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SECTORAL SHIFT THEORIES OF UNEMPLOYMENT: EVIDENCE FROM PANEL DATA

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This paper examines the response of sectoral real wages and location probabilities to oil price shocks using U.S. micro-panel data (the National Longitudinal Survey of Young Men). The goal is to determine whether the observed response patterns are consistent with so-called "sectoral shift" theories of unemployment. These theories predict that shocks that change sectoral relative wages should increase unemployment in the short run and lead to labor reallocation in the long run. Consistent with these predictions, the oil price changes of the 1970s resulted in substantial movements in industry relative wages and significant reallocation of labor across industries, while both oil price increases and decreases resulted in short run increases in unemployment. However, equilibrium sectoral models imply that real shocks that change relative wages across sectors should induce flows of labor into those sectors where relative wages rise. In fact, real oil price shocks are found to have substantially reduced respondents' location probability in the construction industry, which had a wage increase relative to all large industries. The industry with the greatest increase in employment share was services, which had among the greatest wage declines. These are clear contradictions of the predictions of equilibrium sectoral models. Nevertheless, a more general class of models where both relative wage movements and quantity constraints generate labor flows appears to be quite consistent with the data.

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1. Introduction

The goal of this paper is to determine whether equilibrium sectoral shift theories of unemployment can claim broad consistency with the observed dynamics of employment and wages in the U.S labor market. In a recent survey article, Hall and Lilien (1986) conclude that among theories of unemployment currently extant, these form one of only two classes of theory that do not suffer from serious inconsistencies with labor market data.[1] This paper, however, uncovers wage and employment patterns which contradict the predictions of equilibrium sectoral models. Nevertheless, a more general class of models (such as those considered by Harris and Todaro [1970], Hall, [1975] and Pissarides [1978]), where both relative wage movements and quantity constraints generate flows of labor across industries, is quite consistent with the data. The paper's approach, it should be noted, is not to formally test the equilibrium sectoral models' abilities to explain data, but simply to study patterns in wage and employment data to determine whether they are consistent with such models' predictions.

Sectoral shocks are defined as events which change sectoral relative marginal products of labor. Equilibrium sectoral models such as Hamilton (1988), Lilien (1987) and Rogerson (1987), imply that, following such shocks, labor should be reallocated from those sectors where relative wages fall to those where they rise. The "sectoral shift hypothesis" states that a significant part of measured unemployment is due to time-consuming movement of workers across sectors in response to sectoral shocks. This paper examines the response of sectoral real wages and employment probabilities of individual workers in the National Longitudinal Survey of Young Men (NLS) to a particular sectoral shock, changes in real oil prices. Note that oil price shocks, although they are not sector specific, still conform to the definition of sectoral shocks because they have sector specific wage and productivity effects. The existing literature contains no such direct examination of the effects of observed sectoral shocks on relative wages and location probabilities. Pissarides (1978) examines how net movement of labor into a sector depends on the sector's relative wage and excess demand conditions, but does not directly examine the effects of exogenous sectoral shocks. Shaw (1989) examines the effects of proxies for sectoral shocks on sectoral relative wages but does not look at actual sectoral shocks such as the oil price shocks examined here.[2] Given the

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[1] They also judge theories of unemployment based on nominal contracting to be broadly consistent with the data.

[2] The present paper is much closer in approach to Shaw's than to other work in this literature, however. Other empirical work on the sectoral shift hypothesis can be divided into two groups: (1) studies like Lilien (1982), Loungani (1986), Abraham and Katz (1986) and Davis (1987) which test whether proxies

estimated effects of oil price shocks, we may judge whether these are consistent with the predictions of equilibrium sectoral models.

There are four main findings in the paper. The first is that oil price changes have a substantial and persistent impact both on aggregate real wages and on relative wages across sectors. Second, oil price increases and decreases, both of which are sectoral shocks because they change relative wages, both cause short run increases in unemployment. This is consistent with sectoral shift theories of unemployment. Third, oil price changes induce significant labor reallocation, but not in directions consistent with wage movements. Specifically, an industry which has among the smallest wage declines in response to oil price increases, namely construction, also has among the largest employment declines, while an industry which has among the largest wage declines, namely services, has the largest employment increase. The fourth finding, which is quite surprising, is that oil price increases in the 1970s cannot explain any significant part of either the decline in manufacturing's employment share or the increase in service's share over that period.

The large relative wage effects of sectoral shocks point toward the potential importance of variation in search unemployment in response to relative wage changes as a source of cyclical unemployment variation. The inconsistency between wage movements and labor reallocation patterns is damaging for equilibrium sectoral models, but does not point toward abandonment of all sectoral models. Rather, since the result would be consistent with job rationing in the construction industry, it points toward the importance of sectoral models like Harris and Todaro (1970) and Hall (1975) which include both competitive and non-competitive sectors, and Pissarides (1978), where quantity constraints as well as relative wage movements determine employment flows. In these models, relative wage changes generate increased search unemployment without necessarily increasing employment in sectors where relative wages rise.

The finding that a particular sector has a relative wage increase and a large employment decline following an oil price increase could be reconciled with an equilibrium sectoral model if it were low wage

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for the aggregate volume of sectoral labor reallocation are positively correlated with the aggregate unemployment rate, and (2) studies like Murphy and Topel (1987) and Loungani and Rogerson (1989) which examine micro-data to determine whether the number of people who change sectors within a period is positively correlated with the aggregate unemployment rate. In these studies, the implications of the sectoral shift hypothesis for movements in sectoral relative wages and location probabilities are not directly examined.

workers who tended to leave the sector following the shock. Then, the labor force quality effect on an aggregate sectoral wage measure could mask much larger offer wage declines occurring on an individual level. Thus it is essential to use micro-panel data to test the wage movement implications of sectoral models. These allow one to correct for compositional biases in wage movements by controlling for unobserved individual effects and possible selection biases. Thus a fixed effects selection model is used to obtain estimates of quality constant wage movements in the present paper.

2. Theoretical Issues and Review of the Literature

Hamilton (1988), Lilien (1987), Rogerson (1987), Davis (1985), and Lucas and Prescott (1974), have constructed equilibrium sectoral models in which it takes time for workers to change sectors. When a sectoral shock occurs, changing sectoral relative marginal products of labor, workers in adversely affected sectors weigh the potential wage gains from moving to a favorably affected sector against the opportunity and monetary costs involved. Workers for whom the expected benefits outweigh the costs will leave the adversely affected sector(s), engage in search for a time, and finally gain employment in a favorably affected sector. Since search requires time, workers in transit between sectors experience unemployment.

In the Lucas-Prescott model, shocks to product demand cause the allocation of labor to fluctuate around a stationary equilibrium. Since the shocks are i.i.d. across sectors and over time, they generate a constant natural rate of unemployment. Lilien (1982a) argues that the variance of product demand shocks is not constant over time. In the decade of the 1970s, for example, events like the two oil shocks made product demand more variable than in the relatively tranquil 1960s. Such an increase in the variance of sectoral shocks would cause an increase in the natural rate. Lilien's claim, known as the "sectoral shifts hypothesis," is that much of the cyclical fluctuation in unemployment is due not to aggregate demand shocks but rather to fluctuations in the natural rate.[3]

Lilien's evidence for the sectoral shift hypothesis consists of regressions of the aggregate unemployment rate on the across-sector variance of employment growth rates, which he calls the

[3] The policy implications of Lilien's argument are obvious and striking. If unemployment were principally due to aggregate shocks, as in the more traditional Keynesian view, then the "solution" would consist of proper aggregate demand management policies aimed at restoring equilibrium. If fluctuations in the natural rate are driving unemployment the traditional policy prescriptions are useless. The only potential means of reducing unemployment would be retraining programs or other such means of accelerating the job matching process.

"dispersion index." This index is meant as a proxy for the variance of sectoral shocks.[4] Lilien finds that a fitted natural rate series derived from movements in the dispersion index has a correlation of .74 with the actual unemployment rate over the 1949-1980 period. He also finds that the dispersion index is essentially orthogonal to unanticipated money growth. He takes these findings as evidence that fluctuations in the natural rate induced by changing variance of sectoral shocks induce a large portion of unemployment rate fluctuations.

Abraham and Katz (1986) argue that Lilien's dispersion index is a poor proxy for the variance of sectoral shocks because it may vary countercyclically in response to aggregate shocks.[5] A more fundamental objection to the dispersion index is that different rates of sectoral employment growth do not necessarily imply that individual workers are changing sectors. With a growing labor force, differences in sectoral employment growth rates can be due solely to different rates of hiring new entrants.[6] With a static labor force, sectoral employment growth rates can differ solely due to differential rates of temporary layoff and recall of workers who never change sector. Hence, even if the dispersion index is a good proxy for the variance of sectoral shocks, it is not necessarily an indicator of volume of across-sector labor flow.

Abraham and Katz claim that the behavior of job vacancies should indicate whether it is primarily aggregate shocks or sectoral shocks which drive the business cycle. The argument is that adversely affected firms will lay off workers immediately following a sectoral shock, while favorably affected firms

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[4] That the dispersion index is a good proxy is based on two assumptions. First, that the across-sector variance of employment growth rates is a good indicator of the actual volume of labor reallocation and second, that the actual volume of labor reallocation is highly correlated with the desired volume, which is the quantity that actually varies proportionally with the variance of sectoral shocks according to the theory.

