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The effect of new technology on energy consumption

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Abstract

This paper uses patent data to estimate the effect of new technologies on energy consumption. Matching energy patent counts to the industries using these patents, I create stocks of energy knowledge for 13 industries. Including the stocks in restricted variable cost functions, I estimate the median present value of long run savings from a new patent to be over US$ 14.5 million. Combining these results with estimates of price-induced innovation, I conclude that two-thirds of the change in energy consumption with respect to a price change is due to simple price-induced factor substitution, while the remaining third results from induced innovation.

JEL classification: Q41 Energy: demand and supply; O33 Technological change: choices and consequences

Keywords: Energy; Technology; Induced innovation; Patents; Yale Technology Concordance (YTC)

1. Introduction

This paper uses data on energy patents to estimate the effect of new technology on industrial energy consumption. Using the Yale Technology Concordance (YTC) to map energy patents to the industries in which they are used, I construct stocks of energy-efficient knowledge. By including these knowledge stocks in cost functions for various energy intensive industries, I estimate the effect of new technology on energy consumption. Finally, by combining these estimates with the results of Popp (2000), which estimates the elasticity of energy R&D with respect to energy prices, I calculate the effect of induced innovation on energy consumption.

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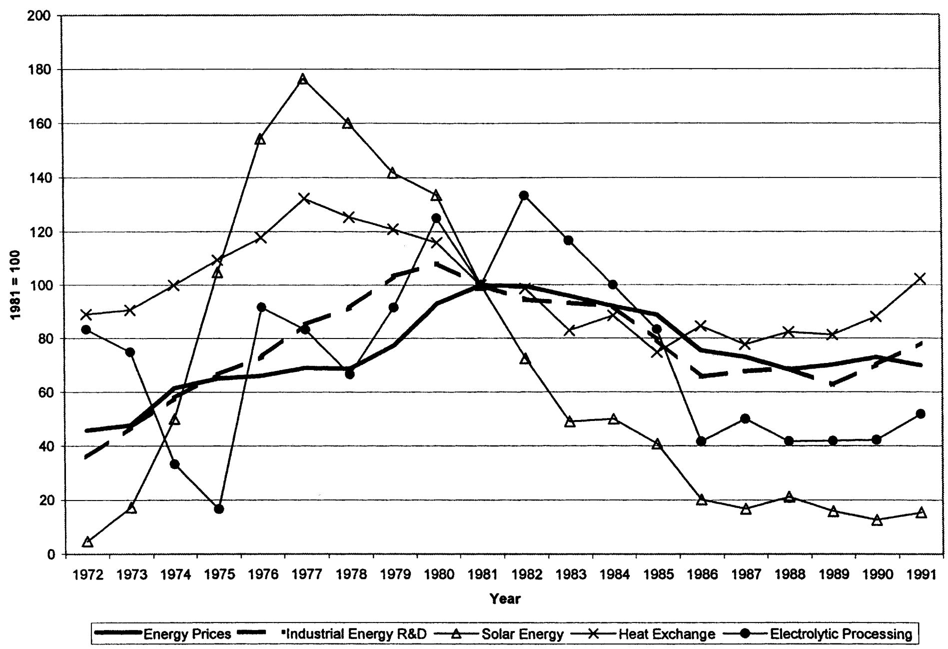

Fig. 1. Energy prices and energy innovation: plots changes in energy prices and patents in three technology fields related to energy consumption. All data has been normalized so that 1981 = 100.

The effect of new technologies on energy consumption has important policy implications. Many environmental policy proposals can be expected to lead to the development of new technologies. In fact, the Clinton administration made the development of more efficient technologies one of the cornerstones of its proposal for the 1997 Kyoto summit on climate change. Furthermore, environmental policy proposals, such as carbon taxes, often take aim at energy consumption. As these policies increase the cost of energy, they will lead to the development of more energy-efficient technologies.[1] For example, Fig. 1 shows how industrial spending on energy R&D and patenting activity in three energy-related fields increased along with energy prices.[2] Understanding the role that technology plays in energy consumption is crucial to understanding the total impact of such policies.

Although the main goal of the paper is to estimate the energy-savings resulting from induced innovation, knowledge of the impact of new energy technologies on energy consumption can also help economists understand recent trends in energy consumption and make projections about future consumption. As shown in Fig. 2, energy intensity, defined

[1] The notion that prices (or policy) lead to new innovations follows from the induced innovation hypothesis, first suggested by Hicks (1932) and further developed in the 1960s and 1970s in papers such as Ahmad (1966), Kamien and Schwartz (1968), and Binswanger (1974, 1978a,b). Recent papers demonstrating a positive link between either policy or prices and environmental-friendly innovation include Popp (2000), Newell et al. (1999), Jaffe and Palmer (1997), and Lanjouw and Mody (1996).

[2] The patent data is taken from Popp (2000), which uses patent data from 21 different technologies to estimate the elasticity between energy prices and energy patents.

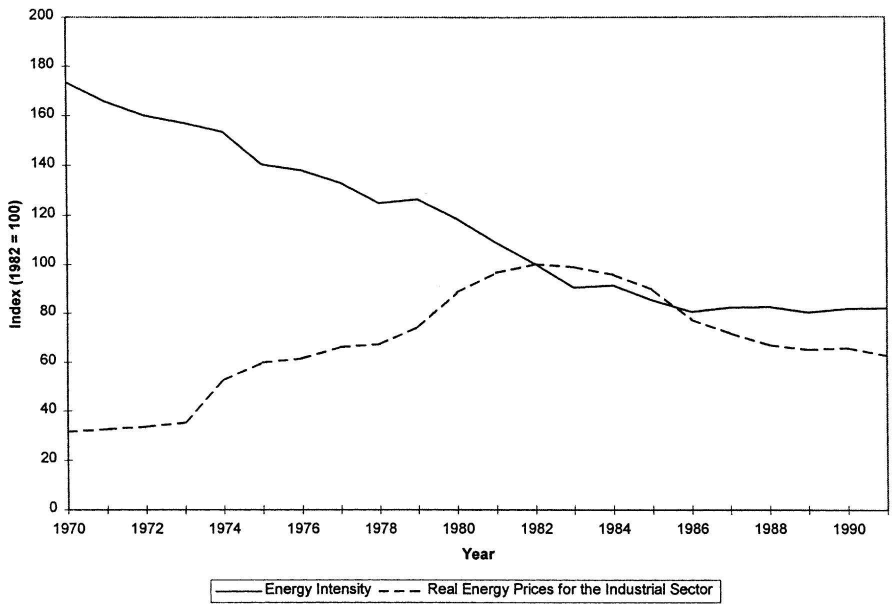

Fig. 2. Industrial energy efficiencies: energy intensity is Btu of energy per dollar of input. Energy prices are defined as dollars per million Btu of industrial energy consumption. Both are normalized so that 1982 = 100.

as Btu of energy per dollar of output, fell dramatically during the late 1970s and early 1980s. Price-induced substitution away from energy certainly played a role in the decline of energy intensity, but it does not tell the whole story. Real energy prices peaked in 1982 before beginning to fall. Yet, even when energy prices returned to pre-crisis levels, energy intensity continued to fall. If the available technology had not changed, there would have been no reason for firms to make costly adjustments to capital after prices had fallen. Presumably they made these adjustments because the new technology, developed in response to the energy crisis, was better than the previously existing technology. The results of this paper help explain how changing technology influenced energy consumption.[3]

2. Previous literature

This paper uses patent data to construct a stock of energy knowledge. These stocks are then used in a quadratic formulation of a restricted variable cost function to estimate the effect of

[3] As one referee noted, capital adjustment costs are also important here. In particular, it may be that adjustment costs slow the rate at which firms switch to energy-efficient technologies that were known before the energy crisis, so that it is not actually new technologies that are driving the reduction in energy prices. The main goal of my work is to estimate the energy savings that result from energy patents. An important question is when the savings occur. In the empirical work that follows, I estimate rates of decay and diffusion of the knowledge represented in these patents, so that the time it takes for the patents to take effect can be discerned. In most cases, new patents have the strongest effect just a few years after the patent application is filed, suggesting that it was relatively new technologies reducing energy consumption during the 1980s.

new knowledge on energy consumption. As such, it borrows from two branches of previous economic literature. The first are previous studies of the effect on energy consumption over time. The present paper improves upon these studies by using patent data to more carefully measure technological progress. The second group of related work is studies of the productivity of R&D. Using patent data offers improvements to this work as well. The following section describes previous work in both areas, and details how using patent data improves the results of each.

