# Why Do Energy Prices Matter? The Role of Inter-Industry Linkages in U.S. Manufacturing*

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**Abstract**

There is considerable empirical evidence that energy prices had a large effect on the U.S. economy between World War II and the 1980s. This paper argues that linkages between manufacturing industries amplify the effect of an energy price shock, and help explain the large effect. In particular, energy intensive industries are important input suppliers to other industries. When the price of energy increases, energy intensive industries contract, raising materials prices for other industries. Because of the reduction in materials supply, the downstream industries also contract, which I refer to as the supply effect. Using data from the Census of Manufactures, I find that the supply effect accounted for about one half of the sensitivity of value added to the price of energy. I use plant level Census data to show that the supply effect caused similar changes in value added per plant as in value added per industry. A price increase caused a small, though statistically significant, decrease in entry and had no effect on exit. Finally, the supply effect reduced plant level labor demand.

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# 1 Introduction

Past research has documented a strong correlation between oil prices and economic activity, both in individual sectors and at the aggregate level. Davis and Haltiwanger (2001) find that oil shocks explained much of the variation in manufacturing employment from 1972-1988. Rotemberg and Woodford (1996) find that a one percent increase in the price of oil caused GDP to decline by 0.25 percent.[1] Although some authors have argued that the actual effect may be smaller (e.g., Bernanke, Gertler and Watson, 1997), it appears that oil shocks played an important role in business cycles from World War II at least until the 1980s.[2]

This result constitutes a puzzle. A simple neoclassical model of the U.S. economy would suggest that the elasticity of GDP to the price of oil should be similar to the cost share of oil, which was about 0.04 (see, e.g., Rotemberg and Woodford). Previous research has found a much larger elasticity.

Economists have proposed many explanations for the large effect, but there is little direct evidence.[3] Davis and Haltiwanger argue that adjustment costs amplify the effect of a price shock and reduce capital utilization. For example, the 1970s oil shocks increased the demand for small automobiles. Most manufacturers used equipment designed to produce large vehicles, and could not adjust the types of inputs they used, which caused capital utilization to decline. Bresnahan and Ramey (1993) support this argument with data from the automobile industry, but there is little evidence from other industries.

I provide an alternative explanation for the large effect of oil prices on value added, and present empirical evidence from across the manufacturing sector. I use a simple model, similar to Horvath (1998 and 2000), to argue that demand and supply linkages between industries can amplify an energy price shock.[4] I use data from the Census of Manufactures to show that these mechanisms significantly increase the effect of a shock on industry value added. In the remainder of the analysis I use plant data to investigate how energy prices affect individual

[1] Hamilton (1983) was one of the earliest, and most influential, studies that estimated this relationship using aggregate data. Subsequent work (e.g., Mork, 1989) argued that the effect is asymmetric; a price increase has a larger effect than a price decrease. More recent research (e.g., Hooker, 1996) has documented a decline in the effect of a price shock on GDP since the 1980s.

[2] Some authors have argued that this correlation may be spurious, or that oil prices affected GDP via monetary policy, particularly in the 1970s and 1980s. For example, Bernanke, Gertler and Watson (1997) argue that after controlling for changes in monetary policy, oil prices have a very small effect on GDP. Hamilton and Herrera (2004) have questioned their empirical analysis, concluding that Bernanke, Gertler and Watson understate the effect of a price shock on GDP.

[3] Rogoff (2006) summarizes much of the literature. Other proposed explanations include uncertainty (Bernanke, 1983 and Pindyck and Rotemberg, 1984); irreversable investment (Atketson and Kehoe, 1999); and the effect of oil prices on monetary policy, noted previously.

[4] Horvath (1998 and 2000) shows that input-output relationships among industries can amplify a small productivity shock. Computable general equilibrium models (e.g., Hanson *et al.*, 1993) also account for such linkages, but they usually provide little insight into the sources of amplification.

plants and generate the large aggregate effects, i.e., I ask whether energy prices affect entry, exit or average production per plant. I find that an energy price increase caused a large decline in average plant production and labor demand, but had a small effect on entry and exit; these results are consistent with the utilization argument of Davis and Haltiwanger.

More specifically, I focus on three mechanisms by which energy prices can affect industry level value added. First, the direct effect is the change in value added when an energy price increase raises energy costs. The direct effect is proportional to the cost share of energy, and should be small for the average industry.

Second, if an industry uses energy intensive materials, an increase in the price of energy may cause materials prices to rise. For example, because paper is energy intensive, an energy price increase causes the price of paper to rise. Publishing relies on paper, so the supply effect would cause the publishing industry to contract as well.[5] I refer to the supply effect as the change in value added for an industry, due to an energy price-induced change in materials prices. For a given industry, the supply effect increases with the energy intensity of its materials. The effect would be large if many industries rely on energy intensive inputs.

It is also possible that demand linkages amplify a price shock. If the output of an industry is used by energy intensive industries, the demand for its product may fall as the energy intensive industries contract. The demand effect increases with the average energy intensity of the other industries that use the industry's product. The demand effect would be large if energy intensive industries use materials produced by other industries.

This study estimates the importance of demand and supply linkages both at the industry and plant levels. I first document the strength of the direct, supply and demand effects in explaining variation in industry value added. I identify the three effects using cross-industry variation in input requirements and time series variation in the price of oil. For example, there is considerable variation in the energy intensity of industries' materials, which allows me to estimate the magnitude of the supply effect.

Using Census of Manufactures data from 1963-1982, I find that a one percent increase in the price of oil caused value added to decline by 0.07 percent for the average industry. This elasticity is about four times as large as the energy cost share in manufacturing, which is consistent with previous research. The supply effect accounts for about one half of the response of value added to a price shock. In other words, when the price of energy rises, industries that use energy intensive inputs experience a large decrease in value added. The demand effect is much smaller, which is consistent with supply and demand relationships across industries; energy intensive industries are

[5] It is possible that an energy price increase causes industries to substitute towards less energy intensive inputs, though this effect does not appear to be important.

important input suppliers to other industries, but use few manufacturing materials themselves.

There is very little evidence about how energy prices affect individual plants, in particular, whether energy prices affect entry, exit or average plant production. In the second part of the analysis, I use plant level data from the Census of Manufactures to investigate these possibilities. It appears that oil shocks mainly affected average plant production. The direct and supply effects caused similar changes in value added per plant as in value added per industry. By comparison, a price increase caused a small and precisely estimated decrease in entry, and had no effect on exit.

A reduction in value added should be associated with a reduction in inputs: labor, materials or energy. I further investigate the plant level response to an energy shock by estimating how input demands respond to the direct, supply and demand effects. I find that the direct and supply effects cause large reductions in production worker hours and wages, implying that the labor demand curve shifts towards the origin.

This paper expands on the work of Lee and Ni (2002). They define an oil-intensive industry as an industry that uses oil directly, or that uses materials with a large oil cost share. For example, the petroleum refining industry, which uses oil directly, and the industrial chemicals industry, which uses oil intensive materials, are both considered to be oil intensive. By estimating a vector autoregression (VAR) for fourteen roughly two digit manufacturing industries, they characterize the response over time to an oil shock. They find that a positive oil shock causes a contraction of oil-intensive industries, and they find large demand effects for some industries, such as automobiles.

This paper differs in several respects. First, I characterize the cross sectional response to an oil shock, rather than the dynamic response. Second, I quantify the importance of linkages between industries across the entire manufacturing sector. Third, I use plant data to investigate whether the aggregate effect is due to entry, exit or average production per plant.

## 2 Estimating the Effect of Supply and Demand Linkages

### 2.1 The Price of Energy, Linkages and Value Added

The model in this section highlights the importance of linkages between industries. The economy is composed of a set of industries, and each industry has a number of identical plants. There is one time period.

I partition the industries into two subsets. The first subset, $I$, consists of industries that produce intermediate goods used by other industries. The intermediate goods industries do not use other materials themselves. The second set, $J$, includes industries that produce final

goods. These industries demand the products from the first set of industries. Horvath (1998) uses a similar framework to demonstrate the importance of inter-industry linkages in amplifying a productivity shock.

I derive the supply curve of plants in final goods industry $j$. The industry has a fixed number of price-taking plants; the price of output is exogenous.[6] Each plant, $n$, produces output, $Y_{jn}$, from one unit of capital, $E_{jn}$ units of energy, and $M_{ijn}$ units of intermediate materials from industry $i$. The production function is Cobb Douglas:

$$\ln Y_{jn} = s_j^E \ln(E_{jn}) + \sum_{i \in I} s_{ij}^M \ln(M_{ijn}), \tag{1}$$

where $s_i^E$ and $s_{ij}^M$ are parameters. I assume that all firms in the industry have the same production function, and that $s_i^E + \sum_{i \in I} s_{ij}^M < 1$. I do not include labor in the production function for simplicity; the results are similar if labor is modeled as a variable input. In equation (1), capital is fixed, but the plant can smoothly adjust energy and materials. I relax these, and the Cobb-Douglas, assumptions in the empirical analysis.

