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

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Abstract—In this paper, we use micro panel data to examine the effects of oil price changes 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 an oil price increase on aggregate employment is negative, the long-run effect is in fact positive. We find that changes in oil prices induce changes in employment shares and relative wages across industries. However, we find little evidence that oil price changes cause labor to consistently flow into those sectors with relative wage increases.

I. Introduction

IT is 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 focused on the effects of oil price changes 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 focused on aggregate data, our results are disaggregated in two important dimensions.

First, we examine sectoral differences in responses to oil price changes. From a theoretical point of view, as well as from a policy perspective, it is important to know whether oil price fluctuations affect all sectors in a similar fashion. For instance, if aggregate unemployment increases in the short run following an oil price increase, it may reflect frictions involved in the sectoral reallocation of factor inputs necessitated by asymmetric sectoral responses (see Hamilton (1988)). If so, the use of aggregate demand management or other policy measures to respond to the oil price increase 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 increase, positive policy measures may be useful.

The second level of disaggregation in this study is the differentiation among workers on the basis of skill level. In our empirical work, we use education, labor market 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 relationship between skill levels and the nature of employment and wage responses to oil price changes, we cast light on the role of oil price fluctuations in generating movements in the wage differential between skilled and unskilled workers.

Studying the wage and employment effects of oil price changes 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 changes 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 also contributes to the development of a set of stylized facts concerning the effects of real shocks on the economy that could aid in the development of business cycle 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. The detailed micro data enable us to control for systematic changes in workforce composition induced by oil price fluctuations. Such compositional changes may induce bias in estimates of oil price effects based on 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.

The issue of aggregation bias in measuring real wage variability has been studied by Keane, Moffitt, and Runkle (1988), Kydland and Prescott (1994) and others. 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 by 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

Received for publication March 18, 1992. Revision accepted for publication February 9, 1995.

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We thank two anonymous referees for helpful comments. The views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of Minneapolis or the IMF.

level. At the aggregate level, and in most industries, all workers face a decline in wages following oil price increases, but the relative wage of skilled workers tends to rise. Further, our results indicate that changes in labor force composition induced by oil price changes produce substantial bias in estimates of these wage effects based on aggregate data. 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 aggregate employment in the short run and shift industry employment shares in the long run. The long-run effect of an oil price increase on aggregate employment is positive, possibly indicating substitution between energy and labor in the aggregate production function. These results are consistent with 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 unemployment 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 changes in industry relative wages and employment shares reveals little support for this prediction.

In the next section, we describe the econometric techniques used in the paper and discuss in greater detail some important measurement issues. Section III describes the dataset used in the estimation. Section IV contains the empirical results. Section V contains a discussion and interpretation of the results. Section VI summarizes the main findings and concludes.

II. Econometric Framework

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

$$\ln W_{it} = X_{it}\beta + P_t\alpha + P_tE_{it}\gamma + \mu_i + \epsilon_{it} \quad \forall\, i = 1,2,\ldots,N;\ t = 1,2,\ldots,T. \tag{1}$$

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. 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 $\alpha + E_{it}\gamma$. The error term consists of two components: μ_i is a vector of unobserved individual-specific characteristics that are fixed over time, while ϵ_{it} is assumed to be i.i.d. over time and across individuals.

Estimating equation (1) by ordinary least squares (OLS), with $\mu_i + \epsilon_{it}$ being the composite error term, would yield biased estimates of β and γ if the variables in μ_i were correlated with the regressors. To deal with such unobserved ability bias, we employ the following fixed effects model that is estimated by OLS

$$\ln \widetilde{W}_{it} = \tilde{X}_{it}\beta + \tilde{P}_t\alpha + \widetilde{P_tE}_{it}\gamma + \tilde{\epsilon}_{it} \tag{2}$$

where, for instance, $\tilde{X}_{it} \equiv X_{it} - T^{-1}\sum_{t=1}^{T} X_{it}\ \forall\, i = 1,2,\ldots,N$. This transformation causes the individual fixed effects to drop out. The error term $\tilde{\epsilon}_{it}$ 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.

To estimate the effects of oil price changes on wages at the industry level, we include interactions of P_t and P_tE_{it} with industry dummies as follows:

$$\ln W_{it} = X_{it}\beta + \sum_{j=1}^{J} I_{ijt}P_t\alpha_j + \sum_{j=1}^{J} I_{ijt}P_tE_{it}\gamma_j + \mu_i + \epsilon_{it} \tag{3}$$

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. With appropriate transformations of the variables as described in (2), a similar pooled regression could be used to estimate the fixed effects model at the industry level:

$$\ln \widetilde{W}_{it} = \tilde{X}_{it}\beta + \sum_{j=1}^{J} I_{ijt}\tilde{P}_t\alpha_j + \sum_{j=1}^{J} I_{ijt}\widetilde{P_tE}_{it}\gamma_j + \tilde{\epsilon}_{it}. \tag{4}$$

The above discussion assumed that the mean of $\tilde{\epsilon}_{it}$ conditional on individual i being employed in period t was zero. But this may not be true since wages are observed only for those individuals who are employed in a given period, thereby creating a source of potential selection bias. To deal with this source of bias, 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:

$$\ln W_{ijt} = X_{it}\beta_j + P_t\alpha_j + P_tE_{it}\gamma_j + \mu_{ij} + \epsilon_{ijt} \quad \text{observed iff } I_{ijt} = 1 \tag{5}$$

where $I^*_{ijt} = Z_{it}\theta_j + P_t\delta_j + P_tE_{it}\,\eta_j + \psi_{ij} + \omega_{ijt}$ and where $I_{ijt} = 1$ if $I^*_{ijt} \geq 0$, while $I_{ijt} = 0$ if $I^*_{ijt} < 0$. Here I^*_{ijt} is the latent index of a 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.[1] The corresponding coefficient vector is denoted by θ_j. Individual fixed effects in the employment choice equation are represented by ψ_{ij}.

