# SECTORAL UNCERTAINTY AND UNEMPLOYMENT

bу

Robert Topel

University of California, Los Angeles

and

NBER

and

Laurence Weiss

University of California, San Diego

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#### Introduction

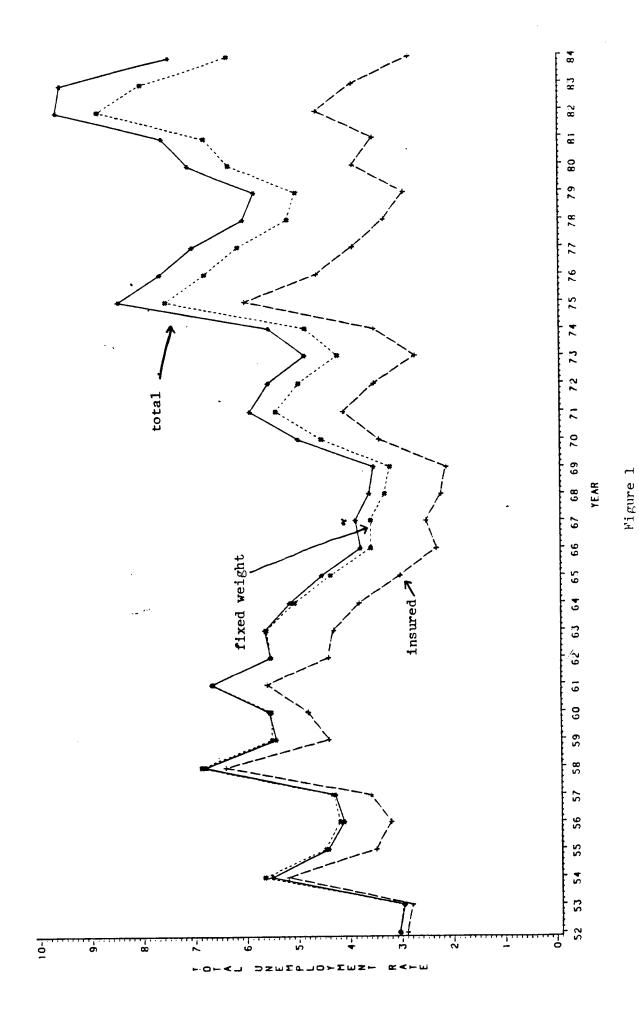
Both the level and variability of measured unemployment in the United States have increased dramatically since 1975. The average unemployment rate over the past decade was 60 percent higher than the average post-war rate up to 1975 (7.7% vs. 4.7%). Indeed, the recent cyclical low unemployment rate of 7.1% (1984:4) is only slightly below the maximum cyclical peak rate prior to 1975 (7.4% in 1958:2). Evidently, the level about which measured unemployment fluctuates is now higher than in comparable periods of the past.

In this paper we propose a new theory that may help to explain this phenomenon. The theory emphasizes the role of costly, irreversible, industry-specific human capital investments for determining an individual's lifetime labor supply decision. These costs require that agents consider future, as well as present, industry relative wages when choosing a job. In particular, we show that an increase in future relative wage uncertainty will tend to diminish the return to industry specific human capital and increase the relative attractiveness of current period unemployment. We propose that much of the increase in recent unemployment can be attributed to greater sectoral uncertainty during this period. We present two distinct types of empirical evidence in support of this view. The first uses time series evidence to show that several empirical proxies for agents' (unobservable) expectations of future relative wage uncertainty have increased in the period after 1975. The second kind of evidence uses cross-sectional data to show that the demographic incidence of unemployment and sectoral mobility are consistent with the theory.

There are suprisingly few empirically convincing alternative theories attempting to explain the trend rise in unemployment. Factors thought to be important for determining the "natural rate" such as unemployment insurance, minimium wage laws, and union behavior exhibit no sharp changes since the

early seventies (see Barro (1984), ch. 9). One common explanation is that changing labor force composition is responsible for the rise in the aggregate measure. While it is certainly true that there is greater participation among groups with traditionally higher measured unemployment (e.g. youths and women), this factor can account for only about one third of the rise in aggregate unemployment (see Figure 1 and Table 1). A less easily dismissable explanation is that aggregate participation rates have risen over the recent past. Adherents of this view emphasize the relative constancy in aggregate employment to population ratios (see Table 2). However, we know of no completely articulated theory that could explain a positive relationship between aggregate participation and unemployment rates. A third possibility is that the large influx of workers associated with the post-war "baby-boom" has lowered average labor productivity, which affects both earnings (Welch, 1979) and labor supply. By itself, however, this model has little to say about the concomitant rise in unemployment among older workers, nor does it address the sluggish behavior of aggregate output during this period.

The work that comes closest to our theory is that of Lilien (1982, 1984), who has attempted to show empirically that the rise in unemployment since the early seventies is due to the greater pace of reallocation of labor among different sectors over this period. Lilien's evidence for this is based partly on the observation that the fraction of employment in manufacturing has fallen sharply (from 30 percent in 1964 to 26 percent in 1974 and 20 percent in 1984) and that periods of most rapid adjustment coincided with the aggregate contractions of 1971, 1975 and 1979-81. More formally, Lilien has documented a statistically significant positive relationship between measured unemployment and the cross-sectional standard deviation of industry employment growth rates, which he takes as a good proxy for relative sectoral changes.



Total, Fixed Demographic Weight, and Insured Unemployment, 1952-84

Table 1

Total, Fixed Demographic Weight, and Insured

Unemployment Rates 1955-84

	1955-59	60-64	65-69	70-74	75-79	80-84
Total	5.01	5.72	3.06	5.36	7.00	8.30
Fixed Demographic Weights	5.08	5.68	3.60	4.78	6.12	7.26
Insured	4.22	4.58	2.42	3.44	4.14	3.74

Source: Handbook of Labor Statistics and Handbook of Unemployment Insurance Financial Data. The fixed-weight unemployment rate uses age x race x sex labor force shares for 1960

Table 2

Labor Force Participation and Employment Rates,

Persons Aged 16-64

	1955-59	60-64	65-69	70-74	75-79	80-84
Labor Force/ Population	59.5	<b>59.</b> 0	59.5	60.6	62.4	64.0
Employment/ Population	56.5	55.6	57.2	57.3	58.0	58.7

