Environmental Policy in the Presence of Induced Technological Change

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Abstract

We examine the hypothesis that induced technological change (ITC) can dramatically lower the cost of a carbon tax in a static optimal tax model. The research and development sector is represented by an aggregate stock of energy-saving technology, which acts as a weak substitute with a polluting resource in the energy generation sector. Using this model, we analytically show how ITC occurs and affects the cost of a carbon tax. Applying quantitative estimates of the size of ITC to numerical simulations calibrated to the U.S. economy, we find that existing empirical evidence can reduce the welfare cost of environmental tax reform by 12%. Our tests of alternative parameters show that this result is highly sensitive to the assumptions used, suggesting that ITC could result in much larger reductions in cost.

Keywords: Induced technological change, double dividend, carbon taxes, optimal environmental tax, returns to specialization.

JEL classification numbers: H21, Q41, Q54, Q55, Q58

1 Introduction

"I have long believed that the most elegant way to drive innovation and to reduce carbon emissions is to put a price on it. This is a classic market failure." *President Barack Obama, December 1, 2015.*

There is widespread belief in the idea that pricing carbon will drive technological innovation. One form of this innovation is induced technological change (ITC), factor productivity augmentation whose speed has been encouraged by a policy instrument. Some analysts have pointed out that ITC could be influential. For example, a chapter in the Stern Review (2006) is devoted to arguments that government policy should accelerate technological innovation; carbon taxes feature prominently as one such strategy.

The idea that carbon taxes can generate new energy efficiency innovation is often credited to Hicks (1932), who wrote: "Change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind." While carbon taxes will clearly influence the tradeoff between energy and other inputs, the ITC hypothesis claims that the productivity of each unit of energy will be improved as well.

Recent research has delivered substantial empirical evidence on the existence of ITC. Using a dataset gathered from the Sears catalogue, Newell et al. (1999) examined whether higher energy prices induced innovation in the air conditioner product category. They concluded that prices clearly affect the direction of innovation for many products, but have no effect on its rate. Popp (2002) examined the correlation between energy prices and energy patents as a share of total patents, and found that this correlation is strong and positive in direction. Crabb and Johnson (2010) performed a similar exercise within the automobile sector, and confirmed this relationship, even generating a very similar elasticity estimate to Popp (2002).

Earlier results quantifying the importance of ITC have been mixed. Some work have found large roles for ITC in policy calculations of climate change policy. Goulder and Mathai (2000), using a long-run, dynamic optimal policy model, found that the cost of ITC could lower the cost of a carbon tax by 30%, but their estimate is calibrated on early work and does not benefit from recent advances measuring the size of ITC. Jakeman et al. (2004) finds that ITC can reduce the required carbon tax by 25% and significantly decrease the drop in GDP. Gerlagh (2008), using a long-run endogenous growth model, finds that ITC can reduce the required carbon tax by half and reduces the cost of emissions stabilizing policy by half.

Other work have found relatively small consequences of ITC. Nordhaus (2002) included ITC in his large, general equilibrium model of climate change. He found that the reduction in carbon intensity from ITC is "modest": 6% in the first 50 years, and 12% after 100 years. Popp (2004) applied endogenous technological change to the Dynamic Integrated Climate-Economy (DICE) model of climate change, and found that including ITC increased welfare gains by 9.4%. In part because of the results of these studies, induced technological change seems to take a relatively smaller role in the debate about the cost of regulating emissions.

We provide new evidence on the impactfulness of ITC on the cost of a carbon tax through a static model of optimal environmental taxes which includes tax-induced technological change. In this model, the research and development (R&D) sector is represented by an aggregate stock of energy-saving technology, which acts as a weak substitute with a polluting resource in the energy generation sector. The size of the R&D sector is driven by demand for energy efficiency technologies from the energy sector, and adjusts upward when new environmental taxes incentivize firms to shift away from polluting inputs in the production of energy. Energy efficiency technologies augment polluting factor productivity in an increasing-returns-to-scale fashion with respect to the size of the R&D sector. The environmental tax then stimulates R&D activities and creates social benefits in the form of improved efficiency in the overall use of resources. We dub this last result the "ITC effect" and show that this effect helps welfare when technology can be used in the production of energy in an increasing returns-to-scale fashion. The ITC effect can offset the "tax interaction effect," a negative welfare impact that results when new environmental taxes exacerbate preexisting distortionary taxes (Bovenberg and de Nooij, 1994; Parry, 1995).

After analytically deriving these effects, we devise a numerical simulation that applies recent empirical estimates from the literature to estimate the cost impacts of revenue-neutral carbon tax reform where revenue from the environmental tax is used to cut the pre-existing tax. One useful aspect of our approach is that we can easily test the sensitivity of our estimates to broad sets of alternate parameters.

Our baseline result is quantitatively similar to the prior literature: the welfare cost of a policy reducing carbon emissions by 10% can be reduced by 12% when ITC is considered. However, we find this estimate is highly sensitive to the assumptions of the model. Specifically, the model results change substantially depending on our assumptions regarding which sectors of the economy benefit from ITC. Results are highly sensitive to the elasticity of energy efficiency knowledge with respect to energy prices, and to the elasticity of energy with respect to knowledge. If ITC is extended to the entire energy sector of the U.S., the welfare cost is reduced by 30%. If one of the above elasticities is perturbed within reasonable ranges, the welfare cost can be reduced by 40% or more.

Our paper is the first to examine ITC using a static general equilibrium tax framework that has been increasingly deployed to examine how carbon taxes can comprise a part of the optimal tax system. This work starts from the perspective of a tax system that consists of a uniform commodity tax. It examines how much welfare is changed under a fiscal reform that adds an environmental tax and reduces the pre-existing tax under the condition of revenue neutrality. Because a uniform commodity tax is optimal in the simplest framework, welfare is always lowered when an environmental tax is introduced. However, when real world distortions are present, the welfare cost of the carbon tax can be lowered.