The model in (5) is estimated by maximum likelihood. The error terms ϵ_{ijt} and ω_{ijt} are assumed to be bivariate normal 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. In the absence of a selection correction, this could impart a downward bias to the estimated effect of oil price increases on real wages.[2]

Note that the fixed effects specification in (4) restricts individual fixed effects to be the same across all industries, which could bias the coefficients of industry-level estimates if there were industry-specific unobserved fixed effects. Further, equations (3) and (4) restrict the coefficient vector β to be the same across industries, thereby restricting the returns to observed characteristics to be the same across all industries. To obviate these additional sources of bias, we estimate binomial selection models separately for each industry, which allows fixed effects to vary across industries and also allows the coefficient vector β to vary across industries.

III. 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 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 consisted of 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, 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.[3] 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.

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 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, averaged over the 12 months prior to the interview date. This variable is a broad index of the real 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.[4]

[1] The vector Z_{it} in the choice equation typically contains all elements that enter into X_{it} and 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}.

[2] 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 (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.

[3] 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.

[4] This and all other macroeconomic variables used in this study were taken from Citibase. The annual data are 12-month or 4-quarter averages of the respective variables.

TABLE 1.—ESTIMATED EFFECTS OF OIL PRICE CHANGES ON EMPLOYMENT PROBABILITIES

	Linear Probability Models with Degree Interactions				Linear Probability Models with Experience Interactions			
Industry	*OIL*	*OIL* DEGREE*	*DOIL*	*DOIL* DEGREE*	*OIL*	*OIL* EXPERIENCE*	*DOIL*	*DOIL* EXPERIENCE*
All Workers	0.0195[a]	0.0259[a]	−0.0909[b]	0.0387	0.0329[b]	−0.0005	−0.0573	−0.0021
	(0.0102)	(0.0139)	(0.0275)	(0.0526)	(0.0152)	(0.0012)	(0.0477)	(0.0047)
Durable Manufacturing	0.0179	0.0259	−0.0347	0.0193	0.0151	0.0012	0.0117	−0.0046
	(0.0129)	(0.0176)	(0.0347)	(0.0665)	(0.0192)	(0.0016)	(0.0603)	(0.0059)
Nondurable Manufacturing	−0.0040	−0.0201	−0.0229	0.0139	0.0023	−0.0013	−0.0459	0.0032
	(0.0102)	(0.0139)	(0.0274)	(0.0525)	(0.0151)	(0.0012)	(0.0476)	(0.0047)
Construction	−0.0367[b]	0.0281[b]	0.0401	−0.0028	−0.0589[b]	0.0029[b]	0.0393	−0.0007
	(0.0095)	(0.0129)	(0.0255)	(0.0488)	(0.0141)	(0.0011)	(0.0443)	(0.0044)
Transportation & Utilities	−0.0084	0.0153	0.0087	0.0176	−0.0031	−0.0001	0.0078	0.0008
	(0.0088)	(0.0120)	(0.0236)	(0.0452)	(0.0130)	(0.0011)	(0.0410)	(0.0040)
Wholesale Trade	0.0045	−0.0055	−0.0107	−0.0410	−0.0005	0.0003	−0.0296	0.0007
	(0.0067)	(0.0091)	(0.0180)	(0.0345)	(0.0100)	(0.0008)	(0.0313)	(0.0031)
Retail Trade	−0.0266[b]	0.0296[b]	−0.0533[b]	0.0591	−0.0014	−0.0014	0.0096	−0.0044
	(0.0098)	(0.0133)	(0.0263)	(0.0503)	(0.0145)	(0.0012)	(0.0456)	(0.0045)
Finance, Insurance, and Real Estate	−0.0072	−0.0145[a]	0.0153	−0.0360	−0.0278[b]	0.0015[b]	−0.0107	0.0012
	(0.0060)	(0.0081)	(0.0160)	(0.0307)	(0.0088)	(0.0007)	(0.0278)	(0.0027)
Services	0.0416[b]	−0.0505[b]	0.0010	−0.0057	0.0223	0.0006	0.0059	−0.0012
	(0.0103)	(0.0141)	(0.0278)	(0.0533)	(0.0154)	(0.0013)	(0.0484)	(0.0048)
Government	0.0078	0.0102	−0.0272	0.0161	0.0541[b]	−0.0044[b]	−0.0469	0.0040
	(0.0076)	(0.0104)	(0.0205)	(0.0393)	(0.0113)	(0.0009)	(0.0356)	(0.0035)
Agriculture	0.0052	−0.0021	0.0010	0.0127	0.0069	−0.0002	0.0114	−0.0007
	(0.0048)	(0.0066)	(0.0129)	(0.0248)	(0.0071)	(0.0006)	(0.0225)	(0.0022)
Mining	0.0015	0.0070	0.0058	−0.0139	0.0105[a]	−0.0008[a]	−0.0181	0.0025
	(0.0038)	(0.0052)	(0.0103)	(0.0197)	(0.0057)	(0.0005)	(0.0179)	(0.0018)

Notes: Standard errors are in parentheses. 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; 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.

[a] Significant at the 10% level.

[b] Significant at the 5% level.

IV. Empirical Results

Employment Effects of Oil Price Changes

Table 1 reports results from a set of linear employment probability models that estimate the employment effects of oil price changes. *TENURE* was not used as a regressor in these models since it would be endogenous in what are essentially reduced-form employment choice equations.[5] In order to separately identify the short-run and long-run effects of oil price changes on employment, we report regressions that include the level of oil prices lagged by one year (*OIL*) and the change in the *OIL* variable from $t-1$ to t, where t is the interview year (*DOIL*).[6]

The first panel of table 1 reports results from regressions that include interactions of oil prices with the *DEGREE* variable. For the full sample, the short-run effect of oil price increases on the employment probabilities of workers without a college degree, indicated by the coefficient on *DOIL*, is strongly negative. The *DOIL*DEGREE* coefficient is positive but not significant, indicating that workers with a degree are not protected from these general declines in employment. However, the significant positive coefficient on *OIL* (the one-year lag of the *OIL* variable) indicates that long-run employment probabilities for workers without a degree actually increase when the price of oil rises.[7] Further, the positive coefficient on *OIL*DEGREE* shows that this effect is even stronger for workers with a degree.[8] At the aggregate level, the restriction that the coefficients on *OIL* and *DOIL* (and the corresponding interaction terms) are equal was rejected at the 5% level, indicating that the short-run and long-run effects of an oil price increase on employment probabilities are significantly different. The top row of the second panel confirms the positive long-run aggregate employment effect of an oil price increase and also shows that this effect does not differ by level of labor market experience.

