THE JOURNAL OF INDUSTRIAL ECONOMICS 0022-1821
Volume LI September 2003 No. 3

POLICY-INDUCED TECHNOLOGY ADOPTION: EVIDENCE FROM THE U.S. LEAD PHASEDOWN*

SUZI KERR†
RICHARD G. NEWELL‡

Theory suggests that economic instruments, such as pollution taxes or tradable permits, can provide more efficient technology adoption incentives than conventional regulatory standards. We explore this issue for an important industry undergoing dramatic decreases in allowed pollution – the U.S. petroleum industry's phasedown of lead in gasoline. Using a duration model applied to a panel of refineries from 1971–1995, we find that the pattern of technology adoption is consistent with an economic response to market incentives, plant characteristics, and alternative policies. Importantly, evidence suggests that the tradable permit system used during the phasedown provided incentives for more efficient technology adoption decisions.

I. INTRODUCTION

Economic and policy discussions have become increasingly permeated by issues related to technological change, particularly in the environmental arena. Policy interventions create constraints and incentives that influence the process of technological change, and these induced effects of policy on technology may have substantial implications for positive analysis of the impact of alternative policies, as well as the normative analysis of policy decisions. The theoretical literature has long recognized that alternative types of policy instruments can have significantly different effects on the rate and direction of technological change, typically finding that economic incentive – based instruments (e.g., pollution taxes and tradable pollution permits) can provide more efficient incentives for technology adoption than

*We thank Nancy Bergeron, Oscar Melo, and Kelly See for research assistance. We also thank the editor, two anonymous referees, Severin Borenstein, Ian Parry, William Pizer, David Simpson, Robert Stavins, and participants at various seminars for useful comments on previous versions of the paper. Aspects of the research would not have been possible without permission from several firms to use certain confidential lead-trading data. We acknowledge support from the U.S. Environmental Protection Agency Grant No. CX827515.

†Author's affiliations: Motu Economic and Public Policy Research, 19 Milne Terrace, Island Bay, Wellington, New Zealand.
email: suzi.kerr@motu.org.nz
‡Resources for the Future, 1616 P St. NW, Washington, DC 20036.
email: newell@rff.org

conventional regulations (e.g., technology and performance standards).[1] Despite a reasonable amount of theoretical attention, little empirical evidence exists on the dynamic effects of environmental regulation, particularly with respect to the relative effects of alternative policy instruments.[2] We provide some of the first such evidence.

This paper reports a detailed empirical study of these issues for an important industry undergoing technological responses to a dramatic decrease in allowed pollution levels. While many are familiar with the success of the tradable permit system for sulfur dioxide [Joskow, Schmalensee, and Bailey 1998], the phasedown of lead in gasoline by U.S. petroleum refineries during the 1970s and 1980s was the first major success in implementing a market-based environmental policy. Historically, lead was added to gasoline to inexpensively boost octane levels, but it also has serious side effects on human health. We assess the pattern of technology adoption by refineries during the lead phasedown, both across refineries and across time, with the intent of understanding how various economic incentives, market factors, and the stringency and form of regulation influenced this process.

Toward this end, we develop a model of the technology adoption decision in the presence of regulation and derive an econometrically testable duration model. Our econometric approach is related to that taken by several applied industrial organization studies of technology adoption[3], although those studies do not assess the influence of regulation on the process of technological change. The model suggests that firms will gradually adopt the technology as its costs fall and increased regulatory stringency increases the value of adoption; firms with lower benefits or higher costs will adopt more slowly. We also test the proposition that there will be a divergence in the adoption propensities of low versus high compliance cost plants during periods with a tradable permit system versus an individually binding

[1] Jaffe *et al.* [2003] provide a broad review of the literature on technological change and the environment. Zerbe [1970], Orr [1976], and Magat [1978] provide early theoretical discussions of the firm's incentives to innovate and adopt pollution-reducing technology. More recently, Downing and White [1986] look at firms' incentives, Malueg [1989] compares the differential effects of tradable permits and performance standards on high versus low-cost pollution controllers, Milliman and Prince [1989] consider the effects of different instruments when market effects are taken into account. Laffont and Tirole [1996a, 1996b] explore the use of spot and futures markets for pollution permits in inducing optimal rates of diffusion and innovation.

[2] Nelson *et al.* [1993] consider the effect of constraints on the use of economic instruments on capital turnover in the electric power industry. Jaffe and Stavins [1995] estimate the factors determining adoption of energy-efficient building insulation. Newell *et al.* [1999] study the effects of energy prices and government regulation on energy-saving product innovation.

[3] See Hannon and McDowell [1984] and Saloner and Shepard [1995] on adoption of ATMs, Karshenas and Stoneman [1993] on adoption of computer-assisted machine tools, Stoneman and Kwon [1994] on the diffusion of multiple process technologies, and Rose and Joskow [1990] on electrical utility adoption of supercritical coal-fired steam-electric generation.

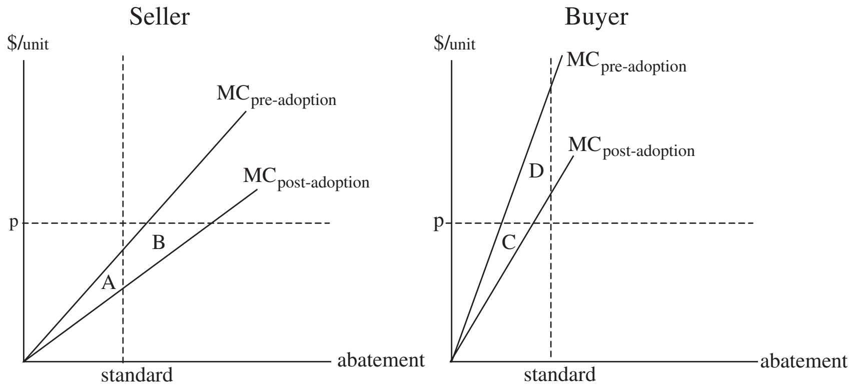

Figure 1
Adoption Incentives for 'Sellers' vs. 'Buyers' under Alternative Policies

performance standard [Malueg 1989]. Plants with relatively low costs of compliance (i.e., sellers in a permit market) will have greater incentives for cost-saving technology adoption within a trading regime. At the same time, relatively high-cost plants (i.e., permit buyers) will have decreased adoption incentives under the permit system.

The intuition behind this latter proposition is illustrated in Figure 1, which shows the marginal cost of abatement (e.g., lead reduction) for buyers versus sellers, with and without the adoption of technology that lowers pollution control costs.[4] The price of permits that would exist in a tradable permit market is given by the dashed horizontal line at p, and the level of pollution reduction required under an individually-binding performance standard is given by the dashed vertical line at 'standard'. The tradable permit system encourages all plants to take action until their marginal cost of pollutant reduction equals the permit price, while the individual standard forces all plants to attain a fixed target.

Under the individual standard, low-cost sellers could save cost area A by adopting the new technology, while they could gain areas A + B under a permit market policy. Sellers' incentives to adopt are therefore higher under the permit system because they can undertake additional reductions and get profit area B by selling permits. Relatively high-cost buyers, on the other hand, would save areas C + D by adopting the new technology under a uniform standard, while they would save only area C under a permit market policy. The incentives to adopt would thus be lower for buyers under the permit system, since they can buy permits rather than being forced to self-

[4] By 'seller' ('buyer') we mean seller (buyer) both before and after technology adoption. The case of a buyer before, but a seller after technology adoption leads to an ambiguous effect of instrument on adoption propensity, while the case of a seller before, but a buyer after technology adoption does not make economic sense [Malueg 1989].

comply with relatively expensive reductions. Thus, the tradable permit system provides incentives for *more efficient* adoption, but it can lower adoption incentives for some plants with high compliance costs.[5] Under a nontradable performance standard, such opportunities for flexibility do not exist to the same degree. If plants face individually binding standards, they will be forced to take individual action – such as technology adoption – regardless of the cost, with the resultant inefficiency reflected in a divergence across plants in the marginal costs of pollution control.

We employ a unique panel dataset on petroleum refineries covering the full period of the U.S. lead phasedown, which began with a requirement that new cars after 1974 use unleaded gasoline. This was followed by performance standards on lead in gasoline, a tradable permit market controlling the lead in leaded gasoline (1983–1987), ending with a more stringent performance standard and ultimately a ban in 1996. The adoption of pentane-hexane isomerization technology – a substitute for lead as a source of octane – was one of the major responses to the increased severity of regulation.

We find that increased regulatory stringency (which raised the effective price of lead) encouraged greater adoption of lead-reducing technology. We also show that larger and more technically sophisticated refineries were more likely to adopt the new technology. Importantly, we further find that the tradable permit system provided incentives for more efficient technology adoption decisions. The relative adoption propensity of refineries with low versus high compliance costs was significantly greater under the tradable permit regime than under a nontradable performance standard.

