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Three essays on biofuel, environmental economics, and international trade

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Three essays on biofuel, environmental economics, and international trade

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DEDICATION

This dissertation is dedicated to my wife Shu and to my daughter Iris, who supported me each step of the way. I would also like to thank my family for their unconditional love and support throughout the course of this work.

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ABSTRACT

This dissertation focuses on two independent areas: the analysis of biofuel and related energy policies, and the relationship between trade and the environment with heterogeneous firms. Chapter 1 provides quantitative estimates of the welfare benefits of U.S. biofuel and related energy polices. The remaining two chapters investigate the firm-level relationship between trade and the environment using theoretical model and empirical evidence. Chapter 2, theoretical in nature, explores the impact of the stringency of environmental policy and exposure to trade on the induced clean technology adoption and on firm dynamics. Using a unique detailed facility-level dataset containing criteria air emissions and economic activity data, chapter 3 investigates whether exporters are more environmentally friendly than non-exporters in terms of lower emissions per value of sales.

CHAPTER 1. WELFARE IMPACTS OF ALTERNATIVE BIOFUEL AND ENERGY POLICIES

1.1 Introduction

Two interrelated critical issues facing the U.S. and world economies are the dwindling supply of fossil fuels and the increasing emissions of carbon into the atmosphere. The U.S. dependence on imported oil has increased sharply in the past quarter century, with a number of significant economic and political consequences. Oil imports worsen the U.S. balance of trade deficit and, together with growing energy consumption from developing countries such as China, lead to higher prices. This dependence on oil imports weakens U.S. national security and entails significant military and defense expenditures to ensure continued U.S. access to world oil supplies. Separately, there is the concern with greenhouse gas (GHG) emissions associated with fossil energy use. While some disagreement exists on the potential implications of carbon buildup in the atmosphere, it seems major industrialized countries are moving toward a regime in which these emissions will be regulated and (or) priced.

Partly in response to such issues, government support for biofuels has led to rapid growth in U.S. ethanol production. U.S. fuel ethanol production has increased from 1.65 billion gallons in 2000 to 10.76 billion gallons in 2009, making the U.S. the largest world producer of ethanol. U.S. ethanol production currently benefits from a \$0.45/gallon subsidy (technically an excise tax credit), an out-of-quota *ad valorem* import tariff of 2.5% and a \$0.54/gallon duty on ethanol imports.[1] In addition, the Energy Policy Act of 2005 specified a renewable fuel standard that "mandates" specific targets for renewable fuel use, the level of which has been considerably expanded by the Renewable Fuel Standard (RFS2) of the Energy Independence and Security

[1] On January 1, 2012, U.S. ended a subsidy of \$0.45/gallon on ethanol, and also terminated a tariff of \$0.54/gallon on ethanol imports.

Act of 2007. Since then, the ethanol mandates under the RFS2 have been more than met. Under the RFS2, the renewable fuel requirement rises from 12.95 billion gallons in 2010 to 20.5 billion gallons in 2015, and to 36 billion gallons in 2022; of these latter amounts, up to 15 billion gallons may come from ethanol, while the rest are meant to come from "advanced biofuels," such as cellulosic biofuel.

The purpose of this paper is to provide an economic analysis of the welfare implications of U.S. policies that impact biofuels production. Facets of this topic have been the subject of a few studies. de Gorter and Just (2009a) analyze the impact of a biofuel blend mandate on the fuel market. They find that when tax credits are implemented along with the blend mandate, tax credits subsidize fuel consumption instead of biofuels. de Gorter and Just (2009b) also develop a framework to analyze the interaction effects of a biofuel tax credit and a price-contingent farm subsidy. The annual rectangular deadweight costs-which arise because they conclude that ethanol would not be commercially viable without government intervention-dwarf in value the traditional triangular deadweights costs of farm subsidies. Elobeid and Tokgoz (2008) set up a multimarket international ethanol model to analyze the influence of trade liberalization and the removal of the federal tax credit in the U.S. on ethanol markets. They find that the removal of current tariffs on imported ethanol would lead to a 13.6% decrease in the U.S. domestic ethanol price and a 3.7% increase of ethanol's share in U.S. fuel consumption, and that the removal of both tax credit and tariffs would cause U.S. ethanol consumption to fall by 2.1% and the price of ethanol to fall by 18.4%.

The foregoing studies do not account explicitly for the impact of climate policies on GHG emissions associated with the fuel energy sector. Khanna, Ando, and Taheripour (2008) examine the welfare impact of a carbon tax ($25/tC) on fuel consumption, when the purpose of the tax is to correct the pollution externality from carbon emissions and to account for the other external costs associated with congestions and accidents. At the time of their study, they found that the fuel tax of $0.387/gallon and then-current ethanol subsidy of $0.51/gallon reduces carbon emissions by 5% relative to the no-tax situation (*laissez faire*). Their second best policy of a $0.085 mile tax with a $1.70/gallon ethanol subsidy could reduce gasoline consumption by

16.8%, thereby reducing carbon emissions by 16.5% (71.7 million metric tons).[2]

In assessing the effectiveness of ethanol in reducing GHG emissions, an issue that has commanded considerable attention is that of "indirect land use" effects: diverting feed corn to ethanol production in the United States increases aggregate demand for agricultural output and might bring new marginal land into production (Searchinger et al. 2008). To assess the global economic and land-use impacts of biofuel mandates, Hertel, Tyner, and Birur (2010) use a computable general equilibrium model, which is built upon the standard Global Trade Analysis Project modeling framework. To jointly meet the biofuel mandate policies of the United States (15 billion gallons of ethanol used by 2015) and the EU (6.25% of total fuel as renewable fuel by 2015), they find that coarse grains acreage in the United States rises by 10%, oilseeds acreage in the EU increases dramatically, by 40%, cropland areas in the United States would increase by 0.8%, and about one-third of these changes occur because of the EU mandate policy. The U.S. and EU mandate policies jointly reduce the forest and pasture land areas of the United States by 3.1% and 4.9%, respectively. The most recent RFS2 pronouncement by the Environmental Protection Agency (EPA) accounts for international indirect land use changes (ILUC) and makes several changes for GHG emissions reduction of ethanol from all feedstocks (EPA, 2010). Accounting for ILUC, the EPA finds that corn ethanol still achieves a 21% GHG reduction compared to gasoline. The EPA also finds, using its ILUC modification, that sugarcane ethanol qualifies as an advanced biofuel since it achieves an average 61% GHG reduction compared to baseline gasoline, which exceeds the 50% GHG reduction threshold for advanced biofuels.

Lapan and Moschini (2009) note that most existing work does not explicitly account for the welfare consequences to the U.S. of policies supporting biofuel production (such as the externality of GHG emission or the benefits to the U.S. that accrue either from improved terms of trade or "improved national security" due to decreased reliance on oil imports). To consider first- and second-best policies within that normative context, they build a simplified general equilibrium (multi-market) model of the United States and the rest-of-the-world economies that

[2]Some studies discuss emissions in terms of metric tons of carbon (tC), other in terms of metric tons of carbon dioxide (tCO_2). One ton of carbon is equivalent to 3.67 tons of carbon dioxide. Of course, when reductions are expressed in percentages, units will not matter.

links the agricultural and energy sectors to each other and to the world markets; they model the process by which corn is converted into ethanol, accounts for byproducts of this process, and allows for the endogeneity of world oil and corn prices, as well as the (different) carbon emissions from gasoline derived from oil and that which is blended with ethanol. The analysis in Lapan and Moschini (2009) is theoretical in nature, aiming at providing analytical insights and results. They find that the first best policy would include a tax on carbon emissions, an import tax on oil, and an export tax on corn. If policy is constrained, for example by international obligations, they find that a fuel tax and an ethanol subsidy can be welfare enhancing. They also find that an ethanol mandate is likely to welfare-dominate an ethanol subsidy.

In this paper we construct a tractable computational model that applies and extends the analytical setup of Lapan and Moschini (2009), and we use the model to provide quantitative estimates of the welfare benefits of alternative policies. The model specification allows endogenous determination of equilibrium quantities and prices for oil, corn and ethanol and is calibrated to represent a recent benchmark data set for the year 2009, using the available econometric evidence on elasticity estimates. By varying government policy, we explore how these policies affect equilibrium (domestic and world) prices of corn, oil, ethanol and gasoline. Using standard welfare measures, we compare the net welfare implications of alternative policies and show how different groups are affected by the policies. In addition to characterizing the first best policy, we consider a number of second best interventions involving various combinations of ethanol mandates, ethanol subsidies and a fuel tax. Using the model, we calculate the optimal values for the policy instruments (given the constraint on which instruments are used) and the associated welfare gains. We then explore the robustness of our conclusions by varying the values of various parameters.

Our results consistently show that the largest economic gains to the U.S. from policy intervention come from the impact of policies on the U.S. terms of trade, particularly on the price of oil imports. We also find that first best policy outcomes, which would require oil import tariffs that are not consistent with U.S. international obligations, can be closely approximated by second best tools such as fuel taxes. Furthermore, our results probably underestimate the gains that come from reducing U.S. oil imports because the model does not account for any of the "national security" gains that could arise from reduced U.S. dependence on imported oil.

1.2 The Model

We adapt and extend the model developed in Lapan and Moschini (2009) to make it more suitable for simulating the consequences of alternative policies directed toward reducing U.S. emissions and reducing U.S. reliance on oil imports. The extension recognizes that when oil is refined, other products, in addition to gasoline, are produced (e.g., distillate fuel oil, jet fuel, etc.). We aggregate all the non-gasoline output into a single good called petroleum byproducts. The model is a stylized economy with three basic commodities: a numeraire good, corn (food) output and oil. In addition, there is a processing sector that refines oil into gasoline and other petroleum byproducts, and another sector that converts corn into ethanol, which may then be blended with gasoline to create "fuel" used by households. Consumers are assumed to have quasi-linear preferences (which can then be aggregated into a representative consumer) with utility function

$$U = y + \phi(D_f) + \theta(D_c) + \eta(D_h) - \sigma(x_g + \lambda x_e) \tag{1.1}$$

where y represents consumption of the numeraire, and (D_f, D_c, D_h) represent consumption of fuel, of food, and of petroleum byproducts, respectively. The last term, $\sigma(\cdot)$, represents environmental damages from carbon emissions due to aggregate combustion of gasoline and ethanol. The parameter λ reflects the relative pollution emissions of ethanol as compared to gasoline (we will return to this parameter later).

The basis elements of the model consists of the following:

(I) U.S. demand for corn as food/feed, represented by $D_c(p_c)$

(II) U.S. demand for fuel $D_f(p_f)$

(III) U.S. demand for petroleum byproducts $D_h(p_h)$

(IV) U.S. corn supply equation $S_c(p_c)$

(V) U.S. oil supply equation $S_o(p_o)$

(VI) Foreign oil export supply curve $\bar{S}_o(p_o^w)$

(VII) Foreign corn import demand curve $\bar{D}_c(p_c^w)$

(VIII) U.S. oil refining sector, which converts oil into gasoline and petroleum byproducts

(IX) U.S. ethanol production sector, which converts corn into ethanol, and produces a byproduct of dried distillers grains with solubles (DDGS), which becomes part of the food/feed supply

Components (I)-(VII) of the model are self-explanatory. In particular, the (household) demand curves (I-III) come from utility maximization, and thus are the inverse of the marginal utility relations $\phi'(D_f)$, $\theta'(D_c)$, and $\eta'(D_h)$, respectively, and p_f, p_c, p_h are the prices facing households.[3] The domestic supply relations (IV and V) come from competitive profit maximization so that (assuming no externalities associated with their production) they are the inverse of the marginal private (and social) costs; because we assume no taxes on domestic corn or oil producers, (p_c, p_o) represent both supply and demand prices.[4] The foreign relations (VI and VII) represent aggregate excess world oil supply and world corn demand, and distinguishing the world prices (p_o^w, p_c^w) from domestic prices allows for the possibility of U.S. border policies (tariffs or quotas) that would cause U.S. prices to diverge from world prices. Note that if the United States were a small country, world prices (p_o^w, p_c^w) would be exogenous to U.S. economic conditions. However, in reality, the U.S. is a large economic agent in both markets and our simulation will reflect that fact. Finally, components (VIII) and (IX) of the model require a bit more elaboration.

[3] Since the marginal utility of the numeraire is one, the marginal rate of substitution between each one of the three consumption goods (food, fuel and petroleum byproducts) and the numeraire is the same as the marginal utility of that good. The price of the numeraire is (by definition) normalized to one, so p_f, p_c, p_h represent relative prices.

[4] We do allow for taxes or subsidies on fuel and ethanol, which is equivalent to taxes or subsidies on gasoline and ethanol.

1.2.1 Oil Refining Sector

The refinement of oil yields gasoline x_g and petroleum byproducts x_h. We assume a fixed coefficients production technology so that the process is represented as follows:[5]

$$x_g = \text{Min}[\beta x_o, z_o] \tag{1.2}$$

$$x_h = \beta_2 x_g / \beta \tag{1.3}$$

where x_g is gallons of gasoline output, x_h is gallons of the petroleum byproduct, x_o is barrels of oil input (where domestically produced oil and imported oil are perfect substitutes), and z_o is the amount of a composite input, which aggregates all other inputs used in the oil refining process. Thus, β is the number of gallons of gasoline per barrel of crude oil, and β_2 is the number of gallons of the petroleum byproduct per barrel of oil. This technology and perfect competition imply the following relationship among input and output prices:

$$\beta p_g + \beta_2 p_h = p_o + \beta w_g \tag{1.4}$$

where w_g represents the unit cost of the composite input z_o, including the rental price of capacity.

1.2.2 Ethanol Production Sector

We also assume a fixed coefficients production process for ethanol production:

$$x_e = \text{Min}[\alpha x_c, z_e] \tag{1.5}$$

where x_e is ethanol output and z_e the amount of other inputs used per unit of ethanol output. Because the energy content of ethanol is much lower than that of gasoline, and given our working assumption that consumers' demand take that into account (e.g., they ultimately care about the miles traveled with any given amount of fuel, as discussed in de Gorter and Just, 2010), it is important to keep track of this fact to handle the blending of ethanol and gasoline (into fuel) in a consistent fashion. Consequently, x_e in equation (1.5) and in what follows is

[5] Although in reality there is some substitutability among the various products produced from crude oil, it seems that this substitutability is limited and that the assumption of fixed proportions in output provides a reasonable approximation.

measured in what we term ”gasoline-energy-equivalent gallon” (GEEG) units.[6] Furthermore, we wish to account for the valuable bioproducts of ethanol production by counting only the ”net” use of corn in the technological relation in (1.5). That is, if one bushel of corn used in ethanol production also yields δ_1 units of distillers dried grains with soluble (DDGS), which, being a close corn-substitute in feed use, we assume commands a price of $\delta_2 p_c$, then the net amount of corn required to produce a gallons of ethanol is only $(1-\delta_1\delta_2)$. Hence, the production parameter α in (1.5) satisfies

$$\alpha = \frac{a\gamma}{1-\delta_1\delta_2} \tag{1.6}$$

where a is the number of gallons of ethanol (in natural units) per bushel of corn; γ captures the lower energy content of ethanol (relative to gasoline); δ_1 represents the units of DDGS per bushel of corn used to produce ethanol; and δ_2 represents the relative price of DDGS.

Given perfect competition in the ethanol sector, this implies the following price relation between the supply price of ethanol and the price of corn:

$$p_e = \frac{p_c}{\alpha} + w_e \tag{1.7}$$

where w_e is the cost of all inputs other than corn, including the rental cost of plant capacity, required to produce one unit of ethanol (measured in gasoline energy equivalent units) and p_e is the price of one GEEG of ethanol.

1.3 Equilibrium

In order to simulate the model, we need to specify the equilibrium conditions that must hold and the set of policy instruments that are considered. For the purpose of our policy analysis, the policy instruments that we allow are border policies, fuel taxes and ethanol subsidies/taxes (or border policies, ethanol mandates and ethanol subsidies).[7] We assume there is trade in

[6]This measure is related to the more common notion of a ”gasoline gallon equivalent,” which is defined as the amount of alternative fuel it takes to equal the energy content of one gallon of gasoline (essentially this represents the reciprocal of our measure).

[7]If we also allowed, for example, a tax/subsidy on corn production, we would have to distinguish between the supply and demand prices for corn.

crude oil but no trade in the refined products, which is a fair approximation of the *status quo*.[8] Given all that, the equilibrium conditions are as follows:

$$S_c(p_c) = D_c(p_c) + \bar{D}_c(p_c^w) + x_e/\alpha \qquad \text{(Corn Market Equilibrium)} \qquad (1.8)$$

$$D_f(p_f) = \beta \left\{ S_o(p_o) + \bar{S}_o(p_o^w) \right\} \qquad \text{(Fuel Market Equilibrium)} \qquad (1.9)$$

$$D_h(p_h) = \beta_2 \left\{ S_o(p_o) + \bar{S}_o(p_o^w) \right\} \qquad \text{(Petroleum Byproduct Equilibrium)} \qquad (1.10)$$

$$\beta p_g + \beta_2 p_h = p_o + \beta w - g \qquad \text{(Zero Profit Condition Oil Refining)} \qquad (1.11)$$

$$p_e = \frac{p_c}{\alpha} + w_e \qquad \text{(Zero Profit Condition Ethanol Industry)} \qquad (1.12)$$

$$p_o = p_o^w + \tau_o \qquad \text{(Oil Import Arbitrage Relation)} \qquad (1.13)$$

$$p_c^w = p_c + \tau_c \qquad \text{(Corn Export Arbitrage Relation)} \qquad (1.14)$$

Note that equation (1.8) embeds the technological relationship $x_c = x_e/\alpha$. In equations (1.13) and (1.14), (τ_o, τ_c) are the oil-import-specific and corn-export-specific tariffs, respectively (assumed to be non-prohibitive, so trade still occurs). To close the model, consider first the hypothetical case of *laissez faire* equilibrium, in which $\tau_o = \tau_c = 0$ and there are no other active policy instruments that interfere with the competitive equilibrium. Then we must also have $p_e = p_g = p_f$, and subject to this restriction, conditions (1.8)-(1.14) can be solved for the equilibrium prices $(p_c, p_c^w, p_o, p_o^w, p_f, p_h)$ and for the ethanol quantity x_e. For scenarios in which there are active policy instruments, on the other hand, model closure needs to be tailored to the specifics of the policy that applies (e.g., the case of fuel taxes and ethanol subsidies, or that of a binding ethanol "mandate").

