results by Subgroups

That demographic groups have different labor market outcomes is a well established fact among labor economists. For example, women earn less than men on average. Blacks earn less than whites on average. Of relevance here is the impact of the business cycle on the dispersion of wages within subgroups of workers.

One might expect differences in the cycle's effect on dispersion because of differences in group labor market behavior on average. If skills or industry affiliation differ by group, the business cycle may affect within-group dispersion differently than the workforce as a whole.

To begin the analysis of these potential differences, a logical point of departure is the portion of changes in the variance of wages attributable to changes in the variance and coefficients of the race and sex dummies. For each of

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[14]Assuming that the assumptions under which the elasticities in the manufacturing section of column 4 of Table 4.4 are correct, a t-test for the hypothesis that the elasticity is 0 could not be rejected. This is also true of the full sample.

these dummies, this calculation is computed by using portions of Expressions 4.3 and 4.4. As above, 4.3 measures the portion of the change in the variance of log wages accounted for by the variance of worker characteristics. In this case, the race and sex dummies (and their covariances with the other independent variables) in Tables 4.1 and 4.2 are the portions of the formula of concern.[15] And Expression 4.4 summed only over terms involving race and sex coefficients gives the portion of the change in variance attributable to the change in the sex and race coefficients. Both of these quantities are small relative to the total change in dispersion, each accounting for 2 to 11 percent of the total change from one turning point to another. These numbers are consistent for both the total sample and the sample of manufacturing workers.

The next logical step in the analysis is to decompose the variance of the natural logarithm of the wage rate for each subgroup. The results of the decomposition for whites, nonwhites, females, and males are given in the appendix.

The estimates suggest that the cyclical sensitivity of dispersion for nonwhites and females in the manufacturing sector is probably larger than for whites and males, respectively. The evidence is less clear for the full sample: nonwhites appear slightly more sensitive to the

[15]These calculations are not shown separately in the tables. This calculation is a subset of the entire sum show in Expressions 4.3 and 4.4.

cycle than whites; females may actually have a slight decline in dispersion as unemployment rises, though the effect appears to be quite small. In both the full and manufacturing samples, the range of estimates is wide and imprecise.[16]

The decomposition for manufacturing and the full sample yields no consistent cyclical patterns of adjustment over the cycle due to changes in the variance of worker characteristics or the coefficients of those characteristics. While the magnitudes of the changes differ by subgroup, the direction of the effects are generally the same.

Conclusion

This chapter estimates wage equations in order to decompose the variance of into its component parts--the variances and covariances of characteristics, the coefficients of those characteristics, and the residual variance. The residual provides information on dispersion, controlling for worker heterogeneity and changing returns to characteristics over the cycle.[17]

Using data from several years of the Current Population Survey, this decomposition shows that changes in worker

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[16]See Tables A.9 and A.10 in the appendix.

[17]See Blank (1990) for speculation regarding this point.

characteristics over the business cycle are an important part of cyclical adjustment. However, the estimates of the relationship between the unemployment and dispersion is still generally small and positive. The pattern among subgroups of the population was less clear, however. The race and gender composition of the workforce seemed to have little to do with changes in dispersion, but the cyclical sensitivity of nonwhites and females in the manufacturing sector seemed relatively large.

CHAPTER 5

Conclusion

The time-series and cross-section results presented here provide an interesting picture of what happens to dispersion over the business cycle. The time-series results lead one to believe that changes in dispersion across industries are small in the economy as a whole and practically non-existent in the manufacturing sector. The importance of the omitted labor quality variables makes the conclusions tenuous, even though the estimation technique attempts to compensate for the deficiencies.

The cross-section results show that a significant portion of the change in dispersion is indeed accounted for by the omitted labor quality variables in both the manufacturing and total samples.[1] The omission may be more serious in the manufacturing sector. While the time-series estimates show no cyclical impact, the cross-sections yield estimates of the elasticity that are generally positive and larger for manufacturing than in the total sample (though

[1]Note that the importance of the variables does not necessarily mean that the time-series results will be biased from their omission. The bias would occur if the human capital variables are not stationary and if the first difference of these variables is correlated with the independent variables.

the range of estimates is rather broad). The mean of the estimates is 0.39. The cross-sectional estimates are even larger than the two-digit interindustry estimates by Wachter, who found a long-run elasticity of interindustry wage dispersion of 0.25.[2]