Plants take prices as given and maximize profits by purchasing energy and materials:

$$\max_{E_{jn}, \{M_{ijn}\}_{i \in I}} p_j Y_{jn} - p^E E_{jn} - \sum_{i \in I} p_i M_{ijn} - R, \tag{2}$$

where $p_j$ is the output price for industry $j$ (i.e., the price of good $j$), $p^E$ is the price of energy and $R$ is the cost of capital. The first order conditions for input demands are the standard Cobb-Douglas equations, and the parameters $s_j^E$ and $s_{ij}^M$ are the cost shares of energy and materials. Using the first order conditions and equation (1), I obtain the following supply curve for each plant:

$$\ln Y_{jn} = -\frac{s_j^E}{r_j} \ln(P^E) - \sum_{i \in I} \frac{s_{ij}^M}{r_j} \ln(P_i) + k_j, \tag{3}$$

where $r_j = 1 - s_j^E - \sum_{i \in I} s_{ij}^M$; $P^E$ is the real price of energy for industry $j$, $p^E/p_j$; $P_i$ is the real price of material $i$, $p_i/p_j$; and $k_j$ is a constant that depends on parameters. Each plant's output is decreasing in real input prices. The elasticity of output with respect to the real price of energy is proportional to the cost share of energy, $s_j^E$. The elasticity of output with respect to the real price of material $i$ is proportional to the cost share of material $i$, $s_{ij}^M$.

Free entry in the intermediate goods industries determines the price of good $i$. Because these industries do not use goods produced by other industries, the price of intermediate good $i$ is

[6] The perfect competition and exogeneity assumptions simplify the analysis, but are not necessary to obtain the main results.

given by:

$$\ln p_i = s_i^E \ln(p^E) + k_i. \tag{4}$$

The elasticity of the price of good $i$ to the price of energy is equal to the industry's cost share of energy, $s_i^E$.

Combining equations (3) and (4) gives the supply curve for final good industry $j$, in terms of the real price of energy. To simplify the notation I define the supply elasticity for industry $j$, $S_j$, as: $S_j = \sum_i s_{ij}^M s_i^E$. The variable is the inner product of the materials cost share for good $i$ and the energy intensity of the material. The supply curve is given by:

$$\ln Y_{jn} = -\frac{1}{r_j} s_j^E \ln(P^E) - \frac{1}{r_j} S_j \ln(P^E) + k_j, \tag{5}$$

where the constant, $k_j$, has absorbed additional parameters. The equation shows two effects of the price of energy on output. The first term is the direct effect. Plants in energy intensive industries have lower output. The second term is the supply effect. Plants that use large amounts of energy intensive materials have a large value of $S_j$. These plants have higher materials costs, reducing output.

Equation (5) shows the effect of the price of energy on gross output per plant. I use equation (5) and the first order conditions for energy and materials to obtain an expression for value added, which excludes energy and materials:

$$\ln V_{jn} = B_1 s_j^E \ln(P^E) + B_2 S_j \ln(P^E) + k_j, \tag{6}$$

where $B_1$ and $B_2$ are nonlinear functions of the cost shares, and are constant. This equation is similar to the output equation, and shows two effects on value added: the direct effect, which is proportional to the industry's energy cost share, and the supply effect, which is proportional to the (weighted) average energy intensity of the industry's materials.

### 2.2 Estimation of the Direct, Supply and Demand Effects

Equation (6) characterizes value added per plant, and is the basis for the estimating equation. Because the number of plants is fixed in the model, industry output is a constant multiple of output per plant, and there is no demand effect. I add to this model an approximation of the demand effect that is analogous to the supply effect. In particular, I define the demand elasticity, $D_j$, as: $D_j = \sum_k s_{jk}^M s_k^E$. If an industry's output is used by energy intensive industries, the demand for that output should be relatively small.

I add the demand effect to obtain the value added of industry $j$ in year $t$, $V_{jt}$:

$$\ln V_{jt} = \beta_1 s_j^E \ln P_t^E + \beta_2 S_j \ln P_t^E + \beta_3 D_j \ln P_t^E + \iota_j + \tau_t + \varepsilon_{jt}, \tag{7}$$

where $\beta_1$, $\beta_2$ and $\beta_3$ are parameters, $P_t^E$ is the real price of oil in year $t$, $\iota_j$ is an industry specific intercept and $\tau_t$ is a year dummy.

Equation (7) is the baseline estimating equation, which I estimate by Ordinary Least Squares. The dependent variable is log real value added by industry and year. The year dummies control for aggregate shocks in a particular year. The industry dummies allow each industry to have a different intercept, absorbing industry-specific production parameters that do not vary over time, such as capital intensity, location and plant size.

The first three independent variables are the interactions of the price of oil with the direct, supply and demand elasticities ($s_j^E$, $S_j$, and $D_j$).[7] The variables are computed using cost shares and input-output relationships constructed from the Census of Manufactures, described in the next section. The interaction $s_j^E \ln P_t^E$ captures the effect of the price of oil on energy costs. The variable $S_j \ln P_t^E$ measures the effect of the price of oil on materials costs, and the third variable reflects energy price-induced changes in demand. I assume that these independent variables are uncorrelated with other time-varying variables, such as shocks to labor or capital demand; consequently, I omit other production inputs as control variables, because they may be endogenous. The exogeneity assumption is supported by the fact that adding the interactions of the price of oil with other industry characteristics does not affect the results.

I identify the direct, demand and supply effects using cross sectional variation in cost shares and time series variation in the price of oil. For example, there is considerable variation across industries in the energy intensity of their inputs. As a result, the supply effect varies across industries and over time. For reasons discussed below, I use the cost shares from the initial year of the sample to construct the variables $s_j^E$, $S_j$ and $D_j$.

The estimates of $\beta_1$, $\beta_2$ and $\beta_3$ quantify the relative importance of the three effects. I interpret $\beta_1 s^E$ as the average direct effect across industries, where $s^E$ is the average energy cost share. Similarly, $\beta_2 S$ and $\beta_3 D$ are the average supply and demand effects. As I show below, energy intensive industries were important input suppliers to other industries, but they did not consume many materials; this pattern suggests that the supply effect should be larger than the demand effect.

Equation (7) shows the relationship between aggregate (i.e., industry) value added and energy costs, materials costs and output demand. Any change in industry value added, however, arises

[7] I use the price of oil in the equation instead of an energy price index because the price of oil is more likely to be exogenous. The price of oil and other energy prices are highly correlated (Linn, 2006), and I obtain similar results using an industry by year energy price index.

from plant level responses: entry, exit or average production per plant. Furthermore, if plant output changes, input demands (i.e., labor, energy and materials) must also respond. The second part of the empirical analysis, described below, investigates the plant level responses.

This section concludes with a discussion of the measurement of the independent variables in equation (7) and potential omitted variable bias. There are several measurement issues. First, the estimated direct, supply and demand effects are first order approximations, derived from the model in section 2.1. I use several alternative measures of the independent variables, described below, to assess the robustness of the approximations. They allow for potential nonlinear relationships between inputs and output, and account for the fact that input demand elasticities may differ from one, as implied by the Cobb-Douglas production function. The main results are similar to the baseline estimates, which suggests that equation (7) is a reasonable approximation.[8]

Second, industry classification may introduce measurement error. I compute the variables in equation (7) by four digit industry and year. Plants in most four digit industries produce fairly homogeneous products. The degree of homogeneity may vary across industries, however, and the baseline regression could include cost shares calculated from a diverse set of plants in a given industry. This does not seem to be a significant source of bias, though, since I obtain similar results by restricting the analysis to plants that produce products classified in their own industry.[9]

Third, there may be measurement error due to changes in cost shares that are uncorrelated with energy prices. Since energy prices were relatively stable from 1963-1972, changes in cost shares during this period are probably uncorrelated with energy prices. By omitting the years 1963-1972 from the baseline regression, I would obtain larger estimates if random variation were a significant source of bias. Both the cost shares and the estimates are quite stable, however, suggesting that this is not a major concern.