1.3.1 Equilibrium with Fuel Taxes and Ethanol Subsidies

Let t be the consumption tax on fuel, per gallon, and b be the volumetric blending subsidy per gallon of ethanol. Then, because gasoline and ethanol are modeled as perfect substitutes for consumers once measured in GEEG units, and because one gallon of ethanol is equivalent

[8] Although imports account for over 50% of U.S. crude oil consumption, over the period 2007-2009 net imports of gasoline averaged about 1.7% of total consumption and net trade of "Refinery and Blender Finished Petroleum Product" averaged (in absolute value) under 3% of total consumption (calculated from the "Supply and Disposition Tables" of the U.S. Energy Information, http://tonto.eia.doe.gov/dnav/pet/pet_sum_snd_d_nus_mbbl_m_cur.htm).

to γ GEEGs, arbitrage relations imply,[9]

$$p_g = p_f - t \tag{1.15}$$

$$p_e = p_f + \frac{b}{\gamma} - \frac{t}{\gamma} = p_g + \tilde{b} \tag{1.16}$$

where $\tilde{b} \equiv (b - t(1-\gamma))/\gamma$ is the effective net subsidy to ethanol, as compared to gasoline, per GEEG unit.[10] Thus, for the case of taxes and subsidies, equations (1.8)-(1.14), (1.15) and (1.16) can be used to calculate the equilibrium, given the policy parameters $\{\tau_o, \tau_c, t, b\}$.

1.3.2 Equilibrium with Mandates

With a binding ethanol mandate (denoted by x_e^M) equations (1.8)-(1.14) still apply, but with $x_e = x_e^M$ exogenously set. Note that in this case the amount of corn utilized by the ethanol industry is fixed at x_e^M/α, and so, as equation (1.8) makes clear, the corn price is effectively determined in the corn market. Furthermore, the prices of fuel, gasoline and ethanol will have to be such that arbitrage possibilities are exhausted, i.e., blenders that combine ethanol and gasoline earn zero profit. This zero profit condition, allowing for the existence of exogenous fuel taxes and ethanol subsidies, can be expressed as

$$(p_f - t) \cdot D_f(p_f) = p_g \left[D_f(p_f) - x_e^M \right] + (p_e - \tilde{b}) \cdot x_e^M \tag{1.17}$$

Equation (1.17) states that the price of fuel is a weighted average of the price of its components (ethanol, gasoline), where the amount of ethanol is exogenously determined. Thus, with a mandate, the equilibrium is calculated using equations (1.8)-(1.14) and (1.17). As shown in Lapan and Moschini (2009), the impact of an ethanol mandate is that of combining a fuel tax with an ethanol subsidy in a revenue neutral fashion.

1.4 Welfare

In defining welfare, we assume all tax revenue is returned to domestic consumers and that there are no externalities other than those due to carbon emissions. Domestic welfare could be

[9] The assumption of perfect substitutes seems valid up to at least a 10% utilization rate for ethanol.

[10] Note that (1.16) also accounts for the fact that the tax on fuel t is levied per volume unit. Because it takes $1/\gamma > 1$ gallons of ethanol to make one GEEG of fuel, the effective tax on ethanol is higher than that on gasoline.

calculated using the indirect utility function along with the profit function for the domestic oil and corn industries and government tax revenue, or by using the direct utility function along with the production costs for domestic oil and corn, and the net imports from world trade in oil and corn. Using the latter approach, and consumer preferences in equation (1.1), we have

$$\begin{aligned} W = & \Big\{ I - C(Q_c) - \Omega(S_o) - w_e x_e - w_g x_g - \Big[p_o^w \bar{S}_o - p_c^w \bar{D}_c \Big] \Big\} \\ & + [\phi(x_g + x_e) + \theta(D_c) + \eta(D_h)] - \sigma(x_g + \lambda x_e) \end{aligned} \tag{1.18}$$

The term in curly brackets in (1.18) measures consumption of the numeraire good, y, while the term in square brackets on the second line measures consumer utility derived from consumption of fuel, corn and petroleum byproducts, and the last term measures the disutility due to pollution arising from energy consumption.[11] Consumption of the numeraire in (1.18) is total income I (taken as exogenous and measured in numeraire units) less (i) $C(Q_c)$, the cost of aggregate corn output; (ii) $\Omega(S_o)$, the cost of domestic oil production; (iii) $\{w_e x_e + w_g x_g\}$, the cost of the other inputs used in ethanol production and oil refining; and (iv) $[p_o^w \bar{S}_o - p_c^w \bar{D}_c]$, the value of net imports of oil and corn, which are paid for with the numeraire good. Note that the competitive equilibrium conditions $C'(Q_c) = p_c$ and $\Omega'(S_o) = p_o$ yield the inverse supply curves, so specification of the supply curves for the two goods, used in equilibrium conditions (1.8) and (1.9), implies the form of the cost relations in (1.18). Similarly, specification of the demand relations used in (1.8)-(1.10) imply the forms of the sub-utility functions in (1.18), so the only additional specification of functional forms needed for the welfare calculations is that of the externality term, $\sigma(\cdot)$. Thus, for the simulation exercise, welfare comparisons for different policy tools $(\tau_c, \tau_o, t, b; x_e^M)$ can be made by solving the equilibrium conditions from section 3, specifying $\sigma(\cdot)$ and then using (1.18) to calculate welfare.

To understand how the optimal (or second best) policies are determined, take the total differential of (1.18) and rearrange terms to yield (Lapan and Moschini, 2009)

$$\begin{aligned} dW = & (\theta' - C')dD_C + (\phi' - \lambda\sigma' - w_e - (C'/\alpha))\, dx_e + ([\phi' + (\beta_2/\beta)\eta' - \sigma'] - w_g - (\Omega'/\beta))\, dx_g \\ & + \Big(\Omega' - \Big[p_o^w + \bar{S}_o(dp_o^w/d\bar{S}_o)\Big]\Big)\, \bar{S}_o' dp_o^w + \Big(\Big[p_c^w + \bar{D}_c(dp_c^w/d\bar{D}_c)\Big] - C'\Big)\, \bar{D}_c' dp_c^w \end{aligned} \tag{1.19}$$

[11]This formulation does not explicitly impute pollution to the use of distillates. However, because gasoline and distillates are derived from a barrel of oil in fixed proportions in the model, then a tax on any one of them - properly adjusted - will have the same effect.

The first three terms in (1.19) relate to domestic resource allocation decisions, whereas the last two relate to trade decisions, and for each term, optimality entails equating marginal benefit to marginal cost. Thus, θ' is the value to consumers of additional corn consumption, C' is the marginal cost of corn production, and hence optimality requires that marginal benefit equals marginal cost $\{\theta' = C'\}$. Similarly, the second term-relating to ethanol production-says that the marginal value of fuel to consumers, less the pollution cost, should be equated to the marginal cost of producing ethanol. A similar interpretation applies to the third term, where the term in square brackets is the net social value of another unit of refined gasoline and byproducts, and $[w_g + \Omega'/\beta]$ is the extraction and refining cost of producing that gallon. The two terms in the second row relate to trade decisions and are the only places where (world) prices appear explicitly; domestic prices affect domestic welfare only insofar as they affect resource allocation, but changes in world prices affect domestic welfare directly. Thus, the last two terms state that the marginal cost of producing oil domestically should equal the marginal cost of importing oil, and that the marginal cost of producing corn domestically should equal the marginal revenue derived from corn exports.

In a market economy, rational consumers equate the marginal private value of a good to the market price they face, and competitive profit-maximizing firms will equate the marginal private cost to the prices they face. Hence, the rationale for government intervention arises when there is some divergence between private and social costs or benefits. In our model this divergence obviously occurs when fuel is consumed, because of the externality generated by the combustion of that fuel. Furthermore, from the perspective of the domestic economy, a divergence between private and (domestic) social costs also occurs if the country's trade decisions affect world prices. For example, for a competitive firm importing oil, the marginal private cost of the import is its price p_o^w, but from the perspective of the economy as a whole, if additional imports increase world price, the marginal cost of the import is higher than that, namely, $p_o^w + \bar{S}_o(dp_o^w/d\bar{S}_o)$. Similarly, for corn exports, the marginal value perceived by a competitive corn exporter is p_c^w, whereas the marginal revenue for the country as a whole is $p_c^w + \bar{D}_c(dp_c^w/d\bar{D}_c)$. Thus, as shown in Lapan and Moschini (2009), the first best policy entails oil import tariffs, corn export tariffs and a tax on carbon emissions.[12] As for the latter, the "carbon tax" is fully equivalent, in this model, to a fuel tax (i.e., a tax on both gasoline and ethanol) along with an ethanol subsidy (because of the assumed differential pollution of ethanol, captured by the parameter λ).[13] Specifically, it is shown that the "first best" policy instruments are[14]

$$\begin{aligned} t^* =& \sigma'(\cdot) \\ \tilde{b}^* =& (1-\lambda)\sigma'(\cdot) \\ \tau_o^* =& \bar{S}_o(\cdot)/\bar{S}_o'(\cdot) \\ \tau_c^* =& \bar{D}_c(\cdot)/\bar{D}_c'(\cdot) \end{aligned} \tag{1.20}$$

In our analysis, such a first best scenario provides an important (and insightful) benchmark for other, perhaps more realistic, policy scenarios. Another useful benchmark is the "*laissez faire*" scenario, i.e., the unfettered competitive equilibrium with $t = b = \tau_o = \tau_c = 0$. In fact, all welfare calculations are reported as differences relative to the *laissez faire*, and comparisons of each policy scenario with the first best provide information as to the efficacy of the various second best policies considered. Note that in all scenarios except the first best we restrict tariffs to be zero (i.e., $\tau_o = \tau_c + 0$) so that, realistically, they presume that the United States is in compliance with its WTO obligations.[15] Once we impose this restriction, we are operating in a "second best" environment and the (constrained) optimal values of these second best instruments depend on the feasible policy space. As noted, we assume the feasible policy instruments are fuel taxes and/or ethanol subsidies (or ethanol mandates and/or ethanol subsidies or fuel taxes).[16] Using these policy restrictions and the behavioral conditions outlined earlier, (1.19)

[12] Article 1, Section 9 of the U.S. Constitution states "No Tax or Duty shall be laid on Articles exported from any State" so that the first best policy could not be supported through export tariffs on corn. However, there are other constitutionally permissible policies that have the same economic consequences of export tariffs.

[13] The first best net ethanol subsidy, $\tilde{b}$, reflects the differential pollution rates between the two energy sources. The fact that the statutory fuel tax is in gallon terms implies a higher effective tax on ethanol in GEEG units. Thus, even if ethanol caused the same amount of pollution as gasoline, the first best would require a positive gross subsidy b to ethanol to offset the higher fuel tax.

[14] To calculate the actual values of the instruments, the equilibrium conditions described in Section 3 must be used in conjunction with (1.19).

[15] Because an import tariff on a given good is equivalent to a domestic production subsidy and a domestic consumption tax of the same amount, banning import tariffs is equivalent to placing a restriction on domestic policies, which explains the second best nature of these policy scenarios.

[16] Thus, for example, we do not allow a tax on domestic corn production.

can be rewritten as

$$dW = (p_f - p_e - \lambda\sigma')dx_e + (p_f - p_g - \sigma')dx_g - \bar{S}_o dp_o + \bar{D}_c dp_c \tag{1.21}$$

Thus, when tariffs are not permitted, in determining the welfare consequences of domestic policy instruments, one must consider their impact on the terms of trade as well as on carbon emissions. As we shall see from the simulations, under many plausible scenarios, it is these "large country" effects that dominate the welfare calculations. When there are no border policies, it can be shown that (1.21) reduces to[17]

$$dW = \left(p_f - p_e - \lambda\sigma' + \frac{\bar{D}_c}{\alpha Q'(p_c)}\right)dx_e + \left(p_f - p_g - \sigma' - \frac{\bar{S}_o}{\Delta'(p_o)}\right)dx_g \tag{1.22}$$

Here $\Delta(p_o) \equiv \beta(\bar{S}_o(p_o) + S_o(p_o))$ is the supply of unblended gasoline, and $Q_(p_c) \equiv \{S_c(p_c) - D_c(p_c) - \bar{D}_c(p_c)\}$ is the residual supply of corn for ethanol. When both fuel taxes and ethanol subsidies can be used, the second best policies are

$$\begin{aligned} t^{sb} =& \sigma' + \frac{\bar{S}_o}{\Delta'} \\ \tilde{b}^{sb} =& (1-\lambda)\sigma' + \frac{\bar{S}_o}{\Delta'} + \frac{\bar{D}_c}{\alpha Q'} \end{aligned} \tag{1.23}$$

where the superscript "sb" denotes second best. The tax t^{sb} can be thought of as the tax levied on gasoline, which incorporates two positive components because increased gasoline use worsens the U.S. terms of trade for oil and increases pollution costs. The difference between the tax and subsidy optimal levels, $\tilde{b}^{sb} - t^{sb} = \bar{D}_c/\alpha Q' - \lambda\sigma'$, represents the effective overall subsidy (or tax) on ethanol; the positive component reflects the fact that increased ethanol use benefits the United States by increasing world corn prices, while the negative component reflects the pollution costs associated with ethanol use.

When the ethanol subsidy is the only choice variable, the government cannot independently control gasoline and ethanol consumption. For this case it can be shown that the optimal

[17] The paper by Lapan and Moschini (2009) contains the details, but the logic underlying (1.22) is direct. If the government induces increased ethanol use, this increases the price of corn: specifically, $dp_c/dx_e = 1/\alpha Q'$. Similarly, increased gasoline use will drive up the price of oil, harming the country by making imports more expensive.

ethanol subsidy, as a function of the exogenous fuel tax, t^0, is[18]

$$\tilde{b}^{sub} = \frac{\bar{D}_c}{\alpha Q'} - \lambda\sigma' + \rho\left(\sigma' + \frac{\beta \bar{S}_o}{\psi'}\right) + (1-\rho)t^0 \tag{1.24}$$

where

$$\rho = \frac{\beta\Delta'}{\beta\Delta - D'_f + \beta\Delta'(\beta_2/\beta)^2(D'_f/D'_b)} \in (0,1)$$

Note that $\tilde{b}^{sub} = \tilde{b}^{sb} + (1-\rho)(t^0 = t^{sb})$. Hence, when the fuel tax is not a choice variable and $t^0 < t^{sb}$, then the subsidy will generally be lower than the second best subsidy and this subsidy will be increasing in the exogenous tax rate.

When only the mandate is the choice variable, it can be shown that the first-order condition for an optimal choice of the mandate reduces to[19]

$$\frac{dW}{dx_e} = \left(p_f - p_e - \lambda\sigma' + \frac{\bar{D}_c}{\alpha Q'}\right) + \left(p_f - p_g - \sigma' - \frac{\bar{S}_o}{\Delta'}\right)\left(\frac{dx_g}{dx_e}\right)^{man} = 0 \tag{1.25}$$

where the superscript "man" denotes the mandate scenario, and

$$\left(\frac{dx_g}{dx_e}\right)^{man} = \frac{-\left(1 + \left(\frac{-D'f}{\alpha^2 Q'}\right)s + (1-s)\delta\left(\frac{-D'f}{x_f}\right)\right)}{1 + (-D'f)\left(\frac{1}{\beta\Delta'} + \frac{(\beta_2/\beta)^2}{-D'_f}\right)(1-s) + \frac{s\delta D'f}{x_f}}$$

where $s \equiv x_e/(x_e + x_g) \in (0,1)$ denotes the share of ethanol in total fuel, and $\delta \equiv (p_f - p_g - \tilde{b}) > 0$. In the simulations that follow, we consider each of the cases discussed above.

1.5 Calibration of the Model

The baseline model is calibrated to fit 2009 data using linear supply and demand curves. In order to calibrate the model, we need to specify the values of the exogenous parameters and the value of the policy variables in this baseline period. In addition, we also need to specify the domestic and world import demand functions for corn $D_c(p_c)$ and $\bar{D}_c(p_c^w)$, the domestic supply of corn $S_c(p_c)$, the domestic and world export supply functions for oil $S_o(p_o)$ and $\bar{S}_o(p_o^w)$, the demand for fuel $D_f(p_f)$ and the demand for petroleum byproducts $D_h((p_h)$. If these functions

[18]This formula differs from the corresponding one in Lapan and Moschini (2009) because here we explicitly allow for the presence of petroleum byproducts, a feature that is important for the quantitative results of interest in this study. In the special case where $\beta_2 = 0$ (i.e., no byproducts), of course, the two conditions are identical.