I(i). *U.S. Regulation of Lead in Gasoline*

Lead was added to gasoline for many decades to raise octane levels cheaply.[6] The decision to reduce lead in gasoline in the United States came in response to two main factors. First, as is summarized in Table I, the phasedown of lead in gasoline began in 1974 when the U.S. Environmental Protection Agency (EPA) introduced rules requiring the use of unleaded gasoline in new cars equipped with catalytic converters. The introduction of catalytic converters for emissions control required that motorists use unleaded gasoline, because lead destroys the emissions control capacity of catalytic converters. A large

[5] Whether any of these policies provide incentives for fully efficient technology adoption depends on a comparison with the social benefits of technology adoption and the usual weighing of marginal social costs and benefits.

[6] Octane is a characteristic of fuel components that improves the performance of engines by preventing fuel from combusting prematurely in the engine. The availability of high-octane fuel allows more powerful engines to be built. Cars will not operate efficiently with a lower-octane fuel than that for which they were designed. In addition, some older cars need more than a minimum level of lead (less than 0.1 grams of lead per gallon) to prevent a problem called valve seat recession.

TABLE I
FEDERAL STANDARDS FOR LEAD PHASEDOWN

Deadline	Standard	Small Refinery Exceptions
July 4, 1974	Gasoline retailers must offer unleaded gasoline for use in cars with catalytic converters.	—
October 1, 1979	Refineries must not produce gasoline averaging more than 0.5 glpg per quarter, pooled (leaded and unleaded).	Small refineries ($\leq$ 50,000 bpd crude oil capacity, owned by company with $\leq$ 137,500 bpd capacity) are subject to less stringent standard of 0.8–2.65 glpg varying by capacity.
November 1, 1982	Refineries must meet a leaded gas standard of 1.1. Interrefinery averaging of lead rights is permitted among large refineries and among small refineries, but not between refineries of different sizes.	Very small refineries ($\leq$ 10,000 bpd gasoline production, owned by company with $\leq$ 70,000 bpd production) are subject to a less stringent pooled standard of 2.16 or 2.65 varying by capacity.
July 1, 1983	Very small refineries are also subject to a standard of 1.1 (leaded). Averaging is permitted among all refineries.	—
January 1, 1985	During 1985 only, refineries are permitted to 'bank' excess lead rights for use in a subsequent quarter.	—
July 1, 1985	The standard is reduced to 0.5 (leaded).	—
January 1, 1986	The standard is reduced to 0.1 (leaded).	—
January 1, 1988	Interrefinery averaging and withdrawal of banked lead usage rights are no longer permitted. Each refinery must comply with the 0.1 standard.	—
January 1, 1996	Lead additives in motor vehicle gasoline are prohibited.	—

Source: United States Code of Federal Regulations [1996].
Note: glpg = grams of lead per gallon; bpd = barrels per day.

proportion of the eventual phasedown of lead in gasoline is in fact attributable to the decreasing share of leaded gasoline that resulted from the transition to a new car fleet. To help promote the supply of unleaded gasoline, EPA also scheduled performance standards requiring refineries to decrease the average lead content of gasoline beginning in 1975, but these were postponed until 1979 through a series of regulatory adjustments.

Second, by the 1980s, studies showed adverse effects of atmospheric lead on the IQ of children and on hypertension in adults [U.S. EPA 1985]. In 1982, new rules changed the basis of the standard from a refinery performance standard measured in terms of lead content per pooled volume of leaded plus unleaded gasoline, to a standard that specifically limited the allowable content of lead in leaded gasoline to a quarterly average of 1.1 grams of lead per gallon (glpg). Very small refineries faced less stringent standards until 1983. During 1985 the standard was reduced to 0.5 glpg, and beginning in 1986 the allowable content of lead in leaded gasoline was reduced to its final level of 0.1 glpg. Lead was banned as a fuel additive in the United States beginning in 1996.

To ease the transition for refineries, the regulations permitted both trading and banking of lead permits through a system of 'inter-refinery averaging.' Trading of lead permits among refineries was allowed from late 1982 through the end of 1987. Banking was allowed during 1985–1987. Beginning in 1988, EPA reimposed a performance standard of 0.1 glpg applicable to individual refineries. See Hahn and Hester [1989] and Nichols [1997] for a general overview of trading behavior and other aspects of the lead trading program. The estimated cost to the refining industry of complying with lead regulations in 1988 alone was about $500 million [Nichols 1997]; total costs were in the billions of dollars.

Before late 1979 and from late 1982 through the end of 1987, refineries had extensive flexibility in their response to the lead regulations. They could choose how much unleaded gasoline to produce and could purchase lead permits to maintain a high level of lead in leaded gasoline if they chose. We characterize the form of regulation during these periods as an economic instrument. In contrast, from late 1979 through late 1982 and after 1987, each refinery faced an individual performance standard. We characterize the form of regulation in these periods as a performance standard.

For a given demand for octane in gasoline, a constraint on the amount of lead that can be used to boost octane will increase the demand for more expensive substitute sources of octane. At the aggregate level there are two basic approaches to reducing the need for lead. One is the use of other octane-enhancing additives, such as MTBE (methyl tertiary-butyl ether). These are more expensive than lead and only a part of the long-term solution. Another approach, on which we focus, is to increase refineries' abilities to produce high-octane gasoline components. In the short run, existing equipment can be run more intensively to increase octane production, but eventually new investment is required. At an individual level, a refinery can also adjust by altering the type of crude oil it purchases, by buying intermediate products with higher octane content, or by changing its output mix to one requiring less octane.

Pentane-hexane isomerization (henceforth referred to simply as isomerization) is one technology that can be used to replace octane lost when lead usage is reduced. Isomerization was a new technology in the early 1970s, but by 1985–1988, investments in isomerization were projected to provide around 40% of additional octane requirements.[7] Isomerization can be used in a refinery of any size and complexity and can be installed at any time in an

[7] Additives including MTBE provided about one third, and alkylation, catalytic cracking, and reforming together provided most of the remaining increase. Prior to 1986, isomerization played a smaller role in octane production, and increased severity of reforming and fluid catalytic cracking provided much of the octane increases [*Oil and Gas Journal* 1986].

existing refinery.[8] In 1986, the minimum investment required for a 5,000-barrel-per-day unit was around \$2.6 million [*Oil and Gas Journal*, 1986], which is a relatively small investment in the refining industry. Because the primary purpose of isomerization is to increase gasoline octane, the specialization of the technology makes it ideal for assessing the impact of lead regulation on technology adoption.[9]

In Section 2 we develop an analytical and econometric model of the incentives to adopt technology as a function of economic and regulatory variables and individual characteristics. Section 3 describes our data and the results of our empirical application using a panel of 378 refineries from 1971 to 1995. We conclude in Section 4.

II. TECHNOLOGY ADOPTION IN RESPONSE TO REGULATION

II(i). *A Model of the Technology Adoption Decision*

We consider a situation where a new technology is available to each refinery i at a cost $C(\mathbf{Z}_{it},t)$ at time t where $\mathbf{Z}_{it}$ is a vector of refinery-specific characteristics that may affect the cost of adoption. We treat the adoption decision as a discrete choice, which is reasonable for the case at hand.[10] We define Π^0 as the profit without isomerization and Π^1 as the profit after adoption (gross of the cost of adoption). Each refinery maximizes profits and chooses T, the time of adoption, to solve the following dynamic optimization problem:

$$(1) \qquad \max_T \int_0^T \Pi^0(\mathbf{Z}_{it}, R_{it}, K_t, t)\mathrm{e}^{-rt}dt - C(\mathbf{Z}_{iT}, T)\mathrm{e}^{-rT} + \int_T^\infty \Pi^1(\mathbf{Z}_{it}, R_{it}, K_t, t)\mathrm{e}^{-rt}dt,$$

[8] Many new technologies must be adopted when other changes are being made to the existing plant or when old technology is replaced. Rose and Joskow [1990] show how to control for this situation econometrically. This is not the case for isomerization.

[9] Unlike some other refining technologies, isomerization was relatively unaffected by the other major changes in the refinery industry during the 1980s because of its low level of previous adoption. The two other technologies that were key in replacing lead in gasoline were catalytic reforming and alkylation. The industry had large amounts of these technologies before the lead phasedown began because these technologies produce intermediate inputs used in the production of a wide range of outputs. The most important change in the industry during this period is the removal, in 1981, of price and allocation controls on crude oil, which had effectively subsidized the crude oil used by smaller refineries [Energy Information Administration 1993]. After 1981, many small refineries closed and larger refineries took over their supply of gasoline. Refinery technologies such as catalytic reforming and alkylation were rationalized in response to this restructuring. Whereas a change in the level of either of these technologies could be interpreted as a response to many factors other than the regulation of lead, a change in the level of isomerization can be interpreted primarily as a response to the phaseout of lead from gasoline.