Finally, the estimated effects may include indirect relationships among industries. For example, tire production (SIC 3011) uses synthetic rubber (SIC 2822), which requires petroleum products (SIC 2911). The estimate of $\beta_2$ accounts for both the effect of rubber prices on tire production, and the indirect effect of petroleum prices. That is, the empirical estimates of the three effects account for higher-order relationships between industries.

[8] The alternative independent variables do not directly address the possibility that input demand elasticities may not be constant, and may vary with the price of energy. In that case the estimates would be different in an alternative sample (e.g., post-1982), in which energy prices were different (Frondel and Schmidt, 2006). I interpret the baseline estimates as characterizing the average effect of an oil price increase on value added during the sample period.

[9] This approach addresses possible measurement error due to vertical integration, which would also cause plants in the same industry to produce different products.

I now discuss several approaches to address potential omitted variable bias. An important feature of equation (7) is that I use the 1963 cost shares to calculate the direct, supply and demand variables. I use the initial cost shares because the cost shares in later years may be affected by energy prices or omitted variables, such as shocks to labor or capital demand, causing biased or spurious results.

Price-induced technical change may have affected industries' cost shares. Linn (2006) documents considerable technology adoption in the early 1980s. If technical change were correlated with the initial cost shares, the results would be biased by an omitted variable. To reduce the likelihood of such bias, I estimate equation (7) for the years 1963-1982. I obtain similar results if I end the sample in 1977, but I prefer to include the second major oil shock at the end of the 1970s.

One of the main conclusions of the paper is that price-induced increases in materials prices (i.e., the supply effect) cause value added to decline. I estimate two additional regressions, similar to equation (7), to provide evidence against the possibility that the supply effect is driven by an omitted variable. I replace the dependent variable in equation (7) with the materials price of the industry. If the interpretation of $\beta_2$ is correct, the variable $S_j \ln P_t^E$ should be positively correlated with the average price of an industry's materials. This would not likely be the case if an omitted variable, correlated with the supply effect, were driving the results. In practice, I find that the variable $S_j \ln P_t^E$ is positively correlated with materials prices.

Because of data limitations, I cannot measure an external demand effect, from industries outside of the manufacturing sector and from consumers. The limitation is much smaller for the supply effect, which should accurately measure the effect of energy prices on materials prices. It is possible, however, that the omitted demand effect leads to a spurious estimate of the supply effect. If that were the case, the variable $S_j \ln P_t^E$ would be negatively correlated with the industry's output price. On the other hand, if $S_j \ln P_t^E$ measures the supply effect, the variable would be positively correlated with the price of output. As reported below, I find a positive correlation, suggesting that the results are not driven by an omitted demand variable.

Finally, some authors (e.g., Hamilton, 1996) have argued that because capital stock adjustment is lumpy, the response of value added to a price shock may be nonlinear and it may not be immediate. I investigate both of these issues below, and find some evidence for a nonlinear effect, but most of the effect appears to occur within about a year.

### 2.3 Entry and Exit

There are three ways the direct, supply or demand effect could reduce industry level value added: entry, exit or value added per plant. In the model in section 2.1, the number of plants in the industry is constant, an assumption I now relax.

I construct two variables to measure the effect of energy prices on entry and exit. The variable $EN_{jt}$ is the total value added in year $t$ of plants in industry $j$ that entered between the previous and current years. The variable $EX_{jt}$ is the value added of the plants that exited between the previous and current years. The entry variable measures the contribution of entry to the change in total industry value added; the exit variable measures the contribution of exit.

The logs of these variables are the dependent variables in the following two regressions:

$$\ln EN_{jt} = \delta_1 s_j^E \ln P_t^E + \delta_2 S_j \ln P_t^E + \delta_3 D_j \ln P_t^E + \iota_j + \tau_t + \eta_{jt}, \tag{8}$$

$$\ln EX_{jt} = \gamma_1 s_j^E \ln P_t^E + \gamma_2 S_j \ln P_t^E + \gamma_3 D_j \ln P_t^E + \iota_j + \tau_t + \nu_{jt}, \tag{9}$$

where $\{\delta_1, \delta_2, \delta_3\}$ and $\{\gamma_1, \gamma_2, \gamma_3\}$ are parameters to be estimated. Equations (8) and (9) have the same independent variables as equation (7). The three parameters in each equation correspond to the direct, supply and demand effects of the price of oil on entry and exit. Multiplying the parameters by the appropriate cost shares yields elasticities; for example, a one percent increase in the price of oil causes the value added of entrants to rise by $\delta_1 s^E$ percent, via the direct effect. To interpret these elasticities, however, the estimates must be scaled by the share of entry and exit in value added. The value added of entering and exiting plants is about 10 percent of total value added in the main sample. Thus, if the estimates of $\delta_1$, $\delta_2$ and $\delta_3$ imply that a one percent increase in the price of oil causes a 0.1 percent increase in the value added of exiting plants, this would correspond to a 0.01 percent decrease in total value added for the average industry.

### 2.4 Plant Value Added and Input Demands

An energy price shock could also affect average value added per plant. I estimate two types of plant level regressions. First, I estimate an equation similar to equation (7), where the sample includes a balanced panel of plants from 1963-1982. The dependent variable is log value added by plant and year, $V_{nt}$. The independent variables are the same as in equation (7), replacing the industry dummies with plant dummies:

$$\ln V_{nt} = \lambda_1 s_j^E \ln P_t^E + \lambda_2 S_j \ln P_t^E + \lambda_3 D_j \ln P_t^E + \nu_n + \tau_t + \omega_{nt}, \tag{10}$$

where $\nu_n$ is a plant fixed effect. The coefficients $\{\lambda_1, \lambda_2, \lambda_3\}$ are the estimates of the three effects on average value added per plant. These coefficients and the coefficients in equation (7) are directly comparable. A similarity would indicate that most of the effect of oil prices on value added occurs via average production per plant, rather than entry or exit. Note that because of the plant fixed effects in this equation, I do not include other control variables that are commonly used in plant level regressions, such as size, location, industry or ownership type (see, e.g., Dunne *et al.*, 1989).

Equation (10) shows the relationship between value added and energy costs, materials costs and demand. In order for these effects to reduce value added, they must also reduce input demands. In the second type of plant level regression, I investigate the response of labor, energy and materials to the three effects.

As mentioned above, it is possible that input demands and value added do not respond immediately to a price shock, and that the response may be nonlinear. These effects would cause both the plant and industry level results to be biased. In practice, however, the plant level results are similar to the industry level analysis. It appears that input demands respond within about a year and there is limited evidence for a nonlinear response, but the importance of the supply effect is robust.

## 3 Data and Variable Construction

### 3.1 Industry Value Added and Independent Variables

The data sources are the Census of Manufactures (CM), the Manufacturing Productivity Database (MPD) and the Department of Energy (DOE). I estimate equation (7) using a balanced panel of 427 industries. The dependent variable is log real value added by industry and year (1963 and every five years from 1967-1982), constructed from plant data in the CM. A plant's nominal value added is defined as total shipments, net of energy and materials expenditures. I aggregate across plants to calculate nominal value by four digit industry and year.[10] Real value added equals nominal value added divided by an industry specific value added deflator.[11]

The variable $P_t^E$ is the real price of oil in year $t$. The nominal oil price is the refiner acquisition cost of imported oil, obtained from the DOE.[12] The DOE used several surveys to collect the data from refineries, and the price is a national average. I use the imported price, which is plausibly

[10] As is customary with using plant data from the CM, I omit administrative records plants, for which most variables are imputed.

[11] I compute the value added deflator using industry specific gross shipments and materials deflators, and the Tornqvist approximation. I use the deflators in the MPD.

[12] The data is available from 1968-1997. I assume that the nominal price was constant from 1963-1968. Other measures of oil prices support this assumption. For example, the domestic first purchase price of crude oil increased by less than 2 percent over this time period.

exogenous to the U.S. economy for this time period (see Rotemberg and Woodford). I use an aggregate value added deflator for the manufacturing sector to calculate the real price of oil.[13]

The 1963 CM is the other data source for the independent variables. The energy cost share of each industry is the ratio of energy expenditure to shipments (using the same sample of plants as the value added calculation).[14]

I use the materials file in the 1963 CM to compute materials cost shares. The file contains detailed information about materials use, including each plant's expenditure by six digit product code. Using the same plants from the value added calculation, I compute the variable $M_{ij}$, which is the expenditure on good $i$ by plants in industry $j$. The variable is aggregated across industries and products to the four digit level. I divide $M_{ij}$ by the total output of industry $j$ in 1963 to obtain the cost share of material $i$, $s_{ij}^M$.