2.1. Studies of energy consumption across time

Studies of energy consumption across time began with a series of papers in the 1970s by authors such as Dale Jorgenson, Ernst Berndt, and David Wood. Typically, a flexible form cost or production function would be used to derive factor demand equations. In a series of papers in the 1970s, these authors investigated the demand for energy in American industries, using translog cost functions.[4] Jorgenson was the first to introduce technological change into these models. His paper, as well as those that follow, simply modeled technological change by including a time trend in the regressions. Jorgenson and Fraumeni (1981) use a time trend to represent technological change, and find that technological change was energy-using — that is, that energy use per unit output increased over time. Their paper, however, used data from 1958 to 1974. As shown earlier, the two energy crises of the 1970s led to much innovation designed to save energy. Such technological change was not included in the data used by Jorgenson and Fraumeni (1981). Thus, it is reasonable to expect that the results may be different today.

More recent work does find that technological change is energy saving. Examples include Berndt et al. (1993), Mountain et al. (1989), and Sterner (1990). One feature common to all of the above papers is that they simply model technological change by introducing a time trend to their model. The use of a time trend has two drawbacks. One is that advances in energy-saving technology do not occur randomly over time, but are instead correlated with changes in energy prices. Thus, the results of these papers are sensitive to the time period studied. Technological advancements are energy-using when energy prices are low, and energy-saving when energy prices are high. Secondly, the time trend can only capture the *overall* impact of technological change. It can only tell us whether all of the technological advances that occurred during the period studied led to more or less energy use. For example, technological advances that lead to an increased reliance on capital might increase energy-use per unit output, as more energy would be required to run additional machines. However, the energy may be used more efficiently than before.

In both cases, the problem is that using a time trend makes it impossible to attribute to technological change the effect of *only* those technologies that are related to energy consumption. For example, the Mountain et al. (1989) paper finds that technological change was natural gas-using during the period studied. This occurred because natural gas prices were low during this period. As a result, new technologies tended to take advantage of low natural gas prices by using gas more than other energy sources. Nonetheless, there may have been technologies that improved the efficiency of natural gas use during the period

[4] See, for example, Berndt and Wood (1975) and Griffin and Gregory (1976).

studied. However, the effect of these innovations would not be identified in the study by Mountain et al. (1989) since it only captures the *overall* effect of technological change.

Using patents as an indicator of technological change, as is done in this paper, avoids these pitfalls. By identifying those patents that are related to energy efficiency, it is possible to identify the effect of technologies specifically related to energy consumption. In addition, using patent counts allows for fluctuations in the level of technological advancement over time. Energy prices and technological opportunities both play an important role in the direction of energy-saving technological change. Patent data can identify both of these effects. Combining information on the development of new patents with information on the energy-savings resulting from new patents makes policy simulations possible.

2.2. Studies of the productivity of R&D

The second branch of literature related to this paper are studies that estimate the productivity of R&D, such as those by Griliches, F.M. Scherer and others during the 1980s. These papers use either firm or industry data to estimate production functions using R&D expenditures as an input. Two different approaches are used. In the first, R&D expenditures are used to create a stock of knowledge, usually by assuming a rate of depreciation of 15% on old R&D. The equation to be estimated is of the form

$$\log Y = \alpha + \beta(\log X) + \gamma(\log K) + \varepsilon, \tag{1}$$

where Y is output, X the traditional inputs, such as labor and capital, and K the stock of knowledge, represented by a weighted sum of past R&D expenditures. The second approach uses growth rates to avoid the problem of constructing a stock of knowledge by using R&D as a measure of the change in the stock of knowledge. These studies estimate an equation of the form

$$\frac{\partial \log Y}{\partial t} = \alpha + \beta \frac{\partial \log X}{\partial t} + \gamma \frac{R}{Y} + \varepsilon, \tag{2}$$

where R is a measure of R&D expenditures, and R/Y a measure of R&D intensity. A survey of both types of studies can be found in Griliches (1995).

The results of these studies are mixed. Estimates of the rate of return to R&D range from 0.2 to 0.5. However, estimation of these equations, particularly those like Eq. (1) are complicated by the usual pitfalls of estimating production functions, such as simultaneity. For example, both Griliches and Mairesse (1984) and Cuneo and Mairesse (1984) find a correlation between firm R&D and productivity across firms, but little correlation over time. These models are also handicapped in that they do not measure the spillovers from R&D very well.

Finally, using R&D expenditures as a measure of knowledge is problematic because we do not know the goal of the R&D spending. R&D expenditures can be divided into two broad categories: process innovations and product innovations. *Process innovations* are technological advances that improve the efficiency of production. *Other innovations* are product innovations. They either provide new products or improve the quality of an existing product. Process innovations should affect the production function of the firm. Product innovations should not affect the production function, but do affect the quality of output. However, if the price indices used to normalize the value of output do not adequately account for improvements in the quality of output, the benefits of R&D affecting quality will be underestimated. [5]

3. Constructing the stock of knowledge

To estimate the effect of technological innovation on energy consumption, the first step is to construct stocks of energy knowledge. I do this using data on energy patents granted in the United States since 1918. This section details the construction of the knowledge stocks, and discusses some of the benefits (and drawbacks) of working with patent data, rather than R&D data.

3.1. Energy patents by industry — the Yale Technology Concordance

For each industry, i, included in the paper, I construct a stock of energy knowledge by using a count of patents, $\mathrm{PAT}_{i,t}$, over time, t. To construct the stock of knowledge, a rate of decay, represented by β_1, is used to capture the obsolescence of older patents. Over time, the knowledge embodied in a patent becomes obsolete, as new and better inventions take its place. In addition, it takes time for the knowledge embodied in a new patent to spread throughout the economy. A new patent represents invention, the first step in technological change. Before it can have an effect on the economy, the new invention represented by a patent must be developed for commercial use. This stage of development is known as innovation. [6] By measuring the effect of knowledge on energy consumption, I am measuring the results of this commercialization, rather than simply the benefits of discovery of the new invention. Thus, the stock of knowledge also includes a rate of diffusion, β_2, to capture delays in the flow of knowledge. Both β_1 and β_2 are parameters that will be estimated. Defining s as the number of years before the current year, the stock of knowledge in industry i at time t is written as

$$K_{i,t} = \sum_{s=0}^{\infty} \mathrm{e}^{-\beta_1(s)}(1 - \mathrm{e}^{-\beta_2(s+1)})\mathrm{PAT}_{i,s} \tag{3}$$

The rate of diffusion is multiplied by $s + 1$ so that diffusion is not constrained to be zero in the current period.

As discussed in Section 2, to capture the effect of new technologies on industrial energy consumption, it is important that the stock of knowledge capture *process* innovations, rather than product innovations. To use patents as a measure of the knowledge available to a firm, I use the Yale Technology Concordance (YTC) to identify patents that are used in each industry.

The Yale Technology Concordance (YTC) uses actual patent data to map patents from their International Patent Classification (IPC) code to both the industries that use the patent

[5] To demonstrate this point, Scherer (1993) finds that estimates on the return to R&D from 1973 to 1989 falls from 0.36 to 0.13 when the computer industry is removed from his dataset. Because of the rapid change in computer technology, the Bureau of Labor Statistics (BLS) uses hedonic methods to construct price indices for the computer industry. However, at the time, the BLS did not adjust the price indices of other industries for changes in quality.

[6] For a discussion of the distinction between invention and innovation in energy technologies, see Grübler et al. (1999).

and the industries that manufacture the patent.[7] When a patent is granted in Canada, it is not only assigned to a technology classification, but also given an industry of use and industry of manufacture, using the Canadian Standard Industrial Classification System (CSIC). Since a patent examiner makes these classifications, we can be confident that the assigned industries are related to the patent in question, as each examiner is an expert in his or her technology field. Using the actual Canadian data, the YTC authors develop a probability distribution of possible industries to which a patent in a given technology field may be assigned. The distribution can then be applied to patents in other countries.[8]

I use the Yale Technology Concordance to develop a stock of energy knowledge for US industries. Since I am able to identify patents used by various industries, whether or not the R&D to invent the patent occurred in that industry, spillovers across industries are captured. Because Canada uses the International Patent Classification, I first developed a list of IPC patent classifications related to energy consumption, including both classifications related to energy supply and classifications related to energy demand. I assembled the list of technologies using resources from the Department of Energy and from the academic sciences. Descriptions of these technologies were matched with IPC patent subclassifications.[9,10] The paper makes use of counts of successful patent applications in these classifications from 1918 to 1991.[11]

The next step is to find the industry of use for these patent classes. This is done using the concordance. Four-digit CSIC codes are used. Only industries that made significant use of the energy patents are considered. There are many instances of industries that had one

[7] For more information on the Yale Technology Concordance, see Evenson et al. (1991) and Kortum and Putnam (1989, 1997). The most recent version of the concordance, as well as detailed instructions for its use, are available on the Internet at http://www.wellesley.edu/Economics/johnson/jeps.html.