[10] Isomerization capacity in our data was always added as a discrete, one-time, investment.

where the set of refinery-specific characteristics $\mathbf{Z}_{it}$ also affects profits, K_t is the stock of capacity of the new technology already installed in the industry, R_{it} represents the stringency and form of regulation faced by each refinery[11], and r is the discount rate. The variables $\mathbf{Z}_{it}$, R_{it}, and K_t can change over time.

A refinery will adopt at the first time T where the investment is profitable as long as it is not even more profitable to wait until a later period because of falling investment costs. The first order condition from Equation 1 is known as the arbitrage condition:

$$(2) \qquad V(\mathbf{Z}_{iT}, R_{iT}, K_T, T) - rC(\mathbf{Z}_{iT}, T) + \frac{\partial C(\mathbf{Z}_{iT}, T)}{\partial t} \geq 0,$$

where $V(\mathbf{Z}_{iT}, R_{iT}, K_T, T) = \Pi^1(\mathbf{Z}_{iT}, R_{iT}, K_T, T) - \Pi^0(\mathbf{Z}_{iT}, R_{iT}, K_T, T)$ is the gross value of the adopted technology at time T. The arbitrage condition is a sufficient condition if the adoption cost is nonincreasing and convex, and the gross value of adoption, V, is nondecreasing with respect to time.[12] We also note that in order for adoption to take place in finite time, these conditions together imply that adoption must be profitable:

$$\int_T^{\infty} V(\mathbf{Z}_{it}, R_{it}, K_t, t)\mathrm{e}^{-rt}dt - C(\mathbf{Z}_{iT}, T)\mathrm{e}^{-rT} > 0.$$

The gross value of adoption varies across refineries, as does the cost and the change in cost over time. Refineries with the highest value will tend to adopt first; then, as the costs of technology adoption fall or its benefits rise (e.g., because of increased regulatory stringency), other refineries begin to adopt. This is known as the *rank effect* because refineries are ranked by the profitability of the new technology [Karshenas and Stoneman 1995]. The gradual sweeping across this distribution of values tends to produce the S-shaped pattern that is typically found for the diffusion of new technologies (assuming a single-peaked distribution). A second important effect is known as the *stock effect*. As more refineries adopt the technology and the stock of installed capacity rises, the supply of high-octane intermediate products will

[11] There is some ambiguity with the definition of R_{it} when there is advanced knowledge of future regulatory stringency – as when announced regulatory deadlines include significant lead time – and/or lags in the technology adoption process, due for example to construction timeframes. We do not, however, feel this is a serious problem in the particular case we examine empirically. Refineries generally faced little if any incentive to reduce lead usage before they were required to, and the time given to them from regulatory announcement to compliance deadline was adequate relative to the time required for technology installation. As described below, the pattern of adoption corresponds closely with the trajectory of compliance deadlines.

[12] Specifically, the second-order condition that is sufficient if it holds everywhere is:

$$\partial V(Z_{it}, R_{it}, K_t, t)/\partial t - r\partial C(Z_{it}, t)/\partial t + \partial^2 C(Z_{it}, t)/\partial t^2 \geq 0.$$

These conditions are likely to hold over our period of analysis because regulatory stringency was increasing and because adoption costs generally fell at a decreasing rate over time, eventually tending to a constant level; the general pattern is convex.

rise and the price of octane will fall, as will the return to adoption. We allow for each of these effects within our econometric model.[13]

In addition to the above representation of adoption behavior, which models adoption as the result of value-maximizing decisions by heterogeneous adopters, the literature on technology diffusion has traditionally emphasized the role played by the gradual dissemination of information about a new technology. Adopting technology can be a risky undertaking requiring considerable information. It takes time for information to diffuse sufficiently, and the diffusion of technology is limited by this diffusion of information. In the epidemic model of technology diffusion [Griliches 1957; Stoneman 1983], this process is represented in a manner similar to the spread of a disease, with adoption rates depending on the interaction between adopters and potential adopters. The presumption is that one of the most important sources of information about a new technology is firms that have already adopted. Under typical assumptions, the epidemic model also yields the characteristic S-shaped diffusion pattern. As described below, within the duration framework used in our econometric analysis, this information dissemination process can be represented through the baseline hazard function, and its importance ascertained by assessing the degree of duration dependence of the baseline hazard.

II(ii). *Econometric Model of the Timing of Technology Adoption*

Econometric modeling of technology adoption decisions lends itself naturally to the use of statistical techniques developed for analysis of duration data. Duration data describe processes and events where it is typically not only the duration of the process *per se* that is interesting, but also the likelihood that the event will now occur, given that the process has lasted as long as it has. Duration models were originally developed in

[13] Sometimes so-called *order effects* are distinguished from the closely related stock effects concept, but with an emphasis on the strategic behavior of firms that could arise when earlier adopters achieve greater returns than later adopters. In the game-theoretic approach of Fudenberg and Tirole [1985], this strategic behavior results in a race to be high in the order of adoption due to first-mover advantages through which preemptive early adoption influences the timing of later adoption. While a decline in the value of adoption as a function of the magnitude of previous adoption can theoretically occur with or without any strategic behavior [Quirmbach 1986], distinguishing empirically between these is extremely difficult if not impossible with available data (see, for example, Karshenas and Stoneman [1993]). In addition, although not clearly addressed in the relevant theoretical literature, the effectiveness of any strategic behavior presumably would decline as the number of firms gets large. With markets for both refinery outputs and inputs typically involving many firms at a regional or national level, we think it is unlikely that strategically motivated technology adoption behavior would be very prevalent or have much influence on our results. The variable *STOCK*, which is a national aggregate, therefore seems unlikely to be picking up any strategic effects. To the extent higher regional concentration of refineries is associated with earlier adoption by some refineries, this may be captured as a negative effect of the variable *DENSITY*, although it is not clear that the *average* probability of adoption in a concentrated region would be higher.

biomedical science to describe such events as the survival times of patients with heart transplants, and in industrial engineering to model such events as the risk of equipment failure. Within the economics literature, duration analysis has been applied to labor issues, such as the measurement of unemployment spells, and to a more limited extent, issues related to technology adoption [Hannan and McDowell 1984; Rose and Joskow 1990; Karshenas and Stoneman 1993; Saloner and Shepard 1995]. Kalbfleisch and Prentice [1980], Kiefer [1988], and Lancaster [1990] provide introductions to duration analysis, both in general and in its specific application within economics.

A duration model of technology adoption is based on formulating the problem in terms of the conditional probability of adoption at a particular time, given that adoption has not already occurred and given the characteristics of the individual and its environment. Note the correspondence between this conceptualization of the problem and the technology adoption decision as framed in the previous section. In addition to the intuitive appeal of framing the technology adoption decision in this way, duration models provide a convenient framework for incorporating data on explanatory variables that change over time (so-called time-varying covariates) and other elements of the dynamic process of technological change. Estimating the effect of regulations and other determinants of technology adoption that change over time (e.g., technology costs, stocks, epidemic and learning effects) is in fact central to our specific research interest. After the general structure of the probability model has been specified, along with some additional functional form and distributional assumptions, the model can be estimated by maximum-likelihood methods.

We therefore proceed by formulating the timing of technology adoption within a duration model as a function of the explanatory variables that we found through the arbitrage condition (Equation 2) to be fundamental to this decision. Specifically, the rate at which individuals will adopt the technology in period t, conditional on having not adopted before t, is known as the 'hazard rate' at time t. The *hazard function* for each individual is denoted $h(t, \mathbf{X}_{it}, \boldsymbol{\theta})$ and it is given by the conditional probability

$$h(t, \mathbf{X}_{it}, \boldsymbol{\theta}) = \frac{f(t, \mathbf{X}_{it}, \boldsymbol{\theta})}{1 - F(t, \mathbf{X}_{it}, \boldsymbol{\theta})},$$

where $F(t, \mathbf{X}_{it}, \boldsymbol{\theta}) = \Pr(T < t)$ is the cumulative distribution function specifying the probability that the random variable T (i.e., time until adoption) is less than some value t, $f(t, \mathbf{X}_{it}, \boldsymbol{\theta}) = dF(t, \mathbf{X}_{it}, \boldsymbol{\theta})/\mathrm{d}t$ is its density function, $\mathbf{X}_{it}$ is a set of explanatory variables which may change over time, (e.g., the superset of $\mathbf{Z}_{it}$, R_{it}, and K_t from above), and $\boldsymbol{\theta}$ is a set of parameters to be estimated. The behavior of the hazard function over time depends on the distributional assumption for $F(t, \mathbf{X}_{it}, \boldsymbol{\theta})$ and on the way that the explanatory variables $\mathbf{X}_{it}$

change over time. Estimation of the parameters $\boldsymbol{\theta}$ can proceed using maximum likelihood.

