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Fueling the Innovative Process: Oil Prices and Induced Innovation in Automotive Energy-Efficient Technology

By

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Abstract

This paper tests the induced innovation hypothesis that higher oil prices will lead to increased innovation in energy-efficient automotive technology. We find robust empirical support for the hypothesis, while using various measures of oil and gas prices and controlling for other factors including constructed knowledge stocks and macroeconomic variables.

JEL Codes O3, Q4, Q55

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Fueling the Innovative Process:
Oil Prices and Induced Innovation in Automotive Technology

I. Introduction

In light of U.S. automotive industry woes, there has been concern expressed recently about how quickly automobile manufacturers respond to changes in the marketplace. In particular, U.S. firms have been criticized as slow to innovate in the arena of hybrid or fuel-efficient vehicles, instead losing that market to Japanese producers even as oil prices reach historic highs in nominal terms.

If necessity is the mother of invention, then it seems natural that as energy prices rise, manufacturers would find means of curbing costs by innovating in energy-efficient directions. Consumers should likewise demand lower energy bills, expressing that demand in part through the purchase of fuel-efficient vehicles. Induced innovation is precisely that idea, that "a change in the relative prices of the factors of production is itself a spur to invention" (Hicks, 1932).

This paper seeks to evaluate the responsiveness of U.S. inventors, both corporate and independent, to energy prices over the period between 1980 and 1999. We build upon the existing literature's methods and results, but use new data to test the induced innovation hypothesis for energy-efficient automobile technology in particular. Do applications for patents on relevant automotive products and processes respond to oil prices, ceteris paribus? And if so, is it imported oil prices, domestic wellhead oil prices or gasoline prices that matter?

As the price of oil is intimately connected to the state of the macroeconomy, and to the economic health of the automotive industry in particular, we use a set of control variables to ensure that we are truly capturing the induced innovation impact of oil prices, and not merely the secondary impact of economic contraction or recession.

