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Explaining Long-Run Changes in the Energy Intensity of the U.S. Economy

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Abstract

Recent events have revived interest in explaining the long-run changes in the energy intensity of the U.S. economy. We use a KLEM dataset for 35 industries over 39 years to decompose changes in the aggregate energy-GDP ratio into shifts in sectoral composition (structural change) and adjustments in the energy demand of individual industries (intensity change). We find that although structural change offsets a rise in sectoral energy intensities from 1960 until the mid-1970s, after 1980 the change in the industrial mix has little impact and the average sectoral energy intensity experiences decline. Then, we use these data to econometrically estimate the influence on within-industry changes in energy intensity of price-induced substitution of variable inputs, shifts in the composition of capital and embodied and disembodied technical progress. Our results suggest that innovations embodied in information technology and electrical equipment capital stocks played a key role in energy intensity's long-run decline.

JEL classification: Q300, Q400

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1. Introduction

 \overline{a}

This paper investigates the sources of changes in the energy intensity of the U.S. economy during the period 1958-1996, including the impact of technological change and its importance relative to that of other influences. This issue, with which economists have wrestled for three decades, is again a focus of interest, stimulated by recent energy price increases and proposals to reduce the greenhouse gas emissions associated with fossil fuel use. Our approach is to identify and disentangle the separate factors affecting energy use. effects of technological change from other influences on the energy intensity of production in the U.S.

The OPEC oil price shocks of the 1970s and their associated adverse economic effects generated a groundswell of empirical research on the reaction of technology to such price changes. In spite of those investigations, both the sign and magnitude of the effects of energy prices on innovation, and the follow-on impact of technological change on the intensity of energy use, remain open to doubt. More recently the problem of climate change has again focused economists' attention on the potential impacts of energy price increases, in this case, if limits were imposed on carbon dioxide $(CO₂)$ emissions. In view of the current lack of largescale substitutes for hydrocarbon-based energy supplies, energy-saving technological change is frequently adduced as the saving grace that will moderate the costs of $CO₂$ abatement over the long time-horizon on which these limits are anticipated to bind. Some authors (e.g., Grubb 1997; Williams 1990) even argue that the very act of controlling $CO₂$ emissions will, through its effect on relative prices, induce the necessary energy and emissions-saving technological change.

Figure 1 shows time series of energy prices and energy intensity for the U.S. Its most striking feature is the sustained reduction in the energy intensity of GDP from 1970 onward, with the steepest decline occurring in the period prior to 1986, during which energy prices first jumped due to the OPEC oil shocks and then collapsed. The decline in energy intensity has been casually attributed by some authors to energy-saving innovation, induced by rising energy prices (e.g., Brown et al 1998: 294-295; Holdren 2001: 45). Recent econometric results by Newell at al (1999) and Popp (2001, 2002) lend indirect support for this argument, suggesting that a significant amount of energy-saving technological change did in fact respond to energy price increases, and was reflected in the characteristics of durable goods.¹ However, because these studies do not quantify either the influence of energy prices on *non-energy* innovation or the latter's effect on the aggregate energy-saving *or -using* bias of technological progress, they do not establish a direct causal link between the changes in energy technologies and the observed aggregate intensity decline.

Other empirical analyses that focus at the aggregate and sectoral levels tell a more complicated and somewhat contradictory story about the impacts of the energy price increases of the 1970s (see the surveys by Berndt 1992 and Berndt and Wood 1987). Previous results by Jorgenson and Fraumeni (1981) and Jorgenson (1984) indicate that in the majority of U.S. industries there was actually an energy-using bias to technical change over this period. In particular, this finding is inconsistent with the assumption of energy-saving technical change (the autonomous energy efficiency improvement, or AEEI) that is a central feature of most models

¹ Newell at al (1999) find that energy prices and regulatory stimuli positively affect the energy-efficiency characteristics of consumer durables for heating and cooling. Popp (2002) finds that the propensity to patent in energy technology fields was significantly increased by rising energy prices in the 1970s. Popp (2001) attributes one third of the reduction in energy demand per unit output in manufacturing industries to energy-saving knowledge, for which he uses cumulated energy technology patents as a proxy.

used to forecast future energy use and the baseline levels and costs of abating $CO₂$ emissions.² Indeed, based on this finding Hogan and Jorgenson (1991) argue that the AEEI may actually have been negative throughout the period in question. Attempts to reconcile these differences at the micro and macro levels have focused on the consequences of sectoral structural change for aggregate energy use. Much of the decline in aggregate energy intensity has been attributed to shifts in the composition of output (e.g., Rose and Chen 1991), particularly in manufacturing industries (Hirst et al 1983; Schipper et al 1990).

We are, therefore, confronted with five stylized facts whose relative significance is not immediately apparent:

- 1. Declining aggregate energy intensity;
- 2. Evidence of induced energy-saving innovation at the micro level, associated with significant energy-saving technological change in a number of energy-intensive manufacturing industries;
- 3. Indications of the embodiment of energy-saving innovations in durable goods;
- 4. Evidence of structural change as a significant source of reduction in aggregate energy intensity; and
- 5. Evidence of an energy-using bias of technical progress in the majority of industries. To clarify and reconcile these separate pieces of evidence we disentangle the effects of

technological change, over the period 1958-1996, from the influences on energy intensity of price-induced input substitution and changes in the composition of capital. We provide a more complete context for technology's energy-saving role in the long run, by employing Berndt, Morrison and Watkins' (1981) econometric model of production with multiple quasi-fixed inputs to estimate the sources of energy intensity within 35 approximately 2-digit industries in the U.S.

The ability of the model to incorporate many of the influences on energy demand that have been shown to be important gives us a number of advantages over previous studies. First, we isolate the contribution of technological change to aggregate energy intensity change across the full range of producing sectors, not just manufacturing industries, taking factor price substitution and sectoral composition effects into account. Second, we use longer time series to provide a more complete picture of the long-run energy-saving or -using influence of technical change within each sector. Finally, by also identifying the consequences of changes in the composition of capital we can distinguish the effects of both disembodied and embodied technological change.

The plan of the paper is as follows. In Section 2 we develop an model of producer behavior that we estimate using the data base and analytical strategy that we describe in Section 3. In Section 4 we present and discuss the results of our analyses. Section 5 concludes by summarizing their implications, and outlining unsolved puzzles in explaining U.S. energy intensity's long-run decline.

2. Modeling The Sources of Change in Energy Demand

 \overline{a} ² As discussed by Hogan (1990), Manne and Richels (1992) and Williams (1990), the AEEI is a secular trend reflecting the technologically-motivated rate of reduction in the demand for energy that, without any directed effort, decreases the amounts of CO₂-emitting fossil fuel necessary for any given level of economic output. Its first documented use is Edmonds and Reilly (1985), who cite the historical decline in the energy intensity of GDP with increasing economic development as justification for a declining coefficient on energy input. They construct a simulation model that incorporates an increasing index of energy-saving technology, whose inverse is applied as an attenuation factor to the model's fuels demand functions. This trick is still employed in the majority of climate policy models.

2.1. A Model of Producer Behavior

The economy is modeled as a collection of industries, indexed by *i* = 1, ..., *N*. In each industry there is a representative producer with a short-run restricted variable cost function (RVCF) $G_i[\mathbf{p}_i, \mathbf{x}_i, \dot{\mathbf{x}}_i, Y_i, t]$, in which \mathbf{p}_i is a vector of variable input prices, \mathbf{x}_i is the level and $\dot{\mathbf{x}}_i$ is the change in the vector of quasi-fixed inputs to production, Y_i is the level of output and *t* is time. Each producer's problem is to choose the trajectory of quasi-fixed inputs to minimize the present discounted value of costs:

(1)
$$
\min_{\mathbf{x}_i, \dot{\mathbf{x}}_i} \int_{0}^{\infty} e^{-rt} \Big\{ G_i[\mathbf{p}_i, \mathbf{x}_i, \dot{\mathbf{x}}_i, Y_i, t] + \mathbf{u}_i \cdot \mathbf{x}_i \Big\} dt,
$$

where *r* is the interest rate, $\mathbf{u}_i = r\mathbf{a}_i + \mathbf{d} \cdot \mathbf{a}_i$ is the user cost of the vector of quasi-fixed inputs, \mathbf{a}_i is the vector of their normalized acquisition (asset) prices, and **d** is the vector of asset-specific rates of depreciation. Berndt, Morrison and Watkins (1981) show that in the stationary equilibrium where $\dot{\mathbf{x}}_i = 0$ and the quasi-fixed inputs have fully adjusted to their long-run optimal levels $\mathbf{x}_i = \mathbf{x}_i^*$, the solution to the problem in eq. (1) is given by the equilibrium condition:

(2)
$$
-\frac{\partial G_i[\mathbf{p}_i, \mathbf{x}_i^*]}{\partial \mathbf{x}_i} = \mathbf{u}_i + r \frac{\partial G_i[\mathbf{p}_i, \mathbf{x}_i^*]}{\partial \dot{\mathbf{x}}_i}.
$$