We place further structure on the hazard function by means of a convenient and widely used approach in which the hazard function (and parameter set $\boldsymbol{\theta}$) is factored into two parts. One part is the *baseline hazard*, $h_0(t)$, which may depend on time but not on the other explanatory variables. The baseline hazard captures any effects on duration that are not represented by the other explanatory variables included in the analysis; it is assumed to be common to all individuals. In the context of technology adoption, the baseline hazard captures possible epidemic effects described above.

The second part of the factored hazard model depends on the explanatory variables $\mathbf{X}_{it}$ and associated parameter vector $\boldsymbol{\beta}$ in an exponential manner, which both permits straightforward estimation and inference and ensures that the hazard is positive without additional restrictions. The hazard function becomes

$$(3) \qquad h(t, \mathbf{X}_{it}, \boldsymbol{\beta}) = h_0(t)\exp(\mathbf{X}_{it}'\boldsymbol{\beta}).$$

An estimated parameter β is interpretable as the effect on the log hazard rate of a unit change in an explanatory variable at time t. If the explanatory variables are normalized to equal zero at some sensible reference case (e.g., the variable means), then $h_0(t)$ is interpretable as the hazard function for the reference case, and $\exp(\beta) - 1$ gives the percentage effect of the explanatory variable on the hazard rate relative to the reference case. We employ this type of normalization in our empirical application, as explained below.

Estimation of the hazard model through maximum-likelihood methods (based on Equation 3) can proceed either in a completely parametric fashion by choosing $h_0(t)$ from a parametric family, or by using the Cox [1975] partial-likelihood approach, which does not require specifying the form of h_0. A variety of alternative parametric functions have been used for the first approach. The most widely used is an exponential distribution of duration times (i.e., $F(t) = 1 - \exp(-\gamma t)$ and $f(t) = \gamma \exp(-\gamma t)$), which leads to a constant baseline hazard $h_0(t) = \gamma$. Coupled with specification tests, its simplicity and ease of interpretation make the exponential distribution a natural point of departure for analysis.

We also estimate models using the Weibull, Gompertz, and gamma distributions, which allow for nonconstant baseline hazards (i.e., duration dependence) and include the exponential distribution as a special case, thereby enabling specification testing. If, for example, as described above, uncertainty about the value of isomerization falls in unobservable ways over time as adoption spreads and learning occurs through an epidemic effect, we might expect that the hazard rate would rise over time. Nonetheless, because we control for many of the variables that are thought to govern the timing of technology adoption, it should not be surprising if the remaining baseline hazard is essentially constant.[14] To further check the appropriateness of our parametric form of the hazard model, we also estimate the Cox partial-likelihood model.

III. ESTIMATION OF THE TECHNOLOGY ADOPTION DECISION

III(i). *Explanatory Variables*

Using information from the Department of Energy, trade journals, EPA, and individual oil companies, we compiled a 5,647-observation database of the annual technical and operating characteristics of 378 refineries spanning the 25-year period 1971–1995. These data cover virtually the entire population of U.S. refineries over a period that predates the first recorded adoption of isomerization in the United States, in 1972. We coupled these data with information on lead regulations, technology costs, the lead-trading behavior of individual refineries, and other relevant economic and refinery market variables.[15] The sources, definitions, and construction of individual variables are further described below; basic descriptive statistics of each of the variables are given in Table II. To facilitate interpretation of estimated parameters, we normalized continuous variables so that a unit change in each transformed variable represents a 10% change from its mean value, or in the case of our regulatory stringency variable (*REGULATE*), a 10% change in the level of stringency.[16]

[14] Unobserved heterogeneity in individual characteristics raises additional issues specific to duration analysis. In particular, if individuals have differing duration distributions after controlling for included explanatory variables, this can result in a downward bias in estimated duration dependence [Kiefer 1988]. Intuitively, as time passes those individuals remaining will tend to have lower hazard rates, and this will show up as a decline in the hazard function relative to its true value. We test for the importance of unobserved heterogeneity in our sample by introducing it parametrically as an unobserved multiplicative effect on the hazard function [Hougaard 1986]. We assess two possible distributions for the unobserved heterogeneity, the Gamma distribution and the Inverse-Gaussian distribution. Likelihood ratio tests did not support the presence of either form of unobserved heterogeneity.

[15] In addition to the variables described below, we also tested the effect of the price of crude oil to refiners [Energy Information Administration, 2000], but found that its effect was very small in magnitude and statistically insignificant. The price of crude oil could in theory influence the adoption decision both due to its effect on overall refining costs and profits, and because the price of MTBE (an important substitute for lead and isomerization) tends to be closely associated with the price of crude oil [U.S. International Trade Commission, 1999]. An adequate time series of the price of MTBE was not directly available because MTBE was not produced in the U.S. until 1979 and price data is not available until many years later.

[16] We accomplished this by first dividing each variable by its mean, then multiplying by 10, and finally taking deviations from each mean (by subtracting 10), resulting in a mean of zero for the transformed variables. We normalized *REGULATE* by dividing by its maximum and then multiplying by 10, so that it equals zero at its minimum and 10 at its maximum.

TABLE II
VARIABLE DEFINITIONS AND DESCRIPTIVE STATISTICS

Variable	Name	Mean	Standard deviation	Minimum	Maximum
Dependent Variable					
Isomerization indicator	—	0.09	0.28	0	1
Refinery Characteristics					
Refinery size (kb/cd)	*REFSIZE*	67.11	85.75	0.05	640
Company size (kb/cd)	*COSIZE*	356.27	440.52	0.05	1841
Large refinery indicator	*LARGE*	0.40	0.49	0	1
Catalytic reforming indicator	*COMPLEX*	0.71	0.45	0	1
Regulatory Variables					
Leaded gas standard (glpg)	*L*	1.71	1.31	0.10	3.00
Percent share of leaded gasoline consumption in region	*S*	0.53	0.32	0	0.96
Regulatory stringency	*REGULATE*	2.16	1.45	0.15	4.09
Economic instrument indicator	*ECON*	0.56	0.50	0	1
Predicted value from seller probit	*SELLER*	0.47	0.24	0.02	0.95
Market Variables					
National isomerization capacity (kb/sd)	*STOCK*	147.71	142.90	0.00	406.95
Number of refineries in region	*DENSITY*	31.24	12.41	4	61
Discount rate	*R*	0.04	0.02	0.00	0.09
Cost of isomerization ($1995/b/sd)	*COST*	608.16	48.60	554.22	767.11
Annualized cost of isomerization ($1995/b/sd)	*RCOST*	26.16	12.54	0.62	55.00
Rate of change in cost of isomerization	*DCOSTDT*	– 0.01	0.03	– 0.12	0.01

Note: Descriptive statistics are for untransformed data; see the text for a description of how we transformed the data for estimation. kb/cd = thousand barrels of capacity per calendar day; kb/sd = thousand barrels of capacity per stream day; g/lg = grams per leaded gallon. The number of observations for the full sample is $N = 5647$.

Refinery characteristics

We expect certain characteristics of individual refineries to raise or lower the net value of isomerization and thus raise or lower a refinery's propensity to adopt this new technology. Data on the technical and operating characteristics for refineries come from annual issues of the *Petroleum Supply Annual* [Energy Information Administration 1980–1995] and the *Oil and Gas Journal* [1971–1979]. These sources and information from the American Petroleum Institute [1996] were used to assign refineries to companies and to verify the years in which the refineries were in operation.

Dependent variable – presence of isomerization. The dependent variable is whether a refinery has adopted isomerization at each point in time within the sample. Capacity information is recorded as of January 1 each year, so a refinery is treated as having adopted isomerization at the start of 1986 if it had no such capacity at the beginning of 1985 but did so as of the start of 1986. If the refinery had not adopted by 1995 or the refinery shut down, the observation is treated as censored in that year. Figure 2 shows the cumulative adoption of isomerization over the period of interest. Adoption

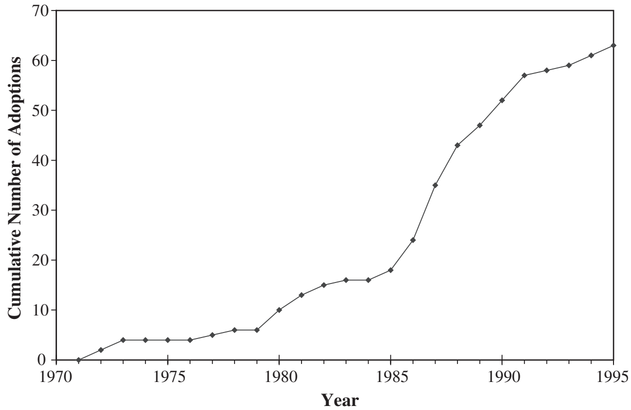

Figure 2
Cumulative Adoption of Isomerization

is slow in the 1970s, but increases around 1980 under the individually binding lead performance standard, and then again more dramatically in the mid to late 1980s as the standards became more stringent and then individually binding again. The annual count of adoptions ranges from 0 to 10 annually.