[5] Abraham and Katz show that traditional aggregate demand driven business cycle models produce a positive correlation between the dispersion index and the unemployment rate if industries' trend growth rates and cyclical sensitivities are negatively correlated. This is certainly true for the manufacturing and non-manufacturing sectors in the postwar U.S. data. They also show that in the model of Weiss (1984), where firms have different cyclical sensitivities and hiring costs exceed firing costs, the dispersion index will move countercyclically. Thus, there are obvious problems with using the dispersion index as a proxy for the variance of sectoral shocks. However, if the effects described by Abraham and Katz are quantitatively important, it is difficult to understand Lilien's finding that the dispersion index is essentially orthogonal to monetary surprises.

[6] Consider the extreme example of a growing two-sector economy with no labor mobility. Even though workers never change sectors, the economy could still adjust to a sectoral shock just by having new labor force entrants attach to the favorably affected sector at a higher rate for a certain period of time. Those laid off in the adversely affected sector would eventually be re-employed in that same sector because of the economy's secular growth and/or labor force attrition. In this scenario, one finds a positive correlation between the unemployment rate and a dispersion index despite the fact that workers never change sectors, and never engage in search.

cannot immediately increase employment -- they can only increase vacancies. Thus, sectoral shocks increase both vacancies and unemployment, creating a positive correlation between the two. Abraham and Katz find a negative correlation, which they take as evidence for the relative importance of aggregate shocks. However, Davis (1987) points out that cyclical movement in the duration of vacancies can produce a negative correlation between the stock of vacancies and unemployment in a model driven by sectoral shocks. The sectoral shift theory requires only that the <u>flow</u> of new vacancies be positively correlated with unemployment.

As this discussion makes clear, no correlation among aggregate variables necessarily indicates that search activity in response to sectoral shocks is prevalent on the micro-level.[7] A proper test of the sectoral shift hypothesis requires that one follow a panel of workers through time to determine whether substantial numbers of individuals respond to sectoral shocks by leaving sectors where relative wages fall, entering the non-market (search) sector for a time, and then changing their sector of employment to one where relative wages rose.

The first authors to examine cross-sectoral mobility in micro data were Murphy and Topel (1987). In CPS data, which contain two annual observations on each respondent, they observe an empirical regularity which may appear quite damaging to the sectoral shifts hypothesis -- namely, that incidence of unemployment spells among workers who switch sectors is a virtually constant fraction of total incidence of unemployment. The first generation of sectoral models required that this quantity move countercyclically. However, in the more recent Hamilton model, sectoral shocks generate both search and wait unemployment, with the relative quantity of each depending on the parameters of the model.[8] Therefore, the portion of unemployment due to industry switchers need not move countercyclically. Thus, the Murphy-Topel finding, while being an important observation on the behavior of the labor market, does not necessarily contradict sectoral models of unemployment fluctuations.[9]

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[7] As Katz (1988) has stated, "the bottom line appears to be that sectoral-shifts and aggregate-shock models of cyclical unemployment fluctuations yield observationally equivalent predictions concerning aggregate variables."

[8] Hamilton generates "wait" unemployment by combining a time to move constraint and indivisible labor supply, as in Hansen (1985), with a stochastic structure in which workers in adversely affected sectors may expect conditions in that sector to improve.

[9] Murphy and Topel's finding has been challenged by Loungani and Rogerson (1989). Since the CPS tracks workers for only two years, it cannot be used to detect industry switchers who experience very long intervening spells of unemployment. Loungani and Rogerson instead use the PSID data for 1974 to 1984. This dataset allows individuals to be tracked for several years. Loungani and Rogerson follow workers over

In addition to the fact that models where sectoral shocks drive the cycle do not necessarily produce a positive correlation between volume of sectoral labor reallocation and aggregate unemployment, there also exist aggregate demand driven business cycle models which do predict such a positive correlation. These are the "reallocation timing" theories of unemployment discussed by Darby, Haltiwanger and Plant (1985) and Rogerson (1986). In these theories changes in the pace of labor reallocation are induced by aggregate rather than sectoral shocks. If labor reallocation involves an opportunity cost of lost work time (i.e., the wage), then an aggregate shock which reduces productivity in all sectors reduces this cost and increases labor reallocation.

It appears then that looking at the correlation between the portion of unemployment due to industry switchers and the aggregate unemployment rate cannot distinguish between sectoral shock and aggregate demand driven business cycle models.[10] This observational equivalence problem arises because the key idea of the original Lucas-Prescott model and all other sectoral models -- that sectoral shocks change relative wages and that these relative wage changes induce mobility -- is not being tested. If sectoral shocks are an important driving force behind cycles, they must cause changes in relative wages large enough to induce immediate labor mobility, rather than inducing workers to wait for a subsequent aggregate shock to reduce wages before they move. To my knowledge, the only published work examining the effect of sectoral shocks on real wages is the paper by Shaw (1989). Using residuals from industry employment equations (after controlling for GNP and trend growth) to proxy for sectoral shocks to an industry, Shaw finds that sectoral shocks have much stronger effects on absolute and relative real wages than do aggregate shocks.[11] This finding is strong evidence against reallocation timing theories. In related

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four year periods and define a switcher as someone who is employed in the first year, who is observed in a different industry or unemployed in the second year, and who has not returned to the original industry by the fourth year. They find that incidence of unemployment among industry switchers as a proportion of total incidence of unemployment does move countercyclically. For total weeks of unemployment, the percentage contributed by industry switchers is also countercyclical. They argue that countercyclical movement in the incidence of long unemployment spells among industry switchers accounts for the differences between their results and those of Murphy and Topel.

[10] We have not escaped from Katz's observational equivalence problem regarding the predictions of these models (see footnote 7). This should not be surprising, because total unemployment due to industry switchers is actually an aggregate variable.

[11] In particular, she finds that sectoral shocks account for an 0.79 percent decline in the durable manufacturing real wage from 1982 to 1986, and an 0.95 percent increase in the real wage in services. At the same time, the percentage of the labor force employed in services grew rapidly while that in manufacturing declined.

work, Topel (1986) uses residuals from regressions of local employment on quadratic trends as proxies for local labor market conditions and finds local market conditions have significant effects on local wages and cross-regional mobility.[12]

The present paper is a further attempt to determine whether the response of sectoral wages and employment to sectoral shocks is consistent with the sectoral shifts hypothesis. The methodology, however, is quite different from that of Shaw and Topel. Rather than using employment equation residuals to proxy for sectoral shocks, the effects of actual sectoral shocks -- specifically changes in the real price of refined petroleum -- are examined. By using an actual sectoral shock variable rather than employment equation residuals, the effects of shocks on employment and wages may be examined independently. This approach also responds to the frequent objection to empirical work on real business cycle theories that the source of the real shocks driving the economy is never identified with real world events (see Lucas [1985], Summers [1986], and Barro [1986]). Oil price movements are examined because Hamilton (1983) has shown their strong effect on real GNP and employment in postwar U.S. data, and because Loungani (1986) has shown that they explain most of the fluctuation of the across-sector variance of employment growth rates that is correlated with unemployment fluctuations. Their important effect on wages is shown by the fact that they explain 81% of the variance around a quadratic trend in the BLS average wage series over the '64 – '88 period (quadratic trend alone explains 69 percent of the variance, while inclusion of oil prices raises the explained variance to 94 percent).

In this paper, micro-panel data are used to estimate sectoral wage and employment equations which include real oil prices in addition to controls for individual characteristics and time trends to capture secular trends in wages and employment. The goal is to determine whether oil price changes induce significant changes in sectoral relative offer wages, and if labor is reallocated towards those sectors where offer wages rise.