Rents from fixed factors such as oil and natural gas are not taxed away in modern tax systems. Bento and Jacobsen (2007) examined the importance of this incomplete taxation and found that the cost of carbon taxes can be reduced by 33% or more. Tax evasion of energy taxes is more difficult than tax evasion of other taxes, and Liu (2013) showed that this margin reduced the cost of carbon taxes by 28% in the U.S., with much larger cuts in settings with higher ex-ante tax evasion. All modern economies have an untaxed sector, the "shadow economy." Bento et al. (2015) found that the shadow economy can reduce the cost of carbon tax policy in the U.S. by 62%. Carson et al. (2015) combined the three factors above, and found, for China and the U.S., carbon emissions could be cut by more than 10% with a *negative* gross cost. In their work, although carbon taxes can replace a pre-existing uniform commodity tax, they nevertheless improve welfare by undoing the distortions described above.

Our work contributes to this literature[1] by quantifying the impact of ITC, a factor that can further lower the cost of a carbon tax. Since it deploys the same framework, our model can easily be incorporated into this earlier work, and will contribute to the nascent hypothesis that carbon taxes should comprise a non-zero part of the optimal tax system. This work should be particularly salient in today's global economy, where many countries are considering how best to meet their pledges under the recently signed Paris Agreement without hurting their economies.

The second contribution of our paper is the finding that ITC can play an important role in the consideration of an optimal environmental tax. We find much larger impacts of ITC on the cost of the carbon tax under three conditions. First, evidence tying broader amounts of energy use to technological change would increase the importance of ITC. Second, more precise evidence

[1]Another notable contribution to this literature is Williams (2002), who examines how feedbacks in pollution on labor productivity might affect the cost of carbon tax reform. Because this work had no simulation model and did not include parameters quantifying its effects, we did not include it in our above discussion.

could be found of the elasticities relating energy efficiency to patents. Third, our results rely on only one mechanism: productivity improvements via increasing returns-to-scale technology. Other mechanisms might be elucidated that extend the impact of ITC.

Our model does not include crowdout, the possibility that additional innovation in energy might displace other forms of R&D, as noted by Sue Wing (2003) and more recently by Gans (2012). Crowdout effects, which depend on the assumption of imperfect substitutability between R&D and other forms of production, are difficult to model in a framework with neoclassical assumptions including perfect labor mobility. Popp and Newell (2012) find no empirical evidence of crowdout; increases in energy R&D had no impact on other forms of R&D. If crowdout effects exist, they have been shown, as in Popp (2004), to partially offset the impacts of ITC. As a result, our results might be interpreted as an upper bound to the effect of ITC.

Our work is also related in some ways to Acemoglu et al. (2012), who argue that carbon taxes should be used to direct technological change. While they focus on the first-best policy setting, ours is rather on the second-best setting with a preexisting distortionary tax system. The existence of directed technological change was documented in the automobile industry by Aghion et al. (2012), who find in a panel of countries that higher fuel prices induce firms to redirect technical change towards clean innovation and away from dirty innovation.

In Section 2, we present our model of induced technological change, and determine analytically the new effects of the resource efficiency benefit. In Section 3, we present our numerical model. Section 4 concludes.

2 Model

2.1 Firms

Consider a four sector economy. Two sectors produce final consumption goods X and Y. A third sector produces the dirty natural resource R, and the fourth produces the knowledge stock H. Labor is the only underlying factor of production.

The two firms producing consumption goods use labor inputs (L_X, L_Y) and the natural resource (R_X, R_Y), and use of the resource emits pollution as a byproduct. Firms in sector Y can improve their productivity with respect to energy production by adopting technology intermediates.[2]

[2] One might naturally question why some sectors do not benefit from ITC. The largely arbitrary assumption that one sector benefits from energy efficiency while others do not

Since labor is the only underlying factor of production, firms employ labor L_R to produce the dirty natural resource R. Finally, firms use labor L_h to create the technology intermediates h, which aggregate into the knowledge stock of energy efficiency H. In all there are four uses of labor: L_X, L_Y, L_R, and L_h.

All markets in this economy are competitive, so after-tax wages are normalized to 1. Firms pay unit taxes on labor and pollution emissions, τ_L and τ_P; all revenues are used to finance a lump-sum transfer to households.

2.1.1 Consumption Good X

Firms produce good X by using labor L_X and natural resource R_X under constant-returns-to-scale (CRS) technology:

$$X = x\left(L_X, R_X\right). \tag{1}$$

The first-order conditions for profit maximization are:

$$p_X \frac{\partial x}{\partial L_X} = 1 + \tau_L; \qquad p_X \frac{\partial x}{\partial R_X} = p_R, \tag{2}$$

where p_R is the price of the dirty natural resource. Because $x(\cdot)$ is CRS, the price of good X is:

$$p_X = (1+\tau_L)\frac{L_X}{X} + p_R \frac{R_X}{X}. \tag{3}$$

2.1.2 Consumption Good Y

Similarly, firms produce good Y by using labor L_Y and the natural resource R_Y. Unlike firms in sector X, firms in Y also benefit from energy efficiency technology H, which is a weak substitute for the dirty natural resource:

$$Y = y\left(L_Y, e\left(R_Y, H\right)\right). \tag{4}$$

The function $e(\cdot)$ is increasing in its inputs, but experiences diminishing marginal returns: e_H, $e_{R_Y} > 0$ and e_{HH}, $e_{R_Y R_Y} < 0$. We assume that the natural resource and energy-saving technology are gross substitutes, i.e., $e_{R_Y H} > 0$.

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is primarily for the benefit of our simulations. Energy efficiency innovation has only been demonstrated empirically for a small set of sectors. Modeling the possibility that other sectors do not benefit from ITC allows us to show how the welfare cost of the environmental policy will differ if benefits from ITC are limited to these sectors, or if they are more widespread.

Each technology intermediate h in the economy is indexed by the variable i. The set of continuously differentiated intermediates is h_i for $i \in [0, n]$ where n is the number of available intermediates. For intuition's sake, one can think of each firm's output h_i as a "blueprint," and n as the number of blueprints in the stock of knowledge related to energy savings. Together, the set of intermediates composes the technology stock H:

$$H = \left(\int_0^n h_i^\sigma di \right)^{1/\sigma}, \tag{5}$$

where σ is a parameter related to the elasticity of substitution between blueprints. We assume that blueprints are gross substitutes for each other, i.e., $0 < \sigma < 1$. Note that if all blueprints are the same size, that is: $h_i = h_j = h \; \forall i \neq j$ and $i, j \in [0, n]$, equation (5) is reduced to $H = n^{1/\sigma} h$. H thus exhibits constant returns to scale in the size of each blueprint and increasing returns to scale in the number of blueprints. This type of production has been referred to as "returns to specialization" in the prior literature (e.g. Ethier, 1982, Romer, 1987; Devereux et al., 1996). The degree of returns to specialization is measured by $1/\sigma$.