[19]Again, the procedure for deriving this result is similar to that in Lapan and Moschini (2009), but the specific result differs because of the presence, in our model, of petroleum byproducts.

come from a two-parameter family of functions, as for the linear functional forms that we will be using, each demand or supply function can be "calibrated" using an estimate of the elasticity (of supply or demand) for that function and the value of the relevant variables in the baseline period.

Table 1.1 gives the assumed baseline values, and sources, for the primitive parameters (e.g., elasticities) used in the calibration of the model, and Table 1.2 gives the value of some other calculated parameters, and their method of calculation, which are provided to ease the interpretation of the model. Tables 1.3 and 1.4 give the primary sources (or methods of calculation) and the 2009 value used for each baseline variable, including the policy variables. Some parameters are drawn from a comprehensive survey of the literature, while others are calculated from their definitions in terms of more primitive terms. In general, data for corn utilization and price are gathered from the Feed Grain Database of the U.S. Department of Agriculture (USDA) at http://www.ers.usda.gov/Data/FeedGrains/, and data for oil, gasoline and oil refinery byproducts are obtained from the U.S. Energy Information Administration (EIA) website at http://www.eia.doe.gov/. Ethanol quantity data are from the Renewable Fuels Association (RFA) website and ethanol prices are provided by the Nebraska Energy Office (NEO) website at http://www.neo.ne.gov/statshtml/66.html. More specific information on sources of data used is provided in the tables that follow.

1.5.1 Prices in the Baseline

Because ethanol has a lower energy content than gasoline, its quantity, price, fuel tax and subsidy level used in the simulation are all converted to be expressed per GEEG. Currently, fuel consumption (blended gasoline with ethanol) is subject to the federal tax of \$0.184/gallon plus state-level taxes, which are, on average, equal to \$0.203/gallon. Hence, for gasoline, $t^0 = \$0.39$. However, because one gallon of ethanol equals only 0.69 GEEG, the fuel tax on ethanol is t^0/γ, that is, \$0.565/GEEG. Ethanol production has a tax credit of \$0.45/gallon when blended with gasoline, which is equivalent to a net subsidy to ethanol of $\tilde{b}^0 = \$0.475$/GEEG. The U.S. ethanol price of \$1.79/gallon is the 2009 average rack price F.O.B. Omaha, Nebraska, and this

Table 1.1: Primitive Parameters Used to Calibrate the Model

Parameter	Symbol	Value	Source/Explannation
Domestic supply elasticity of oil	ε_o	0.20	de Gorter and Just (2009b)
Foreign supply elasticity of oil	$\bar{\varepsilon}_o$	3.00	de Gorter and Just (2009b)
Domestic supply elasticity of corn	ε_c	0.30	Westhoff (2010)
Foreign demand elasticity of corn	$\bar{\eta}_c$	-1.50	FAPRI (2004)
Domestic demand elasticity of corn	η_c	-0.20	de Gorter and Just (2009b)
Demand elasticity of fuel	η_f	-0.50	Toman, Griffin and Lempert (2008)
Demand elasticity of petroleum byproducts	η_h	-0.50	Assumed equal to η_f
Ethanol produced by one bushel of corn (gallons/bushel)	a	2.8	Eidman (2007)
DDGS production coefficient	δ_1	0.303	$\delta_1 = 17/56$
DDGS relative price to corn	δ_2	0.776	$\delta_2 = (114.4 \times 56)/(3.74 \times 2205)$
Gasoline production coefficient (gallon/barrel)	β	23.6	$\beta = x_g/x_o$
Ethanol heat content (BTUs/gallon)	γ_e	76,000	NREL (2008)
Gasoline heat content (BTUs/gallon)	γ_g	110,000	NREL(2008)
CO_2 emissions rate of gasoline (kg/gallon)	CE_g	11.29	Wang (2007)
CO_2 emissions rate of ethanol (kg/GEEG)	CE_2	8.42	Farrel et al. (2006)
Marginal emissions damage ($\$tCO_2$)	$\tilde{\sigma}'(\cdot)$	20	Stern (2007), NHTSA (2009)

corresponds to a price of \$2.59/GEEG.[20] Prices of fuel and (unblended) gasoline are calculated from arbitrage conditions, which are assumed to hold in the *status quo*, that is, $p_f = p_e - \tilde{b}^0 + t^0 =$ \$2.50/GEEG, and $p_g = p_e - \tilde{b}^0 =$ \$2.11/GEEG.[21] The crude oil price of \$61.00/barrel is the refiner's composite acquisition cost of crude oil, the weighted average of acquisition costs of domestic and imported oil. The corn price of \$3.74/bushel uses the averaged farm price. The USDA price of the byproduct in ethanol production, DDGS, is \$114.40/t (metric ton), which reflects the wholesale price in Lawrenceburg, IN. We used EIA data to calculate a weighted average retail price, excluding taxes, for petroleum byproducts in the oil refining process; this price index is denoted p_h, and its 2009 value is \$1.76/GEEG.[22] The prices of the "other" inputs used in gasoline and ethanol production, w_g and w_e, are derived from the zero profit condition, $w_g = p_g + \beta_2 p_h/\beta =$ \$1.10/GEEG and $w_e = p_e - p_c/\alpha =$ \$1.11/GEEG, respectively. The estimated productivity parameters α, β and β_2 are discussed next.

1.5.2 Productivity Parameters

One bushel of corn produces approximately 2.80 gallons of ethanol (Eidman, 2007); thus $a = 2.80$. The production of ethanol generates bioproducts that are useful as animal feed (and thus can replace corn in that use). The nature of such bioproducts depends on whether ethanol is produced in a dry milling plant or in a wet milling plant. Because dry milling plants are much more common, we construct the model as if all ethanol is produced in dry milling plants.[23] According to industry sources (RFA), such a process generates as a byproduct about 17 lbs of DDGS per bushel of corn; given that there are 56 pounds in a bushel, then $\delta_1 = 0.303$. The DDGS price relative to the corn price is captured by the parameter $\delta_2 = 0.776$, calculated as described in Table 1.1 from the data discussed in the foregoing. Given the assumption of

[20] See http://www.neo.ne.gov/statshtml/66.html for the primary data.

[21] This calculation method ensures the internal consistency of our model. A question, perhaps, is how close this calculated value is to 2009 observed data. From EIA data, the average retail price of all grades and all formulations of gasoline in 2009 was \$2.406/gallon, which is fairly close to the calculated fuel price. Also, from the same source, the average wholesale (rack) price of gasoline in 2009 was \$1.75/gallon, which is not too close to our computed gasoline price.

[22] Because prices for all the byproducts of the refining process were not available, the price index we constructed only uses the prices of aviation gasoline, kerosene-type jet fuel, kerosene, distillate fuel oil, and residual fuel oil. Together, these products account for 70%, by weight, of all petroleum byproducts in the oil refining process.

[23] According to the RFA, more than 80% of corn used in ethanol production is processed via dry milling plants, with the remaining 20% processed via wet milling plants.

Table 1.2: Calculated Parameters Used in the Model

Parameter	Symbol	Value	Source/Explanation
Derived supply elasticity of ethanol	ε_g	5.01	$\varepsilon_e = (\varepsilon_c^s S_c - \eta_c D_c - \bar{\eta}_c \bar{D}_c)\alpha p_e / Q_c p_c$
Derived supply elasticity of gasoline	ε_g	1.61	$\varepsilon_g = (\varepsilon_o S_o + \bar{\varepsilon}_o \bar{S}_o)\beta p_g / x_o p_o$
Portion value of DDGS returning to corn market	$\delta_1\delta_2$	0.24	calculated
Ethanol produced by one bushel of corn accounting for DDGS value (GEEG/bushel)	α	2.53	$\alpha = \frac{a\gamma}{1-\delta_1\delta_2}$
Petroleum byproduct production coefficient (GEEG/barrel)[1]	β_2	21.1	$\beta_2 = 42 \times 1.065 - \beta$
Ethanol energy equivalent coefficient (GEEG/gallon)	γ	0.69	$\gamma = \gamma_e \gamma_g$
Relative pollution efficiency	λ	0.75	$\lambda = \mathrm{CE}_g / \mathrm{CE}_g$
Normalized marginal emissions damage of gasoline ($/gallon)	$\sigma'(\cdot)$	0.226	$\sigma'(\cdot) = \tilde{\sigma}'(\cdot)\mathrm{CE}_g/1000$

[1] A 42-U.S. gallon barrel of crude oil provided around 6.5% average gains from processing crude oil in 2009 (see Refinery Yield Rate Table (EIA) accessible at http://tonto.eia.doe.gov/dnav/pet/pet_pnp_pct_dc_nus_pct_m.htm

perfect substitution between corn and DDGS in feed use, then each processed bushel of corn generates, as a byproduct, the equivalent of $\delta_1\delta_2 = 0.24$ bushels of corn.[24] Hence, the ethanol production coefficient, accounting for byproduct value, is $\alpha = 2.53$ GEEG/bushel.

1.5.3 Quantities in the Baseline

For the baseline scenario, we use domestic production including stock changes and other adjustments to measure domestic supply, net exports of corn to measure foreign demand and net imports of oil to measure foreign oil supply. In the *status quo* (for 2009), there are 13.15 billion bushels of corn and 1.93 billion barrels of domestic oil produced in the U.S. The quantities of foreign corn demanded (U.S. exports) and oil supplied (U.S. imports) were 1.86 billion bushels and 3.29 billion barrels, respectively. Corn utilization consists of three main uses: domestic food/feed use (exclusive of ethanol use), foreign demand (exports) and ethanol use. The U.S. ethanol production of 10.76 billion gallons (RFA data) corresponds to 7.43 billion GEEG. Given

[24] EPA now assumes that 1 pound of distillers grains will replace 1.196 pounds of total corn and soybean meal for various beef cattle and dairy cows in 2015. The displacement ratio remains at 1:1 for swine and poultry (EPA 2010).

the assumed fixed-proportion technology of ethanol production, the net amount of corn used in ethanol production is calculated to be $Q_c = x_e/\alpha = 2.94$ billion bushels. The corn food/feed use is then obtained from market balance, where $D_c = S_c - \bar{D}_c - Q_c = 8.35$ billion bushels. EIA reports data for the finished motor gasoline product, including blended ethanol, of 134.4 billion gallons, which measures total fuel consumption in volumetric units. Subtracting ethanol production (in volumetric units) from the figure for finished motor gasoline gives unblended gasoline's contribution to total fuel consumption, $x_g = 123.6$ billion GEEG units. Final fuel consumption, measured in GEEG units is the sum of gasoline and ethanol consumption in the same units, $x_f = x_g + x_e = 131.0$ billion GEEG units. The assumed fixed-proportions technology in oil refining gives the calculated yield of gallons of gasoline per barrel of crude oil as $\beta = x_g/x_o = 23.6$ GEEG/barrel.[25] Given β, the yield of petroleum byproducts (in gallons) from a barrel of crude oil is calculated to be $\beta_2 = 21.1$.[26]

1.5.4 Carbon Emissions

We use the carbon emission rate of gasoline, measured as carbon dioxide (CO_2), of 11.29 kg/GEEG (Wang, 2007).[27] As for the net carbon dioxide emissions of ethanol, in our baseline we apply the rate of 8.42 kg/GEEG of CO_2 from the life cycle perspective suggested by Farrel et al. (2006), which is close to the emission rate of corn ethanol with feedstock credits but without land-use changes reported in Searchinger et al. (2008).[28] These values, in turn, imply that the relative pollution efficiency of ethanol to gasoline (i.e., the parameter γ) is around 0.75 in our benchmark case, a parameterization that is consistent with EPA (2010). There

[25] Alternatively, one could recover the parameter from refinery yields data reported by EIA, e.g., β = (42 gallon/barrel) $\times$ (1 $-$ Annual Average Process Gains) $\times$ (Finished Motor Gasoline Yield). Note that this formula accounts for the fact that EIA measures gains as negative numbers. This procedure would yield $\beta = 20.6$ GEEG/barrel. The discrepancy of this value with the one we use, as explained in the text, is likely due to the additives in blended gasoline.

[26] As explained in Table 1.1, there are 42 gallons per barrel of crude oil, and because of a yield gain in the refining product, there are approximately 44.7 gallons of refined product per barrel of oil. Subtracting the calculated value of 23.6 gallons of gasoline per barrel of crude oil provides the calculated value of β_2.

[27] Numerous factors complicate the choice of an appropriate emissions rate. Fixed proportions between gasoline and distillates (and no trade in these products) imply the emissions rate used here should reflect the pollution generated by both gasoline and distillates. On the other hand, because in our model U.S. policy depresses the world oil price, the lower U.S. oil consumption is partly offset by increased usage in the rest of the world (i.e., a leakage effect), which leads to a lower net emissions rate. Our parametric assumptions essentially presume that these effects offset each other.

[28] The feedstock credits refer to the carbon benefit of devoting land to biofuels (Searchinger et al. 2008).

Table 1.3: Value of Variables at the Calibrated Point (raw data for year 2009)

Variable	Symbol	Value	Source/Explanation
Fuel tax ($/gallon)	t^0	0.39	sum of federal tax 18.4c/gal and weighted average of state tax 20.6c/gal (EIA).[1]
Ethanol subsidy ($/gallon)	b^0	0.45	RFS2
Oil price ($/barrel)	p_o	61.0	composite acquisition cost of crude oil (EIA).[2]
Corn price ($/bushel)	p_c	3.74	weighted average farm price of corn (Feed Grains Database, USDA).[3]
Ethanol price ($/gallon)	p_e^v	1.79	ethanol average rack price in Omaha, Nebraska
DDGS price ($/ton)	p_d	114.4	wholesale price in Lawrenceburg, IN (Feed Grains Database, USDA).[4]
Domestic oil supply (billion barrels)	S_o	1.93	production plus adjustments and stock changes (EIA).[5]
Foreign oil supply (billion barrels)	$\bar{S}_o$	3.29	net import (EIA).
Ethanol supply (billion gallons)	x_e^v	10.76	domestic production (RFA).
Fuel demand (billion gallons)	D_f^v	134.4	finished motor gasoline including ethanol (EIA).
Domestic corn supply (billion bushels)	S_c	13.15	domestic production (Feed Grains Database, USDA).[6]
Foreign corn import demand (billion bushels)	$\bar{D}_c$	1.86	net export (Feed Grains Database, USDA).

1. These tax values are taken from the EIA table "Federal and State Motor Fuels Tax" at: http://www.eia.doe.gov/pub/oil_gas/petroleum/data_publications/petroleum_marketing_monthly/current/pdf/enote.pdf.
2. Oil price comes from table "Refiner Acquisition Cost of Crude Oil" (EIA) http://tonto.eia.doe.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm.
3. Corn price comes from table "Corn and Sorghum: Average Prices Received by Farmers" (Feed Grains Data, USDA), http://www.ers.usda.gov/Data/FeedGrains/Table.asp?t=09.
4. DDGS price comes from table "Byproduct Feeds: Average Wholesale Price, Bulk, Specified Markets" (Feed Grains Data, USDA), http://www.ers.usda.gov/Data/FeedGrains/Table.asp?t=16.
5. Oil domestic/foreign supply and fuel/ethanol supply on volumetric basis come from table "Supply and Disposition" (EIA), http://tonto.eia.doe.gov/dnav/pet/pet_sum_snd_d_nus_mbbl_m_cur.htm.
6. Corn supply and foreign demand come from table "Corn: Supply and Disappearance" (Feed Grains Data, USDA), http://www.ers.usda.gov/Data/FeedGrains/Table.asp?t=04.

is, of course, considerable uncertainty (and controversy) about ethanol's actual carbon dioxide emissions. For example, Searchinger et al. (2008) estimate that, when they account for land-use changes, the net carbon emission of ethanol is 93% larger than gasoline.[29] To capture the influence of such uncertainty, the sensitivity analysis carried out later will consider the range $[0.5, 2]$ for the parameter λ.

Table 1.4: Variables at the Calibrated Point (calculated values)

Variable	Symbol	Value	Source/Explanation
Net ethanol subsidy ($/GEEG)	$\tilde{b}^0$	0.477	$\tilde{b}^0 = b^0/\gamma - (1-\gamma)t^0/\gamma$
Ethanol price ($/GEEG)	p_e	2.59	$p_e = p_e^v/\gamma$
Fuel price ($/GEEG)	p_f	2.50	$p_f = p_e - \tilde{b}^0 + t^0$.[1]
Gasoline price ($/GEEG)	p_g	2.11	$p_g = p_e - \tilde{b}^0$
Price of inputs other than corn in ethanol production ($/GEEG)	w_e	1.11	$w_e = p_e - p_c/\alpha$
Price of inputs other than oil in gasoline production ($/GEEG)	w_g	1.10	$w_g = p_g + \beta_2 p_h/\beta - p_o/\beta$
Price of petroleum byproducts ($/GEEG)	p_h	1.76	weighted average retail price excluding taxes (EIA).[2]
Quantity of petroleum byproducts (billion GEEG)	x_h	110.3	$x_h = \beta_2 x_o$
Oil supply (billion barrels)	x_o	5.22	$x_o = S_o + \bar{S}_o$
Corn used in ethanol production accounting for byproduct value (billion bushel)	Q_c	2.94	$Q_c = x_e/\alpha$
Domestic corn demand as foodn/feed uses (billion bushels)	D_c	8.35	$D_c = S_c - \bar{D}_c - Q_c$
DDGS supply (billion bushels)	x_d	0.89	$x_d = \delta_1 Q_c$
Ethanol supply (billion GEEGs)	x_e	7.43	$x_e = \gamma x_e^v$
Gasoline supply (billion GEEGs)	x_g	123.6	$x_g = D_f^v - x_e^v$
Fuel demand (billion GEEGs)	D_f	131.0	$D_f = x_g + x_e$

1. Ethanol subsidy, quantity and price are converted into GEEG units in simulation.
2. Price index includes resale prices to end users excluding taxes for aviation gasoline, kerosene-type jet fuel, kerosene, distillate fuel oil, and residual fuel oil, which come from table "Refiner Petroleum Product Prices by Sales Type" (EIA), http://tonto.eia.doe.gov/dnav/pet/pet_pri_refoth_dcu_nus_m.htm.

