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Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion*

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We develop a framework for comparing empirically the effects of alternative environmental policy instruments on the diffusion of new technology. "Market-based" and "command-and-control" approaches can be quantitatively compared by estimating the economic penalty that firms, through their actions, reveal to be associated with violation of standards. In the context of concerns about global climate change, we empirically examine the likely effects of Pigouvian taxes, technology adoption subsidies, and technology standards. We employ state-level data on the diffusion of thermal insulation in new home construction, comparing the effects of energy prices, insulation cost, and building codes.

I. INTRODUCTION

There is an ongoing debate—much of it between economists and others in the policy community—about the most effective and desirable mechanisms for achieving environmental protection objectives. Most economic arguments support increased use of market-based approaches, such as emission charges and tradeable permits, but policymakers seem to favor conventional command-and-control approaches, such as performance and technology standards. Though the theoretical attractiveness of market-based approaches is relatively clear, and policymakers have been giving more attention to them recently, there is little systematic empirical evidence documenting the effectiveness of market-based policy mechanisms in changing behavior in ways desired by regulators. This, in turn, is primarily because of the relatively limited use of market-based approaches in actual policies; very little data has been generated with which these policies can be evaluated.[1]

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[1] Studies that have sought to compare the costs of conventional environmental policy instruments with the costs of market-based instruments have tended simply to compare the costs of actual conventional instruments with the costs of theoretical, least-cost benchmarks. On this, see [12].

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There are two major dimensions along which market-based and conventional environmental policies are thought to differ. First, market-based policies can lead to "cost-effective" (cost-minimizing) allocations among firms of the burden of achieving given levels of environmental protection, in contrast with conventional standards, which typically do not lead to cost-effective allocations [2]. Second, market-based systems are believed to provide continuous dynamic incentives for adoption of environmentally superior technologies, since under such systems it is always in the interests of firms to clean up more if sufficiently inexpensive clean-up technologies can be found [3].

There are substantial literatures that examine in theoretical terms the cost effectiveness and the dynamic efficiency properties of market-based compared with conventional environmental policy instruments. But there have been few empirical analyses of the actual, relative cost effectiveness of alternative instruments, and virtually no empirical analyses of their relative dynamic efficiency attributes.[2] The major contribution of the present paper is that we develop a conceptual framework for carrying out such an empirical analysis (by specifying a model that includes the economic effects on firms of complying with market-based and conventional environmental regulations), and we demonstrate this framework's applicability with an examination of the technology-diffusion effects of three of the most frequently proposed instruments for addressing global climate change—energy taxes, energy-efficiency subsidies, and technology standards.

The remainder of the paper is organized as follows. In Section 2, we review the major theoretical arguments that have been advanced regarding the relative impacts on technological change of alternative environmental policy instruments, and we introduce a general model of technology-adoption decisions in the context of constraints and incentives provided by alternative policy instruments. In Section 3, we demonstrate how this conceptual approach can be used in the context of global climate change to compare policy instruments by examining available information from a natural experiment that has taken place with economic incentives (energy prices and adoption costs), conventional direct regulations (building codes), and environmental (energy-efficiency) technology adoption decisions in the home construction industry. We develop an econometrically estimatable model, describe available data, document the process and results of parameter estimation, and employ dynamic simulations to assess quantitatively the effects of alternative instruments. Finally, in Section 4, we draw some conclusions.

2. ENVIRONMENTAL PROTECTION, TECHNOLOGY CHANGE, AND ALTERNATIVE POLICY INSTRUMENTS

In the long run, the development and widespread adoption of new technologies can greatly ameliorate what, in the short run, sometimes appear to be overwhelming conflicts between economic well-being and environmental quality. Therefore, the effect of public policies on the development and spread of new technologies

[2] Hahn's extensive, empirical research on the U.S. Environmental Protection Agency's (EPA) experiences with its Emissions Trading Program stands out, but it has focused exclusively on aggregate costs of control, i.e., cost effectiveness. See, for example, [11]. Neither Hahn nor others have empirically examined the dynamic incentives for technological change that are claimed for market-based approaches.

may, in the long run, be among the most important determinants of success or failure in environmental protection [17].

2.1. *The Impact of Environmental Regulation on Technological Change*

In order to achieve widespread benefits from a new technology, three steps are required: *invention*—the development of a new technical idea; *innovation*—the incorporation of a new idea into a commercial product or process and the first marketplace implementation thereof; and *diffusion*—the typically gradual process by which improved products or processes become widely used [31]. It is now well understood that rates of invention, innovation, and technology diffusion are endogenously determined within the economic system, affected by the opportunities that the economy creates for firms and individuals to profit from investing in research, in commercial development, and in marketing and product development [33].

Governments often seek to influence each of these directly, by investment in public research, subsidies to research and technological development, dissemination of information, and other means [25], but it is inevitable that direct policy inducements will have only modest effects on the overall incentives to engage in the activities that produce technological progress. Hence it is crucial that policies with large economic impacts—such as many of those designed to protect or enhance environmental quality—be designed to foster rather than inhibit technological invention, innovation, and diffusion [16].

For our purposes, policies to reduce pollution can be crudely characterized as falling into one of three categories: *market-based approaches*, such as pollutant emission taxes, subsidies, or tradeable emission permits, *performance standards*, such as requirements that firms not emit more than specified amounts of pollutants per unit of economic activity; and *technology standards*, such as requirements that particular industrial equipment or processes be employed.

All of these forms of intervention have the potential for inducing or forcing some amount of technological change, because by their very nature they induce or require firms to do things they would not otherwise do. Performance and technology standards can be explicitly designed to be "technology forcing," mandating performance levels that are not currently viewed as technologically feasible or mandating technologies that are not fully developed. The problem with this approach, however, is that while regulators can typically assume that some amount of improvement over existing technology will always be feasible, it is impossible to know how much. Standards must either be made unambitious, or else run the risk of being ultimately unachievable, leading to great political and economic disruption [10].

Theoretical economic analyses have generally supported the notion that market-based approaches provide the most effective *long-term* incentives for invention, innovation, and diffusion [2, 7, 22, 24, 28, 32, 35, 36].[3] This is because they provide continuous incentives for emissions reductions, since any reductions in emissions

[3] Where these analyses have distinguished among the various market-based instruments—taxes, subsidies, and permits—the results are less conclusive and less consistent. Moreover, other theoretical research has come to less definitive conclusions across the board, finding that which policy instruments are most effective in encouraging innovation and diffusion depends upon specific elements of instrument design and/or characteristics of affected firms [19, 20, 21, 23].

generate revenues or reduce costs—in the form of permits that can be sold, subsidies that can be obtained, or taxes that can be avoided. In contrast, once a performance standard has been satisfied, there may be little benefit to developing and/or adopting even cleaner technology. In addition, regulated firms may fear that if they do develop a cleaner technology, the performance standard will be tightened. Finally, technology-based standards appear to perform worst in stimulating innovation, since by their very nature they constrain the technological choices available, and may thereby remove all incentives to develop new technologies that are environmentally beneficial [20].