Size and industry setting. Theoretical and empirical work on technology diffusion suggests that size (e.g., of establishments, firms, plants) may play an important role in adoption decisions, perhaps as a proxy for such factors as economies of scale, risk aversion, investment hurdle rates, management quality, or participation in research and development activities. The empirical literature generally finds that smaller entities adopt new technologies more slowly.[17] For the specific case at hand, the trade press suggests that small refineries generally have higher costs of adopting isomerization [*Oil and Gas Journal* 1967]. We employ two indicators of size – the size of each refinery and the size of the company that owns it. Refinery size (*REFSIZE*) is defined as its operating crude distillation capacity in thousand barrels per calendar day (kb/cd). One of the categorical variables used in our test of regulatory form, *LARGE*, is that refinery capacity be greater than 50 kb/cd, the standard industry definition of a larger refinery. The expected effect of company size on isomerization adoption is more ambiguous. Adoption may be less likely at refineries in larger

[17] Karshenas and Stoneman [1995] and Geroski [2000] provide surveys, and Levin *et al.* [1987], Rose and Joskow [1990], Karshenas and Stoneman [1993], and Saloner and Shepard [1995] provide specific evidence of a positive effect of size on adoption propensity. Oster [1982] is one of the few studies finding a negative effect of firm size on adoption, attributing the large U.S. steel firms' 'technologically laggard' behavior to their insulation from competition.

companies because these refineries tend to have better access to high-octane intermediate products from affiliated refineries and may have greater flexibility in their output choice because other affiliated refineries supply parts of their market. They may also face higher bureaucratic barriers to adoption if decisions are not all made at the refinery level. On the other hand, adoption may be more likely at refineries within larger companies if larger companies have greater access to capital and to the skills, knowledge, and information from affiliated refineries that lower the cost of adoption. We define the size of the company that owns each refinery (*COSIZE*) as the sum of operating crude capacity (kb/cd) in all affiliated refineries. We also include the variable *DENSITY*, which measures the number of refineries in each region. We expect that refineries in regions with a greater number of other refineries will have greater access to intermediate products and greater output flexibility, and may thus have lower adoption propensities. On the other hand, if refineries learn about new technologies from geographically proximate refineries, increased refinery density could have a positive affect on adoption. The geographic distribution of refineries across the United States is illustrated in Figure 3. Regions in our analysis are based on Department of Energy definitions.[18]

Technological sophistication. The variable *COMPLEX* is a categorical variable indicating that a refinery had catalytic reforming capacity, a technology that distinguishes simple from more complex refineries.[19] One option for installing isomerization is to adapt an existing catalytic reforming unit; refineries without this option face higher adoption costs. We also expect that simple refineries may have less knowledge of the technology or face greater uncertainty about its value. These higher costs of adoption for simple refineries should tend to lower their relative adoption propensity, particularly when regulation allows such flexibility.

Technology cost and stock

Cost of isomerization. Both theory and common sense suggest that the cost of a technology is an important determinant of whether and when it will be adopted. We gathered typical costs of construction for an isomerization

[18] The 10 regional definitions we use are from the Department of Energy's Refinery Evaluation Modeling System. These regions were developed to provide a reasonable geographic aggregation for petroleum refining modeling purposes, and are derived from a combination of 13 Bureau of Mines districts with five Petroleum Administration for Defense (PAD) districts. The additional inclusion of regional dummies in the model did not add significant explanatory power.

[19] Alkylation capacity also tends to be present at more sophisticated refineries. We do not include this variable in the final results, however, because we found that it had a small and statistically insignificant independent effect.

Figure 3
Geographic Density of Refineries (average number by state).
Note that the size of the circles is proportional to the number of refineries.

unit from the trade journal *Hydrocarbon Processing* [1966–1994]. We deflated these costs into constant dollars using the Nelson Refinery Cost Index [American Petroleum Institute 1998] and then normalized the cost to equal one in 1971, resulting in the variable *COST*. [20]As illustrated in Figure 4, the real costs of isomerization dropped by about 30 percent over the period of analysis, to about $5.5 million for a 10,000-barrel-per-stream-day unit in 1995. Although *COST* is purely a time-series variable, we also capture cross-sectional differences in adoption costs through the variables for size (*REFSIZE*) and technological sophistication (*COMPLEX*).

Stock of isomerization capacity. As more refineries adopt isomerization, they increase the supply of high-octane intermediate outputs, hence lowering the price differential between leaded and unleaded gasoline and the marginal value of octane. This should lower adoption propensities as the installed stock of isomerization increases. On the other hand, if the installed

[20] We also created two other cost variables suggested by theory: *RCOST*, which is annualized cost where the discount rate is the Moody's AAA corporate bond rate from the Economic Report of the President [Council of Economic Advisors 1997], and *DCOSTDT*, which is the percentage annual change in the cost of isomerization. Neither of these variables added any explanatory power to the model once the more basic measure of cost was included.

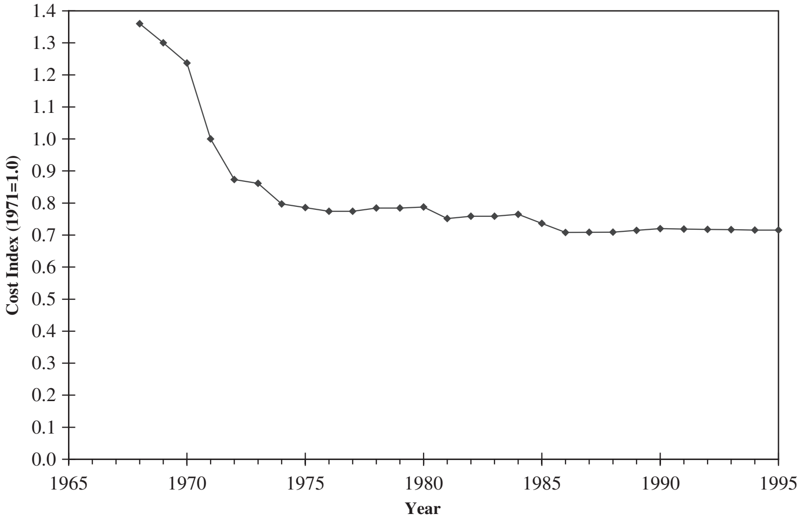

Figure 4
Cost of Isomerization Equipment

stock of isomerization acts as a proxy for cumulative experience with this technology, the learning and reduced uncertainty associated with it could have a positive effect on adoption. Our *STOCK* variable is defined as the total industry isomerization capacity in thousand barrels per stream day (kb/sd), lagged one period to avoid an endogeneity problem.

Regulatory variables

See Table I for a summary of the federal lead regulations that form the basis for our construction of the regulatory variables. We explore two types of regulatory variables that capture the effects of both the stringency and the form of regulation (i.e., performance standard or economic instrument).

Regulatory stringency. The overall stringency of lead regulations is inversely related to the average amount of lead allowed per gallon, which depends on the stringency of the standard for leaded gasoline and on the share of leaded gasoline in total gasoline. As the allowable level of lead in leaded gasoline decreases, and the share of leaded gasoline decreases as post-1974 unleaded-only cars replace older ones, effective stringency will increase. Increased regulatory stringency should increase the propensity to adopt isomerization because isomerization is a substitute for lead in octane production. Because octane responds in an approximately log-linear manner to the addition of lead [Leffler 1985], this suggests the following definition for our regulatory stringency variable (*REGULATE*):

$$REGULATE_{it} = S_{it} \ln\left(B/L_{it}\right) + (1 - S_{it}) \ln(B/U),$$

where S is the share of leaded gasoline consumption, B is the baseline unregulated level of lead per gallon, L is allowable content of lead per leaded gallon, $1 - S$ is the share of unleaded gasoline consumption, and U is the (very low) content of lead per unleaded gallon. L, S, and thus $REGULATE$ vary across refineries and over time.

The share of leaded gasoline consumed, S, varies by location and over time from 1 in 1970 to 0 in 1995. We construct S using state-level data based on the *Petroleum Marketing Monthly* [Energy Information Administration 1983–1992], a study by Ethyl Corporation,[21] and the *U.S. Statistical Abstract* [U.S. Bureau of the Census 1971–1995]. We then aggregate values to the regional level using the ten regional definitions described earlier.

Federal regulations define unleaded gasoline as having a lead level of 0.05 grams of lead per gallon or less ($U = 0.05$). In 1970, leaded gasoline had a pre-regulation baseline lead level of approximately $B = 3$ grams of lead per gallon [U.S. Department of Energy 1986]. $REGULATE$ thus varies from 0 in 1970 to a maximum of 4 by 1995, when leaded gasoline was virtually eliminated (i.e., $REGULATE_{\max} = \ln(B/U) = \ln(3/.05) = 4.09$ *prior to our normalization*). Beginning in 1979, lead in leaded gasoline was restricted to a level L, which was initially the pooled gas standard divided by the leaded gas share and then the leaded standard from November 1982 on (see Table I). Small refineries were treated differently from 1979 until July 1983, and this is also incorporated in our measure of L (See Table I). L is prorated when regulations span partial years.