As in previous investigations of energy demand, we write industry *i*'s normalized RVCF using a quadratic approximation for *G*: 3

$$
G_{i} = L_{i} + \frac{p_{E i}}{p_{Li}} E_{i} + \frac{p_{Mi}}{p_{Li}} M_{i} = L_{i} + \tilde{p}_{E i} E_{i} + \tilde{p}_{Mi} M_{i}
$$
\n
$$
= Y_{i} \bigg[\alpha_{0i} + \alpha_{ii} t + \alpha_{i} \sum_{v} \alpha_{vi} \tilde{p}_{vi} + \frac{1}{2} \sum_{v} \alpha_{vvi} \tilde{p}_{vi}^{2} + \sum_{v} \alpha_{vi} \tilde{p}_{vi} t + \sum_{v} \sum_{j \neq v} \alpha_{vji} \tilde{p}_{vi} \tilde{p}_{ji} \bigg]
$$
\n
$$
+ \sum_{k} \alpha_{ki} x_{ki} + \frac{1}{2} \sum_{k} \alpha_{kki} \frac{x_{ki}^{2}}{Y_{i}} + \sum_{k} \alpha_{kii} x_{ki} t + \sum_{k} \sum_{v} \alpha_{kvi} x_{ki} \tilde{p}_{vi}
$$
\n
$$
+ \sum_{k} \beta_{ki} \dot{x}_{ki} + \frac{1}{2} \sum_{k} \beta_{kki} \frac{\dot{x}_{ki}^{2}}{Y_{i}} + \sum_{k} \beta_{kii} \dot{x}_{ki} t + \sum_{k} \sum_{v} \beta_{kvi} \dot{x}_{ki} \tilde{p}_{vi}
$$
\n
$$
+ \sum_{k} \gamma_{kki} \frac{x_{ki} \dot{x}_{ki}}{Y_{i}}
$$

In this equation p_{vi} are the prices of the *v* types of variable inputs ($v = \{\text{labor } (L) \}$, energy (E) , materials (M) }); \tilde{p}_{vi} are these variable input prices normalized by the price of labor, which we treat as the numeraire; x_{ki} and \dot{x}_{ki} are the levels and changes in *k* classes of capital stocks, which we discuss in the next section, and α , β , γ and δ are vectors of parameters to be estimated.⁴

Watkins and Berndt (1992) note that separation of scale and technology effects tends to be empirically difficult, with results often exhibiting strong increasing long-run returns to scale accompanied by technological retrogression despite the plausibility and empirical evidence for

³ See, e.g., Berndt, Morrison and Watkins (1981); Watkins and Berndt (1992); Popp (2001).

⁴ For simplicity, we omit the second-order interaction terms among different quasi-fixed inputs. In tests of alternative specifications for *G*, the coefficients on these terms were either insignificant or had to be dropped due to problems with convergence of the estimator.

long-run constant returns to scale (LRCRTS) at the industry level. We therefore impose LRCRTS by employing a net investment model, in which industry *i*'s internal costs of adjustment C_i are represented by all the terms in the variable cost function involving \dot{x}_{ki} :

(4)
$$
C_{i} = \sum_{k} \beta_{ki} \dot{x}_{ki} + \frac{1}{2} \sum_{k} \beta_{kki} \frac{\dot{x}_{ki}^{2}}{Y_{i}} + \sum_{k} \beta_{ki} \dot{x}_{ki} t + \sum_{k} \sum_{v} \beta_{kvi} \dot{x}_{ki} \tilde{p}_{vi} + \sum_{k} \gamma_{kki} \frac{x_{ki} \dot{x}_{ki}}{Y_{i}}
$$

When the stocks of quasi-fixed inputs have fully adjusted to their optimal levels, x_{ki}^* , both the change in the levels of these stocks, \dot{x}_{ki} , and the marginal adjustment costs must be zero. Together, these conditions imply that:

.

$$
\left. \frac{\partial C_i}{\partial \dot{x}_{ki}} \right|_{x_{ki} = x_{ki}^*, \dot{x}_{ki} = 0} = \sum_k \beta_{ki} + \sum_k \beta_{kni} t + \sum_k \sum_{\nu} \beta_{kvi} \widetilde{p}_{\nu i} + \sum_k \gamma_{kki} \frac{x_{ki}^*}{Y_i} = 0,
$$

which in turn requires:

(5) $β_{ki} = β_{kti} = β_{kvi} = γ_{kki} = 0.$

By Shepard's Lemma, the optimal short-run input demand functions are given by the derivative of *Gi* with respect to the normalized prices of the variable inputs. Imposing LRCRTS using eq. (5) then yields dynamic input demand functions for energy and materials:

(6)
$$
\frac{E_{i,t}}{Y_{i,t}} = \alpha_{Ei} + \alpha_{EEi} \tilde{p}_{Ei,t} + \alpha_{EMi} \tilde{p}_{Mi,t} + \alpha_{Eii} t + \sum_{k} \alpha_{Eki} \frac{x_{ki,t-1}}{Y_{i,t}}
$$

and

$$
(7) \qquad \frac{M_{i,t}}{Y_{i,t}} = \alpha_{Mi} + \alpha_{EMi} \widetilde{p}_{Ei,t} + \alpha_{MMi} \widetilde{p}_{Mi,t} + \alpha_{Mi} t + \sum_{k} \alpha_{Mi} \frac{x_{ki,t-1}}{Y_{i,t}}.
$$

The corresponding demand function for labor is derived as a residual from eq. (3):

$$
\frac{L_{i,t}}{Y_{i,t}} = \frac{G_i}{Y_i} - \frac{\tilde{p}_{Ei}E_i}{Y_i} - \frac{\tilde{p}_{Mi}M_i}{Y_i}
$$
\n(8)
$$
= \alpha_{0i} + \alpha_{ii}t - \frac{1}{2}(\alpha_{EEi}\tilde{p}_{Ei,t}^2 + 2\alpha_{EMi}\tilde{p}_{Ei,t}\tilde{p}_{Mi,t} + \alpha_{MMi}\tilde{p}_{Mi,t}^2)
$$
\n
$$
+ \sum_k \alpha_{ki}\frac{x_{ki,t-1}}{Y_{i,t}} + \frac{1}{2}\sum_k \alpha_{kki}\frac{x_{ki,t-1}^2}{Y_{i,t}^2} + \sum_k \alpha_{ki}\frac{x_{ki,t-1}t}{Y_{i,t}} + \frac{1}{2}\sum_k \beta_{kki}\frac{x_{ki,t-1}^2}{Y_{i,t}^2}.
$$

Finally, differentiating eq. (3) with respect to x_{ki} yields, in long-run equilibrium:

$$
\left.\frac{\partial G_i}{\partial x_{ki}}\right|_{x_{ki}=x_{ki}^*,\dot{x}_{ki}=0} = \alpha_{ki} + \alpha_{kki}\frac{x_{ki}^*}{Y_i} + \alpha_{ki}t + \sum_{v} \alpha_{kvi}\widetilde{p}_{vi}.
$$

This condition, combined with the fact that:

$$
\left. \frac{\partial G_i}{\partial \dot{x}_{ki}} \right|_{x_{ki} = x_{ki}^*, \dot{x}_{ki} = 0} = 0 ,
$$

implies that eq. (2) may be solved to yield an expression for the optimal quantity of quasi-fixed inputs per unit of output:

$$
(9) \qquad \frac{x_{ki}^*}{Y_i} = -\frac{1}{\alpha_{kki}} \left(\alpha_{ki} + \alpha_{ki} t + \sum_{v} \alpha_{kvi} \widetilde{p}_{vi} + u_i \right).
$$

Eqs. (6)-(8) form our econometric model of producer behavior. In each equation the coefficients on the prices reflect the impact of substitution among variable inputs. The coefficients on the quasi-fixed stocks give the effects of changes in the level and composition of capital, and those on the time trend proxy for the influence of technological progress on the demand for each input.

2.2. The Sources of Change in Energy Demand in the Short and the Long Run

The model outlined above provides a unifying framework within which to understand and compare the sources of long run change in energy intensity. Unlike econometric models in which capital adjusts instantaneously, our specification enables us to distinguish between the consequences for energy demand of the short-run influence of movements in variable input prices and the and long-run influence of movements in the quantities of quasi-fixed inputs. The short-run elasticity of unit energy demand with respect to the price of the v^{th} variable input, ε_{Evi} , is given by:

(10)

$$
\varepsilon_{Evi} = \frac{\partial (E_i/Y_i)}{\partial \widetilde{p}_{vi}} / \frac{\overline{(E_i/Y_i)}}{\overline{p}_{vi}}
$$

$$
= \alpha_{Evi} \frac{\overline{p}_{vi}}{\overline{(E_i/Y_i)}},
$$

where \overline{p}_{vi} and $\overline{E_i/Y_i}$ denote, respectively, the values of the normalized price of *v* and the unit energy demand at the mean of the sample. The corresponding long-run elasticities *ηEvi* are defined at the equilibrium levels of the quasi-fixed inputs, the effect of \tilde{p}_{vi} on which can be found by differentiation of eq. (9):

(11)
\n
$$
\eta_{Evi} = \left(\frac{\partial (E_i / Y_i)}{\partial \widetilde{p}_{vi}}\bigg|_{x_{ki} = \overline{x}_{ki}} + \sum_k \frac{\partial (E_i / Y_i)}{\partial (x_{ki}^* / Y_i)} \frac{\partial (x_{ki}^* / Y_i)}{\partial \widetilde{p}_{vi}}\right) / \frac{\overline{(E_i / Y_i)}}{\overline{p}_{vi}}
$$
\n
$$
= \left(\alpha_{Evi} - \sum_k \frac{\alpha_{Eki}^2}{\alpha_{kki}}\right) \frac{\overline{p}_{vi}}{(\overline{E_i / Y_i})}.
$$

The short-run elasticities of unit energy demand with respect to the k^{th} quasi-fixed input, ε_{Eki} , are zero by definition, while the corresponding long-run elasticities, η_{Eki} , are given by:

(12)
\n
$$
\eta_{Eki} = \left(\frac{\partial (E_i / Y_i)}{\partial (x_{ki} / Y_i)} \Big|_{x_{ki} = \bar{x}_{ki}} + \sum_k \frac{\partial (E_i / Y_i)}{\partial (x_{ki}^* / Y_i)} \frac{\partial (x_{ki}^* / Y_i)}{\partial (x_{ki} / Y_i)} \right) / \frac{\overline{(E_i / Y_i)}}{\overline{(x_{ki} / Y_i)}}
$$
\n
$$
= \alpha_{Eki} \frac{\overline{(x_{ki} / Y_i)}}{\overline{(E_i / Y_i)}}
$$

where $\overline{x_{ki}/Y_i}$ is the unit demand for quasi-fixed input *k* at the sample mean.

