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THE EMPLOYMENT AND WAGE EFFECTS OF OIL PRICE SHOCKS: A SECTORAL ANALYSIS

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ABSTRACT

In this paper we use micro panel data to examine the effects of oil price shocks on employment and real wages, at the aggregate and industry levels. We also measure differences in the employment and wage responses for workers differentiated on the basis of skill level. We find that oil price increases result in a substantial decline in real wages for all workers, but raise the relative wage of skilled workers. The use of panel data econometric techniques to control for unobserved heterogeneity is essential to uncover this result, which is completely hidden in OLS estimates. While the short-run effect of oil price increases on aggregate employment is negative, the long-run effect is negligible. We find that oil price shocks induce substantial changes in employment shares and relative wages across industries. However, we find little evidence that oil price shocks cause labor to flow into those sectors with relative wage increases.

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1. INTRODUCTION

It has come to be widely accepted that fluctuations in the world price of oil have substantial real effects on the U.S. macroeconomy (see, e.g., Hamilton (1983), Loungani (1986), Shapiro and Watson (1988), Perron (1989)). However, most previous studies have only examined the effects of oil price shocks on GNP and aggregate employment. This paper provides new evidence on both the wage and employment effects of oil price fluctuations. Further, while earlier studies have looked only at aggregate data, our results are disaggregated along two important dimensions.

First, we examine sectoral differences in responses to oil price shocks. From a theoretical point of view, as well as from a policy perspective, it is important to know whether oil shocks affect all sectors in a similar fashion. For instance, if aggregate unemployment increased in the short run following an oil price shock, it may merely reflect the frictions involved in sectoral reallocation of factor inputs necessitated by asymmetric sectoral responses to that shock (see Hamilton (1988)). If so, the use of aggregate demand management or other policy measures to respond to the shock may prove futile or even counter-productive. On the other hand, if all sectors faced a decline in productivity and employment following an oil price shock, positive policy measures may have a useful role.

The second level of disaggregation in this study is the differentiation among workers on the basis of their skill levels. In our empirical work, we use education, experience, and tenure on the current job as proxies for skill level and estimate a series of models that independently analyze their effects on wage and employment variability. By studying the relation between skill levels and the nature of employment and wage responses to oil price shocks, we cast light on the role of these shocks in generating movements in the wage differential between skilled and unskilled workers.

Studying the wage and employment effects of oil price shocks is particularly relevant in the context of recent attempts to identify the sources of business cycle fluctuations (e.g., Shapiro and Watson (1988), Blanchard and Quah (1989)). In particular, real business cycle (RBC) models view exogenous real shocks that shift the aggregate production function as the primary driving force behind business cycle fluctuations. To the extent that they affect labor productivity, oil price shocks are ideal candidates for this type of real shock. From the point of view of the U.S. economy, the world price of oil is largely exogenous. Further, time series data on oil prices have statistical properties that are very similar to those posited for technology shocks in RBC models. Changes in oil prices are largely unanticipated, especially over our sample period, and are also highly persistent. Thus, this paper contributes to the development of a set of stylized facts concerning the effects of real shocks on the economy, that should aid in the development of RBC theory.

The dataset used in this paper is the National Longitudinal Survey of Young Men, a panel containing twelve surveys over the period 1966-81. The substantial variation in oil prices over this period enables us to obtain efficient estimates of the effects of oil price changes for workers in different industries and of different skill levels. The detailed micro data enable us to control for systematic changes in workforce composition induced by oil price fluctuations, that may bias aggregate wage measures. For instance, an oil price increase may cause firms to lay off lower ability (lower wage) workers, causing average labor force quality to increase. Then, even with no change in the wage distribution for efficiency units of labor, the average observed wage per manhour will rise, causing an increase in aggregate wage measures. Hence, changes in aggregate average wages may not accurately reflect true underlying movements in the offer wage distribution.

The issue of aggregation bias in measuring real wage variability has been studied by Keane, Moffitt, and Runkle (1988), Kydland and Prescott (1989), and others, in a different context. As described by these authors, the use of a panel data set enables one to correct for compositional effects by constructing fixed-weight wage indices that hold fixed the efficiency units of labor per manhour. In the present paper, this is done by controlling for observed indicators such as education levels that are likely to be correlated with worker productivity, and also correcting for two other potential sources of bias in aggregate data:

unobserved individual fixed effects and sample selectivity.

Our main finding is that oil price increases result in substantial wage declines in virtually all sectors of the economy. However, the magnitude of these wage declines varies considerably by industry and, within each industry, by skill level. At the aggregate level, and in most industries, all workers take wage cuts following oil price increases but the relative wage of skilled workers tends to rise. That is, the skill premium rises following an increase in the price of oil. Further, our results indicate that changes in labor force composition induced by oil price shocks produce substantial bias in aggregate measurements of the wage effects of oil price shocks. Thus, the use of panel data econometric techniques to correct for unobserved worker heterogeneity turns out to be essential for consistent estimation of the effect of oil price shocks on the skill premium.

We find that oil price increases reduce employment in the short run and shift industry employment shares in the long run.[1] However, the long-run effect on aggregate employment is negligible, possibly indicating substitution between energy and labor in the aggregate production function. These results provide some support for the sectoral shift models of unemployment of Lilien (1982), Hamilton (1988) etc. Hamilton's model suggests that, even though energy inputs account for a rather small fraction of total input costs, changes in their price may lead to substantial frictional employment in the short run as labor is reallocated across sectors in response to relative productivity changes. An additional prediction of sectoral shift models is that workers would tend to move towards those sectors where the relative productivity of labor (as reflected in wages) increases following a real shock. A comparison of estimated industry relative wage changes and employment share changes reveals serious inconsistencies with this prediction.

In the next section, we describe the econometric techniques used in the paper and

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[1] The term 'employment share' refers to the level of employment in an industry expressed as a percentage of aggregate employment.

discuss in greater detail some of the relevant measurement issues. Section 3 describes the dataset used in the estimation. Section 4 contains the empirical results. Section 5 contains a discussion and interpretation of the results. Section 6 summarizes the main findings of the paper and concludes.