The long-run effect of oil price increases on industry location probabilities for workers without a college degree, as captured by the *OIL* coefficients in the first panel, is negative

[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 fixed effects and selection correction results for each of the human capital variables separately.

[6] Note that if $\ln W_t = \alpha_1 OIL_{t-1} + \alpha_2(OIL_t - OIL_{t-1})$ + other variables, then α_2 is the short-run effect of an increase in *OIL* on $\ln W_t$ and α_1 is the long-run effect.

[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 long-run effect of oil price changes on employment probabilities at the mean of the data (0.0259*0.23 + 0.0195 = 0.0255). A one standard deviation around trend increase in oil prices (0.28 in our sample) thus yields an average increase of 0.7 percentage points in aggregate long-run employment probabilities.

[8] The point estimates of 0.0195 on *OIL* and 0.0259 on *OIL*DEGREE* indicate that a one standard deviation around trend increase in the price of oil induces an increase of 1.27 percentage points ((0.0195 + 0.0259)*0.28) in the long-run probability that a worker with a degree will be employed.

and substantial in magnitude in construction and retail trade, and positive in durable manufacturing and services. For workers with a degree, the long-run effect of oil price increases, given by the sum of the coefficients on *OIL* and *OIL∗DEGREE*, is positive and large in durable manufacturing and government, and negative in nondurable manufacturing and *FIRE*. The results in the second panel show that, for workers with little labor market experience, an oil price increase leads to substantial declines in employment probabilities in construction and *FIRE*, but leads to increases in employment probabilities in services, government and mining. With the exception of services, the *OIL∗EXPERIENCE* coefficients in these industries are significant and of the opposite sign relative to the *OIL* coefficients, indicating that these effects are mitigated for workers with higher levels of labor market experience. Setting experience equal to its sample mean of 7.9, the point estimates imply that, at the mean of the data, an increase in oil prices has substantial negative long-run effects on the employment shares of construction, retail trade and *FIRE* and positive effects on the employment shares of durable manufacturing, services and government.[9]

Turning to the coefficients involving *DOIL*, we find that they are significantly different from the *OIL* coefficients only for construction in the first panel and for construction and government in the second panel. In construction, there is no evidence of a negative short-run effect of oil price increases on employment probabilities for workers without a degree or with little labor market experience. In government, there is no evidence of a positive short-run effect of oil prices on location probabilities for workers with low levels of labor market experience. The insignificant industry coefficients on *DOIL∗DEGREE* and *DOIL∗EXPERIENCE* indicate that, at the industry level, oil price changes do not have a differential short-term impact on the employment probabilities of workers with different levels of education or labor market experience.

By replacing the *OIL* and *DOIL* variables in the aggregate employment equations with time dummies and then comparing the sum of squared errors (SSE) to the SSE from a model with no time effects (except trend), we are able to determine the total variation in employment due to time effects. We then compare the variance explained by the oil price variables to that explained by time effects and find that oil price changes account for 21% of the time effects (other than trend) in employment variation, a significant but not large fraction. It is possible that the oil price variables are significant in the employment equations only because they are correlated with omitted aggregate variables. To examine this issue, we include unanticipated changes in M1 money supply growth, along with interactions of this variable with *DEGREE* and *EXPERIENCE*, in the employment equations.[10] The results indicate that unanticipated increases in M1 growth increase employment and that almost the entire effect is in durable manufacturing. However, the estimates of the *OIL* and *DOIL* coefficients as well as the interactions are little changed by the inclusion of the M1 variables. This gives us some comfort that our estimates of oil price effects are robust to omitted aggregate shocks.

Our findings that oil price increases reduce employment in the short run, significantly change the allocation of labor across industries, and increase employment in the long run appear to provide support for the sectoral shift models of Lilien (1982), Hamilton (1988) etc. These models imply that oil price increases 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.

Wage Effects of Oil Price Changes

Table 2 presents estimates of wage equations that incorporate the *OIL∗DEGREE* interaction term. The first two columns contain results from OLS regressions at the aggregate and industry levels. The significant negative coefficients on *OIL* indicate that, for workers without a degree, oil price increases have a strong negative effect on real wages at the aggregate level and in all industries. The OLS coefficients on the *OIL∗DEGREE* interaction term are also negative at the aggregate level and in virtually every industry, suggesting that, when the price of oil rises, workers with a college degree face a larger decline in wages than workers without a degree. This result appears puzzling. While the employment of college-educated workers rises following an oil price increase, 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, this coefficient changes from -0.0796 to 0.0379. The change in the sign of the FE coefficient from the OLS estimate reflects the fact that, while oil price increases lead firms to hire more skilled labor, the quality of this additional skilled labor, in terms of unobservable attributes, declines.[11] This compositional effect induces negative bias in the OLS estimate of the *OIL∗DEGREE* coefficient. The positive FE estimate of this coefficient implies that, adjusting for changes in labor-force quality, the offer wage for workers with a

[9] We also examined the effects of oil price fluctuations 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.

[10] Unanticipated M1 growth is defined as the residual from a regression of M1 growth on lagged annual CPI inflation, lagged annual M1 growth, lagged annual changes in industrial production and *OIL*, and the contemporaneous annual change in government purchases of durable goods.