Source: Handbook of Labor Statistics

Although Lilien's work is suggestive, two types of criticism have been The first is that the model of unemployment underlying the sectoral shift hypothesis is not completely worked out. Thus it is not clear what features of the labor market give rise to an increase in unemployment as a response to a shock that requires labor to move between different sectors. The second criticism is that Lilien's formal evidence is consistent with a conventional view of business cycles (e.g. Mitchell, 1941) that incorporates non-neutralities across sectors (see Weiss (1984), Neumann and Topel (1984), and Abraham and Katz (1984)). Indeed, measures of sectoral dispersion are concentrated around cyclical contractions in aggregate output. This leaves unexplained the higher, non-cyclical unemployment rates that have been observed throughout the past decade (Neumann and Topel, 1984). This is not to deny that Lilien's tenet may be correct; it only points out that this work has little power to discriminate against the conventional view that attempts to explain aggregate output without reference to its sectoral composition, and that it fails to account for the secular increase in average unemployment rates.

Two other prime features of rising aggregate unemployment must be addressed by candidate theories. First, a demographic breakdown of unemployment rates (Table 3) reveals that the increase in aggregate unemployment has fallen disproportionately on young workers. For example, unemployment rates among males aged 25-34 were only about 10% higher than the post-35 group prior to 1970, but since that time their rate has been about 50% higher. A possible objection is that these relative changes partly reflect the well documented decline in labor force participation among older males, which could conceivably reduce measured unemployment in these groups. The more detailed breakdown by separate age intervals shows that unemployment of younger workers

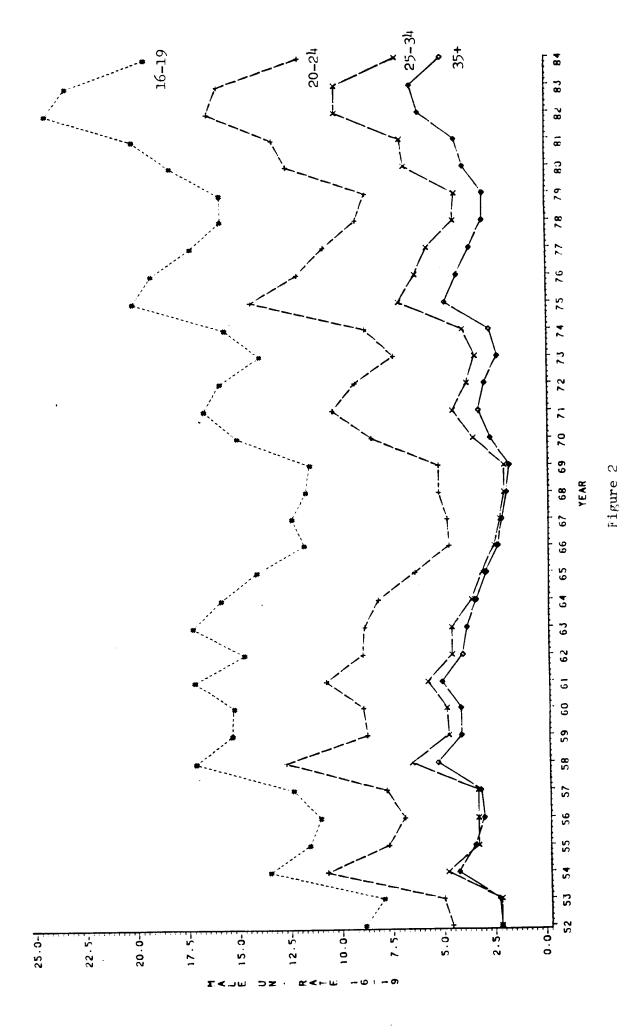
Table 3
Unemployment Rates of Males Aged 35 and Over Relative
to Unemployment of Males Aged 25-34; 1955-1984

	Years	Years						
Age	1955-59	1960-64	1965-69	1970-74	1975-79	1980-84		
<u>&gt;</u> 35	<b>.9</b> 0	.88	•92	•71	•66	.62		
35-44	. 82	<b>.8</b> 0	.83	.68	• 67	.69		
45-54	•90	.86	.84	•67	•64	•59		
55-64	1.01	1.00	1.06	.76	•64	•58		

Source: Handbook of Labor Statistics.

has risen relative even to prime age (35-44) males, for whom changes in participation have been minor. In Though this evidence is not a direct criticism of Lilien's model (which treats labor as homogeneous), it is difficult to reconcile with a pure sectoral shift hypothesis. Even if older workers remain longer in declining industries because of greater mobility costs or sector specific human capital, should this not be offset by the greater opportunities for young workers in expanding sectors?

The second, related feature of aggregate unemployment comes from comparing the insured unemployment rate with the broader measure derived from the current population Survey (see Table 1). The insured rate is the fraction of covered workers currently receiving unemployment insurance benefits. It differs from the CPS measure by excluding (i) individuals who have exhausted their benefits and (ii) those who are ineligible for benefits. The latter are primarily individuals who have not worked long enough to be eligible. As shown in Table 1, the discrepancy between these measures has increased



Male Unemployment Rates by Age Intervals, 1952-84

sharply. During the 1980's the insured rate is less than half of the total, compared to 80 percent in the 1960's and 60 percent in the 1970's. This, too, is difficult to reconcile with the view that the increase in aggregate unemployment is driven by a prolonged shift out of the traditional manufacturing sectors, whose experienced workers are mainly eligible to receive benefits. It is also inconsistent with an alternative view that the recent behavior of unemployment is due to a prolonged period of "deficient" labor demand: insured unemployment is strongly cyclical (Figure 1), yet unlike total unemployment it displays no secular increase. Evidently, the increase in total unemployment is accounted for mainly by individuals with comparatively weak attachments to prior employment or the labor force.

Our theory is formulated to be consistent with these facts. In contrast to Lilien who implies that the <u>occurrence</u> of a sectoral shock which requires labor to be reallocated raises unemployment, we argue that <u>the prospect of future shocks</u> is a more likely candidate for explaining the observed rise in unemployment, especially among younger individuals. Of course, to the extent that the occurence of sectoral shocks is correlated over time, a sectoral shock may increase expectations of future shocks, so it may be difficult to completely separate the two theories empirically. In this sense, models of costly sectoral mobility and sectoral uncertainty are complementary theories of rising unemployment.