2. Econometric Framework

The basic regression model used in our analysis is as follows:

$$(1) \qquad \ln W_{it} = X_{it}\beta + P_t\alpha + \mu_i + \varepsilon_{it} \qquad \forall \;\; i = 1,2,..,N \; ; \; t = 1,2,..,T$$

W_{it} is the real hourly wage rate of individual i at time t. The vector X_{it} contains observed individual-specific variables that affect this wage rate, with associated coefficient vector β. The oil price variable is P_t. μ_i stands for a vector of unobserved individual-specific characteristics that are fixed over time. The regression error ε_{it} is assumed to be i.i.d.. To estimate the effects of observed measures of skill level on the sensitivity of a worker's real wage to oil price shocks, we include an appropriate interaction term as follows:

$$(2) \qquad \ln W_{it} = X_{it}\beta + P_t\alpha + P_tE_{it}\gamma + \mu_i + \varepsilon_{it} \qquad \forall \;\; i = 1,2,..,N \; ; \; t = 1,2,..,T$$

The variable E_{it} is a measure of skill level (it is also included in X_{it}). The coefficient γ on the interaction term P_tE_{it} captures differences in the variability of wages for workers with different skill levels. A positive (negative) estimate of γ would indicate that the wage premium for skills increases (decreases) when the oil price rises. The total effect of an oil price increase on the log wage of a worker with skill level E_{it} is given by $\alpha + E_{it}\gamma$.

Estimating (2) by ordinary least squares (OLS), with $\mu_i + \varepsilon_{it}$ being the composite error term, would yield biased estimates of β and γ unless the variables in μ_i were uncorrelated with the regressors. This is not likely to be true in general. Workers with a high (unobserved) value of μ_i are high ability workers. If high ability workers were less likely to be laid off following oil price increases than were low ability workers, the mean level of μ_i for employed workers would covary positively with the oil price level. The correlation between such unobserved individual fixed effects and the price of oil would induce an upward bias in the estimated oil price coefficient.

The interaction coefficient γ is subject to similar bias. For instance, if an increase in the price of oil caused the average unobserved ability of employed workers within lower skill categories (i.e. those with lower values of E_{it}) to rise relative to the average unobserved ability of workers in higher skill categories, γ would be biased downward. This downward bias in the estimate of γ would spuriously indicate a narrowing of (or understate the increase in) the skill premium following an oil price increase.

To deal with this unobserved ability bias, we employ a fixed effects model that involves using OLS to estimate the following transformed equation:

$$(3) \qquad \ln \tilde{W}_{it} = \tilde{X}_{it}\beta + \tilde{P}_t\alpha + P_t\tilde{E}_{it}\gamma + \tilde{\varepsilon}_{it}$$

where, for instance, $\tilde{X}_{it} \equiv X_{it} - T^{-1}\sum_{t=1}^{T} X_{it} \quad \forall\ i=1,2,..,N$. This transformation causes the individual fixed effects to drop out. The error term $\tilde{\varepsilon}_{it}$ is i.i.d. and is uncorrelated with the regressors. Note that, to implement the fixed effects model, we need to leave out control variables that are constant over time or collinear with the time trend.[2]

To estimate the effect of oil price shocks on the average wage and the skill premium at the industry level, we may include interactions of P_t and P_tE_{it} with industry dummies.

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[2] In specification (2), assuming that the individual effects μ_i are uncorrelated with X_{it} would yield the random effects model. However, we find that the individual effects are in fact highly correlated with observed worker characteristics, thereby inducing bias in the random effects estimates. Hence, we limit our analysis and reported results to fixed effects specifications.

Specifically, the following counterpart to the OLS model (2) may be employed:

$$\ln W_{it} = X_{it}\beta + \sum_{j=1}^{J} I_{ijt}P_t\alpha_j + \sum_{j=1}^{J} I_{ijt}P_tE_{it}\gamma_j + \mu_i + \varepsilon_{it} \tag{4}$$

I_{ijt} is a binary indicator variable that takes the value one if worker i locates in industry j at time t, and is zero otherwise. The coefficients α and γ are now indexed by industry. For instance, γ_j measures the effect of an oil price shock on the skill premium in industry j. With appropriate transformations of the variables as described in (3), a similar pooled regression could be used to estimate the fixed effects model at the industry level:

$$\ln \tilde{W}_{it} = \tilde{X}_{it}\beta + \sum_{j=1}^{J} I_{ijt}\tilde{P}_t\alpha_j + \sum_{j=1}^{J} I_{ijt}\tilde{P_tE}_{it}\gamma_j + \tilde{\varepsilon}_{it} \tag{5}$$

Apart from unobserved individual fixed effects, there remains another potential source of bias. All of the above discussion assumed that the mean of $\tilde{\varepsilon}_{it}$ conditional on individual i being employed in period t was zero. If this is not true, a selection bias problem arises. For instance, changes in P_t may cause workers with systematically high or low values of the time-varying unobserved productivity component (reflected in high or low values of $\tilde{\varepsilon}_{it}$) to enter or leave employment in an industry. The effect of changes in average labor force quality resulting from the inflow or outflow of workers with high or low transitory wage components would then bias the oil price coefficient. If, in addition, the magnitude of this effect differed by skill levels, a fixed effects estimate of γ_j would be a biased estimate of the change in the mean offer wage differential in industry j.

To deal with this potential selection bias problem created by missing wages, we use a fixed effects version of Heckman's (1979) self-selection model. This model estimates a wage equation for each industry jointly with a probit employment choice equation. The model is written as follows:

$$(6) \qquad \ln W_{ijt} = X_{it}\beta_j + P_t\alpha_j + P_tE_{it}\gamma_j + \mu_{ij} + \varepsilon_{ijt}$$

observed iff $I_{ijt} = 1$

where $$I^*_{ijt} = Z_{it}\theta_j + P_t\delta_j + P_tE_{it}\eta_j + \psi_{ij} + \omega_{ijt}$$

$$I_{ijt} = \begin{cases} 1 \text{ if } I^*_{ijt} \geq 0 \\ 0 \text{ if } I^*_{ijt} < 0 \end{cases}$$

Here I^*_{ijt} is the latent index of the probit employment equation that determines whether worker i is employed in industry j at time t. Z_{it} is a vector of individual-specific regressors that affect the probability of employment in industry j at time t. The corresponding coefficient vector is denoted by θ_j. Individual fixed effects in the employment choice equation are represented by ψ_{ij}.

The estimator in (6) is implemented by full-information maximum likelihood. The error terms ε_{ijt} and ω_{ijt} are assumed to have a bivariate normal distribution with correlation ρ_j and respective standard deviations σ_{ε_j} and 1. The latter variance is normalized to one for identification of the probit choice equation. The parameter ρ_j, the correlation of the wage and employment equation residuals, is crucial in correcting for selection bias. A negative estimate of ρ_j, for instance, indicates that workers with a high transitory wage component are more likely to be laid off following an oil price increase. This would, if a selection correction was not employed, impart a downward bias to the estimated effect of oil price changes on the real wage and the skill premium.[3]

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[3] In the fixed effects selection model, estimates of the choice equation fixed effects are inconsistent for small T. Monte-Carlo experiments by Heckman (1981) show that this inconsistency is small for T>8. In our data set, T is on average 6 (with a maximum value of 12), indicating that inconsistency is a potential problem. However, estimates of ρ_j in the model with fixed effects in both the wage and employment equations always went to 1 or −1

In the specification of selection models, Z_{it} in the choice equation typically contains elements that enter into X_{it} as well as additional variables that may affect labor supply propensity but not worker productivity. Since our data set does not contain any variables that clearly fall into this category, we include the same set of controls in the wage and employment choice equations. Further, our results were not sensitive to the overidentifying restrictions of omitting variables from X_{it}.