I compute the supply and demand variables in equation (7) by matching the energy cost share of industry $i$, $s_i^E$, with the corresponding cost share of material $i$ in the output of industry $j$, $s_{ij}^M$.[15] A few industries, such as ready-mix concrete (SIC 3273) primarily use one input (cement, SIC 3241), but most four digit industries use materials from multiple manufacturing industries.[16]

I check the robustness of the results by using four alternative measures of the independent variables. First, I use the energy cost share of the good that is the most important input to the industry. To compute the other three measures for industry $j$, I construct the set $\{M_{ij}\}_{i=1}^I$, where $M_{ij}$ is expenditure of industry $j$ on good $i$. I select the five industries with the largest values of $M_{ij}$ for industry $j$.[17] I compute three statistics: the mean, median and the maximum energy cost share of the five industries. I calculate the corresponding demand measures analogously.

Table 1 reports summary statistics. The first column of Panel A shows that the mean energy cost share is small, 0.015; the direct effect of an energy price shock should be relatively small.

The second and third columns show that energy intensive industries are important suppliers

[13] This specification is appropriate if the price of oil follows a random walk. The data supports this assumption during the sample period. I obtain similar results if I detrend the price of oil using an AR(2) specification instead of taking first differences.

[14] I use output, rather than costs, to compute the cost shares because there is not suitable data to measure capital costs at the plant or four digit industry level.

[15] I match the energy cost share, $s_j^E$, with the materials share of good $j$. Note that $s_j^E$ is the cost share of plants in industry $j$, which is not necessarily equal to the cost share required to produce good $j$. This could create measurement error if the energy cost share of industry $j$ is not equal to the cost share of producing good $j$, for example, if plants produce multiple goods. However, most plants in a given industry primarily produce products classified in the same industry, and in practice, the energy cost share should accurately measure the importance of energy in producing good $j$. I obtain similar results if I construct the independent variables using plants that produce products classified in their own industry, suggesting this is not a major concern (see Table 3).

[16] The coding of the industries and materials is not exactly the same, and in some cases the materials codes do not have a matching four digit industry code. In practice, I use the energy cost share of the least aggregated matching industry. For example, if I can match the material code to an industry code by the first three digits, I use the average energy cost share of plants in the corresponding three digit industry. Unfortunately, it is not possible to combine input-output tables from the Bureau of Economic Analysis to construct the independent variables.

[17] In the sample, the five most important materials comprise about 95 percent of total materials costs.

to other industries, but use few materials from other manufacturing industries. For each industry, I compute the fraction of output used as inputs by other manufacturing industries. The second column reports the correlation between this variable and the industry's energy cost share. This correlation is positive, 0.14, meaning that the output of energy intensive industries is more likely to be used as an input by other industries. For the third column I compute the correlation between an industry's energy cost share with the cost share of manufacturing materials. The correlation is negative, -0.18, which means that energy intensive industries use few manufacturing materials. These patterns suggest that the supply effect should be larger than the demand effect.

Panel B reports the five measures of the supply and demand elasticities. The first row shows the mean across industries of the baseline supply and demand elasticities, $S_j$ and $D_j$, with standard deviations in parentheses. The supply elasticity is larger than the demand elasticity, and there is considerable variation in both cases. The baseline supply elasticity is 0.0062 with a standard deviation of 0.0071, while the baseline demand measure is 0.0026 with standard deviation 0.0073 (note that the numbers in the table have been multiplied by 10 for clarity). Recalling the definitions of $S_j$ and $D_j$, this pattern reflects the correlations reported in Panel A.

The alternative measures of the supply and demand effects in Panel B show the same pattern. For example, the energy share of the primary industry (i.e., the most important material) is larger than the average energy cost share. Thus, energy intensive industries are more likely to be the primary input supplier. In comparison, the energy share of the most important demanding industry is smaller than the average energy intensity.

### 3.2 Entry, Exit and Plant Value Added Variables

The entry and exit equations ((8) and (9)) contain the same independent variables as equation (7). I measure the dependent variables, log entry and exit by industry and year, using plant identifiers that link observations over time.[18] An entrant in year $t$ is a plant that did not appear in the previous Census. For each industry and year I calculate the total value added of plants that entered between the previous and current Census years. I divide entrants' value added by the value added deflator in the current year to obtain the dependent variable in equation (8), $EN_{jt}$.

An exiting plant appeared in the previous Census but not in year $t$. I calculate $EX_{jt}$ as the total value added of plants that exit between the previous and current Census years, divided by the value added deflator from the previous Census.

Finally, the plant level regression, equation (10), is estimated using a balanced panel of

[18] More precisely, the plant identifiers are in the Longitudinal Research Database, which links the Census of Manufactures over time.

39,485 plants that report positive value added each Census year from 1963-1982. The dependent variable is log real value added by plant and year, equal to the log of nominal value added divided by the corresponding industry's value added deflator. I also calculate plant level measures of production worker hours, production worker real hourly wage, real energy consumption and materials use, and investment.[19]

## 4 Effect of a Price Shock on Industry Value Added

### 4.1 Baseline Estimates

Table 2 reports the estimates of the direct, supply and demand effects in equation (7). The sample includes a balanced panel of 427 four-digit industries, with observations each Census year from 1963-1982. The regression is estimated by OLS and all variables are in first differences. The dependent variable is log real value added by four digit industry and year. The independent variables are a full set of year dummies and the direct, supply and demand variables (taking first differences eliminates the industry dummies in equation (7)). The independent variables are computed using energy and materials costs shares in 1963.

Column 1 shows the baseline estimates.[20] Standard errors are in parentheses, clustered by industry. The estimate of $\beta_1$is -2.19 with standard error 0.58, which is significant at the 1 percent level. The mean cost share is 0.015, so a one percent increase in the price of oil caused value added to decrease by 0.03 percent in the average industry, holding materials prices and output demand constant.[21]

The estimate of $\beta_2$ is -4.89 with standard error 2.49, which is significant at the 5 percent level. The demand estimate, $\beta_3$, is much smaller, -0.68, and is not significant. The last two rows of the table quantify the relative importance of the three effects. The total effect of the price of oil on value added includes all three effects, using the reported coefficients and the sample means of the corresponding variables.[22] From 1963-1982, a one percent increase in the price of oil caused value added to fall by 0.07 percent, which is about four times larger than the average

[19] I use production workers instead of other labor categories because of data availability. The hourly wage is defined as total production worker hours divided by total production worker wages and the price of output. Real energy and materials use are calculated using reported expenditures and industry level deflators from the MPD. Investment is defined as the change in log machines, i.e., as the percent growth in the capital stock. This definition accounts for plants with zero investment (see, e.g., Greenstone, 2002).

[20] The low $R^2$ in these regressions is due to the first difference specification. The results are qualitatively similar and the $R^2$ is much larger, close to 0.9, using industry fixed effects instead of taking first differences. The estimates are also somewhat larger with first differences, but there may be some drift in the industry-specific constant terms. I focus on the first differenced estimates because they are more robust.

[21] The supply and demand effects for industry $j$ are computed by taking the inner product over all industries other than $j$. Some industries contain plants that use materials classified in the same industry. Consequently, $\beta_1$ measures the direct effect, plus the supply and demand effects from within the industry. However, these materials cost shares are typically small, and this should not greatly affect the estimate of $\beta_1$.

[22] I use the arithmetic means of the elasticity measures to calculate the total and supply effects. I obtain similar results if I use means weighted by value added.

energy cost share. It is difficult to compare this result with VAR estimates (e.g., Lee and Ni, 2002), but the magnitude reported in this paper appears to be broadly consistent.

The last row shows that the supply effect caused value added to decline by 0.03 percent when the price of oil increased by 1 percent. The supply effect explains about one half of the total effect of a price shock, which is consistent with the fact that energy intensive industries were important input suppliers.

### 4.2 Measurement of the Independent Variables

I discuss several approaches to check the robustness of the supply and demand elasticities, $S_j$ and $D_j$, and to assess whether measurement error is biasing the estimated coefficients. The results are fairly similar using different measures of the independent variables, and measurement error does not appear to be a significant source of bias.

Recall that the independent variables, $s_j^E$, $S_j$ and $D_j$, approximate the effect of the price of energy on energy costs, materials costs and demand. I consider column 1 of Table 2 to be the baseline, and I check the robustness of the approximations by using four alternative measures of materials costs and demand, in place of $S_j$ and $D_j$. Column 2 uses the energy cost share of the industry that is the largest supplier of intermediate materials, or the largest user of the industry's output. Column 3 uses the mean energy cost share of the five most important supplying and demanding industries. Column 4 uses the median energy cost share of the five industries and column 5 uses the largest energy cost share of the five industries.