By solving the cost minimization problem of technology adoption ($\int_0^n p_{hi} h_i di$) subject to (5) with given H, we derive the demand for h_i:

$$h_i = \left(\frac{p_H}{p_{hi}} \right)^{\frac{1}{1-\sigma}} \cdot H,$$

where p_H is the unit cost for H defined as $p_H = \left(\int_0^n p_{hi}^{-\frac{\sigma}{1-\sigma}} di \right)^{-\frac{1-\sigma}{\sigma}}$. As derived in (11), prices of all blueprints are equivalent, i.e., $p_{hi} = p_{hj} = p_h$ $\forall i \neq j$. Hence, we can simplify the unit cost of H to: $p_H = p_h \cdot n^{-\frac{1-\sigma}{\sigma}}$ and derive the following identical demand for each blueprint:

$$h = n^{-1/\sigma} H. \tag{6}$$

Using (6), we can calculate the minimized cost for technology adoption: $\int_0^n p_{hi} h_i di = n^{-\frac{1-\sigma}{\sigma}} p_h H$. Moreover, we can calculate the profit for firm Y: $\pi_Y = p_Y Y - (1 + \tau_L) L_Y - p_R R_Y - n^{-\frac{1-\sigma}{\sigma}} p_h H$. The first-order conditions for profit maximization are:

$$p_Y \frac{\partial y}{\partial L_Y} = 1 + \tau_L; \quad p_Y \frac{\partial y}{\partial e} \frac{\partial e}{\partial R_Y} = p_R; \quad p_Y \frac{\partial y}{\partial e} \frac{\partial e}{\partial H} = n^{-\frac{1-\sigma}{\sigma}} p_h. \tag{7}$$

Since good Y is produced under CRS technology, its price satisfies:

$$p_Y = (1 + \tau_L) \frac{L_Y}{Y} + p_R \frac{R_Y}{Y} + n^{-\frac{1-\sigma}{\sigma}} p_h \frac{H}{Y}. \tag{8}$$

2.1.3 Natural Resource

Each unit of the natural resource R generates one unit of emissions P, so $P = R$. We produce the natural resource by employing labor in a constant returns-to-scale fashion, $R = L_R$. Also, all of the natural resource is employed in the production of either good X or good Y, implying:

$$R = R_X + R_Y. \tag{9}$$

When the labor tax τ_L and the pollution tax τ_P are levied, the price of the natural resource is:

$$p_R = 1 + \tau_L + \tau_P \tag{10}$$

2.1.4 R&D Sector

The R&D sector produces blueprints h that together comprise the stock of energy efficiency technology H. The production of each blueprint requires a fixed unit of labor input, F, and so the cost of research and development is $(1 + \tau_L)F$.

We assume for simplicity that each R&D firm produces exactly one unit of output, making the profit of the ith R&D firm $\pi_{hi} = p_{hi} - (1+\tau_L)(1+F)$, where p_{hi} is the price of blueprint i. Because profits are reduced to zero in an equilibrium with free entry, the price of each blueprint is identical:[3]

$$p_{hi} = (1 + \tau_L)(1 + F). \tag{11}$$

Consequently, demand for each blueprint is derived as (6) through symmetric pricing of blueprints. Since we have assumed that the size of each blueprint is 1, the equilibrium number of blueprints is:

$$n = H^{\sigma}. \tag{12}$$

The quantity of R&D is driven purely by firm demand for energy efficiency blueprints, H, which is in turn driven by the relative prices of these blueprints and the natural resource. The policy increases the price of the natural resource, making it less attractive and increasing demand for blueprints. A

[3] We note that this is a departure from many other models of innovation, where monopoly rents provide the incentive for R&D firms to innovate. We do not use this model structure in our paper because the presence of imperfect competition would constitute a second source of distortions: the under-provision of the research good through the exercise of market power.

critical parameter in the production function for energy efficiency technology is the returns-to-scale parameter, $\sigma > 0$. Because production of energy is constant returns-to-scale in H, an increase in the number of blueprints implies factor productivity augmentation related to natural resource use. When policy such as a tax on carbon drives increases in the number of blueprints, we term these increases "induced technological change (ITC)."

If there are n firms, then the amount of labor used in the production of R&D is:

$$L_h = n(1 + F). \tag{13}$$

2.2 Households

We model a single representative household with preferences over the two consumption goods X and Y, leisure l, and environmental quality. Leisure is equal to the consumer time endowment T less the labor supply L. Environmental quality is deteriorated by pollution emission, P. So utility is:

$$U = u(X, Y, l) - \phi(P). \tag{14}$$

The household receives an after-tax wage of 1. The individual budget constraint is written as:

$$p_X X + p_Y Y = (T - l) + G \tag{15}$$

where G is the lump-sum transfer from government.

The first order conditions for utility maximization are:

$$u_X = \lambda p_X, \qquad u_Y = \lambda p_Y, \qquad u_l = \lambda, \tag{16}$$

where λ is the marginal utility of income.

Total labor demand comes from labor production of goods X, Y, R, and h. Demand for labor must equal labor supply L:

$$L = L_Y + L_X + L_R + n\,(1 + F)\,, \tag{17}$$

2.3 Government

The government imposes unit taxes on labor and pollution emissions to finance the lump-sum transfer:

$$G = \tau_L L + \tau_P P. \tag{18}$$

2.4 Welfare Effects of a Pollution Tax

We consider the impact on welfare of a policy that increments the tax on pollution, when its revenue is used to cut the labor tax in a revenue-neutral fashion. We first differentiate the household optimization problem in section 2.2 with respect to the pollution tax, and impose revenue neutrality through the government budget constraint. The net effect is to tilt the tax system toward a pollution tax, while holding total government revenue fixed.