Apart from selection bias, another potential problem with the fixed effects specification in (5) is that it restricts individual fixed effects to be the same across all industries. This would bias the coefficients of industry-level estimates if there were industry-specific unobserved fixed effects that were correlated with any of the regressors. Further, both (4) and (5) restrict the coefficient vector β to be the same across industries. This implies the strong assumption that the returns to observed characteristics are the same in all industries. To deal with these additional sources of bias, we estimate binomial selection models separately for each industry. This allows fixed effects to vary across industries and, thus, obviates the potential bias from restricting the fixed effects for any given individual to be the same across all industries. Further, this also allows the coefficient vector β to vary across industries.

3. Data

The data set used in this paper is the National Longitudinal Survey of Young Men (NLS), a nationally representative sample of 5,225 young males. They were between 14 and 24 years of age in 1966 and were interviewed in 12 of the 16 years from 1966 to 1981. Data were collected on their employment status, wage rates and sociodemographic characteristics. The

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(Keane, Moffitt and Runkle (1988) report a similar phenomenon). Hence, the results we will report are from a model with fixed effects in the wage equation alone. In this model, we always obtain estimates of ρ_j very close to zero. Hence, any transfer of inconsistency from the choice equation to the wage equation would be negligible.

sample was screened to include only those persons who, as of the interview date, were at least 21 years of age, had completed their schooling and military service, and had available data for all variables used in our analysis. The final sample contained 4,439 males and a total of 23,927 person-year observations. The employment status dummy was non-zero in 21,203 of these person-year observations. Table A1 in the appendix reports sample means for the individual-specific variables used in the estimation. Workers were classified into eleven broadly defined industries on the basis of the 3-digit census industrial classification (CIC) codes. The list of industries, their CIC codes and the sample size for each industry are reported in the appendix in Table A2.

The wage measure we use is the hourly straight time earnings reported by workers for the survey week. This measure was deflated by the Consumer Price Index (CPI) to provide a real wage measure normalized in terms of 1967 CPI dollars. It is important to note that this is a point-in-time wage measure taken as of the date of the interview. This obviates the recall bias that may contaminate annual measures that are obtained by dividing annual earnings by annual hours worked.[4] The NLS does not include data on overtime earnings in all of the survey years. Hence, we restrict ourselves to using a straight-time wage measure rather than attempting to impute overtime earnings for years in which it was not available. To adjust for nonwage compensation, such as variation in fringe benefits across industries, the hourly wage rate for each worker was multiplied by the ratio of total labor costs to wages in the corresponding industry. Data on total labor costs were obtained from the National Income and Product Accounts. The log of this adjusted real wage measure, denoted by WCPI, is used in all of our analysis. This variable has a sample mean of 1.065 in 1967 CPI dollars.

The three variables used as proxies for human capital are DEGREE, EXPERIENCE and TENURE. DEGREE is a dummy variable that equals one if the worker has a college degree and

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[4] Keane, Moffitt and Runkle (1988) discuss the other sorts of bias that may result from using annual survey data on wage income rather than the point-in-time measure used here.

zero otherwise. EXPERIENCE is defined as the total number of years of labor market experience. It was calculated as the interview date minus the completion date of a worker's schooling or military service, whichever was later. It is important to note that the EXPERIENCE variable is a measure of labor force participation rather than of actual work experience. TENURE is defined as the length of uninterrupted tenure (in years) on the current job.

The variable OIL used in this paper represents a measure of the real price of refined petroleum products. It is calculated as the producer price index for refined petroleum products deflated by the overall producer price index. This variable is a broad index of the price of energy inputs, although changes in the index tend to be dominated by oil price fluctuations. The variable OIL is normalized to unity in 1967. We also experimented with two other oil price variables but found virtually no differences from any of the results reported in the next section.

4. Empirical Results

Employment Effects of Oil Price Shocks

Table 1 reports results from a set of linear employment probability models that estimate the employment effects of oil price changes. The first panel reports results from regressions that include the OIL*DEGREE interaction term. The second panel contains results from similar regressions but with the OIL*EXPERIENCE interaction term. TENURE was not used as a regressor in the employment probability models since it would be endogenous in what are essentially reduced-form employment choice equations.[5]

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[5] In this and all the tables that follow, we run separate regressions for each of the interaction terms. We do this to compare the effects of different proxies for human capital. Further, it is instructive (and much less tedious) to examine and interpret the magnitude of fixed effects and selection corrections for each of the human capital variables separately.

The top row of the table contains results for the full sample. In panel 1, the coefficient on OIL is -.0041 (s.e. .0079), while the OIL*DEGREE term has a coefficient of .0272 (s.e. .0097). The insignificant coefficient on OIL indicates that, at the aggregate level, changes in oil prices do not have a significant effect on employment probabilities for workers without a degree. The large positive sum of the coefficients on OIL and OIL*DEGREE (-.0041 + .0272 = .0231) indicates that, for workers with a college degree, employment probabilities actually rise following an oil price increase.[6] In the top row of panel 2, the coefficients on OIL and OIL*EXPERIENCE are both close to zero, indicating negligible employment effects of oil price shocks for workers at all levels of experience. At the mean of the data, the effect of oil price changes on employment probabilities is close to zero.[7]

Our finding of a negligible overall employment effect of oil price shocks (and a positive effect for workers with a degree) may appear to contradict the results of other authors, such as Hamilton (1983). However, the high degree of persistence in the oil price series over the sample period and the annual frequency of the data make it likely that our estimates reflect medium to long-run effects of oil price shocks. To check for consistency of our results with the existence of short-run negative employment effects of oil price increases, we ran regressions with the change in oil prices in the year prior to the interview date included as a regressor. The results are reported in table 2.

In the first regression (column 1), the coefficient on the variable measuring oil price changes in the year prior to the interview (for each person-year observation) was

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[6] Over our sample period, a one standard deviation around trend increase in the OIL variable is 0.28. The point estimates of -.0041 on OIL and .0272 on OIL*DEGREE indicate that this magnitude of an oil price increase induces an increase of 0.65 percentage points ((-.0041+.0272)*.28) in the probability that a worker with a degree will be employed.