The estimates of $\beta_1$ in columns 2-5 are between negative one and negative two, and are statistically significant. The different magnitudes of $\beta_2$ partially reflect the different normalizations of the independent variables. The estimates of the supply effect, reported at the bottom of the table, vary somewhat, but in all specifications the supply effect explains a substantial share of the total effect. The demand effect is not significant in any of the specifications.

I next argue that measurement error, arising from fluctuations in cost shares that are uncorrelated with energy prices, probably does not bias the estimates. Energy and materials prices were relatively stable from 1963-1972. Consequently, changes in energy or materials cost shares during this period would likely be due to measurement error or other random sources of variation, which are uncorrelated with prices.

Figure 1 shows that such fluctuations were relatively small. In Figure 1 I plot the percent change of each industry's energy cost share between 1963 and 1972 versus the initial value in 1963.[23] The figure shows that there was little change in the energy cost share, and that the

[23] Due to confidentiality concerns, I cannot report the data points for all 427 industries in the sample. Figure

change was not correlated with the initial level. The coefficient in a univariate regression of the percent change on the initial cost share is small and is not significantly different from zero.

The results in column 1 of Table 3 support this conclusion. If random variation of the cost shares were biasing the results, I would obtain different estimates by omitting the years 1963 and 1967 from the estimation model. I obtain similar results using data from 1972-1982, which suggests that measurement error is not a significant concern.

Because an industry may include plants that produce a heterogenous mix of products, industry classification is another potential source of measurement error. For example, many sausage plants (SIC 2013) produce products of the meat packing industry (SIC 2011), possibly creating measurement error for the independent variables of either industry. As a specification check I compute the direct, supply and demand measures using plants that produce one product (i.e., plants for which at least 95 percent of output includes a product from the same four digit industry). The results in column 2 are similar to the baseline.

By using energy cost shares in the baseline specification, I am assuming that oil prices are highly correlated with other energy prices. If they are not, the estimated effect of an energy price shock could be biased. Consequently, it may be more appropriate to use oil and natural gas cost shares in place of the energy shares. I compute the oil/gas shares by four digit industry from the 1977 Annual Survey of Manufacturers (ASM) Fuel Supplement.[24] The direct effect in column 3 is close to the baseline estimate. The estimate of $\beta_2$ is larger, but this is due to the different scales of the supply measures. The last row of the table shows that the supply effect is similar to the baseline. The demand effect is larger than the baseline, and is significant at the 5 percent level. This suggests that measurement error may bias the demand estimate towards zero in the baseline specification. The demand effect is much smaller than the supply effect in column 3, however, supporting the conclusion that the supply effect was more important than the demand effect in U.S. manufacturing.

### 4.3 Potential Omitted Variables

This section discusses several specifications, which show that omitted variables are unlikely to be causing biased or spurious estimates of the supply effect. I first estimate the following equation:

$$\ln P_{jt}^{M} = \phi_1 s_j^E \ln P_t^E + \phi_2 S_j \ln P_t^E + \phi_3 D_j \ln P_t^E + \iota_j + \tau_t + \varepsilon_{jt}. \tag{11}$$

1 includes 164 industries with at least 25 firms. The subsample of industries that meet the disclosure criteria is representative; the pattern is quite similar using the full sample of industries.

[24] I use the oil/gas cost share because natural gas and oil prices are highly correlated and because manufacturing industries use much more natural gas than oil (Linn, 2006). The necessary data is not available to compute oil/gas cost shares in 1963.

The dependent variable is the log average materials price for industry $j$ in year $t$, and the independent variables are the same as in equation (7). In equation (7) the parameter $\beta_2$ captures the effect of materials prices on value added. If this interpretation is correct, in equation (11) the coefficient on the variable $S_j \ln P_t^E$, $\phi_2$, should be positive. On the other hand, the coefficient may be zero or negative if an omitted variable were correlated with $S_j \ln P_t^E$ and were driving the results. The estimate of $\phi_2$ is 3.55 with standard error 0.57, supporting the interpretation of $\beta_2$ as measuring the importance of oil price-induced changes in materials prices.

Due to data limitations, there is an omitted demand effect. If the omitted variable were causing a spurious estimate of the supply effect, I would likely find a negative correlation between $S_j \ln P_t^E$ and the price of output. I re-estimate equation (11), using the average log output price for industry $j$ in year $t$ as the dependent variable. The results provide evidence against a spurious supply effect. The estimate of $\phi_2$ is positive, 3.10, with standard error 1.59.

Transportation costs represent a potential source of omitted variable bias. Manufacturing industries rely on a variety of energy intensive forms of transportation. If industries with a high measure of $S_j$ or $D_j$ also have high transportation costs, the estimates could be biased.

I use the 1993 Commodity Flow Survey to construct two transportation cost variables.[25] I first compute a demand measure of transportation costs. Industries that ship their output over large distances have a relatively high average shipping cost. An oil price increase would raise shipping costs and reduce the demand for the industry's output. As a proxy for shipping costs, I compute the number of ton-miles of goods shipped via trucking for each industry, divided by the industry's output.[26]

The second transportation measure is the supply effect of transportation costs. During a price shock, industries that rely on materials shipped by trucks would experience a large change in the delivered price of those materials. For a given industry, I compute the weighted average shipping cost of its inputs, using the corresponding input cost shares ($s_{ij}^M$) as weights. I add to equation (7) the interactions of both transportation variables with the log real price of oil.

Column 4 in Table 3 shows that including these variables does not affect the results. The coefficients on the transportation variables (not reported) are negative, indicating that an energy price increase raises transportation costs and reduces value added.[27] The estimates reported in

[25] The data are available at the three digit level. It would be preferable to use transportation data from the beginning of the sample or before the major oil price shocks, but the data is not available. The 1993 Commodity Flow Survey can be found at: www.census.gov/prod/2/trans/93comflo/. The Census of Manufactures does not contain data sufficient for measuring transportation costs.

[26] I focus on trucking because it is a relatively oil intensive form of transportation. I obtain similar results using other measures of transportation costs.

[27] I do not report the estimates of the transportation variables in the text because they are probably measured with error; nonetheless, they should be correlated with actual transportation costs, and be sufficient for addressing concerns about omitted variable bias. The estimate of the supply transportation measure is large and significant,

Table 3 are close to the baseline, suggesting that the independent variables are not highly correlated with transportation costs.

The baseline specification assumes that all inputs except capital adjust to an oil shock within one year, and that the relationship between the log price of oil and log value added is linear. The first assumption may not hold in practice, for example, if an oil shock occurs near the end of the year. I can investigate this possibility by using the one year lag oil price in place of the current price. It is difficult to reach a strong conclusion with this specification, however, because the current and lagged are highly correlated. Nevertheless, I would be concerned if the estimates with the one year lag are much larger than the baseline. In column 5, they are quite similar to the baseline.[28] The estimates are smaller using the two year lag price (not reported), so there is no evidence that the effect of an oil shock is delayed by more than one year.

Furthermore, lumpy investment may cause the effects of the price of oil to be nonlinear. To address this issue, I calculate the 90th percentile of the direct, supply and demand elasticities ($s_j^E$, $S_j$, and $D_j$). I construct three indicator variables, equal to one if the industry is above the 90th percentile for the particular measure. I add to the baseline specification the interaction of these indicator variables with the price of oil (not reported). This specification allows industries that use large amounts of energy intensive materials, for example, to have a different response to an oil shock than other industries. These interactions are positive, and the estimates of $\beta_1$ and $\beta_2$ are somewhat larger than the baseline; for example, the estimate of $\beta_2$ is -8.57. These estimates provide some evidence that the relationship between the price of oil and value added may be nonlinear. The estimated total effect and supply effects are -0.07 and -0.04, as in the baseline specification, however, and the conclusion that the supply effect explains much of the response of value added is robust; I continue to use the linear specification as an approximation.

In the baseline specification I assume that the price of oil and the industry's 1963 cost shares are uncorrelated with other shocks to input demands (e.g., labor-biased technical change). Such shocks would likely be correlated with industry characteristics, such as labor or capital cost shares. Columns 6 and 7 include the interactions of the price of oil with the industry's initial labor cost share and capital cost share.[29] The estimates are similar to the baseline, though the supply effect is somewhat smaller in column 7. The same conclusion holds when including other industry characteristics, such as plant size and region (not reported).

while the demand measure is also negative, but is smaller and insignificant.

[28] The correlation between the current and lag prices prevents me from estimating a specification with both prices. Consequently, it is difficult to compare these results with previous VAR estimates, which often show that the peak response follows about one year after the initial shock.