Chapter 2 noted several possible scenarios that would explain the positive relationship between the unemployment rate and the dispersion of wages. Chapter 3 results suggest that most of the responsiveness of dispersion to the cycle occurs because of the reallocation of labor to industries that have relatively fixed wage premia. The cross-section estimates confirm that this reallocation is a contributor to the change in dispersion over the cycle, but this explanation is only a part of what happens. The dispersion of wages is also altered by the changes in industry wage premia, though the change in these estimated industry coefficients is not cyclical in nature. The results presented in this chapter cannot clearly distinguish the cause of these changes in the relative return to industry affiliation. As Bell and Freeman have shown, sector-specific productivity shocks rather than cyclical activity may largely account for this phenomenon. There is no reliable way to separate the two in these cross sections. The time-series estimates indicate that the short-term wage

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[2]This number is not directly comparable since the dispersion measure is different, and the total unemployment rate was used in that computation.

responsiveness to the cycle is small. Consequently, the change in the industry differentials may be safely assumed to be largely acyclical.

The cross-section results control for individual characteristics, and the decomposition accounts for the portion of the change in the dispersion attributable to changes in the returns to these characteristics. In the cross-sections, the cyclical activity comes from intraindustry variation. Since broad industry classifications are used in the analysis, there is considerable scope for intraindustry variation with both wage and quantity adjustment within the industry. How much is due to each is impossible to say, but in comparing the broad one-digit results to the narrower two-digit results, the analysis suggests that, in the short run, quantity adjustment is more important.

This work has shown that wages show little response to the cyclical variation of the economy. Instead, the labor market is characterized by persistent differentials across industries, and labor market adjustment to the cycle occurs by adjusting the number of workers, not their wages. The cross-sectional evidence of Chapter 4 shows that observed labor quality also changes to some degree, more so for the manufacturing sector than the economy as a whole.

Katz and Summers (1989) have argued that government policies that subsidize high-wage industries may be welfare augmenting in the presence of persistent wage differentials, ignoring the collateral cost of the policy. While this analysis does not address their argument directly, it does highlight the persistence of the differentials and their lack of sensitivity to the cycle.

Under the Katz-Summers framework, increases in high-wage employment would be welfare augmenting. If employment in high wage industries is relatively less sensitive to business cycle activity, as suggested by the manufacturing results in Chapter 3, then macroeconomic policies might be less effective than specific policies directed toward high-wage industries. Persistent wage differentials provide some scope for government action to increase economic welfare. The appropriateness of such action is determined not by the ability to increase welfare but by the benefits (and, perhaps, distributional consequences) of any action relative to its costs.

APPENDIX

APPENDIX

Results by Subgroup

Table A.1 Decomposition, Male--Full Sample

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	-0.019	0.015	-0.003	-0.001
Differences[3] in coefficients	-0.017	-0.003	0.025	0.008
Differences in residual variance	-0.012	-0.012	0.020	0.005
Actual difference in variance	-0.008	-0.020	0.037	0.012

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.2 Decomposition, Female--Full Sample

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	-0.027	0.007	0.002	0.001
Differences[3] in coefficients	-0.033	-0.005	0.028	0.013
Differences in residual variance	-0.023	-0.011	0.015	0.008
Actual difference in variance	-0.005	0.001	0.031	0.026

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{x_{ti}} - \sigma^2_{x_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{x_{ti} x_{tj}} - \sigma_{x_{t-1,i} x_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{x_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{x_i x_j}$$

Table A.3 Decomposition, White--Full Sample

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	-0.021	-0.015	-0.003	0.000
Differences[3] in coefficients	-0.013	-0.032	0.009	0.005
Differences in residual variance	-0.017	-0.013	0.018	0.006
Actual difference in variance	-0.038	-0.009	0.027	0.015

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.4 Decomposition, Nonwhite--Full Sample

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	-0.024	0.014	-0.007	-0.008
Differences[3] in coefficients	-0.026	0.010	-0.003	0.038
Differences in residual variance	-0.009	-0.018	0.019	0.005
Actual difference in variance	-0.032	-0.003	0.013	0.026

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.5 Decomposition, Male--Manufacturing

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	0.001	0.001	0.009	-0.011
Differences[3] in coefficients	0.004	0.000	0.031	-0.014
Differences in residual variance	-0.010	0.008	0.028	-0.029
Actual difference in variance	-0.005	0.007	0.076	-0.051

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.6 Decomposition, Female--Manufacturing

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	0.001	0.000	0.001	-0.013
Differences[3] in coefficients	0.002	0.019	0.021	-0.008
Differences in residual variance	-0.000	0.013	0.055	-0.037
Actual difference in variance	0.003	0.027	0.089	-0.048