An additional advantage provided by our model is that the coefficient on the time trend, a_{Eti} , gives a direct estimate of the secular trend in energy intensity within each industry. The short-run average rate of change in energy intensity, *εEti*, is given by the elasticity:

(13)
$$
\varepsilon_{Eii} = \frac{\partial (E_i / Y_i)}{\partial t} / (\overline{E_i / Y_i})
$$

$$
= \frac{\alpha_{Eii}}{(\overline{E_i / Y_i})}.
$$

The corresponding long-run average rate, *ηEti*, is given by:

$$
\eta_{Eii} = \left(\frac{\partial (E_i / Y_i)}{\partial t}\Big|_{x_{ki} = \bar{x}_{ki}} + \sum_k \frac{\partial (E_i / Y_i)}{\partial (x_{ki}^* / Y_i)} \frac{\partial (x_{ki}^* / Y_i)}{\partial t}\right) / (\overline{E_i / Y_i})
$$
\n
$$
= \left(\alpha_{Eii} - \sum_k \frac{\alpha_{Eki} \alpha_{kii}}{\alpha_{kki}}\right) / (\overline{E_i / Y_i})
$$
\n
$$
= \varepsilon_{Eii} + \sum_k \omega_{Eki},
$$

where, by a chain rule argument,

$$
(15) \qquad \omega_{Eki} = -\eta_{Eki}\eta_{ki} / \alpha_{kki},
$$

 $($

and η_{kti} is the time elasticity or average rate of growth of the k^{th} quasi-fixed input:

$$
\eta_{\scriptscriptstyle{kt\bar{i}}} = \frac{\alpha_{\scriptscriptstyle{kt\bar{i}}}}{(\overline{x_{\scriptscriptstyle{ki}} / Y_{\scriptscriptstyle i}})}.
$$

It is customary to interpret *εEti* as the rate of disembodied energy-saving or -using technical progress. The term *ηEti*, by incorporating the additional influence of technological change associated with the adjustments of quasi-fixed stocks, captures the joint effects on energy demand of disembodied and embodied technical progress. The difference between these variables, *ωEki*, therefore indicates the influence on the trend in energy intensity of innovations that are capitalized into each category of quasi-fixed inputs. Our model therefore provides the means to evaluate the aggregate impact of an influence that Newell et al's (1999) results suggest may be an important long-run driver of change in energy intensity.

A key implication of our analysis is that, in general, both ε_{Et} and η_{Et} , which are rates of change of energy intensity, will diverge from a measure of the energy-saving or -using bias of technical progress. This latter measure, which we denote *ζEi*, is defined as:

$$
\xi_{Ei} = \frac{\partial \ln s_{Ei}}{\partial t},
$$

where *Yi i* $E_i = \frac{P_{E_i}L_i}{p_{Y_i}Y_i}$ $p_{E_i} = \frac{p_{E_i} E_i}{r}$ is the share of energy in *i*'s cost of production and p_{Y_i} is the price of *i*'s output

(Binswanger and Ruttan 1978). The definition above, along with eqs. (13) and (14), imply that the short-run and long-run biases of technical change with respect to energy are:

(16) $\zeta_{Ei}^{SR} = \varepsilon_{Eii} + \frac{d \ln(p_{Ei} / p_{Yi})}{dp_{Ei}^{T} / p_{Yi}}$ and $\zeta_{Ei}^{LR} = \eta_{Eii} + \frac{d \ln(p_{Ei} / p_{Yi})}{dp_{Ei}^{T} / p_{Yi}}$, respectively. The first term on the right hand side of the equal sign is the average rate of change in energy intensity, and the second term is the average rate of change in the price of energy relative to that of output.

Eq. (16) implies that *ζEi* is an unbiased indicator of the direction of intensity change if $\overline{d \ln(p_{Ei}/p_{Yi})} = 0$, a condition which corresponds to isolating the secular effect of time on energy's cost share by means of statistical controls for both energy prices and the price of output. By comparison, Jorgenson and Fraumeni (1981) and Jorgenson (1984) model s_{E_i} as a linear

function of a time trend and input prices, but it appears that they neither include the price of output as an explanatory variable, nor use it to deflate their input price series. This is a potentially important omission, for it is only after movements in p_{Y_i} are accounted for that the coefficient on the time trend in their model will give an unbiased estimate of the average change in energy intensity, analogous to a_{Eti} . Nevertheless, despite this possible source of error, the direction of intensity change may still be accurately indicated if ζ_{Ei} and ζ_{Ei} and η_{Eti} have the

same sign. A sufficient condition for this is that
 $(17) \quad \text{sgn}(\varepsilon_{Eii}) = \text{sgn}(\overline{d \ln(p_{Eii} / p_{Yi})})$ and (17) $\text{sgn}(\varepsilon_{Eij}) = \text{sgn}\left(\frac{d \ln(p_{Ei} / p_{yi})}{dp_{Ei} / p_{yi}}\right)$ and $\text{sgn}(\eta_{Eij}) = \text{sgn}\left(\frac{d \ln(p_{Ei} / p_{yi})}{dp_{Ei} / p_{yi}}\right)$.

Figure 1 suggests that, on average across sectors, the foregoing condition is likely to be satisfied during the periods when declining energy intensity coincides with falling relative prices of energy, which occur prior to 1965 and after 1981. However, it seems unlikely that eq. (17) will hold throughout the latter half of the 1960s, when energy intensity rose sharply as energy prices continued to fall, or during the crucial decade of the 1970s, when energy intensity resumed its downward trend while energy prices increased drastically. The latter periods make up a substantial fraction of the length of the samples in the Jorgenson studies, which estimate the bias of technical change over the period 1958-1979. Therefore, by estimating our model over this time-frame we can assess the implications of Jorgenson's findings for the long-run change in energy intensity.

The final benefit afforded by our framework is that it puts into context Popp's (2001) recent finding of substantial reductions in manufacturing sectors' energy use associated with induced innovation. In contrast to our use of time as the index of technological change, Popp uses the cumulated stocks of energy patents in each industry as a direct and tangible measure of the output of innovation. Each of these approaches to modeling technological change has its advantages and disadvantages. However, the differences between them cause the two models to exhibit different implications, not only about the influences of new technology on energy intensity, but also about the mechanisms through which these influences operate.

The first point turns on the fact that although our secular time-trend omits the fluctuations in innovation activity that are captured by Popp's energy patent stocks, our estimate of a_{Eti} will capture an influence that Popp omits, namely the additional energy-saving or energy-using effect of the innovation represented by industries' stocks of *non-energy* patents. Popp computes longrun and short-run elasticities of unit energy demand with respect to energy patents: SR $\varepsilon_{E, EPATH, i}$ and LR $\varepsilon_{E, FPAT}$, respectively. By the chain rule, the former estimate implies the following analogue of our measure of the influence of disembodied technical change on energy intensity:

(18)
$$
\varepsilon'_{Eii} = \text{SR} \varepsilon_{E, EPATH,i} \left(\frac{\partial EPATH_i}{\partial t} / \overline{EPATH_i} \right),
$$

where $EPATH_i$ is the number of energy patents in each sector and the term in brackets is its average rate of growth of patenting in energy technologies. *εEti* and *ε′Eti* are not comparable, however, because the former measures the influence on energy intensity of *all* innovation, while the latter captures only the component which is associated with innovation in energy technologies.

Comparability is ensured by incorporating the additional unmeasured influence of nonenergy patents, say *NPAT_i*, through the short-run elasticity of energy demand with respect to this series, say SR *εE, NPAT, i*:

(19)
$$
\varepsilon_{Eti} = \varepsilon'_{Eti} + \text{SR}\varepsilon_{E,NPAT,i} \left(\frac{\partial NPAT_i}{\partial t} / \overline{NPAT_i} \right).
$$

We can ascertain the importance of the second term on the right hand side of this expression by comparing ε_{Eti} , calculated according to eq. (13) using estimates produced by our model, against *ε′Eti*, calculated according to eq. (18) using Popp's estimates.

The second point stems from the fact that Popp's model does not distinguish embodied technical change as a separate channel through which innovation influences industries' long-run energy intensity. This because his treatment of energy patent stocks as a distinct quasi-fixed input implicitly restricts disembodied technological change to be the only mechanism through which it is possible for innovation to influence energy demand. Thus, although Popp's long-run energy-patent elasticity, LR *εE, EPAT, i*, captures the cumulative influences of knowledge decay due to obsolescence and of knowledge diffusion due to the spillover effect of patent citations, it does not reflect the interaction between the index of technical change and the adjustment of *physical* capital in our eq. (14).

One might be tempted to argue that this omission is merely a question of accounting. Simply put, innovation generates a certain amount of knowledge, and eq. (14), by imputing the long-run influence of knowledge dynamics to changes in the quality of capital, re-classifies some of the effects of disembodied knowledge as attributable to other sources. But this reasoning is incorrect. There is a good reason to make the interaction between knowledge and capital explicit. The greater propensity to patent product innovations as opposed to process innovations (Levin et al 1987) means that LR *εE, EPAT, i* disproportionately reflects the characteristics of the former, which are more likely to influence energy demand through embodiment in purchased durable inputs than by disembodied means. Therefore, in addition to the direct effect of patents on energy intensity there is the additional indirect influence of embodied technical change, which is determined by the interaction of the rate of embodiment of new technology and the rate of adjustment of the capital stock.