[11] 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

TABLE 2.—ESTIMATED EFFECTS OF OIL PRICE CHANGES ON REAL WAGES: DEGREE INTERACTIONS
DEPENDENT VARIABLE—LOG REAL WAGE

	OLS Estimates		Fixed Effects Estimates		Fixed Effects Estimates with *DOIL* Terms			
Industry	*OIL*	*OIL* DEGREE*	*OIL*	*OIL* DEGREE*	*OIL*	*OIL* DEGREE*	*DOIL*	*DOIL* DEGREE*
All Workers	−0.0956[b]	−0.0796[b]	−0.1381[b]	0.0379[b]	−0.1434[b]	0.0615[b]	−0.1074[b]	−0.0618
	(0.0096)	(0.0117)	(0.0071)	(0.0127)	(0.0094)	(0.0158)	(0.0235)	(0.0418)
Durable Manufacturing	−0.0831[b]	−0.0879[b]	−0.1308[b]	0.0329[b]	−0.1278[b]	0.0274	−0.1699[b]	0.2259[b]
	(0.0124)	(0.0143)	(0.0092)	(0.0147)	(0.0128)	(0.0191)	(0.0464)	(0.0995)
Nondurable Manufacturing	−0.0759[b]	−0.0487[b]	−0.1306[b]	0.0394[b]	−0.1209[b]	0.0508[b]	−0.1933[b]	0.0551
	(0.0149)	(0.0159)	(0.0111)	(0.0168)	(0.0158)	(0.0218)	(0.0626)	(0.1237)
Construction	−0.1316[b]	−0.1309[b]	−0.1519[b]	0.0407[b]	−0.1349[b]	0.0591[b]	−0.2575[b]	−0.0182
	(0.0152)	(0.0181)	(0.0114)	(0.0185)	(0.0159)	(0.0253)	(0.0662)	(0.1757)
Transportation & Utilities	−0.0424[b]	−0.1077[b]	−0.1060[b]	0.0118	−0.1159[b]	0.0457[a]	−0.0433	0.1988
	(0.0157)	(0.0164)	(0.0118)	(0.0176)	(0.0173)	(0.0243)	(0.0698)	(0.1485)
Wholesale Trade	−0.1145[b]	0.0052	−0.1069[b]	0.0753[b]	−0.0885[b]	0.0872[b]	−0.2217[b]	0.0669
	(0.0208)	(0.0186)	(0.0158)	(0.0175)	(0.0235)	(0.0231)	(0.1084)	(0.1699)
Retail Trade	−0.1268[b]	−0.0522[b]	−0.1517[b]	0.0534[b]	−0.1749[b]	0.0712[b]	−0.0084	0.0005
	(0.0160)	(0.0171)	(0.0121)	(0.0169)	(0.0163)	(0.0219)	(0.0677)	(0.1490)
Finance, Insurance, and Real Estate	−0.1295[b]	−0.0266	−0.1578[b]	0.0875[b]	−0.1330[b]	0.0961[b]	−0.3176[b]	0.1289
	(0.0237)	(0.0190)	(0.0188)	(0.0192)	(0.0276)	(0.0255)	(0.1369)	(0.1738)
Services	−0.1353[b]	−0.0627[b]	−0.1857[b]	0.0499[b]	−0.2163[b]	0.0935[b]	0.0679	0.3062[b]
	(0.0148)	(0.0141)	(0.0113)	(0.0142)	(0.0163)	(0.0182)	(0.0718)	(0.0889)
Government	−0.0685[b]	−0.0752[b]	−0.1332[b]	0.0412[b]	−0.1427[b]	0.0721[b]	−0.0632	0.1427
	(0.0183)	(0.0157)	(0.0143)	(0.0169)	(0.0214)	(0.0226)	(0.0899)	(0.1308)
Agriculture	−0.1060[b]	−0.0243	−0.0930[b]	−0.0099	−0.1306[b]	0.0147	0.1367	0.1446
	(0.0286)	(0.0294)	(0.0221)	(0.0382)	(0.0326)	(0.0510)	(0.1492)	(0.3398)
Mining	−0.1177[b]	−0.0918[b]	−0.1598[b]	0.0475	−0.1417[b]	0.0864[a]	−0.2405	0.2312
	(0.0328)	(0.0323)	(0.0252)	(0.0337)	(0.0397)	(0.0525)	(0.1689)	(0.3975)

Notes: Standard errors are in parentheses. Sample size = 21,004. Controls are a time trend; education; experience and its square; four dummies for types of college degrees; five dummies for fields of degree; 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.
[a] Significant at the 10% level.
[b] Significant at the 5% level.

degree rises relative to the wage offered to uneducated workers following an oil price increase.

In going from the OLS to the FE estimates, the *OIL* coefficient for all workers drops from −0.0956 to −0.1381, indicating that the effect of oil price changes on the unskilled wage is larger than was indicated by the biased OLS estimates. Also, while the FE estimate of the *OIL*DEGREE* coefficient is positive, it does not offset the negative coefficient on *OIL*, indicating that skilled workers also face wage cuts following an oil price increase. At the aggregate level, the average real wage is estimated to decline by about 3.6% when the real price of oil increases by one standard deviation around its trend (about 19%).[12] For workers without a college degree, the decline is 3.9%, while it is only 2.8% for those with a degree. Although the magnitudes differ, this pattern is repeated in virtually all industries.

The third panel of table 2 incorporates the lagged level and the current change in oil prices in order to separately identify the short-run and long-run effects of oil price changes. At the aggregate level, the coefficients on *OIL* and *DOIL* are similar but the coefficient on *OIL*DEGREE* is significantly positive while the *DOIL*DEGREE* coefficient is negative and insignificant. This suggests that workers with a degree are relatively better protected from wage reductions following oil price increases only in the long run but not in the short run. However, the F-test statistic for the hypothesis that the *OIL* and *OIL*DEGREE* coefficients are equal, respectively, to the *DOIL* and *DOIL*DEGREE* coefficients is 2.49 compared to the 5% critical value of 3.00. Also, although the two *DOIL* coefficients differ noticeably from the two *OIL* coefficients in a few industries, the F-test statistic for the hypothesis that these two sets of coefficients are equal in each industry (not across industries) is 1.52 compared to a 5% critical value of 1.54. Thus, we conclude that there is no strong evidence for substantial differences between the short-run and long-run effects of oil price changes on wages, either at the aggregate or industry level. This is not surprising when one considers that the *OIL* variable is defined as the average price of refined petroleum products over the entire year prior to the interview. Thus, our results suggest only that wages adjust to oil price changes in well under a year, but not that they adjust instantaneously.