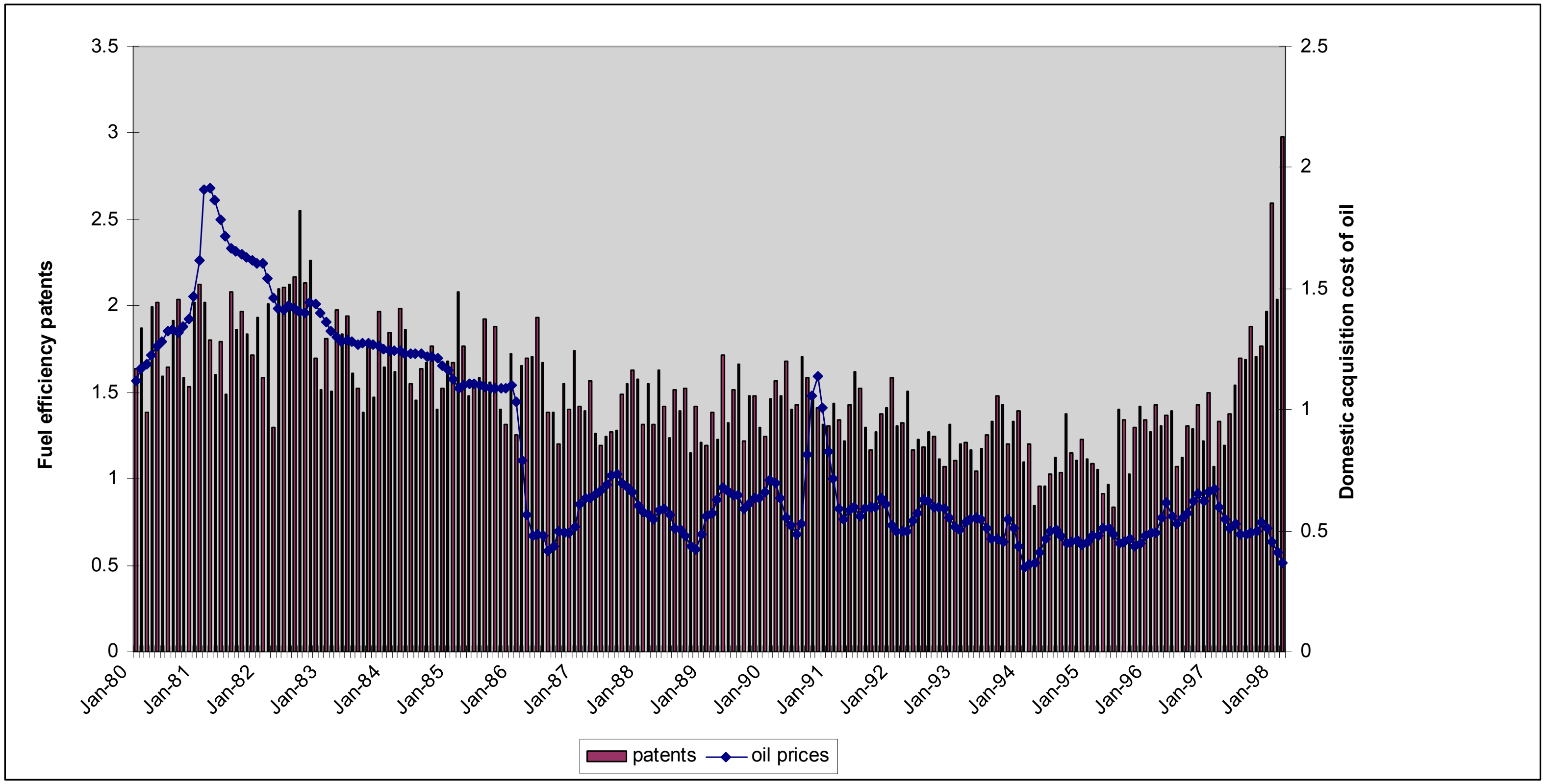
Figure 1 demonstrates that visually, comparing the pattern of patent activity in automotive energy-efficient technologies with the domestic wellhead price of oil. Here patent activity is expressed as the share of all U.S. patent applications which qualify as energy-efficiency automotive patents (see below for a complete definition), and the price of oil is expressed in constant 2007 dollars per gallon. The lack of obvious correlation between the series could be the final story, or it could be due to a conflicting set of effects: as the price of oil rises, there is pressure to innovate but simultaneously there is pressure to cut back on non-essential expenditures such as those devoted to research. This paper aims to disentangle those effects, to empirically test the induced innovation hypothesis for the automotive industry.

Section II of this paper briefly reviews the literature on induced innovation, while Section III describes the model and estimation methodology. Section IV presents the data. Results are presented in Section V, leaving conclusions for Section VI.

II. Literature

The Hicksian idea of induced innovation has been applied to many areas, especially within environmental and natural resource economics (for a good review, see Ruttan 2001). Three prominent recent papers in particular have brought this idea to the study of energy efficiency innovations.

Figure 1: Energy-efficiency automotive patents and the price of oil



Berry et al (1996) used a hedonic cost function approach to ask whether economic and regulatory changes had affected the rate and degree of new technology adoptions in the automotive industry. In particular, they refer to the fact that fuel emissions standards immediately led to the adoption of the catalytic converter in 1975. While their use of patent data as an indicator of innovation is cursory, they find that "gas price shocks… induced significant increases in patent applications (in internal combustion engines)".

Newell, Jaffe, and Stavins (1999) tackled the induced innovation hypothesis directly, testing whether increasing energy prices lead to technological change in, and sales of, capital goods that are less energy intensive in use. In particular, they considered air conditioning and water heater technologies sold via Sears catalogs between 1958 and 1993, estimating the changing parameters in the transformation surfaces between product cost and energy flow. They find "little evidence of significant inducement effects on overall technological change", although more impact in cooling than in heating technology. However, more efficient units (which were already technologically feasible) were increasingly offered for sale as energy prices rose.