[7] The mean of the degree variable is 0.23 in our sample. Multiplying this number and the OIL*DEGREE interaction coefficient and adding the product to the coefficient on OIL gives the effect of oil price changes on employment probabilities, at the mean of the data (.0272*0.23 - .0041 = .0022). Of course, the same result may be obtained using the model that includes the OIL*EXPERIENCE interaction term.

significantly negative (-.2046, s.e. .0390). Adding one lag of the change in oil prices (column 2) strengthened this result. Interestingly, when we ran the regression including the absolute value of the change in oil prices in the year prior to the interview (column 3), the coefficient on that term was also significantly negative (-.1632, s.e. .0518). We also created two variables that measured only the positive and negative changes in oil prices, respectively. In a regression with these two variables included as regressors (column 4), the coefficients on both terms were significantly negative.

These results appear to provide support for the sectoral shift models of Lilien (1982), Hamilton (1988) etc. These models imply that oil price changes, whether positive or negative, change relative labor productivities across sectors, thereby inducing sectoral reallocation of labor. Frictions in the process of reallocating labor across sectors then result in a short-run increase in aggregate unemployment.

We turn now to an examination of the effects of oil price shocks on employment at the industry level. These results are contained in rows 2 through 12 of table 1. The OIL coefficients should now be interpreted as the effect of changes in the price of refined petroleum products on the probability that workers will locate in a particular industry as opposed to the universe of alternatives (i.e. unemployment or employment in another industry).

Panel 1 contains estimates from models that include the OIL*DEGREE interactions. For workers without a degree, oil price increases have a strong negative effect on their location probabilities in construction and retail trade and a positive effect in services. For workers with a degree, an oil price increase causes location probabilities to increase in durable manufacturing and transportation and utilities, and to decline in wholesale trade, F.I.R.E., and services. At the mean of the data, oil price increases result in an increase in the employment shares of durable manufacturing and services and a decline in the share of construction and retail trade.

Panel 2 contains estimates from models that incorporate the OIL*EXPERIENCE interactions.

We find that the coefficient on OIL is significantly negative in construction and F.I.R.E., indicating that recent labor-force entrants face a decline in their location probabilities in those industries following an oil price increase. In both those industries, the significant positive coefficients on OIL*EXPERIENCE indicate that the reduction in employment share is less at higher experience levels. This pattern of differential impact of oil price increases is reversed in government. In retail trade, the insignificant OIL coefficient indicates that oil price shocks have no effect on the probability that new entrants locate in that industry. However, the significantly negative coefficient on OIL*EXPERIENCE shows a reduced share of more experienced workers located in retail trade following an oil price increase. In other industries, oil price shocks appear to have no significant effect on employment shares for workers at all experience levels.[8]

Wage Effects of Oil Price Shocks

Table 3 presents estimates from a set of wage equations that incorporate the OIL*DEGREE interaction term. The first two columns contain results from OLS regressions (specification (4) in section 3). The next two columns contain results from a fixed effects estimator (specification (5)). The last two columns report results from a selection corrected fixed effects model (specification (6)).[9]

In the first panel of table 3, the significant negative coefficients on OIL indicate that, for workers without a degree, oil price increases have a strong negative effect on real

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[8] We also examined the effect of oil price shocks on weekly hours worked. Fixed effects estimates of the hours equation indicated that, at the aggregate level, average weekly hours decline by about half a percent for every one standard deviation around trend increase in the real price of oil. This pattern was roughly similar across industries and seemed to hold for workers of all skill levels. The hours regressions are not reported here, but are available from the authors.

[9] Panels containing selection corrected fixed effects estimates do not report estimates from the probit employment choice equations that were estimated jointly with the wage equations. The effect of changes in the price of oil on employment probabilities must be read off from the OLS employment probability models in table 1.

wages at the aggregate level and in all industries. The coefficients on the OIL*DEGREE interaction term are striking. At the aggregate level, and in virtually every industry, the OLS estimates of this coefficient are negative. This indicates that, when the price of oil rises, workers with a college degree face a larger decline in wages than workers without a degree. At the aggregate level, the average real wage is estimated to decline by 3.2 percent when the real price of oil increases by one standard deviation around its trend (the standard deviation of the OIL variable is 0.28 and its mean is 1.53).[10] Workers without a degree face a 2.7 percent cut in their wages following a one standard deviation around trend increase in oil prices, while workers with a degree have their wages declining by as much as 4.9 percent.[11] This result is at first quite puzzling. While the employment of college-educated workers rises following an oil price shock, their hourly wage seems to decline even more than the wage for workers without a college degree.

The fixed effects estimates in the second panel resolve this anomaly. The change in the OIL*DEGREE coefficients from the OLS estimates is substantial. For all workers, the coefficient changes from -.0795 (s.e. .0012) to .0381 (s.e. .0126). The positive interaction coefficient implies that, adjusting for changes in labor-force quality, the offer wage for workers with a degree rises relative to the wage offered to uneducated workers. The change in the sign of the coefficient from the OLS estimate reflects the fact that workers with degrees who are hired by firms following oil price increases are, on average, of lower ability relative to other workers with degrees. The OLS coefficients only indicate that the average observed wage for workers with a degree falls. While oil price increases lead firms to hire more skilled labor, the quality of this additional skilled labor, in terms of unobservable

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[10] The average decline in wages for all workers is given by the sum of OIL and the product of the OIL*DEGREE coefficient and the mean of the DEGREE dummy in the sample (-.0958 + (-.0795*0.23) = -.1141). This number multiplied by the standard deviation of the OIL variable in our sample (.28) yields a product of -.0319.

[11] For workers with a degree, the full effect on real wages is obtained by summing the coefficients on OIL and OIL*DEGREE.

attributes, declines.[12] The fixed effects correction accounts for this effect and shows that, after correcting for compositional changes, the skilled wage rises relative to the unskilled wage following an oil price increase.

However, in absolute terms, both skilled and unskilled workers take wage cuts following an oil price increase. In going from the OLS to the FE estimates, the OIL coefficient for all workers drops from -.0958 (s.e. .0096, OLS) to -.1383 (s.e. .0072, FE), indicating that the unskilled wage drops by a larger percentage than was indicated by the biased OLS estimates. While the OIL*DEGREE coefficient is positive (.0381, s.e. .0126), it does not offset the negative coefficient on OIL, indicating that skilled workers also take wage cuts following an oil price increase. A one standard deviation around trend increase in the price of oil is estimated to lead to a 3.9 percent decline (-.1383*0.28) in the real hourly wage for workers without a degree, but only a 2.8 percent decline ((-.1383+.0381)*0.28) for workers with a degree. Although the magnitudes differ, this pattern is repeated in virtually all industries.