Thus, the theoretical arguments are relatively clear; only empirical analysis has been missing. In preparation for such an empirical investigation, we now turn to a general model of technology adoption decisions in the context of alternative forms of environmental regulation.

2.2. *A General Model of Environmental Regulation and Technology Adoption*

We begin with a generic pollution abatement technology choice problem, where a firm needs to choose both whether or not to adopt some environmental protection technology and the time of any such adoption. While the most general model would allow the policy instruments to affect the fundamental nature of the technological choices that firms make, we model the more tractable problem of the decision of whether and when to adopt some particular technology that the firm knows to be available. We assume the firm seeks to minimize the present discounted value of the sum of the following streams of costs: the costs prior to adoption of "normal" variable costs plus any payments of Pigouvian pollution taxes (where the vector of input quantities and the level of pollutant emissions are both functions of input prices and technology); the costs subsequent to technology adoption of variable costs plus Pigouvian tax payments; the costs of adoption (including any government subsidy); the implicit costs of violating any performance standard and/or technology standard prior to adoption; and the implicit costs of violating any binding performance standard subsequent to adoption.[4] Thus, the firm chooses the time of technology adoption, T,

$$\begin{aligned}\min_{\{T\}} PV(T) = &\int_0^T [\mathbf{P}\cdot\mathbf{X}(\mathbf{P}, I_0) + Z\cdot E(\mathbf{P}, I_0)]\cdot e^{-rt}\,dt \\ &+ \int_T^\infty [\mathbf{P}\cdot\mathbf{X}(\mathbf{P}, I_1) + Z\cdot E(\mathbf{P}, I_1)]\cdot e^{-rt}\,dt \\ &+ C_T\cdot e^{-rT} + \int_0^T \left[\gamma_1\cdot D_t^u\cdot F[E(\mathbf{P}, I_0)] + \gamma_2\cdot D_t^s\right] \\ &\times e^{-rt}\,dt + \int_T^\infty \left[\gamma_1\cdot D_t^u\cdot F[E(\mathbf{P}, I_1)]\right]\cdot e^{-rt}\,dt,\end{aligned} \tag{1}$$

[4] To keep things simple, we assume that if the technology is adopted, the technology standard is satisfied. Also, we ignore uncertainty, although it would be possible to focus on that aspect of the technology adoption process. For a broad treatment of that perspective, see [29].

where

- T time (t) of adoption of pollution-control technology ($T \geq 0$)
- $\mathbf{P}$ vector of input prices[5]
- I indicator variable for technology adoption, where no technology is represented by the value $I_0 = 0$ and the presence of technology is represented by $I_1 = 1$
- $\mathbf{X}(\cdot)$ vector of input quantities as a function of prices and technology
- Z environmental (Pigouvian emission) tax
- $E(\cdot)$ optimal pollutant emissions, a function of input prices and technology
- e base of natural logarithms
- γ_1 implicit cost of violating a performance standard
- γ_2 implicit cost of violating a technology standard
- D_t^u dummy variable for existence of a (uniform) performance standard in year t
- D_t^s dummy variable for existence of a technology standard in year t
- $F[\cdot]$ probability of a sanction for violating a performance standard, a function of level of pollutant emissions
- C_T cost of technology adoption, including any government subsidies.

We thus provide a means in Eq. (1) for comparing in a single economic context the impacts of two types of price instruments—taxes and subsidies—and quantity instruments. We do this by positing that there is an implicit cost, γ_2, of violating an existing technology standard (where this is specified as a parameter to be estimated econometrically) and an implicit cost, γ_1, of violating a performance standard. In the case of this second implicit cost, we posit that the probability of a sanction being imposed is a function of the level of (excess) pollutant emissions (whether or not a technology standard is also in place and being obeyed or not).[6] So, a necessary condition for "optimal" adoption at time T is

$$\begin{aligned}&\left[\mathbf{P}\cdot[\mathbf{X}(\mathbf{P},I_1)-\mathbf{X}(\mathbf{P},I_0)]+Z\cdot[E(\mathbf{P},I_1)-E(\mathbf{P},I_0)]\right]\cdot e^{-rT}\\&\quad+\left[\gamma_1\cdot D_T^u\cdot[F[E(\mathbf{P},I_1)]-F[E(\mathbf{P},I_0)]]+\gamma_2\cdot D_T^s-r\cdot C_T+\frac{\partial C_T}{\partial T}\right]\\&\quad\times e^{-rT}\geq 0,\end{aligned}\tag{2}$$

which yields

$$\begin{aligned}&\mathbf{P}\cdot[\mathbf{X}(\mathbf{P},I_1)-\mathbf{X}(\mathbf{P},I_0)]+Z\cdot[E(\mathbf{P},I_1)-E(\mathbf{P},I_0)]\\&\quad+\gamma_1\cdot D_T^u\cdot[F[E(\mathbf{P},I_1)]-F[E(\mathbf{P},I_0)]]+\gamma_2\cdot D_T^s\geq\left[r\cdot C_T-\frac{\partial C_T}{\partial T}\right].\end{aligned}\tag{3}$$

Equation (3) tells us that a firm will adopt the pollution-control technology at time T if operating cost savings[7] plus savings from avoided emission taxes plus any avoided penalties for not adopting the technology or exceeding a performance

[5] Variables in bold face (**P** and **X**) are vectors. The time subscript is suppressed from **P**, **X** I, Z, and E, for convenience of presentation. This does not affect the results, as seen below.

[6] It would be possible, of course, to model the penalty structure for a performance standard to be a multiple of the magnitude of emissions, but in the limit such a performance standard is indistinguishable from an emission tax.

[7] These "operating cost savings" can be positive, negative, or zero.

standard are greater than adoption costs (including any subsidy) minus the time rate of change of (subsidized) adoption costs. The left-hand side of the equation essentially says that higher avoided costs (due to technology adoption) can encourage adoption. The first term on the right-hand side of the equation indicates that higher adoption costs and higher interest rates discourage adoption (and that government subsidies can encourage adoption). Finally, the presence of the last term—the time derivative of adoption cost—indicates that adoption is discouraged by expectations of decreased (effective) costs of adoption in the future. Thus, even if the sum of current savings in operating costs, avoided emission taxes, and avoided regulatory penalties is greater than (the annual annuity of) adoption costs, it can pay to wait if those adoption costs are expected to fall over time at a sufficiently rapid rate.