The paper is organized as follows: in section 1 we present the basic model, emphasizing the role of training costs for determining agents' labor supply decisions. The second section is an empirical attempt to show that an appropriate measure of sectoral uncertainty has increased in the period after 1975. To do this we use evidence on sector-specific stock market returns and the observed sectoral composition of the labor force. Although the results

are generally supportive, we were unsuccessful in formulating a testable time series version of the model. The third section introduces some new evidence on the differential incidence of unemployment by age and education and shows how the model may be appended to be consistent with observed patterns. The model has implications for the relationship between industry mobility and education, which we show to be supported by the data. The fourth section is the conclusion.

#### 1. The Model

Our model is designed to illustrate how the level of uncertainty about future relative wages may effect an individual's current employment decisions and, in particular, lead to voluntary abstentions from employment that are concentrated among young workers. In many ways this mechanism is similar to that of Bernanke (1983) who considers the effects of uncertainty on the decision to undertake costly irreversible physical investment. We emphasize the role of uncertainty on human capital acquisition.

Our model does not differentiate between non-employment and unemployment. As noted in the introduction, most of the variations in unemployment within the prime age male workforce are closely associated with variations in employment. Since our model is designed to explain variations within this group we simplify and identify non-employment as unemployment.

Consider a continuous time model in which all agents seek to maximize discounted utility of the form

(1) 
$$U^{i} = \int e^{-\delta t} (c(t) - r^{i} l(t)) dt$$

where c(t) is consumption,  $r^1$  is the individual-specific reservation wage and l(t) is labor supply at t, taken to be either 0 (not working) or l (working). Note that the linear specification of individual preferences

implies a labor supply income elasticity of zero. This rules out income effects as a possible source of cross-sectional heterogeneity and greatly simplifies the analysis.

There are two industries, or sectors, in which an individual may work. In order to work in either industry each individual must first pay an industry specific "training cost",  $k^{i}$ , which differs among individuals (some individuals learn faster than others) but is common across industries. Incurring  $k^{i}$  qualifies the individual to work in only one industry. Thus, the parameters that characterize an individual are his costs of learning and reservation wage,  $(k^{i}, r^{i})$ .

The pattern of industry relative wages arises from the following technology. At any point in time, one, and only one, of the two industries is "productive". If a trained worker is employed in a productive industry over any interval of time dt he produces a "lump" of perishable output of size  $(2q/\mu)$  with probability  $\mu$ dt. If he is employed in a non-productive sector he produces nothing. (We may think of a job as standing on an island and catching random output from heaven. Standing on islands is unpleasant, but if output is not caught it hits the ground and breaks. The islands are large, so there is no congestion and no return to any factor other than labor.) With this technology the wage expressed as flow per unit time is 2q in the productive industry and 0 in the non-productive industry.

Aggregate uncertainty in this economy arises because sometimes it is common knowledge which of the two industries is productive. We call such intervals "certain" periods. We assume that the duration of certain periods is random and generated by a Poisson probability distribution with parameter  $\beta$ . Thus the expected duration of a certain interval is  $1/\beta$ . When a certain period comes to an end, previous information on sectoral output becomes

irrelevant. Everybody knows that each industry is productive with probability one-half, so that the expected wage in either sector is  $(1/2) \times 2q + (1/2) \times 0 = q$ . "Uncertain periods" last until information is revealed via one of the two sectors producing output; this happens with probability  $\mu$ dt over an interval dt, so that the expected duration of uncertain periods is  $1/\mu$ .

To simplify matters we make the following, somewhat artificial, assumption about the durability of industry specific human capital. We assume that so long as an individual works in an industry his capital does not depreciate. An individual may also choose not to work during uncertain periods without jeapordizing his skills. However, should an individual decide not to work in an industry during a certain period any skills previously acquired in that industry depreciate fully. Thus an individual will at any time be trained to work in at most one industry. These assumptions are designed to capture the idea that skills dissipate if not used. Since the duration of uncertain periods is taken to be relatively brief compared to certain periods (that is  $\beta << \mu$ ), we take the depreciation during uncertain periods to be negligible and the depreciation during certain periods to be total.

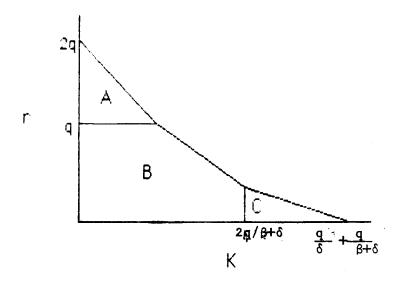
Our model is designed to show how unemployment among young (inexperienced) workers will rise by a greater amount than unemployment among older workers during uncertain periods. The distinction between "old" and "young" in our model arises because experienced workers have already incurred the costs of training, while young workers must first pay the training cost in order to produce. We emphasize that all workers live forever, or alternatively, face a mortality probability independent of age, so the relevant distinction is between trained and untrained labor. It would be preferable to introduce finite working lives to explain the incidence of industry mobility

by age (in section 4 we document that older workers are less likely to change industries) but we neglect this additional complication to emphasize the role of training costs.

Each agent must decide when to enter the labor force, when to take temporary layoff and when to switch sectors. We first consider the problem of a young (untrained) worker who is born during "certain" periods -- that is, when the identity of the productive sector is known. It is clear that, should he enter the labor force, he will do so in the productive sector. His first non-trivial decision comes at the moment the uncertain period begins. His expected wage falls from 2q to q. Since he can "rest" during this interval without foregoing the value of his human capital, his decision rule is simplework, if and only if  $r^1 < q$ , that is, if his reservation wage is less than the expected wage. His next decision comes when the identity of the productive sector is announced at the beginning of a certain period. If he finds himself in the non-productive sector should he switch sectors? Since the value of either type of training is identical at the beginning of the next uncertain period, the decision to switch is governed by weighing the additional expected income generated by switching over the current certain period against the cost of training, ki. Suppose the current certain period lasts exactly T periods. The value of switching is the present discounted value of the difference in the wages between the two sectors:  $\int_{-\infty}^{T} e^{-\delta s} 2q \, ds$ . Since the probability of the certain period lasting T periods is  $\beta e^{-\beta T}$ , the expected value of switching is  $\int \beta e^{-\beta T} \int_{-\delta}^{T} e^{-\delta s} 2q \, ds \, dT = 2q/(\delta+\beta)$ . Thus the agent will switch if and only if  $k^{1} < 2q/(\delta+\beta)$ , so switching is less likely when "certain" periods are perceived as transitory. If the above inequality is not satisfied, the agent will remain in the non-productive sector even though the wage is zero in order to maintain his skills.