To clarify this point, consider the analogue of eq. (14) derived using Popp's long-run elasticity.⁵ Treating knowledge as completely disembodied yields:

(20)
$$
\eta'_{Eii} = \text{LR} \varepsilon_{E, EPATH,i} \left(\frac{\partial EPATH_i}{\partial t} \right) / \overline{EPATH_i} \,,
$$

which is just the long-run counterpart of eq. (18), while admitting the possibility of embodiment results in:

(21)
$$
\eta_{Eii}'' = \text{LR} \varepsilon_{E,EPAT,i} \left(\frac{\partial EPATH_i}{\partial t} \bigg|_{x_{ki} = \bar{x}_{ki}} + \frac{\partial EPATH_i}{\partial (x_{ki}^* / Y_i)} \frac{\partial (x_{ki}^* / Y_i)}{\partial t} \right) / \overline{EPATH_i}
$$

$$
= \eta_{Eii}' + \omega_{E,EPAT,ki}.
$$

Our focus is on the second term in this expression, $\omega'_{E, EPATH, ki}$, which is the embodiment effect given by the analogue of eq. (15):

 (22) $\omega'_{E,EPAT,ki} = \text{LR}\varepsilon_{E,EPAT,i} \eta_{EPAT,ki} \eta_{ki}$.

Here, η_{kt} is the average growth rate of the physical capital stock, as before, and the elasticity of energy patents with respect to the stock of capital, *ηEPAT, ki*, is the critical interaction term.

Eq. (22) ties movements in the stock of knowledge to equilibrating adjustments in the capital stock via the feedback effect of *ηEPAT, ki* on the propensity to patent. This is a form of induced technical change. It is the key interaction that we capture in eq. (14), but Popp's

⁵ For ease of exposition we ignore the influence of non-energy patents for the time being, and assume that each industry has a single stock of jelly capital.

elasticity estimates do not. The magnitude of this omission can be understood by including the additional complicating influence of non-energy patents in eq. (21), to yield an expression that is comparable to eq. (14):

(23)
$$
\eta_{Eii} = \eta'_{Eii} + \begin{cases} \text{LR}\varepsilon_{E,NPATH,i} \left(\frac{\partial NPATH_i}{\partial t} / \overline{NPATH_i} \right) + \\ \eta_{ki} \left(\text{LR}\varepsilon_{E,EPAT,i} \eta_{EPAT,ki} + \text{LR}\varepsilon_{E,NPATH,i} \eta_{NPAT,ki} \right) \end{cases}.
$$

Popp's results allow us to compute only the first term in this expression. The collection of terms in curly braces represents the unmeasured effects of disembodied technical change due to nonenergy patents and of embodied technical change due to both energy- and non-energy patents. We can ascertain the importance of this unmeasured effect by comparing *ηEti*, calculated according to eq. (14) using estimates produced by our model, against η'_{Et} , calculated according to eq. (23) using Popp's estimates.

The implication of eqs. (19) and (23) is that patents, intangible asset stocks or other indices of the fruits of innovation in different fields of technology are likely to have different energy-saving or energy-using effects, which enter through different channels of influence to differing degrees, depending on the sector in which they are employed. The best empirical model would therefore include as explanatory variables indices of technological progress that reflect the differences in innovation across the full range of technological fields, making it possible to separately identify their heterogeneous influences on each industry's energy demand. However, while it is easy to specify such a model, the current lack of available data on detailed innovation within industries precludes its empirical implementation. This is an important area for future research.

3. Data and Analytical Approach

3.1. Data

 \overline{a}

For comparability between our own work and previous studies of the bias of technical change, and to maximize the industry coverage of our econometric results, we use the KLEM dataset developed by Jorgenson and associates. This dataset records the real prices and quantities of output and inputs of capital, labor, energy and intermediate materials in 35 industries over the 39-year period $1958-1996$.⁶ These data define the set of variable input categories *v*: labor, energy, materials. We augment these series with detailed data from the BEA on the values of real cost net capital stocks for 61 classes of assets in 62 industry groups over the 75-year period 1925-1999.⁷ The industry-by-asset series are truncated to match the time period of the Jorgenson dataset and aggregated across industry categories to match Jorgenson's sectoral disaggregation (approximately 2-digit SIC). We also aggregate the values of the different assets into five broad classes that define our set of quasi-fixed input categories *k*: information and communication technology (ICT), electrical equipment, machinery, vehicles, and buildings and structures. Finally, we adjust Jorgenson's sectoral energy price and quantity series to make them consistent

⁶ We use the version of the dataset that is publicly available on Dale Jorgenson's website

⁽http://post.economics.harvard.edu/faculty/jorgenson/data/35klem96.dat).
⁷ These data are available online at the BEA's website (<u>http://bea.gov/bea/dn/faweb/Details/Index.html</u>). They are the estimates that underlie the aggregate stocks tabulated in BEA (2003).

with published data on energy use by industries.⁸ Descriptive statistics for the resulting dataset are shown in Table 1.

3.2. Approach

In order to isolate the impact of technical change on aggregate energy intensity, the effects of changes in industrial composition are first separated from the changes in energy intensity within industries using a simple decomposition technique. We then account for the sources of change in energy intensity within individual industries using our econometric model of producer behavior. Finally, we combine our econometric estimates with the results of the decomposition analysis to aggregate the contributions of each of these sources across industries, which enables us to estimate and compare the impacts of different sources on the energy intensity of U.S. production in its entirety.

To move between the aggregate and sectoral levels of the economy, a simple additive decomposition of aggregate intensity change into industry-level intensity change and structural change is performed. We model the ratio of aggregate energy *E** to GDP *Y** at time *t* as the weighted average of the energy intensities of the *N* industries in the economy in that period:

(24)
$$
\frac{E_t^*}{Y_t^*} = \frac{1}{N} \sum_{i=1}^N \phi_{i,t} \left(\frac{E_{i,t}}{Y_{i,t}} \right)
$$

 \overline{a}

where industry *i*'s weight (ϕ_i) is the ratio of its share of GDP to its share of total energy use.⁹ The logarithmic derivative of this expression is:

(25)
$$
d \ln \left(\frac{E_i^*}{Y_i^*} \right) = \underbrace{\frac{1}{N} \sum_{i=1}^N d \ln \phi_{i,t}}_{\Phi} + \underbrace{\frac{1}{N} \sum_{i=1}^N d \ln \left(\frac{E_{i,t}}{Y_{i,t}} \right)}_{\Psi}.
$$

The observed fractional change in aggregate energy intensity, *d*ln(*E**/*Y**), is thus the result of two effects, given by the terms on the right hand side of this expression. These are, respectively, the average of changes in industries' contributions to aggregate energy intensity—a "structural change effect", which we denote Φ, and the average of changes in energy intensity within industries—an "intensity change effect", which we denote Ψ.

We further decompose the drivers of Ψ by estimating eqs. (6)-(8) industry by industry as a system with 40 free parameters using GMM, with the normalized variable input price series, the lagged levels of the quasi-fixed input series, and a time trend as instruments.¹⁰ The contributions of each source to the intra-industry change in energy intensity in eq. (6) are then

⁸ We do this by constructing new quantity indices of sectoral energy input. For manufacturing industries we used derived annual estimates of consumption of total energy from the Manufacturing Energy Consumption Survey. These data, which enabled us to make adjustments for only the post-1973 period, are available online at the EIA website (http://www.eia.doe.gov/emeu/mecs/mecs94/consumption/dtotal1.html and

http://www.eia.doe.gov/emeu/mecs/mecs94/consumption/dtotal.html). For energy transformation and supply industries we use data from the EIA Annual Energy Review (DOE 2002), and for primary and tertiary non-energy industries, we use data for the U.S. from the IEA Energy Balances (IEA 2001). We then take as given the value of sectoral energy input in the original dataset, and divide it by our quantity series to construct new series of energy prices by industry.

 9 Our decomposition is inspired by Hogan and Jorgenson (1991) eq. (8). Although more sophisticated formulas are available (see e.g., Ang and Zhang 2000), we employ eq. (24) because it is simple and generates results that are easy to interpret.

¹⁰ The system of equations was also estimated using Zellner's seemingly unrelated regressions (SUR) technique. The values of the coefficients were very similar, but the GMM estimates were generally of higher precision.

aggregated across the 35 industries in our dataset according to the second term in eq. (25), and compared with the predicted values of Ψ. This allows the assessment of the contributions to the changes in energy intensity within industries made by price-induced substitution of variable inputs, changes in the accumulation and composition of capital and technological progress.

4. Results

 \overline{a}

4.1. Decomposition of the Trend in Aggregate Energy Intensity

Values for the indices Φ and Ψ are computed using data on the quantities of output and energy input for the 35 industries in our dataset. We also calculate *d*ln(*E**/*Y**) using real GDP from the NIPAs and aggregate energy consumption from DOE (2002) .¹¹ Figure 2 presents chained indices of the structural change effect, the intensity change effect, and aggregate energy intensity. The joint impact of these effects (i.e., the sum of the chained indices of Φ and Ψ) closely tracks *d*ln(*E**/*Y**), indicating that disparate data sources at the aggregate and sectoral levels tell a consistent story about the character of changes in U.S. energy intensity.

The trajectories of Φ and Ψ help to explain the marked reduction in aggregate energyintensity in the U.S. from 1958-1996. They indicate that until 1973, this was due to changes in the sectoral composition of the economy. The latter changes are responsible for a 14 percent reduction in aggregate energy intensity from its 1958 level. This early decline is largely balanced by increases in energy intensity within industries. After the first OPEC oil shock the effects of the two sources of change are virtually reversed, however. Subsequently, throughout the 1980s and 1990s changes in the sectoral composition of output have little persistent impacts on aggregate energy intensity, while energy intensity within industries declines rapidly until the end of the sample period, at which point it is 25 percent below its 1958 level.