Regulatory form. With our regulatory form variable we seek to test the hypothesis that firms with relatively low (high) costs of individual compliance (e.g., 'sellers' versus 'buyers' in tradable permit markets) face higher (lower) incentives to adopt under an economic incentive – based instrument than under an individually binding performance standard. Ideally, we would like to observe whether a refinery's marginal cost of compliance if it acts alone is above or below the market price determined by the economic instrument. If a refinery's marginal costs are below the market permit price, it would face higher returns to adoption when the economic instrument is employed. If a refinery's marginal costs are above the permit price, it would face higher returns to adoption under an individually binding performance standard.

Because we have neither individual compliance costs nor the permit price over time, we approach this question in two alternative ways. We begin by defining the variable $ECON$ to indicate periods during which, at year end, refineries had flexibility in their individual lead use (i.e., 1971–1978 and 1982–1986) versus periods when they were subject to individually binding

[21] These data for 1980–1982 were kindly provided by Severin Borenstein.

performance standards (i.e., 1979–1981 and 1987–1995). We then interact this regulatory form variable with indicators of individual refinery compliance costs. These interactions take two forms. In the first model, we simply interact *ECON* with two indicators of low compliance cost, *LARGE* and *COMPLEX*.[22] We include *ECON* and these interaction terms in the duration model along with the other variables described above.[23]

In the second model, we employ a two-stage procedure. First, we take the intermediate step of creating a variable *SELLER*, which represents the expected probability that a refinery is a seller of permits, indicating it has relatively low compliance costs. Second, we interact *SELLER* with *ECON* as in the first model and include it in the main equation. To construct the variable *SELLER*, we use data on lead-trading activity that was generated by the self-reporting requirements of the EPA lead-trading program.[24] For each refinery, we compute the net purchases or sales of lead permits in 1983, the first full year of operation of the trading program.[25] We then construct a discrete variable indicating whether a refinery was a net seller or buyer of permits, and we estimate a probit model of this variable with relevant explanatory variables that may affect compliance costs. The results are shown in Table III; most of the variables have the expected sign. Finally, we compute the predicted values from this probit equation for the entire sample – this is the variable *SELLER* that we use in our duration analysis. One way

[22] Kerr and Maré [1999] suggest that small refineries had higher transaction costs in the lead permit market. Thus, because small refineries also tend to have higher adoption costs, although they might have wanted to defer adoption by buying permits, they faced relatively high costs of doing so. Therefore, their propensity to adopt may have fallen less than expected under the permit market. This could reduce the size of the estimated negative effect on *ECON*; accounting for such an effect would strengthen our results.

[23] If *LARGE* or *SELLER* (see below) are included as separate (not interacted) explanatory variables in the estimation, their coefficients are small and statistically insignificant and their inclusion does not qualitatively alter the results. Furthermore, including these variables independently would confuse the interpretation of the other size and cost variables already included in the equation, without providing further explanatory power.

[24] The data were collected confidentially by the U.S. Environmental Protection Agency via Form 40-CFR80.20, including information on each refinery's production of leaded and unleaded gasoline, as well as the number of permits bought, sold, and banked each quarter from 1983 through 1987. We have these data for a subset of oil companies, including data both on those directly observed and on their trading partners. We observe full trading behavior for only 77 refineries but with their trading partners included, we have a total of 114 observations. Although we do not observe complete trading for their trading partners, we assume that their observed direction of trade is an unbiased proxy for the direction of their total net trade. This is not an unreasonable assumption, since most refineries make only one trade per quarter, or around four per year. Our fully observed sample accounts for 61% of sales and 49% of purchases by refineries. We observe 48% of all trades. One concern we had was that there might be a sample selection problem with regard to the refineries for which we observed trading data. However, a Heckman test rejected any sample selection problem.

[25] We chose 1983 rather than another time period to avoid complications from the allowance of permit banking in later years.

TABLE III
INFLUENCE OF REFINERY CHARACTERISTICS ON LEAD PERMIT SELLING

Variable	Probit model results
LARGE	0.69*
	(0.33)
COMPLEX	1.42*
	(0.65)
REFSIZE	– 0.03*
	(0.01)
COSIZE	0.01
	(0.01)
DENSITY	0.07*
	(0.03)
Constant	– 1.38**
	(0.62)
Log likelihood	– 69**
Observations	114

Note: Asterisks denote statistical significance at various levels:
* = 95%,
** = 99%. Dependent variable indicates whether the refinery was observed to be a net seller of lead permits in 1983, the first year of trading. Variables are described in more detail in Table II and in the text. Estimation method is probit maximum likelihood. Robust standard errors are reported in parentheses.

to think about the variable *SELLER* is as a summary measure of relative compliance costs across refineries, based on the relationship between the role of the refinery in the larger market (i.e., seller versus buyer) and the many variables we have that are indicators of compliance costs. This is precisely the type of variable we need to test our regulatory form hypothesis. Thus, the two models we estimate are based on Equation 3, where:

$$
\begin{aligned}
\mathbf{X}_{it}'\boldsymbol{\beta} = {} & \beta_0 + \beta_1 REGULATE_{it} + \beta_2 ECON_t + \beta_3 ECON_t \\
& * LARGE_{it} + \beta_4 ECON_t * COMPLEX_{it} \\
& + \beta_5 STOCK_t + \beta_6 COST_t + \beta_7 REFSIZE_{it} \\
& + \beta_8 COSIZE_{it} + \beta_9 COMPLEX_{it} + \beta_{10} DENSITY_{it},
\end{aligned}
\tag{4}
$$

and

$$
\begin{aligned}
\mathbf{X}_{it}'\boldsymbol{\beta} = {} & \gamma_0 + \gamma_1 REGULATE_{it} + \gamma_2 ECON_t + \gamma_3 ECON_t \\
& * SELLER_{it} \\
& + \gamma_4 STOCK_t + \gamma_5 COST_t + \gamma_6 REFSIZE_{it} \\
& + \gamma_7 COSIZE_{it} + \gamma_8 COMPLEX_{it} + \gamma_9 DENSITY_{it},
\end{aligned}
\tag{5}
$$

TABLE IV
TECHNOLOGY ADOPTION RESPONSE TO REGULATORY AND MARKET VARIABLES

	Model 1 (with indicators of low cost)	Model 2 (with probability of being a *SELLER*)
REGULATE	0.33**	0.35**
	(0.11)	(0.10)
ECON	– 14.02**	– 3.39**
	(0.73)	(1.33)
*ECON*LARGE*	1.83*	—
	(0.78)	
*ECON*COMPLEX*	11.67**	—
	(1.01)	
*ECON*SELLER*	—	4.25*
		(2.08)
STOCK	– 0.08**	– 0.09**
	(0.03)	(0.03)
COST	– 0.26	– 0.29
	(0.56)	(0.53)
REFSIZE	0.04**	0.05**
	(0.01)	(0.01)
COSIZE	– 0.06**	– 0.07**
	(0.02)	(0.02)
COMPLEX	1.95**	1.77*
	(0.75)	(0.76)
DENSITY	– 0.16**	– 0.19**
	(0.04)	(0.04)
Constant	– 7.97**	– 8.10**
	(0.91)	(0.90)
Log likelihood	– 109**	– 111**
Observations	5,141	5,141
Refineries	378	378

Note: Asterisks denote statistical significance at various levels:
* = 95%,
** = 99%. Dependent variable indicates whether refinery has adopted isomerization capacity; a total of 63 refineries had adopted isomerization within the sample time frame. Variables are described in more detail in Table II and in the text. Estimation method is maximum likelihood. Robust standard errors are reported in parentheses. Percentage effects of a unit change in a variable on the hazard rate are equal to $\exp(\beta) - 1$, where β is the parameter estimate. Given our normalization of the data, a unit change in a continuous variable is equal to about a 10% change from its mean, or a 10% increase in the level of *REGULATE*.

where the βs and γs are parameters to be estimated and subscripting indicates whether variables vary by refinery i or only time t. For simplicity we have omitted subscripting from the text. While *REFSIZE*, *COSIZE*, *DENSITY*, *COMPLEX*, *LARGE*, and *SELLER* vary primarily along the cross-section and *REGULATE* varies primarily along the time-series dimension, each of these variables has non-neglible variation along the other dimension as well.