[8] Other concordances are available, but not as reliable.The US Office of Technology Assessment and Forecast (OTAF) has developed a concordance between US patents and industries, but several problems have been found with it. When a patent is granted, it is assigned to a technology class and subclass. The OTAF concordance assigns patents from each subclass to an industry of use. However, if there is more than one industry that would be reasonably considered to use the patents of a certain subclass, the patents were assigned to all of the industries. This method led to serious double counting and surprising discrepancies in the data (Griliches, 1990). By developing a distribution of patents across industries, the YTC authors avoid the problem of double counting that occurs in the OTAF concordance.

[9] More information on the technologies used in this paper, including a list of all the IPC classifications, can be found on the Internet at: http://faculty.maxwell.syr.edu/dcpopp/index.html. Of course, there may be other technologies that have an effect on energy consumption. Thus, the results of this paper should be interpreted as the energy savings resulting from the technologies included in the knowledge stock, and not the energy-savings resulting from all technological change.

[10] The list is similar to the list of US classifications used in Popp (2000). However, for some technologies, such as insulated windows, it was impossible to find a corresponding IPC classification. In addition, additional technologies, such as combustion, have been added. The added classifications are ones that have some energy saving benefit, but also other uses. Ambiguous classes were not included in the earlier papers, because the goal there was to estimate the effect of energy prices on patent counts. For example, a combustion patent may lead to a more efficient engine, or it may lead to a more powerful engine. In addition, combustion patents related to efficiency were influenced not only by energy prices, but fuel economy regulations in the US. These factors would have complicated the regressions in the earlier papers. However, for this estimation, as long as the patents have some energy-savings benefit, that effect can be identified in the data.

[11] The year of the patent application is used because patents sorted by application years are closely correlated with R&D expenditures (Griliches, 1990).

Table 1
Major energy patent classifications in industry groups

Industry group	IPC classification	Patents assigned to industry/ total patents in sample	Share
Aluminum	C22B 21: producing aluminum	36/47	0.766
	C25C: electrolytic apparatus	126/387	0.326
Automotive	C25D: electrolytic apparatus	11/676	0.016
	F02: combustion	741/2277	0.325
	F23: combustion	23/1530	0.015
	F28: heat exchange	55/745	0.074
Chemical	C23C: coating metal	58/1145	0.051
Copper	C22B 4: electrothermal treatment	14/24	0.583
	C25C: electrolytic apparatus	118/387	0.305
Electrometallurgical	C21D: treating metal	4/526	0.008
	C22B 4: electrothermal treatment	2/24	0.083
Glass	C23C: coating metal	31/1145	0.027
Iron foundries	B22D 11: continuous casting	15/565	0.002
	C21D: treating metal	7/526	0.013
Metal coating	C21D: treating metal	12/526	0.023
	C23C: coating metal	527/1145	0.460
	C25C: electrolytic apparatus	11/387	0.028
	C25D: electrolytic apparatus	428/676	0.633
Plastic film and sheet	C23C: coating metal	53/1145	0.046
	C25D: electrolytic apparatus	15/676	0.022
Pulp and paper	D21C 11: black liquor	107/113	0.947
Rolling and casting	B22D 11: continuous casting	418/565	0.740
	C21D: treating metal	255/526	0.485
	C23C: coating metal	60/1145	0.052
	C25C: electrolytic apparatus	14/387	0.036
	C25D: electrolytic apparatus	28/676	0.041
Steel foundries	B22D 11: continuous casting	81/565	0.143
Steel pipes and tubes	C21D: treating metal	13/526	0.002

or two patents from a particular class assigned to them. Such industries are not included in this paper. Industries for which the patents were obviously product, rather than process, inventions are also dropped. The results are a list of 13 industry groups used in this paper. The first column of Table 1 lists the 13 industries.[12]

[12] For estimation, the knowledge stocks created will be merged with data from the NBER Manufacturing Productivity Database, which classifies industries by the 1972 US SIC codes. Thus, it is necessary to map the Canadian industries into the corresponding US industries. As Canadian industries are typically smaller, there are often two or three US industry codes corresponding to a single Canadian industry code. In addition, since there is frequently a partial correlation among codes, it is often necessary to group two or three similar Canadian industries into a group, and then find the corresponding group of American industries. A list of the industry groups, along with their Canadian and US SIC codes, is included in the data appendix found at: http://faculty.maxwell.syr.edu/dcpopp/index.html.

Next, using the concordance, the number of energy patents used in each of the 13 industry groups is calculated. The calculation is as follows. From the Yale Technology Concordance, I obtain $\omega_{i,j}$, which represents the share of patents from IPC classification *j* that are used by industry *i*. Let $\mathrm{PAT}_{j,t}$ represent the number of successful patent applications in IPC classification, *j* in year *t*. The number of energy patents from any given year, *t*, assigned to industry *i* is simply

$$\mathrm{PAT}_{i,t} = \sum_{j} \omega_{i,j}\, \mathrm{PAT}_{j,t} \tag{4}$$

where the summation is over all energy IPC's used by industry *i*. Table 1 shows the IPC classifications of the energy patents used most in the various industry groups, along with the share of patents in that class assigned to the industry and the total number of patents in that class in the YTC sample. For example, the table shows that 76% of patents in IPC classification C22B 21 are used by the aluminum industry. If there are 10 patents in this classification for a given year, 7.6 of them would be assigned to the aluminum industry.

Finally, the energy patents used by each industry are utilized to construct the stock of energy knowledge, as represented by Eq. (3). The rates of decay and diffusion, β_1 and β_2, are parameters to be estimated by the model.

3.2. Pros and cons of using patent data

Using patent counts as a measure of the stock of knowledge allows me to avoid some of the pitfalls encountered when using R&D expenditures. Most importantly for this paper, using patent data enables me to identify process innovations, as opposed to product innovations. By sorting patents by their industry of use, I can be reasonably sure that the patents represent changes to the production process, rather than changes to the quality of output. In addition, knowing the innovations represented by each patent classification allows me to eliminate any remaining innovations that are clearly product innovations.

Patent data also offer other advantages. Unlike other data on inventive activity, such as R&D expenditures, patent data are available in highly desegregated forms. For example, data on energy R&D are only available at an economy-wide level. [13] Furthermore, using patent data allows me to construct a longer time series, as data on energy R&D by industry are not available until 1972.

However, when working with patent data, it is important to be aware of its limitations. The existing literature on the benefits and drawbacks of using patent data is quite large. [14] An important concern is that the quality of individual patents varies widely. Some inventions are extremely valuable, whereas others are of almost no commercial value. This is partly a result of the random nature of the inventive process. Accordingly, the results of this paper are best interpreted as the effect of an "average" patent, rather than any specific invention.

However, there are other reasons for variation in the quality of patents that can be controlled. For example, the propensity to patent varies widely by industry. In some industries, such as the chemical industry, many new innovations are patented. In other industries,

[13] Some energy R&D data is available for industries at the two-digit SIC level, but its availability is limited.

[14] Griliches (1990) provides a useful survey.

secrecy is a more important means of protection. In these industries, the cost of revealing an idea to competitors is often not worth the gains from patent protection. As a result, the correlation between R&D and patents varies across industries. [15] It is for this reason that separate regressions are done for each industry. Within each industry, my interest lies in the time series aspects of the patent data — that is, how does energy consumption vary as the knowledge stock varies. To allow for comparisons across industries with different propensities to patent, the energy-savings resulting from a new energy patent are compared to the average R&D expenditure per patent in each industry.