The third panel of table 3 contains selection corrected fixed effects (SCFE) estimates. The estimated parameter ρ (not reported here) was insignificantly different from zero in the aggregate and also for all industries. This indicates that, once fixed effects are accounted for, the correlation between the transitory components of workers' wages and their employment probabilities is small. Apparently, most of the compositional changes in the workforce induced by oil price shocks can be measured by the combination of observed characteristics of workers and unobserved individual fixed effects. The selection correction has little impact

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[12] Note that the variable OIL trends upward over our sample period. Hence, workers who take longer to get a degree and enter our sample towards the end have larger mean OIL*DEGREE values. In general, such workers are likely to be of lower ability since it took them longer to get their degrees. Such workers also tend to have lower wages. Thus, a negative correlation is generated between unobserved ability and the OIL*DEGREE variable, thereby leading to a downward bias in OLS estimates of the interaction coefficient. The fixed effects estimates obviate this problem by considering only the effects of deviations of variables from their individual means.

on the estimates at the aggregate level.[13]

At the industry level, the coefficients for most industries change from the FE estimates. Since the estimated ρ is very small and insignificant for all industries, this change is attributable to the bias in the FE estimates resulting from restricting both the fixed effects and the returns to observed worker characteristics to be the same across all industries.[14] The selection models were estimated separately for each industry, thereby controlling for both these sources of potential bias in the industry level FE estimates.[15]

In industries such as durable manufacturing and retail trade, the OIL*DEGREE coefficient turns even more strongly positive in the SCFE estimates. Not surprisingly, those two industries also have the largest inflow of educated workers (cf. table 1). Recent entrants into those industries are likely to have lower levels of industry-specific individual fixed effects. The SCFE estimates correct for this effect and indicate that the relative offer wage for skilled workers in those industries rises substantially following an oil price increase. The coefficients on the interaction term are also significantly positive in F.I.R.E., services, and government, indicating that the skill premium in those industries rises following oil price increases.

Next, we look at the effect of another human capital variable, TENURE. As discussed

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[13] This finding contradicts the fixed effects results in Keane, Moffitt and Runkle (1988), which indicate that selection is still important after controlling for fixed effects. We discovered that FE selection model estimates are very sensitive to starting values, and that the results obtained by Keane et al. were only a local maximum. After extensive experimentation with different starting values, we have concluded that the estimates with ρ close to zero are the global maxima.

[14] Industry-specific fixed effects are a potential source of bias only if individuals in the sample switch industries. Employing the same dataset as in this paper, Jovanovic and Moffitt (1990) find that gross flows across sectors average as much as 17.2 percent of the sample between adjacent two-year survey waves. Moreover, their three-sector classification probably understates the gross flows relative to the finer industry classification used in this paper. Such high mobility is partly attributable to the young age of the sample.

[15] Fixed effects models estimated separately for each industry yielded point estimates that were mostly identical to the SCFE industry estimates. Rather than present yet another set of estimates, we choose to report only the SCFE estimates since they correct for all the sources of bias discussed earlier.

before, length of job tenure is likely to be the best proxy for industry-specific skills. Table 4 contains OLS and fixed effects estimates of wage equations that include the OIL*TENURE interaction term.[16] In panel 1, the OLS coefficient on OIL*TENURE is significantly positive for all workers (.0028, s.e. .0011). Most industries follow this pattern, except for construction and agriculture, where the OIL*TENURE interaction is significantly negative. In the fixed effects estimates, the results are very similar at both the aggregate and industry levels. The OIL*TENURE interactions are significantly positive in almost all industries, and the significant negative interactions found in the OLS estimates for construction and agriculture disappear.

These tenure results provide strong evidence that, following oil price increases, skilled workers find their wage rising relative to that of unskilled workers. However, as pointed out earlier, oil price increases do cause substantial declines in the absolute real wages of all workers, irrespective of their skill levels. This is evident from the fact that, while the estimated OIL*TENURE coefficients are generally significantly positive, they are small compared to the large negative coefficients on OIL.

Finally, in table 5, we examine the influence of labor market experience on wage variability subsequent to oil price shocks. The first panel of table 5 contains OLS estimates of the wage equation with the OIL*EXPERIENCE interaction term. For all workers, the coefficient on OIL*EXPERIENCE is close to zero (.0003, s.e. .0011). At the industry level, the coefficients on the interaction term are significantly positive in construction, retail trade, and F.I.R.E.. In those three industries, workers with more experience seem to be partially shielded from the substantial decline in average wages following oil price increases. Increased experience has the reverse effect in nondurable manufacturing. Since the coefficient on OIL is insignificantly different from zero in that industry, it appears that

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[16] As noted earlier, TENURE would be endogenous in the employment choice equation. Hence, we are unable to estimate the selection corrected fixed effects model using this variable.

the brunt of the decline in wages following an oil price shock is borne by workers with more experience. In the remaining industries, wage effects of oil price shocks seem to differ little for workers with different levels of experience.

The fixed effects estimates are more indicative of an increasing negative effect of oil price shocks on wages for workers with more experience. The coefficient on OIL*EXPERIENCE for the full sample is negative but not quite significant. At the industry level, the OIL*EXPERIENCE interaction coefficients are no longer significantly positive in any industry. In fact, they turn significantly negative in wholesale trade and services and remain significantly negative in nondurable manufacturing.

Turning to the selection corrected fixed effects estimates in panel 3, the coefficients on OIL (-.1083, s.e. .0095) and OIL*EXPERIENCE (-.0017, s.e. .0006) for all workers are similar to the FE estimates. This is as expected since the estimates of the parameter ρ were close to zero in the aggregate and also for all industries. However, the coefficient on the interaction term is now significantly negative and indicates that a one standard deviation around trend increase in the price of oil causes the relative wage of experienced workers to fall by 0.05 percent for every added year of labor market experience that they possess. At the industry level, the results are mixed. In terms of protecting workers from wage declines subsequent to oil price shocks, experience has a positive effect in construction and wholesale trade and a negative effect in nondurable manufacturing, retail trade, F.I.R.E., services and government.

Note that the OLS interaction coefficient is positive or insignificantly different from zero at the aggregate level and in retail trade, F.I.R.E., services, and government, but the corresponding SCFE interaction coefficients turn significantly negative. This shows that the relative wage for experienced workers may appear to rise following an oil price increase simply because, among workers with more labor market experience, workers from the low end of the wage distribution are more likely to be laid off. Correcting for this effect reveals that the relative wage of experienced workers falls by a greater extent, the more experience they have. These results again reveal the importance of controlling for unobserved heterogeneity.