Next, we look at the effect of another human capital variable, *TENURE*. As discussed before, length of job tenure is likely to be the best proxy for industry-specific skills. Table

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.

[12] 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 ($-0.1381 + (0.0379*0.23) = -0.1294$). This number multiplied by the standard deviation of the *OIL* variable (in our sample, *OIL* has a standard deviation of 0.28 and its mean is 1.53) yields a product of −0.0362. For workers with a degree, the full effect on real wages is obtained by summing the coefficients on *OIL* and *OIL*DEGREE*.

TABLE 3.—ESTIMATED EFFECTS OF OIL PRICE CHANGES ON REAL WAGES: TENURE INTERACTIONS
DEPENDENT VARIABLE—LOG REAL WAGE

	OLS Estimates		Fixed Effects Estimates		Fixed Effects Estimates with *DOIL* Terms			
Industry	*OIL*	*OIL*TENURE*	*OIL*	*OIL*TENURE*	*OIL*	*OIL*TENURE*	*DOIL*	*DOIL*TENURE*
All Workers	-0.1334^{b}	0.0031^{b}	-0.1437^{b}	0.0034^{b}	-0.1448^{b}	0.0042^{b}	-0.1342^{b}	-0.0003
	(0.0115)	(0.0011)	(0.0091)	(0.0010)	(0.0119)	(0.0015)	(0.0309)	(0.0048)
Durable Manufacturing	-0.1278^{b}	0.0031^{b}	-0.1392^{b}	0.0035^{b}	-0.1335^{b}	0.0037^{b}	-0.1510^{b}	0.0026
	(0.0157)	(0.0014)	(0.0128)	(0.0011)	(0.0174)	(0.0017)	(0.0689)	(0.0085)
Nondurable Manufacturing	-0.1032^{b}	0.0025	-0.1443^{b}	0.0038^{b}	-0.1264^{b}	0.0034^{a}	-0.2329^{b}	0.0082
	(0.0190)	(0.0015)	(0.0159)	(0.0013)	(0.0213)	(0.0020)	(0.0886)	(0.0123)
Construction	-0.1053^{b}	-0.0053^{b}	-0.1444^{b}	0.0017	-0.1170^{b}	0.0011	-0.2967^{b}	0.0082
	(0.0177)	(0.0016)	(0.0141)	(0.0013)	(0.0192)	(0.0021)	(0.0829)	(0.0160)
Transportation & Utilities	-0.0905^{b}	0.0028^{a}	-0.1389^{b}	0.0051^{b}	-0.1489^{b}	0.0067^{b}	-0.0362	-0.0115
	(0.0195)	(0.0015)	(0.0167)	(0.0014)	(0.0233)	(0.0021)	(0.1010)	(0.0133)
Wholesale Trade	-0.0945^{b}	0.0027	-0.1095^{b}	0.0058^{b}	-0.0903^{b}	0.0065^{b}	-0.1821	-0.0039
	(0.0232)	(0.0019)	(0.0186)	(0.0016)	(0.0266)	(0.0025)	(0.1274)	(0.0202)
Retail Trade	-0.1646^{b}	0.0055^{b}	-0.1743^{b}	0.0060^{b}	-0.1921^{b}	0.0060^{b}	-0.0479	0.0071
	(0.0188)	(0.0016)	(0.0154)	(0.0014)	(0.0200)	(0.0020)	(0.0881)	(0.0137)
Finance, Insurance, and Real Estate	-0.1615^{b}	0.0065^{b}	-0.1472^{b}	0.0056^{b}	-0.1214^{b}	0.0080^{b}	-0.2345^{a}	-0.0194
	(0.0253)	(0.0020)	(0.0209)	(0.0018)	(0.0299)	(0.0030)	(0.1394)	(0.0234)
Services	-0.1707^{b}	0.0024^{a}	-0.1629^{b}	0.0008	-0.1670^{b}	0.0006	-0.1350^{a}	0.0046
	(0.0154)	(0.0014)	(0.0131)	(0.0012)	(0.0183)	(0.0019)	(0.0717)	(0.0124)
Government	-0.1510^{b}	0.0049^{b}	-0.1272^{b}	0.0015	-0.1419^{b}	0.0042^{a}	0.0347	-0.0284^{a}
	(0.0224)	(0.0017)	(0.0212)	(0.0016)	(0.0296)	(0.0024)	(0.1197)	(0.0161)
Agriculture	-0.0357	-0.0098^{b}	-0.0740^{b}	-0.0020	-0.0535	-0.0110^{b}	-0.3200^{a}	0.0967^{b}
	(0.0324)	(0.0026)	(0.0277)	(0.0023)	(0.0387)	(0.0036)	(0.1801)	(0.0275)
Mining	-0.0956^{b}	-0.0037	-0.1388^{b}	0.0012	-0.0976^{b}	-0.0020	-0.4039^{a}	0.0355
	(0.0371)	(0.0028)	(0.0319)	(0.0024)	(0.0484)	(0.0042)	(0.2303)	(0.0347)

Notes: Standard errors are in parentheses. Sample size = 20,309. Same set of controls is used as in table 2, except that tenure is included as an additional control variable.
[a] Significant at the 10% level.
[b] Significant at the 5% level.

3 contains OLS and fixed effects estimates of wage equations that include the *OIL*TENURE* interaction term. The OLS coefficients on *OIL*TENURE* are significantly positive for all workers and in several industries, although the interaction term is significantly negative in construction and agriculture. The FE results are quite similar at both the aggregate and industry levels. The *OIL*TENURE* interactions remain significantly positive in several industries, but the significant negative interactions found in the OLS estimates for construction and agriculture disappear. The third panel of table 3 reports results with the *DOIL* and *DOIL*TENURE* terms. As was the case with the degree interactions, the hypothesis that these two coefficients are equal to those on *OIL* and *OIL*TENURE*, respectively, cannot be rejected at the 5% level at the aggregate or industry level (the F-test statistics are 0.32 and 1.42, respectively).