Finally, Popp (2002) investigated several industrial categories of energy-efficient innovation (coal liquefaction, coal gasification, solar energy, solar batteries, fuel cells, waste fuel, waste heat, heat exchange, heat pumps, Stirling engines, and continuous casting), to measure the effect of energy prices on innovation. He used annual patent data from 1970 through 1994, and introduced a model which we will emulate below. Using patent citations as a measure of knowledge decay and diffusion, he modeled the growth of knowledge over time, and then used those knowledge stocks to underpin subsequent innovation. In a formulation very similar to ours below, he found a strong, positive but economically small impact of energy prices on new innovation.

III. Model and methodology

We construct a model similar to Popp (2002) but consider variables customized for the automotive sector. In particular, we propose that energy-efficient automotive patents (EPAT) as a share of all patents are a function of expected future oil prices, existing knowledge about the technology, and expected values of other control variables that provide a picture of the state of the industry and economy. Specifically, we propose that:

$$\log\,(\mathrm{EPAT}/\mathrm{TOTPAT})_t = \beta_0 + \beta_P(1-\lambda_P)P_t^* + \beta_K K_t + \sum_{i=1}^{4} \beta_i (1-\lambda_i) Z_i^* \qquad (1)$$

where EPAT = successful energy-efficient automotive technology patents applied for in month t
TOTPAT = successful patent applications in all technologies applied for in month t
P^* = expected next-period price of oil in month t
K = knowledge stock in energy-efficient automotive technology in month t
Z_i^* = expected next-period value of potential control variables in month t:
Federal Funds Rate (FFR)
and unemployment rate (u)

The dependent variable is presented as a fraction of successful patent applications, in order to control for changes in the role that patents have played over time. For example, in the 1980s as patent law and its enforcement changed, applications grew enormously. The Bayh-Dole Act, which permitted government-funded researchers to obtain patents on results of that funded research, and the formation of the District Circuit Court of Appeals which dramatically increased the proportion of rulings upheld on behalf of patentholders, both encouraged a rapid rise in applications. We aim to explain why EPATs changed relative to total patents, pulling out the effects of factors which impacted all patent applicants.

We consider three alternative but complementary definitions of the price of oil: domestic wellhead oil price, imported crude oil price, and retail regular grade gasoline price. Since all three are highly correlated, but we wish to ascertain the possible impact of each, we use as our explanatory price variables the real domestic wellhead oil price, the difference between domestic and imported refiner oil acquisition costs, and the monthly change in real retail prices for regular grade gasoline. All are measured in May 2007 real prices.

Two control variables, the federal funds rate and the unemployment rate, were chosen from all possible alternatives for both theoretical and practical reasons. On a theoretical level, they offer proxies for the cost of capital and cost of labor, while serving as indicators about the state of the economy and therefore potentially the state of the automobile industry. Further, they are both available on a monthly basis, unlike many other statistics of interest (e.g. automobile sales data).

We model the expected price (P_t^*) and expected control variables (Z_t^*) using adaptive expectations with a 24-month memory, so that

$$P_t^* = P_t + \lambda_P P_{t-1} + \lambda_P^2 P_{t-2} + \ldots + \lambda_P^{24} P_{t-24} \qquad (2)$$

$$Z_{i,t}^* = Z_{i,t} + \lambda_i Z_{i,t-1} + \lambda_i^2 Z_{i,t-2} + \ldots + \lambda_i^{24} Z_{i,t-24} \qquad (3)$$

We estimate the value of each adaptive expectations parameter (λ_P and a separate λ_i for each control variable), using all Z variables as first differences to avoid multicollinearity issues. As a result we diverge from the literature by estimating a semi-log function of equation (1), since frequent negative changes in the explanatory variables precluded the use of a log-log formulation. Should the reader be uncomfortable with this model, consider instead that energy-efficiency patents could instead be merely a function of past oil prices and Z values, regardless of expectations about the future, since the research required for each patent occurred in the past and was potentially affected by the concurrent values of P and Z.

The variable K_t represents the stock of knowledge accrued from past years, as more patents may be enabled by previous learning (i.e. new avenues of innovation unlocked via previous innovation) or may be curtailed by previous patenting (i.e. certain sub-areas protected by patent thickets or exhausted of new patentable material). The stock of knowledge is found through a two-step process, following the literature's precedent (e.g. Caballero and Jaffe 1993; Jaffe and Trajtenberg 1996; Popp 2002; Johnson and Popp 2003).