It remains only to determine if the agent will enter the labor force at all. This is governed by the requirement that the present discounted value of expected utility, under the optimum rest and switch decisions, be greater than zero. The results of this calculation are summarized in Figure 3.

Figure 3



Each individual's characteristics, his own reservation wage r<sup>1</sup> and cost of acquiring industry specific training K<sup>1</sup>, are represented by a point in the figure. If the individual lies above the regions marked A, B, or C he will never enter the labor force. People in A will work only during the certain periods and take leisure (unemployment) during the uncertain period, since they have a high reservation wage. They will always switch to the productive sector since their training costs are sufficiently low. More formally, individuals in area A satisfy

 $2q > r^{i} > q$  (employed during certain periods)

$$k^{\frac{1}{2}} < \frac{2q-r^{\frac{1}{2}}}{\beta+\delta} + \frac{1}{2} k^{\frac{1}{2}} \frac{\mu}{\mu+\delta} \frac{\beta}{\beta+\delta} \quad \text{(choose to enter)}$$
 
$$k^{\frac{1}{2}} < \frac{2q}{\beta+\delta} \quad \text{(switch sectors)}$$

Similarly, agents in area B will always switch, but because of their lower reservation wage they will continue to work during the low wage uncertain period. This continuous participation induces some workers with higher training costs than in A to enter the market. Specifically, area B is defined by

$$\begin{array}{l} \mathbf{r^i} < \mathbf{q} \\ \\ \mathbf{k^i} < \frac{2\mathbf{q} - \mathbf{r^i}}{\beta + \delta} + \frac{\mathbf{q} - \mathbf{r^i}}{\mu + \delta} \frac{\beta}{\beta + \delta} + \frac{1}{2} \frac{\mathbf{k^i} \mu}{\mu + \delta} \frac{\beta}{\beta + \delta} \\ \\ \mathbf{k^i} < \frac{2\mathbf{q}}{\beta + \delta} \end{array}$$

Finally, agents in area C will never switch sectors because of their high costs of (re)training, and they will work in the sector they originally entered, even if the sector is non-productive, in order to maintain their capital. Area C is defined by

$$r^{i} < q$$

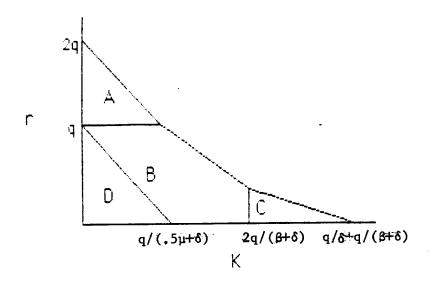
$$k^{i} < \frac{q}{\beta + \delta} + \frac{q - r^{i}}{\delta}$$

$$k^{i} > \frac{2q}{\beta + \delta}.$$

Now consider the problem faced by a young (untrained) worker who comes of age during an uncertain period. Assume that  $k^{1} < 2q/(\beta+\delta)$  so that the agent will always switch to the productive sector. (It is shown below that if this condition is not satisfied the agent should always wait until a certain period to enter the labor force.) Should the agent joint the labor force now, or should he wait until the certain period? If he decides to work now he pays  $k^{1}$  and receives a expected wage of q over the duration of the current

uncertain period which has present value  $(q-r^i)/(\mu+\delta)$ . In addition, with probability one-half he will have selected the productive industry so he will save the training costs at the onset of the certain period; this is worth  $(1/2)k^i\mu/(\mu+\delta)$  in present value. Thus he should work today if  $(q-r^i)/(\mu+\delta)+(1/2)k^i\mu/(\mu+\delta)-k^i>0$ . This region is shown as region D in Figure 4 below.

Figure 4



It is now clear why unemployment among untrained individuals will rise disproportionately in uncertain times. Only those agents with very low reservation and training costs will find it optimal to join the labor force during such periods. This occurs because there is a high probability that the individual's newly acquired industry specific skills will become obsolete soon. The flow of untrained people into "unemployment", defined here to be agents who will eventually work but choose not to do so immediately, consists of all people coming of age whose characteristics fall in regions A, B, and

C in Figure 4. The flow into employment consists only of those who fall into region D. Note that the size of this flow depends negatively on  $\mu$ , so participation is less likely (unemployment is more likely) if uncertain periods are expected to be short. It pays to wait until uncertainty is resolved before investing. By contrast, only those older workers who fall in region A above will choose temporary layoffs during uncertain periods. Other experienced individuals choose to work.

One might argue that our characterization of unemployment among young workers as a form of leisure is unrealistic, especially since most unemployment spells are comparatively short and do not constitute formal withdrawal from the labor force for an extended period. Our response is that the driving force of our model is postponement of sector-specific investments that generate attachments to continuous employment. The model could be extended to include intermittent spells of temporary employment during uncertain periods, which would formally incorporate the increased incidence of uninsured spells, but that model offers few additional insights.

Our specification of the human capital technology as point input-flow output is obviously unrealistic. It would be more natural, but more complicated, to introduce industry specific "learning by doing" as formulated by Arrow (1962) to capture the capital theoretic elements of labor supply. This would not alter our main conclusions that periods of sectoral uncertainty affect the employment of young workers relatively more, since a relatively higher proportion of their remuneration comes from acquiring skills to be used in future employment.

A more crucial and arguable assumption of our model is identifying human capital as sector or industry specific rather than occupational or task specific. Presumably elements of both are operative and both types of uncertainty

may affect macroeconomic outcomes. A possible justification for our assumption is that "learning by doing" affects primarily groups of people working together. This interpretation would point to individual firm or workplace uncertainty as affecting aggregate outcomes. To the extent that firms are correlated within an industry this is consistent with our emphasis on sectoral uncertainty. However, this focus is derived more from data availability than by any independent studies of the human capital process.