These tenure results provide further evidence that the relative wage of skilled workers tends to rise following an oil price increase. However, oil price increases do result in substantial real wage declines for 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*. The point estimates in panel 2 indicate that, for workers with very short tenure on the current job (less than 12 months as of the interview date), a one standard deviation around trend increase in oil prices reduces real wages by about 4.0%. For every additional year of tenure that a worker has on the current job, this effect is reduced by 0.1 percentage points.[13]

Next, in table 4, we examine the effect of labor market experience on the real wage response to oil price changes. At the aggregate level, the *OIL*EXPERIENCE* coefficient is statistically insignificant in both the OLS and FE estimates. In the FE estimates, the *OIL*EXPERIENCE* interaction term is significantly negative in three industries: nondurable manufacturing, wholesale trade, and services. In those three industries, workers with more labor market experience seem to face markedly larger wage declines following increases in the price of oil. In the remaining industries, the wage effects of oil price changes seem to differ little for workers with different levels of experience.

The results in the third panel, which include the *DOIL* variables, are particularly interesting. The *DOIL*EXPERIENCE* interaction coefficient is positive and significant at the aggregate level and for workers in durable and nondurable manufacturing, agriculture and mining. This indicates that workers with more labor market experience face smaller short-run wage declines than inexperienced workers following oil price increases. However, the *OIL*EXPERIENCE* coefficient is significantly negative, both in the aggregate and in several industries, indicating that workers with more

[13] Setting *TENURE* equal to its sample mean of 4.0, the estimated effect of a one standard deviation around trend increase in the real price of oil is to reduce the aggregate average real wage by 3.6% $((-0.1437 + 0.0034*4.0)*0.28 = -0.0364)$. This is identical to the result using the degree interactions.

TABLE 4.—ESTIMATED EFFECTS OF OIL PRICE CHANGES ON REAL WAGES: EXPERIENCE INTERACTIONS
DEPENDENT VARIABLE—LOG REAL WAGE

	OLS Estimates		Fixed Effects Estimates		Fixed Effects Estimates with *DOIL* Terms			
Industry	*OIL*	*OIL** *EXPERIENCE*	*OIL*	*OIL** *EXPERIENCE*	*OIL*	*OIL** *EXPERIENCE*	*DOIL*	*DOIL** *EXPERIENCE*
All Workers	−0.1237[b]	0.0003	−0.1093[b]	−0.0016	−0.0808[b]	−0.0046[b]	−0.1927[b]	0.0082[b]
	(0.0151)	(0.0011)	(0.0170)	(0.0013)	(0.0220)	(0.0018)	(0.0415)	(0.0041)
Durable Manufacturing	−0.1150[b]	0.0005	−0.0947[b]	−0.0021	−0.0501[a]	−0.0061[b]	−0.3077[b]	0.0188[b]
	(0.0200)	(0.0013)	(0.0214)	(0.0014)	(0.0272)	(0.0019)	(0.0879)	(0.0077)
Nondurable Manufacturing	−0.0282	−0.0039[b]	−0.0511[b]	−0.0045[b]	0.0081	−0.0087[b]	−0.3256[b]	0.0167[a]
	(0.0237)	(0.0015)	(0.0249)	(0.0016)	(0.0316)	(0.0021)	(0.1139)	(0.0105)
Construction	−0.2035[b]	0.0026[a]	−0.1962[b]	0.0022	−0.1586[b]	0.0002	−0.2285[a]	−0.0033
	(0.0257)	(0.0015)	(0.0259)	(0.0016)	(0.0327)	(0.0021)	(0.1362)	(0.0116)
Transportation & Utilities	−0.0594[b]	−0.0009	−0.1186[b]	0.0003	−0.1012[b]	−0.0021	−0.1061	0.0028
	(0.0246)	(0.0015)	(0.0264)	(0.0016)	(0.0341)	(0.0023)	(0.1307)	(0.0123)
Wholesale Trade	−0.1027[b]	0.0003	−0.0385	−0.0030[a]	0.0201	−0.0065[b]	−0.3013[a]	0.0112
	(0.0311)	(0.0018)	(0.0289)	(0.0018)	(0.0373)	(0.0025)	(0.1807)	(0.0180)
Retail Trade	−0.1992[b]	0.0040[b]	−0.1273[b]	−0.0011	−0.1203[b]	−0.0041[b]	−0.1233	0.0127
	(0.0250)	(0.0015)	(0.0252)	(0.0016)	(0.0308)	(0.0021)	(0.1254)	(0.0115)
Finance, Insurance, and Real Estate	−0.2239[b]	0.0064[b]	−0.1086[b]	−0.0010	−0.0898[a]	−0.0001	0.0960	−0.0421[b]
	(0.0357)	(0.0022)	(0.0374)	(0.0023)	(0.0475)	(0.0031)	(0.1959)	(0.0210)
Services	−0.1625[b]	−0.0003	−0.1268[b]	−0.0032[b]	−0.1129[b]	−0.0057[b]	−0.1228	0.0023
	(0.0194)	(0.0013)	(0.0215)	(0.0015)	(0.0285)	(0.0020)	(0.0897)	(0.0099)
Government	−0.0624[b]	−0.0029[a]	−0.1175[b]	−0.0008	−0.1100[b]	−0.0016	0.0170	−0.0172
	(0.0253)	(0.0016)	(0.0287)	(0.0018)	(0.0379)	(0.0025)	(0.1366)	(0.0147)
Agriculture	−0.1025[b]	−0.0006	−0.0928[b]	−0.0064	−0.0705	−0.0060[a]	−0.3386	0.0429[a]
	(0.0438)	(0.0022)	(0.0472)	(0.0023)	(0.0603)	(0.0031)	(0.2635)	(0.0217)
Mining	−0.0809[a]	−0.0036	−0.1275[b]	−0.0017	−0.0301	−0.0083[b]	−0.7414[b]	0.0464[a]
	(0.0499)	(0.0024)	(0.0511)	(0.0025)	(0.0677)	(0.0037)	(0.3304)	(0.0282)

Notes: Standard errors are in parentheses. Sample size = 21,004. Same set of controls as in table 2.
[a] Significant at the 10% level.
[b] Significant at the 5% level.

labor market experience face larger wage reductions in the long run. In the case of the experience interactions, the F-test for the hypothesis that the *OIL* and *DOIL* coefficients and corresponding interactions are equal in each industry is rejected at the 5% level (1.59 compared to a critical value of 1.54). Hence, the hypothesis of equivalent short-run and long-run effects is rejected here. The evidence shows that, for workers with more labor market experience, oil price increases lead to smaller wage reductions in the short run but larger wage reductions in the long run.