4.2. The Effects of Changes in Variable and Quasi-Fixed Inputs on Energy Intensity

To determine the magnitude of technology's role relative to those of the accumulation and use of tangible inputs we turn to the results of our econometric estimations. The appendix tabulates the values, standard errors and levels of significance of the estimated parameters of the energy intensity equation (6) for each of the 35 sectors. The estimates generally explain a great deal of the variation in the data, as shown by the high adjusted r-squared values. The Durbin-Watson statistics suggest that first-order serial correlation is a problem in almost half of the industries.12 Accordingly, the standard errors were corrected for autocorrelation of up to third order.¹³

The overall influence of variable input prices appears to be negative. The coefficients on energy prices are almost all significant and are overwhelmingly negative, as expected.¹⁴ The coefficients on the prices of intermediate material inputs are significant in 25 industries, but their signs are mixed, with 18 sectors exhibiting positive coefficients. The overall influence of quasi-

¹¹ In this calculation we are concerned with energy intensity change that is solely due to domestic production. We therefore use GDP net of imports as the denominator in aggregate E/Y .

 12 Serial correlation is positive and significant in ten sectors and negative and significant in four.

 13 The method employed by the software package (TSP 4.5) is due to Andrews (1991).

¹⁴ Because the model treats energy as a homogeneous commodity, the sign and magnitude of the coefficient on energy prices indicates the consequences of interfuel substitution for energy demand *in toto*, but masks the underlying demand responses for individual fuels, which may exhibit substantial heterogeneity. To address this problem fully would require us to disaggregate Jorgenson's sectoral energy price and quantity series to reveal the prices and quantities of the individual fuels used by each industry. The dearth of appropriately detailed data on fuel use (especially in non-manufacturing sectors) rules out such a task at this time.

fixed inputs is less clear. The coefficients on information and communication technology are significant in three-fifths of the industries, where they are predominantly negative, while those on both electrical equipment and machinery are significant in a similar number of sectors, but are split more evenly between amplifying and attenuating energy demand. The coefficients on vehicle capital are significant in 21 industries, 15 of which are positive, while the coefficients on structures are significant in 26 sectors, 18 of which are positive.

These estimates allow us to distinguish between the short-run and long-run impacts of variable input prices and quasi-fixed inputs on energy demand, which are indicated by elasticity estimates shown in Table 2. With the exception of a handful of industries the estimated short-run own-price elasticities, ε_{FE} , are significant, and the overwhelming majority of these are of the expected sign, and less than one in magnitude. Only in the motor vehicles, metal mining and government enterprises sectors are the own-price energy elasticities positive and significant, and in the last two of these sectors unit energy demand has an elastic own-price response.

The short-run cross-price elasticities for energy and materials, ε_{EM} , are significant in three-fifths of the industry groups, and exhibit a preponderance of energy-using impacts, with negative and significant elasticities in seven sectors and positive and significant elasticities in 14 sectors. The energy-saving influence of materials prices is concentrated in the service sectors, while the energy-using impacts seem to be spread across the mining and non-durable manufacturing sectors. Energy's price-responsiveness is positive and elastic in agriculture, and negative and elastic in metal mining and government enterprises.

With regard to long-run impacts, far fewer of the own-price elasticities, η_{EE} , are significant—only 15—and, except for the motor vehicle manufacturing and government enterprises sectors, all of the significant estimates have the anticipated sign. Energy exhibits an elastic own-price response in the metal mining and government enterprises sectors. The shortand long-run own-price energy elasticities also have broadly similar magnitudes. We do not report the long-run energy-material cross-price elasticities *ηEM*, which are only significant in the coal mining industry, where the estimate of η_{EM} is positive (0.2).

Table 2 also illustrates the long-run impacts of changes in the accumulation and composition of capital stocks on sectoral energy intensity, which is indicated by estimates of the elasticities of unit energy demand with respect to the quantities of quasi-fixed inputs. Energy's response to the information technology, electrical equipment and vehicle capital stocks, as given by the elasticity estimates ($\eta_{E, ICT}$, $\eta_{E, E_{\text{cubic}}}$ and $\eta_{E, \text{Velicles}}$, respectively) is significant in about half of the 35 industries. ICT appears to have an overall energy-saving impact, exerting a significant negative effect on energy intensity in 12 sectors and a significant positive effect in 5. Electrical equipment also seems in general to be slightly energy-saving, with significant negative effects in ten sectors and significant positive effects in nine. Vehicle capital tends to be energyusing, with negative and significant effects in five industries, and positive and significant effects in 13. Energy demand responds inelastically to changes in these stocks in the majority of industries, exhibiting a negative elastic response to equipment capital only in the non-metal mining sector, and a positive elastic response in metal mining, electrical machinery and communications. Similarly, energy's response to vehicle stocks is positive and elastic in agriculture, and negative and elastic in FIRE and communications.

Estimates of the elasticities of energy demand with respect to stocks of machinery, *ηE, Machinery*, and structures, *ηE, Structures*, are significant in the majority of industries (20 and 22, respectively). Machinery appears to be neutral in its overall energy-saving or -using impact, with significant estimates that are positive and negative in an equal number of industries. Elastic

responses to changes in this stock are positive in metal mining, crude oil and gas, textile products and FIRE and negative in the manufacture of food products, lumber and wood products, nonelectrical machinery, motor vehicles and government enterprises. Buildings and structures have a strong energy-using impact, with positive and significant elasticities in 15 sectors—nine of which exhibit elastic energy responsiveness, and with negative and significant elasticities in 7 sectors, of which agriculture, metal mining and apparel exhibit elastic responses.

The overall picture painted by the summary statistics in Table 3 is one in which in which substitution of variable inputs appears to reduce energy intensity, but the impact of quasi-fixed inputs is mixed. With regard to variable inputs, energy prices have a strongly energy saving influence in both the long and the short run, and materials prices have an approximately neutral effect. As regards quasi-fixed inputs, it seems that the influence of ICT capital is strongly energy saving while that of electrical equipment capital is approximately neutral. By contrast, the influences of machinery and vehicular capital seem to be moderately energy using, while that of buildings and structures is strongly energy using.

4.3. The Bias of Technical Progress and the Secular Trend in Energy Intensity

The non-price influence of technical change on industries' intensities of energy demand are indicated by the coefficients on the time trend in the energy equation (6), a_{Eti} , whose estimates are summarized in Table 3. Panels A and B report the estimates of the bias of technical change with respect to energy from Jorgenson and Fraumeni (1981) and Jorgenson (1984), which we include for the purpose of comparison. Panel C presents our estimates of a_{Eti} for the period 1958-1979 which correspond to Jorgenson's sample, while panel D tabulates the results for the full sample period 1958-1996.

Jorgenson and Fraumeni's estimates are significant in all but six industries and indicate that the bias of technical change is overwhelmingly energy using. Jorgenson's results exhibit more variability, but still show a dominant pattern of energy-using technical progress across industries. His estimates for both electric and non-electric energy inputs are positive and significant in 14 sectors, and negative and significant in only three. For the remaining sectors, either the bias of technical change with respect to one or the other of the energy commodities in columns I and II is not estimated precisely, or the estimates are both significant but have different signs, implying that the sign of the overall bias of technical change with respect to energy is ambiguous.¹⁵ The magnitude of these estimates is generally small, and their crossindustry distribution is negatively skewed. For both electric and non-electric energy, the average of the significant estimates is negative while the median is positive, reflecting Jorgenson's finding that prior to 1980 the influence of technological change on energy demand was small and positive in many industries, but large and negative in a small number of industries.¹⁶

We have suggested that movements in industries' prices of output over Jorgenson's sample period may play a key role in explaining the apparent contradiction between the foregoing results and the decline in aggregate energy intensity. We explore this possibility by estimating our econometric model on data for 1958-1979, for which the estimates of a_{Eti} are

¹⁵ The latter situation prevails in nine industries.

¹⁶ In the case of electric energy input, the industries with the five largest estimated coefficients all exhibit an energysaving bias, while in the case of non-electric energy inputs, the largest estimated coefficient is negative and an order of magnitude bigger than the next-largest.

tabulated in panel $C¹⁷$ In general, the magnitude of these estimates is similar to those of Jorgenson, but their distribution is different, with technical change being significantly energy saving in 9 sectors and significantly energy using in 13. The overlap between our estimates and Jorgenson's is low, however, because of the pattern of sectors for which his estimates in panel B differ in sign between columns I and II, and for which our estimates in panel C are not significant.¹⁸ But despite the difficulty in reconciling our estimates with those of Jorgenson, our findings nevertheless support his overall conclusion that technological change exerted a predominantly energy using influence prior to 1980. This finding remains a puzzle, which we return to in subsequent sections.

Our estimates of *αEti* for the full sample are shown in panel D of Table 3. We find that the impact of technical change is significant in 18 sectors, for eight of which it is energy saving and for ten of which it is energy using. Compared to our results in panel C, the significant estimates have the same signs in only 13 industries, in six of which the magnitudes are greater.¹⁹ While there is no clear pattern of the energy-using or -saving impact of technical change across industries, the means and medians of the cross-industry distribution of the parameter estimates suggest that moving to the longer sample period coincides with a shift toward energy-saving technical change.

4.4. The Consequences of Embodied and Disembodied Technical Change

We now turn to our estimates of the influence of embodied and disembodied technical progress on the rate of change of energy intensity. These are reported in Table 4 for the short and the full sample periods. Over the period of Jorgenson's sample in panel A, disembodied technical change, which is indicated by the short-run elasticity ε_{Eti} , has a significant energy-using influence in 13 industries and a significant energy-saving influence in nine, while over the full sample in panel B, technology's influence is significantly energy using in ten industries and significantly energy saving in eight. The inter-industry pattern of these influences in generally stable, with our significant estimates of ε_{Eti} for both samples exhibiting the same sign in ten industries, and opposite signs in three. For the period 1958-1979, the joint influence of embodied and disembodied technical change, which is indicated by the long-run elasticity *ηEti*, is significantly energy using in 8 industries and significantly energy saving in two, while over the period 1958- 1996 its influence is significantly energy using in one industry and significantly energy saving in four. Only in one sector does the significant estimates of *ηEti* have the same sign in both samples.