### 2. Time Series Evidence

The model presented in section 1 shows how the level of sectoral uncertainty can change from period to period and explains why periods of high uncertainty are associated with high unemployment, particularly among younger workers. In this section we present evidence to support our contention that this type of uncertainty has increased in the period after 1975, which we interpret to mean that recent experience has been dominated by unusually long episodes of uncertain periods. We note at the outset that constructing a single convincing measure of sectoral "uncertainty" is difficult. We focus on the ability to statistically predict various measures of relative sectoral performance.

The model emphasizes the role of relative wage uncertainty on individual's work decision. Recent work by Freeman (1985) shows that the dispersion of average wages among broadly defined sectors in the U.S. has increased in the recent past relative to historical norm. To the extent that this represents the realization from an ex ante distribution with greater variance in which the identity of the winners and losers was not known ex ante to market participants it is consistent with our theory. However, we must be careful in utilizing ex post average wage data as a proxy for the distribution of ex ante relative wages faced by a typical worker. Changing labor force

composition across sectors will greatly distort this view. Declining industries may maintain mostly older, higher skilled workers so their average wage might remain high even though their relative attractiveness to younger workers has fallen. In fact, this appears to have been the case in manufacturing: averages wages have risen in this sector in spite of its declining importance as a source of employment.

To circumvent this problem, we focus on employment data across two-digit industry level classifications. Specifically, we will attempt to show that there has been greater disparity in sectoral employment growth rates which was unforeseen in the sense that it could not have been predicted from simple time series models. Furthermore, we will attempt to show that this greater level of sectoral uncertainty cannot be attributed to the greater level of aggregate fluctuations which have obviously occurred in the post 1970 period.

To implement these ideas, we use quarterly time series data on employment in one digit (SIC) industries in the United States. For each sector, j, let  $E_{jt}$  denote the natural logarithm of employment in quarter t (t=1948I-1983IV). At each t, we estimate a rolling regression using the previous eight years' data of the form

$$E_{jt} = A^{j}(L)E_{jt-1} + B^{j}(L)Q_{t} + \varepsilon_{jt}$$

where  $Q_t$  is the deviation of the natural logarithm of real GNP from quadratic trend and  $A^j(L)$  and  $B^j(L)$  are fourth order polynomials in the lag operator L. We then use this model to predict employment in sector j at time t+h conditional on the actual values of employment up to time t and the actual values of aggregate income up to t+h. We condition the forecasts on <u>future</u> (period t+h) values of aggregate income in order to purge our measure of sectoral disturbances from "pure" business cycle effects. We "overcontrol" for these effects in the sense of using information that is not

available to agents at time t. Note that the effects of aggregate fluctuations are allowed to be non-neutral across sectors. Denoting the forecasts by  $\tilde{E}$ , we then compute the share-weighted mean squared error of these predictions,

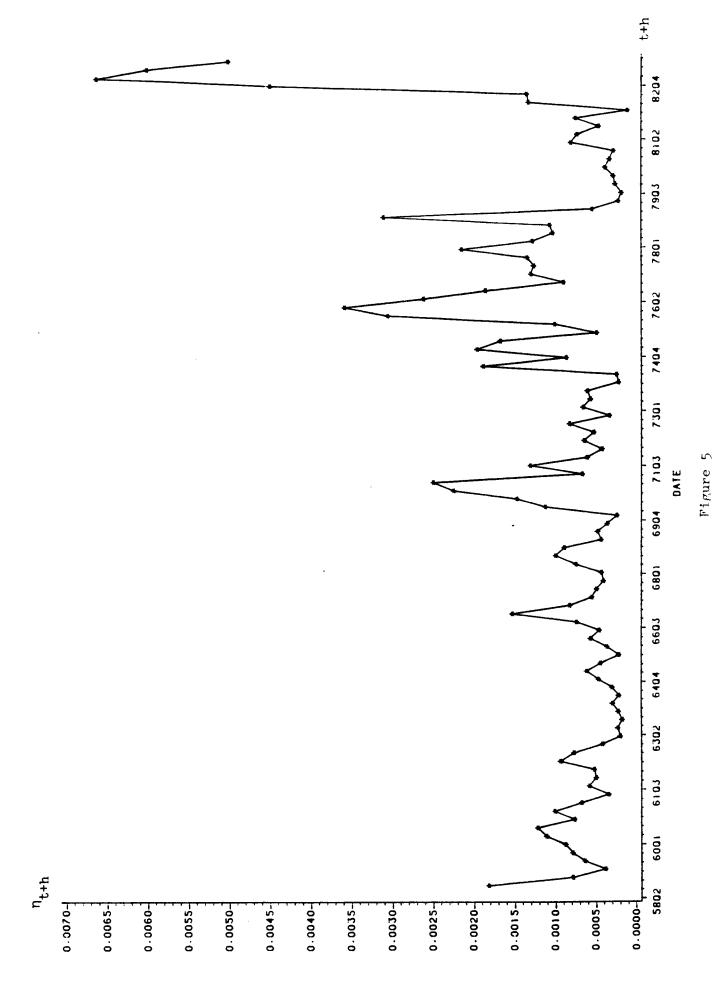
$$\eta_{t+h} = \sum_{i} (E_{jt}/E_{t})(\tilde{E}_{jt+h} - E_{jt+h})^{2}$$

We report two types of output from this procedure. The first simply reports the computed values of  $\,\eta\,$  when  $\,h\,$  is chosen alternatively as 4 or 8 quarters. The second set of estimates accumulates the value of  $\,\eta\,$  from  $\,h\,$  = 1 to 4 or 8 quarters, alternatively. Means of the estimates over five-year intervals are reported in Table 4. Figures 5 and 6 illustrate the complete series for  $\,h\,$  = 4 quarters.