Using equations (14) and (15), the optimization problem of the household is given by:

$$W = u(X, Y, T - L) - \phi(P) - \lambda(p_X X + p_Y Y - L - G). \tag{19}$$

Taking the total derivative of this equation with respect to τ_P and substituting (16) yields:

$$\frac{1}{\lambda}\frac{dW}{d\tau_P} = -\frac{\phi'(P)}{\lambda}\frac{dP}{d\tau_P} - X\frac{dp_X}{d\tau_P} - Y\frac{dp_Y}{d\tau_P}. \tag{20}$$

We take the derivative of p_X from (3) by using (2) and the derivative of (1):

$$X\frac{dp_X}{d\tau_P} = (L_X + R_X)\frac{d\tau_L}{d\tau_P} + R_X. \tag{21}$$

Likewise, we take the derivative of p_Y from (8) by using (7) and the derivative of (4):

$$Y\frac{dp_Y}{d\tau_P} = \{L_Y + R_Y + n(1+F)\}\frac{d\tau_L}{d\tau_P} + R_Y - \frac{1-\sigma}{\sigma}(1+\tau_L)(1+F)\frac{dn}{d\tau_P}. \tag{22}$$

We differentiate the government budget constraint, equation (18), and set the constraint of revenue neutrality to yield:

$$L\frac{d\tau_L}{d\tau_P} = -\left[\tau_L\frac{dL}{d\tau_P} + \left(P + \tau_P\frac{dP}{d\tau_P}\right)\right]. \tag{23}$$

Substituting (21), (22) and (23) into (20) yields:

$$\frac{1}{\lambda}\frac{dW}{d\tau_P} = \underbrace{\left(\tau_P - \frac{\phi'(P)}{\lambda}\right)\frac{dP}{d\tau_P}}_{\text{Environmental effect}} + \underbrace{\tau_L\frac{dL}{d\tau_E}}_{\text{Tax base effect}} + \underbrace{\frac{1-\sigma}{\sigma}(1+\tau_L)(1+F)\frac{dn}{d\tau_P}}_{\text{ITC effect}}. \tag{24}$$

This equation decomposes the welfare effects of a pollution tax into three pathways. First, the "environmental effect" is the impact of the tax reform operating through environmental quality. Households benefit from reduced pollution; these gains are partially offset by direct costs to businesses from the pollution tax. In the absence of the pre-existing tax ($\tau_L = 0$) and ITC ($dn/d\tau_P = 0$), the optimal pollution tax rate should be set at the Pigouvian level of ϕ'/λ.

The second effect, the "tax base effect," is the impact of the reform on labor supply. The prior literature (e.g., Bovenberg and de Mooij, 1994; Parry, 1995) has shown that the tax-base effect can be decomposed into two opposing effects. Cutting labor taxes with pollution tax revenue results in the "revenue recycling effect", where revenue from the new environmental tax reduces distortions in the labor market and improves welfare. However, the pollution tax exacerbates pre-existing tax distortions. The prior literature demonstrates that this "tax interaction effect" is quantitatively larger than the "revenue recycling effect" (e.g. Bovenberg and de Mooij, 1994). As a direct consequence, an optimal policy should set the pollution tax below the Pigouvian level.

The third effect is the focus of this paper, the impact of the tax change on welfare operating through induced technological change. We dub this term the "ITC effect." Intuitively, the ITC effect stems from the positive spillovers generated when more energy efficiency blueprints are created.

The ITC effect is positive in magnitude, improving welfare, under a set of easy-to-achieve conditions. We know that the tax on labor, τ_L, and the fixed cost of each blueprint, F are positive. The first condition is that energy efficiency technology is increasing returns-to-scale: $\sigma \in (0, 1)$. If the R&D sector is constant-returns-to-scale ($\sigma = 1$), there are no innovation externalities and the ITC effect disappears.

The second condition to guarantee the ITC effect is welfare-improving is: $\frac{dn}{d\tau_P} > 0$. As we noted in footnote , the number of blueprints, n, is entirely driven by the demand for the energy efficiency technology. This, in turn, is a function of the relative prices of the natural resource and the technology. Since the policy reform involves an increase in the environmental tax and a revenue-neutral decrease of the pre-existing tax, the technology will become relatively cheaper than the natural resource, and the number of blueprints will increase as a result of the reform.[4]

The size of the ITC effect increases as the returns-to-scale of the energy efficiency technology increases (i.e. $\sigma \to 0$). It also increases with the initial

[4]The number of blueprints demanded is determined in general equilibrium, and as such is a function of the demand for the consumer good Y. The tax reform may or may not increase the quantity of Y demanded. However, if energy constitutes only a small fraction of Y, the quantity of Y demanded is unlikely to change very much, and these general equilibrium effects are likely to be second-order compared to the substitution effects we discuss above.

size of the pre-existing tax and the cost of each blueprint, since these make the resources saved more valuable to welfare. Finally, it increases with the number of new energy efficiency patents innovated as a result of the tax reform.

3 Simulation Model

The prior section analytically derived the change in welfare when induced technological change is considered in an optimal environmental tax framework. The purpose of this section is to estimate the magnitude of these effects. We apply the elasticities from the empirical literature to calibrate a numerical simulation that estimates the importance of ITC to the U.S. economy.

3.1 Structural Model

3.1.1 Firms

We follow closely the analytical model from Section 2.1, substituting constant elasticity of substitution (CES) functional forms instead of general production functions for the production of X, Y, and $e(\cdot)$:

$$X = \gamma_X \left(\alpha_{LX}^{\frac{1}{\sigma_X}} L_X^{\frac{\sigma_X - 1}{\sigma_X}} + \alpha_{RX}^{\frac{1}{\sigma_X}} R_X^{\frac{\sigma_X - 1}{\sigma_X}} \right)^{\frac{\sigma_X}{\sigma_X - 1}} \tag{25}$$

$$Y = \gamma_Y \left(\alpha_{LY}^{\frac{1}{\sigma_Y}} L_Y^{\frac{\sigma_Y - 1}{\sigma_Y}} + \alpha_{eY}^{\frac{1}{\sigma_Y}} e^{\frac{\sigma_Y - 1}{\sigma_Y}} \right)^{\frac{\sigma_Y}{\sigma_Y - 1}} \tag{26}$$

$$e = \gamma_{eY} \left(\alpha_{ReY}^{\frac{1}{\sigma_{eY}}} R_Y^{\frac{\sigma_{eY} - 1}{\sigma_{eY}}} + \alpha_{HeY}^{\frac{1}{\sigma_{eY}}} H^{\frac{\sigma_{eY} - 1}{\sigma_{eY}}} \right)^{\frac{\sigma_{eY}}{\sigma_{eY} - 1}} \tag{27}$$

In these equations, σ_X, σ_Y, and σ_{eY} are coefficients governing the elasticities of substitution of X, Y, and $e(\cdot)$, respectively. Each α parameter is calibrated to allow for the appropriate initial amount of each input factor in producing the goods.