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.7 Decomposition, White--Manufacturing

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	0.000	0.004	0.004	-0.018
Differences[3] in coefficients	0.004	0.001	0.032	0.005
Differences in residual variance	-0.006	0.011	0.031	-0.034
Actual difference in variance	-0.001	0.013	0.081	-0.069

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti} X_{tj}} - \sigma_{X_{t-1,i} X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti} \beta_{tj} - \beta_{t-1,i} \beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.8 Decomposition, Nonwhite--Manufacturing

YEARS[1]	1974-75	1975-80	1980-83	1983-85
Differences[2] in covariances	0.001	-0.008	0.012	-0.009
Differences[3] in coefficients	0.017	0.003	0.013	-0.041
Differences in residual variance	-0.018	0.014	0.061	-0.023
Actual difference in variance	-0.004	0.006	0.089	0.005

[1]Differences in covariances and coefficients are weighted by the earliest year in the calculation, 1974 in the first column, 1975 in the second, and 1980 in the third. The decomposition may not add up to the actual difference in the variance since the decomposition is an approximation. The remainder may be attributed to rounding error and the interaction of the differences in the covariances and the differences in the coefficients.

[2]Estimates were obtained by computing the following expression:

$$\Sigma_i \beta_i^2 (\sigma^2_{X_{ti}} - \sigma^2_{X_{t-1,i}}) + \Sigma_i \Sigma_j \beta_i \beta_j (\sigma_{X_{ti}X_{tj}} - \sigma_{X_{t-1,i}X_{t-1,j}})$$

[3]Estimates were obtained by computing the following expression:

$$\Sigma_i (\beta^2_{ti} - \beta^2_{t-1,i}) \sigma^2_{X_i} + \Sigma_I \Sigma_J (\beta_{ti}\beta_{tj} - \beta_{t-1,i}\beta_{t-1,j}) \sigma_{X_i X_j}$$

Table A.9 Arc Elasticities

	detrended adjusted variance	adjusted variance	variance	detrended total	total variance
			Nonwhite (Total sample)		
1974-1975	-0.134	-0.124	-0.056	-0.042	
1975-1980	0.099	-0.230	0.741	0.289	
1980-1983	0.097	0.509	0.219	0.275	
1983-1985	-0.314	-0.344	-0.088	-0.151	
average				0.093	
			White (Total sample)		
1974-1975	-0.141	-0.131	-0.114	-0.099	
1975-1980	0.224	-0.119	0.577	0.085	
1980-1983	0.183	0.226	0.217	0.277	
1983-1985	-0.153	-0.194	-0.111	-0.175	
average				0.022	
			Nonwhite (Manufacturing)		
1974-1975	-0.025	-0.066	-0.183	-0.228	
1975-1980	-0.264	1.032	-0.997	0.600	
1980-1983	0.911	0.894	1.013	1.021	
1983-1985	-0.063	0.103	0.412	0.732	
average				0.531	
			White (Manufacturing)		
1974-1975	-0.003	-0.042	-0.061	-0.090	
1975-1980	-0.434	0.755	-0.648	0.259	
1980-1983	0.675	0.609	0.451	0.370	
1983-1985	0.714	1.065	0.679	0.949	
average				0.372	

Table A.9 (continued)

detrended adjusted variance	adjusted variance	variance	detrended total	total variance
		Male (Total sample)		
1974-1975	-0.033	-0.028	-0.082	-0.071
1975-1980	0.525	0.356	0.524	0.187
1980-1983	0.269	0.289	0.236	0.277
1983-1985	-0.131	-0.153	-0.092	-0.138
average				0.064
		Female (Total sample)		
1974-1975	-0.251	-0.362	-0.161	-0.143
1975-1980	-0.035	0.320	0.499	-0.107
1980-1983	0.276	-0.451	0.190	0.265
1983-1985	-0.330	-0.240	-0.154	-0.226
average				-0.053
		Male (Manufacturing)		
1974-1975	-0.029	-0.062	-0.098	-0.138
1975-1980	-0.267	0.768	-0.500	0.815
1980-1983	0.718	0.669	0.424	0.291
1983-1985	0.595	0.869	0.594	1.004
average				0.493
		Female (Manufacturing)		
1974-1975	0.027	-0.067	-0.005	-0.067
1975-1980	-1.539	1.307	-0.011	0.991
1980-1983	1.081	1.137	0.893	0.860
1983-1985	0.634	1.574	0.696	1.227
average				0.753

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