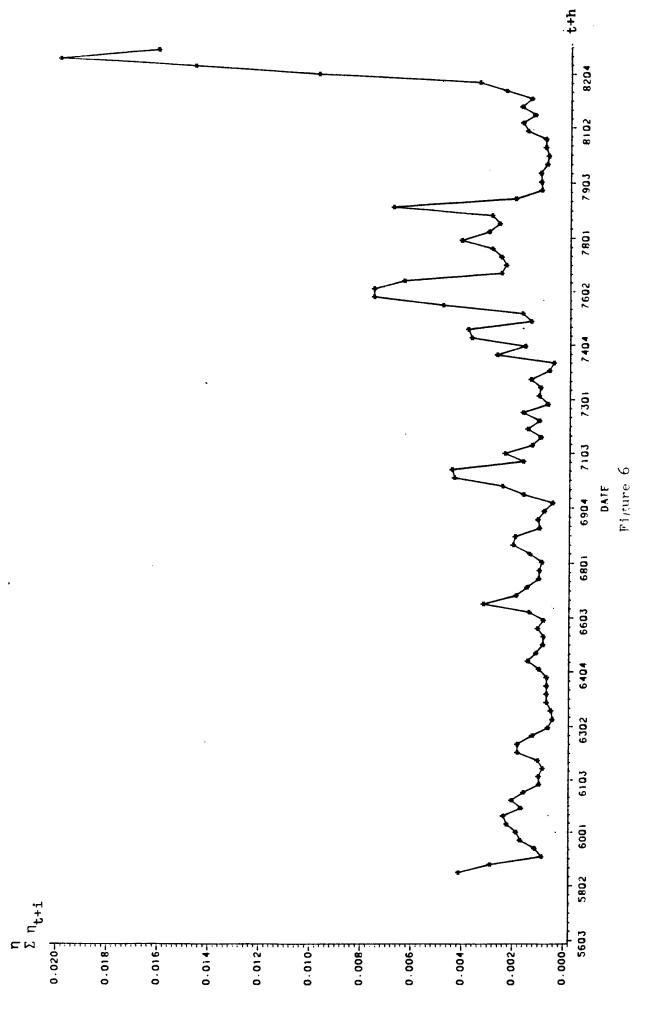
Table 4
Weighted Mean Squared Errors in Forecasting
Sectoral Employment 1957-83

				Period t+h			
h = 4 quarters	1957-59	1960-64	1965-69	1970-74	1975-79	1980-84	
n t+h	0.88	0.57	0.60	0 <b>.9</b> 0	1.54	1.84	
h Ση <sub>t+i</sub>	2.14	1.23	1.29	1.65	3.51	4.84	
h = 8 quarters							
η t+h	2.89	2.77	2.38	5.24	4.06	4.25	
h Ση τ+i	11.72	8.74	7.35	14.19	14.75	12.43	

Note: See text for description of variables. All estimates are multiplied by  $10^3$ .



Mean Squared Error of Log Employment Forecasts: Four-quarter Horizons



Cumulative Mean Squared Errors of Log Employment Forecasts: Four-quarter Horizon

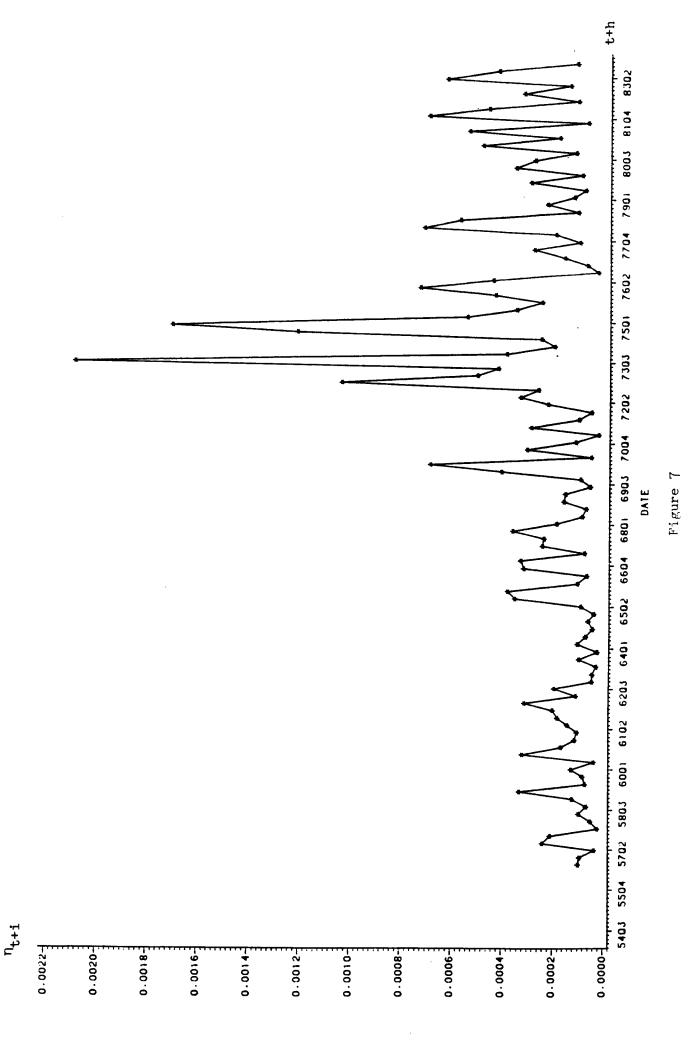
The results for employment provide support for the notion of increased sectoral uncertainty. Controlling for aggregate fluctuations, for h=4 the average estimated mean squared errors in forecasting are more than twice as high in the post-1974 period as in earlier years. For the cumulative forecast errors, the difference is even larger. As Figures 5 and 6 show, these differences are due mainly to a sharp increase in the volatility of  $\eta_{t+h}$  in the 1970's and 1980's. Evidently, even controlling for the differential effect of the cycle across sectors, the sectoral composition of the demand for labor was much less predictable during this period than in the relatively docile decade of the 60's.

An alternative source of information on changes in the sectoral composition of demand is the value of the capital stock in these sectors. For the same one-digit industry classifications, we constructed industry-wide stock portfolios for the period 1948I-1983IV. Denoting the rate of return on the sector j portfolio by  $\rho_{jt} = \log(\frac{p_j^j}{p_{t-1}^j})$ , we purge these series of the effects of fluctuations in aggregate output by estimating