Notice that Eq. (3) is a statement about the *current* rate of savings; it does not involve present values of future streams (in contrast with the condition we establish later in the new-source case). This may seem counterintuitive, but note that it is the standard condition for the purchase of a capital asset; the instantaneous rate of earnings from the asset should be greater than or equal to the carrying cost minus the instantaneous rate of capital appreciation. "Earnings" from the asset in this case are the cost savings, and the cost of the asset is the adoption cost adjusted for the effects of regulation and subsidies. The capital appreciation rate is the time rate of change of the cost of adoption. To the extent that the overall cost of adoption is expected to fall, it is as if the asset were suffering a capital loss; instantaneous earning will have to be greater to justify the investment. To put it concretely, to the extent that one expects that a relevant pollution-control technology is becoming cheaper, one might wait until the next year to purchase and install it, even if it is currently economical.[8]

If it still seems counterintuitive that the adoption condition depends only on current values (and not on present values of future expectations), note that if the second-order condition is satisfied, the function $PV(T)$ will have (at most) a single optimum, which will be just at the point when the instantaneous investment condition (Eq. (3)) holds. It does not matter how large the savings will be in the future; overall costs are minimized by adopting at the instant when marginal costs equal marginal benefits, as represented by Eq. (3).[9]

Many environmental laws and regulations give particular attention to new sources of emissions. To address this situation, we posit a second generic problem wherein a firm is expanding an existing facility or constructing a new one and must decide whether or not to incorporate a given abatement technology. Again, a very general formulation of this problem would allow the existence of policy instruments to alter the very structure of the problem. In particular, if regulations are stricter for new plants than for existing ones, firms may never build the new plant, and hence never face the question of whether to incorporate new technology in the

[8] This is parallel to results derived in models with explicit uncertainty [6].

[9] The intuition that expectations of future prices should matter would be correct, however, if the second-order condition is violated. In this case, the first-order condition of Eq. (3) is a necessary but not a sufficient condition for optimal adoption. The condition could hold at a local maximum of discounted costs that is not a global maximum, as it could at a local minimum that is not globally optimal. Hence, present discounted values would matter and thus future costs (prices) would matter.

new plant. We abstract from this, and allow the firm to choose the value of the indicator variable, I, to maximize present value net benefits,

$$\max_{\{I\}} \pi_T = I_1 \cdot \int_T^{\infty} [\mathbf{P} \cdot [\mathbf{X}(\mathbf{P}, I_1) - \mathbf{X}(\mathbf{P}, I_0)] + Z \cdot [E(\mathbf{P}, I_1) - E(\mathbf{P}, I_0)]] \cdot e^{-rt}\, dt$$
$$- I_1 \cdot \left[C_T - \int_T^{\infty} [\gamma_1 \cdot D_t^u \cdot [F[E(\mathbf{P}, I_1)] - F[E(\mathbf{P}, I_0)]] \right. \tag{4}$$
$$\left. + \gamma_2 \cdot D_T^s] \cdot e^{-rt}\, dt \right],$$

where the appropriate concept of the "cost of technology," C_T, is the overall difference in capital costs with and without the new technology. For this problem, where we specify that the technology standard is of the "new-source-only type," a necessary condition is

$$\int_T^{\infty} [\mathbf{P} \cdot [\mathbf{X}(\mathbf{P}, I_1) - \mathbf{X}(\mathbf{P}, I_0)] + Z \cdot [E(\mathbf{P}, I_1) - E(\mathbf{P}, I_0)]] \cdot e^{-rt}\, dt$$
$$+ \int_T^{\infty} [\gamma_1 \cdot D_t^u \cdot [F[E(\mathbf{P}, I_1)] - F[E(\mathbf{P}, I_0)]] + \gamma_2 \cdot D_T^s] \cdot e^{-rt}\, dt \geq C_T. \tag{5}$$

Equation (5) indicates that a firm will adopt the pollution-control technology if expected savings on operating costs and avoided emission taxes and avoided penalties for not adopting the technology or failing to comply with performance standards exceed (subsidized) adoption costs. This condition is parallel but not identical to Eq. (3), since here expectations of future streams of variables do matter. This is consistent with intuition, since in this new-source case the firm has to decide whether or not to adopt the technology now; there is no option of waiting a year to revisit the decision. Hence, expectations of future prices and other conditions matter. Also in contrast with the result from the "retrofit problem," the time rate of change of adoption costs is not relevant.

This pair of simple models provides a useful framework for thinking about the relationship between environmental compliance and technology adoption. By adding a bit more structure, the framework can be used to examine empirically the relative impacts on technology diffusion of alternative policy instruments.

3. AN APPLICATION TO CO_2 EMISSIONS REDUCTIONS THROUGH ENERGY EFFICIENCY INVESTMENTS

The most obvious application of the model that we have described would be to pollution emissions from some industrial process that has been subject (at different times or in different jurisdictions) to both command-and-control and incentive-based regulation. Unfortunately, real-world applications of incentive-based regulation are too limited to facilitate such an experiment. For this reason, we turn to a slightly different, but analogous setting, the decisions of builders regarding energy-conserving technology, made in the presence of varying economic incentives (in the form of energy prices) and command-and-control regulations (in the form of building codes). This application is intended as an illustration of the possible uses of the approach in a broad class of situations and also to provide some quantitative estimates of the response to different instruments for an environmental problem that is of significant policy importance in its own right.

Concern about the "greenhouse effect" and related global climate change has focused renewed attention on energy conservation because of the importance of fossil fuel combustion as a source of carbon dioxide (CO_2) emissions. The relative effectiveness of alternative policy instruments intended to reduce energy use and hence CO_2 emissions will depend on the nature of the energy-conserving technology diffusion process. Thus, the climate-change/energy-conservation arena presents a particularly timely example of the broader debate about the relative merits of alternative policy instruments.[10]

World events affecting energy markets have generated a "natural experiment" that provides information that is potentially useful for comparing these policy instruments in terms of their impacts on technological diffusion. The dramatic rise in oil prices and the coincident shortages in the 1970's led to a variety of regulatory efforts designed to reduce consumption of energy. At the same time, the rise in the cost of energy itself generated strong economic incentives for conservation. The subsequent significant drop in the price of oil reduced those incentives considerably. This natural experiment enables us to analyze empirically the use of energy-saving practices across geographic areas and over time.

We focus on the use of thermal insulation in the construction of new single-family homes. The economic attractiveness of this technology varies because of climate, availability of particular fuels, and changes in world energy prices. The use of the technology may also be affected by building codes enacted by various jurisdictions. Our maintained hypothesis is that people's responses to these "natural" differences in economic costs and benefits can be used to infer their likely response to economic incentives that the government might create with the express purpose of influencing behavior. Additionally, by comparing the historical response to building codes and economic variables, we seek to assess the likely relative effectiveness of the broader set of potential policy instruments.[11]

Much of the discussion surrounding the rate of diffusion of energy efficiency technologies has revolved around the question of whether the relatively slow adoption of these technologies involves market failures, or, equivalently, whether the observed rate of adoption is slower than would be socially optimal [8, 15, 34]. Our purpose here, however, is simply to measure the extent to which various factors have affected historical diffusion, and to infer from that what the likely effect of policy interventions might be. In other words, we do not attempt to determine whether carbon taxes, insulation subsidies, or energy-efficient building

[10] Widely discussed possibilities of market-based instruments include carbon and energy (BTU) taxes and energy efficiency technology subsidies; frequently discussed command-and-control approaches include uniform national building codes and mandatory energy efficiency standards for heating and cooling equipment and other major appliances. See [9].