[29] As noted earlier, I cannot directly measure capital costs. I define the capital cost share as $1 - s_j^L - s_j^E - s_j^M$, where $s_j^L$ and $s_j^M$ are the cost shares of labor and materials for industry $j$.

As a specification check, I replace the dependent variable with log gross output by industry and year, which may be a more appropriate measure of industry level output. In column 8, the magnitudes are similar to the baseline. I prefer the value added specification because the primary motivation of the paper is to explain the response of total value added to an oil shock.

Finally, because of data limitations, the regressions include observations from Census years, which are roughly every five years. I do not use ASM data to estimate value added in the intervening years for two reasons. First, the estimates would be less precise than the Census measures. Second, it is not possible to measure entry, exit or value added per plant for each year from 1963-1982. Consequently, I focus on the industry level results from Census years for comparability with the plant results, which are discussed below. The drawback to this approach is that taking first differences over the five year intervals may mean that the baseline estimates include medium-term effects of the price of oil on value added, in addition to short term effects. In the last two columns of Table 3 I use value added data from the MPD to show that this does not appear to be the case. To compare with the results using annual data, in column 9 I use the MPD data from Census years. The results are quite similar to the baseline. In column 10 I use data from the MPD for every year from 1963-1982, and the results are nearly identical to those in column 9.[30]

## 5 Plant Level Results

### 5.1 Effect of a Price Shock on Entry and Exit

Changes in industry level value added could be due to entry, exit or to changes in average value added per plant. I first show that the price of oil had little effect on entry and exit.

Tables 4 and 5 report the estimates of equations (8) and (9), which characterize the direct, supply and demand effects on entry and exit. The dependent variables are the log real value added of plants entering or exiting between the previous and current Census years. The regressions include the same independent variables as the corresponding columns in Table 2.

The coefficients capture the importance of the three effects on entry and exit. To interpret the magnitudes, it is necessary to account for the fact that the value added of entering and exiting plants is about 10 percent of total industry value added. Thus, if the entire effect of oil prices on value added were due to entry and exit, the coefficients in Tables 4 and 5 would be about 10 (1/0.1) times larger than the coefficients in Table 2. The reported total and supply effects at the bottom of Tables 4 and 5 include this correction.

[30] Because there is much less annual variation in the price of oil, I do not estimate equation (7) by taking first differences, but instead I include industry fixed effects. As noted earlier, the fixed effects results are similar to those in Table 2 for the baseline sample, so this should not be a major concern.

Table 4 shows that entry does not explain much of the effect of oil prices on value added. The direct and supply estimates are negative and significant in column 1. The total effect implies that a one percent price increase caused industry value added to fall by 0.015 percent due to the reduction in entry. This is about 20 percent of the total effect on industry value added reported in Table 2; the standard errors imply that I can reject the hypothesis of large entry effects.

There is no evidence in Table 5 that a price increase caused an increase in exit. As the last two rows show, the data rejects the hypothesis of a large effect of exit on industry value added.[31]

### 5.2 Effect of a Price Shock on Average Value Added Per Plant

Table 6 reports the estimates of equation (10) using plant level data. The results suggest that oil shocks had large effects on average value added per plant.

The independent variables are the same as in Table 2, but observations are at the plant level. The sample includes a balanced panel of plants that appear in every Census from 1963-1982. The dependent variable is log real value added. The coefficients are directly comparable to Table 2; a close similarity would suggest that the price of oil mainly affected average output per plant.

The estimates are, in fact, similar to the results in Table 2. In column 1 the direct and supply effects are negative and significant. The total effect of a one percent price increase on value added is about -0.07, and the supply effect is -0.04. The corresponding estimates in Table 2 were -0.07 and -0.03, suggesting that most of the effect of a price shock on total value added is due to changes in plant level production. The other measures for $S_j$ and $D_j$ in Table 6 yield the same conclusion.[32]

Because I estimate equation (10) using first differences, I do not include plant-specific characteristics that do not vary over time, e.g. age or initial size. It is possible, however, that there were plant specific shocks during the sample period that were correlated with the independent variables. To address this concern, I have estimated a number of alternative specifications to equation (10), analogous to those shown in Table 3. I do not report them due to space considerations, but the results are robust to interacting other plant-level characteristics (e.g., capital intensity) with the price of energy, using gross output as the dependent variable, using the lag price of oil or allowing for nonlinear effects.

The results suggest that an increase in the price of oil caused average value added per plant

[31] The results are similar if I use the lagged price of oil instead of the current price, which allows for delayed entry or exit responses.

[32] As another check for measurement error, I construct the direct and supply variables at the plant level (it is not possible to construct a plant-specific demand variable). For the direct effect, I use the plant's energy cost share in 1963. I measure the supply variable similarly to equation (7), except that I use the plant's materials cost shares in 1963, instead of the cost shares of the corresponding industry. I obtain smaller estimates than the baseline, though the supply effect explains a comparable fraction of the total variation of value added.

to decline because of the direct and supply effects. In contrast, oil shocks had little effect on entry and exit. This conclusion is consistent with other authors (e.g., Davis and Haltiwanger, 2001), who have argued that an oil price increase causes capital utilization to decline.[33]

### 5.3 Effect of a Price Shock on Input Demands

Finally, I estimate the response of labor, energy and materials demands to an oil shock. I estimate an equation similar to (10), using four alternative dependent variables: log production worker hours, log production worker hourly wage, log energy use and log materials use. Table 7 reports the results of these specifications, showing estimates from using either the current or one year lag oil price; the latter allows for a delayed response of input demands to an oil shock.

The results show that the direct and supply effects cause input use and the real wage to decline. It appears that plants respond to a price shock within one year, as the effects are at least as large using the current price.[34]

## 6 Conclusion

This paper quantifies the importance of demand and supply linkages between industries, arguing that supply linkages in particular can help explain the large effect of oil prices on value added. Energy intensive manufacturing industries are major input suppliers to other industries. Using data from 1963-1982, I find that an oil price increase caused energy intensive industries to contract, raising materials prices and causing other industries to contract. This supply effect was economically and statistically significant in explaining variation in industry value added. In contrast, I find little evidence that demand shocks from within the U.S. manufacturing sector played an important role.

Oil shocks primarily affected average production per plant, rather than entry and exit. The direct and supply effects caused similar changes in value added per plant as value added per industry. There is no evidence that entry and exit responded by economically significant amounts to a price shock. A price increase caused a small, though statistically significant, decrease in entry, and had no effect on exit. Finally, the direct and supply effects appear to have reduced input demands and wages. These results are consistent with the argument that energy prices have large effects on capital utilization, but additional research is needed in this area.

[33] Because of data limitations there is little direct empirical work on capital utilization. Barsky and Killian (2002) argue that the existing evidence implies a small effect of energy prices on utilization, because capital rental rates are not correlated with oil prices.

[34] I have also investigated the response of investment to a price shock. The LRD investment data is fairly limited, and I do not report the results, but there is some evidence that the direct and supply effects cause a reduction in investment.

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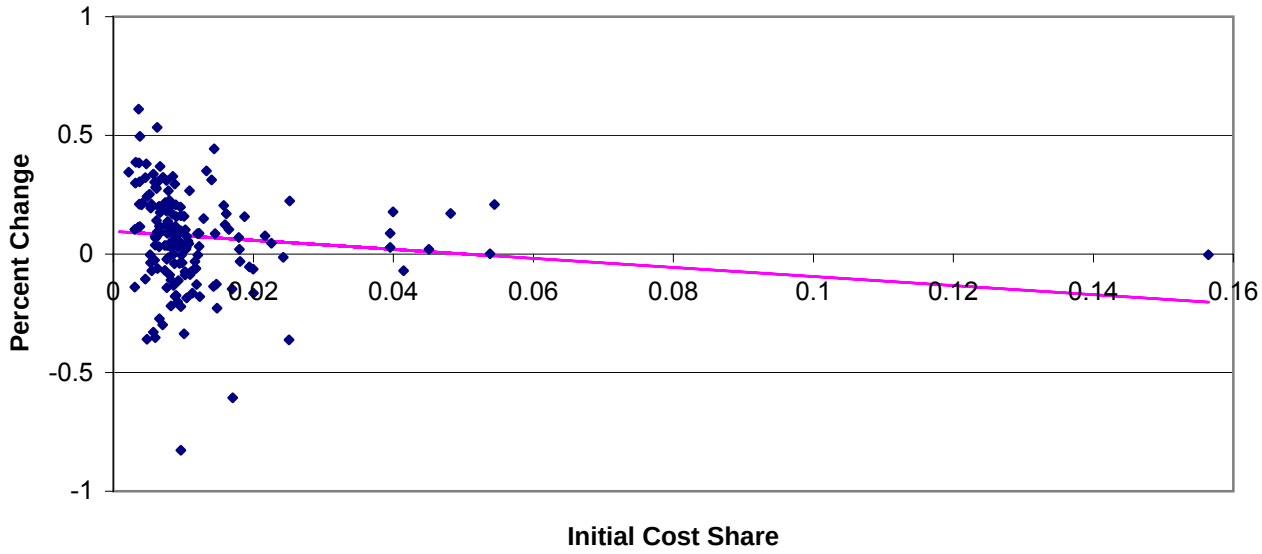
**Figure 1: Percent Change of Energy Cost Share vs. Initial Cost Share, 1963 - 1972**




Notes: The figure plots the percent change in energy cost share from 1963-1972 against the energy cost share in 1963 for each industry, computed from the Census of Manufactures (see text). The line shows the predicted values from an OLS regression of the percent change on the initial cost share.