5. Discussion

Our estimates indicate that oil price increases have a substantial negative effect on real wages. It is possible, of course, that the large wage effects that we have estimated could be the result of fluctuations in other aggregate variables that are highly correlated with the price of oil. To test for this, we included several variables that could plausibly affect real wages, such as inflation in the year prior to the interview date, exchange rates, net exports, imports as a share of GNP etc. Inclusion of these variables had a negligible effect on the coefficients on OIL and the interaction terms in the wage regressions. Further, we also estimated models where a series of year dummies were substituted for the OIL and TREND variables, and then regressed the fitted year dummies on OIL and TREND. This yielded almost identical results, with the OIL coefficients being highly significant and OIL and TREND explaining over 75 percent of the yearly wage effects in most industries.[17]

Note that the effect of an oil price shock on labor demand depends on the substitutability between labor and energy in the production process. If labor and energy were gross substitutes, oil price increases would actually increase labor demand. Given the extensive production function literature for manufacturing (Hudson and Jorgensen (1974), Berndt and Wood (1975), Pindyck (1978), Halvorsen and Ford (1978)), the plausible case is that labor and energy are good net substitutes, but are not gross substitutes. Thus, our finding that oil price shocks have negative wage effects is not surprising.

We have also found that oil price shocks do not have an adverse effect on aggregate

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[17] It would be interesting to examine the effect of noncompetitive factors such as union contracts on the magnitude of wage and employment responses to oil shocks. Unfortunately, except in a couple of years, our dataset doesn't contain a variable that could be used to make the union-nonunion distinction among workers.

employment in the long run.[18] That oil price increases substantially reduce wages, while workers continue to supply as much or more labor, might well seem surprising. Given a fixed labor supply curve, wage declines accompanied by negligible or positive employment effects would imply that the aggregate labor supply curve was vertical or backward-bending. However, over our sample period, deviations of oil prices from trend are highly persistent. Hence, the negative wage effects of oil price increases would tend to be long-lived, thereby generating a potentially important income effect. If this income effect shifted labor supply sufficiently far to the right to offset any leftward shift in labor demand induced by an oil price increase, we would obtain the observed pattern of wage declines with no accompanying fall in employment.

We have found that skilled workers do better than unskilled workers in terms of facing higher employment probabilities and less of a decline in their real offer wage following oil price increases. This finding is consistent with the robust results on capital-skill complementarity (see Hamermesh (1986) for a survey) and capital-energy substitutability (see Pindyck (1978)), which, together, suggest that skilled labor is a much better net substitute for energy than unskilled labor. If skilled labor is complementary while unskilled labor is substitutable with capital, and if both capital and labor are substitutes for energy, then energy price increases lead to shifts toward production using more capital and skilled labor. Our results indicate that the rising wage premium for skills in the U.S. economy over the last couple of decades, and especially in the 1970's, may be related to the sustained increase in the real price of oil over that period.

At the industry level, we find that oil price shocks have substantial effects on industry relative wages for workers in a given skill category. For example, for workers

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[18] In simulations of their dynamic factor demand model, Pindyck and Rotemberg (1983) also find that oil price increases have an insignificant effect on the optimal level of labor inputs in the long run. Little direct evidence appears to be available on the nature of labor-energy substitutability outside of manufacturing.

without a college degree, a one standard deviation around trend increase in the OIL variable (0.28 compared to its mean of 1.53, i.e. a 19 percent increase at the mean of the data) results in wage declines of almost 7 percent in F.I.R.E. and around 5.5 percent in construction and services, but only a 3 percent wage decline in durable and nondurable manufacturing. Oil price shocks also have substantial industry employment share effects. For instance, for workers without a degree, an oil price increase of the same magnitude as above results in a 1 percentage point increase in the probability of one of these workers being in services, but leads to a 0.9 percentage point decline in the probability of such a worker being in retail trade.[19]

Since industries differ in terms of energy intensity and the substitutability between energy and other inputs in their production processes, oil price shocks have asymmetric effects on labor productivity across sectors.[20] Therefore, oil price shocks are also good candidates for the 'sectoral shocks' that generate unemployment in multi-sector models such as Lilien (1982) and Hamilton (1988). Consistent with the prediction of the sectoral shifts literature, we find that both increases and decreases in the price of oil increase aggregate unemployment in the short run, but do not significantly affect employment in the long run.

Equilibrium sectoral models also predict that, following a real shock, labor should flow towards those sectors where the relative productivity of labor rises. This prediction is not borne out by the data. For example, among workers without a degree, services has the largest increase in employment share, even though that industry has one of the largest wage declines for such workers. In F.I.R.E. and government, uneducated workers face well above average wage declines, with no concomitant effect on their employment. Similarly, for workers with a

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[19] Using data from the PSID, Shaw (1989) has also found evidence that sectoral shocks have substantial effects on industry employment shares.

[20] It can be shown that the leftward shift (or decline) in industry labor demand following an oil price increase is greater (i) the greater is the share of oil in value added, and (ii) the lesser is the degree of substitutability between energy and labor in the production process of a particular industry.

degree, location probabilities actually rise in construction and in transportation and utilities, although educated workers face among the largest wage declines in those two industries. In nondurable manufacturing, educated workers have a relatively small wage decline accompanied by the largest decline in employment share.

A few industries do reveal patterns consistent with the predictions of equilibrium sectoral models. For workers without a college degree, the largest declines in location probabilities are in construction and retail trade, which also have relatively large wage declines. For workers with a degree, the largest increase in employment share is in durable manufacturing, where their offer wage declines much less than in most other industries. The employment share for educated workers falls substantially in F.I.R.E., where they face among the largest wage cuts.

It is also of interest to note that the three proxies we used for skills yield different results in many of the regressions. In particular, for workers in most industries, having a college degree or more tenure reduces the negative wage effect of an oil price increase, while having more experience exacerbates this negative effect. Since the EXPERIENCE variable is simply defined as current age minus age at entry into the labor force, it is possible that the results with the EXPERIENCE interactions are dominated by age effects rather than the effects of some aspect of human capital.

6. Conclusion

In this paper, we have provided estimates of the wage and employment responses in various sectors of the U.S. economy to changes in oil prices. We also differentiated between skilled and unskilled workers and showed how various human capital variables interact with real shocks to affect wage and employment variability. Using a detailed panel data set enabled us to correct for various sources of aggregation and selectivity bias embedded in aggregate measurements of the effects of oil price shocks on real wages.

We find that oil price increases unambiguously cause real wages to decline at the aggregate level and in virtually all sectors. On average, real wages fall between 3 and 4 percent following a one standard deviation around trend (approx. 19 percent) increase in the real price of refined petroleum products over our sample period. Oil price increases lead to large absolute wage cuts for workers of all skill levels, but also lead to a substantial rise in the relative wage of skilled workers. Panel data econometric techniques that control for unobserved heterogeneity turned out to be crucial for obtaining this result, which is completely hidden in OLS estimates that fail to correct for variation in unobserved labor-force quality.