[11] Although our motivation is the generic issue of the relative effectiveness of alternative policy instruments, the specific application to energy-conserving building practices does have significant policy relevance in and of itself. The current Administration continues to give serious attention to policy proposals addressed to reducing the emission of greenhouse gases, particularly in the energy sector [5]. In the future, it is likely that there will be major debates about the relative merits of, for example, carbon/energy taxes, technology subsidies, and some form of uniform national energy conservation building code.

codes of any particular magnitude are a good idea; instead, we provide estimates of the likely impacts of these alternative policies on energy-efficiency investments. With the United States embarking on a range of actions intended to reduce CO_2 emissions, it is important to understand the effectiveness of these instruments.

3.1. A Model of Energy Efficiency Investments

We build upon our second generic model, above, of new-source regulation (Eqs. (4) and (5)) by examining a residential builder's decision to choose among alternative levels of thermal efficiency for ceilings, walls, or floors of a newly constructed home.[12] We assume that the choice of efficiency level[13] in, for example, ceilings, is separable from the other efficiency decisions, as well as from broader decisions about house design.[14] We assume the builder is risk-neutral, and holds some set of expectations regarding house buyers' willingness to pay for energy efficiency.

Under these conditions, we anticipate that the expected willingness to pay for an energy efficiency attribute will be determined by the present value of the expected future monetary savings likely to be brought about by the attribute in question. This expected willingness to pay (W_{ijt})—the benefit of adopting the technology—for house i in jurisdiction j in year t is thus

$$W_{ijt} = \delta\mu\left[1 - \exp(-\sigma R_{ijt})\right]\left[\int_t^{\infty} P_{j\tau} e^{-r\tau} d\tau\right]^{\beta_1} (G_{ijt})^{\beta_2} \exp(\epsilon_{ijt}), \qquad (6)$$

where R_{ijt} is the chosen efficiency level, $P_{j\tau}$ is the price of energy expected to prevail in year τ, G_{ijt} is an observable index of expected energy use in the house, and ϵ_{ijt} is an unobservable shifter of energy use. The parameter δ captures the possibility that the housing market does not correctly reflect the present discounted value of energy savings. If difficulties in credibly conveying the magnitude of these savings causes buyers to undervalue efficiency, then $\delta < 1$; if conservation is fashionable and buyers overpay for efficiency, then $\delta > 1$. We treat the discount rate r that consumers apply to future energy savings as some constant (known to them); in our empirical analysis, it is a parameter to be estimated. The model does not assume that it is equal to any particular value.

The parameter μ (≤ 1) is the fraction of total energy use in the house saved if this component (for example, ceiling insulation) achieves 100% energy efficiency. The parameter σ (> 0) captures how rapidly maximum energy savings are approached as R increases.[15] This is illustrated in Fig. 1 where, for example, with

[12] Another class of residential energy conservation decisions are associated with retrofitting technologies in existing homes. These decisions are inherently dynamic, since it is necessary to decide not only whether but also when to adopt a given technology. For a theoretical analysis of this problem, see [15].

[13] We treat efficiency as a continuous rather than discrete choice. This is appropriate for insulation, but not for the choice of some other energy efficiency technologies, such as single-, double-, or triple-pane glass in home windows. For an examination of the discrete choice problem in the windows context, see [14].

[14] It might be more desirable to model the choice of the overall efficiency of the thermal envelope of the house. Our data would not support such an approach, since we know the distribution of R-values in each house component but not how they are combined in particular structures.

[15] This particular functional form for the relationship between R and energy savings is chosen to approximate the reality that as one adds more and more insulation in the ceiling of a house, for example, there is a limit to the amount of energy savings that can result.

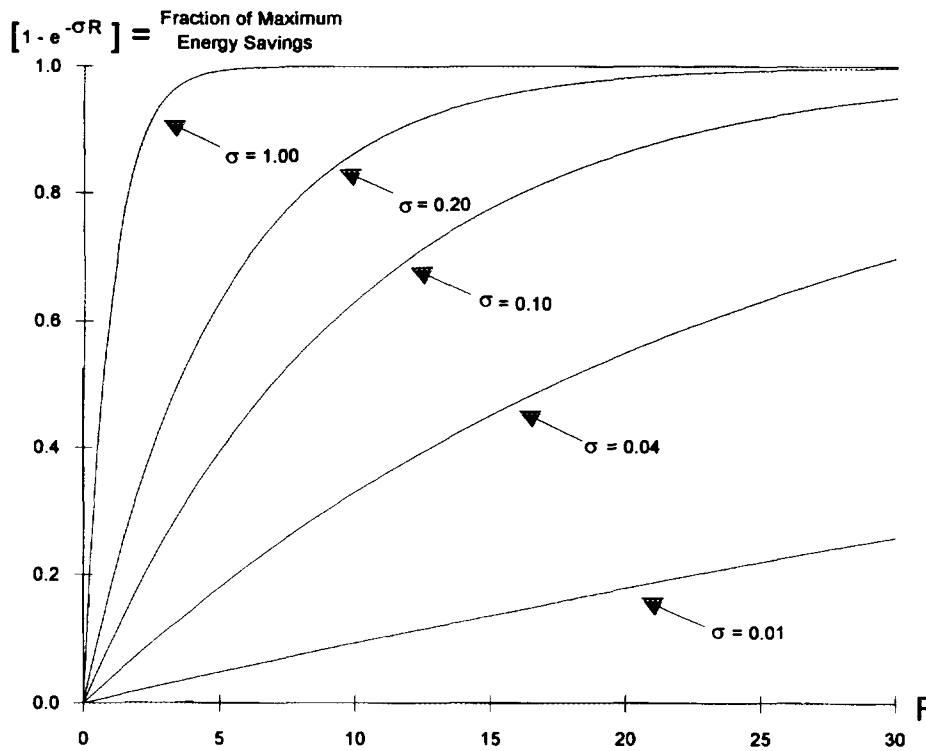

FIG. 1. Effect of insulation on energy savings.

$\sigma = 1$ potential savings are essentially exhausted at $R = 5$, while for $\sigma = 0.01$ there are still returns to additional insulation at $R = 30$. The β parameters, which might be expected to be unity because savings are proportional to energy price and quantity, are included to allow the data to provide evidence of their actual magnitude.