Estimating different regressions for each industry controls for variations in the propensity to patent across industries. Another possible problem is that the propensity to patent may vary over time. Historically, the ratio of patents to R&D expenditures has fallen in the United States (as well as in other industrialized nations). Some researchers, such as Evenson (1991) and Kortum and Lerner (1998), consider the falling ratio to be evidence of diminishing returns to R&D. [16] Other researchers, most notably Griliches (1989), claim that research opportunities have not declined, but rather that the fall in the patent-to-R&D ratio is due to changes in the willingness of inventors to patent new inventions. An exogenous fall in the willingness to patent — caused, for example by changes in patent laws that affect the benefits of holding a patent — would result in a falling patent-to-R&D ratio even if the productivity of research spending remained the same. For this paper, a second set of regressions was run using patents weighted by the patent-to-R&D ratio as an attempt to control for possible changes in the quality of patents over time. The weighting had no affect on the final results. [17]

4. Modeling

R&D is a dynamic process. The energy-savings resulting from a new innovation will be realized for years to come. In addition, the diffusion of benefits across firms in an industry takes time. As such, a dynamic model is needed for estimation. I use a normalized, restricted variable cost function (RVCF), described in Berndt et al. (1981) and Watkins and Berndt (1992). The model allows for dynamic adjustment of quasi-fixed inputs. In this model, short run demand equations of the variable inputs can be viewed as utilization equations, based on the current stock of quasi-fixed inputs.

Define the following variables. $\boldsymbol{v} = [L, E, M]'$ is the vector of variable inputs used by a firm: labor, energy, and materials. $\boldsymbol{x} = [C, K_E]'$ is the vector of quasi-fixed inputs available to the firm in any given period. C is the stock of physical capital, and K_E is the stock

[15] Levin et al. (1987) discusses the variation in patenting behavior across industries.

[16] Here, diminishing returns to research refers to the expected return on the inputs to the research process, not the returns to the output. The notion that there are increasing returns to the output of knowledge, usually attributed to the public good nature of knowledge, is by no means compromised by claiming that the inputs to research experience diminishing returns. Diminishing returns to research simply implies that it becomes more and more difficult to develop new inventions as time progresses.

[17] This result does not necessarily mean that the interpretation of diminishing returns to R&D is incorrect. Since the patent-to-R&D ratio tends to fall monotonically over time, simply correcting for autocorrelation in the regressions may be enough to correct for changes in the quality of patents.

of energy-related knowledge. Installing new capital is costly. Resources must be diverted from the production of output, Y, to installation. In the short run, firms minimize restricted variable costs, $G=\boldsymbol{w}'\boldsymbol{v}$, where $\boldsymbol{w}'=[1,\ p_E/w,\ p_M/w]$ is a vector of normalized variable input prices. The prices of inputs are given by the wage rate, w, and the price of energy and materials, p_E and p_M, respectively. Restricted variable costs are minimized conditional on $\boldsymbol{w}$, $\boldsymbol{x}$, $\dot{\boldsymbol{x}}$, Y, and t, where t is a time trend used to capture technological change not related to energy.[18] The result is the normalized restricted cost function (RVCF)

$$G=G(\boldsymbol{w},\boldsymbol{x},\dot{\boldsymbol{x}},Y,t) \tag{5}$$

Write the normalized price of a variable input, p_j/w, as $\hat{p}_j$.[19] In equilibrium, the partial derivative of the RVCF with respect to the normalized price of a variable input equals the short run cost-minimizing demand for v_j

$$\frac{\partial G}{\partial \hat{p}_j}=v_j,\quad j=E,M. \tag{6}$$

To proceed with estimation, a functional form must be provided for G. As in Watkins and Berndt (1992), a quadratic approximation is used.

$$\begin{aligned}G&=L+p_E E+p_M M\\&=Y\left[\alpha_0+\alpha_t t+\alpha\sum_j\alpha_j\hat{p}_j+\frac{1}{2}\alpha_{tt}t^2+\frac{1}{2}\sum_j\alpha_{jj}\hat{p}_j^2+\sum_j\alpha_{jt}\hat{p}_j t+\sum_j\sum_{k\neq j}\alpha_{jk}\hat{p}_j\hat{p}_k\right]\\&\quad+\sum_i\alpha_i x_i+\frac{1}{2}\sum_i\alpha_{ii}\frac{x_i^2}{Y}+\sum_i\alpha_{it}x_i t+\sum_i\sum_j\alpha_{ji}x_i\hat{p}_j+\sum_i\sum_{k\neq j}\alpha_{ik}\frac{x_i x_k}{Y}\\&\quad+\sum_i\phi_i\dot{x}_i+\frac{1}{2}\sum_i\phi_{ii}\frac{\dot{x}_i^2}{Y}+\sum_i\phi_{it}\dot{x}_i t+\sum_i\sum_j\phi_{ji}\dot{x}_i\hat{p}_j+\sum_i\sum_{k\neq i}\phi_{ik}\frac{\dot{x}_i\dot{x}_k}{Y}\\&\quad+\sum_i\sum_{k\neq j}\gamma_{ik}\frac{x_i\dot{x}_k}{Y}\end{aligned} \tag{7}$$

$\hat{p}_j$ is the normalized price of the jth input (energy or materials), x_i is the level of the ith capital stock (physical capital or energy knowledge), and $\dot{x}_i$ is the change in this capital stock.

Before proceeding, it is necessary to distinguish between net and gross investment models, as outlined by Watkins and Berndt (1992). Net investment is investment that adds to the

[18] Rather than use a time trend to capture non-energy technological change, one could construct a separate knowledge stock from patents used by the industry that did not pertain to energy use. However, the results of such regressions are problematic. Recall that the advantage of using patent data for the energy knowledge stock is that we know the patents are related to saving energy. However, we do not know whether other patents are cost-saving patents or product innovations that improve the quality of output. Thus, the same problems that arise with using R&D expenditure data as an input arise, as discussed in Section 2.

[19] The results are sensitive to the normalization. If materials prices are used as the numeraire, many of the resulting price elasticities are positive.

capital stock, rather than simply replacing depreciated capital. Gross investment includes both new investments that add to the capital stock and investment that only aims to replace depreciating capital. Thus, gross investment is the sum of net investment and replacement investment.

In the steady-state, all inputs are at their optimal level. As a result, net investment is equal to zero. Gross investment is equal to replacement investment only. That is, the only investment that occurs in the steady-state is investment that replaces depreciated capital. The net investment model assumes that this replacement investment is frictionless. It has no effect on costs in the steady-state. The assumptions of the net investment model imply that the coefficients on $\dot{x}_i$ in the restricted variable cost function, (7), are equal to zero.[20] Conversely, the gross investment model assumes that there are adjustment costs to replacement investment. Thus, even in the steady-state, the costs of investment must be accounted for, since replacement investment is still necessary.

As noted by Watkins and Berndt (1992), the assumption of frictionless replacement investment of physical capital is not supported by economic theory. As such, the gross investment assumption will be made for the capital stock. However, the net investment assumption does make sense for the stock of knowledge. To see this, consider why the need for replacement investment arises. In the steady-state, net investment is zero. Steady-state replacement investment occurs because the existing capital stock is decaying. Although, the theoretical model outlined in this paper allows the knowledge stock to decay over time, this is merely a simplification for estimation purposes. In reality, it is not time itself that makes knowledge obsolete. Rather, the replacement of old knowledge with new and improved knowledge makes the old knowledge obsolete. Thus, the creation of new patents makes old patents obsolete. Schumpter referred to this process as “creative destruction”. However, in the steady-state, there is no desire for a net increase in knowledge, since the knowledge stock is, by definition of the steady-state, at its optimal level. Thus, there is no demand for new patents. If new patents are not being created, the old knowledge will not decay. Thus, constraining the coefficients on $\dot{x}_i$ to zero seems reasonable for the stock of knowledge parameters.[21]

Using the net investment model form knowledge, the corresponding short run factor demand equations are[22]

$$\frac{E_t}{Y_t} = \alpha_E + \alpha_{EE}\hat{p}_{E,t} + \alpha_{EM}\hat{p}_{M,t} + \alpha_{Et}t + \alpha_{EC}\frac{C_{t-1}}{Y_t} + \phi_{E\dot{C}}\frac{\dot{C}_t}{Y_t} + \alpha_{EK_E}\frac{K_{E,t-1}}{Y_t} + \varepsilon_{E,t} \tag{8}$$

[20] Algebraically, this is to ensure that marginal adjustment costs, defined by $\partial G/\partial \dot{x}_i$, are equal to zero in the steady-state. This requires that all coefficients on $\dot{x}_i$ be equal to zero except for φ_{ii}, the coefficient on x_i^2/Y.