Although oil price increases reduce wages, we find that they do not reduce aggregate employment in the long run. This is consistent with a scenario where oil and labor are net substitutes but not gross substitutes in production, and where oil price increases cause labor supply to shift rightward because they cause long-lived wage declines (and, hence, have a positive income effect). Employment of skilled labor actually rises following oil price increases, suggesting that skilled labor is a particularly good substitute for energy in the production function for most industries.

As implied by the sectoral shift models of Lilien (1982), Hamilton (1988) etc., we find that positive as well as negative oil price shocks induce increases in short-run aggregate unemployment. However, we do not find conclusive evidence to support the implication of equilibrium sectoral models that labor flows into sectors where the relative productivity of labor (as reflected in real wages) rises. In our sample, this implication is borne out conclusively for only a couple of industries, with most industries showing no clear pattern and many industries even providing evidence to the contrary.

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APPENDIX

Table A1

Means of Variables in NLS Analysis Samples

Variable	Mean
Log Real Wage - WCPI	1.065
Real Price of Refined Petroleum - OIL	1.53
Unemployment Rate - U-RATE	6.38
Education (years) - EDUC	12.57
Experience on Current Job (years) - TENURE	4.00
Labor Market Experience (years) - EXPER	7.90
Experience Squared - $EXPER^2$	87.05
White Rate Dummy - WHITE	.74
Wife Present Dummy - WIFE	.69
SMSA Resident Dummy - SMSA	.70
South Resident Dummy - SOUTH	.41
Children in Household - KIDS	1.30
College Degree Dummy - DEG	.23
Employed Dummy	.89
OCCUPATIONAL DUMMIES:	
Professional and Technical Workers (0–370)	.31
Craftsmen and Foremen (401–545)	.19
Salesmen (380–395)	.05
Services (801–890)	.05
Operatives, Laborers, Farmers (200–222, 601–775, 901–985)	.29

NOTE: Census 3-digit occupation codes are used.

APPENDIX

Table A2

Sample Size by Industry

Industry	CIC Codes	Person-Year Observations
Durable Manufacturing	206–296	4,693
Nondurable Manufacturing	306–459	2,580
Construction	196	2,217
Transportation and Utilities	506–579	1,852
Wholesale Trade	606–629	1,039
Retail Trade	636–696	2,343
Finance, Insurance, Real Estate	706–736	833
Services	806–898	3,252
Government	906–998	1,389
Agriculture	16–18	535
Mining	126–156	327
Unemployed	---	2,724
Employed with Industry n/a	---	143

NOTE: Person-year observations for employed workers total 21,203. For 143 of these, the industry or occupation code is not available. This leaves 21,004 observations for employed workers that were used in analysis.

Table 1

Estimated Effects of Oil Price Changes on Employment Probabilities

	Panel 1		Panel 2	
INDUSTRY	OIL	OIL* DEGREE	OIL	OIL* EXPERIENCE
All Workers	-.0041	.0272**	.0132	-.0008
	(.0079)	(.0097)	(.0124)	(.0009)
Durable Manufacturing	.0063	.0245**	.0109	.0002
	(.0100)	(.0123)	(.0157)	(.0011)
Nondurable Manufacturing	-.0073	-.0147	-.0049	-.0006
	(.0079)	(.0097)	(.0124)	(.0009)
Construction	-.0209**	.0237**	-.0408**	.0024**
	(.0073)	(.0090)	(.0115)	(.0008)
Transportation & Utilities	-.0047	.0158*	-.0003	.0000
	(.0068)	(.0084)	(.0107)	(.0008)
Wholesale Trade	.0004	-.0114*	-.0063	.0003
	(.0052)	(.0064)	(.0082)	(.0006)
Retail Trade	-.0316**	.0342**	-.0008	-.0019**
	(.0075)	(.0093)	(.0119)	(.0009)
F.I.R.E.	-.0028	-.0179**	-.0245**	.0015**
	(.0046)	(.0057)	(.0072)	(.0005)
Services	.0338**	-.0435**	.0177	.0003
	(.0080)	(.0099)	(.0126)	(.0009)
Government	.0004	.0109	.0383**	-.0031**
	(.0059)	(.0073)	(.0093)	(.0007)
Agriculture	.0046	.0003	.0075	-.0002
	(.0037)	(.0046)	(.0059)	(.0004)
Mining	.0019	.0036	.0065	-.0003
	(.0030)	(.0036)	(.0046)	(.0003)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. A * indicates the 10% level. Sample size = 23,927. Controls are a time trend, education, experience, and its square, four dummies for types of college degrees, five dummies for fields of degree, four dummies for occupation, an SMSA dummy, a south dummy, a race dummy, a marriage dummy, number of children, and interactions of experience with education, a college degree dummy and a race dummy.

Table 2

Estimated Effects of Oil Price Changes on Employment Probabilities
Short-run Aggregate Results

	(1)	(2)	(3)	(4)
OIL (t)	0.0294** (.0075)	0.0314** (.0076)	0.0297** (.0075)	0.0218** (.0073)
DOIL (t)	-0.2046** (.0390)	-0.2126** (.0393)		
DOIL (t−1)		-0.0574* (.0338)		
ABSDOIL (t)			-0.1632** (.0518)	
PDOIL (t)				-0.1329** (.0522)
NDOIL (t)				-0.5111** (.1532)

NOTE: *Standard errors are in parenthesis. ** indicates significance at 5% level. * indicates significance at 10% level. Sample size = 23,927. Same controls as in Table 1. Variable definitions in this table are as follows (t represents year of interview):*

DOIL (t) = OIL (T) − OIL (t−1)

ABSDOIL (t) = |DOIL (t)|

$$\text{PDOIL(t)} = \begin{cases} \text{DOIL(t)} & \text{if DOIL(t)} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad \text{NDOIL(t)} = \begin{cases} |\text{DOIL(t)}| & \text{if DOIL(t)} < 0 \\ 0 & \text{otherwise} \end{cases}$$

Table 3

Estimated Effects of Oil Price Changes on Real Wages
Dependent Variable - Log Real Wage