We take the cost of choosing efficiency level R to depend on existing practice in the area, the presence of effective building codes; and engineering estimates of installation cost,

$$C_{ijt} = \theta \cdot (c_{jt})^{\alpha_1} (R_{jt})^{-\alpha_2} \exp(-\gamma D_{jt}) R_{ijt}, \tag{7}$$

where the lower case c_{jt}, represents the "engineering cost" or cost estimate (per efficiency unit) of installing the technology, R_{jt} represents the average level of efficiency currently being achieved in jurisdiction j at time t, and D_{jt} is a dummy variable for the presence of a building code that specifies a minimum allowable level of thermal insulation.

The parameter γ, to be estimated, thus represents the implicit effective cost reduction that is created by the presence of the code. It can be thought of as deriving from the avoidance of hassle or delays, or a reduction in expected fines or other penalties [30]. Alternatively, it can be thought of as deriving from flexibility created for the builder in her dealings with the building inspector, created by the use of a high efficiency level when such a level is mandated by the code. The parameter α_2 measures the reduction in the effective cost of achieving a given efficiency level brought about by the increased use of the efficiency technology by other builders in the area. This is intended to allow for positive externalities associated with generalized learning about the technology. The parameter α_1, like the parameter on the price of energy in Eq. (6), is expected to be unity, but we do not impose this constraint.

Note that Eq. (7) embodies constant marginal cost per unit of R. This is appropriate for insulation technologies, within reasonable ranges, where additional efficiency is achieved by adding additional inches of material.[16] The constant θ is a normalization parameter included merely to adjust for the units of c_{jt} and R_{jt} in Eq. (7).[17]

The optimal efficiency level will be achieved by equating marginal benefits and marginal costs. This first-order condition is simply

$$\begin{aligned} \delta\mu\sigma \exp(-\sigma R_{ijt})\left[\int_t^{\infty} P_{j\tau} e^{-r\tau}\, d\tau\right]^{\beta_1} (G_{ijt})^{\beta_2} \exp(\epsilon_{ijt}) \\ = \theta (c_{jt})^{\alpha_1} (R_{jt})^{-\alpha_2} \exp(-\gamma D_{jt}) \end{aligned} \tag{8}$$

or, taking logs and rearranging,

$$\begin{aligned} R_{ijt} = \lambda + \frac{\beta_1}{\sigma}\log\left[\int_t^{\infty} P_{j\tau} e^{-r\tau}\, d\tau\right] + \frac{\beta_2}{\sigma}\log(G_{ijt}) - \frac{\alpha_1}{\sigma}\log(c_{jt}) \\ + \frac{\alpha_2}{\sigma}\log(R_{jt}) + \gamma D_{jt} + \epsilon_{ijt}, \end{aligned} \tag{9}$$

where the intercept

$$\lambda = \frac{\log\delta + \log\mu + \log\sigma - \log\theta}{\sigma}. \tag{10}$$

Below we estimate versions of Eq. (9) for ceilings, walls, and floors using a panel of state-level data. As indicated, the parameters δ and μ are absorbed in the intercept and hence not identified. Thus the model allows for a discount (or premium) in the new home market on the "true" value of energy savings, but does not provide an estimate of the magnitude of that discount. The parameter σ is also not identified without additional constraints on the other parameters. Indeed, the presence of this parameter modifies the theoretical expectation that the coefficients on the price of energy and cost of the technology should be unity. Given the

[16] It is less appropriate at the margin where, for example, to increase wall insulation the house framing has to be changed from 2 × 4 to 2 × 6 framing.

[17] One interpretation is that the value of θ is such that the engineering cost estimate is the actual cost for a builder with the median or mean level of practice and building code.

chosen functional forms, these coefficients will be smaller (in absolute magnitude) the faster that diminishing returns to additional efficiency set in (the larger is σ). Theory does suggest, however, that these coefficients should be equal in magnitude but of opposite sign.

3.2. *The Data*

The data used come primarily from the National Association of Home Builders' (NAHB) annual survey of its members. The data reported are state-wide totals or averages for the lower 48 states for the period 1979–1988 [26]. In the survey, builders are asked the total square footage insulated to various R-levels. From these data, we calculate the average R-level.[18] We construct a proxy for the expected future price of energy by averaging the prices in the state in the previous year for natural gas, oil, coal, and electricity, weighting by the share of new homes built to use each fuel (according to the NAHB survey).[19]

The engineering cost estimate is an estimate of the 1988 cost by region (based on wage differentials) constructed by Lawrence Berkeley Laboratory [18], multiplied by an annual insulation price index provided to us by Owens–Corning.[20] As proxies for the index of energy use, G_{ijt}, we use heating degree days, cooling degree days, income, education, and the fraction of the state that is in urban areas, as defined by the Bureau of the Census.[21]

The greatest empirical challenge is created by the model variable R_{jt}, the prevailing efficiency practice in the jurisdiction. In the absence of disaggregated data that would allow us to distinguish the firm i from the jurisdiction j, we cannot precisely capture this effect. As a substitute, we use the *lagged value* of the dependent variable, and interpret its effect in terms of the learning effects used to motivate the model. Of course, with this solution we cannot distinguish our "learning" interpretation of the lagged dependent variable effect from other explanations as to why the lagged R_{jt} should matter.

State-wide energy building codes can be characterized using published indexes produced by the National Conference of States on Building Codes and Standards [27]. These references indicate the maximum u-value,[22] if any, and indicate the

[18] Note that the equation to be estimated, Eq. (9), is linear in the R-value and depends on the log of the continuous right-hand side variables. Because of the linearity, no error is introduced by aggregating and expressing the equation in terms of the state-wide average R-values. The energy price variable is constructed as the average of the logs of the prices, rather than the log of the average. The other right-hand side variables are available only as a state-wide average, and hence we simply used the log of the average. Experimentation with other functional forms suggests that the qualitative nature of the results is not sensitive to the choice of functional form.

[19] The average of the previous year's prices provided a marginally better fit than the average of contemporaneous prices. Inclusion of distributed lags does not materially affect the estimated overall price effect.

[20] Personal communication from Mr. Edward Zinn, Marketing Program Manager, Owens–Corning, Inc., Toledo, Ohio.

[21] The three demographic variables can equivalently be interpreted as shifting the cost of the technology or even the market discount/premium parameter δ. We treat them as "control" variables and do not emphasize their interpretation.

[22] The "R-value" for "resistance" is proportional to the reciprocal of the u-value, which measures heat loss.

enforcement status of state codes. In many states, the state code is merely a guide for local jurisdictions, which may adopt or modify it as they see fit. In others, the state code is, in principle, mandatory statewide. There are also a few states that have no state-wide building code or no state-wide energy provisions in their code. For those states that do have codes, the actual u-levels specified are, in most cases, based on ASHRAE standards that specify appropriate R-levels based on climatic factors. The approach we adopt here is to include a dummy variable indicating the presence or absence of a mandatory state-wide provision for each technology and a second dummy variable indicating the presence or absence of a voluntary state-wide provision.[23] These code variables are each cross sections without time variation.[24]

Descriptive statistics are provided in Table I. The insulation adoption variables have all been trending upward, although there is significant variation across states. The fuel-share-weighted price of energy peaked in 1983–1984 and has fallen since. The real price of insulation was approximately constant in the first part of the period, but has fallen significantly since 1984.