Table 1:

## Summary Statistics: Energy Cost Share and Supply and Demand Elasticities

| | (1) | (2) | (3) |
|---|---|---|---|
| | | Panel A | |
| | Energy Cost Share | Correlation of Energy Share with Use as Material | Correlation of Energy Share with Materials Share |
| | 0.015<br>(0.020) | 0.144 | -0.184 |
| | | Panel B | |
| | Supply Elasticity | | Demand Elasticity |
| Inner Product Using Energy Share (x 10) | 0.062<br>(0.071) | | 0.026<br>(0.073) |
| Energy Share of Primary Industry | 0.035<br>(0.026) | | 0.011<br>(0.015) |
| Mean Energy Share | 0.032<br>(0.015) | | 0.014<br>(0.013) |
| Median Energy Share | 0.028<br>(0.015) | | 0.011<br>(0.010) |
| Maximum Energy Share | 0.060<br>(0.031) | | 0.030<br>(0.035) |

Notes: All variables are computed from plant data from the 1963 Census of Manufactures, for the sample of 427 four digit industries. Columns 2 and 3 of Panel A report correlations across industries. All other cells report means across industries, with standard devations in parentheses. Energy cost share is the ratio of total energy expenditure to total shipments by industry. Column 1 of Panel A reports the energy cost share. Use as material is the share of an industry's output used as inputs by other manufacturing industries. The second column in Panel A reports the correlation of an industry's energy cost share with the industry's use as material. Materials share is the share of manufacturing inputs in total costs. The third column in Panel A reports the correlation of this variable with the industry's energy cost share. In Panel B, the supply elasticity inner product using energy share is the inner product of the materials share of the supplying industry with the corresponding energy cost share, multiplied by 10. The supply elasticity energy share of primary industry is the energy cost share of the supplying industry with the largest share in materials costs. The supply elasticity mean energy share is the mean energy cost share of the five industries accounting for the largest shares in materials costs. The supply elasticity median energy share is the median energy cost share of the five industries. The supply elasticity maximimum energy share is the largest energy cost share of the same five industries. The demand elasticities in Panel B are computed similarly, using the share of the industry's output in the total cost of the demanding industry. See text for details.

Table 2:

## Effect of an Energy Price Shock on Industry Value Added, 1963-1982

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Inner Product Using Energy Share | Energy Share of Primary Industry | Mean Energy Share | Median Energy Share | Maximum Energy Share |
| | Dependent Variable: Log Real Value Added | | | | |
| Direct Elasticity x Oil Price | -2.19<br>(0.58) | -1.98<br>(0.55) | -1.45<br>(0.59) | -1.43<br>(0.63) | -1.92<br>(0.57) |
| Supply Elasticity x Oil Price | -4.89<br>(2.49) | -1.03<br>(0.67) | -2.36<br>(1.27) | -3.16<br>(1.29) | -0.34<br>(0.53) |
| Demand Elasticity x Oil Price | -0.68<br>(1.51) | 0.34<br>(0.84) | -0.06<br>(1.25) | 0.56<br>(1.54) | -0.21<br>(0.47) |
| $R^2$ | 0.04 | 0.03 | 0.04 | 0.04 | 0.03 |
| Number of Observations | 1,708 | 1,708 | 1,708 | 1,708 | 1,708 |
| Total Effect | -0.066<br>(0.020) | -0.063<br>(0.025) | -0.098<br>(0.040) | -0.103<br>(0.036) | -0.056<br>(0.032) |
| Supply Effect | -0.030<br>(0.015) | -0.037<br>(0.024) | -0.074<br>(0.040) | -0.087<br>(0.036) | -0.021<br>(0.032) |

Notes: The table reports the results of estimating equation (7) by Ordinary Least Squares (OLS). Standard errors are in parentheses, clustered by industry. The sample includes a balanced panel of 427 four digit industries. All regressions include year dummies and all variables are in first differences. All deflators are constructed from the Manufacturing Productivity Database (MPD). The dependent variable is the log of real value added by four digit industry and year, computed from the Census of Manufactures and the MPD. The log real price of oil is the log of the imported price of oil, obtained from the Department of Energy, divided by the sector-wide value added deflator. Energy cost share is defined as in Table 1. All columns include the interaction of the energy cost share and the log real price of oil. Regressions use the supply and demand elasticities indicated in the column headings, computed as in Table 1. The regressions include the interactions of these variables with the log real price of oil. Total effect is the percent change in real value added caused by a one percent increase in the real price of oil, using the estimated coefficients and the mean values of the corresponding elasticities. Supply effect reports the percent change in value added due to the supply effect, using the estimate of $\beta_2$ and the mean of the supply elasticity.

Table 3:

## Alternative Specifications

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sample Includes 1972-1982 | Indep Vars Use Single Product Plants | Indep Vars Use Oil/Gas Share | Control For Transport Costs | Use One Year Lag Oil Price | Control for Labor Cost Share | Control for Capital Cost Share | Dep Var Is Log Gross Output | MPD Value Added For Census Years | MPD Value Added For All Years |
| Direct Elasticity x Oil Price | -2.26 | -2.02 | -2.48 | -1.88 | -2.21 | -2.25 | -2.43 | -1.66 | -3.20 | -2.29 |
| | (0.58) | (0.52) | (0.66) | (0.78) | (0.55) | (0.60) | (0.57) | (0.53) | (0.82) | (0.65) |
| Supply Elasticity x Oil Price | -5.30 | -4.68 | -9.75 | -4.03 | -5.74 | -4.57 | -3.51 | -5.07 | -6.12 | -4.16 |
| | (2.47) | (2.13) | (1.96) | (2.52) | (2.33) | (2.48) | (2.57) | (1.95) | (2.76) | (2.52) |
| Demand Elasticity x Oil Price | -0.69 | -0.50 | -3.71 | 0.33 | -0.58 | 0.12 | -0.26 | 0.65 | -1.67 | -0.91 |
| | (1.52) | (1.51) | (1.87) | (1.71) | (1.37) | (1.63) | (1.48) | (1.35) | (1.59) | (1.56) |
| $R^2$ | 0.02 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.06 | 0.91 | 0.92 |
| Number of Observations | 810 | 1,708 | 1,708 | 1,556 | | 1,708 | 1,708 | 1,708 | 1,708 | 8,540 |
| Total Effect | -0.070 | -0.068 | -0.055 | -0.053 | -0.071 | -0.063 | -0.060 | -0.055 | -0.092 | -0.064 |
| | (0.020) | (0.019) | (0.010) | (0.020) | (0.019) | (0.020) | (0.020) | (0.016) | (0.023) | (0.020) |
| Supply Effect | -0.033 | -0.030 | -0.023 | -0.025 | -0.036 | -0.028 | -0.022 | -0.032 | -0.038 | -0.026 |
| | (0.015) | (0.014) | (0.005) | (0.016) | (0.014) | (0.015) | (0.016) | (0.012) | (0.017) | (0.016) |

Notes: Standard errors are in parentheses, clustered by industry. All regressions are estimated by OLS and the dependent variable is log real value added, except in column 8 where it is log gross output. In columns 1-8 all variables are in first differences. All columns include a full set of year dummies, and columns 9 and 10 include industry fixed effects. The sample of industries is the same as in Table 2 for columns 2-8. Column 1 includes observations from 1972-1982. Column 9 uses value added by industry from the MPD, and includes a balanced panel of industries for the same years as in Table 2. Column 10 uses observations from the MPD for each year from 1963 - 1982. Energy cost share, upstream share, downstream share and real price of oil variables are constructed as in column 1 of Table 2 for columns 1, 4 and 6-10. In column 2 the independent variables are constructed from plants that produce products classified in their primary industry. Column 3 uses oil/gas cost shares computed from the 1977 Annual Survey of Manufactures in place of energy cost shares. Column 5 uses the one year lag price of oil in place of the current price of oil to construct the independent variables. Column 4 includes the interaction of the log price of oil with the supply and demand transportation measures. Column 6 includes the interaction of the industry's 1963 labor cost share with the price of oil and column 7 includes the interaction of the industry's 1963 capital cost share with the price of oil. The total and supply effects are computed as in Table 2. See text for details.