III(ii). *Estimation Results*

As described above, we estimate a duration model of the influence of refinery characteristics, market factors, and regulations on the timing of technology adoption using maximum-likelihood estimation.[26] The results for estimation of Equations 4 and 5 are given in Table IV. The parameter estimates changed very little under more flexible distributional assumptions, including the Cox partial-likelihood approach, which leaves the baseline hazard function unspecified.[27] Moreover, tests of the exponential distribution relative to more flexible parametric distributions in which it is nested do not reject the exponential distribution. In addition, we were concerned that refineries that exit might also be less likely to adopt because they may have less to gain or have other unobserved characteristics that influence adoption (e.g., low productivity). We therefore explored whether refinery exit or entry had a significant additional influence on adoption behavior – we found that it did not.[28] Finally, further specification checks found that our use of the standard hazard model was appropriate, the functional forms for our explanatory variables were adequate, and the model fit the data reasonably well.[29] We therefore focus our attention on the results in Table IV, which assumes an exponentially distributed baseline hazard.

The results show a large, statistically significant positive influence of increased regulatory stringency on isomerization adoption. The estimate on *REGULATE* indicates that a 10% increase in the stringency of gasoline lead regulations was associated with about a 40% increase in probability of new adoptions by refineries. In fact, the magnitude of this effect suggests that virtually all isomerization adoption over this period can be explained by the increased octane requirements necessitated by the lead regulations on fuel additives and the car fleet.

[26] Because observations in our dataset represent repeated observations on the same subjects (i.e., individual refineries), the usual assumption of independent observations is questionable. We therefore use a robust (Huber-White) estimate of the variance-covariance matrix for the standard errors of our parameter estimates, which relaxes the independence assumption and requires observations to be independent only across refineries.

[27] Kerr and Newell [2000] provides results for different distributional assumptions for the baseline hazard function, demonstrating the robustness of the results to various distributional assumptions and suggesting that the use of an exponential baseline hazard function is appropriate in this case.

[28] First, we included in the duration models a variable indicating whether a refinery shut down during the sample period. The estimated sign on this variable was negative, as one might expect, but it was statistically insignificant and did not significantly alter the other results. Second, we included a continuous variable representing the time of exit, but again the variable had an insignificant influence on the results. Analogous estimates for late entry also yielded insignificant effects. Finally, we estimated the models using only the 118 refineries (out of 378) that were in the sample from beginning to end, omitting any refineries that shut down or entered late. The estimates supported the same conclusions as the model estimated on the full sample.

[29] Using a test developed by Grambsch and Therneau [1994], we use Schoenfeld residuals from the Cox partial likelihood estimates to conduct a joint test of the assumption that the explanatory variables have constant effects over time; the test did not reject the assumption ($P(\chi^2(5) > 1.74) = 0.88$). We also conducted many visual checks of the residuals from the estimation, which had the desired properties (see Lancaster [1990]). In addition, we explored higher-order functions of our continuous variables (which we found to be small and statistically insignificant), as well as their logarithmic transformations (which did not qualitatively alter the results).

The form taken by lead regulations – individually binding performance standard or market-based regulation – also had a marked influence on the pattern of technology adoption. As theory suggests, we found a significant divergence in the adoption behavior of refineries with low versus high compliance costs. Namely, the positive differential in the adoption propensity of expected permit sellers (i.e., low-cost refineries) relative to expected permit buyers (i.e., high-cost refineries) was significantly greater under market-based lead regulation compared to under individually binding performance standards. High-cost refineries (i.e., small, simple refineries or expected permit buyers), in particular, were much less likely to adopt under market-based regulation. This is evident in the parameter estimates for variables representing low-cost refineries during economic incentive regimes (i.e., *ECON∗SELLER*, *ECON∗LARGE*, and *ECON∗COMPLEX*), which are significantly positive, versus the parameter estimates for high-cost refineries in the same period (i.e., *ECON*), which are significantly negative.[30] Overall, our results are consistent with the finding that the tradable permit system provided more efficient incentives for technology adoption decisions.[31]

The other explanatory variables generally had effects consistent with economic expectations. Consistent with most empirical research on technology adoption, we found that larger refineries had significantly higher adoption propensities. The parameter estimate for *REFSIZE* indicates that a 10% increase from the mean in individual refinery capacity was associated with a 4% increase in the rate of adoption.[32] The influence of a refinery's company size (*COSIZE*), on the other hand, was found to be negative; a 10% increase in company-wide capacity was associated with a 6% decrease in the rate of adoption. As we described above, this result is consistent with the tendency for refineries in larger companies to have better access to octane-supplementing substitutes for isomerization from affiliated refineries. These factors presumably offset any positive influence that company size might have had on adoption. Similarly, we found that an increased concentration of other refineries in the same geographic region (*DENSITY*) had a negative effect on isomerization adoption; a 10% increase in the number of refineries in a region was associated with a 16%

[30] *SELLER* is an econometrically generated variable, so while the coefficient estimate on *ECON∗SELLER* is consistent, its standard error may be biased upward or downward depending on the covariance of the disturbances in the first-step (i.e., probit) and second-step (i.e., duration) models (see Murphy and Topel [1985] and Pagan [1984]). In any event, the models yield qualitatively similar conclusions whether they employ the generated variable *SELLER* (Model 2) or direct proxies for cost (Model 1).

[31] To check that this is not simply showing that large, complex refineries exhibit some form of duration dependence, we tested a range of time breaks from 1983–1990 and found that the likelihood increases monotonically toward the break at the end of 1987 and peaks there. This suggests that the change in hazard is indeed in response to the change in the form of regulation.

[32] Note that this hazard rate increases for large refineries when flexible regulations are in force, as indicated by the coefficient on *ECON∗LARGE*.

decrease in the rate of adoption. As with company size, this result suggests that refineries in close proximity to other refineries have greater access to isomerization substitutes, and that any positive geographic spillovers regarding learning about isomerization were more than offset.

We also found that more technologically complex refineries had substantially higher adoption propensities, which we would expect because the variable we used to measure complexity (i.e., catalytic reforming capability) has a direct effect on the cost of adopting isomerization. We estimate that complex refineries were six times more likely to adopt than simple refineries whenever the performance standards were binding, with this relative likelihood increasing dramatically when flexible regulations were in force.

Although our direct measure of how the cost of isomerization equipment evolved over time (*COST*) was estimated to have a negative relationship with adoption, the estimated coefficient was not statistically significant, even though it was moderately large. The point estimate is that a 10% reduction in the cost of isomerization was associated with about a 23% increase in the rate of adoption, although a 95% confidence interval on this estimate does not exclude zero. Given that the *COST* variable is highly correlated with *STOCK*, and that most of the decline in isomerization costs occurred prior to the sample period, our inability to precisely estimate its effect is not that surprising.

Finally, our estimate of the influence of the already-installed stock of isomerization (*STOCK*) demonstrates a negative effect on adoption. A 10% increase in the existing stock of isomerization capacity was associated with an 8% reduction in the rate of adoption. As discussed earlier, this negative 'stock effect' of installed capacity on adoption propensity is consistent with the prediction that existing investment would decrease the value of further investment. This effect seems to have dominated any positive influence of learning from previous installation of the technology.

IV. CONCLUSIONS

Theory has long contended that economic instruments for environmental protection would lead to the cost-effective adoption of new technologies, thus enhancing dynamic efficiency. Our empirical evidence supports this hypothesis. With a natural experiment involving a technology intended almost exclusively to eliminate a pollutant, and a detailed panel of 378 refineries over 25 years, we find evidence of an adoption response to the stringency and form of regulation in an expected manner. We found a large positive response of lead-reducing technology adoption to increased regulatory stringency, as well as a divergence in the behavior of refineries with different compliance cost characteristics during periods of flexible market-based lead regulation. The relative adoption propensity of refineries with low versus high compliance costs was significantly greater under market-based lead regulations than under a nontradable performance standard. Where environmentally appropriate, this suggests that more flexible regulation can achieve environmental goals while providing incentives for more efficient technology diffusion.

Consistent with previous literature, we also find that larger refineries adopt sooner, which is typically attributed to scale economies, lower investment hurdle rates, management quality, or participation in research and development activities. On the other hand, refineries that are part of larger companies or in regions with many other refineries have lower adoption propensities, likely because the greater flexibility in input and output choice makes adoption less profitable. Higher levels of previously installed technology have a dampening effect on adoption, as do higher technology costs, although the latter effect was not statistically significant – both of these factors tend to lower the profitability of adoption. Finally, we find no evidence of an epidemic or learning effect. Once we have controlled for changes in costs, technology stocks, and other factors, an exponential specification with a constant baseline hazard fits as well as any other. This suggests that information dissemination was probably not a significant issue for these firms.

REFERENCES

American Petroleum Institute, 1998, 'Nelson Refinery Operating Cost Indexes', *Basic Petroleum Data Book, Petroleum Industry Statistics, Volume XVIII, No. 1, Section VIII* (American Petroleum Institute, Washington, D.C.).