Besides using oil prices as sectoral shocks, the other main difference between the present paper and the work of Shaw and Topel is that careful attention is paid to the effects of labor mobility itself on wages. Heckman and Sedlacek (1985) point out that mobility-induced changes in labor force composition can bias estimates of the offer wage effects of shocks. For example, if a sectoral shock adversely affects

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[12] In another recent paper, Pissarides and McMaster (1990) find that regional wage differentials are important determinants of regional migration.

manufacturing and causes low wage manufacturing workers to move to services, the average wage in manufacturing could actually rise relative to that in services, even though the effect of the shock is to raise the offer wage of all service workers and lower the offer wage of all manufacturing workers. This could lead to false rejection of equilibrium sectoral models because a researcher only looking at average wages would falsely conclude that workers were moving to the sector where the shock reduced offer wages. In the present paper, a fixed effects selection model is used to estimate labor force quality constant changes in sectoral wages.[13]

3. A Statistical Model of Sectoral Choice and Wage Determination

This section describes the statistical model used to consistently estimate the effects of sectoral shocks on sectoral offer wages. Given changes in sectoral labor force composition, OLS estimates of the offer wage effects of sectoral shocks will, in general, be biased because they confound true shifts in the offer wage distribution with compositional effects (see Keane, Moffitt and Runkle [1988] for a detailed discussion of this issue). The appropriate estimation framework is a model that allows for both time invariant unobserved ability components (i.e., individual effects) and correlation between the time varying component of the wage equation error and the industry choice equation error (as in the selection model of Heckman [1974]). Given a panel of N individuals who choose between employment in sector j and the universe of alternatives (i.e., unemployment or employment in any other sector) in each of T_i time periods, we write the model as:

$$\ln w_{ijt} = X_{it}\beta_j + \mu_{ij} + \epsilon_{ijt}$$

$$\text{observed iff } d_{ijt} = 1$$

$$d_{ijt} = \begin{cases} 1 \text{ if } u_{ijt} \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

$$u_{ijt} = Z_{it}\Gamma_j + \phi_{ij} + \omega_{ijt}$$

Here ln w_{ijt} is the log of the hourly offer wage rate of individual i at time t in sector j. It is only observed if the individual chooses to be employed in sector j. d_{ijt} is a binary indicator for choice of sector j as

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[13] Shaw has used selection correction techniques to adjust for bias in her wage equation that may be caused by selection into employment vs. unemployment, but does not consider the issues of selection from among alternative market sectors considered by Heckman and Sedlacek.

opposed to any of the universe of alternatives. The u_{ijt} are latent indices that may, if desired, be interpreted as utilities. The individual chooses sector j if it gives a higher value of the latent index (i.e., a higher utility) than can be obtained by choice of the set of alternatives. Using binomial selection models, selection adjusted wage equation estimates can be obtained for any particular sector j of interest by defining d_{ijt} as equal to one if a worker is employed in that sector and equal to zero otherwise (i.e., if the worker is unemployed or employed in any other market sector). Normalization to 0 of the utility that can be obtained by choice of the set of alternatives is necessary for identification. Z_{it} and X_{it} are row vectors of regressors, and Γ_j and β_j are the associated coefficient vectors. The oil price variable is included in both X_{it} and Z_{it}, along with characteristics of workers that affect their wages and industry choices.

The error terms in the wage and industry choice equation contain the time invariant individual effects μ_{ij} and ϕ_{ij} and the time varying error components ϵ_{ijt} and ω_{ijt}. Alternative statistical models are obtained by making different assumptions about the error structure. If the wage equation individual effects μ_{ij} are set to zero for all i and j (so that there is no unobserved component of individual ability), and if the time varying error components in the wage and choice equations are assumed uncorrelated, we simply have an OLS regression model. However, if the time varying error components (ϵ_{ijt} and ω_{ijt}) are assumed to have the bivariate normal distribution with correlation ρ_j, so that the choice equation is a binomial probit, we have the standard Heckman binomial selection model.

It is simple to see the nature of the selection bias that arises if $\rho \neq 0$ but we estimate an OLS regression using only workers employed in industry j. Letting the oil price variable be the kth element of X_{it} and Z_{it} we have:

$$\frac{\partial E(\ln W_{ijt} | I_{ijt} = 1)}{\partial X_{itk}} = \beta_{jk} - \rho\sigma_\epsilon m_{ijt}\Gamma_{jk}$$

where σ_ϵ is the standard deviation of the wage equation error, $m_{ijt} \equiv \lambda_{ijt}(\lambda_{ijt} + Z_{it}\Gamma_j)$ and λ_{ijt} is the Mill's ratio. It can be shown that $m_{ijt} > 0$. Hence, for example, if $\Gamma_{jk} < 0$, so that oil price increases reduce employment in industry j, and if $\rho_j > 0$, so that it is workers with low transitory wage components who are most likely to leave the industry, then $\rho_j\sigma_\epsilon m_{ijt}\Gamma_{jk} < 0$ and the OLS estimate of the true oil price effect on wages (β_{jk}) is biased upward. In other words, when oil prices increase it is low wage workers who tend to leave the industry, and this compositional effect increases average wages. Thus, failure to control for labor force quality will bias estimates of the true oil price effect on the offer wage distribution. The selection model produces consistent estimates of β_{jk} by accounting for the correlation ρ_j.

To proceed, if the individual effects μ_{ij} and ϕ_{ij} are assumed to be uncorrelated with X_{it} and Z_{it} and to have a bivariate normal distribution with correlation ψ_j, we have the random effects selection model. If individual effects are present and the stated assumptions are correct this model is efficient relative to the no-effects selection model, but the two models give asymptotically equivalent estimates of β_j and Γ_j.

If the individual effects are treated as individual specific constants that may be correlated with X_{it} and Z_{it} then we have the fixed effects selection model. If the wage equation fixed effects are in fact correlated with X_{it}, then the estimates of β_j from the OLS, no-effects selection and random effects selection models are all biased. For example, suppose it is workers with low values of the unobserved ability component μ_{ij} who are most likely to leave industry j following an oil price increase. Then the oil price variable X_{itk} is positively correlated with the mean μ_{ij} among employed workers in industry j. When oil prices increase, the mean μ_{ij} among employed workers increases, thus increasing labor force quality. Again average wages increase due to a compositional effect, biasing estimates of the true oil price effect on offer wages in any model that does not control for individual effects.

A problem with the fixed effects selection model is that it is inconsistent for finite T. This is because the choice equation fixed effects cannot be estimated consistently for finite T, and if $\rho_j \neq 0$ this inconsistency is transferred to the estimates of the wage equation parameters. As we shall see below, this problem is unimportant in the present case because our fixed effects estimates of ρ_j are all nearly equal to zero. Thus, selection bias appears to be unimportant after allowing for wage equation fixed effects.

4. Data

The National Longitudinal Survey of Young Men (NLS) is a nationally representative sample of 5,225 U.S. males aged 14 to 24 which was drawn in 1966. They were interviewed in 12 of the 16 years from 1966 to 1981, with data collected on their employment status, wage rates and sociodemographic characteristics. The sample was stratified by race and other characteristics (with an over sampling of blacks), so sampling weights are used in all analysis. The sample is restricted to those at least 21 years of age at the interview date, who had completed their schooling and military service, and who had available data for all variables used in the study. The final analysis sample contains 4,439 males and 23,927 person-year observations, giving an average of 5.4 observations per person.[14]

Table 1 reports a complete listing of the variables in the analysis sample. Table 2 reports sample means of the individual specific variables. For the analysis of section 5.1, the workers are classified into three sectors on the basis of 3-digit census industrial classification codes. These are manufacturing (codes 279-459), services (codes 579-998, which includes wholesale and retail trade, FIRE, services and government) and construction, transportation and utilities (CTU), which is dominated by workers in these three industries but which also contains a few smaller industries (all other codes). Section 5.3 reports results using an eleven-industry (census 1-digit level) breakdown. The wage measure used in the analysis is an hourly straight-time measure in 1967 consumer price index (CPI) dollars.

Several aggregate time series are also used in the micro-data analysis. These are also described in table 1 and their descriptive statistics given in table 3. The producer price index for refined petroleum products divided by the producer price index (both equal to 100 in 1967) is the measure of the real price of oil. Twelve month CPI inflation and M1 growth rates are constructed using data from the Citibase dataset.

In addition to the micro-data analysis, aggregate time series results for the postwar period are reported in section 5.2 for comparison purposes. Time series data on wages and employment of production and non-supervisory workers on private non-agricultural payrolls for the 1964 to 1988 period are obtained from the Bureau of Labor Statistics (BLS) Handbook of Labor Statistics. For these years data by industry are available for all industries used in the micro-data analysis except government. Thus, the service sector time series results differ from the micro-data results due to exclusion of government workers. Data for all employees on non-agricultural payrolls are obtained from the BLS Handbook for the 1947-1988 period, but these data are less complete. Real compensation indices are available only for all workers and for manufacturing, but not for services and CTU. These data do contain government employment however.

[14] This sample is identical to that used by Keane et al. except that they use a random half sample instead of the full sample. A detailed description of the number of observations lost due to each data screen can be found in appendix B of Keane et al.

5. Results

5.1 NLS Data Analysis: Three Sector Level

To interpret the results which follow, it is useful to examine the general properties of the real oil price series over the postwar period. The persistence of oil price shocks is examined by estimating forecasting equations for changes in the OIL variable over the 1949-1988 period. Annual forecasting equations produce an R^2 of .13, while equations for monthly forecasts of annual changes produce an R^2 of .02.[15] These small R^2s indicate that only a small portion of the changes in the OIL variable can be predicted, so that OIL itself is close to being a random walk. From these results we can conclude that changes in the real price of refined petroleum are largely unanticipated and highly persistent. This simplifies our further analysis, because equilibrium sectoral models give simple predictions for the effects of such shocks--a current period energy price change that was unanticipated and is expected to show some persistence must cause labor to flow from sectors where relatives wages fall to those where they increase.