[29] Hertel et al. (2010) provide a lower estimate of ILUC emissions, which is roughly one-fourth the value estimated by Searchinger et al. (2008). But their estimates still suggest the pollution inefficiency of ethanol relative to gasoline when accounting for ILUC.

1.5.5 Carbon Emissions Cost

There are many estimates regarding the social cost of carbon dioxide emissions. Tol (2009) surveys 232 published estimates of the marginal damage cost of carbon dioxide. The mean of these estimates is a marginal cost of carbon emissions of \$105/tC (metric ton carbon), which is equivalent to \$28.60/tCO_2, with a standard deviation equivalent to \$243/tC (\$66/tCO_2), where social costs are measured in 1995 dollars. The widely cited "Stern Review" (Stern, 2007) has a higher estimate of approximately \$80/tCO_2, due to a lower discount rate applied to future economic damage from climate change. The National Highway Traffic Safety Administration (NHTSA) calculates their proposed corporate average fuel economy (CAFE) standard by relying on Tol's (2008) survey, which includes 125 estimates of the social carbon cost published in peer-reviewed journals through the year 2006 (NHTSA, 2009). Tol (2008) reports a \$71/tC mean value, and a \$98/tC standard deviation of these estimates of the social carbon cost (expressed in 1995 dollars). Adjusted to reflect increases of emissions at now-higher atmospheric concentrations of GHGs, and expressed in 2007 dollars, Tol's (2008) mean value corresponds to \$33/tCO_2, and this is the mean value for the global cost of carbon used by NHTSA (2009). The EPA (2008) derives estimates of the social carbon cost using the subset of estimates in Tol's (2008) survey and reports average global values of \$40/tCO_2 (for studies using a 3% discount rate) and \$68/tCO_2 (for studies using a 2% discount rate).

Because of the U.S.-centered welfare function used here, the pollution externality cost used in our modeling framework should arguably reflect local and global warming costs to the United States. In the baseline we use a value of \$20/tCO_2, which essentially is the estimate provided by the Stern review, adjusted to reflect the U.S. share of the world economy. Whereas some might think that the reference parameter of the Stern review is perhaps too high,[30] others might yet argue that it is the global damage due to carbon emission that ought to be considered. Also, as noted by a reviewer, other externality costs associated with congestion, accidents and non-carbon pollution are not explicitly taken into account.[31] In the end, because of the uncertainty

[30] Using a more conventional discount rate, Hope and Newbery (2008) find that the (global) carbon cost from the Stern report could be reduced to the range of \$20-\$25/tCO_2.

[31] Parry and Small (2005) take the lower and upper limit of pollution damages to be \$0.7/tC and \$100/tC respectively, and the central value to be \$25/tC (expressed in year 2000 dollars). They also account for external congestion costs of 3.5c/mile, and an external accident cost of 3c/mile.

and controversy surrounding this parameter, one might want to rely on sensitivity analysis to explore the impact of alternative parametric assumptions. For the sensitivity analysis discussed later, we take the global value of the Stern Review estimate of \$80/tCO_2 as the upper bound of the range we consider, with a lower bound of \$5/tCO_2. Given the assumed linear cost function of the emissions externality $\sigma(\cdot)$, the marginal effect $\sigma'(\cdot)$ represents the normalized constant marginal emissions damage from gasoline. Given our assumption of \$20/tCO_2 for the cost of carbon dioxide pollution, $\sigma'(\cdot) = \$0.23/\text{GEEG}$.

1.5.6 Elasticities

The elasticity values that we use are taken from the literature to reflect the consensus on the available econometric evidence. For the corn supply elasticity we rely on FAPRI estimates (Westhoff, 2010) and set $\varepsilon_c = 0.3$ in our benchmark,[32] with a range of $[0.1, 0.5]$ used in the sensitivity analysis. The elasticity of domestic food/feed demand of $\eta_c = -0.2$ is from de Gorter and Just (2009b), and we explore the range $[-0.5, -0.2]$ in the sensitivity analysis. The estimates for the elasticity of foreign corn import demand range from an inelastic value of -0.30 (short-run value) used by Gardiner and Dixit (1986), to a considerably more elastic value reported by the country commodity linked system performed by the Economics Research Service at the USDA. The latter, following a sustained exogenous shock to the world price of corn only, obtain an implied elasticity of net foreign corn imports in the third year of -2.41. We use a benchmark value for this parameter of $\bar{\eta}_c = -1.5$, which is consistent with a popular modeling platform (FAPRI, 2004), and also carry out sensitivity analysis within the range of $[-3, -1]$.

For the elasticities of domestic oil supply we follow de Gorter and Just (2009b) and assume $\varepsilon_o = 0.2$, with the range $[0.1, 0.5]$ explored in the sensitivity analysis. This is a more inelastic assumption than that suggested in Toman, Griffin, and Lempert (2008), who provides a range of $[0.2, 0.6]$ for the long-run domestic oil supply elasticity with a baseline value of 0.4. For the foreign export oil supply elasticity we assume the baseline value of $\bar{\varepsilon}_o = 3$, which is similar to

[32] Gardner (2007) uses a short-run elasticity of 0.23 and a long-run elasticity of 0.5; de Gorter and Just (2009b) use 0.2 as the elasticity of corn supply.

the 2.63 value used by de Gorter and Just (2009b), and analyze the range $[1, 5]$ in the sensitivity analysis. The elasticity of fuel demand is assigned a benchmark value of $\eta_f = -0.5$, with the range $[-0.9, -0.2]$, as suggested by Toman, Griffin, and Lempert (2008), which is fairly similar to the value and range considers by Parry and Small (2005). Not much explicit evidence exists on the elasticity of petroleum byproduct demand, hence we adopt the same baseline value and range as the elasticity of fuel demand. As for elasticities of gasoline and ethanol supply, the construction of our model does not need these as primitive parameters, although the implied elasticities of the derived ethanol supply and gasoline supply are easily derived for the purpose of comparison with other models.[33]

1.6 Results

Given the assumed parameters discussed in the foregoing section, the remaining parameters of the model are calibrated (i.e., the coefficients of the postulated linear supply and demand curves are computed) to replicate price and quantity data of the baseline (or *status quo*) scenario for the calendar year 2009. We then consider a number of policy environments; only in the first-best situation are border policies (import and export tariffs) allowed. These scenarios are as follows:[34]

(i) *Laissez faire*, with no border or domestic taxes or subsidies.

(ii) No ethanol policy: current fuel tax but without ethanol subsidy or mandates.

(iii) *Status quo*, with the current fuel tax and ethanol policy.

(iv) The first best: border policies and domestic policies are used.

(v) The second best: the fuel tax and ethanol subsidy are chosen optimally.

(vi) The ethanol subsidy is chosen optimally; the fuel tax is set at its current level.

[33] Quantities are given by production technology, and prices are found from long-run equilibrium conditions, as explained in the text. Given these quantities and prices, the implied elasticities (in the baseline case) of the derived ethanol supply and gasoline supply can be calculated as per the formulae reported in Table 1 to yield $\varepsilon_e = 5.01$ and $\varepsilon_g = 1.61$, respectively.

[34] Our analysis does not consider other farm policies, such as deficiency payments. The policies we do consider may make the economic impact of these other policies essentially irrelevant.

(vii) An ethanol mandate is chosen optimally; the fuel tax is set at its current level.

For each scenario, we report in Table 1.5 the values of the policy instruments and the equilibrium value of the simulated variables. In Table 1.6, for the same sets of scenarios, we report the welfare impacts (as changes from the fictitious *laissez faire* equilibrium), broken down into their components so as to illustrate the distributional effect, as well as the impact of each scenario on the total carbon emission.[35] The overall net welfare gains are calculated in the usual manner, by summing the (changes in) producer surpluses, consumer surpluses, government tax revenue and the pollution damages.[36] Our results show that all the policy scenarios improve upon the *laissez faire* equilibrium solution. The presence of a market failure implies that optimally chosen policies must do so, of course, but it is perhaps a bit surprising that seemingly ad hoc policies (like the *status quo*) also do so. In particular, the *status quo* equilibrium with ad hoc levels of the ethanol subsidy and the fuel tax captures over one-half of the maximum gain that can be achieved with first-best policies.[37]

1.6.1 *Status Quo* and *Status Quo Ante* Ethanol

The *status quo* values for prices and quantities reflect the actual (average) values of those variables for 2009. Compared to the simulated *laissez faire* equilibrium, the fuel tax of $0.39/GEEG and the gross ethanol subsidy of $0.45/gallon lead to higher (retail) fuel prices, higher ethanol prices, a modest 3% decline in (world and domestic) oil prices but a significant 18% increase in corn prices. Consequently, the combined policy causes domestic fuel consumption to fall somewhat, as a 6.9 billion gallon decline in gasoline consumption is only partly offset by a 4.73 billion gallon (equivalent to 3.26 billion GEEG) increase in ethanol consumption. This

[35] The producer surpluses for ethanol producers and oil refiners are zero because of the assumed constant-returns-to-scale technology and competitive behavior in these sectors

[36] Because ethanol production for 2009 exceeds the mandate level, in calibrating the model we assume that the mandate does not bind, and that it is the fuel tax and ethanol subsidy policies that affect equilibrium values.

[37] We note at this juncture that we do not explicitly model the fact that energy is an input in the production of corn and ethanol (the calculation of emissions, which uses the lifecycle approach, does account for the energy content of this production). Because in this model resources have to be diverted from production of other goods (the numeraire) to increase corn and ethanol production, this omission would matter if corn and ethanol production were more energy-intensive than other sectors in the economy. In such a case, the resulting corn and ethanol supply curves would depend upon energy prices and be more inelastic since increased corn production will raise energy prices, shifting the supply curve leftward. In this case, policies promoting ethanol are likely to lead to even higher increases in corn prices than in our model.

Table 1.5: Market Effects of Alternative Policy Scenarios

	Laissez Faire	No Ethanol Policy	*Status Quo*	First Best	Optimal Tax & Subsidy	Optimal Subsidy	Optimal Mandate
Fuel tax ($/gallon)	0.00	0.39	0.39	0.23	0.96	0.39	0.39
Ethanol subsidy ($/gallon)	0.00	0.00	0.45	0.11	1.02	0.67	0.00
Oil tariff ($/barrel)	0.00	0.00	0.00	17.53	0.00	0.00	0.00
Corn tariff ($/bushel)	0.00	0.00	0.00	1.26	0.00	0.00	0.00
Fuel price ($/GEEG)	2.36	2.64	2.50	2.75	2.74	2.44	2.47
Gasoline price ($/GEEG)	2.36	2.25	2.11	2.52	1.78	2.05	1.98
Ethanol price ($/gallon)	1.63	1.43	1.79	1.78	1.95	1.96	2.01
U.S. oil price ($/barrel)	62.8	62.0	61.0	75.7	58.7	60.5	60.1
U.S. corn price ($/bushel)	3.17	2.44	3.74	3.71	4.32	4.38	4.56
Petroleum byproduct price ($/GEEG)	1.56	1.65	1.76	2.00	2.02	1.81	1.86
Gasoline quantity ($/GEEG)	130.5	127.4	123.6	115.1	114.3	121.7	119.9
Ethanol quantity (billion gallons)	6.03	0.05	10.76	13.94	15.51	16.02	17.45
Corn production (billion bushels)	12.55	11.78	13.15	13.12	13.76	13.83	14.01
Corn demand (billion bushels)	8.61	8.93	8.35	8.37	8.10	8.07	7.99
Corn export (billion bushels)	2.29	2.83	1.86	0.94	1.43	1.38	1.25
Oil domestic supply (billion barrels)	1.94	1.94	1.93	2.03	1.92	1.93	1.93
Oil import (billion barrels)	3.57	3.45	3.29	2.84	2.91	3.21	3.14

Notes: Although we use GEEG units for ethanol price, subsidy and quantity in our simulation, as discussed in the text, for ease of interpretation the results reported here are converted into natural units.

(small) drop in fuel consumption, and the substitution of some ethanol for gasoline, leads to a 3% (or a 50.9 million tCO_2) decrease in carbon emissions; at the baseline cost of \$20/tCO_2, this is equivalent to a \$1 billion decrease in pollution costs. As Table 1.6 shows, the principal beneficiaries of this *status quo* policy are the government (higher tax revenue) and corn producers, while oil producers are hurt by the fuel tax and consumers are hurt by higher prices (but they benefit, however modestly, because of the reduced externality incidence). Relative to the *laissez faire* there is a \$6.7 billion increase in net welfare, which amounts to 58% of the maximum gain achievable by optimum policies. U.S. dependence on foreign oil also declines, as oil imports fall by about 8%.

The column "no ethanol policy" in Tables 1.5 and 1.6 looks at the scenario in which the current fuel tax of \$0.39/GEEG continues to apply, but there is no subsidy or other policy supporting ethanol production. When compared to the *status quo* scenario, this case provides a useful characterization of the marginal impact of current U.S. ethanol policies. Specifically, without such policies the ethanol industry would be almost non-existent (only 0.05 billion gallons of production). The lack of explicit government support is not the only effect working against ethanol production in this scenario: the fuel tax, being levied per volume of fuel, implicitly taxes ethanol at a higher rate (because of the latter's lower efficiency level in GEEG terms). The fuel price is also higher with no ethanol policy than in the *status quo*, which illustrates an aspect of current policies discussed by de Gorter and Just (2009b): the ethanol subsidy has a consumption subsidy effect for final consumers. As for welfare effects, the introduction of the current ethanol support policy is beneficial (the welfare measure of the *status quo* exceeds that of the no ethanol policy scenario by \$6.2 billion). But note that the mechanism by which this happens is not by reducing pollution, which actually is higher under the *status quo* than under the no ethanol policy scenario (by 19.2 million tCO_2). Instead, ethanol policies are mostly useful because of their terms-of-trade effects. Comparison of these two scenarios in Table 1.6 also illustrates that the big winners from the ethanol policy are corn producers and fuel consumers.

Table 1.6: Welfare Effects of Alternative Policies (change relative to *laissez faire*)

	Laissez Faire	No Ethanol Policy	*Status Quo*	First Best	Optimal Tax & Subsidy	Optimal Subsidy	Optimal Mandate
Social welfare ($ billion)	–	0.5	6.7	11.5	9.9	7.5	8.2
Pollution effect ($ billion)	-30.2	1.4	1.0	2.6	2.6	0.8	1.1
Tax revenue ($ billion)	0	49.7	47.6	78.5	108.5	43.0	53.6
P.S. oil supply ($ billion)	–	-1.5	-3.4	25.8	-7.9	-4.3	-5.2
P.S. corn supply ($ billion)	–	-8.8	7.4	7.0	15.2	16.0	18.4
C.S. corn demand ($ billion)	–	6.4	-4.9	-4.6	-9.6	-10.1	-11.5
C.S. fuel demand ($ billion)	–	-36.4	-18.7	-49.6	-48.3	-9.8	-14.3
C.S. petroleum byproduct ($ billion)	–	-10.2	-22.3	-48.1	-50.5	-28.2	-33.9
CO_2 emissions (million tCO_2)	1509.0	-70.1	-50.9	-128.7	-128.7	-41.4	-54.2

1.6.2 The First Best Policies

In the baseline scenario, the marginal emissions damage is \$20/tCO_2 and thus the first best policy entails a tax on carbon emissions of \$20/tCO_2, in addition to oil import and corn export tariffs. This carbon tax is equivalent, in our model, to a gasoline tax of \$.23/GEEG, which is actually smaller than the *status quo* (average) fuel tax of \$0.39. Since in the baseline model ethanol is assumed to pollute less than gasoline, and since the \$0.23 tax is assumed levied on gallons of fuel, then a gross subsidy to ethanol of \$0.11/gallon is required to support the first best solution. Thus, the first best policies entail a 17c/GEEG tax on ethanol, a 23c/GEEG tax on gasoline, a \$17.5/barrel import tariff on oil, and a \$1.26/bushel export tariff on corn. These policies would increase welfare by \$11.5 billion compared to the *laissez faire* scenario, and \$4.8 billion relative to the *status quo*. Compared to the *laissez faire* scenario, the combined effect of these policies is to increase U.S. oil prices by about 21%, while world oil prices fall by about 7%. Despite the corn export tariff, U.S. corn prices increase by 17% (world corn prices rise by 58%); because of the conversion of corn into ethanol, the negative impact on U.S. corn prices of the corn export tariff is overwhelmed by the positive impact of higher domestic oil prices. Overall fuel consumption falls significantly, and ethanol replaces some gasoline, so carbon emissions fall by 8.5%. U.S. dependence on foreign oil falls sharply, as imports fall by 20%, oil consumption falls and domestic oil production rises. From a welfare perspective, domestic oil producers and corn producers both gain and the government gains significant tax revenue, but consumers lose both because of higher oil (and fuel) prices and because of higher corn prices.