First, while we recognize the obvious limitations inherent in using patent counts as a measure of innovation (see Griliches 1990 for a review), we also admit that short of direct surveys, no better measure exists. The literature recognizes that all patents are not equally important, nor do they create immediate or permanent knowledge for other innovators. Each patent application includes a reference list which cites all patents that the inventor feels either a) circumscribe the claims of the current application, b) contributed to the development of the current application, or c) illustrate the novelty or usefulness of the current application. The patent examiner examines these citations, and may add or delete at their discretion. Previous literature (e.g. Lanjouw et al. 1998) has shown that the number of citations to a patent are highly correlated with other measures of value (e.g. multiple renewals, long pendency lags), so we use citations to approximate the value of a patent as well.

Following the literature started by Caballero and Jaffe (1993), we estimate the rates of diffusion and decay of knowledge in our chosen technology, recognizing that the number of subsequent citations received by a patent are a function of its age and of the changing legal environment. It may require several years for others to recognize the inherent value of a newly published patent (diffusion rate), but most technologies become less valuable and even obsolete as more time passes (decay rate). Over the past thirty years, there has been documented citation inflation as the number of references per patent rises, meaning that we wish to account for this trend as well in interpreting citation values of patents.

Since actual citations between patents are a small share of all citations which could potentially be made, we follow the well-established tradition of grouping the data into cohorts by year. Each cohort consists of patents granted in year s and potentially cited by patents granted in the subsequent year t. We model the share of all potential citations that actually occur as a function of decay and diffusion.

$$C_{s,t} / C^{pot}_{s,t} = \alpha_t \,(EXP\,(-\beta_1\,(t-s)))*(1- EXP(-\beta_2(t-s))) \qquad (4)$$

where $C_{s,t}$ is the number of citations actually received by patents granted in month s by patents granted in the subsequent month t

$C^{pot}_{s,t}$ is the number of potential citations from all patents granted in month t to all patents granted in previous month s

α_t is a month-specific effect for the citing patent's application month t to control for citation inflation

β_1 is the rate of knowledge decay

β_2 is the rate of knowledge diffusion

To counteract heteroskedasticity, estimation of (4) is accomplished via weighted nonlinear least squares (Greene, 1993).

Based on the estimates of β_1 and β_2, knowledge stocks are constructed as

$$K_t = \sum_{s=1}^{t} \hat{\alpha}_S EPAT_S (\exp(-\hat{\beta}_1(t-s)))(1-\exp(-\hat{\beta}_2(t-s))) \qquad (5)$$

In robustness tests, we calculated eight versions of this variable, using our own estimated values of the decay and diffusion parameters, calibrated values from the literature, and values based on alternative assumptions about the speed of knowledge obsolescence. All versions showed results similar to those presented here.

As in other studies (e.g. Popp 2002), it was infeasible to separately estimate each time-specific effect at the monthly level, so instead annual estimates of α_t are estimated.

IV. Data

The definition of EPAT is critical, and is based upon the classification system used by the U.S. Patent and Trademark Office. For this paper, EPATs are defined as portions of U.S. Patent Classes 60, 73, 123, 180, 701 and 903. Specifically, from Class 60 (Power Plants), we include only subclasses 272, 39.01, 516, and 698 which cover innovations relating to internal combustion engines and the handling of exhaust. From Class 73 (Measuring and Testing), only subclasses relating to Automobile Fuel Consumption (112-115) are included. The entirety of Class 123 is included as it relates to internal combustion engines. From Class 180 (Motor Vehicles), only subclasses 65.1 through 65.8, which deal with electric power, are included. Within Class 701 (Data Processing: Vehicles, Navigation, and Relative Location) we include subclasses 101, 103-110, 113, 123, and 29 which deal with internal combustion engines, fuel consumption, and engine starting. Finally, from Class 903 which is titled Hybrid Electric Vehicles, we only include subclasses 902-927, 930, 940-948, 951, 952, and 960 (engine and other fuel efficiency components such as the fuel pumps).