Consider now the effects of oil price changes on real wages. Coefficients of the OIL variable from log wage equations estimated on NLS data are presented in table 4.[16] This table presents results both for all workers and for a three sector breakdown of the economy into manufacturing, services and CTU

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[15] The annual forecasting equation is:

$$\underset{}{\Delta \ln OIL} = \underset{(2.010)}{-.830} + \underset{(.164)}{.387^{**}} \Delta \ln OIL(-1) + \underset{(.485)}{.341} \Delta \ln GNP(-1) \qquad R^2 = .13$$

with a Durbin-Watson statistic of 2.044 and a first autocorrelation of $-.042$. The figures in parenthesis are standard errors. Using data on 12 month rates of change recorded monthly from January 1949 to December 1988 (468 observations), the monthly forecasting equation for annual changes is:

$$\Delta \ln OIL = \underset{(.735)}{.502} + \underset{(.046)}{.079^{*}} \Delta \ln OIL(-1) + \underset{(.091)}{.204^{**}} \Delta \ln GNP(-1) \qquad R^2 = .02$$

This equation has a very poor Durbin-Watson of .07 because the errors are, of course, MA(11) by construction. Thus, the standard errors are greatly understated. Additional lagged oil price changes and other time series variables were not significant when added to the above equations.

[16] The specification of the statistical model is based on the assumption that the log wage equations should contain only variables that directly affect an individual's marginal product, and that the choice equations should include all these variables (since the wage affects utility and is a determinant of employment status) plus additional ones that may affect hours of work and employment status independent of the wage. I include a time trend, EDUC, EXPER, $EXPER^2$ and WHITE in the log wage equation and, additionally, KIDS and WIFE in the choice equation. Results were not found to be sensitive to additions or deletions of variables from this specification. Deletions were 1) removing WIFE and KIDS from the choice equation, and 2) removing all individual specific regressors from both equations. Additions were including SMSA residence and Southern residence dummies in both equations.

(construction, transportation, utilities, etc.). Results using four estimation methods -- OLS, the selection model, the random effects selection model, and the fixed effects selection model -- are presented. According to the OLS point estimate for all workers (−.1085), a 1 std. dev. around trend increase in the OIL variable (which is 0.28) results in a 3 percent drop in the real wage. Of course, it is possible that this apparently large oil price effect on wages is the result of spurious correlation -- that there exist other variables that are highly correlated with oil prices and that strongly affect wages. However, a search over several variables thought to influence wages (inflation in the year prior to the interview date, net exports, import share of GNP, exchange rates) revealed that inclusion of these variables has no significant effect on the oil price coefficient.

The table 4 results also indicate that oil price shocks have very different effects on wages in different sectors of the economy. Surprisingly, oil price increases cause much greater real wage reductions in services than in manufacturing. According to the OLS point estimates a 1 std. dev. around trend increase in OIL reduces the wage in services by 3.5 percent and that in manufacturing by only 2.1 percent. This pattern is maintained across all the estimation methods considered. However, the estimated OIL price effect on the relative wage in CTU varies considerably across estimators. Notice that, according to the OLS estimator, the relative wage decline in CTU is roughly equal to that in services. However, the point estimate of the OIL coefficient in the no-effects selection model (−.0708) implies that CTU has the smallest wage decline of any sector, while both the random effects and fixed effects selection models imply that CTU has the largest wage decline of any sector.

Note that the no-effects selection model estimates may be biased either due to the presence of fixed effects or due to failure of the joint normality assumption on the wage and choice equation errors. The random effects selection model estimates may be biased either because of the presence of fixed effects, failure of the equicorrelation assumption (see Avery, Hansen and Hotz [1983]), or failure of joint normality of either the time varying or time invariant components of the wage and choice equation errors. The fixed effects model estimates will be biased if $\rho \neq 0$ because the estimates of the choice equation fixed effects are inconsistent for finite T and this bias is transferred to the wage equation, but another potential source of bias if $\rho \neq 0$ is failure of the joint normality assumption for the time varying parts of the wage and choice equation errors.

A key point is that the estimates of ρ were highly significant in all four no-effects selection models estimated in table 4, and that the estimates of ψ and ρ were highly significant in all four random effects selection models estimated in table 4. However, the fixed effects selection models all produced estimates of ρ that were insignificant and very close to zero. This indicates that, once fixed effects in the log wage equation are accounted for, the correlation between the transitory components of workers' wages and their employment probabilities is negligible. Thus, most of the change in unobserved workforce quality induced by oil price shocks can be accounted for by individual fixed effects. Notice that, with $\rho = 0$, both possible sources of bias in the fixed effects selection model estimates disappear. Thus, I have chosen the fixed effects selection model as the preferred specification.

To summarize, the fixed effects OIL coefficient point estimates imply that a 1 std. dev. around trend increase in the OIL variable (0.28) results in a 3.5 percent drop in the real wage overall, a 2.7 percent drop in manufacturing, a 3.9 percent drop in services, and a 4.1 percent drop in CTU. The size of these relative wage effects becomes more apparent when one considers that both oil shocks in the '70s were on the order of 2 to 2.5 standard deviations. Note that for *all* workers and in *all* three sectors, the fixed effects estimates imply wage declines of roughly 0.5 percent greater than those implied by the OLS estimates. This indicates that oil price increases tend to result in low wage/low ability workers (i.e., those with low values of the individual fixed effect) leaving employment. This causes an improvement in labor force quality (i.e., an increase of the mean value of the fixed effect in the employed population), so that OLS estimates understate the true quality constant wage decline.

We turn now to the employment effects of oil price shocks. Table 5 presents estimates of employment probability effects of changes in the OIL variable obtained from linear probability, probit and random effects probit models. According to the linear probability models, a 1 std. dev. around trend increase in the OIL variable (0.28) results in an 0.43 percentage point increase in the probability of employment overall, an 0.55 percentage point increase in manufacturing, an 0.17 percentage point increase in services, and an 0.29 percentage point decline in CTU. Given the percentages of workers employed in each sector (see table 1), these translate into a 1.81 percent increase in manufacturing employment, an 0.45 percent increase in services employment, and a 1.41 percent decline in CTU employment. The probit results are consistent with the linear probability model results and the random effects probit models indicate that the employment probability increase in manufacturing and decrease in services are both highly significant.

Viewed in conjunction with the estimated wage effects of oil price changes, these estimated employment effects are perfectly consistent with the predictions of equilibrium sectoral models. The manufacturing sector has both a relative wage and probability of employment increase, while the CTU sector has the largest wage decline and a probability of employment decline.

While consistent with equilibrium sectoral models, the results appear inconsistent with our prior notions. The fact that manufacturing is more energy intensive than non-manufacturing makes the finding that oil price increases raise manufacturing employment and wages relative to those in non-manufacturing rather surprising. However, it is simple to show (see Keane [1990]) that it is not necessarily the more energy intensive sector which is adversely affected (in the sense of relative wage and employment reductions) by an energy price increase. Rather, it may be the sector in which energy-labor substitution is more difficult. Given the many empirical studies indicating strong energy-labor substitutability in manufacturing, (Hudson and Jorgenson [1974], Berndt and Wood [1975], Humphrey and Moroney [1975], Griffin and Gregory [1976], Fuss [1977], Pindyck [1979] and Chung [1987] all find that energy and labor are highly substitutable in manufacturing production (i.e., they are strong net substitutes]), it is plausible that non-manufacturing is the adversely affected sector.[17] Furthermore, aggregate data results, described fully in section 5.2 below, also show relative wage increases in manufacturing and failure of oil price increases to produce the expected fall in manufacturing relative to non-manufacturing employment.

Given the results of Hamilton (1983) indicating that oil price increases have a strong negative effect on real GNP, it is also surprising that we find a significant positive effect of oil price increases on overall probability of employment for the NLS young men. A regression of real GNP on OIL (and other control variables) using 1947-88 annual time series data produced a point estimate indicating that a 1 std. dev. around trend increase in OIL (which is 29.9) reduces real GNP by 2 points given a 1967 base of 100.

[17] Unfortunately, I am not aware of any energy-labor substitutability studies for non-manufacturing. Note that there is no contradiction among the three facts that: 1) energy and labor are strong net substitutes in manufacturing production, 2) oil price increases reduce manufacturing absolute wages, 3) that oil price increases increase manufacturing employment. The negative wage effect indicates that energy and labor are gross complements in manufacturing, but because they are better net substitutes there than in other sectors, relative wages fall in other sectors. This shifts the labor supply curve for manufacturing to the right, allowing a simultaneous wage decline and employment increase. The adverse income effect of a persistent oil price increase magnifies the labor supply shift.

However, the same regression using the BLS index of employment of nonagricultural workers (1967 = 100) as the dependent variable shows no significant employment effect of oil price increases.[18] The obvious explanation of these results is that oil price increases cause firms to substitute labor for energy, so that GNP falls more than employment.

Finally, the fact that oil price increases significantly shift sectoral relative wages but are not found to significantly reduce employment may appear to indicate that sectoral shocks are not an important source of unemployment fluctuations. This is an incorrect interpretation, because any change in oil prices, whether positive or negative, is a sectoral shock which changes relative wages and may thereby generate search unemployment. When the percentage change in the OIL variable in the year prior to the interview date is constructed, and positive and negative changes are allowed to have separate coefficients in the linear employment probability model, the former have a coefficient of −.0013 (standard error is .0005), the latter have a coefficient of −.0053 (standard error is .0016) and OIL itself has a coefficient of .0297 (standard error .0075). When the absolute value of the percentage change in OIL is included in the linear probability model it has a coefficient of −.0016 (standard error is .0005) and OIL itself has a coefficient of .0218 (standard error is .0072). These results indicate that any change in oil prices reduces employment in the short run. The point estimates for the absolute value model imply that employment is reduced by roughly 2.3 percent in the year following a one standard deviation around trend oil price increase, which is 18.3 percent at the mean of the data ((.28 + 1.53) × 100).