Compared to current policies, the first best policy leads to a significant reduction in oil imports, fuel consumption and pollution, and a significant increase in ethanol production. Corn prices fall as the negative impact of the lower ethanol subsidy and the corn export tariff more than offset the positive impact on corn prices because of the oil import tariff. Thus, while the implementation of first best policies brings a welfare gain of $4.8 billion compared to the *status quo*, there is a significant redistribution of income away from consumers and corn producers to oil producers and the government. About a third of the welfare gain is accounted for by the decline in pollution costs.

1.6.3 Second Best Policies: Fuel Taxes and Ethanol Subsidies

The second best fuel tax and ethanol subsidy are presented in the fourth column of Tables 1.5 and 1.6. Interestingly, we see that these policies perform almost as well as the first best policies in terms of the welfare gain, and actually result in an equal reduction in carbon emissions. In addition, oil imports are only 2.5% larger than under first best policies. The first best oil tariff of $17.5/barrel (at 23.6 gallons per barrel) amounts to a gasoline tax of $0.74/gallon; combined with the $0.23/gallon tax for pollution damages, this means the first best policies are similar to an overall fuel tax of $0.97, which is remarkably close to the second best tax of $0.96, as given in Table 1.5.[38] We also see from the table that, relative to the first best, the ethanol subsidy increases significantly. Note that the second best policy can be characterized as a tax on gasoline at the rate of $0.96/gallon and a small net subsidy on ethanol of $0.09/GEEG (the second-best subsidy of $1.02/gallon for ethanol more than offsets the fuel tax). Ethanol

[38] The reason the gasoline tax is not equivalent to an oil import tariff, despite the assumed Leontief technology for converting oil to gasoline, is because the gasoline tax is also levied on domestic production.

production in this scenario reaches 15.5 billion gallons, slightly above the 2015 mandate level of 15 billion gallons. Relative to the first best, the domestic corn price increases 16%. Thus, the fuel tax increase largely substitutes for the unavailability of the oil import tariff, and the ethanol subsidy increase partially offsets the impact on the world corn price of the unavailability of the corn export tariff.[39] Compared to the *laissez faire*, these policies reduce world oil prices by 6.5% and increase world corn prices by 36%. Relative to the first best, world oil prices increase by a very modest $0.53/barrel and world corn prices fall by a more substantial $0.65/bushel.

Even though the second best policy captures 86% of the gains achievable by the first best policy mix (relative to *laissez faire*), the distributional effects differ. Compared to the first best policy mix, consumers lose more, largely because of higher domestic corn prices; domestic oil producers suffer significant losses as the domestic price of oil falls, but corn producers gain and government tax revenue increases. Overall, the policy largely redistributes income from oil producers to the government. Perhaps the principal surprise is how well this second best policy mix performs compared to the first best policy mix.

It should also be noted that the crucial difference between this second best scenario and the first best scenario discussed earlier is that, here, border policies (oil import and corn export tariffs) are precluded. Having restricted the policy space to taxing fuel while supporting ethanol production, which policy instrument is used in the ethanol market does not matter. More precisely, the second best policy mix could be alternatively characterized as comprising an ethanol mandate equal to the second best ethanol production (15.51 billion gallons) along with the appropriate fuel tax (which can be shown to equal $0.86/gallon).

1.6.4 Optimal (Constrained) Ethanol Policy

Columns 6 and 7 of Tables 1.5 and 1.6 report the results of two scenarios in which ethanol policy instruments are the only levers, with the fuel tax fixed at its current rate of $0.39/gallon. Specifically, in the scenario of column 6 an ethanol subsidy is the only discretionary policy instrument, and in the scenario of column 7, an ethanol mandate is the only instrument. For both cases it is seen that, while there are significant welfare gains relative to the *laissez faire*

[39] Of course, the fuel tax affects corn prices and the ethanol subsidy has a modest affect on oil prices.

equilibrium, the gains compared to the *status quo* are not large; thus, in terms of our second best policy instruments, the fuel tax has a potentially larger impact on welfare than does ethanol policy. As shown in the sixth column of Table 1.5, the optimal ethanol subsidy, when the fuel tax is fixed at \$0.39/GEEG, is \$0.67/gallon, higher than the status quo subsidy level but, as predicted by the theory, well below the second best subsidy level that applies when fuel taxes are also chosen optimally. However, because here the fuel tax is held at \$0.39/gallon fuel tax, the "net" subsidy to ethanol is actually \$0.40/GEEG (as opposed to a net subsidy of only \$0.09/GEEG in the second best scenario). Compared to the second best scenario, ethanol production increases by 3.3%, and slightly exceeds the 2015 mandate level of 15 billion gallons. Compared to the second best, the lower fuel tax means that gasoline consumption also increases, so CO_2 emissions are not only higher than in the second best, they are higher than in the *status quo* situation (Table 1.6). Overall, then, given the fuel tax, the welfare benefits of adjusting the subsidy away from its *status quo* value are minimal, and the environmental benefits are actually negative.

As noted in Lapan and Moschini (2009), an ethanol mandate is equivalent to a revenue neutral ethanol subsidy and fuel tax. Since column 7 combines this mandate with the *status quo* fuel tax, and since this combined effective fuel tax is lower than the second best combination of fuel tax and ethanol subsidy, the optimal mandate yields higher welfare than the optimal subsidy policy (column 6). Of course, by construction, the welfare level that is attained here is lower than that associated with the optimal second best policy (column 5). Compared to the optimal subsidy policy, since raising the ethanol mandate simultaneously raises the effective fuel tax, gasoline consumption is lower under the mandate than under the subsidy whereas ethanol production (and hence the price of ethanol) exceeds that under any other policy.[40] This ethanol consumption level exceeds the RFS2 mandate requirement of 15 billion gallons per year of conventional biofuel (corn ethanol) by 2015. The mandate also leads to higher domestic corn prices than under any of the other policies, and world corn prices are higher only in the first best case when a corn export tariff is used. World oil prices are lower than under

[40] In the case in which the mandate is the only choice variable, raising it has the additional effect of reducing gasoline consumption and imports; under either first or second best policies, gasoline consumption can be controlled through its own policy instrument.

the *status quo* or the optimal ethanol subsidy, but higher than under the first or second best policies.[41] Carbon emissions are lower than under the optimal ethanol subsidy but higher than under the first or second best policies. These emissions decrease relative to the *status quo*, even though total fuel consumption increases slightly, because of the replacement of some gasoline by ethanol. Welfare, by definition, is higher than under the *status quo*, and also higher than under the optimal subsidy, but considerably lower than under first or second best policies.

1.6.5 Summary of Baseline Results

By definition, the inability to use the first best policies, including import and export tariffs, must result in lower welfare. Nevertheless, when we are free to choose optimally the ethanol subsidy and fuel tax, this second best policy combination comes surprisingly close to matching the first best policy in terms of welfare gains and carbon emission reductions. Naturally, the additional restriction to only one free policy instrument-the ethanol subsidy or the ethanol mandate-leads to further welfare declines. In either of these cases, since fuel taxes (or oil import tariffs) are not choice variables, it is desirable to increase ethanol consumption (and price), with the larger increase coming under the mandate because of the fact that raising the mandate increases the effective tax on fuel. Because of this effective tax, the ethanol mandate yields higher welfare and higher ethanol utilization than does the ethanol subsidy, and, as noted, the optimal mandate leads to fulfillment of the RFS2 mandate on conventional biofuel by 2015, as do all of the second best policies we considered. Still, the clear lesson is that fuel taxes are a more powerful instrument for reducing carbon emissions and increasing welfare than are ethanol policies.

1.6.6 Sensitivity Analysis

In order to investigate the robustness of our conclusions, we varied the key nine parameters one at a time, recalibrated the model (when necessary) to the *status quo* 2009 baseline, and then explored the welfare implications of alternative policies. The alternative values for each of

[41] World corn and oil prices are important because they reflect the terms of trade for the United States and thus are one component of the welfare impact of each policy.

the parameters that we considered are summarized in Table 1.7. Needless to say, the optimized value of the relevant policy instruments changed with the change in these basic parameters. Whereas the Appendix, and Tables A.1-A.9 therein, provide more details, there are several results that are common to all sensitivity analysis experiments:

- For all cases considered, the *status quo* policies dominated *laissez faire* and in all cases, except when foreign oil export supply is relatively inelastic, delivered at least 44% of the maximal benefits achievable with first best policies.
- The basic result that the fuel tax/ethanol subsidy regime is a close substitute for first best policy holds for all cases.
- The optimal mandate policy dominated the optimal subsidy policy in all cases and it resulted in the highest use of ethanol in all cases considered. Nevertheless, in most cases it did not significantly outperform the *status quo* in welfare terms, the one exception being when foreign oil export supply was very inelastic.
- In all cases in which ethanol emitted less pollution than gasoline (per GEEG), the optimal mandate resulted in lower pollution than the optimal ethanol subsidy (even when carbon dioxide was priced at $5/tCO$_2$). The mandate also resulted in lower pollution than *laissez faire* in all cases except when ethanol pollutes more than gasoline ($\lambda = 2.0$).)
- In all cases, though, the carbon emissions reductions achieved through either the first best or the second best policy of fuel taxes and ethanol subsidies were very close to each other and far exceeded those achieved under any other considered policy. Not surprisingly, oil imports were always lowest under the first best, when oil tariffs were used, but the second best was a very close second in reducing U.S. dependence on foreign oil.
- The welfare gains achievable with the second best policy of fuel taxes and ethanol subsidies was greater than 76% of the maximum gains achievable in all cases (the average of this fraction of the maximum welfare gain, over all experiments reported in the Appendix, is 86%).

- The case in which optimal policy delivered small gains-and hence did not improve much on other policies such as the *status quo* or the optimal mandate-was when the world oil export supply elasticity was large ($\bar{\varepsilon}_o = 5$). This illustrates the dominating role played by the oil market on the potential gains from government policy.

- Varying the parameters of the model does not change one of our basic results: the case for ethanol is not largely about pollution, but rather, it is about the policy's impact on the U.S. gains from trade (through its impact on the terms of trade).

Table 1.7: Parameters and Values Used in the Sensitivity Analysis

Parameter	symbol	baseline	range
Cost of CO_2 emission (\$/tCO_2)	$\sigma'(\cdot)$	20	[5 , 80]
Ethanol CO_2 emission efficiency	λ	0.75	[0.5 , 2.0]
Elasticity of fuel demand	η_f	-0.5	[-0.9 , -0.2]
Elasticity of petroleum byproduct demand	η_h	-0.5	[-0.9 , -0.2]
Elasticity of foreign corn import demand	$\bar{\eta}_c$	-1.5	[-3.0 , -1.0]
Elasticity of foreign oil export supply	$\bar{\varepsilon}_o$	3.0	[1.0 , 5.0]
Elasticity of domestic corn demand	η_c	-0.20	[-0.5 , -0.1]
Elasticity of domestic corn supply	ε_c	0.30	[0.1 , 0.5]
Elasticity of domestic oil supply	ε_o	0.20	[0.1 , 0.5]

As an additional sensitivity analysis exercise we carried out a Monte Carlo simulation meant to represent our uncertainty about the model's true parameters. Specifically, the parameters of the model were randomly drawn 100,000 times, from a beta distribution consistent with the ranges reported in Table 1.7, with the shape parameters of this distribution calibrated with the so-called PERT (Program Evaluation and Review Technique) methodology (Davis, 2008) - see the Appendix for more details - and for each parameter vector we calculated the optimal values of the policy instruments for the various scenarios analyzed. One way to interpret the results of this Monte Carlo experiment is as a robustness check on the magnitude of the policy tool parameters that we computed in our baseline. Within this perspective, some of our main conclusions are re-emphasized by the Monte Carlo simulation. For example, for the second best scenario we find that the optimal fuel tax and ethanol subsidy remain significantly above the *status quo* level. Specifically, taking the 10% and 90% of the empirical distribution from the simulation, the fuel tax ranges from \$0.75/gallon to \$1.27/gallon and the ethanol subsidy ranges from \$0.86/gallon to \$1.28/gallon. More details concerning this and other scenarios are reported in Table A.10.

1.7 Conclusion

This paper constructs a tractable computational model, which applies and extends the analytical model of Lapan and Moschini (2009), to analyze the market and welfare impacts of U.S. energy policies. Specifically, using this framework, we formally solve the optimal values for policy instruments under alternative policy scenarios. We then calibrate the model to fit the baseline period of 2009, and use simulation to compare equilibrium quantities, prices and net welfare under the alternative policy settings. Not surprisingly, the simulations support the policy rankings in Lapan and Moschini (2009), and in particular the conclusion that an ethanol mandate dominates an ethanol subsidy policy.

There are several interesting findings. First, the second best instruments of a fuel tax and an ethanol subsidy come close to replicating the outcomes under the first best policy combination of oil import tariffs, corn export tariffs and a carbon tax. For our baseline model, the second best fuel tax of \$0.96/GEEG and ethanol subsidy of \$1.02/gallon would increase ethanol consumption to 15.51 billion gallons, a 44% increase compared to the current (*status quo*) situation, it would decrease gasoline consumption by 7.5% and it would reduce emissions by 5.3%, as compared to the *status quo*.

In addition, the ethanol mandate, when used optimally in conjunction with the existing fuel tax, would achieve the highest ethanol consumption of approximately 17.5 billion gallons, which exceeds the RFS2 mandate on conventional biofuels (15 billion gallons per year by 2015). However, since the effective tax on fuel is lower than under either the first or second best policy, it would achieve a smaller reduction in carbon emissions and a smaller welfare gain than would either of these policies. Finally, because of the magnitude of U.S. oil imports, the greatest economic gain arising from any policy intervention considered is due to the terms of trade effects through the world oil market. Because we have not included any other putative gain from reducing oil imports (e.g., national security effects arising from a reduced dependence on imports), we probably still significantly underestimate the potential gains associated with policies that reduce oil imports.

Finally, a few caveats. In our analysis we have ignored the ”blend wall” issue, which might make it difficult to increase ethanol consumption beyond ten percent of total fuel use. But of course the blend wall is also ignored by RFS2 and, in any event, such an issue might be addressed as an increasing fleet of vehicles that can utilize E85 fuel becomes available, and/or by allowing newer standard vehicles to use E15 fuel. We have also assumed, as is the norm, that markets are competitive. If imperfect competition were present in some of the markets, this would affect the model both through the specification of equilibrium conditions and through the analysis of optimal policy. For example, if there were monopoly power exercised by a U.S. firm in the corn export market, then this would reduce the benefits derived from government policies which restrict corn exports. On the other hand, if foreign oil exporters were exercising monopoly power, this would mean higher world prices than would otherwise prevail and thus could increase the desirability of U.S. oil import policy or ethanol policies that reduce the demand for oil.

CHAPTER 2. INDUCED CLEAN TECHNOLOGY ADOPTION AND INTERNATIONAL TRADE WITH HETEROGENEOUS FIRMS

2.1 Introduction

U.S. manufacturers contribute to about 20 percent of gross domestic output,[1] and roughly 70 percent of the total value of exports,[2] while at the same time, emit around one-fourth of the total amount of air emissions (U.S. Environmental Protection Agency, 2010). The entire manufacturing industry has been cleaning up air pollutants over the last decade. This cleanup is mainly attributable to the improvement of production or abatement technologies (Levinson, 2009). The technology improvement could be achieved through manufactures' decisions of adopting production or pollution abatement technologies. How are the decisions of polluting manufactures affected by environmental regulations and openness to trade? This is the most fundamental question for policy implication. The economic consequences of environmental policies and the effects of the openness to trade on the U.S. manufacturers are the subjects of heated public debates and high-pitched academic discourses. Disentangling these effects will set out to gain further insights in the assessment of comprehensive climate legislation that will curb our global warming pollution.

The literature in environmental economics - until recently - remains silent on the role of heterogeneous productivity in the context of an open economy. The increasing availability of micro datasets, however, has demonstrated that this heterogeneity performs a substantial role in firms that are exposed to export activities. The stylized facts that heterogeneous firms suffer differential impacts of the openness to trade have emerged from these datasets, and suggest the need to shift the focus from countries and industries to firms, when it comes to the effects

[1] Bureau of Economics Analysis, U.S. Department of Commerce.
[2] U.S. International Trade in Goods and Services - Annual Revision for 2010.

of environmental regulations in an open economy with costly trade.

To that end, this paper introduces a factor-biased technology choice and environmental pollution into the trade model with heterogeneous firms, which is the so-called Melitz framework (Melitz, 2003). The main purpose of this research is to study dynamic decisions of heterogeneous firms in response to the further exposure to trade and stringency of environmental regulations. The model setup starts from a closed economy with two exogenous technologies (i.e., dirty and clean) in a single (manufacturing) industry, then extends it to an open economy with costly trade. Production requires labor used as a primary input and emits pollution byproducts (e.g., air emissions), which are regarded as inputs of the production. The government implements a domestic emission permit cap-and-trade program. Technologies are represented by cost functions exhibiting (constant) marginal cost with fixed production costs. The clean technology is a factor-biased technical change as compared with the dirty technology. Adopting the clean technology requires a higher fixed production cost, but provides a lower marginal cost than adopting the alternative dirty technology as long as emitting pollution is not free from charges. The model predicts that a continuum of heterogeneous firms is partitioned by technology choice and export status. The paper focuses on a scenario in which all firms adopting the clean technology (hence called clean firms) select to export, while only a fraction of productive firms adopting the dirty technology (hence called dirty firms) choose to participate in the export market. The comparative statics with respect to trade cost and emission permit cap are carried out assuming that the aforementioned partitioning pattern would not be reversed in response to changes in policy instruments.