3.1.2 Households

Similarly, we give the representative household nested CES utility:

$$U = \left(\alpha_{UA} A^{\frac{\sigma_U - 1}{\sigma_U}} + \alpha_{Ul} (l)^{\frac{\sigma_U - 1}{\sigma_U}} \right)^{\frac{\sigma_U}{\sigma_U - 1}} \tag{28}$$

$$A = \left(\alpha_{XA} X^{\frac{\sigma_A - 1}{\sigma_A}} + \alpha_{YA} Y^{\frac{\sigma_A - 1}{\sigma_A}}\right)^{\frac{\sigma_A}{\sigma_A - 1}} \tag{29}$$

In these equations, l is household leisure, and is calculated by subtracting total labor L from the household's time endowment T. A is the aggregate good, composed of the two consumption goods X and Y. The parameters σ_U and σ_A govern the elasticities of substitution between goods in the household utility function. Each α parameter is calibrated to control for the share of income spent on each good.

Because we are primarily interested in studying the impact of induced technological change, we abstract from disutility caused by emissions from the environment. Although pollution is not included in utility, the same results apply in the case of separable environmental damages or an emissions target.

3.1.3 Government

The government in this simulation collects revenues and distributes them lump-sum to consumers, as described in (18). Real government spending is held constant.

3.1.4 Model Solution

When an emissions target is chosen, the government adjusts the emissions tax and labor tax in a revenue-neutral fashion until the emissions target is reached. The model is solved when the household budget balances, the government budget balances, and the factor market for labor clears.

3.2 Calibration

The model is calibrated to represent the United States in 2010, the last year for which comprehensive energy consumption estimates are available. We set the energy intensity of the economy at 8.1% of GDP, using estimates by the U.S. Energy Information Administration on total consumer expenditures on energy in the U.S. between 2005-2010.

The first key parameter in this analysis is the size of the energy sector impacted by induced technological change. There is piecemeal evidence suggesting that induced technological change may be broad. Newell et al. (1999), as we discussed earlier, found evidence for ITC in the air conditioning market. Jaffe and Palmer (1997) showed that increases in compliance expenditures within an industry are associated with increases in R&D shortly thereafter.

However, only one paper, Popp (2001), presents direct estimates tying technological change to energy efficiency. This study focused on a small set of industries, chosen because they are both very energy intensive and receive high numbers of energy efficiency patents. Collectively, these use 40.8% of the economy's energy and produce 5.8% of GDP.

We use three set of simulations. The first set of simulations, which we label the "Small" simulations, examines how ITC affects welfare when ITC impacts only those sectors that have been empirically shown to improve energy efficiency with an increased knowledge stock. The second set of simulations, which we label the "Medium" simulations, assumes that ITC will extend to all industrial production in the U.S. There are two assumptions underlying this scenario. First, higher energy prices raise the amount of energy efficiency innovation throughout the entire industrial sector; second, the entire industrial sector benefits from this development. The third category of simulations, the "Large" simulations, assumes that the entire U.S. economy, including both industry and services, benefits from induced technological change. There are two assumptions embodied here: higher energy prices affect the entire stock of energy efficiency patents, and growth in energy efficiency technology affects the energy efficiency of the entire economy.

In a static model such as that of this paper, the economy switches from one long-run equilibrium to another as a result of the policy change. As a result, we are most interested in the size of long-run knowledge stocks, and the long-run response of energy efficiency to changes in those knowledge stocks.

First, we need to assemble an estimate of the size of the stock of knowledge of energy efficiency. We compile the energy efficiency stock by estimating the number of energy efficiency patents using data from PatentsView, an online service provided through the U.S. Patent and Trademark Office. These data include how many patents were issued between 1976 and 2015, along each patent's U.S. patent class number and International Patent Classification number. Some patents receive more than one classification.

We quantify three knowledge stocks, corresponding to our "Small," "Medium," and "Large" scenarios. The first knowledge stock is the number of energy efficiency patents that were issued to the industry groups described in Popp (2001) and Crabb and Johnson (2010).[5] We term these industry groups the "energy intensive industries," because they use a large amount of energy relative to their output; these industries also receive many more energy ef-

[5]These industries consist of aluminum, automobiles, chemicals, copper, electrometallurgical, glass, iron foundries, metal coating, plastic film and sheet, pulp and paper, rolling and casting, steel foundries, and steel pipes and tubes.

ficiency patents than the average firm. The "Medium" knowledge stock is the number of these patents that were issued to any industrial firm. The "Large" patent stock is the total number of energy efficiency patents issued to the entire economy.

Popp (1997) and Popp (2001) detail which patent class numbers and subclass numbers correspond to energy efficiency patents. We can segregate the number of patents that relate to energy efficiency using these codes, giving us the yearly count of patents granted in the entire economy, the "Large" scenario. These data also contain IPC classifications; we match these with the industry classes detailed in Popp (1997) to calculate the yearly count of patents in the "Small" scenario.

To calculate the "Medium" scenario, corresponding to the number of energy efficiency patents granted to all industrial firms, we applied the Silverman IPC-U.S. Standard Industrial Classification (SIC) concordance. This concordance maps the likelihood that a patent with a given IPC number was received by a firm with a given SIC number. Firms with a 2-digit SIC number below 50 are industrial firms; using the probabilities from the Silverman concordance, we can thus estimate the number of patents received by all industrial firms.

We aggregate the knowledge stock using the perpetual inventory method, following Aghion et al. (2012):

$$K_{it} = PAT_{it} + (1 - \delta) K_{it-1} \tag{30}$$

In this formula, K_{it} is the stock of knowledge in sector i at time t, PAT_{it} is the number of new patents at time t, and δ is the rate of knowledge decay. Following the method of Aghion et al., we assume a $\delta = 0.2$, and robustness test this parameter.