Since trend terms are included in all the above models, the coefficients on OIL may be interpreted as measuring effects of deviations in oil prices from trend. Since OIL price movements are close to a random walk, deviations around trend are very persistent, and the oil price coefficients cannot be interpreted as measuring short-run effects of oil price changes. Thus the positive OIL coefficients estimated

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[18] The regression results are:

$$\underset{(2.71)}{\text{GNP} = 53.83^{**}} - \underset{(.0177)}{.0669^{**}}\ \text{OIL} + \underset{(.14)}{1.83^{**}}\ \text{TREND} + \underset{(.004)}{.033^{**}}\ \text{TREND}^2 + \underset{(.028)}{.011}\ \text{DUR}$$

with R^2 = .995, Durbin-Watson = .751 and the first autocorrelation equal to .624, and:

$$\underset{(2.74)}{\text{EMP} = 63.33^{**}} - \underset{(.0179)}{.0149}\ \text{OIL} + \underset{(.146)}{.995^{**}}\ \text{TREND} + \underset{(.004)}{.033^{**}}\ \text{TREND}^2 - \underset{(.016)}{.011}\ \text{DUR}$$

with R^2 = .991, Durbin-Watson = .640 and the first autocorrelation equal to .679.

above are indicating a rather long-run positive employment effect and are not at all inconsistent with a negative short-run employment effect. Note that if oil price increases are long lived, and reduce labor productivity, they will have a negative income effect causing labor supply to shift right. Then, if energy and labor, while being net substitutes, are gross complements (i.e., an oil price increase shifts labor demand to the left), the observed pattern of wage declines without employment declines may emerge.

Finally, we turn to the econometric problems raised by time effects. Coleman (1984) points out that inclusion of aggregate time series, which have no cross-sectional variation, in micro-data regressions will give downward biased standard errors if there are unobserved time-specific error components. This problem is somewhat mitigated in the NLS data because within each survey wave there is cross-sectional variation in interview month, and the aggregate time series used are monthly. The problem is still potentially important, however.

As Coleman describes, a procedure to correct standard errors for time effects is to replace the aggregate time series (the time trend and the OIL variable in the present case) with time dummies when estimating the model of interest, and then, in a second stage, to regress the estimated dummy coefficients on these aggregate time series. This procedure is impractical in the present case, because ML estimation of models including twelve years of month dummies in both the wage and choice equations is computationally infeasible. Therefore, Coleman's procedure was implemented using year dummies. There are two problems with this approach. First, since both the individual wage and employment status variables are measured monthly, regressing these on year dummies introduces errors-in-variables bias. Second, since there is monthly variation in the time series, the standard errors obtained from this procedure will be overstated. Nevertheless, the use of year dummies will give some idea of the importance of time effects for our estimates of standard errors.

The results obtained using year dummy coefficients estimated from the no-effects selection model are reported in table 6. The no-effects selection model was used despite the fact that the fixed effects selection model is preferred for two reasons. First, it is much less expensive to estimate a large number of dummy coefficients using this model than the individual effects models. Second, since errors-in-variables bias is present we cannot expect to get consistent estimates. Thus there is little to be gained by using the preferred model. Comparing the wage equation results to those in table 4, we see that for sectors other than services the OIL coefficient standard errors slightly more than double. In services the standard error increase is small. In all sectors the estimated offer wage effects of oil price shocks remain highly significant. The only OIL coefficient point estimate to change noticeably is that for the CTU sector which moves from −.0708 to −.1062. This change may be due simply to the error-in-variables bias resulting from use of year dummies. The employment equation results show the same pattern of point estimates as in table 5, with CTU having the only employment decline. The OIL coefficient estimates in these employment equations are not significant, but it is important to remember that efficiency is being lost by ignoring monthly variation in the data. Interestingly, the R^2s in the wage equations for all workers, manufacturing and services are .783, .784 and .845 respectively, indicating that oil price changes and the time trend, rather than unobserved time effects, explain most of the aggregate offer wage variation over this period. For CTU, the R^2 is only .411.

5.2 Aggregate Data Comparisons

The NLS data analysis of section 5.1 produced the rather surprising finding that oil price increases raise manufacturing employment and wages relative to those in non-manufacturing. However, this flatly contradicts the conventional view that oil price increases can at least partially explain the decline of manufacturing employment relative to services in the 1970s and 1980s. The finding that oil price changes have substantial effects on real compensation also seems to contradict a rather common view that real wages were very flat over the 1973 to 1988 period. In order to determine whether these findings are anomalies of the NLS data or features of the aggregate economy, aggregate postwar data on sectoral real wages and employment are examined.

Using BLS data for all employees on non-agricultural payrolls, figure 1 plots the percentages of the labor force employed in manufacturing and services on the same axes as the OIL and GNP variables (the latter two variables both have a 1967 base of 100 in the graph). The visual impression is that the share of the labor force employed in services trends steadily upward over the whole 1947-1988 period while the share in manufacturing trends steadily downward. There is no indication that these trends are affected by the oil price surge in 1973-1981 or by the subsequent sharp oil price decline in 1981-1988. Figure 2 plots aggregate, manufacturing and services employment (in millions) against the OIL and GNP series for the same 1947-1988 period. The reader can easily verify (with a ruler) that manufacturing employment in 1981 (the peak year of oil prices) was equal to that in 1973 (before the first oil shock). Furthermore, manufacturing employment was slightly lower in 1988 than in 1981 despite seven years of oil price declines. These figures provide additional confirmation that oil price movements cannot explain the secular decline in manufacturing's employment share.[19]

Turning to wage effects, figure 3 plots real total compensation (COMP) and real total compensation in manufacturing (COMPM) on the same axes as the OIL and GNP series (all these variables have a 1967 base of 100). Both compensation indices rise in every year from 1947 to 1973. Although real compensation is indeed fairly flat over the 1973 to 1988 period when compared to its earlier steady growth, it nevertheless shows a clear upward tendency <u>except</u> for years of sharp oil price increases.[20] Pindyck and Rotemberg (1984) have previously noted the sharp declines in real wages following the two oil shocks, and this strong connection between oil prices and wages is apparent from the figure.

A regression analysis of the time series data is also performed. For the 1964-1988 period, main results of regressions using the BLS data on wages and employment for production and non-supervisory workers on non-agricultural payrolls are reported in table 7.[21]

The point estimate of the OIL coefficient for all workers (−.0785) indicates that a 1 std. dev. around trend increase in the OIL variable results in a 2 percent decline in the average real wage (compared to the 3.5 percent mean offer wage decline in the micro-data). Note that a 1 std. dev. around trend increase in OIL is 31 points compared to a mean of 147 (see table 3). This is very close to the 0.28 point

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[19] Since the level of manufacturing employment does not show any obvious downward trend in the postwar period, these figures reinforce the point made in section 2 that we cannot discern from aggregate data whether substantial numbers of workers actually moved from manufacturing to other sectors (Murphy and Topel, looking at individual data, document that in fact such movement has occurred).

[20] The compensation indices for all workers and for manufacturing both fall during the oil shock of 1973-1974, then continue to rise from 1974 to 1978. Both indices fall sharply during the second oil shock of 1978-1981, and then continue to rise from 1981 to 1983. In 1983-1984 both compensation indices fall despite an oil price decline, the only year this occurs in the whole postwar period. From 1984-1988 overall compensation continues to rise as oil prices decline. Compensation in manufacturing rises in 1984-1986 but falls in 1986-1988, the only time it diverges from aggregate compensation in the postwar period.

[21] These regressions differ from the micro-data regressions in four ways. First, GNP rather than U-RATE was used as the cyclical indicator. Second, a squared trend term was included. This term was not significant in micro-data regressions which included the OIL variable, but it is significant in the aggregate data regressions. Also, unless a squared trend term was included, the services sector is estimated to be more cyclically sensitive than manufacturing, a possibility which can be rejected a priori. Third, real government purchases of durable goods (DUR) was included as a regressor in the aggregate regressions. This variable was found to substantially improve the Durbin-Watson statistic in several of the models. Finally, a 1967 base of 100 instead of 1 was used for the real price of refined petroleum.

change from a mean of 1.53 considered in the micro-data. As was the case in the NLS data, addition of controls for inflation and foreign trade variables had negligible impact on the estimated oil price effects.

Strong effects of oil price changes on relative wages are also apparent in the aggregate data. Table 7 results indicate that a 1 std. dev. around trend increase in OIL results in a 1.2 percent real wage decline in manufacturing, a 2.8 percent decline in services and a 2.9 percent decline in the CTU. These average wage effects are somewhat weaker than the mean offer wage effects found in the micro-data analysis. However, the pattern of much larger wage responses in CTU and services than in manufacturing is qualitatively consistent.