The model developed in this paper offers novel predictions on the impact of a stringent environmental regulation in terms of a lower cap of emission permit. The fundamental mechanism, in which this policy instrument comes into effect, is through its differential impacts on various types of firms (i.e., clean or dirty firms). If the clean technology is labor biased, the clean firms bear relatively less burden of rising emission costs than the dirty firms. The benefits of adopting the labor-biased clean technology rises as the emission costs go up, inducing relatively productive dirty firms to adopt the clean technology while shutting down the least productive dirty firms. Resources are then reallocated from the dirty firms to the clean firms. In contrast, when the clean technology is emission-biased, the reallocation of resources runs in the opposite direction, from the clean firms back to the dirty ones.

This paper also provides insights in the environmental impact of the openness to trade. A reduction in variable trade cost expands the export market for firms which have already been in the market. Moreover, it opens up new avenues of the export market for those which originally serve only the domestic market. Competition in the factor markets is relatively fierce in labor rather than emission permit if the clean technology is labor biased. As a consequence, the trade cost reduction lowers down the permit price relative to the wage rate. On the contrary, if the clean technology is emission biased, the excess demand for emission permits over labor bids up the relative permit price. Even though the total emission level is capped, the further exposure to trade does reshape the composition of the whole industry.

The paper contributes to a large body of literature on environmental economics concerning the clean technology adoption. The related work has given much attention on an efficiency assessment of environmental policies between market-based instruments (e.g., pollution tax, subsidy, tradable permit) and command-and-control regulations (e.g., standards). Several theoretical studies have found that the incentive for adoption and diffusion of new technology is greater under the market-based instruments than under the direct regulations, but the literature has not reached any consensus on the theoretical comparisons among the market-based instruments (Milliman and Prince, 1989, 1992; Jung et al. 1996; Parry, 1998). This issue of the tax-versus-standard, however, is not the focus of this paper, since the quantity of aggregate emission is fixed at the cap level.

Another strand of the literature this paper adds to is the relationship between trade and the environment. The main departure of this paper from the related literature is the feature of the firm-level difference in productivity. The existing theoretical studies, which examine the environmental consequences of international trade, focus on aggregate (e.g., industry, country) variations (Copeland and Taylor, 1994, 1995). Surprisingly, little is known about the impact of environmental regulations on firm dynamics. To my knowledge, Li and Shi (2010) is the only research that addresses the role of heterogeneous productivity in assessing environmental policies (i.e., tax-versus-standard) in a closed economy. In this paper, my model sheds light on the intra-industry impacts of the openness to trade. It captures decisions of technology adoption, entry, exit, and export as heterogeneous firms adjust to further exposure to trade.

The paper is more closely related to the Melitz framework, which has fairly recently enjoyed widespread attention in many topics, in particular, technology adoption. Yeaple (2005) examines the interaction between the characteristics of competing technologies with trade costs and with worker heterogeneity. His analytical study emphasizes a scenario in which only high technology firms export but none of low technology firms do. Bustos (2011) looks at a different scenario, the same scenario upon which my analysis is based, in which all high technology firms export and a fraction of low technology firms select to trade. When the dynamic impact of trade on the technology adoption and diffusion is concerned, Ederington and McCalman (2008) suggest that trade has a generally positive impact on the equilibrium rate of adoption. Differed from the above studies, Unel (2011)'s attention is on the welfare implication of a unilateral reduction in the technology adoption cost in a two-country model. The paper is inspired from these studies in modeling technology adoption. The clean or high technology preserves a factor-augmenting feature relative to the dirty or low technology. Adopting the factor-augmenting technology benefits from lower marginal costs at the expense of higher fixed costs. Whereas the paper differs from them in assuming two factor inputs of production, which in turn draws attention to the factor-biased technical change.

The remaining paper proceeds as follows. Section 2 introduces the model setup and characterizes the equilibrium in a closed economy, then followed by an investigation on the responses of the economy to a lower emission permit cap. Section 3 extends the model into an open economy with costly trade, and examines the intra-industry impacts of reductions in trade cost and emission permit cap. The discussion and concluding remarks come in the last section of the paper.

2.2 Model Setup in a Closed Economy

In this section, I start with a model setup in a closed economy to highlight the essential mechanism through which an environmental policy (i.e., cap-and-trade) comes into play to induce the clean technology adoption. Slight adjustments are required to extend the model to an open economy with costly trade.

2.2.1 Preference

A representative consumer with an infinite life has preference of constant elasticity of substitution (CES) form over a continuum of varieties indexed by ω, and also suffers disutility from pollution externality arising from the production process. The per-period utility function is,

$$U = \left[\int_{\omega \in \Omega} q(\omega)^{\rho} d\omega \right]^{1/\rho} - D(E) \tag{2.1}$$

where the measure of the set Ω represents the mass of varieties; E denotes aggregate emissions; $D(\cdot)$ is an increasing and convex domestic damage function. The potential global pollution damage and long-term pollutant stock effects are not accounted in this paper. Varieties are substitutes with a constant elasticity of $\sigma = 1/(1-\rho) > 1$ and I assume that $\rho \in (0, 1)$. As shown in Dixit and Stiglitz (1977), the consumer problem can be thought by considering the set of varieties consumed as an aggregate good Q associated with an aggregate price P,

$$Q = \left[\int_{\omega \in \Omega} q(\omega)^{\rho} d\omega \right]^{1/\rho}; P = \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega \right]^{1/(1-\sigma)} \tag{2.2}$$

The iso-elastic form of residual demand curve for any varieties can be then derived from these aggregates,

$$q = Q \left(\frac{P}{p} \right)^{\sigma} = \frac{RP^{\sigma-1}}{p^{\sigma}} \tag{2.3}$$

where $R = PQ$ denotes aggregate expenditure; $P^{1-\sigma}$ captures the strength of the market crowding or local competition effect (Baldwin et al. 2003); $RP^{\sigma-1}$ refers to the market potential index (Okubo, 2009), which is decreasing in the market crowding but increasing in the aggregate expenditure.

2.2.2 Production

Irrespective of production technology, each firm with a firm-specific productivity draw, indexed by φ, produces a different variety, and faces a residual demand curve with a constant elasticity of $\sigma > 1$, thus chooses the profit maximizing markup. This specification of monopolistic competition with heterogeneity rules out strategic interactions among firms.

Production requires labor used as both fixed and variable inputs. The labor endowment is given at its aggregate level $\overline{L}$. There exists a choice of technology adoption between either dirty or clean technology. Both technologies create pollution emissions as byproducts but differ in two aspects: (i) the fixed production costs of adopting technology j, denoted by $f_j > 0$, measured in labor thereafter sunk; and (ii) the technology-specific cost share of inputs. Following Copeland and Taylor (1995)'s technique to treat emission as an additional input factor of production, the production function via adopting technology j is assumed to have a CES form:

$$q_j = \varphi \left[(\beta_j e)^{\frac{\eta-1}{\eta}} + (\alpha_j l)^{\frac{\eta-1}{\eta}} \right]^{\eta/(\eta-1)} \tag{2.4}$$

where l is variable labor input; e denotes pollution emissions; φ indexes the firm-specific productivity; β_j and α_j are two separate technology terms, and $\eta \in (0, \infty)$ is the elasticity of substitution between the two factors; $j \in \{c, d\}$ refers to clean and dirty, respectively.

Each firm must purchase emission permits from the government to emit the equivalent amounts of pollution. Given the common wage rate w and permit price p_e, the variable cost function corresponding to the production function (2.4) is:

$$C_j(\varphi, w, p_e) = \frac{q_j c_j(w, p_e)}{\varphi} = \frac{q_j}{\varphi} \left[\left(\frac{p_e}{\beta_j} \right)^{1-\eta} + \left(\frac{w}{\alpha_j} \right)^{1-\eta} \right]^{1/(1-\eta)} \tag{2.5}$$

where $c_j(w, p_e)$ is the marginal cost of production adopting technology j.

Assumption 1 $f_c > f_d$, $c_c(w, p_e) < c_d(w, p_e)$, $\forall w, p_e > 0$

Define $f \equiv f_c - f_d > 0$ as extra fixed costs of adopting the clean technology relative to the dirty one, or the technology upgrade fee. Here I assume that adopting the clean technology requires a higher fixed cost than adopting the alternative dirty technology. The clean technology, however, provides lower marginal costs than the dirty technology because the former is assumed to be factor-augmenting technical change relative to the latter.

The clean technology is emission-augmenting technical change relative to the dirty technology provided that $\alpha_c = \alpha_d$ and $\beta_c > \beta_d$; it is labor-augmenting provided that $\alpha_c > \alpha_d$ and

$\beta_c = \beta_d$; whereas, it is Hicks-neutral provided that $\beta_c/\beta_d = \alpha_c/\alpha_d > 1$. With the elasticity of substitution between labor and emission inputs, the factor-augmenting technical change could be related to factor-biased one. If the two factors are gross substitutes ($\eta > 1$), labor-augmenting technical change is also labor-biased. In contrast, if the factors are gross complements ($\eta < 1$), labor-augmenting technical change is then emission-biased.

Define $s_j^e \equiv \frac{\partial c_j}{\partial p_e}\frac{p_e}{c_j}$ as the cost share of emission permits when the production adopts technology j. Similarly, $s_j^l \equiv \frac{\partial c_j}{\partial w}\frac{w}{c_j}$ refers to the cost share of labor inputs.[3] By the cost function's property, $s_j^e + s_j^l = 1$, $\forall j \in \{c, d\}$.

Remark 1 *If the clean technology is labor-biased, then* $s_c^l > s_d^l$ *&* $\partial(c_d/c_c)/\partial p_e > 0$*; If the clean technology is emission-biased, then* $s_c^e > s_d^e$ *&* $\partial(c_d/c_c)/\partial p_e < 0$*; If the clean technology is Hicks-neutral, then* $s_c^e = s_d^e$ *&* $\partial(c_d/c_c)/\partial p_e = 0$*.*

Proof. See Appendix. ■

The intuition is simple: when the technology is labor-biased, an increase in productivity raises the marginal product of labor more than that of emission input. The increasing marginal product of labor relative to emission requires a higher labor-emission ratio, henceforth a higher labor-emission cost ratio, implying that $s_c^l > s_d^l$. The higher labor cost share of the clean technology relative to the dirty technology also indicates that the gain of lower marginal costs by adopting the clean technology becomes more prominent as the permit price (relative to wage rate) rises, reflected by $\partial(c_d/c_c)/\partial p_e > 0$. This feature ensures that the economy will be favorable for adopting the clean technology in response to the higher permit price. On the contrary, when the technology is emission-biased, implying that $s_c^e > s_d^e$ or equivalently $\partial(c_d/c_c)/\partial p_e < 0$, the economy is not conducive for the clean technology adoption as the permit price keeps rising. If the technical change is Hicks-neutral, however, the cost share of inputs remains unchanged, $s_c^e = s_d^e$, indicating that the gains of adopting clean technology is insensitive to the permit price, $\partial(c_d/c_c)/\partial p_e = 0$. This feature, that the relationship between the relative marginal costs and permit price does not rely on the specific CES production function form but the factor-biased technical change, will play an important role in the discussion below.

[3] $s_j^e \equiv \frac{\partial c_j}{\partial p_e}\frac{p_e}{c_j} = \frac{\partial c_j}{\partial p_e}\frac{p_e q_j \varphi}{c_j q_j \varphi} = \frac{\partial (q_j c_j/\varphi)}{\partial p_e}\frac{p_e}{q_j c_j/\varphi} = \frac{\partial C_j}{\partial p_e}\frac{p_e}{C_j}$. By Shephard's lemma, $\frac{\partial C_j}{\partial p_e}\frac{p_e}{C_j} = \frac{p_e e_j}{C_j}$, which is cost share of emission permit. Likewise for the cost share of labor.

Despite of heterogeneous productivity, there are two types of firms: clean firms for those adopting the clean technology, and dirty firms for those adopting the dirty technology. All firms adopting the same technology share the same amount of fixed production costs, but have different variable costs, which depend upon their productivity draws φ. The static profit maximization of a firm with productivity φ gives rise to the following optimal pricing rule and output level,

$$p_j(\varphi) = \frac{c_j}{\rho\varphi}; q_j(\varphi) = RP^{\sigma-1}\left(\frac{\rho\varphi}{c_j}\right)^{\sigma} \tag{2.6}$$

Note that $c_j \equiv c_j(w, p_e)$ is a function of endogenous input prices. All firm-level outcomes are functions of the firm-specific productivity, endogenous input prices, and aggregate variable indices. Revenue and profit functions of the firm are specified as follows,

$$r_j(\varphi) = RP^{\sigma-1}\left(\frac{\rho\varphi}{c_j}\right)^{\sigma-1}; \pi_j(\varphi) = \frac{RP^{\sigma-1}}{\sigma}\left(\frac{\rho\varphi}{c_j}\right)^{\sigma-1} - wf_j \tag{2.7}$$

The input demand function for the firm adopting technology j could be derived from the cost function using Shephard's lemma,

$$e_j(\varphi) = \frac{\rho s_j^e}{p_e} r_j(\varphi); l_j(\varphi) = \frac{\rho s_j^l}{w} r_j(\varphi) \tag{2.8}$$

where (s_j^e, s_j^l) denote the cost shares of emission input, and of labor input.

2.2.3 Entry and Exit

The timing of events follows exactly as the one in the Melitz model except adding technology choices prior to production. Within each time period, there is a large pool of identical firms prior to entry. To enter the market, each firm pays a time-invariant entrance fee of $f_e > 0$ as an initial investment. The new entrant then draws the firm-specific productivity φ from a common density distribution $g(\varphi)$ with a positive support of $(0, \infty)$. Upon observing the draw, the firm decides to exit immediately. If the firm chooses to produce, it could adopt technology $j \in \{c, d\}$ to operate a plant with an additional fixed production cost of $f_j > 0$. In the end of the period, the firm also faces a constant probability $\delta \in (0, 1)$ of an idiosyncratic shock that forces it to exit regardless of its technology choice. All fixed costs, measured in labor units thereafter sunk, are known to all firms.

There exist two productivity cutoff values: one is the zero-profit productivity cutoff of adopting the dirty technology, denoted by φ_d; the other is the equivalent-profit productivity cutoff of adopting the clean technology, denoted by φ_c. They are defined accordingly,

$$\pi_d(\varphi_d) = \frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_d)^{\sigma-1} - wf_d = 0 \tag{2.9a}$$

$$\pi_d(\varphi_c) - \pi_d(\varphi_c) = \left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]\frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_c)^{\sigma-1} - wf = 0 \tag{2.9b}$$

The above two equations together give rise to the relative equilibrium cutoff values, which depend upon the relative fixed production costs and relative marginal costs:

$$\left(\frac{\varphi_c}{\varphi_d}\right)^{\sigma-1} = \frac{f}{f_d}\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]^{-1} \tag{2.10}$$

Intuitively, an increase in the technology upgrade fee (f) requires firms to draw higher productivity so that they could earn enough revenue to at least cover the fixed production costs. The higher the relative marginal cost is, the more attractive adopting the clean technology will be, because even the less productive dirty firms could benefit from upgrading to the clean technology. Thus, the productivity gap between the least productive clean firms and the least productive dirty firms drops.

Assumption 2 *The cost structure satisfies that* $f/f_d > [(c_d/c_c)^{\sigma-1} - 1]$

Lemma 1 *Given Assumption 2 and* $\sigma > 1$, $\varphi_c > \varphi_d$.

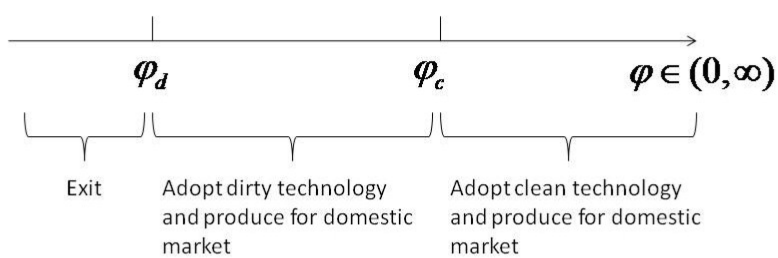


Figure 2.1: Productivity Cutoffs in the Closed Economy

It is not difficult to show that $\varphi_c > \varphi_d$ under Assumption 2. The partitioning of firms by technology choice implies that only relatively productive firms adopt the clean technology. As depicted in Figure 2.1, any new entrants with productivity draws below φ_d immediately exit the market; those with productivity draws between these two cutoffs (φ_d and φ_c) adopt the dirty technology; only those with productivity draws not below φ_c adopt the clean technology. As a consequence, the *ex post* distribution of productivity, denoted by $\mu(\varphi)$, is conditional on successful entry hence is truncated at φ_d:

$$\mu(\varphi) = \begin{cases} \dfrac{g(\varphi)}{1 - G(\varphi_d)} & \text{if } \varphi > \varphi_d \\ 0 & \text{otherwise} \end{cases}$$

where $G(\varphi)$ is the cumulative distribution function for $g(\varphi)$.