3.3. Econometric Estimation

Given the available data, the versions of Eqs. (9) and (10) that we estimate are

$$\begin{aligned} R_{jt} = {} & \lambda - \alpha_1 \log(c_{jt}) + \alpha_2 \log(R_{j,t-1}) + \frac{\beta_1}{\sigma}\log(P_{j,t-1}) + \gamma_1 M_j + \gamma_2 V_j \\ & + \frac{\beta_2}{\sigma}\log(HDD_j) + \frac{\beta_3}{\sigma}\left[\log(HDD_j)\right]^2 \\ & + \frac{\beta_4}{\sigma}\log(CDD_j) + \frac{\beta_5}{\sigma}\left[\log(CDD_j)\right]^2 \\ & + \frac{B_6}{\sigma}\log(E_{jt}) + \frac{\beta_7}{\sigma}\log(U_{jt}) + \frac{\beta_8}{\sigma}\log(I_{jt}) - \epsilon_{jt}, \end{aligned} \tag{11}$$

where the intercept

$$\lambda = \frac{\log\delta + \log\mu + \log\sigma - \log\theta - \beta_1 \log r}{\sigma}. \tag{12}$$

and where $P_{j,t-1}$ is the lagged average price of energy, M_j is a dummy variable indicating the presence of a relevant mandatory provision in the state building code, V_j is a dummy variable indicating the presence of a relevant voluntary provision in the state building code, HDD_j is heating degree days, CDD_j is cooling degree days, E_{jt} is mean education of heads of households, U_{jt} is the fraction of state population resident in urban areas, and I_{jt} is median household income.[25]

[23] We also experimented with versions using the actual R-level (actually the reciprocal of the u-level) specified. The results are no different.

[24] Although six states had minor changes in some aspect of their codes between 1984 and 1989, we do not know when these changes occurred. Given this, and the small number and minor nature of the changes, we treat the state code as characterized in the 1984 directory as measuring the state's code status throughout the period.

[25] We are unable to include a time dummy in the specification because we employ a single time series as a price index to construct the variable $P_{j,t-1}$.

TABLE I
Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Average ceiling R-value	26.96	4.23	16.10	38.00
Average wall R-value	13.24	1.67	10.11	19.00
Average floor R-value	15.41	2.30	7.00	19.00
Average energy price, 1988 \$/MMBTU	12.75	5.74	4.11	33.93
Cost/ft^2 R-30 ceiling ins. (1988\$)	0.52	0.18	0.26	0.89
Cost/ft^2 R-11 wall ins. (1988\$)	0.36	0.063	0.22	0.47
Cost/ft^2 R-11 floor ins. (1988\$)	0.28	0.09	0.16	0.51
Mandatory ceiling code	0.56	0.50	0.00	1.00
Voluntary ceiling code	0.35	0.48	0.00	1.00
Mandatory wall code	0.56	0.50	0.00	1.00
Voluntary wall code	0.35	0.48	0.00	1.00
Mandatory floor code	0.54	0.50	0.00	1.00
Voluntary floor code	0.35	0.48	0.00	1.00
Annual heating degree days	5470	2065	745	9533
Annual cooling degree days	1021	732	169	3331
Mean education of household heads (years)	12.73	0.37	11.68	13.54
Median household income (1988)	36491	4741	26612	54825
Fraction of population in urban areas	0.63	0.23	0.15	1.00

Note that the discount rate parameter, r, is in the intercept, λ, and hence unidentified; the energy price parameter, β_1 in Eq. (11), is unaffected by the discount rate.[26]

The presence of the lagged dependent variable in the panel data context raises difficult estimation issues.[27] If the error term ϵ_{jt} contains a component that is constant across t for a given j—as it will if there are unobserved, fixed characteristics of states—then pooled OLS estimates in the presence of the lagged dependent variable will be biased and inconsistent. One approach to this problem is a two-step procedure from Anderson and Hsiao [1] and described in [13].[28] In the first step, we difference the equation and regress the first difference of the efficiency level on the differences of all those independent variables that vary over time, including the lagged log efficiency level. Any unobserved state effect drops out of such an equation, although the lagged difference is still endogenous. However, the twice-lagged level is a valid instrument for the endogenous lagged difference. Hence instrumental variables estimation of this equation gives consistent estimates of the coefficients of those independent variables that vary over time.

In the second step, we take the estimated parameters, return to the original (undifferenced) model specification, and construct "residuals" for each state by multiplying the parameters from the first step by the state means for the corresponding variables, and then subtracting these "predicted values" from the state

[26] The intuition is that a high discount rate means that higher prices are necessary to make the investment attractive, but the effect of a proportionate change in the price of energy is the same whether the discount rate is high or low.

[27] Note that we actually have the log of the lagged dependent variable, but, obviously, these variables are correlated.

[28] The derivation of the two-step method is summarized in the Appendix.

means for the dependent variable. These residuals are then regressed on those variables that do not vary over time. This estimation approach is consistent.[29] Conceptually, this approach conditions on the starting value of the dependent variable. In other words, the estimates should be interpreted as indicating the partial effect of changes in the independent variables (including the dynamic effect of changes in the efficiency level), given a particular starting level of efficiency.[30]

The estimation results are presented in Table II. The coefficients measure the partial effect of each independent variable, controlling for the 1979 level of the dependent variable. The lagged efficiency parameter is generally significant at normal confidence levels, but the magnitude is small.[31] Energy prices have the expected positive effect; although only the floor coefficient is significant at the 95% level, the joint hypothesis that all the price coefficients are zero is strongly rejected.[32] The technology cost effects have the expected negative sign, are larger than the price parameters, and are of comparable significance[33]; indeed they are approximately twice as great in absolute value as the energy price coefficients. The building code variables are consistently insignificant. Thus, there is no evidence in these data that building codes had any effect on average state efficiency levels.[34] For all three technologies, there are strong and significant positive effects of average state education level and significant negative effects of average state family income. Finally, the climate variables are not individually significant, but they are, of course, highly collinear with one another.

[29] It is not, however, efficient. An alternative is to use minimum distance methods to estimate the matrix of coefficients of the dependent variable on all past and future independent variables and use this to recover the structural parameters. See [4].

[30] Since any public policy initiative would have to take the initial value of the efficiency level as given, this seems to be an appropriate way to look at the problem for policy analysis purposes.

[31] A coefficient of 0.3 indicates, for example, that an exogenous doubling of the lagged dependent variable leads to an increase in the following year of only 0.2 R-units ($0.3 \times \ln(2)$).