Comparison of the values of *εEti* and *ηEti* in panel A indicates that prior to 1980 the sectoral rates of change in energy intensity attributable to disembodied technical progress ranged from -8 percent to +5.9 percent per year (in FIRE and metal mining respectively), while the rates of change in intensity attributable to the joint influence of embodied and disembodied technical progress ranged from -3.6 to +6.6 percent per year (in the coal mining and tobacco products industries, respectively). However, over the full sample in panel B, disembodied technical

 17 In performing these estimations we were forced to aggregate our six quasi-fixed inputs into two—machinery and structures, in order to gain degrees of freedom.
¹⁸ The signs of our estimates agree with those of Jorgenson and Fraumeni (1981) in nine industries and with those of

Jorgenson (1984) in only six. Additional factors that account for the differences between the two sets of results are our adjustments to Jorgenson's energy price and quantity series, our use of multiple quasi-fixed inputs as opposed to a single stock of capital in each industry, and differences in estimation technique, especially Jorgenson's imposition of concavity versus our use of instrumental variables.

¹⁹ Only in three industries (lumber and wood products, motor vehicle manufacturing and communications) do the significant estimates exhibit sign reversals between the short and the full sample.

progress is associated with annual rates of change in energy intensity of -4.6 percent to +5.4 percent (in the lumber and wood products and communications sectors, respectively), while embodied and disembodied technical progress jointly contribute to rates of intensity change that range from -16.1 percent to +8.7 percent per year (in motor vehicle manufacturing and lumber and wood products, respectively).

To put these ranges in perspective, we note that the signs of ε_{Eti} and η_{Eti} agree in only eight industries for the 1958-1979 sample and in only four industries for the full sample. In most of these sectors it appears that the long-run influence of quasi-fixed inputs amplifies the shortrun impact of disembodied technical change. This pattern, along with the general lack of precision in our elasticity estimates, suggests that neither embodied nor disembodied technical progress exerts a strong influence in either an energy-saving or energy-using direction. Moreover, the mean and median values of ε_{Eti} and η_{Eti} in Table 4 indicate that, like the values of *εEti* in Table 3, negative skewness is a pervasive feature of the cross-industry distribution of technology's influences on energy intensity. These statistics suggest that the aggregate impact of embodied technical change was to shift this distribution toward more intensive use of energy prior to 1980 and toward a reduction in energy intensity over the longer sample period.

Further insight into the role of embodied technical progress can be gained by examining the influences on energy intensity of the disaggregate sources of embodiment, *ωEKi*, which are shown in Table 5 for our full sample. The data on quasi-fixed inputs are noisy, consequently our estimates are not significant in the majority of industries. However, the significant estimates indicate that an energy-using influence of technical change is embodied in ICT capital in two industries, in electrical equipment in only one industry, in machinery in three, in vehicles in four, and in structures in seven industries. We find an energy-saving influence embodied in ICT capital in six industries, in electrical equipment in five, in machinery and in vehicles only in one industry, and in structures in three industries. The table's summary statistics suggest that the embodiment of energy-using innovation occurs in machinery and structures, while that of energy-saving innovation occurs in ICT and electrical equipment.²⁰

Finally, we compare our findings on the effects of embodied and disembodied technological change in our full sample with Popp's (2001) estimates of the influence of patents on energy demand in energy-intensive manufacturing industries. The results are presented in Table 6, which matches Popp's disaggregate sectors with the corresponding industry groups in the Jorgenson dataset. Panels A and B reproduce Popp's (2001: Table 2) short- and long-run energy-patent elasticities, which exhibit an energy-saving influence in two-thirds of the industries in his sample. His elasticity estimates indicate that a one-percent increase in patents induces changes in energy intensity that range from approximately -0.4 percent to +0.3 percent in the short run, and from -1 percent to $+1.5$ percent in the long run.

To assess the implications of these estimates, we make them comparable to our own results by applying eq. (18). Estimates of the average annual growth rates of energy patents in Popp's industries, which correspond to the bracketed term in that formula, are tabulated in panel $C²¹$ Their values range from -1.4 percent in pulp and paper to +3.8 percent in steel pipe and tube manufacturing. Multiplying them by the *εE, PAT* coefficient estimates for each industry yields the short- and long-run rates of induced change energy intensity shown in panels D and E. Over both the short- and the long run these rates are generally small in magnitude and indicate that

 20 Innovations embodied in vehicles have a more or less neutral effect with respect to energy.

²¹ We thank David Popp for providing us with his data on counts of energy patents by industry.

technical progress induced by energy prices is predominantly energy-saving, with average impacts of 0.1 percent in the short run and 0.2 percent in the long run.²²

Panels F and G compare these estimates with our elasticities in Table 4 for the aggregate sectors that correspond to Popp's industry sample. The crucial importance of the unmeasured component of eqs. (19) and (23) is highlighted by the magnitudes of our rates of change in energy intensity, which are all far larger than those implied by Popp's estimates, in some industries by two orders of magnitude. The signs of the estimates of disembodied technical change in panel F agree with the corresponding short-run estimates in panel D in only two industries, which indicates that the unmeasured components of disembodied technical change due to non-energy patents generally have different signs than *εEti*. The agreement between the signs of the long-run estimates in panels E and G is very good, however, indicating that the unmeasured components of the joint influence of embodied and disembodied technical change generally have the same sign as *ηEti*.

These result suggest that disembodied innovation in non-energy technological fields tends to attenuate the energy-saving influence of disembodied innovation in energy fields. They also suggest that embodied innovation in both energy and non-energy fields tends to amplify the long-run energy-saving influence of disembodied energy innovation, in line with the results from Table 4. The lack of precision in our estimates for the more aggregate Jorgenson industry groupings, especially of those incorporating the influence of long-run capital stock adjustments, imply the need for caution in drawing broad conclusions from our results. But at the very least, our summary statistics corroborate Popp's finding of energy-saving disembodied technical change in energy-intensive manufacturing industries.

4.5. The Sources of Change in Energy Intensity: Aggregate Impacts

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We now summarize the aggregate-level implications of the foregoing industry-level results. A pervasive feature of these estimates is their substantial heterogeneity across industries, which makes it difficult to get a sense of their overall impacts of variable input prices, accumulation of quasi-fixed inputs and technological progress on the energy intensity of the economy as a whole. Furthermore, the aggregate influence of each of these factors depends on the interaction of the signs, the magnitudes and the significance of the relevant elasticities with the shares in GDP and aggregate energy use of the industries to which they belong. To ascertain the consequences of this interaction, we run the decomposition of aggregate intensity change into industry-level intensity change from section 4.1 in reverse.

We combine the definition of industry-level energy intensity from eq. (6) with the average of the growth rates of these quantities (Ψ) from eq. (25) to express the within-industry energy-intensity effect as the sum of its constituent factors, as follows. Letting a hat over a variable indicate its econometrically estimated value, substituting (6) into (25) yields the discrete approximation:

 22 There are nonetheless a few industries in which technical change is associated with increased energy intensity: primary metal (steel foundries and aluminum), pulp and paper, glass, and fabricated metal (rolling and casting, and metal coating). These results imply that the rates of growth of AEEI routinely employed in climate policy simulations drastically overstate the true secular rate of decline in unit energy demand.

(26)
$$
\hat{\Psi}_{t} = \begin{cases}\n\frac{1}{N} \sum_{i=1}^{N} \left[\left(\hat{\alpha}_{EEi} \Delta p_{Ei,t} + \hat{\alpha}_{EMi} \Delta p_{Mi,t} \right) / \left(\frac{\hat{E}_{i,t}}{Y_{i,t}} \right) \right] & \text{substitution of variable inputs} \\
+ \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{k} \hat{\alpha}_{Eki} \Delta \left(\frac{x_{ki,t-1}}{Y_{i,t}} \right) / \left(\frac{\hat{E}_{i,t}}{Y_{i,t}} \right) \right] & \text{change in the level and composition of} \\
+ \frac{1}{N} \sum_{i=1}^{N} \left[\hat{\alpha}_{Eii} / \left(\frac{\hat{E}_{i,t}}{Y_{i,t}} \right) \right] & \text{disembodied} & \hat{\Psi}_{t}^{T} \\
\text{technical change} & \hat{\Psi}_{t}^{T}\n\end{cases}
$$

which partitions the changes in energy-intensity across industries into the influences of substitution associated with changes in variable input prices $(\hat{\Psi}^{\nu})$, the accumulation of quasifixed inputs ($\hat{\Psi}^{K}$), and disembodied technical change ($\hat{\Psi}^{T}$). The results of this calculation are shown in Figure 3, which presents chained indices of these three effects on the left hand side of eq.(26), and of the fitted values on the right hand side.²³ These series illustrate the temporal evolution of the influences summarized by the elasticity estimates of the previous sections.

The aggregate influence on energy intensity of changes in variable input prices is large and negative during the 1974-1986 period of high oil prices, during which price effects reduce within-industry energy intensity by a maximum of 17 percent from the 1958 level. However, prior to 1974, variable inputs have a negligible impact, indicating a pattern of substitution that shifted away from energy inputs as their prices rose. The aggregate impact of changes in the quantities of quasi-fixed inputs is positive prior to 1986 and negative thereafter, in both periods contributing significantly to changes in energy intensity within industries. The energy-using influence of quasi-fixed inputs peaks in 1975, increasing energy intensity by 23 percent relative to the 1958 level before inducing a drastic decline by over 50 percent over the succeeding two decades.

Somewhat surprisingly, the impact of disembodied technical progress is energy-using. However, its overall influence is modest, increasing energy intensity by only 15 percent over the 39-year period. This result, while confirming Jorgenson's findings, represents a puzzle. Interpreted in light of eq. (18), it suggests that the energy-using influence of non-energy patents has dominated the energy-saving effect of energy patents found by Popp. Nevertheless, it remains unclear what exactly these disembodied effects are, and through what channels they influence the intensity of industries' energy use.