Finally, in table 5, we report selection corrected fixed effects (SCFE) estimates of the wage equations.[14] The estimated parameter ρ 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 changes can be measured by the combination of observed characteristics of workers and unobserved individual fixed effects.[15] Since the effects of the selection correction were similar in the regressions with and without the *DOIL* terms, we report only the results from specifications that included both lagged *OIL* and *DOIL*.

Although the selection correction has little impact on the estimates at the aggregate level, the industry-level estimates differ from the FE estimates in some cases. These differences are mostly in the magnitudes rather than the sign or significance levels of the coefficients. Since the estimates of ρ are small and insignificant for all industries, this change in coefficients 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.[16] The selection models were estimated separately for each industry, thereby controlling for both these sources of potential bias in the industry level FE estimates.[17]

The first panel of table 5 presents results with the degree interactions. Compared to the FE estimates, the main differences are in wholesale trade, agriculture and mining. In these industries, the *OIL* coefficients become close to zero while the *OIL*DEGREE* coefficients become significantly nega-

[14] Panels containing SCFE 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. As noted before, *TENURE* would be endogenous in the employment choice equation. Hence, we are unable to estimate the SCFE model using this variable.

[15] We found that FE selection model estimates are very sensitive to starting values. After extensive experimentation with different starting values, we have concluded that the estimates with ρ close to zero are the global maxima.

[16] 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% 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.

[17] Fixed effects models estimated separately for each industry yielded point estimates that were similar to the SCFE industry estimates.

TABLE 5.—ESTIMATED EFFECTS OF OIL PRICE CHANGES ON REAL WAGES: SELECTION MODELS
DEPENDENT VARIABLE—LOG REAL WAGE

	Selection Models with Degree Interactions				Selection Models with Experience Interactions			
Industry	*OIL*	*OIL∗ DEGREE*	*DOIL*	*DOIL∗ DEGREE*	*OIL*	*OIL∗ EXPERIENCE*	*DOIL*	*DOIL∗ EXPERIENCE*
All Workers	−0.1422[b]	0.0590[b]	−0.1090[b]	−0.0595	−0.0950[b]	−0.0035[b]	−0.1832[b]	0.0073[a]
	(0.0078)	(0.0064)	(0.0230)	(0.0408)	(0.0100)	(0.0008)	(0.0402)	(0.0037)
Durable	−0.0964[b]	0.0492[b]	−0.1923[b]	0.1439[a]	−0.0713[b]	−0.0022	−0.3083[b]	0.0144[b]
Manufacturing	(0.0119)	(0.0138)	(0.0379)	(0.0851)	(0.0227)	(0.0018)	(0.0795)	(0.0067)
Nondurable	−0.0833[b]	0.0431[b]	−0.2253[b]	−0.0343	−0.0000	−0.0065[b]	−0.2637[b]	0.0043
Manufacturing	(0.0161)	(0.0172)	(0.0454)	(0.1011)	(0.0291)	(0.0022)	(0.0920)	(0.0087)
Construction	−0.2087[b]	0.0422[a]	−0.1505[b]	−0.1744	−0.3138[b]	0.0078[b]	−0.2332[b]	0.0050
	(0.0189)	(0.0244)	(0.0560)	(0.1628)	(0.0403)	(0.0029)	(0.1172)	(0.0099)
Transportation &	−0.1701[b]	0.0253	−0.0914[a]	−0.1872	−0.1240[b]	−0.0038	−0.1875[a]	0.0070
Utilities	(0.0209)	(0.0236)	(0.0561)	(0.1535)	(0.0373)	(0.0029)	(0.1136)	(0.0101)
Wholesale Trade	0.0202	−0.0393[b]	−0.3498[b]	0.1583	−0.0410	0.0030	−0.4747[b]	0.0213
	(0.0242)	(0.0187)	(0.0775)	(0.1149)	(0.0402)	(0.0034)	(0.1365)	(0.0145)
Retail Trade	−0.2217[b]	0.1160[a]	0.0035	0.1599	−0.1573[b]	−0.0049[b]	−0.0220	0.0074
	(0.0187)	(0.0221)	(0.0514)	(0.1175)	(0.0316)	(0.0023)	(0.1092)	(0.0099)
Finance, Insurance,	−0.2394[b]	0.0776[b]	−0.2723[b]	0.0791	−0.1235[b]	−0.0056	−0.0642	−0.0200
and Real Estate	(0.0390)	(0.0240)	(0.1069)	(0.1333)	(0.0628)	(0.0053)	(0.1489)	(0.0162)
Services	−0.2279[b]	0.0581[b]	−0.0557	−0.1048	−0.1505[b]	−0.0034[a]	−0.0569	−0.0089
	(0.0197)	(0.0144)	(0.0714)	(0.0829)	(0.0195)	(0.0019)	(0.0831)	(0.0092)
Government	−0.2431[b]	0.1171[b]	−0.0326	−0.1340	−0.0427	−0.0144[b]	0.0231	−0.0138
	(0.0249)	(0.0152)	(0.0740)	(0.1040)	(0.0338)	(0.0030)	(0.1183)	(0.0131)
Agriculture	0.0185	−0.2991[b]	0.2035	0.1090	−0.0661	0.0036	0.2711	−0.0048
	(0.0476)	(0.0717)	(0.1584)	(0.4488)	(0.1005)	(0.0080)	(0.3279)	(0.0280)
Mining	−0.0053	−0.2617[b]	−0.1362	−0.1157	−0.0024	−0.0007	−0.2361	0.0058
	(0.0533)	(0.0527)	(0.1543)	(0.3092)	(0.1116)	(0.0080)	(0.3152)	(0.0297)