Results from these calculations are displayed in Table 2. The knowledge stock in 2010 in the entire economy was 10,191 patents. We see that industrial firms, in column 2, received 96% of these patents, suggesting that they accounted for the vast majority of energy efficiency innovation. The "energy intensive" industries, detailed in column 3, account for 30% of all industrial patents.[6]

With the sizes of our three knowledge stocks established, we turn to the literature to find estimates of two other key parameters in this model: the response of the knowledge stock to energy prices, and the response of energy efficiency to the knowledge stock. Popp (2002), testing the response of the stock of patents received by U.S. applicants to domestic energy prices, estimated the first of these elasticities at 0.354. Crabb and Johnson (2010),

[6] "Energy intensive" industries account for about one-sixth of industrial output.

using a similar method while limiting their study to only automobile patents, found a remarkably similar result of 0.368. Verdolini and Galeotti (2011) estimate the impact of energy prices on energy-related patents over a panel of 17 OECD countries, and also find an elasticity of 0.4.[7]

To our knowledge, the second elasticity has been estimated by only one paper: Popp (2001). This paper estimates the long-run elasticity of energy use with respect to patents for a variety of industries. The mean of these estimates is -0.079, and we treat this as the central value of our simulations. There is a large amount of variance between industries, with a lowest elasticity estimated at -0.991, and the highest at 1.504. Accordingly, we are careful to conduct many sensitivity tests of this particular parameter in our simulations.

Table 3 summarizes the key parameters from this calibration.

3.3 Results

3.3.1 Key Model Parameters

We begin with simulations illustrating how the mechanisms in our model are affected by three key parameters. Figure 1 illustrates the first of these key parameters: the size of the knowledge stock. Each point on the horizontal axis represents a separate simulation where the labor tax and environmental tax are adjusted until emissions are cut 10%.[8] In the "Small" scenario, we assume only energy used by "energy intensive" industry is affected by ITC; in the "Medium" scenario, we assume that all energy used by industry is affected. In the "Large" scenario, we assume that all energy use in the economy is impacted.

Figure 1: Simulations Varying the Initial Knowledge Stock of the Economy

[7]Verdolini and Galeotti (2011) estimate the impact of global energy prices on each individual country's stock of energy patents, without considering knowledge spillovers between countries. If these knowledge spillovers were to occur, they might further decrease the welfare cost of environmental policy, all these forms of international spillovers are outside the context of our model.

[8]For reference, our model estimates that a carbon tax of about 16% of the price of energy must be levied to reduce emissions 10% in the U.S. using a revenue-neutral carbon tax. If the U.S. were to meet its commitments under the Paris Agreement of reducing emissions between 26-28%, it would require a carbon tax of between 51-55% under this style of carbon tax reform.

The diagonal line with square markers represents the additional amount of patents induced as a result of the tax reform. Since each scenario has the same starting size of economy and the same starting amount of the polluting resource, each requires virtually the same tax change to enact our policy reform. Since each scenario also has the same elasticity of patents with respect to energy prices, the number of new patents induced from each knowledge stock level will be the same. As a result, the number of new patents induced from the tax reform is the same in all three scenarios, and one line can be used to represent the number of patents induced in all three scenarios.

The three lines with no markers represent the improvements in efficiency realized in the production of energy for the Y sector. As the policymaker adjusts the environmental tax upwards, the polluting resource becomes more expensive, incentivizing the firm to employ more of the knowledge stock in the production of energy. The knowledge stock is increasing returns to scale in nature, so expansions in it allow efficiency savings in terms of production per unit of resource. The line is upward sloping because, as more innovation occurs, the stock of knowledge expands more and more, allowing fewer total resources to be spent on the production of energy.

The solid blue line is the improvements in efficiency under the "Small" scenario, where only energy used by energy intensive firms is affected by ITC. This line is the result of differencing two scenarios. The first is the amount of resources spent on the production of energy when no ITC occurs. The second is the amount of resources spent on this sector when ITC is present. The dashed purple and dashed orange lines correspond to the "Medium" and "Large" scenarios; these lines are higher since these scenarios have correspondingly larger energy sectors affected by ITC.

The second key parameter in our model is illustrated by Figure 2. Each set of simulations uses the appropriate parameters of Table 3, varying only the elasticity of patents with respect to energy prices. Again, each point on the horizontal axis represents a separate simulation increasing emissions taxes and adjusting labor taxes until emissions are cut 10%. In Figure 2, the three upward sloping lines with markers indicate how many new patents are generated under each reform. The smallest number of patents is generated under the "Small" scenario, where the starting number of patents is smallest. The "Medium" and "Large" scenarios have very similar numbers of patents generated, since they each start with nearly equivalent knowledge stocks in our calibration.

These increases in the number of patents generate efficiency savings in a similar manner to Figure 1. Since energy efficiency technology is increasing returns to scale, larger numbers of patents generate greater energy efficiency savings.

Figure 2: Simulations Varying the Elasticity of Patents with respect to Energy Prices - Effect on Patents

The third key parameter in our model, the elasticity of the natural resource with respect to the number of patents, is illustrated by Figure 3. For these simulations, we perform a policy experiment in which we create a 10% reduction in the amount of the energy aggregate ($e(\cdot)$), rather than the amount of emissions (R_Y).[9] Focusing first on the three lines with markers denoting the percentage increase in the number of patents, we find that the number of new patents increases as the elasticity of natural resources with respect to patents goes up. As this elasticity increases, it becomes easier to substitute the knowledge stock for the natural resource, and so a larger pollution tax is necessary to reduce the use of energy. This larger pollution tax drives more induced technological innovation. Similar to the previous graphs, a larger knowledge stock will substitute for more of the natural resource because of the increasing returns-to-scale property of the knowledge stock, generating the efficiency gains we see in the three downward sloping lines in Figure 3.

Figure 3: Simulations Varying the Elasticity of the Natural Resource with respect to Patents

3.3.2 Central Parameter Results

Figure 4 illustrates how the mechanisms described in section 3.3.1 combine in the setting of the central parameters of each of the three simulations. In these simulations, an environmental tax is enacted reducing emissions by varying amounts, with commensurate cuts in the representative tax that maintain revenue neutrality. The three lines with markers represent the number of energy efficiency patents induced by the tax reform in each scenario. Because larger taxes are needed for larger amounts of abatement, and higher taxes

[9] Simulations holding fixed the amount of emissions are less illuminating: each simulation results in the same amount of the natural resource consumed and the same knowledge stock.

create larger incentives to increase the knowledge stock, increased amounts of abatement induce more patents; the slopes of these lines curve upwards.