Table 4:

## Effect of a Price Shock on Entry, 1967-1982

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Inner Product Using Energy Share | Energy Share of Primary Industry | Mean Energy Share | Median Energy Share | Maximum Energy Share |
| | | | Dependent Variable: Log Entry | | |
| Direct Elasticity x Oil Price | -2.18<br>(0.89) | -1.90<br>(0.94) | -0.75<br>(1.00) | -0.85<br>(1.06) | -1.22<br>(0.95) |
| Supply Elasticity x Oil Price | -9.56<br>(2.85) | -0.91<br>(0.98) | -5.38<br>(1.76) | -5.57<br>(1.76) | -2.16<br>(0.79) |
| Demand Elasticity x Oil Price | -4.72<br>(2.91) | -0.71<br>(1.31) | 0.21<br>(1.70) | 0.06<br>(2.39) | 0.22<br>(0.62) |
| $R^2$ | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 |
| Number of Observations | 1,233 | 1,233 | 1,233 | 1,233 | 1,233 |
| Total Effect | -0.015<br>(0.003) | -0.010<br>(0.005) | -0.025<br>(0.008) | -0.023<br>(0.007) | -0.020<br>(0.007) |
| Supply Effect | -0.008<br>(0.002) | -0.005<br>(0.005) | -0.024<br>(0.008) | -0.022<br>(0.007) | -0.018<br>(0.007) |

Notes to Tables 4 and 5: Table 4 reports the results of estimating equation (8) and Table 5 reports the results of estimating equation (9). Standard errors are in parentheses, clustered by industry. All regressions are estimated by OLS and include year dummies. All variables are in first differences. Entry and exit variables are constructed from the Census of Manufactures, 1963-1982. The sample incudes a balanced panel of industries with at least one entrant and one exiting plant for each Census year. The dependent variable in Table 4 is the log real value added of entrants by industry, between the previous and current Census years. The dependent variable in Table 5 is the log real value added of plants exiting between the previous and current Census years. The regressions include the same independent variables as Table 2, and the total and supply effects are computed similarly to Table 2, accounting for the average shares of entry and exit in industry value added (see text).

Table 5:

## Effect of a Price Shock on Exit, 1967-1982

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Inner Product Using Energy Share | Energy Share of Primary Industry | Mean Energy Share | Median Energy Share | Maximum Energy Share |
| | | | Dependent Variable: Log Exit | | |
| Direct Elasticity x Oil Price | 0.52<br>(1.38) | 1.12<br>(1.41) | 0.99<br>(1.43) | 1.59<br>(1.46) | 0.15<br>(1.36) |
| Supply Elasticity x Oil Price | -2.58<br>(4.33) | -1.46<br>(1.20) | -4.84<br>(2.21) | -6.41<br>(2.11) | -0.87<br>(1.02) |
| Demand Elasticity x Oil Price | -8.90<br>(3.54) | -3.23<br>(2.01) | 2.15<br>(2.20) | 0.56<br>(3.11) | 0.92<br>(0.79) |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.10 |
| Number of Observations | 1,233 | 1,233 | 1,233 | 1,233 | 1,233 |
| Total Effect | -0.003<br>(0.003) | -0.007<br>(0.004) | -0.010<br>(0.006) | -0.014<br>(0.005) | -0.002<br>(0.006) |
| Supply Effect | -0.001<br>(0.003) | -0.005<br>(0.004) | -0.014<br>(0.007) | -0.017<br>(0.005) | -0.005<br>(0.006) |

Table 6:

## Effect of a Price Shock on Plant Value Added, 1963-1982

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Inner Product Using Energy Share | Energy Share of Primary Industry | Mean Energy Share | Median Energy Share | Maximum Energy Share |
| | Dependent Variable: Log Real Value Added | | | | |
| Direct Elasticity x Oil Price | -2.08<br>(0.54) | -1.73<br>(0.53) | -0.82<br>(0.52) | -0.87<br>(0.47) | -1.10<br>(0.46) |
| Supply Elasticity x Oil Price | -5.66<br>(2.29) | -1.32<br>(0.45) | -3.76<br>(1.01) | -3.62<br>(0.95) | -1.39<br>(0.47) |
| Demand Elasticity x Oil Price | 0.91<br>(1.96) | 0.51<br>(0.34) | 0.28<br>(0.76) | -0.08<br>(0.80) | 0.02<br>(0.27) |
| $R^2$ | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Number of Observations | 157,940 | 157,940 | 157,940 | 157,940 | 157,940 |
| Total Effect | -0.072<br>(0.020) | -0.072<br>(0.020) | -0.132<br>(0.033) | -0.119<br>(0.026) | -0.104<br>(0.031) |
| Supply Effect | -0.042<br>(0.017) | -0.051<br>(0.017) | -0.123<br>(0.033) | -0.104<br>(0.027) | -0.088<br>(0.030) |

Notes: Table 6 reports the results of estimating equation (10) by OLS. Standard errors are in parentheses, clustered by industry. All regressions include year dummies and all variables are in first differences. The sample includes a balanced panel of plants with positive value added in all Census years from 1963-1982. The dependent variable is the log of real value added for each plant and year. The regressions include the same independent variables as in Table 2. The total and supply effects are computed as in Table 2.

Table 7:

## Effect of a Price Shock on Plant Input Demands, 1963-1982

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Log Production Worker Hours, Current Oil Price | Log Production Worker Hours, Lag Oil Price | Log Production Worker Wage, Current Oil Price | Log Production Worker Wage, Lag Oil Price | Log Energy Use, Current Oil Price | Log Energy Use, Lag Oil Price | Log Materials Use, Current Oil Price | Log Materials Use, Lag Oil Price |
| Direct Elasticity x Oil Price | -0.59 | -0.64 | -0.83 | 0.39 | -1.33 | -0.87 | -1.08 | 0.55 |
| | (0.33) | (0.55) | (0.23) | (0.43) | (0.32) | (0.80) | (0.93) | (1.59) |
| Supply Elasticity x Oil Price | -2.88 | -0.83 | -1.96 | -0.65 | -3.99 | 1.58 | -4.40 | -0.02 |
| | (1.23) | (1.58) | (1.05) | (1.14) | (1.94) | (2.10) | (1.02) | (2.73) |
| Demand Elasticity x Oil Price | 0.61 | 0.17 | -0.42 | -0.74 | -1.60 | 1.27 | 0.52 | 2.86 |
| | (0.72) | (1.23) | (1.33) | (1.00) | (1.42) | (2.49) | (1.05) | (2.87) |
| $R^2$ | 0.07 | 0.07 | 0.05 | 0.05 | 0.08 | 0.08 | 0.05 | 0.05 |
| Number of Observations | 157,440 | 157,440 | 156,996 | 156,996 | 157,940 | 157,940 | 155,140 | 155,140 |
| Total Effect | -0.029 | -0.016 | -0.029 | -0.001 | -0.055 | 0.002 | -0.048 | 0.017 |
| | (0.011) | (0.012) | (0.008) | (0.008) | (0.015) | (0.016) | (0.014) | (0.022) |
| Supply Effect | -0.021 | -0.006 | -0.014 | -0.005 | -0.029 | 0.012 | -0.032 | 0.000 |
| | (0.009) | (0.012) | (0.008) | (0.008) | (0.014) | (0.015) | (0.008) | (0.020) |

Notes: Standard errors are in parentheses, clustered by industry. All regressions include year dummies and all variables are in first differences. The sample includes a balanced panel of plants with nonzero values of the dependent variable in all Census years from 1963-1982. The dependent variable in columns 1 and 2 is the log of production worker hours. The dependent variable in columns 3 and 4 is the log of the real hourly production wage. The dependent variable in columns 5 and 6 is the log of energy expenditure divided by the price of energy. The dependent variable in columns 7 and 8 is the log of materials expenditure divided by the price of materials. Output, energy and materials deflators are taken from the MPD. The independent variables in columns 1, 3, 5 and 7 are the same as in column 1 of Table 6. The independent variables in columns 2, 4, 6 and 8 are constructed similarly, using the one year lag price of oil in place of the current price.