	OLS Estimates		Fixed Effects Estimates		Selection Corrected Fixed Effects	
INDUSTRY	OIL	OIL* DEGREE	OIL	OIL* DEGREE	OIL	OIL* DEGREE
All Workers	-.0958** (.0096)	-.0795** (.0012)	-.1383** (.0072)	.0381** (.0126)	-.1378** (.0064)	.0379** (.0056)
Durable Manufacturing	-.0833** (.0124)	-.0879** (.0144)	-.1310** (.0092)	.0332** (.0147)	-.1164** (.0098)	.0639** (.0112)
Nondurable Manufacturing	-.0761** (.0149)	.0487** (.0159)	-.1308** (.0112)	.0396** (.0168)	-.1184** (.0127)	.0215 (.0155)
Construction	-.1318** (.0152)	-.1308** (.0181)	-.1520** (.0114)	.0410** (.0185)	-.1984** (.0150)	-.0038 (.0205)
Transportation & Utilities	-.0426** (.0157)	-.1076** (.0163)	-.1063** (.0118)	.0121 (.0176)	-.1529** (.0161)	-.0203 (.0196)
Wholesale Trade	-.1146** (.0208)	.0052 (.0186)	-.1072** (.0158)	.0755* (.0175)	-.0628** (.0187)	-.0106 (.0173)
Retail Trade	-.1270** (.0160)	-.0522** (.0171)	-.1519** (.0121)	.0537** (.0169)	-.1698** (.0150)	.1398** (.0203)
F.I.R.E.	-.1296** (.0237)	-.0266 (.0191)	-.1579** (.0188)	.0876** (.0191)	-.2490** (.0275)	.0781** (.0199)
Services	-.1355** (.0148)	-.0627** (.0141)	-.1858** (.0112)	.0502** (.0142)	-.1883** (.0156)	.0266** (.0118)
Government	-.0687** (.0183)	-.0751** (.0157)	-.1335** (.0143)	.0414** (.0169)	-.1952** (.0188)	.0705** (.0135)
Agriculture	-.1060** (.0285)	-.0243 (.0294)	-.0931** (.0221)	-.0097 (.0381)	.0584 (.0397)	-.2239** (.0610)
Mining	-.1178** (.0328)	-.0917** (.0322)	-.1599** (.0252)	.0477 (.0337)	-.0356 (.0412)	-.2460** (.0454)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. * indicates the 10% level. Sample size = 21,004. Controls are a time trend, education, experience and its square, four dummies for types of college degree, five dummies for fields of degree, four dummies for occupation, an SMSA dummy, a south dummy, a race dummy, a marriage dummy, number of children, and interactions of experience with education, a college degree dummy and a race dummy. Estimates for the selection models use the full sample of 23,927 person-year observations. The probit employment choice equation estimates from the selection models are not reported here.

Table 4

Estimated Effects of Oil Price Changes on Real Wages
Dependent Variable - Log Real Wage

	OLS Estimates		Fixed Effects	
INDUSTRY	OIL	OIL* TENURE	OIL	OIL* TENURE
All Workers	-.1232**	.0028**	-.1349**	.0035**
	(.0110)	(.0011)	(.0086)	(.0009)
Durable Manufacturing	-.1210**	.0029**	-.1321**	.0035**
	(.0150)	(.0013)	(.0122)	(.0011)
Nondurable Manufacturing	-.0981**	.0023	-.1385**	.0039**
	(.0181)	(.0015)	(.0151)	(.0013)
Construction	-.1054**	-.0049**	-.1441**	.0020
	(.0168)	(.0015)	(.0134)	(.0013)
Transportation and Utilities	-.0830**	.0025**	-.1296**	.0050**
	(.0185)	(.0015)	(.0158)	(.0013)
Wholesale Trade	-.0792**	.0027	-.0941**	.0059**
	(.0221)	(.0018)	(.0177)	(.0015)
Retail Trade	-.1438**	.0054**	-.1553**	.0061**
	(.0179)	(.0015)	(.0146)	(.0013)
F.I.R.E.	-.1460	.0062**	-.1326**	.0057**
	(.0241)	(.0020)	(.0199)	(.0017)
Services	-.1541	.0025*	-.1457**	.0011
	(.0147)	(.0013)	(.0125)	(.0012)
Government	-.1515**	.0046**	-.1275**	.0015
	(.0214)	(.0016)	(.0201)	(.0015)
Agriculture	-.0231	-.0090**	-.0640**	-.0013
	(.0308)	(.0024)	(.0264)	(.0022)
Mining	-.0806**	-.0035	-.1226**	.0014
	(.0354)	(.0027)	(.0304)	(.0023)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. * indicates the 10% level. Sample size = 20,309. Same set of controls as in Table 3, except that tenure is added as an additional control.

Table 5

Estimated Effects of Oil Price Changes on Real Wages
Dependent Variable—Log Real Wage

	OLS Estimates		Fixed Effects Estimates		Selection Corrected Fixed Effects	
INDUSTRY	OIL	OIL* EXPER.	OIL	OIL* EXPER.	OIL	OIL* EXPER.
All Workers	-.1241**	.0003	-.1096**	-.0016	-.1083**	-.0017**
	(.0151)	(.0011)	(.0170)	(.0013)	(.0095)	(.0006)
Durable Manufacturing	-.1154**	.0005	-.0953**	-.0021	-.1300**	.0019
	(.0200)	(.0013)	(.0214)	(.0014)	(.0198)	(.0014)
Nondurable Manufacturing	-.0286	-.0039**	-.0515**	-.0045**	-.0733**	-.0033*
	(.0237)	(.0015)	(.0249)	(.0016)	(.0262)	(.0018)
Construction	-.2038**	.0026	-.1964**	.0022	-.2945**	.0071**
	(.0257)	(.0015)	(.0259)	(.0016)	(.0330)	(.0022)
Transportation & Utilities	-.0597**	-.0009	-.1189**	.0003	-.1387**	-.0014
	(.0246)	(.0015)	(.0264)	(.0016)	(.0319)	(.0022)
Wholesale Trade	-.1029**	.0003	-.0388	-.0030*	-.1643**	.0085**
	(.0311)	(.0019)	(.0289)	(.0018)	(.0360)	(.0028)
Retail Trade	-.1995**	.0041**	-.1277**	-.0011	-.1106**	-.0034*
	(.0250)	(.0015)	(.0252)	(.0016)	(.0275)	(.0017)
F.I.R.E.	-.2242**	.0064**	-.1088**	-.0010	-.1141**	-.0087**
	(.0356)	(.0022)	(.0374)	(.0023)	(.0526)	(.0043)
Services	-.1629**	-.0003	-.1271**	-.0032**	-.1204**	-.0051**
	(.1094)	(.0013)	(.0215)	(.0015)	(.0181)	(.0015)
Government	-.0627**	-.0029	-.1178**	-.0008	-.0160	-.0149**
	(.0253)	(.0016)	(.0287)	(.0018)	(.0299)	(.0023)
Agriculture	-.1026**	-.0006	-.0928**	-.0006	.0210	.0005
	(.0437)	(.0022)	(.0472)	(.0023)	(.0772)	(.0049)
Mining	-.0811	-.0036	-.1279**	-.0017	-.0829	.0022
	(.0499)	(.0024)	(.0511)	(.0025)	(.0897)	(.0059)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. * indicates the 10% level. Sample size = 21,004. Same set of controls as in Table 3.