[21] Of course, this may not be entirely correct, as simple forgetting may be possible. However, in addition to being theoretically justifiable, using the net investment model for knowledge is important for calculating the value of energy-savings resulting from a new patent later in the paper.

[22] In principle, it is also possible to estimate capital accumulation equations. However, the amount of data available limits the number of parameters that can be estimated. Since the main focus of this paper is the effect of patents on energy consumption, only the variable factor equations are estimated in this paper. However, since the capital stock equations are properly part of the system of equations to be estimated, instrumental variables estimation will be used.

$$\frac{M_t}{Y_t} = \alpha_M + \alpha_{EM}\hat{p}_{E,t} + \alpha_{MM}\hat{p}_{M,t} + \alpha_{Mt}t + \alpha_{MC}\frac{C_{t-1}}{Y_t} + \phi_{M\dot{C}}\frac{\dot{C}_t}{Y_t} + \alpha_{MK_E}\frac{K_{E,t-1}}{Y_t} + \varepsilon_{M,t} \quad (9)$$

$$\begin{aligned}\frac{L_t}{Y_y} = \frac{G}{Y} - \frac{P_E E}{Y} - \frac{P_M M}{Y} &= \alpha_0 + \alpha_t t + \frac{\alpha_{tt}}{2}t^2 \\ &-\frac{1}{2}(\alpha_{EE}\hat{p}_{E,t}^2 + 2\alpha_{EM}\hat{p}_{E,t}\hat{p}_{M,t} + \alpha_{MM}\hat{p}_{M,t}^2) + \alpha_C\frac{C_{t-1}}{Y_t} + \frac{\alpha_{CC}}{2}\frac{C_{t-1}^2}{Y_t^2} \\ &+\frac{\alpha_{Ct}}{2}\frac{C_{t-1}t}{Y_t} + \frac{\alpha_{CK_E}}{2}\frac{C_{t-1}K_{E,t-1}}{Y_t^2} + \alpha_{K_E}\frac{K_{E,t-1}}{Y_t} + \frac{\alpha_{K_E K_E}}{2}\frac{K_{E,t-1}^2}{Y_t^2} \\ &+\frac{\alpha_{K_E t}}{2}\frac{K_{E,t-1}t}{Y_t} + \phi_{\dot{C}}\frac{\dot{C}_t}{Y_t} + \frac{\phi_{\dot{C}\dot{C}}}{2}\frac{\dot{C}_t^2}{Y_t^2} + \frac{\phi_{Ct}}{2}\frac{\dot{C}_t t}{Y_t} + \frac{\phi_{\dot{K}_E\dot{K}_E}}{2}\frac{\dot{K}_{E,t}^2}{Y_t^2} \\ &+\gamma_{CC}\frac{C_{t-1}\dot{C}_t}{Y^2} + \frac{\gamma_{CK_E}}{2}\frac{\dot{C}_t K_{E,t-1}}{Y_t^2}\varepsilon_{L,t}\end{aligned} \quad (10)$$

5. Data

5.1. Manufacturing data — the NBER Manufacturing Productivity Database

In addition to the knowledge stocks constructed in Section 3, data on inputs and prices are needed to estimate Eqs. (8)–(10), data. Industry data for this study were taken from the NBER Manufacturing Productivity Database, which is available on-line from the NBER web site. It is described in detail in Bartelsman and Gray (1994). The data set provides annual information on 450 manufacturing industries from 1958 to 1991. The data are presented at the four-digit SIC level. Most of the data come from the Annual Survey of Manufactures (ASM) by the US Census Bureau.

Using the NBER database, labor usage is measured as the number of production worker hours. Wages can be calculated as total spending on production workers divided by the number of production worker hours. Total payroll is deflated by the consumer price index to put it in real dollars. [23] The value of the capital stock is calculated in the NBER data set by using the investment data, price deflators for 28 types of capital, and an investment flow matrix to determine the amount of investment in each type of capital for each industry. For the cost of capital, a price deflator for new investment, constructed by NBER, is used. The deflator takes into account the various compositions of capital stocks by industry. Finally, the NBER data set includes both total expenditures on energy and materials and a price deflator for each. The deflators are created by averaging together price deflators for the

[23] Total payroll includes spending on non-production workers. However, data on hours worked for such workers is not available, so only production workers are included in the calculation of the wage rate.

inputs used by each industry,[24] and take into account changes in the mix of inputs used over time.

5.2. R&D expenditure data

Because of variations in the propensity to patent across industries, I use data on R&D expenditures to calculate benefit–cost ratios for energy R&D. R&D expenditure data are available from the National Science Foundation.[25] Unfortunately, the data are not available at the level of detail used in this paper. Rather, they are presented at the two-digit SIC level. To get the level of detail needed for this paper, I use the Yale Technology Concordance once again.

The first step in constructing the R&D data is to find the total number of patents manufactured by industries at the two-digit SIC level. This corresponds to the level of data published by the NSF. The concordance of industry of manufacture is used in this step, because industry of manufacture is more likely to be related to R&D expenditures than industry of use. Next, I find the number of patents manufactured by the industries in the data set. Given this, I can calculate the percentage of patents manufactured by the two-digit industry that were manufactured by industries in the data set. I multiply the R&D data supplied by the NSF by this percentage to get R&D expenditures for the industry groups used in this paper.[26]

6. The effect of new patents on industrial energy consumption

Using the data described in Section 5, the variable factor demand equations can be estimated, and the effect of new patents on energy consumption can be calculated. Before proceeding, I first take a general look at the data. For each industry group, Fig. 3 presents a time series for energy prices (dashed line) and for energy intensity (solid line), with energy intensity defined as energy use divided by total output. Values in 1982 are normalized to 100. In most of the industry groups, energy intensity has been falling. The exceptions are aluminum and metal coating, although energy intensity does fall in the aluminum industry at the end of the sample. In addition, note that for most industries, energy intensity continues to fall even after energy prices level off, suggesting that technological change, in addition to simple factor substitution, plays a role in reducing energy intensity. Such a trend is particularly noticeable in industries such as chemicals, copper, and plastic film and sheets.

The data are used to estimate the variable factor demand Eqs. (8)–(10). To construct the stocks of knowledge, define the decay rate as $\beta_1 = \nu/(1-\nu)$, and the rate of diffusion as

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[24] Price indices for 369 materials and six types of energy are used. The six types of energy are electricity, residual fuel oil, distillates, coal, coke, and natural gas.

[25] R&D data are published in Research and Development in Industry, and are also available on-line.

[26] As one referee noted, using R&D data based on the industry of manufacture ignores costs necessary to absorb knowledge from other industries. For many of the IPC classifications, the share of patents used by the industry is greater than the share manufactured, suggesting that knowledge is flowing across industries in this sample of technologies. As a result, the subsequent results may overstate the total cost savings to industry. However, for energy economists simply interested in the change of total energy consumption due to technology, the results are not affected.

$\beta_2 = \lambda/(1 - \lambda)$, where $0 < \nu < 1$ and $0 < \lambda < 1$. Estimation is carried out by searching over the range of ν and λ for the rates of decay and diffusion that best fit the data. Given β_1 and β_2, the resulting variable factor demand equations are linear in parameters.

Using generalized methods of moments (GMM) estimation, I estimate a separate set of equations for each industry group, using data from 1959 to 1991. GMM estimates of β_1 and β_2 are found by finding the combination of ν and λ that minimizes the GMM criterion. The price of investment is used as an instrument for the capital stock, and lagged prices of energy, R&D, material, and investment are used as instruments for the stock of energy knowledge. To correct for possible autocorrelation and heteroskedasticity, I use the Newey–West estimator of the weighting matrix in the GMM criterion (Newey and West, 1987).