Turning to the employment equations on the bottom of table 7, the point estimates imply that a 1 std. dev. around trend increase in the OIL variable reduces employment by 0.93 percent overall, by 0.87 percent in manufacturing, by 0.84 percent in services and by 1.39 percent in the CTU sector (although only for services is the point estimate significant at the 5 percent level). Thus, the CTU sector experiences the largest employment decline in both the aggregate and NLS data. Consistent with the finding in the NLS data, oil price shocks do not appear to explain any part of the decline in manufacturing's employment share relative to services in the aggregate data.

A difference in the results is that in the NLS data manufacturing employment and overall employment increase significantly with higher oil prices, while in the aggregate data both fall by roughly equivalent small percentages. A plausible explanation for the finding of a positive oil price effect on manufacturing employment in the NLS but an insignificant negative effect in the aggregate data would be that the young men are concentrated in the occupations within manufacturing where labor for energy substitution is greatest. Alternatively, if young workers have higher rates of human capital investment then the general population, and if capital is a substitute for energy, young workers would be better substitutes for energy than are average workers because they would acquire the skills needed to use new capital more quickly.

5.3 NLS Data Analysis: One Digit Industry Level

In section 5.1 we found that observed patterns of wage and employment movement in the NLS Young Men are broadly consistent with the predictions of equilibrium sectoral models using a three sector breakdown of the U.S. economy. In this section, we disaggregate further to the census 1-digit (eleven industry) level in order to determine if the same pattern of increasing (decreasing) employment probabilities in industries with increasing (decreasing) relative wages continues to hold. Table 8 presents both log wage equations (OLS and Fixed Effects Selection Models) and employment probability equations (linear probability and probit) for all eleven 1-digit industries using the NLS Young Men data. As in tables 4 and 5, only the OIL variable coefficients are reported.

At the 1-digit level, the estimates of ρ in the fixed effects selection models were all close to zero and insignificant. Hence, once fixed effects in the log wage equation are accounted for, the correlation between the transitory components of workers' wages and their employment probabilities is negligible. In most industries, however, OLS estimates of wage movements are biased by failure to control for the permanent unobserved component of ability. In nondurable manufacturing, transportation and utilities, retail trade, FIRE and services the fixed effects estimates imply wage declines considerably greater than those implied by the OLS estimates. This indicates that oil price increases tend to result in low wage/low ability workers (i.e., those with low values of the individual fixed effect) leaving employment in those industries. The resultant improvement in unobserved quality of the average employed worker causes the OLS estimates to understate the true quality constant wage declines in those industries. In construction and wholesale trade, on the other hand, the fixed effects estimates imply smaller wage declines than OLS. This indicates that it is high ability workers who tend to leave these industries following oil price increases.

The most striking feature of table 8 is the magnitude of the relative wage movements implied by the fixed effects selection model point estimates. These indicate, for example, that a 1 std. dev. around trend increase in the OIL variable (which is 0.28) results in approximately 1.8% wage declines in construction and wholesale trade, 3% wage declines in durable and nondurable manufacturing and a 4.8% wage decline in services. These are considerably larger relative wage movements that were found for the three sector classification. Apparently, the broad sectoral classifications used in section 5.1 masked some important differences in wage behavior within sectors. Within the CTU sector, construction has one of the smallest wage declines of any industry, while in transportation and utilities the wage decline is substantial. Within the broad services sector, wholesale trade has one of the smallest wage declines of any industry, while the other service sector industries have large wage declines.

Turning to the employment probability equations, these indicate increasing probability of employment following an oil price increase in durable manufacturing and services, and decreasing probability of employment in construction and retail trade. According to the OIL coefficient point estimates from the linear probability models, a 1 std. dev. around trend increase in the OIL variable results in approximately 0.6 percentage point increases in the probabilities of employment in durable manufacturing and services, and approximately 0.5 percentage point decreases in construction and retail trade. Given the percentages of workers employed in each industry, these translate into 2.7 and 3.9 percent increases in durable manufacturing and services industry employment, and 3.8 and 3.6 percent decreases in construction and retail trade employment respectively.[22]

Thus, the failure of oil price increases to significantly affect probability of employment in the broad services sector considered in section 5.1 masks the fact that they do in fact cause significant increases in service industry employment balanced by roughly equal declines in retail trade employment. Within the broad CTU sector, the entire employment decline is in the construction industry.

Comparing the relative wage and employment probability effects at the 1-digit level, they do not appear consistent with the predictions of equilibrium sectoral models. Construction has the smallest wage decline of any large industry (only agriculture and mining have smaller wage declines, and these have very small employment shares). Yet there is a substantial decline in the probability that workers are employed in construction. Services has the second greatest wage decline of any industry, yet it has the greatest increase in employment share.

6. Conclusion

This paper has analyzed the responses of sectoral real wages and location probabilities to real shocks using micro-panel data. The observed response patterns are consistent with sectoral shift theories of unemployment in several important ways. First, changes in the real price of refined petroleum are observable real shocks that are found to have the key property of sectoral shocks: they generate substantial movements in industry relative wages. It was also found that oil price changes result in significant reallocation of labor across industries. Consistent with the predictions of sectoral shift theories of unemployment, both oil price increases and decreases cause short run decreases in employment among the NLS men.

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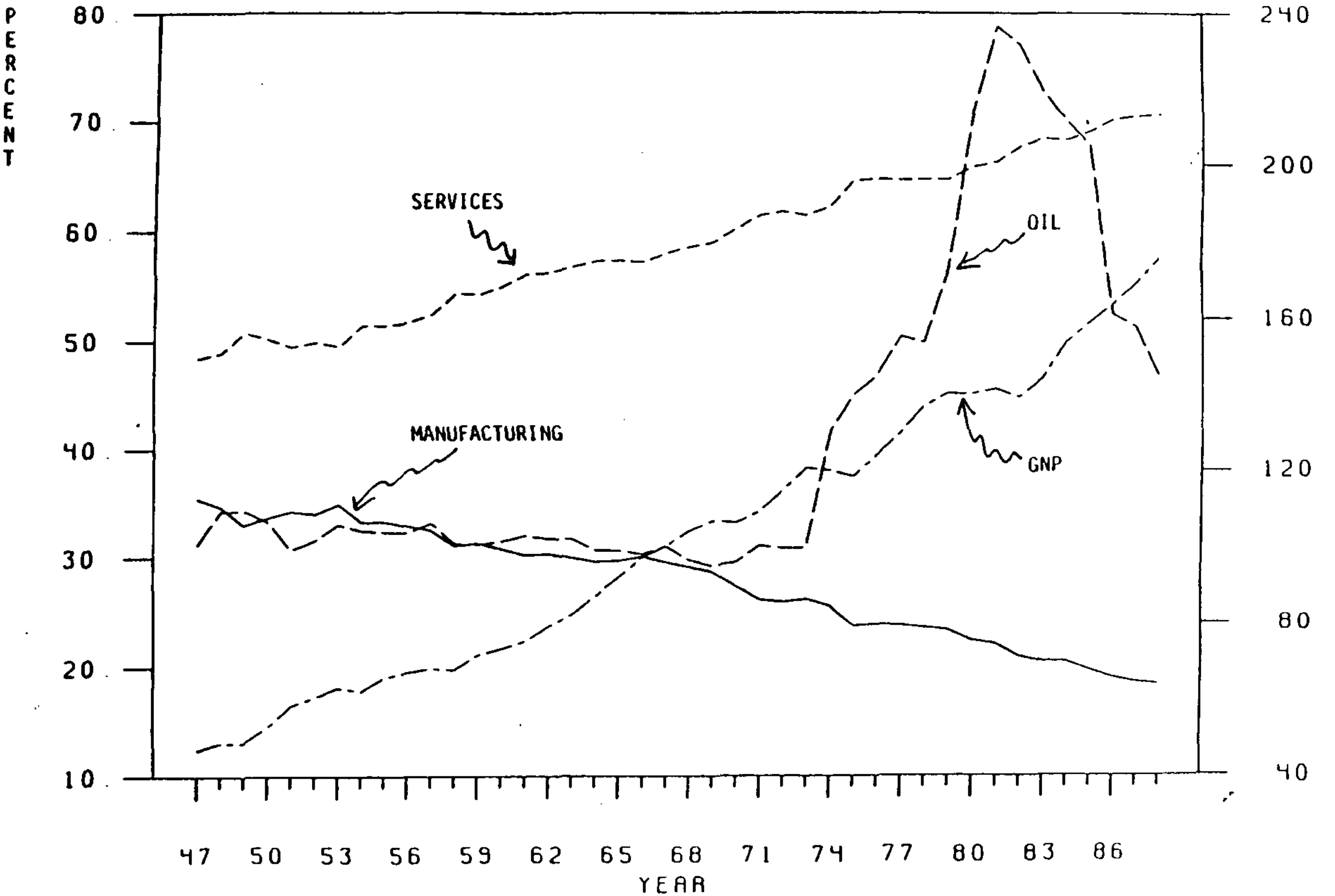
[22] Out of 21,203 person-year observations on employed workers, 4,693 are in durable manufacturing, 3,252 are in services, 2,343 are in retail trade, and 2,217 are in construction. Thus the employment shares of these industries are 22.1%, 15.3%, 11.0% and 10.5% at the mean of the data.