Assumption 3 *The firm-specific productivity φ follows a Pareto distribution, $G(\varphi) = 1 - (k/\varphi)^c$, where $k > 0$, $c > 0$.*

Note that $k > 0$ is the minimum value of productivity draw, and $c > 0$ is a shape parameter that determines the skewness of the Pareto distribution. Assuming $c > \sigma - 1$ so that the variance of log productivity is finite, in which case the term $\varphi^{\sigma-1}g(\varphi) = \xi h(\varphi)$, where $h(\varphi) = \gamma k^{\gamma}\varphi^{-(\gamma+1)}$, $\xi \equiv ck^{c-\gamma}/\gamma$. The corresponding cumulative distribution also follows a Pareto distribution with a form of $H(\varphi) = 1 - (k/\varphi)^{\gamma}$, where $\gamma \equiv c - \sigma + 1 > 0$ provided that $c > \sigma - 1$. The Pareto distribution has been widely used in many extensions of the Melitz model, since it allows to derive the closed form solutions of the equilibrium cutoff values (Bernard, Redding, and Schott, 2007; Okubo, 2009). In this paper, the productivity distribution assumption only helps simplify the proof of comparative statics by relating the *ex post* fractions of firms to the relative cutoffs.

Given an unbounded pool of potential new entrants, in any equilibrium with unrestricted entry, the expected value of entry, denoted by V, must equal its sunk entry cost wf_e. This defines the free entry condition,

$$V = \frac{\bar{\pi}\left[1 - G(\varphi_d)\right]}{\delta} = wf_e \tag{2.11}$$

where the expected value of entry (V) is the *ex ante* probability of successful entry ($1 - G(\varphi_d)$) multiplied by the expected profitability of producing the good and until hit by the bad shock ($\bar{\pi}/\delta$); the expected profit from successful entry, denoted by $\bar{\pi}$, is defined as:

$$\bar{\pi} = \int_{\varphi_d}^{\varphi_c} \pi_d(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} \pi_c(\varphi)\mu(\varphi)d\varphi \tag{2.12}$$

The expected profit could be decomposed into: (i) one from adopting the dirty technology conditional on successful entry, captured by the first integration; and (ii) another from operating a clean plant conditional on successful entry, expressed by the second term. Following the technique of Bernard, Redding, and Schott (2007), the above free entry condition could be rewritten as,

$$f_d \int_{\varphi_d}^{\infty} \left[\left(\frac{\varphi}{\varphi_d} \right)^{\sigma-1} - 1 \right] g(\varphi) d\varphi + f \int_{\varphi_c}^{\infty} \left[\left(\frac{\varphi}{\varphi_c} \right)^{\sigma-1} - 1 \right] g(\varphi) d\varphi = \delta f_e \tag{2.13}$$

In equilibrium, φ_c and φ_d are related according to equation (2.10). Thus, the equilibrium productivity cutoffs are determined by the cost structure and factor rewards, hence environmental policy (i.e., emission permit cap).

In the end, the steady-state equilibrium is characterized by a constant mass of firms entering in each period (called potential new entrants), M_e, and a constant mass of operating firms (called incumbents), M. The mass of successful new entrants exactly replaces the mass of incumbents who are hit by the bad shock and exit,

$$\delta M = [1 - G(\varphi_d)]\, M_e \tag{2.14}$$

The mass of dirty firms, M_d, and of clean firms, M_c, could be related to the equilibrium cutoffs and mass of operating firms in the following ways,

$$M_d = \frac{G(\varphi_c) - G(\varphi_d)}{1 - G(\varphi_d)} M = \lambda_d M; M_c = \frac{1 - G(\varphi_c)}{1 - G(\varphi_d)} M = \lambda_c M \tag{2.15}$$

where ($\lambda_d \equiv [G(\varphi_c) - G(\varphi_d)]/[1 - G(\varphi_d)], \lambda_c \equiv [1 - G(\varphi_c)] / [1 - G(\varphi_d)]$) represent the *ex ante* probability of adopting the dirty technology conditional on successful entry, and that of adopting the clean technology conditional successful entry, respectively. Alternatively, (λ_d, λ_c) also refer to the *ex post* fraction of dirty firms, and of clean firms, respectively. Note that $\lambda_d + \lambda_c = 1$, since there only exist two types of firms, either dirty or clean. With the Pareto distribution specified in Assumption 3, the *ex post* factions are linked with the relative cutoffs,

$$\lambda_d \equiv \frac{G(\varphi_c) - G(\varphi_d)}{1 - G(\varphi_d)} = 1 - \left(\frac{\varphi_d}{\varphi_c} \right)^c ; \lambda_c \equiv \frac{1 - G(\varphi_c)}{1 - G(\varphi_d)} = \left(\frac{\varphi_d}{\varphi_c} \right)^c \tag{2.16}$$

2.2.4 Aggregate Variables

Using the equilibrium individual pricing rule (2.6), the aggregate price index is given by,

$$P^{1-\sigma} = M\left\{\int_{\varphi_d}^{\varphi_c} p_d(\varphi)^{1-\sigma}\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} p_c(\varphi)^{1-\sigma}\mu(\varphi)d\varphi\right\} \tag{2.17}$$

In equilibrium, aggregate expenditure equals aggregate revenue, which is the mass of firms multiplied by the weighted average revenue $\bar{r}$.

$$R = M\bar{r} \equiv M\left\{\int_{\varphi_d}^{\varphi_c} r_d(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} r_c(\varphi)\mu(\varphi)d\varphi\right\} \tag{2.18}$$

The expected variable profit ($\bar{r}/\sigma$) equals the expected fixed cost plus the expected profit due to the free entry condition (2.13), that is, $\bar{r}/\sigma = \bar{\pi} + wf_d + wf\lambda_c$. The aggregate expenditure is the sum of total payments to labor and emission permits in equilibrium,

$$R = w\overline{L} + p_e\overline{E} \tag{2.19}$$

Total emissions generated during the production process are the mass of firms multiplied by the weighted average emission defined as the term in the curly bracket in equation (2.20). Thus the emission permit market clearing condition is,

$$\overline{E} = M\left\{\int_{\varphi_d}^{\varphi_c} e_d(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} e_c(\varphi)\mu(\varphi)d\varphi\right\} \tag{2.20}$$

where $\overline{E}$ is the per-period total emission permit cap elaborated in what follows. Similarly, the labor market clearing condition is,

$$\overline{L} = M\left\{\int_{\varphi_d}^{\varphi_c} l_d(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} l_c(\varphi)\mu(\varphi)d\varphi\right\} + M\left\{\int_{\varphi_d}^{\varphi_c} f_d\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} f_c\mu(\varphi)d\varphi\right\} + M_ef_e \tag{2.21}$$

where the first term in the right hand side denotes the aggregate labor demand used as variable inputs; the rest of two are fixed costs used as technology adoption and initial entrance fees.

2.2.5 Government

The market failure due to the pollution externality arising from the production intrinsically creates room for government intervention, in particular, a domestic emission permit cap-and-trade program. The government sets a time-invariant emission cap and irrevocably precommits to it. This assumption allows one to take a close look at how the steady-state equilibrium responds to a lower permit cap. For future extensions, the model could relax this assumption by allowing a sequence of permit cap declining over time to reflect a certain emission reduction goal (e.g., a 10% reduction by the end of 2015 given the baseline year 2011).

The government sets the emission permit volume (each permit equals 1 ton of pollution emissions) with the total number of permits summing to the cap in each period. The total emission permits, denoted by $\overline{E}$, are auctioned to all operating firms. Each firm must have permits equivalent to the amount of pollution emitted in each period. Moreover, the revenue from auctioning emission permits is transferred to the representative consumer in a lump-sum form. To keep it simple, the paper assumes away the inter-temporal emission permit trade scheme. In the end, the aggregate emissions and permits must satisfy the per-period feasibility constraint: $E = \overline{E}$, which is assumed to be binding.

2.2.6 Equilibrium

An equilibrium in the closed economy is a vector of five variables including the mass of firms, the wage rate, the emission permit price, the productivity cutoff of adopting the dirty technology, and the cutoff of adopting the clean technology: $\{M, w, p_e, \varphi_d, \varphi_c\}$. All other endogenous variables may be written as functions of these variables. The equilibrium vector is determined by the following five equilibrium conditions: the equilibrium relationship between cutoffs (2.10), free entry condition (2.13), the equivalence of expenditure and revenue condition (2.18), emission permit market clear condition (2.20), and labor market clear condition (2.21). One of the conditions is redundant due to Walras' Law. The proof of the existence of the equilibrium could be carried out by sorting out a system of five equations in the same number of unknowns.

2.2.7 Comparative Statics

Throughout this section I assume that the firms' partitioning pattern ($\varphi_d < \varphi_c$) does not reverse in response to changes in policy instruments. A reduction in emission permit cap occurs when the government implements a stringent environmental regulation to clean up pollution.

It is not straightforward to conclude a rising pollution cost as a result of the lower permit cap. With the factor-augmenting assumption on the clean and dirty technologies, however, the monotonic feature of the aggregate emission permit input demand can be established in Proposition 1.[4] The classical debate of the price-versus-quantity in environmental economics does not arise within the context of this framework. The government can find an equivalent tax rate to achieve the impacts that are similar to those by a permit cap.

Proposition 1 *A lower emission permit cap ($d\overline{E} < 0$) reduces permit price, $\partial p_e / \partial \overline{E} < 0$*

Proof. See Appendix. ■

Intuitively, a reduction in the emission permit cap leads to an excess demand for emission permits, bidding up its price consequently. However, there is no further information about how the aggregate permit auction revenue responds to the lower permit cap. Neither does the change in the aggregate revenue.

How do the productivity cutoffs vary with the emission permit cap? Proposition 2 establishes that changes of the cutoffs depend upon whether the adopted technology is labor-biased or emission-biased.

Proposition 2 *A lower emission permit cap ($d\overline{E} < 0$),*

(i) if the clean technology is labor-biased, $\partial \varphi_d / \partial \overline{E} < 0$, $\partial \varphi_c / \partial \overline{E} > 0$;

(ii) if the clean technology is emission-biased, $\partial \varphi_d / \partial \overline{E} > 0$, $\partial \varphi_c / \partial \overline{E} < 0$;

(iii) if the clean technology is Hicks-neutral, $\partial \varphi_d / \partial \overline{E} = 0$, $\partial \varphi_c / \partial \overline{E} = 0$.

Proof. See Appendix. ■

Figure 2.2 depicts the impacts of the tough environmental policy on productivity cutoffs. An increase in permit price, due to the lower cap, puts upward pressure on all operating firms

[4] Benard, Redding, and Schott (2007) assumes a Cobb-Douglas (CD) function form for skilled and unskilled labor inputs used as both variable and fixed costs, and a CD function for preference. By taking advantage of the constant cost shares, it is not difficult to establish the monotonicity of the aggregate input demand, and to show the neutrality of input endowments. Other trade models with heterogeneous firms and technology adoption assume a single input production, hence showing the monotonicity is not a problem either (see e.g., Ederington and McCalman, 2008; Bustos, 2011; Unel, 2011).

with different magnitudes across technologies. The clean firms suffer relatively less pressure than the dirty firms, when the clean technology is labor-biased. The marginal cost advantage of adopting the clean technology becomes more pronounced, attracting even less productive dirty firms to upgrade to the clean technology. However, the least productive dirty firms no longer receive enough revenue to cover the fixed production costs hence exit the market. Resource reallocations induced by the stringent environmental regulation raise the cutoff of adopting the dirty technology, $\varphi_d \uparrow$, but lower the cutoff of adopting the clean technology, $\varphi_c \downarrow$, as illustrated in the upper panel of Figure 2.2.

In contrast, when the clean technology is emission-biased, the emission cost share of the clean firms is higher than that of the dirty firms. The profitable incentive of adopting the clean technology becomes less promising as the permit price keeps rising. Only the productive clean firms can afford emission permits with the higher price. The least productive clean firms have to downgrade their technology to the dirty one, illustrated by a rising φ_c. Whereas for the dirty firms, their unit costs fall as the permit price rises, attracting even less productive new entrants to enter the market and adopt the dirty technology, represented by a falling φ_d, as depicted in the lower panel of Figure 2.2.

When the clean technology is Hicks-neutral, all firms, regardless of types, are bearing burdens of rising permit prices with the same proportions. Resource reallocation between the clean and dirty firms would not be induced by the lower permit cap. Recall Remark 1, the relative cutoffs is independent of factor rewards, henceforth environmental regulation. The tightened policy leaves no effects on the two productivity cutoffs.

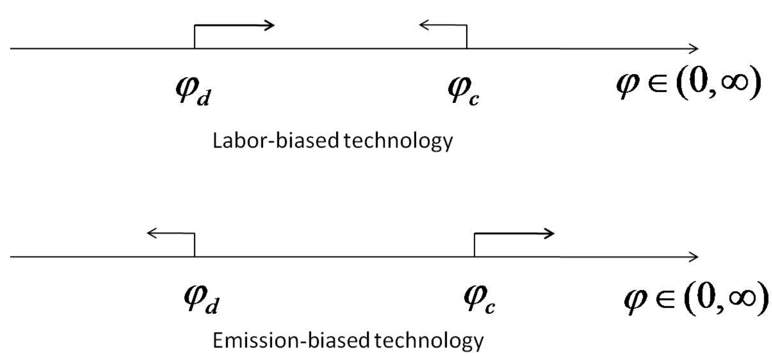


Figure 2.2: Impacts of a Stringent Environmental Policy in the Closed Economy

To illustrate changes in the *ex post* fractions of dirty (λ_d), and of clean firms (λ_c) in response to the regulation, one could link the *ex post* fractions with productivity cutoffs using equation (2.16). The following Corollary is then immediate,

Corollary 1 *A lower emission permit cap ($d\overline{E} < 0$),*

(i) if the clean technology is labor-biased, $\partial\lambda_c/\partial\overline{E} < 0$, $\partial\lambda_d/\partial\overline{E} > 0$;

(ii) if the clean technology is emission-biased, $\partial\lambda_c/\partial\overline{E} > 0$, $\partial\lambda_d/\partial\overline{E} < 0$;

(iii) if the clean technology is Hicks-neutral, $\partial\lambda_c/\partial\overline{E} = 0$, $\partial\lambda_d/\partial\overline{E} = 0$.

When the clean technology is labor-biased, the *ex post* fraction of dirty firms (λ_d) falls but that of clean firms (λ_c) rises. The cost-saving technology adoption effect reallocates market shares towards the relatively productive clean firms, and contributes to an aggregate productivity gain by shutting down the least efficient dirty firms. The whole industry is now shifting towards a green one. When the clean technology is emission-biased, resource reallocation runs the opposite direction where the *ex post* fraction of dirty firms (λ_d) rises but that of clean firms (λ_c) falls. The entire industry consists of less clean firms but more dirty ones. When the clean technology is Hicks-neutral, the stringent environmental policy has no impact on the composition of the industry.

Using Proposition 2 and the free entry condition (2.11), how the expected profit ($\bar{\pi}$) and weighted average revenue ($\bar{r}$) vary with permit cap can be concluded in the next Corollary.

Corollary 2 *A lower emission permit cap ($d\overline{E} < 0$),*

(i) if the clean technology is labor-biased, $\partial\bar{\pi}/\partial\overline{E} < 0$, $\partial\bar{r}/\partial\overline{E} < 0$;

(ii) if the clean technology is emission-biased, $\partial\bar{\pi}/\partial\overline{E} > 0$, $\partial\bar{r}/\partial\overline{E} > 0$;

(iii) if the clean technology is Hicks-neutral, $\partial\bar{\pi}/\partial\overline{E} = 0$, $\partial\bar{r}/\partial\overline{E} = 0$.

When the clean technology is labor-biased. the expected profit ($\bar{\pi}$) must rise as the cutoff of adopting the dirty technology (φ_d) increases. So does the weighted average revenue ($\bar{r}$), since $\bar{r}/\sigma = \bar{\pi} + wf_d + wf\lambda_c$. It is worth noting that the inspection of the increasing expected profit and expected revenue also reveals that potential new entrants are required to draw better productivity to survive in the market. Conversely, when the clean technology is emission-biased, both the expected profit and weighted revenue fall as the permit cap drops by inspecting the free entry condition. Lastly, when the clean technology is Hicks-neutral, neither is affected following the same logic.

To find out how the equilibrium mass of operating firms (M) varies with the stringent environmental policy, further knowledge about the varying aggregate revenue with permit cap is needed. Given no inference can be drawn on the aggregate revenue of permit auction, it is unclear what influence the policy eventually has on the mass of operating firms, of clean firms, and of dirty firms.

The model offers a novel prediction on job creation and destruction, which is completely absent from homogeneous firms models. When the adopted technology is labor-biased, there is gross job creation at high-productive dirty firms that switch to the clean technology combined with simultaneously gross job destruction at low-productive dirty firms that exit the market. An emission permit cap reduction cleans up the environment and creates green jobs. Conversely, when the adopted technology is emission-biased, there exist job reallocations from the clean firms towards the dirty firms.

When it comes to the welfare implication, there is a tradeoff between environmental quality and love-of-variety, since both emissions and varieties fall provided the labor-biased clean technology with gross substitute factors. Without specifying the domestic pollution damage function, whether social welfare gains or loses from the stringent environmental policy cannot be determined.

2.3 Model Setup in an Open Economy

This section starts to examine the impacts of environmental policy and trade cost reductions in the context of an open economy with costly trade. To lay out a theoretical framework for future numerical simulation, I consider a world of two asymmetric countries, home and foreign, which differs in labor endowment, stringency of environmental policy (i.e., permit cap), and technology upgrade fee. For the analysis of comparative statics in the steady-state equilibrium, whereas, I assume the two countries are identical such that the analytical derivation is tractable. Additionally, the inter-temporal and across-border permit trade schemes are assumed away.[5] Other assumptions about the government role remain.