(A)

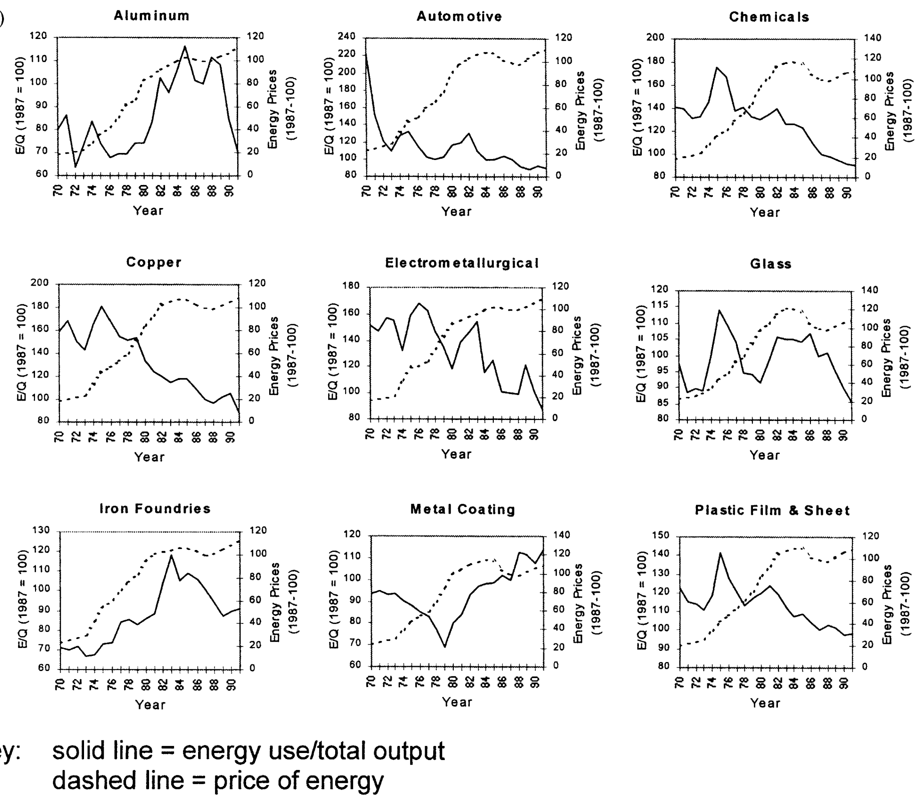
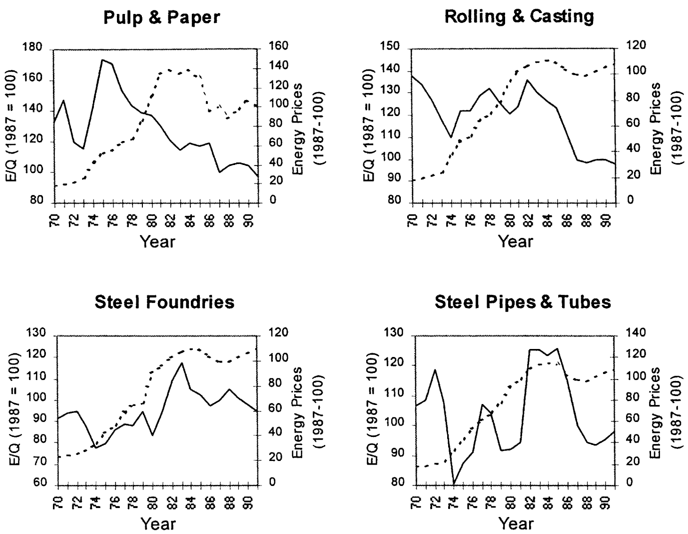


Fig. 3. Energy intensity and energy prices: plot for energy prices and energy intensity for each of the 13 industries is included in the paper. Energy intensity is defined as energy use divided by total output. The data for both trends are normalized so that 1982 = 100. The energy price data comes from the NBER Manufacturing Productivity Database, and is specific to each industry. Note that for most industries, energy intensity and energy prices are negatively correlated. Also, for most industries, energy intensity continues to fall even after energy prices leveled off in the mid 1980s, suggesting that new technologies, and not just factor substitution, played an important role in the fall of industrial energy intensity.

Fig. 3 (*Continued*).

(B)



key: solid line = energy use/total output
dashed line = price of energy

Fig. 3 (*Continued*).

I summarize the main results of the regression here. Complete parameter estimates are presented in an appendix available from the author at http://faculty.maxwell.syr.edu/dcpopp/index.html. In general, the fit of the regressions seems good. Most key parameters, such as the coefficients for own-price elasticities, are significant. Of particular interest is the parameter, α_{EK_E}, which captures the effect of energy knowledge on energy consumption. This parameter is significant at the 99% level in all the 13 equations.

Table 2 presents the estimated price from the regression. All elasticities are calculated using the mean values for input levels and prices. In general, the estimated elasticities are similar to results found in earlier studies. [27] The mean value of the price elasticity of energy is −0.716, and for materials is −0.265.

For a first look at effect of technology on energy consumption, Table 2 also shows the elasticity of energy consumption with respect to energy patents for both the short run and long run. The short run elasticity is the immediate effect of new patents on energy consumption. The long run elasticity uses the present value of energy-savings until the knowledge embodied in the patents becomes obsolete. These are calculated as follows

$$\mathrm{SR}\,\varepsilon_{E,\mathrm{PAT}} = \left(\frac{\partial E_t}{\partial K_{t-1}}\frac{\partial K_{t-1}}{\partial \mathrm{PAT}_{t-1}}\right)\frac{\overline{\mathrm{PAT}}}{\overline{E}} = \alpha_{EK_E}(1-\mathrm{e}^{-\beta_2})\frac{\overline{\mathrm{PAT}}}{\overline{E}} \tag{11}$$

[27] See, for example, Berndt and Wood (1975), Griffin and Gregory (1976), or the papers in Berndt and Field (1982).

Table 2
Elasticities[a]

Industry group	ε_{M,p_M}	ε_{E,p_E}	SR $\varepsilon_{E,\mathrm{PAT}}$	LR $\varepsilon_{E,\mathrm{PAT}}$
Aluminum	−0.554	−0.680	0.000	0.015
Automotive	−0.503	−0.003	−0.043	−0.371
Chemicals	−0.193	−1.378	−0.298	−0.686
Copper	0.003	−0.235	−0.004	−0.205
Electrometallurgical	−0.410	−1.596	−0.386	−0.707
Glass	−0.602	−0.445	0.029	0.371
Iron foundries	−0.357	−0.997	−0.005	−0.119
Metal coating	−0.294	−1.316	0.318	1.504
Plastic film and sheet	−0.076	0.213	−0.069	−0.142
Pulp and paper	−0.145	−0.250	−0.035	−0.065
Rolling and casting	0.068	−0.117	0.008	0.112
Steel foundries	−0.056	−0.741	0.013	0.254
Steel pipes and tubes	−0.324	−1.763	−0.343	−0.991
Mean	−0.265	−0.716	−0.063	−0.079
Median	−0.294	−0.680	−0.005	−0.119

[a] Elasticities calculated using mean levels of inputs. The table presents elasticities for energy and materials. The first two columns are the elasticity of materials and energy with respect to price. The second two columns are the short and long run elasticities of energy with respect to patents, as defined in Eqs. (11) and (12).

$$\begin{aligned}\mathrm{LR}\ \varepsilon_{E,\mathrm{PAT}} &= \left\{\sum_{t=0}^{\infty} \mathrm{e}^{-\rho t}\left(\frac{\partial E_t}{\partial K_{t-1}}\frac{\partial K_{t-1}}{\partial \mathrm{PAT}_0}\right)\right\}\frac{\overline{\mathrm{PAT}}}{\overline{E}} \\ &= \left\{\sum_{t=0}^{\infty} \mathrm{e}^{-\rho t}\left(\alpha_{EK_E}\,\mathrm{e}^{-\beta_1(t-1)}(1-\mathrm{e}^{-\beta_2 t})\right)\right\}\frac{\overline{\mathrm{PAT}}}{\overline{E}} \qquad (12)\end{aligned}$$

A discount rate of 0.07 was used for the long run calculations. This rate is equal to the mean of the preferred dividend rate for medium-risk companies, and is often used in studies such as this (see, for example, Epstein and Denny (1983) and Bernstein and Nadiri (1989)). The results are not very sensitive to other values of the discount rate.

Overall, the results suggest that new technologies do have an important effect on energy consumption. The mean long run elasticity of energy consumption with respect to patents is −0.079. In most industries, the elasticity of energy consumption with respect to new patents is smaller than the price elasticity of energy consumption. The elasticities of energy with respect to new energy patents are negative for 8 of the 13 industries. The five exceptions are aluminum, glass, metal coating, rolling and casting, and steel foundries. Looking back at Fig. 3, we see that these results could have been anticipated. In these industries, energy intensity and energy prices seem to be strongly correlated, suggesting that technological change did not play a crucial role in these industries.