[32] The F-statistic with 3 and 1080 degrees of freedom is 4.88, which corresponds to a p-value of 0.0023. Because of the dynamic feedback effects, the full effect of a change in an exogenous variable has to be examined dynamically, but, for example, the estimate of 11 for the coefficient on the energy price in the floors equation implies that a doubling of the price of energy would result in an immediate increase of about 7.6 R-units in floor insulation.

[33] The F-statistic for the hypothesis that all of the cost effects are zero is 4.56, corresponding to a p-value of .0035. The parameter estimate of about -25 for the floor equation implies that a doubling of the price of floor insulation would result in an immediate reduction of about 17 R-units. This is obviously impossible since the mean floor insulation level is about 15, but a doubling of the cost of insulation is well outside the range of the data.

[34] This conclusion remains if actual mandated R-levels are used instead of dummies, and if dummies are interacted with the mandated R-level. As a final possibility, we considered whether the code effects might be biased due to endogeneity of the codes themselves. One might believe that the codes are passed in precisely those states where building practices are particularly inefficient. If so, this would bias the estimate of the effect of codes downward, possibly explaining their apparent lack of effect. We explored this possibility by treating the codes as endogenous, using as instruments several political economy variables, including the fraction of the state that voted for McGovern, state government spending as a fraction of state income, the magnitude of the state gasoline tax, and the fraction of state revenues coming from income taxes. These variables ought to be correlated with states' "propensity to regulate" but should be uncorrelated with unobserved state effects that are correlated with building practices. Instrumenting for the codes in this way makes no difference. The likely explanation for the lack of effect of codes is that they appear to be frequently nonbinding. In two-thirds of the states (95% for walls), the median square foot at the beginning of the period was at or above the level required by the code. Thus it is perhaps not surprising that the codes do not have measurable effects on average practice.

TABLE II[a]

Econometric Results[b]

Variables[c]	Ceilings	Walls	Floors
Energy price*	6.74	5.14	11.00
	(4.16)	(2.94)	(5.01)
Technology cost*	−10.08	−10.77	−25.15
	(8.62)	(6.06)	(10.33)
Lagged efficiency*	0.302	0.391	0.428
	(0.141)	(0.118)	(0.114)
Mandatory code	0.925	−0.450	−1.433
	(1.97)	(1.101)	(2.18)
Voluntary code	−0.409	−0.560	−0.835
	(1.89)	(1.06)	(2.168)
Heating DD	23.895	−3.89	7.939
	(23.245)	(12.98)	(28.81)
HDD^2	−1.013	0.521	−0.129
	(1.434)	0.800	(1.79)
Cooling DD	−11.95	−9.90	7.24
	(16.90)	(9.45)	(20.57)
CDD^2	1.17	0.859	−0.316
	(1.35)	(0.755)	(1.64)
Education*	123.44	41.87	134.02
	(33.54)	(18.72)	(41.59)
Percentage urban*	−2.97	0.281	1.35
	(1.97)	(1.099)	(2.44)
Income*	−18.23	−9.208	−29.45
	(8.67)	(4.838)	(10.66)
R^2 differences	0.019	0.036	0.048
R^2 Cross section	0.616	0.531	0.412

[a] The dependent variables for ceilings, walls, and floors are the average R-value for each state in the given year. Standard errors are in parentheses.

[b] Estimation method is the two-step, instrumental variables procedure from Anderson and Hsiao [1] described in the text. Variables followed by an asterisk were estimated with the full panel of first differences in the first stage; other variables were estimated with cross-section data only in the second stage.

[c] Independent variables other than dummies are all in logs; squared terms refer to the square of the log. Energy price, technology cost, lagged efficiency, education, percentage urban and income parameters are all estimated using the first differences; the building code and climate parameters are estimated from the cross section. For a description of the estimation procedure, see the Appendix.

In order to examine further the quantitative significance of the effects of prices and costs, we performed dynamic simulations of the model using the estimated parameter values. We began with "base case" simulations, in which we took all of the exogenous variables, plus the initial values of the efficiency variables, to equal their actual values; we then predicted the dependent variables for each state in each year using the estimated coefficients from Table II. Finally, we compared these base case simulations with counterfactual simulations in which prices and costs were exogenously modified. In this way, we found that energy price increases or adoption cost decreases would have noticeable impacts on energy efficiency levels (Table III). For example, a 10% energy price increase, in place throughout

TABLE III

Simulation Results: Dynamic Effects of Energy Prices (Taxes) and Adoption Costs (Technology Subsidies)

	Ceilings			Walls			Floors		
Year	Base case[a]	energy tax[b]	Cost[c] subsidy	Base case	energy tax	Cost subsidy	Base case	energy tax	Cost subsidy
Initial value (1979)	24.7[d]	24.7	24.7	12.2	12.2	12.2	14.4	14.4	14.4
End of period (1988)	29.3	30.0	30.4	14.2	14.7	15.3	18.3	19.4	21.1
Percentage increase	18.6%	21.5%	23.1%	16.4%	20.5%	25.4%	27.1%	34.7%	46.5%

[a] The dynamic simulation method employed to estimate the base case, using the estimated parameters and actual data on independent variables, is described in the text.
[b] A 10% tax on energy in all years.
[c] A 10% subsidy on the cost of adoption in all years.
[d] All figures are national average R-values, unless otherwise noted.

the period, increases diffusion (adoption) by about 6% (in the sense that the end-of-period average floor insulation level is raised from 18 in the base case to about 19 in the energy price increase case, from a 1979 value of 14). A 10% decrease in adoption cost, which we would ordinarily expect to have an identical effect, would achieve substantially more, raising the end-of-period average R-value by almost 17% (to about 21).

In summary, energy prices and technology costs have significant effects on conservation technology decisions, but the effect of technology cost is nearly three times as large as the energy price effect.[35] At first blush, this may seem merely to be evidence that decision makers pay more attention to initial cost than to the value of energy savings over the life of the investment. But recall that within the structure of our model, high consumer discount rates (r), and/or failure of the housing market to reflect the full value of the investments ($\delta < 1$) affect the intercept term but not the coefficients on price or cost (Eqs. (11) and (12)). Thus, even after allowing for high discount rates, adoption externalities, and market-failure in housing prices, we find a striking asymmetry between the effects of up-front technology costs and longer term energy prices on technology diffusion.

There are several possible interpretations of this last finding. First, it is possible that the market failure in new home pricing is more complicated than the way we have modeled it, inducing some sort of nonproportional gap between the actual energy savings and the market valuation. Second, what matters to the model, is, of course, the expected price of energy. In experimenting with various expectations mechanisms, we could not find one that worked better than the simple static expectations assumptions reported here. This does not mean, however, that it is right. In particular, if the elasticity of expected prices with respect to the current

[35] Although none of the coefficients are estimated very precisely, the data do reject the hypothesis of equal and opposite signs for the price and cost coefficients. The F-statistic for the joint hypothesis that all three price and cost effects are equal and opposite in sign is 2.33, corresponding to a p-value of 0.07.

price is less than unity, this would help explain the observed gap between the effects of changes in prices and changes in technology costs.