Monthly data from 1974 through 1999 are used in this paper, in marked contrast to the rest of the literature (which uses annual observations). It is our hope that the use of more frequent observations will shed more light, and eliminate potential noise, in the true relationship between prices and technological change.

Patents are counted by their date of application, regardless of their actual date of grant. For that reason, we end our analysis in 1999, permitting virtually all patentable applications submitted in the last year of analysis to have been granted. Only granted patents are included, partly because our analysis spans a period of time during which only granted U.S. patents were published, and partly because we wish to consider only those innovations of sufficient merit to pass an official test of novelty and usefulness under the eyes of the U.S. Patent and Trademark Office.

Summary statistics of key variables are presented in Table 1. The price of oil is expressed in real May 2007 dollars per gallon, as reported by the Energy Information Administration (U.S. Department of Energy). Other variables were acquired from standard sources (Bureau of Labor Statistics, US Federal Reserve).

Table 1: Summary Statistics

Variable Type	Variable Name	Mean	St. Dev.	Minimum	Maximum
Dependent	EPAT/TOTPAT	0.147	0.003	0.008	0.030
P	Domestic wellhead oil extraction cost ($/gal)	0.732	0.322	0.351	1.541
P	Imported oil price	0.137	0.045	-0.076	0.232

	premium ($/gal)				
P	Change in retail gas price ($/gal)	-0.008	0.058	-0.250	0.210
Z	Federal Funds Rate (change)	-0.040	0.362	-2.470	1.560
Z	Unemployment rate (change)	-0.021	0.168	-0.700	0.500

V. Results and interpretation

Estimated ancillary parameters from equation (4) are reported in Table 2. We present results beside their counterparts from Popp (2002), reminding the reader that they are not strictly comparable (Popp's values are annual, while those presented here are monthly). For brevity we do not present α_t coefficients for each time period, although those are available from the authors.

It appears that knowledge decays more quickly in the automotive sector than in the industrial sectors analyzed by Popp. While our coefficient is smaller, it is a monthly rate, meaning that the annual rate would vastly exceed Popp's result. On the other hand, diffusion appears much slower in automotives.

Table 2: Estimated ancillary parameters

	Automotives	Industrials (Popp)
β_1 decay of knowledge	0.259^{***} (56.65)	0.353^{***} (27.15)
β_2 diffusion of knowledge	$8.54 \times 10^{-6***}$ (26.93)	$1.99 \times 10^{-3***}$ (5.85)

Note : t-statistics are in brackets. *** indicates significance at the one percent level.

Table 3 presents results for the primary regression (column 1) alongside some robustness tests: using separate estimation of the adaptation parameters λ and incorporating them into the main regression as estimated P* and Z* (column 2), omission of control variables (column 3), and alternative price variables (columns 4-6). All variances are White-corrected to counteract heteroskedasticity.

The first obvious result is that domestic oil extraction costs clearly have a positive effect on energy-efficient automotive innovation. Using the primary result coefficient of 0.322 as a best estimate implies that a cost rise of five dollars a barrel (or roughly twelve