To recapitulate, we note that the chained index of the sum of the foregoing impacts, $\hat{\Psi}$, closely tracks the index of historical change in within-industry energy intensity (Ψ) from Figure 2, demonstrating the excellent agreement between our estimates and the data.

Figures 4 and 5 explore the impacts on energy intensity of variable and quasi-fixed inputs in greater detail. Figure 4 decomposes the aggregate impacts of variable input price changes , $\hat{\Psi}^{\nu}$, into the contributions of energy and materials. The effect of materials prices on long-run energy intensity is generally positive but small, with the largest sustained impacts occurring

 $2²³$ Only significant estimates of the coefficients were in computing eq. (15). The inclusion of non-significant coefficients causes a substantial amplification of both the energy-saving effects of variable and quasi-fixed inputs, and of the energy-using effect of technical progress, toward the end of the sample period.

toward the end of the sample. The impacts of the latter are generally negative, most influentially during the 1979-86 period after the second OPEC oil price increase, and reverting to a somewhat smaller effect in the succeeding decade, with a blip in the aftermath of the 1990 oil price shock. Energy prices dominate the pattern of variable input price effects over the time-frame of our study, inducing substitution away from energy that accounts for a substantial and persistent intensity decline.

Figure 5 decomposes the aggregate impact of the accumulation of quasi-fixed inputs, $\hat{\Psi}^{K}$, into the effects of the different types of capital assets. ICT and electrical equipment capital have impacts on intensity that are uniformly negative, negligible prior to 1980, and much stronger thereafter. By 1996, each of these quasi-fixed inputs contributed to a decline in intensity of as much as 20 percent below the 1958 level. Vehicle and machinery capital both contribute to small increases in intensity over most of the study period. However, after the mid 1980s these impacts decline by 10-15 percent, by 1996 resulting in a small decrease in intensity relative to 1958. The impact of buildings and structures on energy intensity is uniformly positive and exhibits a strongly cyclical trend, with temporary peaks occurring after 1971 that occur at fourto six-year intervals. Throughout most of the sample these have a small effect, increasing intensity by less than ten percent over the 1958 level; however the 1991 peak sees the contribution of this type of capital raise energy intensity by over 20 percent.

This last result suggests that the embodiment of technical progress in industries' quasifixed inputs was an important contributor to the recent decline in aggregate energy intensity.²⁴ To account for this influence at the aggregate level, we measure its effect, $\hat{\Psi}^{KT}_t$, by applying the logic of eq. (26) to the components of technical change associated with capital in eq. (14):

$$
(27) \qquad \hat{\Psi}_{t}^{KT} = \frac{1}{N} \sum_{i=1}^{N} \sum_{k} \left(\frac{\hat{\alpha}_{Eki} \hat{\alpha}_{kii}}{\hat{\alpha}_{kki}} / \left(\frac{\hat{E}_{i,t}}{Y_{i,t}} \right) \right).
$$

 \overline{a}

The outcome of this calculation is shown in Figure 6, which plots chained indices of the contributions of technical change embodied in individual quasi-fixed inputs, as well as their overall impact on energy intensity. The results are consistent with Figure 5, and demonstrate that technological change embodied in machinery, vehicles, and particularly building and structures was energy using, while that associated with electrical equipment and particularly information and communication technology was energy saving. Technological embodiment associated with machinery and vehicles each contributed to an eight-percent rise in intensity over the 39 years of our sample, while that associated with structures increased intensity by nearly 30 percent. Embodiment effects due to electrical equipment capital reduced energy intensity by 11 percent from its starting level, while those due to ICT capital reduced it by 37 percent.

The aggregate impact of these influences was to reduce intensity from 1958 levels by nine percent. Interestingly though, this effect reaches its nadir in the mid to late 1980s, subsequent to which it was rapidly attenuated by the energy-using influence of buildings and structures, which had wiped out one third of the aggregate energy-saving impact of embodied technical change by the end of the sample period. In sum, then, the joint effects of embodied and

 24 With the exception of some types of structures, virtually all of the quasi-fixed inputs in our classification use some form of energy. Although it is therefore natural to associate the accumulation of capital with increases in energy demand, a shift in the energy-output ratio associated with additional units of capital implies a change in the energyusing characteristics of capital relative to its contribution to output, or embodied technical progress.

disembodied technical change were largely offsetting, and resulted in a small net increase in energy intensity.

Thus, the change in the energy intensity of the U.S. economy over the latter half of the $20th$ century appears to be one of a slow and steady rise, due to disembodied technological change, coupled with an early, rapid rise due to the accumulation of buildings, structures, machinery and electrical equipment. This upward trend begins to be attenuated after 1970, first by the substitution away from energy in response to high energy prices during the period of the OPEC oil shocks, and subsequently by a prolonged reduction in intensity due primarily to embodied technical progress associated with shifts in the composition of capital stocks. The proliferation of information and communication technology and electric equipment is the key to the latter effect, a finding which is broadly consistent with both the implications of Newell et al (1999) and recent results from the productivity literature.²⁵

5. Conclusions

 \overline{a}

The story of the overall reductions in the energy intensity of the U .S. economy in the latter half of the past century is not a simple one. It is certainly not only the result of disembodied technological change induced by rising energy prices, which we find to be mostly energy using. There have been a number of other energy saving influences: changes in the sectoral composition of the economy, changes in the scale of its constituent sectors, as well as input substitution due to shifts in the relative prices of energy and other variable inputs.

There have also been technological changes embodied in industries' capital stocks that have contributed importantly to reductions in energy intensity, although these innovations may have been pursued for reasons other than to save energy. In particular, a significant portion of the energy-saving technical changes we observe may well have been the coincidental result of innovations which were intended to accelerate production, reduce both labor and capital costs, or make use of alternative materials.

All of these various sources of change were sometimes reinforcing, sometimes offsetting and differed across industries, which were themselves also changing in importance, as well as among types of capital. We have made no attempt to explain the sources of the time-related changes that we interpret as disembodied technical progress, but do observe that the latter seems not to have accelerated when energy prices were rising most rapidly, nor decelerated when energy prices fell. Thus, while we have unraveled some parts of the tangle of effects on the longrun change in U.S. energy intensity, there remain some puzzles.

²⁵ See, e.g., Greenwood et al (1997); Jorgenson and Stiroh (1999).

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Table 1. Descriptive Statistics

Table 2. Variable Input Price and Quasi-Fixed Input Elasticities of Energy Demand Table 2. Variable Input Price and Quasi-Fixed Input Elasticities of Energy Demand

23

+ Energy using, ++ Energy using and significant at the 10% level or better, + Energy saving, -- Energy saving and significant at the 10% level or better, † Significant estimates + Energy using, ++ Energy using and significant at the 10% level or better, + Energy saving, -- Energy saving and significant at the 10% level or better, ^{*} Significant estimates only.

				A. 1958-1979						B. 1958-1996		
		I. ε_{Eti}		II. η_{Eti}				I. ε_{Eti}		II. η_{Eti}		
Agriculture	-0.0053		$\overline{}$	0.0338	$+$		0.0055	$+$		-0.5354		
Metal mining	0.0595	$^{++}$		0.0645	$^{++}$		0.0086	$+$		-2.3685		
Coal mining	-0.0249		$-$	-0.0362		$\overline{}$	-0.0232		$-$	-0.0256		
Crude oil & gas	0.0223	$^{++}$		0.0236	$+$		0.0348	$^{++}$		0.3045	$+$	
Non-metal mining	0.0186	$+$		-0.0028		$\overline{}$	-0.0052		$\overline{}$	-0.0869		\overline{a}
Construction	-0.0309		$--$	-0.0166		\overline{a}	-0.0195		\overline{a}	0.0133	$+$	
Food & allied	0.0112	$^{++}$		-0.0770			-0.0082			0.1049	$\ddot{}$	
Tobacco	0.0365	$^{++}$		0.0662	$^{++}$		0.0398	$^{++}$		-0.0928		
Textile mill prod.	-0.0541		$\qquad \qquad -$	0.2429	$+$		-0.0135		\bar{a}	-0.0386		
Apparel	-0.0136			0.1798	$+$		0.0220	$+$		-0.0165		
Lumber & wood	0.0287	$^{++}$		0.0530	$+$		-0.0459		$\overline{}$	0.0870	$^{++}$	
Furn. & fixtures	0.0071	$+$		0.0121	$^{++}$		0.0215	$^{++}$		-0.0886		\overline{a}
Paper & allied	0.0380	$^{++}$		0.0281	$^{++}$		0.0266	$^{++}$		-0.0013		
Printing & pub.	0.0246	$+$		0.0251	$++$		0.0150	$+$		-0.0120		
Chemicals	-0.0207			5.1310	$+$		0.0172	$+$		-0.0353		
Petroleum & coal	0.0063	$^{++}$		-0.0013		\overline{a}	-0.0020		$\overline{}$	-0.1679		
Rubber & plastics	0.0111	$+$		-0.0140			-0.0192		\overline{a}	-0.0015		
Leather	0.0229	$^{++}$		0.0312	$^{++}$		0.0152	$^{++}$		-0.0777		
Stone clay & glass	-0.0044		\overline{a}	-0.0045		$\overline{}$	-0.0073		$\overline{}$	0.0353	$+$	
Primary metal	-0.0042			0.0085	$+$		0.0149	$^{++}$		-0.3921		$\overline{}$
Fabricated metal	-0.0217		$-$	-0.0039		$\overline{}$	-0.0192		$\overline{}$	0.0817	$+$	
Non-elec. mach.	-0.0040		$\overline{}$	-0.0083		$-$	-0.0175		$\overline{}$	0.0288	$+$	
Electrical mach.	0.0325	$^{++}$		-0.0921			0.0172	$+$		1.0008	$+$	
Motor vehicles	0.0328	$^{++}$		0.0068	$+$		-0.0192		$-$	-0.1609		$-$
Trn. equip. & ord.	0.0009	$+$		0.0041	$+$		-0.0014			0.4270	$+$	
Instruments	-0.0076		$\overline{}$	0.0247	$+$		-0.0102		$\overline{}$	-0.2243		$\overline{}$
Misc. mfg.	0.0105	$+$		0.0119	$+$		0.0419	$^{++}$		0.0168	$+$	
Transportation	-0.0233		$-$	-0.0769		$\overline{}$	-0.0073		$- -$	-0.0180		
Communications	-0.0387		$-$	0.0849	$+$		0.0536	$^{++}$		-0.1500		
Electric utilities	0.0055	$+$		-0.2510		\overline{a}	0.0048	$^{++}$		0.0321	$+$	
Gas utilities	-0.0034		$\overline{}$	0.1309	$+$		-0.0054		$-$	0.0765	$+$	
Trade	0.0578	$^{++}$		0.0281	$^{++}$		-0.0054		\overline{a}	-0.0317		\overline{a}
FIRE	-0.0803		$--$	-0.0100			0.0184	$+$		-0.0146		
Services	0.0172	$^{++}$		-0.0046			0.0276	$^{++}$		0.5968	$+$	
Gov't. enterprises	0.0470	$++$		0.0662	$^{++}$		-0.0135			-0.0963		
$Mean^{\dagger}$	0.0034			0.0236			0.0069			-0.0432		
$Median^{\dagger}$	0.0112			0.0281			0.0098			-0.0386		