American Petroleum Institute, 1996, *Entry & Exit in U.S. Petroleum Refining, 1948–1995* (American Petroleum Institute, Washington, D.C.).

Council of Economic Advisors, 1997, *Economic Report of the President* (Washington, D.C.).

Cox, D. R., 1975, 'Partial Likelihood', *Biometrika*, 62, pp. 269–76.

Downing, P. B. and White, L. J., 1986, 'Innovation in Pollution Control', *Journal of Environmental Economics and Management*, 13, pp. 18–29.

Energy Information Administration, U.S. Department of Energy, 1983–1992, *Petroleum Marketing Monthly* (Washington, D.C.).

Energy Information Administration, U.S. Department of Energy, 1980–1995, *Petroleum Supply Annual* (Washington, D.C.).

Energy Information Administration, U.S. Department of Energy, 2000, *Annual Energy Review* (Washington, D.C.).

Energy Information Administration, U.S. Department of Energy, 1993, *The U.S. Petroleum Industry – Past as Prologue, 1970–1992*, DOE/EIA-0572 Washington, D.C.).

Fudenberg, D. and Tirole, J., 1985, *The Review of Economic Studies*, 52(3), pp. 383–401.

Geroski, P. A., 2000, 'Models of Technology Diffusion', *Research Policy*, 29, pp. 603–25.

Grambsch, P. M. and Therneau, T. M., 1994, 'Proportional Hazards Tests and Diagnostics Based on Weighted Residuals', *Biometrika*, 81, pp. 515–26.

Griliches, Z., 1957, 'Hybrid Corn: An Exploration in the Economics of Technical Change', *Econometrica*, 48, pp. 501–22.

Hahn, R. W. and Hester, G. L., 1989, 'Marketable Permits: Lessons for Theory and Practice', *Ecology Law Quarterly*, 16, pp. 361–406.
Hannon, T. H. and McDowell, J. M., 1984, 'The Determinants of Technology Adoption: The Case of the Banking Firm', *RAND Journal of Economics*, 15(3), pp. 328–35.
Hougaard, P., 1986, 'Survival Models for Heterogeneous Populations derived from Stable Distributions', *Biometrika*, 73, pp. 387–96.
Hydrocarbon Processing, 1966–1994, September and November issues (Gulf Publishing Co., Houston, TX).
Jaffe, A. B. and Stavins, R. N., (1995), 'Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion', *Journal of Environmental Economics and Management*, 29(3)(Part 2), S43–63.
Jaffe, A. B., Newell, R. G. and Stavins, R. N., 2003, 'Technological Change and the Environment', NBER Working Paper 7970, prepared as a chapter for the forthcoming Mäler, Karl-Göran and Vincent, Jeffrey (eds.), *Handbook of Environmental Economics* Vol. 1, pp. 461–516 (Elsevier Science, Amsterdam).
Joskow, P. L., Schmalensee, R. and Bailey, E. M., 1998, 'The Market for Sulfur Dioxide Emissions', *American Economic Review*, 88(4), pp. 669–85.
Kalbfleisch, J. D. and Prentice, R. L., 1980, *The Statistical Analysis of Failure Time Data* (John Wiley & Sons, New York).
Karshenas, M. and Stoneman, P., 1993, 'Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model', *RAND Journal of Economics*, 24(4), pp. 503–28.
Karshenas, M. and Stoneman, P., 1995, 'Technological Diffusion', *Handbook of the Economics of Innovation and Technological Change* (Basil Blackwell Ltd., Oxford).
Kerr, S. and Maré, D., 1999, 'Transaction Costs and Tradable Permit Markets: The United States Lead Phasedown' (Manuscript, Motu Economic and Public Policy Research, New Zealand).
Kerr, S. and Newell, R. G., 2000, 'Policy-Induced Technology Adoption: Evidence from the U.S. Lead Phasedown', Resources for the Future Discussion Paper 01-14 Washington, D.C.).
Kiefer, N. M., 1988, 'Economic Duration Data and Hazard Functions', *Journal of Economic Literature*, 26(2), pp. 646–79.
Laffont, J. and Tirole, J., 1996a, 'Pollution Permits and Compliance Strategies', *Journal of Public Economics*, 62, pp. 85–125.
Laffont, J. and Tirole, J., 1996b, 'Pollution Permits and Environmental Innovation', *Journal of Public Economics*, 62, pp. 127–40.
Lancaster, T., 1990, *The Econometric Analysis of Transition Data* (Cambridge University Press, New York).
Leffler, W. L., 1985, *Petroleum Refining for the Non-Technical Person* (Pennwell Publishing, Tulsa).
Levin, S. G., Levin, S. L. and Meisel, J. B., 1987, 'A Dynamic Analysis of the Adoption of a New Technology: The Case of Optical Scanners', *Review of Economics and Statistics*, 69, pp. 12–7.
Magat, W., 1978, 'Pollution Control and Technological Advance: A Model of the Firm', *Journal of Environmental Economics and Management*, 5, pp. 1–25.
Malueg, D. A., 1989, 'Emission Credit Trading and the Incentive to Adopt New Pollution Abatement Technology', *Journal of Environmental Economics and Management*, 16(1), pp. 52–7.
Milliman, S. R. and Prince, R., 1989, 'Firm Incentives to Promote Technological Change in Pollution Control', *Journal of Environmental Economics and Management*, 12, pp. 247–65.

Murphy, K. M. and Topel, R. H., 1985, 'Estimation and Inference in Two-step Econometric Models', *Journal of Business and Economic Statistics*, 3(4), pp. 370–79.

Nelson, R., Tietenberg, T. and Donihue, M., 1993, 'Differential Environmental Regulation: Effects on Electric Utility Capital Turnover and Emissions', *Review of Economics and Statistics*, 75(2), pp. 386–73.

Newell, R. G., Jaffe, A. B. and Stavins, R. N., 1999, 'The Induced Innovation Hypothesis and Energy-Saving Technological Change', *Quarterly Journal of Economics*, 114(3), pp. 941–75.

Nichols, A. L., 1997, 'Lead in Gasoline', in Richard, Morgenstern ed., *Economic Analysis at EPA*, pp. 49–86 (Resources for the Future, Washington, D.C.).

Oil and Gas Journal, 1967, 'The Unleaded-Gasoline Tab: $4.2 Billion', May 22 (Pennwell Publishing Co., Tulsa, OK).

Oil and Gas Journal , 1971–1979, 'Annual Refining Surveys', *Oil and Gas Journal*, 1986. Refining Report, March 24 (Pennwell Publishing Co., Tulsa, OK).

Orr, L., 1976, 'Incentives for Innovation as the Basis of Effluent Charge Strategy', *American Economic Review*, 56, pp. 441–47.

Oster, S., 1982, 'The Diffusion of Innovation among Steel Firms: The Basic Oxygen Furnace', *Bell Journal of Economics*, 13, pp. 45–56.

Pagan, A., 1984, 'Econometric Issues in the Analysis of Regressions with Generated Regressors', *International Economic Review*, 25(1), pp. 221–47.

Quirmbach, H. C., 1986, 'The Diffusion of New Technology and the Market for an Innovation', *RAND Journal of Economics*, 17, pp. 33–47.

Rose, N. L. and Joskow, P. L., 1990, 'The Diffusion of New Technologies: Evidence from the Electric Utility Industry', *RAND Journal of Economics*, 21(3), pp. 354–73.

Saloner, G. and Shepard, A., 1995, 'Adoption of Technologies with Network Effects: An Empirical Examination of the Adoption of Automated Teller Machines', *RAND Journal of Economics*, 26(3), pp. 479–501.

Stoneman, P., 1983, *The Economic Analysis of Technological Change* (Oxford University Press, Oxford, U.K.).

Stoneman, P. and Kwon, M.-J., 1994, 'The Diffusion of Multiple Process Technologies', *The Economic Journal*, 104, pp. 420–31.

United States Code of Federal Regulations , 1996, 40 C.F.R., Chapter 1, Environmental Protection Agency, Subchapter C, Part 80 – Regulation of Fuels and Fuel Additives (Washington, D.C.).

U.S. Bureau of the Census, 1971–1995, *Statistical Abstract* (Washington, D.C.).

U.S. Department of Energy, 1986, *Trends of Petroleum Fuels* (National Institute for Petroleum and Energy Research).

U.S. Environmental Protection Agency (EPA), Office of Policy Analysis, 1985, *Costs and Benefits of Reducing Lead in Gasoline: Final Regulatory Impact Analysis*, EPA-230-05-85-006 Washington, D.C.).

U.S. International Trade Commission, 1999, Methyl Tertiary-Butyl Ether (MTBE), 'Conditions Affecting the Domestic Industry', Publication 3231 (Washington, D.C.).

Zerbe, R. O., 1970, 'Theoretical Efficiency in Pollution Control', *Western Economic Journal*, 8, pp. 364–76.