Table 3: Regression results for dependent variable EPAT/TOTPAT

	Primary	Separate estimation of λ values	No control variables	Domestic price only	Imported oil premium only	Retail price change only
Impact parameters (β)						
Domestic wellhead price of oil	0.322** (2.01)	2.142*** (7.01)	0.363** (2.00)	0.370*** (4.02)	---	---
Imported oil price premium	-1.126*** (2.59)	7.643*** (2.88)	-1.156*** (2.60)	---	-0.781* (1.70)	---
Change in retail gas price	-2.382 (0.79)	-23.90 (0.95)	0.141* (1.64)	---	---	-8.69 (1.46)
Knowledge stock	-4.538*** (60.54)	-4.659*** (158.35)	-4.556*** (60.04)	-4.726*** (139.13)	-4.354*** (63.57)	-4.498*** (254.88)
Federal Funds rate	-0.076 (1.06)	-0.104* (1.68)	---	-0.179 (1.51)	-0.458*** (4.09)	-0.266** (2.33)
Unemployment rate	0.141 (0.90)	0.583 (1.04)	---	0.013 (0.68)	-0.001 (0.01)	0.133 (0.82)
Adjustment parameters (λ)						
Domestic wellhead price of oil	0.908*** (5.89)	0.897*** (12.65)	0.908*** (5.63)	0.911*** (11.49)	---	---
Imported oil price premium	0.501* (1.71)	0.907*** (48.64)	0.576** (2.17)	---	0.559 (1.30)	---
Change in retail gas price	0.907*** (8.56)	0.827*** (14.93)	-0.855*** (3.70)	---	---	0.965*** (32.35)
Federal Funds rate	0.494 (0.98)	-0.879*** (11.66)	---	0.690*** (3.13)	0.827*** (13.02)	0.775*** (6.43)
Unemployment rate	0.248 (0.36)	-0.847*** (26.47)	---	-0.951*** (3.13)	-4.795 (0.19)	0.194 (0.24)
EPAT/TOTPAT regression diagnostics						
F statistic	12.31	19.91	19.41	18.01	5.30	7.56
Adjusted R^2	0.37	0.33	0.36	0.35	0.12	0.17
Number of observations	193	193	193	193	193	193

Significance is indicated as *** for the one percent level, ** for the five percent level and * for the ten percent level.

cents a gallon) as occurred in early 2002 will lead to an average immediate rise in energy-saving patents of nine percent, and many times that increase over time via distributed lag.

In column 2, using a two-stage estimation process with λs estimated first, the coefficient on domestic oil costs is disproportionately high (and in fact many other coefficients are skewed as well). Estimation errors from the first stage are responsible for this aberrance, but we present them to offer a balanced display of all robustness tests.

It appears that rises in foreign oil prices are not the driving force behind our automotive innovation. Instead, as foreign oil prices rise relative to domestic extraction costs, we innovate less. This might be explained as the result of a feeling of relative abundance, and as long as the Hicksian concept of induced innovation is based on relative prices (which it is) and we can rely more heavily on domestic sources during times of high international prices (which is true at least in the short term), this negative coefficient is entirely consistent with the induced innovation hypothesis. Innovation will be stimulated if domestic prices rise relative to foreign prices, that is, if the foreign price premium falls.

The direction and magnitude of price change does not appear to matter statistically to innovative forces, as witnessed by the coefficient on retail gas price changes. This does not mean that retail gas prices do not matter, for as we indicated earlier, they are so highly correlated with domestic oil acquisition costs as to have the same estimated impact on innovation that costs have.

Knowledge stock has a consistently negative and statistically significant impact on subsequent innovation, a troubling result indicative of an industry at the point of innovative exhaustion. If current innovators view the existing stock of knowledge as a hindrance to progress, either because it serves to fence off potent technological fields with legal thickets or because it appears to strip away from the finite remainder of possible advances, then it is just as well that the decay of the stock is rapid.

The control variables, unemployment and interest rates, play a minor role but it does appear true that as the Federal Funds rate rises (and investment becomes more expensive), innovation falls exactly as theory would predict.

Overall, these regressions do not explain even a majority of the variation in innovative activity, but that limitation was expected. The F-statistics for each regression indicate statistically significant explanatory power, lending empirical support to the theory of induced innovation in this industry.

VI. Conclusion

We have added to the literature on induced innovation by directly testing the fundamental hypothesis on the automotive industry, while not only controlling for supply-side (knowledge stock) effects but also macroeconomic conditions. We have also tested the relative importance of different forms of price inducement.

This study agrees with the preceding literature, finding empirical support for the induced innovation hypothesis in automotive technology. In particular, it is domestic acquisition costs which matter, and innovation is further stimulated if the price premium on foreign oil declines.

Given this empirical support, policy could use incentive-based programs to encourage energy-efficient innovation. In particular, taxes or regulations on domestic oil extraction seem to be able to offer significant power.

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