Table 4. The Effect of Embodied and Disembodied Technical Progress on Energy Intensity

+ Energy using, ++ Energy using and significant at the 10% level or better, + Energy saving, -- Energy saving and significant at the 10% level or better, † Significant estimates only.

+ Energy using, ++ Energy using and significant at the 10% level or better, + Energy saving, -- Energy saving and significant at the 10% level or better, † Significant estimates + Energy using, ++ Energy using and significant at the 10% level or better, + Energy saving, -- Energy saving and significant at the 10% level or better, ^{*} Significant estimates only.

Jorgenson	Popp	A.	B.	\mathcal{C} .	D.	E.	F_{\cdot}	G.
Industry	Industry	SR	LR	Average	$\varepsilon_{Eti}^{\prime}$	η'_{Eti}	ε_{Eti}	η_{Eti}
Groups	Groups	$\varepsilon_{E, EPATH}$	$\varepsilon_{E, EPATH}$	Growth				
				Rates of				
				Energy				
				Patent				
				Stocks				
Motor vehicles	Automotive	-0.043	-0.371	0.038	-0.0016	-0.0142	$-0.019***$	$-0.161*$
Chemicals	Chemicals	-0.298	-0.686	0.027	-0.0082	-0.0188	0.017	-0.035
	Aluminum	0.000	0.015	0.001	0.0000	0.0000		
	Copper	-0.004	-0.205	0.028	-0.0001	-0.0057		
Primary	Electro-	-0.386	-0.707	0.021	-0.0080	-0.0147		
metal	metallurgical						$0.015**$	-0.392
	Iron foundries	-0.005	-0.119	0.016	-0.0001	-0.0019		
	Steel							
	foundries	0.013	0.254	0.029	0.0004	0.0074		
Stone clay	Glass	0.029	0.371	0.038	0.0011	0.0143	-0.007	0.035
& glass								
Rubber $&$	Plastic film	-0.069	-0.142	0.025	-0.0017	-0.0035	$-0.019***$	-0.002
plastics	and sheet							
Paper & allied	Pulp and paper	-0.035	-0.065	-0.014	0.0005	0.0009	$0.027*$	-0.001
	Metal							
	coating	0.318	1.504	0.009	0.0030	0.0141		
Fabricated	Rolling and						$-0.019*$	0.082
metal	casting	0.008	0.112	0.017	0.0001	0.0019		
	Steel pipes	-0.343	-0.991	0.009	-0.0030	-0.0086		
	and tubes							
Mean		-0.063	-0.079	0.019	-0.0014	-0.0022	-0.003^{\dagger}	
Median		-0.005	-0.119	0.021	-0.0001	-0.0019	-0.019^{\dagger}	

Table 6. Comparisons with Popp (2001)

Standard errors in parentheses are robust to third-order autocorrelation. Significance: 10% *, 5% **, 1% ***. † Significant estimates only.

Figure 1. U.S. Energy Intensity and Energy Prices, 1958-1996

Source: BEA (2000); DOE (2002).

Figure 2. Contribution of Structural Change (Φ) and Intensity Change (Ψ) to Change in Aggregate Energy Intensity (*d*ln(*E**/*Y**)), 1958-1996

Figure 3. The Sources of Within-Industry Change in Energy Intensity, 1960-1996

Figure 4. Aggregate Impacts of Variable Input Prices, 1960-1996

Figure 5. Aggregate Impacts of Quasi-Fixed Inputs, 1960-1996

Figure 6. Aggregate Impacts of Embodied Technical Change, 1960-1996

Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***. Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***.

Table A-1. (Continued)												
	Paper & allied		Printing	& publishing	The micals		Petroleum & coal		Rubber & plastics		Leather	
Cons.	-0.0298	$(0.0168)*$	0.0031	(0.0035)	0.0114	(0.0220)	0.2636	(0.0561) ***	0.0530	(0.0068) ***	0.0025	(0.0015)
$p_{\cal E}$	0.0003	(0.0016)	-0.0020	(0.0005) ***	-0.0086	(0.0029) ***	-0.0238	(0.0033) ***	-0.0161	(0.0035) ***	-0.0035	(0.0005) ***
	0.0242	(0.0062) ***	0.0003	(0.0018)	0.0194	(0.0083) **	0.0452	(0.0067) ***	-0.0058	(0.0037)	0.0034	(0.0009) ***
$\begin{array}{c} r \ t \end{array}$	0.0011	(0.0003) ***	0.0001	(0.0001)	0.0008	(0.0008)	-0.0013	(0.0013)	-0.0007	(0.0002) ***	0.0002	(0.0000) ***
$\rm ICI$	-1.0065	$(0.4709)**$	-0.0361	(0.0672)	-0.7983	(0.9194)	47.2927	(6.5747) ***	1.5322	(0.5650) ***	1.3327	(0.0847) ***
Equip. Mach. Vehic. Struct. Struct. Adj-R 2	-0.1116		-0.0616	(0.0874)	0.3199	(0.2171)	6.5532	$(3.6271)*$	-2.8036	(0.4430) ***	-1.9883	(0.1423) ***
	-0.0353	$\begin{array}{c} (0.1332) \\ (0.0460) \\ (0.2789) \end{array}$	0.0505	(0.0470)	-0.2780	(0.1920)	-1.2158	(0.3540) ***	-0.0874	(0.0414) **	0.0944	(0.0109) ***
	0.2582		0.0491	(0.1321)	-0.9829	(2.9440)	4,6022	(1.0480) ***	-2.7968	(0.7042) ***	0.6322	(0.2648) **
	0.1804	$(0.0816)**$	-0.0176	(0.0473)	0.3207	(0.2280)	0.7186	(0.1376) ***	0.3595	(0.0685) ***	-0.0407	(0.0068) ***
	$0.71\,$		0.84		0.61		0.94		0.95		0.95	
D.W.	0.73		1.05		0.42		1.64		0.99		2.35	
		Stone, clay & glass	Primary metal		Fabricated metal			Non-electric machinery		Electrical machinery	Motor vehicles	
Cons.	0.0750	(0.0168) ***	0.0703	(0.0168) ***	0.0397	(0.0073) ***	0.0220	(0.0069) ***	0.0078	(0.0086)	0.0148	(0.0025) ***
$p_{\cal E}$	-0.0014	(0.0026)	-0.0098	(0.0034) ***	-0.0034	(0.0011) ***	-0.0079	(0.0014) ***	-0.0085	(0.0020) ***	0.0060	(0.0008) ***
	-0.0088	(0.0083)	-0.0085	(0.0057)	-0.0039	(0.0035)	0.0047	(0.0031)	0.0033	(0.0034)	-0.0057	(0.0013) ***
$\begin{array}{c} r \ t \end{array}$	-0.0005	(0.0003)	0.0011	(0.0005) **	-0.0005	$(0.0003)*$	-0.0004	(0.0001) **	0.0003	(0.0002)	-0.0002	(0.0001) ***
$\rm ICI$	-0.2079	(0.5066)	-5.5668	(0.7329) ***	0.1288	(0.7137)	-0.1405	(0.1115)	-0.5830	(0.1255) ***	0.3562	(0.3823)
Equip.	-0.7062	(0.1969) ***	0.5730	(0.1443) ***	-0.4881	(0.7117)	0.1288	$(0.0706)*$	0.4333	(0.0699) ***	-0.2192	(0.0758) ***
Mach.	0.0860	(0.0394) **	-0.0968	$(0.0538)*$	-0.0634	(0.0494)	-0.1718	(0.0180) ***	-0.0182	(0.0554)	-0.0613	(0.0170) ***
Vehic.	0.0144	(0.1256)	2.4563	$(0.7670)***$	-1.0393	$(0.4729)**$	0.2285	$(0.1375)*$	1.3103	(0.7225) *	0.4363	$(0.2282)*$
Struct.	-0.0294	(0.0540)	0.0216	(0.0767)	0.2149	(0.1187) *	0.1831	(0.0143) ***	-0.0822	(0.0584)	0.1399	(0.0345) ***
$\mathbf{Adj}\text{-}\mathbf{R}^2$	0.97		$0.83\,$		0.94		0.99		0.93		0.92	
D.W.	1.44		1.26		0.57		1.38		1.09		1.72	

Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***. Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***.

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Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***. Standard errors robust to third-order autocorrelation in parentheses. Significance: 10% *, 5% **, 1% ***.

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