Using a broad three sector disaggregation of the economy, the observed wage and employment responses to oil price shocks also appear consistent with a key prediction of equilibrium sectoral models: oil price changes result in labor reallocation away from sectors with relative wage declines to sectors with relative wage increases. However, at the 1-digit (eleven industry) level this consistency breaks down. Following an oil price increase construction has the greatest relative wage increase of any large industry, yet workers' probability of locating in construction falls substantially. Meanwhile, the service industry has among the greatest relative wage declines of any industry, yet workers' probability of locating in services increases substantially. Such a pattern could emerge easily in a model with quantity rationing in some sectors (e.g., if wage rigidity prevents wages from falling in construction, and those rationed out of jobs there move into services where wages are flexible and are driven down). These results thus point to the importance of sectoral models with wage rigidities and/or quantity rationing, such as Harris and Todaro (1970), Hall (1975) and Pissarides (1978).

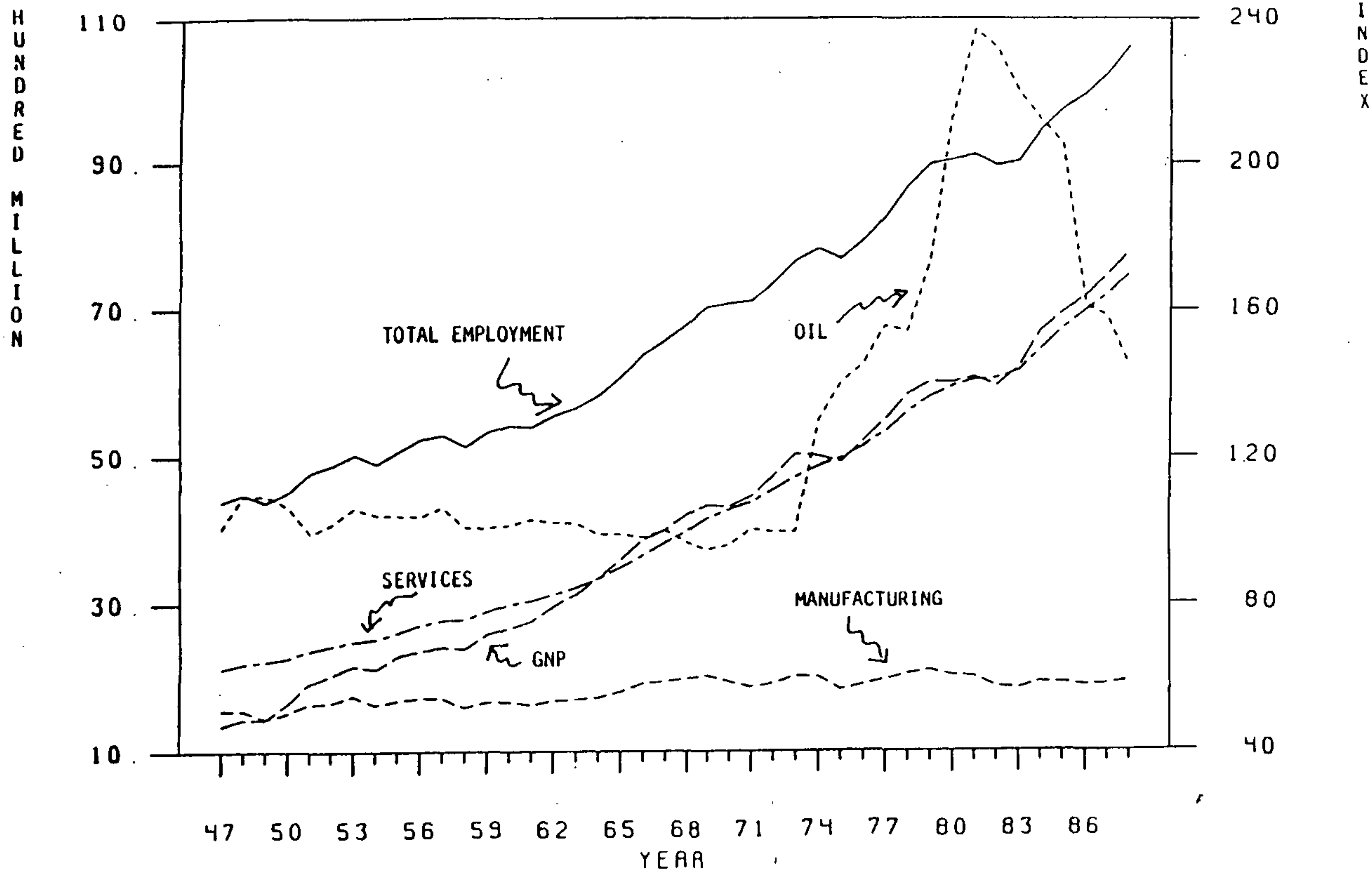
Additional findings flatly contradict the conventional view that oil price increases can at least partially explain the decline of manufacturing employment relative to service sector employment in the 1970s. In the NLS, oil price increases appear to have had no long-run adverse effect on manufacturing employment or positive effect on service sector employment. Within the broadly defined service sector there appears to have been a positive effect on narrowly defined service industry employment, but this was counterbalanced by a roughly equal negative effect in retail trade.

Figure 1 : Manufacturing and Services Employment Shares in the Postwar Period



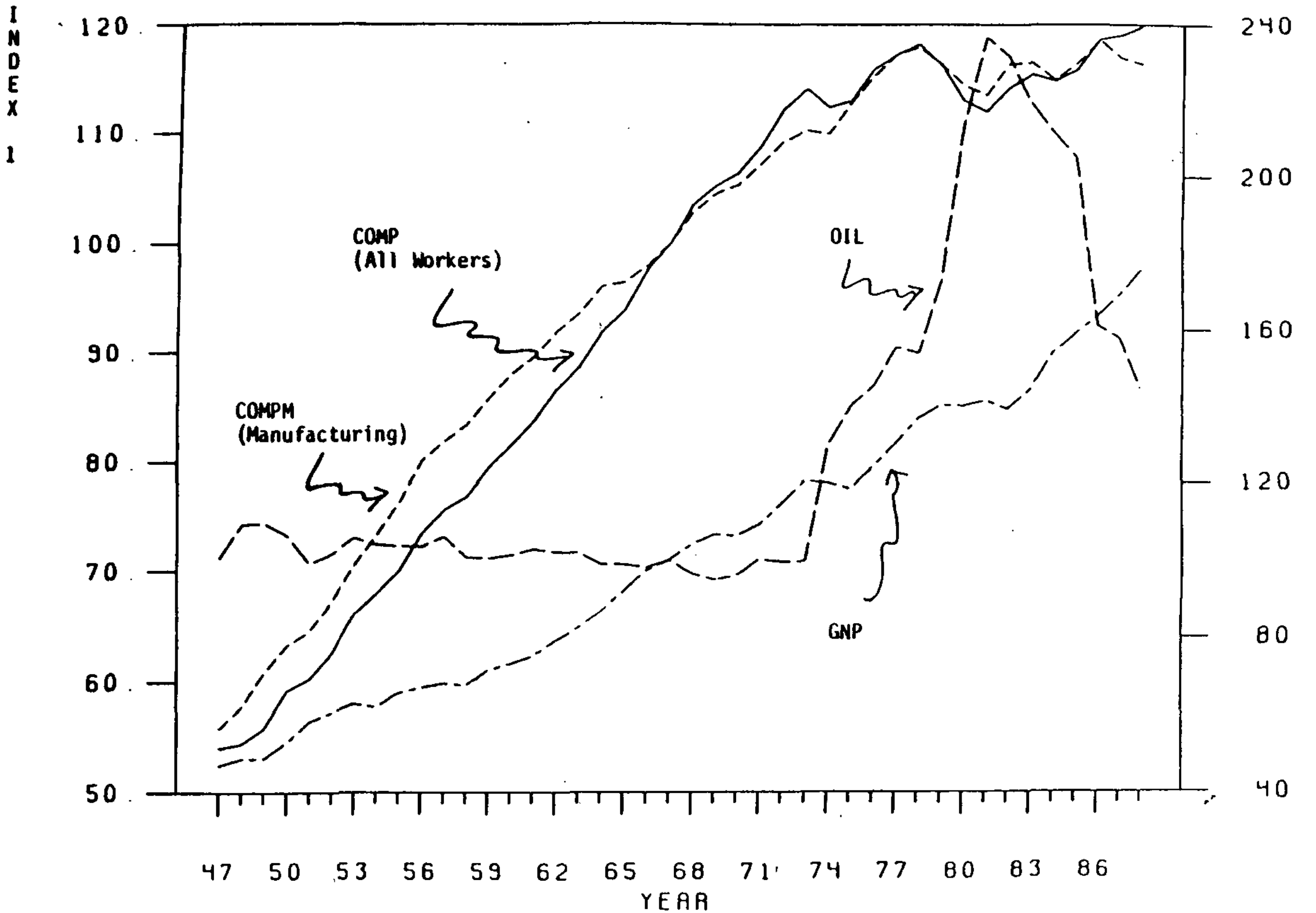
Note: The indices for OIL and GNP equal 100 in 1967.