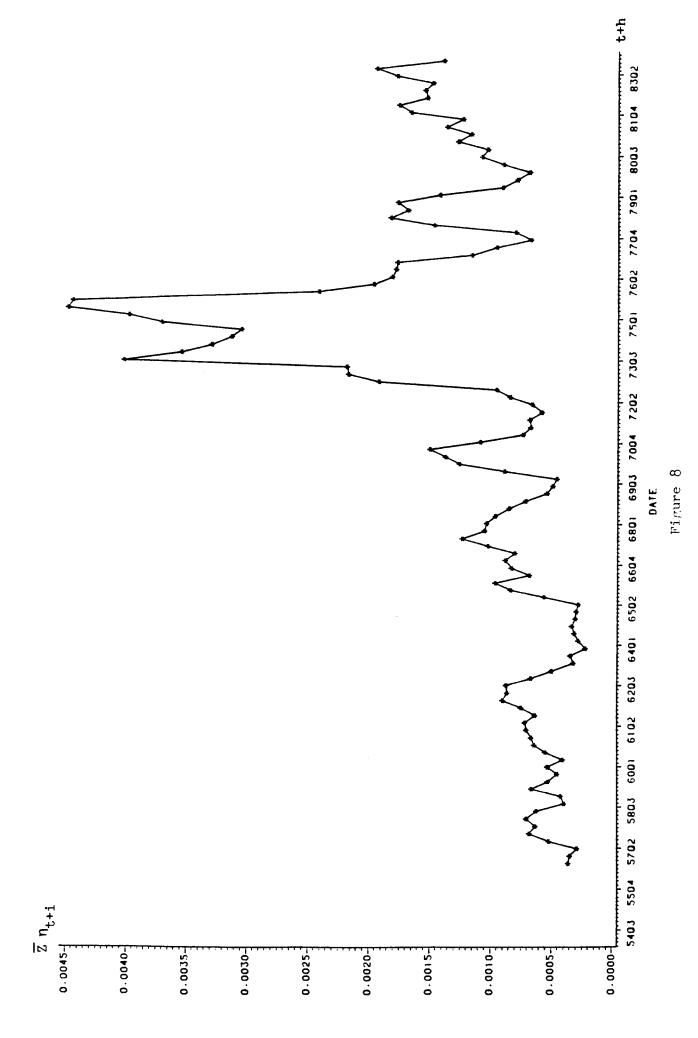
$$\rho_{jt} - \rho_t = \alpha^j + A^j(L)Q_t + V_{jt}$$

where  $\rho_{t}$  is the market rate of return. We calculate the residuals from this model. Forecasts errors for an h-period horizon are achieved by summing the unpredicted excess returns,  $V_{jt+i}$ . As above, this method "overcontrols" for the cycle by using information on  $Q_{t+i}$  that is not available to agents at t. We calculate mean squared errors for these series using sectoral employment shares as weights.

Weighted mean square errors for the stock market data are reported in Table 5 and displayed in Figures 7 and 8. The results are essentially similar to those for employment: controlling for sectoral non-neutralities in



Mean Squared Error of Sectoral Portfolio Forecases: Four-quarter Horizon



Mean Squared Errors of Sectoral Portfolio Forecasts: Four-quarter Horizon

response to the cycle, the average ability to predict sectoral returns on these portfolios declined in the 1970's and 1980's. Over a four period horizon, the average mean squared error in the post-1970 period is more than double the average in the period up to 1969, and for an eight period horizon the average is nearly three times higher. In conjunction with the similar findings for employment, we take this as fairly strong evidence that the ability to predict relative sectoral performance declined sharply during a period of rising aggregate unemployment.

Table 5
Weighted Mean Squared Errors in Forecasting
Sectoral Stock Portfolios, 1957-83

			Period t+h			
h = 4 quarters	1957-59	1960-64	1965-69	1970-74	1975-79	1980-84
η c+h	0.12	0.13	0.17	0.45	0.37	0.31
h Ση t+i	0.51	0.56	0.74	1.73	1.99	1.37
h = 8 quarters						
n t+h	0.12	0.14	0.21	0.47	0.38	0.27
h Ση t+i	0.98	1.15	1.46	2.92	4.03	2.38

Note: See text for description of variables. All estimates are multiplied by  $10^3$ .

#### 3. Further Demographic Evidence

Our model is designed to show how sectoral uncertainty may effect the demographic composition of unemployment. Further insight is gained by

examining the incidence of unemployment by both age and education. Table 6 documents the well known fact that more educated individuals are less likely to be unemployed. More surprisingly, the differential incidence of unemployment by education has increased since 1975, particularly for young people.

Among workers aged 20-29, for example, the average difference in unemployment rates between high school and college graduate has been 7.6 percentage points since 1975, compared to about 3.2 percent for 1968-74.

Table 6

Male Unemployment by Selected Age and Education Categories,

1968-1983

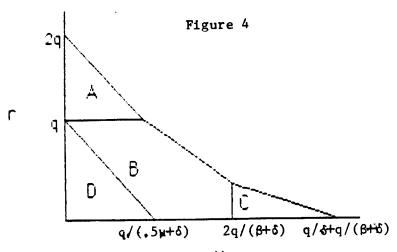
		1968-69	1970-74	1975-79	1980-83
Age 20 - 29		4.8	7.4	10.1	11.5
Education:	<12	8.1	13.4	19.5	23.4
	12	4.5	7.2	10.9	13.0
	<u>≥1</u> 6	1.8	3.7	4.3	4.2
Age 30 - 39	-	2.5	3.7	6.5	6.4
Education:	<12	4.0	5.5	8.2	11.6
	12	2.0	3.2	5.0	6.9
	<u>&gt;</u> 16	0.7	1.5	2.1	2.5
Total: Age	20-65	3.0	4.3	6.5	7.7

This section will sketch how the model presented in section 1 can be easily modified to account for the differential incidence of unemployment

among young workers with different levels of schooling. In thinking about the return to education, economists have tried (generally unsuccessfully) to sort out two sets of issues. The first is how education changes the productivity of a given individual (the productivity effect) and the second is what innate characteristics of individuals may lead them to acquire more education (the selection effect). Our interpretation of the evidence suggests that both factors operate to explain the differential increase in the natural rate of unemployment by education.

Let the basic model be appended to include a new activity called education. In return for an individual specific cost  $C^1$  the individual's productivity is augmented by fixed amount,  $\partial x$  in any sector. Thus education provides general training in the sense of Becker (1964). Since the abilities to acquire general and sector-specific human capital will depend on an agents inate ability, we would expect that  $C^1$  is positively correlated with  $K^1$ , the cost of acquiring sector specific training. Hence this model displays both a direct productivity effect as well as a self selection effect as those agents with relatively low cost of training will select education.