The three lines with no markers represent the efficiency gains from increases in the stock of knowledge. More patents induced create large energy efficiency savings under the mechanisms documented.

Figure 4: Simulations Describing ITC Mechanisms for Varying Amounts of Abatement

Figure 5 is the most important figure we present; it summarizes the welfare cost of a carbon tax when ITC is included.[10] In this graph, we normalize the cost in each scenario to 1 when there is no ITC. The welfare cost of reform is less than 1 with ITC for all levels of abatement, suggesting that the ITC effect has a positive influence on welfare for all parameters considered in these simulations.

We have found previously that increasing amounts of ITC occurs with higher levels of abatement, and that the benefits to welfare from these efficiency gains are roughly linear (Figure 4). However, the cost of achieving increasing levels of abatement are exponentially increasing. As a result, at very low levels of abatement, the cost gains from ITC exceed the welfare cost of the environmental policy, and costs are negative.[11] However, as the amount of abatement increases, the welfare effects of distorting the economy through very heavy carbon taxes dominate, and the relative cost of abatement with ITC converges to 1.

Much of the prior literature focuses on the cost of a 10% cut to emissions. In our “Small” scenario, where only energy intensive industries benefit from ITC, the welfare cost of a revenue-neutral carbon tax is cut by 15%. In our “Medium” scenario, where all industry benefits from energy efficiency ITC, the welfare cost is reduced by 12%. In our “Large” scenario, where the entire economy can benefit from ITC, it lowers the cost of the carbon tax by 29%.

[10] This graph excludes the environmental benefits of a carbon tax, which vary sharply depending on the context under consideration and which study is being referenced. In the context of equation 24, this graph includes only the tax base effect and the ITC effect. We do not include the environmental effect because the benefits from cutting carbon are uncertain and depend heavily on assumptions such as the discount rate.

[11] In this literature, a negative welfare cost is called a “double dividend.” The first dividend arises because there is an improvement in environmental quality; the second because of improved economic efficiency as a result of the tax reform. We find a double dividend only for low levels of emission abatement.

In our simulations, the "Small" scenarios actually cut the welfare cost more than the "Medium" scenarios. This is because the "Medium" scenario has almost as many patents as the entire economy of the "Large" scenario, but only about two-thirds of the energy sector affected by ITC. As a result, since the economy is calibrated so that the elasticity of energy use with respect to the number of patents is fixed, relatively few patents are induced in the "Medium" scenario when use of energy is cut. Fewer returns-to-scale efficiencies are generated, and a smaller welfare reduction relative to the no ITC scenario is realized.

Figure 5: Welfare Cost of a Carbon Tax for Varying Amounts of Abatement

*Total cost is normalized to 1 when there is no ITC

3.3.3 Alternative Parameters

We test the sensitivity of our main simulation findings to alternative parameters, summarized in Table 1. The numbers in the table show the ratio of total cost with induced technological change to total cost without ITC when a fixed reduction of 10% is considered. A value of 0.85, for example, indicates that the welfare cost of environmental reform has been reduced by 15% when resource savings from ITC are included.

Varying the size of the knowledge stock: The knowledge stock in the central case incorporates the key assumption from Aghion et al. (2012) that the rate of knowledge decay on energy efficiency technology is 20% per year ($\delta = 0.2$). We robustness test this assumption by varying the rate of knowledge decay; low rates of knowledge decay produce higher knowledge stocks, and high rates of decay result in lower knowledge stocks.

In our robustness check, we assume in the "Low" knowledge stock scenario that the rate of knowledge decay is 25% per year; this assumption has the effect of decreasing the size of the knowledge stock in the "Small" scenarios by about 20%. In the "High" and "Highest" knowledge stock scenarios, we assume rates of 15% and 10%, respectively; these assumptions increase the size of the knowledge stock by 30% and 80%.[12]

[12]The size of the knowledge stock can alter the calibration by changing the σ parameter governing the returns-to-scale on technology; we assume that the σ parameter is held constant for these robustness simulations.

Table 1: Ratio of Total Cost With ITC to Total Cost Without*

Scenario	Small	Medium	Large
Central Case	0.85	0.88	0.71
Size of Knowledge Stock			
Low	0.88	0.90	0.76
High	0.81	0.85	0.64
Highest	0.72	0.79	0.49
R&D Cost			
10% Smaller	0.86	0.89	0.73
10% Bigger	0.84	0.87	0.70
20% Bigger	0.83	0.87	0.68
Elasticity of Knowledge Stock with Respect to Energy Prices			
10% Smaller	0.87	0.89	0.74
10% Bigger	0.84	0.87	0.69
20% Bigger	0.82	0.86	0.66
Elasticity of Energy with Respect to Knowledge Stock			
25% Smaller	0.87	0.92	0.77
25% Bigger	0.83	0.85	0.66
50% Bigger	0.81	0.81	0.61

*All simulations in this table are relative to a base case where emissions are reduced 10% through the employment of a revenue-neutral environmental tax.

We see that modifications in the rate of knowledge decay can have significant effects on the ending cost. As the size of the knowledge stock is increased, the cost is reduced. In the "Highest" knowledge stock scenarios, the larger knowledge stock size leads to a two-thirds increase in the cost reduction from ITC.

Varying the R&D cost: In our central result, we use the estimate from Popp (2002) that the development cost of each patent is $2.25 million. The analytical model predicts that the "ITC effect" would be enhanced by a larger fixed cost of research, because it amplifies the increasing-returns-to-scale property of technology. We test this prediction and the importance of the estimate on the R&D cost by raising and lowering this cost.

The prediction is largely affirmed: increases in the R&D cost increase the cost savings from ITC. However, the size of the R&D cost appears to have very little impact on the cost savings from ITC; even a 20% increase in the R&D cost tends to have only small effects on the welfare cost.

Varying the elasticity of the knowledge stock: In our central result, we use the empirical estimates from Popp (2001) and Crabb and Johnson (2010) of the elasticity of the knowledge stock with respect to energy prices. These estimates were very close in magnitude; however, we explore the impact of varying this elasticity to be 10% smaller, 10% larger, or 20% larger.

As expected, higher elasticities produce larger impacts on our calculations of cost, but these reductions are relatively modest. In the "Large" scenario, a 10% increase in the elasticity of the knowledge stock increases the cost reduction of ITC by about 4%.