Figure 2 : Manufacturing and Services Employment in the Postwar Period



Note: The indices for OIL and GNP equal 100 in 1967.

Figure 3 : Manufacturing and Aggregate Real Compensation in the Postwar Period



Note: Index numbers on left axis are for compensation. Index numbers on the right axis are for OIL and GNP.

Table 1
Variable Definitions

Variable		Definition
Variables in NLS Analysis Sample		
WCPI	-	Log of real hourly straight time wage in 1967 CPI dollars.
OIL	-	Real price of refined petroleum in month of interview (1967 = 1), equal to producer price index for refined petroleum products divided by producer price index for all commodities.
EDUC	-	Years of eduction.
EXPER	-	Years of labor market experience (interview date minus completion date of schooling or military service, which ever was later).
WHITE	-	Dummy variable equal to 1 if respondent is white.
WIFE	-	Dummy equal to 1 if wife is present in the home.
KIDS	-	Number of children in household.
Variables in Aggregate Data Analysis		
WCPI	-	Real hourly wage of production and nonsupervisory workers on private nonagricultural payrolls, annual average, deflated by CPI (1967 = 100).
EMP	-	Employment of production and nonsupervisory workers in 1964-88 sample and that of nonagricultural workers in 1947-88 sample, annual (1967 = 100).
OIL	-	Real price of refined petroleum, annual average (1967 = 100), equal to produce price index for refined petroleum products deflated by producer price index for all commodities.
GNP	-	Real gross national product, annual (1967 = 100).
IND	-	Industrial production index, monthly (1967 = 100).
COMP	-	Real compensation of employees on nonagricultural payrolls, annual average (1967 = 100).
COMPM	-	Real compensation of manufacturing employees, annual average (1967 = 100).
DUR	-	Real government purchases of durable goods (1967 = 100).

NOTE: The aggregate time series included in the NLS analysis sample are taken or derived from series taken from the Citibase dataset. The time series used in the aggregate data analysis are all taken from the BLS Handbook of Labor Statistics, except for OIL and DUR which are taken from the Board of Governors' FAME dataset.

Table 2
Means of Variables in NLS Analysis Sample

Variable	Mean
WCPI	1.065
EDUC	12.57
EXPER	7.90
$EXPER^2$	87.05
WHITE	.74
WIFE	.69
KIDS	1.30
U-RATE	6.38
OIL	1.53
Percentages of Workers in Each Sector	
Manufacturing	30.40
Nonmanufacturing	58.22
Services	37.61
Construction, Transportation, Utilities	20.61
Unemployed	11.38

NOTE: Variable definitions are given in Table 1. CIC codes for the various industries are given in the text.

Table 3
Means and Standard Deviations of Time Series Variables

Variable	Mean	Standard Deviation	Standard Deviation Around Trend
NLS Data (Monthly) 1966-81			
OIL	1.531	.623	.280
Aggregate Data (Annual) 1964-88			
WCPI	102.419	4.418	---
GNP	127.907	24.909	3.775
OIL	146.531	49.032	30.951
EMP	121.697	19.203	---
Aggregate Data (Annual) 1947-88			
COMP	94.409	22.151	---
GNP	102.168	37.487	4.701
OIL	129.122	43.215	29.949
EMP	104.550	28.491	---

NOTE: Note that the units for OIL are different in the aggregate data and the NLS data (see table 1).

Table 4
OIL Coefficients from NLS Log Wage Equations -- Three Sector Breakdown

Sector	OLS	Selection Model	Random Effects Selection Model	Fixed Effects Selection Model
All Workers	-.1085** (.0100)	-.1113** (.0101)	-.1183** (.0056)	-.1255** (.0057)
Manufacturing	-.0740** (.0141)	-.0789** (.0140)	-.0814** (.0096)	-.0978** (.0079)
Services	-.1262** (.0160)	-.1179** (.0160)	-.1256** (.0092)	-.1391** (.0088)
Construction, Transportation and Utilities	-.1246** (.0223)	-.0708** (.0212)	-.1483** (.0137)	-.1447** (.0112)

NOTE: Standard Errors are in parentheses. A ** indicates significance at the 5 percent level. A * indicates the 10% level. The OLS, Selection and Random Effects Selection models all contain the individual specific regressors EDUC, EXPER, $EXPER^2$ and WHITE in the wage equation, while the latter two models contain these plus WIFE and KIDS in the choice equation. All models include a time trend in both wage and choice equations. The Fixed Effects models must exclude any variables that are constant over time (EDUC, WHITE) or collinear with the time trend (EXPER) from the wage equation.

Table 5
NLS Employment Probability Equations -- Three Sector Breakdown

Sector	Linear Probability	Probit	Random Effects Probit
All Workers	.0154**	.0992**	.0837**
	(.0069)	(.0399)	(.0361)
Manufacturing	.0196*	.0521	.0584**
	(.0106)	(.0323)	(.0190)
Services	.0062	.0234	.0021
	(.0110)	(.0302)	(.0186)
Construction, Transportation and Utilities	−.0154**	−.0390	−.0461**
	(.0069)	(.0346)	(.0220)

NOTE: Standard Errors are in parentheses. A ** indicates significance at the 5% level. A * indicates the 10% level. All models contain the individual specific regressors EDUC, EXPER, $EXPER^2$, WHITE, WIFE and KIDS as well as a time trend.

Table 6
Year Dummy Regressions

Sector	All Workers	Manufacturing	Services	Construction, Transportation, and Utilities
Log Wage Equation				
OIL	−.1234**	−.0874**	−.1304**	−.1062**
	(.0245)	(.0281)	(.0195)	(.0433)
TREND	.0183**	.0182**	.0127**	.0111**
	(.0032)	(.0037)	(.0026)	(.0057)
Employment Equation				
OIL	.1737	.0716*	.0200	−.0275
	(.1084)	(.0416)	(.0372)	(.0285)
TREND	−.0518**	−.0269**	−.0048	.0150**
	(.0142)	(.0054)	(.0049)	(.0037)

NOTE: Standard Errors of the parameter estimates are in parentheses. A ** indicates significance at the 5% level. A * indicates significance at the 10% level. The dependent variables are year dummy coefficients estimated using the no-effects selection model as specified in table 4, except that year dummies replace the time trend and the OIL variable. The dummy coefficients from the selection models' log wage equations are the dependent variable in the log wage equations above, while those from the selection models' employment choice equations are the dependent variables in the employment equations above.

Table 7
Aggregate Log Wage and Employment Equations 1964-88

Dependent Variable: Real Wage (1967 = 100)	
Sector	Oil Coefficient
All Workers	−.0785** (.0084)
Manufacturing	−.0403** (.0114)
Services	−.0911** (.0077)
Construction, Transportation and Utilities	−.0936** (.0105)
Dependent Variable: Employment (1967 = 100)	
Sector	OIL Coefficient
All Workers	−.0368* (.0215)
Manufacturing	−.0342 (.0310)
Services	−.0333** (.0154)
Construction, Transportation and Utilities	−.0549* (.0308)

NOTE: Standard Errors are in parentheses. A ** indicates significance at the 5% level. A * indicates significance at the 10% level. All models *also* include *TREND*, *TREND*^{2}, *DUR* and a constant as regressors.

Table 8
OIL Price Effects on Employment Probabilities and Log Real Wages:
NLS One-Digit Industry Level

	Log Wage Equation		Employment Probability	
One-Digit Industry	OLS	Fixed Effects Selection Model	Linear Probability	Probit
Durable Manufacturing	−.0930** (.0171)	−.1075** (.0098)	.0136 (.0093)	.0761** (.0342)
Non-Durable Manufacturing	−.0399 (.0245)	−.1150** (.0125)	−.0117 (.0073)	−.0218 (.0426)
Construction	−.1335** (.0325)	−.0635** (.0176)	−.0139** (.0068)	−.1217** (.0447)
Transportation and Utilities	−.1010** (.0298)	−.1560** (.0160)	−.0000 (.0063)	.0087 (.0445)
Wholesale Trade	−.0966** (.0443)	−.0664** (.0182)	−.0030 (.0048)	−.0231 (.0483)
Retail Trade	−.1042** (.0317)	−.1526** (.0150)	−.0216** (.0070)	−.1424** (.0403)
FIRE	−.1647** (.0552)	−.2058** (.0254)	−.0081* (.0043)	−.0906 (.0629)
Services	−.1252** (.0277)	−.1726** (.0131)	.0210** (.0074)	.1192** (.0378)
Government	−.1597** (.0322)	−.1704** (.0186)	.0036 (.0055)	−.0247 (.0499)
Agriculture	−.1379** (.0757)	.0280 (.0381)	.0047 (.0035)	−.0071 (.0734)
Mining	−.1007 (.0650)	−.0551 (.0401)	.0030 (.0027)	.0706 (.0845)

NOTE: Standard Errors are in parentheses. A ** indicates significance at the 5% level. A * indicates significance at the 10% level. Controls are the same as were used in tables 4 and 5. Note that wholesale trade, retail trade, FIRE, services and government all comprise the broad services sector considered in section 5.1.

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