It is fairly easy to see that either one of these effects, separately, will lead to lower incidence of unemployment among more educated young workers during periods of uncertainty. Recall Figure 4, reproduced here:



An  $\partial x$  increase in productivity in any state is formally equivalent to an  $\partial x$  reduction in r, the reservation wage (since only their difference enters individuals' utility). Thus even if education is allocated randomly throughout the population, we would expect that more educated people would fall into region D above, which defines the region over which young (untrained) workers will elect employment during uncertain times. Similarly, we would expect educated experienced workers to have lower unemployment as the productivity effect pushes those in the lower region of A (who choose temporary layoff during uncertain times) into region B.

The selectivity effect is a bit more complicated. To the extent that the low K young individuals are educated, they will have lower unemployment during uncertain times so long as K and r are not too negatively correlated, which seems plausible. However, due to the assumed positive correlation between c<sup>1</sup> and k<sup>1</sup>, older educated persons will include a disproportionate number of people with high reservation wages, so the selectivity effect works to increase their relative unemployment during uncertain times. Some selection working in the opposite direction occurs because individuals with high reservation wages, who participate only in certain times, are less likely to acquire an education for any level of c<sup>1</sup>. Table 6 shows that the return to education in terms of differential unemployment has gone up for both groups. But the differential between college and high school educated young has gone up by more among inexperienced workers than among experienced ones, which is consistent with the differential selectivity effects between these two groups.

The model also predicts differences in education and the incidence of unemployment between individuals who choose to change sectors and those who do not. To the extent that the costs of general and specific training,  $c^i$  and

 $k^{1}$ , are positively correlated, more educated individuals will be more likely to move between sectors ( $k^i < 2q/(\beta+d)$ ). Table 7 documents that during the high unemployment period from 1977-1983, college graduates were slightly more likely than those with a high school education or less to change the industry of their primary job between years t and t+1.2 These figures probably understate the greater mobility of educated workers since individuals who change place of residence are not counted in the table, and educated individuals are known to be more geographically mobile. 3 The result is surprising in light of the generally lower rates of job turnover found among more educated workers (Altonji and Shakotko, 1985; Mincer 1984; Abraham and Farber, 1985). Evidently, job mobility among less educated workers occurs mainly within industry aggregates, indicating that the skills of educated workers are more portable across diverse sectors. An additional prediction is that unemployment will be more likely among individuals who choose to switch sectors (areas A and B). This is documented in Table 8, which also shows positive returns to education among industry movers. 4 To the extent that education shifts individuals into full time participation (area B) and selects against persons who do not participate during uncertain times (area A), this letter pattern is also consistent with our model.

## 4. Conclusion

Relative to historical norms, the trend rate of unemployment rose during the 1970's and early 1980's. We have documented that the incidence of this increase was widespread among various demographic groups, but fell disproportionately on individuals with less labor market experience and schooling, and on individuals whose previous labor force attachment does not qualify them for coverage under the unemployment insurance system. In light of these facts, we developed a prototypical model of costly, sector specific human capital

Table 7
Year-to-Year Industry Mobility by Age and Education:
1976-83

(Proportion that change industry in one year expressed

as deviation from sample mean)

Education	Total	20-29	30-45	46
<12	-0.9	6.2	-0.3	-4.1
12	-1.2	3.8	-2.7	-5.0
13-15	1.2	3.3	0.8	-1.3
16	2.5	5.3	2.5	-0.7
>16	2.6	4.9	3.0	0.4

Notes: Tabulated from matched CPS files 1977-84. Estimates are deviated from the sample mean (=20.2%) to adjust for measurement error. See footnote 1.

Table 8

Percent of Reported Industry Changers from Years t to t+1

Who Experience Intervening Unemployment Spells,

by Age and Education, 1976-82

Education				
	Total	20-29	30-44	45+
<12	23.68	33.45	19.95	21.16
12	19.26	26.66	16.05	12.72
13-15	15.38	19.91	14.35	8.86
16	7.36	7.61	7.73	6.28
16+	7.41	8.57	7.28	6.67

Notes: Tabluated from matched CPS files 1977-84. Reported figures are proportions of respondents reporting positive weeks unemployed during the previous calendar year.

investment that generates a rising natural rate as a consequence of the optimizing behavior of individual agents. The key idea is that in the face of sectoral uncertainty, individuals with less experience and those with greater costs of acquiring sector-specific human capital will rationally and optimally postpone employment and human capital investment until uncertainty has been resolved.

Empirical support for this hypothesis requires a quantifiable concept of sectoral "uncertainty". We have provided evidence that during the period in question, both the sectoral composition of employment and the relative returns on claims to sector-specific capital have become less predictable from past information, even conditioning on non-neutral responses to aggregate fluctuations. While more formal econometric evidence is clearly desireable, we were generally unsuccessful in formulating a time-series version of the model relating current period unemployment to future prediction errors.

#### Footnotes

Non-employment ratios show a similar pattern. For example the non-employment rate of 25-34 year old males relative to that of 35-44 year olds averaged .86 from 1955-69 (.82, .85, .92), but only .78 from 1970-84 (.80, .79, .76). For older age groups, the decline in participation generated by social insurance programs (Parsons, 1980; Ward, 1984) dominates the data and makes comparisons of nonemployment rates difficult.

<sup>2</sup>The data are based on tabulations of year-to-year matches of 34,245 males in the March Current Population Surveys, from 1976-83. Industry changers are individuals whose reported three-digit industry in year t was different than in year t-1. Because of measurement and coding errors, the reported proportion of the sample that changes industry will be overstated. (The sample mean rate is 20.2%.) Thus we report the data as deviations from the sample mean on the reasonable assumption that errors in measurement are uncorrelated with age and education.

3The CPS file is a household, or "rooftop" survey. Thus, the survey in year t+1 interviews persons who occupy the same dwelling unit as those interviewed in year t. Thus people who change dwellings leave the survey and are not counted in our tabulations.

<sup>4</sup>Though not tabulated separately, we do find that reported movers are more likely than non-movers to report positive weeks unemployed in the previous year (17.5% vs. 10.1%). The difference in these proportions is understated because many individuals who do not actually change industry are misclassified as changers. For reference, we also find that the difference in unemployment between reported movers and non-movers is larger for young workers with less education: for high school graduates aged 20-29 the

difference is 11.0 percentage points, but it is about 5.0 percentage points among older high school graduates and 4.3 points among college graduates.

4 or 5 Because of coding errors in the matched CPS data, persons who do not actually change industries will be counted as movers. Since unemployment will be lower for this group, Table 8 actually understates the incidence of unemployment among industry changers.

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