4. CONCLUSIONS

We have developed a general approach for comparing empirically the impacts on technology diffusion of alternative forms of market-based and conventional environmental policy instruments, and we have applied this approach to an examination of three of the most frequently considered policy instruments for global climate change—energy taxes, energy efficiency subsidies, and technology standards. In this final section of the paper, we briefly comment on methodological and policy implications. We begin with an examination of the policy implications of our empirical analysis.

First of all, our econometric estimates of the impacts of price changes and cost changes on diffusion can provide first approximations of the likely consequences of energy taxes and technology subsidies. Our estimates suggest that *ad valorem* energy taxes in the 10 to 25% range would have noticeable impacts on the efficiency of new homes, and this impact would be felt rather quickly.[36] As noted, our results suggest that adoption subsidies of the same percentage magnitude would have significantly greater effects. There are, however, important caveats that should be applied to these estimates. One caveat is that the actual effect of an energy tax program will depend very much on its perceived permanence.[37] A second caveat is that the comparison we are making between the likely impacts of energy prices and adoption subsidies is solely in terms of technology diffusion (increased use of insulation), not in terms of residential energy demand.[38]

A second policy implication of our results derives from the small dynamic feedback effects observed in the econometric estimation. The estimated magnitude of these effects does not provide any evidence that there is a large knowledge externality to other builders associated with a particular builder's use of higher insulation levels. This suggests either that imperfect information is not a major issue for these technologies or that adoption by others is not a significant mechanism for information dissemination. Either way, there does not appear to be a significant argument for policy intervention deriving from this form of market failure. Of course, the results could well be different for other technologies.

[36] Of course, significant impact on overall energy use would be much slower because of the very gradual turnover of the housing stock.

[37] If people perceive an energy tax to be permanent, it is possible that the magnitude of responses would be larger than implied by our estimates, since those estimates are based on responses to actual price changes that are presumably perceived to be less than permanent. Likewise, if people systematically perceive new taxes to be less permanent than they perceive other price changes to be, then the magnitude of responses to energy taxes could well be less than implied by our estimates.

[38] Clearly, higher energy prices will have other effects on home energy demand in addition to the insulation-adoption impacts examined here. In particular, other energy efficiency technologies may be adopted (for example, thermally efficient windows, better heating plants, or changes in fuel types). Furthermore, on the subsidy side, if the adoption cost of greater insulation is reduced, it is possible that there would be compensating changes in other areas (less efficient heating plants, for example) that would tend to reduce the energy demand decrease otherwise achieved. As noted at the outset, we have excluded such effects from our analysis by assuming the independence of the technology adoption decision from other home design considerations. In summary, our analysis is of factors affecting technology diffusion, not factors affecting energy demand.

Turning to the impacts of direct regulation, our analysis does not suggest that building codes made any significant difference to observed building practices in the decade 1979–1988. It is possible that stricter codes (that were more often binding relative to typical practice) might have an effect, but this itself ought to remind proponents of conventional regulatory approaches that while energy taxes will inevitably be effective on the margin, typical command-and-control approaches can actually have little or no effect if they are set below existing standards of practice.

Finally, we can comment on the methodological significance of this research. Because there has been such a paucity of empirical examinations of the technology impacts of alternative environmental policy instruments, we have sought to develop a framework within which such analyses could be carried out. We have developed such a framework, which is sufficiently broad and flexible to accommodate a variety of environmental problems and a variety of policy instruments. For example, technologies that permit greater recycling of hazardous wastes pose up-front costs that firms will trade off against future materials and disposal cost savings. Policies to encourage the diffusion of such technologies could take the form of subsidies to adoption, taxation, or other measures that make purchases of raw materials or disposal more expensive, or conventional direct regulation. The models developed here provide a framework for comparing these different options.

On the other hand, we do not mean to suggest that other applications will be simple extensions of the application we have presented. The building sector is by no means typical of the broader economy. On the one hand, builders may perceive economic incentives less directly than manufacturing firms, because they may doubt whether investments in energy efficiency will be returned in consumers' valuations of buildings. On the other hand, because of the fragmented nature of the construction industry, enforcement of regulations may be much more difficult than it is for large manufacturing firms.

We have sought to demonstrate the value of the analytical framework by applying it to a specific, important example—the role of price and quantity instruments for the control of CO_2 emissions. We set out, in part, to contrast the impacts of market-based approaches with those of command-and-control regulations, and indeed our results do provide some evidence in that regard. Of equal interest, however, is the unanticipated finding that—contrary to assertions in the literature—the likely effects on technology diffusion of adoption subsidies appear to be substantially greater than the expected impacts of equivalent Pigouvian taxes. While this finding is at odds with economic thinking, it does appear to be consistent with the conventional wisdom among noneconomists.

APPENDIX

This appendix summarizes the derivation of the two-step estimator from Anderson and Hsiao [1]. Consider a general regression model of the form

$$Y_{jt} = \phi Y_{jt-1} + \beta X_{jt} + \gamma Z_j + \alpha_j + \epsilon_{jt}, \tag{A1}$$

where X_{jt}, represents an independent variable that varies over time, Z_j represents an independent variable that varies across states but not across time, α_j is an unobserved state effect, and ϵ_{jt} is independently distributed across both j and t.

The standard "fixed-effects" estimator would construct a transformed equation expressing all variables as deviations from their state means. The problem with that approach in this context is that the mean of the lagged dependent variable contains in it all of the ϵ_{jt} and hence the deviations from the mean are still endogenous.

As an alternative, take first differences of Eq. (A1),

$$Y_{jt} - Y_{jt-1} = \phi(Y_{jt-1} - Y_{jt-2}) + \beta(X_{jt} - X_{jt-1}) + \epsilon_{jt} - \epsilon_{jt-1}. \quad \text{(A2)}$$

In this formulation, the transformed variable $(Y_{jt-1} - Y_{jt-2})$ is still endogenous, since it contains ϵ_{jt-1}. However, ϵ_{jt-2} is, by assumption, uncorrelated with both ϵ_{jt} and ϵ_{jt-1}, so we can use Y_{jt-2} as an instrument for the lagged difference. Hence estimation of Eq. (A2) by instrumental variables yields consistent estimates of the parameters ϕ and β.

If the unobserved effect α_j is uncorrelated with Z_j, then we can also recover a consistent estimate of the parameter γ by constructing an estimated residual for each state using the estimated parameters and the state means,

$$\hat{e}_j \equiv \overline{Y}_{jt} - \hat{\phi}\overline{Y}_{jt-1} - \hat{\beta}\overline{X}_{jt}, \quad \text{(A3)}$$

leading to the regression equation

$$\hat{e}_j = \gamma Z_j + \alpha_j, \quad \text{(A4)}$$

which can be estimated by ordinary least squares.

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