To see the full impact of energy R&D, Table 3 presents the amount of energy saved in each industry due to a new energy patent. Energy-savings are calculated as follows

$$\text{short run energy savings} = \left(\frac{\partial E_t}{\partial K_{t-1}}\frac{\partial K_{t-1}}{\partial \mathrm{PAT}_{t-1}}\right) = \alpha_{EK_E}(1-\mathrm{e}^{-\beta_2}) \qquad (13)$$

Table 3
Cost savings from a new energy patent (millions of 1987 dollars)[a]

Industry group	R&D/patent	Energy-savings				
		Short run		Long run		
		ΔE	B/C[b]	ΔE	B/C	ror[c]
Aluminum	3.13	0.01	0.00	0.59	−0.19	–
Automotive	4.61	−0.09	0.02	−0.74	0.16	0.001
Chemicals	1.50	−50.02	33.32	−115.14	76.70	3.969
Copper	2.35	−0.07	0.03	−4.09	1.74	0.147
Electrometallurgical	2.54	−36.63	14.43	−67.15	26.45	3.094
Glass	1.90	1.04	−0.55	13.51	−7.10	–
Iron foundries	3.02	−0.74	0.24	−16.37	5.42	0.539
Metal coating	0.34	0.36	−1.05	1.68	−4.95	–
Plastic film and sheet	0.92	−6.25	6.78	−12.90	13.98	2.529
Pulp and paper	2.14	−0.77	0.36	−1.42	0.67	0.282
Rolling and casting	0.70	0.37	−0.53	5.20	−7.39	–
Steel foundries	3.22	0.16	−0.05	2.95	−0.92	–
Steel pipes and tubes	2.85	−9.82	3.45	−28.37	9.96	1.894
Mean	2.25	−7.88	3.51[d]	−17.10	7.60[d]	
Mean of negative		−13.05	5.34[d]	−30.77	12.12[d]	1.56
Median	2.35	−0.09	0.04[d]	−1.42	0.61[d]	
Median of negative		−3.51	1.44[d]	−14.63	5.98[d]	1.22
Number of negative values		8		8		

[a] The table presents the cost savings realized from a new energy patent. Benefit–cost ratios and rates of returns to R&D are included. Savings are represented by negative numbers, and are in millions of 1987 dollars.
[b] Benefit–cost ratio.
[c] Rate of return.
[d] Mean (or median) of benefit–cost ratio calculated using mean (or median) of savings divided by mean cost. It is not the mean (or median) of the individual ratios.

$$\text{long run energy savings} = \left\{\sum_{t=0}^{\infty} \mathrm{e}^{-\rho t}\left(\frac{\partial E_t}{\partial K_{t-1}}\frac{\partial K_{t-1}}{\partial \mathrm{PAT}_0}\right)\right\} = \left\{\sum_{t=0}^{\infty} \mathrm{e}^{-\rho t}\left(\alpha_{EK_E}\,\mathrm{e}^{-\beta_1(t-1)}(1-\mathrm{e}^{-\beta_2 t})\right)\right\}. \tag{14}$$

The average energy-savings are substantial. In the short run, the average savings are US$ 7.9 million. The average of the eight groups with actual savings is US$ 13.1 million. In the long run, the average savings are US$ 17.1 million, and rise to US$ 30.8 million if only the groups that experience savings are included. To put these numbers in perspective, an average of US$ 2.25 million of R&D was spent per patent in these 13 industries. Also, note that the results, are quite skewed, as most of the savings are concentrated in the chemicals and electrometallurgical industries. As a result, the median energy-savings are smaller.

Since the propensity to patent varies across industries, simply comparing the energy-savings from a new patent does not allow interindustry comparisons. For this, the amount of R&D spent per patent must also be considered. As such, Table 3 includes data on R&D spending per patent in each industry, as well as a benefit to cost ratio and a "quasi" rate of return, using the R&D cost data as described in Section 5. These results are not traditional rate of returns on investment, and thus must be interpreted carefully. They are presented only to provide some guidelines as to the magnitude of the savings. However, for two reasons, the estimates serve as an upper bound of the rate of return on energy R&D.

First, note that the rates of return are based on *industry-wide* savings resulting from a new patent, rather than the rate of return to an individual firm or patent holder. Estimates of the rate of return on R&D for firms range from 0.2 to 0.5. Since the "quasi" rates of return use industry-wide energy-savings, we would expect the rates of return to be higher than those of a single firm, due to spillovers between firms within the industry (Griliches, 1995). In fact, there is a correlation between total energy usage in an industry and the calculated "quasi" rate of return. The "quasi" rates of return are highest in industries with the greatest energy use, such as chemicals and plastics, since the potential industry-wide gains from research were highest here. However, it is not necessarily the case that individual innovators were able to capture all of the economic rents resulting from these new inventions.[28,29] Secondly, the "quasi" rates of return only focus on the value of energy-savings from the new patents. It is possible that other costs, such as labor or materials, may increase when new technologies are adopted.[30] Thus, simply calculating the value of energy-savings overstates the total value of new energy innovations to firms.[31]

Having noted the limitations of the "quasi" rate of return calculations, note that the "quasi" rates of return on these investments are quite high. The mean rate of return is 1.56, and the median rate of return is 1.22. In only one of the industries experiencing positive savings, automotives, is the rate of return less than 0.15. It may be the case that, in the auto industry, the energy patents are product, rather than process, patents. For example, combustion patents in the automotive industry may relate to improvements in automobile engines, as opposed to improvements in combustion processes related to the manufacture of automobiles.

Table 4 presents the estimated rates of decay and diffusion. The mean decay rate is 0.44, and the mean rate of diffusion is 2.97. However, in each case, the mean values are driven by a few outliers, as the median values are much lower. The median rate of decay is 0.22,

[28] One referee alertly noted that the opposite is also possible — a monopolistic patent holder could potentially extract nearly all of the economic rent associated with energy cost savings, so that the industry's total costs do not fall. While this is theoretically possible, it seems unlikely to be the case here, as the "quasi" rates of return are very high, even relative to other rates of return on R&D. If monopolistic inventors were capturing rent, one would expect more R&D to have been done, given its highly favorable rate of return.

[29] More research, done at the firm level, would be helpful here. Since, we are concerned with spillovers, what we really need to know is whether there are more firms in the industries with the highest social rates of returns. In these cases, the likelihood of positive spillovers would be greatest. Also, calculations of the rate of return at the firm level would be welcome.

[30] Indeed, the cost of labor and materials do increase for several of the industries after the adoption of these energy technologies. These results are available from the author. Unfortunately, because there are not enough data observations to estimate the capital equations, I cannot determine whether capital expenditures, and, thus, total costs, increase or decrease due to the new technologies.

[31] However, from a societal standpoint, there may be other benefits to reduced energy consumption, such as reduced pollution, that are also left out of the calculation.

Table 4
Rates of decay and diffusion of knowledge[a]

Industry group	Decay	Diffusion	Year of maximum impact
Aluminum	0.01	0.11	21
Automotive	0.32	0.03	2
Chemicals	0.45	19.00	0
Copper	0.06	0.01	14
Electrometallurgical	1.17	0.01	0
Glass	0.15	0.23	3
Iron foundries	0.15	0.02	5
Metal coating	0.15	19.00	0
Plastic film and sheet	1.04	0.01	0
Pulp and paper	1.13	0.08	0
Rolling and casting	0.22	0.02	3
Steel foundries	0.18	0.01	5
Steel pipes and tubes	0.75	0.03	0
Mean	0.44	2.97	4.08
Median	0.22	0.03	2.00
Maximum year of mean decay and diffusion			0
Maximum years of median decay and diffusion			3

[a] The table presents the estimated discount rate and the rates of decay and diffusion. Year of maximum impact is the number of years until a patent has its greatest impact on energy-savings, based on the rates of decay and diffusion for each industry. The final two rows are the year in which patents have their greatest impact, based on the mean and median rates of decay and diffusion.

and the median diffusion is 0.03. Industries with low rates of decay and diffusion, such as copper and steel foundries, are established industries that do not have a reputation for much technological innovation. Industries that are known for greater innovation, such as chemicals, have higher rates of decay and diffusion.