Varying the elasticity of energy: Our central result employs the estimate from Popp (2001), the only piece of direct evidence tying the use of energy to the number of energy efficiency patents. Popp correlates energy use with energy efficiency patents for a number of energy intensive industries; the mean elasticity of these industry groups is -0.079. This estimate masks a wide range of elasticity estimates; some industries have a much larger negative elasticity while others have a positive elasticity.

As a result of this empirical uncertainty, we apply a much larger range for our robustness check. As a lower bound, we use an elasticity 25% lower than the parameter in our central estimate. We also investigate the impact of an elasticity that is 25% higher or 50% higher.

As Table 1 shows, this parameter enables significant swings in the savings from ITC. If this elasticity is 25% larger, the cost benefit from ITC is almost

7% larger; if this elasticity is 50% larger, the cost benefit from ITC is 15% larger.

3.4 Discussion of Results

In our central result, we find a result in line with the prior literature on induced technological change (ITC): it reduces the cost of a carbon tax reducing emissions 10% by 15%, as in the "Small" scenario. Liu (2014) shows how tax evasion can lower this cost by 28%, and Bento et al. (unpublished) suggests that the informal economy can lower this cost by 62%. Compared to these factors, ITC seems to have somewhat smaller impacts.

Our analytical model and simulations are useful because they add ITC to the set of properties by which carbon taxes are differentiated from other forms of taxation. We give the literature seeking to establish a role for carbon taxes in the optimal tax system (like Carson et al. 2015) another mechanism demonstrating how the cost of carbon taxes is lower than presently believed.

However, our "Large" scenario suggests that induced technological change (ITC) has the potential to play an important role in the consideration of the cost of an environmental tax reform where a carbon tax is used to cut emissions and the revenues are used to cut a pre-existing tax in a revenue-neutral manner. If ITC extends to the entire economy of the U.S., cost cuts are the most dramatic, ranging between 23% and 51% depending on the set of assumptions employed.

These results can be interpreted both optimistically and pessimistically. On the one hand, ITC can have a very large impact on the welfare cost of tax reform. On the other hand, current empirical evidence linking both the number of patents to energy prices and energy efficiency to patents directly supports only the "Small" scenario. This scenario directly ties energy prices to the behavior of a relatively small group of industrial companies and their propensity to create energy efficiency patents. Expanded evidence tying the larger body of industry companies, and the energy efficiency patenting behavior of the entire economy would expand the scope of the ITC effect, and its implications on environmental policy reform.

4 Conclusion

In this paper, we have presented an analytical model incorporating induced technological change into an optimal environmental tax framework. We have also developed numerical simulations integrating the empirical evidence tying energy prices and ITC. Our primary conclusion is that the existing evidence supports only limited effects of induced technological change, and that proponents of ITC would benefit substantially from additional empirical evidence. Specifically, additional evidence extending the base of energy that is affected by technological change lead to greater expected reductions in the cost of a carbon tax. Our analysis is sensitive to some of the key parameters in the model, most particularly the decay rate of the knowledge stock and the elasticity of energy with respect to the knowledge stock. Further research would sharpen the estimates of this paper.

We caution that our results do not imply that ITC is an unimportant factor. Rather, we argue that the current evidence supports only a limited importance to be placed on technology in the calculation of the cost of carbon taxes. The current evidence relies on ties between energy prices and energy efficiency patents, and between energy efficiency and energy efficiency patents.

Additional mechanisms may exist where technological change may result because of environmental policy. We study only energy efficiency innovation here, but one could imagine that other changes, like innovation into clean fuel alternatives, would result if energy prices are changed. The effects of technology improvements like learning-by-doing in renewable energy might exceed the sizes of the effects we find here. We lack the parameters to include them in our model, but research invested in developing the magnitude of these effects would be useful.

We consider only domestic spillovers from increased energy efficiency innovation, but international spillovers are possible. While Verdolini and Galeotti (2011) find that energy efficiency patenting behavior increases across a panel of 17 countries as a result of international energy prices, it is unclear whether that innovation originates within those countries or whether it could spill over when a single country experiences an energy shock.

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Table 2: Energy Efficiency Patents Included in Each Knowledge Stock

	All Patents	By Industrial Firms	Energy Intensive Groups
Year	Large	Medium	Small
1976	764	709	298
1977	867	828	343
1978	1072	1027	470
1979	828	799	377
1980	1170	1114	511
1981	1382	1314	607
1982	1272	1195	440
1983	1203	1138	470
1984	1418	1353	624
1985	1278	1221	565
1986	1389	1326	631
1987	1586	1511	654
1988	1391	1316	580
1989	1391	1306	535
1990	1311	1225	569
1991	1303	1237	582
1992	1352	1273	535
1993	1413	1334	511
1994	1428	1345	511
1995	1230	1155	428
1996	1289	1222	461
1997	1179	1111	430
1998	1473	1382	553
1999	1646	1559	560
2000	1735	1652	564
2001	2009	1923	674
2002	1831	1730	465
2003	1844	1741	444
2004	1845	1752	446
2005	1955	N/A	713
2006	2201	2110	594
2007	1966	1886	532
2008	1866	1799	530
2009	2008	1938	632
2010	2607	2504	658
Knowledge stock	10,191	9,744	2,913

Note: All patents included in this table are energy efficiency patents, defined as described in section 3.2. The knowledge stock, representing the total discounted knowledge stock of the economy in 2010, is calculated using equation (30).

Table 3: Central Parameters

Energy Use of Economy:	%
Amount of Abatement in Each Simulation:	10%
Depreciation Rate of Patents (β):	0.20
R&D Cost per Patent:	$2.25 million
Initial Labor Tax rate:	40%
Elasticity of Knowledge Stock with respect to Energy Prices:	0.354
Elasticity of Energy with respect to the Knowledge Stock:	-0.079
Share of Energy Sector Affected by ITC* (Small):	40.8%
Share of Energy Sector Affected by ITC (Medium):	66.1%
Share of Energy Sector Affected by ITC (Large):	100%
Size of Knowledge Stock (Small):	2913 patents
Size of Knowledge Stock (Medium):	9,744 patents
Size of Knowledge Stock (Large):	10,191 patents

* ITC: Induced Technological Change