Notes: Standard errors are in parentheses. Same set of controls as in table 2. 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.
[a] Significant at the 10% level.
[b] Significant at the 5% level.

tive, indicating that wage declines following oil price increases occur only for workers with degrees. The other main difference is in services, where the *DOIL∗DEGREE* coefficient is no longer significant. Turning to the results with the experience interactions in the second panel, the *OIL∗EXPERIENCE* interaction terms, which were significantly negative for seven of the eleven industries in the FE estimates, generally increase towards zero and remain significantly negative in only four industries. Also, the *DOIL∗EXPERIENCE* terms generally decline towards zero. Thus, the finding that oil price increases cause larger wage reductions for workers with lower levels of labor market experience in the short run and for workers with higher levels of experience in the long run is weakened but still remains apparent in the SCFE results. Overall, the SCFE and FE results tell a very similar story.

It is possible, of course, that the large oil price effects on wages that we have estimated could be the result of fluctuations in other aggregate variables that are highly correlated with the price of oil. We compared the sum of squared errors from models with and without time effects (except trend) to that of a model including the *OIL* and *DOIL* variables. The results indicated that changes in oil prices can account for 90% of the variation in real wages that can be attributed to time effects (other than trend). Furthermore, when unanticipated changes in money supply (M1) growth, along with interactions of this variable with *DEGREE* and *EXPERIENCE*, were included in our FE wage equations, the M1 variables were not significant and had a negligible impact on the oil variable coefficients. We also included several other 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 *OIL* and *DOIL* coefficients and associated interactions in the wage regressions.[18] These results are strong evidence that oil price changes had a substantial causal effect on wages over our sample period and that omitted variable bias is not a likely problem in the wage equations.

V. Discussion

The effect of a change in oil prices on labor demand depends upon 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 Jorgenson (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 find-

[18] 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.

ing that oil price increases have negative wage effects is not surprising.

We have also found that increases in the price of oil do not have an adverse effect on aggregate employment in the long run.[19] 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 long-run 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 (1979)) 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 during the 1970s may in part be related to the sustained increase in the real price of oil over that period.

At the industry level, we find that changes in oil prices have moderately large effects on relative wages across industries for workers in a given skill category. For example, for workers without a college degree, a one standard deviation around trend increase in the *OIL* variable results in long-run wage declines of more than 5% in services, but only about a 3% wage decline in durable and nondurable manufacturing. Fluctuations in oil prices also have some sizable effects on industry employment shares. For instance, for workers without a degree, an oil price increase of one standard deviation around trend results in a 1.2 percentage points increase in the probability of being employed in services but a 1.0 percentage point decline in the probability of being employed in construction.[20]

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.[21] Therefore, oil price shocks are also good candidates for the ''sectoral shocks'' that generate unemployment in multi-sector models such as those of Lilien (1982) and Hamilton (1988). Consistent with a key prediction of the sectoral shifts literature, we find that increases in the price of oil increase aggregate unemployment in the short run and generate labor reallocation across industries, but do not reduce employment in the long run. However, equilibrium sectoral models also predict that, following a real shock, labor tends to flow towards those sectors where the relative productivity of labor rises. Our results reveal many inconsistencies with this prediction. Consider, for instance, the following long-run effects of oil price increases. Among workers without a college degree, services has the largest increase in employment share even though that industry has among the largest wage declines for such workers. For workers with a college degree, the largest reductions in location probabilities are in nondurable manufacturing and *FIRE*, two industries with among the smallest wage declines for college-educated workers. A few industries do reveal patterns consistent with the predictions of equilibrium sectoral models following oil price increases. For instance, for workers without a college degree, the largest declines in location probabilities are in construction and retail trade, where such workers face the largest wage declines. For many industries, there is no clear relation between inter-industry relative wage changes and changes in employment shares in response to oil price changes. Thus, at the 1-digit industry level, our results provide little support for the predictions of sectoral shift models regarding labor reallocation.

It is also of interest to note that our three proxies for skill levels 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 this negative effect is often exacerbated for workers with higher levels of labor market experience. Since the *EXPERIENCE* variable is 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.

VI. 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

[19] In simulations of their dynamic factor demand model, Pindyck and Rotemberg (1983) also find that oil price increases do not have an adverse 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.

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

[21] 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.

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 changes 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% in the long run following a one standard deviation around trend (approximately 19%) 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 increase 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.[22]

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 probabilities for skilled labor rise even more strongly following oil price increases, suggesting that skilled labor may be 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 oil price increases induce reallocation of labor across industries and short-run increases in 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 some industries even providing evidence to the contrary.

[22] Using Current Population Survey (CPS) data from 1966 to 1981, Heckman and Sedlacek (1985) find that, even after controlling for observed worker characteristics, selection bias reduces the measured wage decline in manufacturing (relative to the quality-constant decline in task prices) following oil price increases. Our estimates for durable and nondurable manufacturing corroborate this result. However, unlike these authors, we find that a similar bias is also induced in OLS coefficients for the aggregate economy.

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APPENDIX

TABLE A1.—MEANS OF VARIABLES IN NLS ANALYSIS SAMPLE

Variable	Mean
Log real wage—*WCPI*	1.06
Real price of refined petroleum—*OIL*	1.53
Unemployment rate—*URATE*	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 race dummy—*WHITE*	0.74
Wife present dummy—*WIFE*	0.69
SMSA resident dummy—*SMSA*	0.70
South resident dummy—*SOUTH*	0.41
Children in household—*KIDS*	1.30
College degree dummy—*DEGREE*	0.23
Employment dummy	0.89
Occupational dummies:	
Professional and technical workers (0–370)	0.31
Craftsmen and foremen (401–545)	0.19
Salesmen (380–395)	0.05
Services (801–890)	0.05
Operatives, laborers, farmers (200–222, 601–775, 901–985)	0.29

Note: Census three-digit occupation codes are used.

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, and 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 unspecified industry	—	143

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