Given the rates of decay and diffusion, we can find the effect that a new patent has on the stock of knowledge for each year after its initial application. Recall from Eq. (3) that the weight a patent applied for s years earlier has on the stock of knowledge today is equal to $e^{-\beta_1 s}(1 - e^{-\beta_2(s+1)})$. Fig. 4 presents this weight for the first 50 years of a new patent's life, based on the median rate of decay and diffusion. Note that new patents have their largest impact within the first 3 years. After this, the effect of decay dominates the effect of diffusion, and the influence of the patent declines. The number of years that pass before a new patent has its greatest effect on the stock of knowledge is presented in Table 4. These figures can be seen as the peak of the graph in Fig. 4. The mean is 4.08 years, and the median is 2 years. This result is consistent with the notion that the process of disseminating new knowledge, along with adjustment costs necessary to install new equipment, delay the benefits of new research.

Finally, Table 5 considers the full effect that price-induced innovation has on energy consumption. Whereas Table 3 presents the energy-savings resulting from a single new energy patent, Table 5 includes results on induced innovation to calculate the effect of all patents induced by an energy price increase. It uses results on induced innovation from Popp (1997, 2000) to determine the impact of a price increase on both energy innovation and

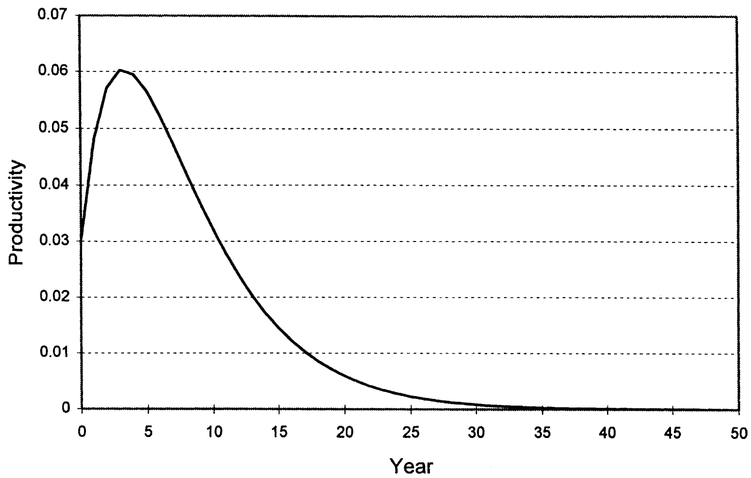


Fig. 4. Effectiveness of energy patents over time: shows the weight given to a patent from year 0 in that year and over the next 50 years. The weight represents a patent's contribution to the stock of knowledge in a given year. As shown in Eq. (3), the weight is a combination of the decay rate and the rate of diffusion, and is equal to $e^{-\beta_1 s}(1 - e^{-\beta_2(s+1)})$, where s is the age of the patent. Calculations are based on the median rates of decay and diffusion.

energy consumption. It distinguishes between *induced innovation* — new technologies that were developed in response to changes in the price of energy — and *factor substitution* — a movement along a production isoquant, holding technology constant. Table 5 is a short run effect only. To allow time for lagged reactions to the price change, Table 5 considers the effect of patents developed a year after an energy price increase. Only industries experiencing energy-savings are included.

The first column of the table presents the elasticity of energy patents with respect to a change in energy prices. These figures were calculated in Popp (1997, 2000).[32] The elasticity of energy use with respect to patents, as calculated above, is in column two. The elasticity of energy use with respect to induced innovation, shown in column three, is the product of these two elasticities. It is the percent change in energy consumption resulting from the new technologies induced by a 1% change in energy prices. Formally, the relationship is

$$\Delta E \text{ due to induced technological change} = f(\text{patents}(\text{price}))$$

Continuing with Table 5, the fourth column presents the elasticity of energy use with respect to price, also calculated above. This is the change in energy consumption resulting

[32] Popp (1997) provides elasticities with respect to energy prices for several different energy technologies. The elasticity for the most important technology for each industry is used in Table 5. For industries that are not represented by a specific technology in Popp (1997), a pooled estimate from all industrial technologies, found in Popp (2000) is used. The technologies used for each industry are: electrolytic production of metals (copper, electrometallurgical, plastic film and sheets), continuous casting (steel and iron foundries), and the pooled results (automotive, chemicals, pulp and paper, and steel pipes and tubes).

Table 5
Breakdown of elasticities of energy consumption[a]

Industry	Elasticity of patents with respect to energy prices (1)	Elasticity of energy use with respect to patents (2)	Elasticity of energy use with respect to induced innovation (3)	Elasticity of energy use with respect to price (4)	Total elasticity of energy use with respect to price (5)	Percentage of elasticity due to induced innovation (6)	Price elasticity without know-ledge stocks (7)
Automotive	1.07	−0.043	−0.046	−0.003	−0.049	94	−33.885
Chemicals	1.07	−0.298	−0.319	−1.378	−1.697	19	−1.652
Copper	4.73	−0.004	−0.018	−0.235	−0.253	7	−0.220
Electrometallurgical	4.73	−0.386	−1.827	−1.596	−3.423	53	−1.478
Iron foundries	6.21	−0.005	−0.033	−0.997	−1.030	3	−0.862
Plastic film and sheet	4.73	−0.069	−0.327	0.213	−0.114	286	−0.587
Pulp and paper	1.07	−0.035	−0.037	−0.250	−0.287	13	−0.307
Steel pipes and tubes	1.07	−0.343	−0.367	−1.763	−2.129	17	−2.592
Mean			−0.372		−1.123	33	−1.100[b]

[a] The table shows the short run breakdown in the effects on energy consumption from a change in energy prices. The first column presents the elasticity of energy patents with respect to a change in energy prices. This figure was calculated in Popp (2000). To allow for the full effect of induced innovation, the elasticity 1 year after the increase in price is used. The second column presents the short run elasticity of energy use with respect to patents, as calculated in Section 6. The elasticity of energy use with respect to induced innovation, presented in column three, is the product of these two elasticities. It is the percent change in energy consumption resulting from the new technologies induced by a 1% change in energy prices. The fourth column is the elasticity of energy use with respect to price, as calculated in Section 6. This is the change in energy consumption resulting from factor substitution. Column five shows the total effect of a change in energy prices. It is the sum of the elasticities in columns three and four. Column six presents the percentage of the total elasticity that is due to induced innovation. Finally, column seven gives the elasticity of energy with respect to price from a regression that excludes the knowledge stocks, so that only a time trend is used to capture technological change. Note that these elasticities are comparable to the combined elasticities presented in column five.

[b] Mean calculated without automotive industry.

from factor substitution. Column five shows the total effect of a change in energy prices. It is the sum of the elasticities with respect to induced innovation and factor substitution found in columns three and four. Column six shows the percentage of the total elasticity that is due to induced innovation. Finally, to show the impact of including the energy knowledge stocks in the regression, column seven presents the elasticity of energy with respect to price from regressions that constrain the coefficients on K_E to be zero, so that only a time trend is used to capture technological change.

The total elasticity of energy consumption ranges from −0.049 for the automotive industry to −3.423 for the electrometallurgical industry. The average total energy elasticity is −1.123. On average, one-third of the total elasticity results from induced innovation, with the remaining two-thirds due to factor substitution. Note that the price elasticities from the regressions without knowledge stocks are similar to the combined elasticities in column five. This suggests that price elasticities taken from regressions that use only a time trend to model technological change include both induced innovation and factor substitution effects. Thus, economists who wish to use these estimates in models that also include induced innovation would be double-counting the effects of induced innovation.

7. Conclusions

This paper has combined patent data and industry-level input and price data to estimate the effect of new energy patents on energy consumption in 13 industry groups. The median present value of long run energy-savings in the nine groups experiencing savings is over US$ 14.5 million. The median rate of decay for a new patent is 0.22, and the median rate of diffusion is 0.03, indicating that a patent has its largest effect on energy consumption for 3 years after the initial patent application.

Combining estimates of the effect of energy patents with elasticities of energy patents with respect to price, I find that two-thirds of the initial change in industrial energy consumption after a price change is due to simple price-induced substitution, while the remaining one-third is due to induced innovation. Also, the results suggest that estimates of energy price elasticities taken from regressions without energy patents include both factor substitution and induced innovation effects. Modelers who wish to use such elasticities in studies incorporating induced innovation must be careful to avoid double-counting the effects of induced innovation. Finally, it is important to remember that the long term effects of induced innovation are likely to be more substantial, both because it takes time for the induced knowledge to diffuse through industry, and because higher prices may induce new innovations for several years. A more complete analysis of the long term effects, however, requires a general equilibrium analysis, to account for adjustments in energy prices that result from induced changes in demand. This is left for future research.

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