I maintain the assumption that international trade is costly throughout this section. Exporting requires a fixed cost of $f_x > 0$ measured in labor, thereafter sunk. It is also subject to the standard iceberg form of variable cost (e.g., transportation cost) whereby $\tau > 1$ units of a good must be shipped in order for one unit to arrive at the destination. The assumption of trade costs is consistent with recent empirical evidence suggested in the trade literature (Bernard et al. 2003), and it is one of essential assumptions creating the partition of firms by exporting status in the Melitz framework. To keep it simple, I assume that the trade costs are irrelevant to the production technology and country, but it is straightforward to relax this assumption and allow the trade costs to vary. The model uses an asterisk to denote foreign country variables to distinguish them from home country variables when necessary. The equilibrium conditions for the foreign country are omitted but could be derived analogously.

2.3.1 Preference and Production

The representative consumer in each country (home and foreign) shares the same preference defined by equation (2.1) in the closed economy. As a result of Dixit-Stiglitz monopolistic competition, for any varieties produced by technology $j \in \{c, d\}$ in home country, the residual demand in the home market, denoted by q_{jh}, and that in the export market, denoted by q_{jx}, have the iso-elastic forms,

$$q_{jh} = \frac{RP^{\sigma-1}}{(p_{jh})^{\sigma}}; q_{jx} = \frac{R^*(P^*)^{\sigma-1}}{(p_{jx})^{\sigma}} \tag{2.22}$$

where the first subscript $j \in \{c, d\}$ denotes technology choice, clean or dirty, respectively; the second subscript (h, x) represents the home and export market, respectively. (p_{jh}, p_{jx}) denote individual variety prices across markets. (P, P^*) are the aggregate prices. (R, R^*) are the aggregate expenditure indices. These aggregate indices will be presented shortly.

[5] In a symmetric setting, the assumption of no across-border permit trade scheme is irrelevant.

Each firm with a heterogeneous productivity parameter faces both the home and export residual demand functions with a constant elasticity of $\sigma > 1$ defined in equation (2.22). Hence the firm chooses optimal price as constant markups over marginal costs. The exporting firm sets a higher price in the export market, reflecting a higher marginal cost of export. The optimal pricing rules and output levels across markets are given by,

$$p_{jx}(\varphi) = \tau p_{jh}(\varphi) = \frac{\tau c_j}{\rho\varphi} \tag{2.23a}$$

$$q_{jx}(\varphi) = \tau^{-\sigma}\Lambda q_{jh}(\varphi) = R^*(P^*)^{\sigma-1}\left(\frac{\rho\varphi}{\tau c_j}\right)^{\sigma} \tag{2.23b}$$

where $\Lambda \equiv R^*(P^*)^{\sigma-1}/\left(RP^{\sigma-1}\right)$ denotes the relative foreign market potential, the ratio of foreign market potential to home market potential. If countries are identical, the relative foreign market potential is then unit in equilibrium, $\Lambda = 1$. Revenues earned from the home and export market could be linked in the following way,

$$r_{jx}(\varphi) = \tau^{1-\sigma}\Lambda r_{jh}(\varphi) = R^*(P^*)^{\sigma-1}\left(\frac{\rho\varphi}{\tau c_j}\right)^{\sigma-1} \tag{2.24}$$

Using Shephard's Lemma, firm's variable labor and emission permit input demands across markets are,

$$l_{jx}(\varphi) = \tau^{1-\sigma}\Lambda l_{jh}(\varphi) = \frac{\rho s_j^l}{w} r_{jx}(\varphi) \tag{2.25a}$$

$$e_{jx}(\varphi) = \tau^{1-\sigma}\Lambda e_{jh}(\varphi) = \frac{\rho s_j^e}{p_e} r_{jx}(\varphi) \tag{2.25b}$$

Each firm's profits are separated into components from its home and export sales. The entire fixed production cost and fixed export cost are apportioned to the home profit, $\pi_{jh}(\varphi)$, and to the export profit, $\pi_{jx}(\varphi)$, respectively. So the profit earned from each market is,

$$\pi_{jh}(\varphi) = \frac{r_{jh}(\varphi)}{\sigma} - wf_j = \frac{R}{\sigma}\left(\frac{P\rho}{c_j}\right)^{\sigma-1}\varphi^{\sigma-1} - wf_j; \tag{2.26a}$$

$$\pi_{jx}(\varphi) = \frac{r_{jx}(\varphi)}{\sigma} - wf_x = \frac{R^*}{\sigma}\left(\frac{P^*\rho}{\tau c_j}\right)^{\sigma-1}\varphi^{\sigma-1} - wf_x; \tag{2.26b}$$

A firm adopting technology $j \in \{c, d\}$ produces for the home market and also exports if $\pi_{jx}(\varphi) > 0$. Thus, the firm's total profits are given by,

$$\pi_j(\varphi) = \pi_{jh}(\varphi) + \max\{0, \pi_{jx}(\varphi)\} \tag{2.27}$$

2.3.2 Entry and Exit

There are two main scenarios with the corresponding assumption on cost structure: one is that no dirty firms export, only a fraction of clean firms select to trade; the other describes that only a fraction of dirty firms export, so do all clean firms.[6] The latter one, on which the remainder of this paper focuses, is consistent with empirical findings emerging from Argentinian firm-level data sets suggested by Bustos (2011).[7]

There exist three productivity cutoffs: the zero-profit productivity cutoff of adopting the dirty technology, denoted by φ_d, above which firms enter the home market and adopt the dirty technology; the zero-profit productivity cutoff of exporting, denoted by φ_x, above which firms export; and the equivalent-profit productivity cutoff of adopting the clean technology, denoted by φ_c, above which firms enter the market and adopt the clean technology. They are defined as follows,

$$\pi_{dh}(\varphi_d) = \frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_d)^{\sigma-1} - wf_d = 0 \tag{2.28a}$$

$$\pi_{dx}(\varphi_x) = \frac{R^*}{\sigma}\left(\frac{P^*\rho}{\tau c_d}\right)^{\sigma-1}(\varphi_x)^{\sigma-1} - wf_x = 0 \tag{2.28b}$$

$$\begin{aligned}&\pi_{ch}(\varphi_c) + \pi_{cx}(\varphi_c) - \pi_{dh}(\varphi_c) - \pi_{dx}(\varphi_c)\\ &= \left(1+\tau^{1-\sigma}\Lambda\right)\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]\frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_c)^{\sigma-1} - wf = 0\end{aligned} \tag{2.28c}$$

Assumption 4 *The cost structure satisfies that*
$\Lambda\tau^{1-\sigma}f_d < f_x < f\left\{\left(1+\Lambda^{-1}\tau^{\sigma-1}\right)\left[(c_d/c_c)^{\sigma-1} - 1\right]\right\}^{-1}$

Lemma 2 *Given Assumption 4 and $\sigma > 1$, $\varphi_d < \varphi_x < \varphi_c$.*

It is easy to show that the cost structure in Assumption 4 guarantees that all clean firms serve both the domestic and export markets, only a fraction of dirty firms export. Intuitively, when the trade barrier is prohibitive ($\tau \to \infty$), the cutoff of exporting converges to infinity ($\varphi_x \to \infty$), implying that no dirty firms are able to export. Neither do clean firms. Hence the economy returns back to autarky. When variable trade cost is unit ($\tau = 1$) and $f_x = f_d$,

[6] Impacts of reductions in trade cost or permit cap vary systematically with scenarios on which one focuses.

[7] Using the National Survey on Innovation and Technological Behavior of Industrial Argentinian Firms during the period 1992-1996, Bustos (2011) finds that, on average, continuing exporters have a 0.33 log points higher level of technology spending per worker than never exporters in 1992.

the productivity cutoff of adopting the dirty technology then equals the cutoff of exporting ($\varphi_d = \varphi_x$), capturing that access to the export market is no more costly than access to the domestic market.

There are three ways of expressing the relative equilibrium cutoffs within the same country. First, look at firms adopting the dirty technology but serving different markets,

$$\left(\frac{\varphi_x}{\varphi_d}\right)^{\sigma-1} = \frac{\tau^{\sigma-1}}{\Lambda}\frac{f_x}{f_d} \tag{2.29}$$

It follows immediately that a lower trade cost (τ or f_x) bridges the productivity gap between the least productive exporting firms and the least productive dirty firms, since exports become more profitable. A rise in fixed costs of adopting dirty technology f_d makes the least dirty firms difficult to survive in the market, hence driving up the productivity gap. If countries are not identical, this gap also depends upon the relative strength of the home and foreign market potential, denoted by $RP^{\sigma-1}$ and $R^*(P^*)^{\sigma-1}$, respectively. This relative strength also reflects the relative size of market across countries. The smaller the relative foreign market potential (Λ) is, the less promising of selling products in the export market is, hence the larger the proportion of dirty firms only serving the domestic market will be.

The second comparison worthy of attention involves those which serve both markets but adopt different technologies,

$$\left(\frac{\varphi_c}{\varphi_x}\right)^{\sigma-1} = \left(\frac{1}{1+\tau^{\sigma-1}\Lambda^{-1}}\right)\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]^{-1}\frac{f}{f_x} \tag{2.30}$$

This expression shows that the proportion of dirty firms serving both the domestic and export markets, represented by φ_c/φ_x, is inversely related to trade costs (both variable and fixed costs), relative marginal costs (c_d/c_c), and relative home market potential index (Λ^{-1}). Factors like a reduction in trade costs or a rise in foreign market size relative the home market are favorable of exporting decisions, and enlarge the productivity cutoff gap between the least clean firms and the least exporters. An increase in the relative marginal costs (c_d/c_c) encourages to adopt the clean technology, thus shortens the cutoff gap.

Equations (2.29) and (2.30) together give rise to the equilibrium relationship between the technology adoption cutoffs,

$$\left(\frac{\varphi_c}{\varphi_d}\right)^{\sigma-1} = \frac{1}{1+\tau^{1-\sigma}\Lambda}\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]^{-1}\frac{f}{f_d} \tag{2.31}$$

This expression is worth several comments. The gap between the least productive clean firms and the least productive dirty firms, captured by φ_c/φ_d, is increasing in variable trade cost but decreasing in relative marginal costs c_d/c_c. If a reduction in the variable trade cost reduces permit price, leading to an indirect negative impact on the relative marginal costs, there then exists an ambiguous effect on the cutoff gap (φ_c/φ_d).

The entry process is exactly the same as the one in the closed economy except adding export decisions during the production as depicted in Figure 2.3. The expected profit now consists of three components: one from adopting the dirty technology and serving only the domestic market; another from adopting the dirty technology but serving both the domestic and export markets; and the other from adopting the clean technology and serving both markets.

$$\bar{\pi} = \int_{\varphi_d}^{\varphi_c} \pi_{dh}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} \pi_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} \left[\pi_{ch}(\varphi) + \pi_{cx}(\varphi)\right]\mu(\varphi)d\varphi \tag{2.32}$$

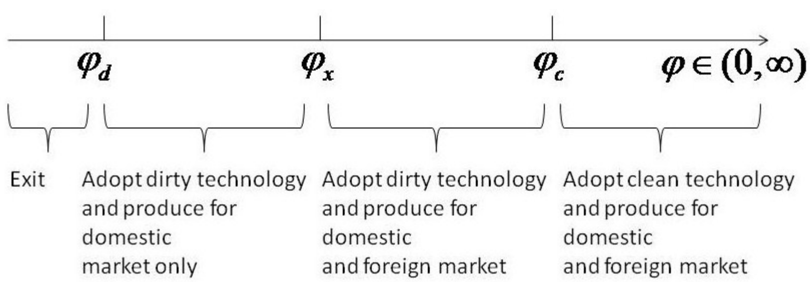


Figure 2.3: Productivity Cutoffs in the Open Economy

With unlimited entry, the free entry condition under costly trade is rewritten as follows,

$$f_d\int_{\varphi_d}^{\infty}\left[\left(\frac{\varphi}{\varphi_d}\right)^{\sigma-1} - 1\right]g(\varphi)d\varphi + f_x\int_{\varphi_x}^{\infty}\left[\left(\frac{\varphi}{\varphi_x}\right)^{\sigma-1} - 1\right]g(\varphi)d\varphi$$
$$+ f\int_{\varphi_c}^{\infty}\left[\left(\frac{\varphi}{\varphi_c}\right)^{\sigma-1} - 1\right]g(\varphi)d\varphi = \delta f_e \tag{2.33}$$

The equilibrium cutoff values are jointly determined by trade costs (f_x & τ), emission permit cap, and other exogenous key parameters, such as death rate (δ), initial investment costs (f_e), and fixed production costs (f_d, f_c). The results vary systematically with technology and market.

In the end, the steady-state equilibrium is still characterized by equation (2.14). The aggregate mass of dirty firms, of exporting firms, and of clean firms, represented by (M_d, M_x, M_c), respectively, are,

$$M_d = \lambda_d M; M_x = \lambda_x M; M_c = \lambda_c M \tag{2.34}$$

where $\lambda_x \equiv [1 - G(\varphi_x)]/[1 - G(\varphi_d)]$ denotes the *ex ante* probability of exporting conditional on successful entry, and also represents the *ex post* fraction of exporting firms; (λ_d, λ_c) are defined in the closed economy. Given the Pareto productivity distribution in Assumption 3, the *ex post* fractions (or the *ex ante* conditional probabilities) associated with the relative equilibrium cutoff values are,

$$\lambda_d = 1 - \left(\frac{\varphi_d}{\varphi_c}\right)^c; \lambda_x = \left(\frac{\varphi_d}{\varphi_x}\right)^c; \lambda_c = \left(\frac{\varphi_d}{\varphi_c}\right)^c \tag{2.35}$$

2.3.3 Aggregate Variables

The aggregate price index (P), aggregate expenditure (R), and market clear conditions of emission permits and labor are given as below. All aggregate indices consist of components from dirty firms serving the home market, dirty firms serving both the home and export markets, and cleans firms serving both markets.

$$\begin{aligned} P^{1-\sigma} =& M \left\{ \int_{\varphi_d}^{\varphi_c} p_{dh}(\varphi)^{1-\sigma} \mu(\varphi) d\varphi + \int_{\varphi_x}^{\varphi_c} p_{dx}(\varphi)^{1-\sigma} \mu(\varphi) d\varphi \right. \\ & \left. + \int_{\varphi_c}^{\infty} \left[p_{ch}(\varphi)^{1-\sigma} + p_{cx}(\varphi)^{1-\sigma} \right] \mu(\varphi) d\varphi \right\} \end{aligned} \tag{2.36}$$

$$R = M \left\{ \int_{\varphi_d}^{\varphi_c} r_{dh}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_x}^{\varphi_c} r_{dx}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_c}^{\infty} \left[r_{ch}(\varphi) + r_{cx}(\varphi) \right] \mu(\varphi) d\varphi \right\} \tag{2.37}$$

$$\overline{E} = M \left\{ \int_{\varphi_d}^{\varphi_c} e_{dh}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_x}^{\varphi_c} e_{dx}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_c}^{\infty} \left[e_{ch}(\varphi) + e_{cx}(\varphi) \right] \mu(\varphi) d\varphi \right\} \tag{2.38}$$

$$\begin{aligned} \overline{L} =& M \left\{ \int_{\varphi_d}^{\varphi_c} l_{dh}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_x}^{\varphi_c} l_{dx}(\varphi) \mu(\varphi) d\varphi + \int_{\varphi_c}^{\infty} \left[l_{ch}(\varphi) + l_{cx}(\varphi) \right] \mu(\varphi) d\varphi \right\} \\ & + M \left\{ \int_{\varphi_d}^{\varphi_c} f_d \mu(\varphi) d\varphi + \int_{\varphi_x}^{\varphi_c} f_x \mu(\varphi) d\varphi + \int_{\varphi_c}^{\infty} (f_c + f_x) \mu(\varphi) d\varphi \right\} + M_e f_e \end{aligned} \tag{2.39}$$

2.3.4 Equilibrium

The costly trade equilibrium in the open economy is a vector of eight variables in each country (home and foreign) $\{\varphi_d, \varphi_x, \varphi_c, w, p_e, P, R, M, \varphi_d^*, \varphi_x^*, \varphi_c^*, w^*, p_e^*, P^*, R^*, M^*\}$ subject to eight conditions in each country: two equilibrium relationships between cutoff values (2.29) & (2.30) (any two conditions could derive the third one), free entry condition (2.33), aggregate price index (2.36), aggregate revenue index (2.37), the equivalent aggregate expenditure condition (2.19), emission permit market clear condition (2.38), and labor market clear condition (2.39). One of the conditions is redundant by Walras' Law.

2.3.5 Comparative Statics

The current model is well-suited to address mechanisms in which the exposure to trade and environmental policy come into play and interact. I consider changes of policy instruments in a bilateral and symmetric way to make derivation tractable. Throughout this section, I maintain the assumption that the firms partitioning pattern stated in Lemma 2 ($\varphi_d < \varphi_x < \varphi_c$) always holds, and also assume the two identical countries. The symmetry assumption ensures that the two countries share the same input prices, aggregate variables, and productivity cutoffs. Thus the relative foreign market potential is unit, $\Lambda = 1$. To shed lights on the effects of policy instruments in an asymmetric setting (including an unilateral policy change), numerical simulations of a parameterized model are required but beyond the scope of this paper.

2.3.5.1 Stringent Environment Policy

A reduction in the emission permit cap occurs when both home and foreign governments cooperatively and simultaneously participate in cleaning up pollution. This stringent environmental policy raises the cost of emitting pollution as established in the following Proposition,

Proposition 3 *A lower emission permit cap ($d\overline{E}^* = d\overline{E} < 0$) increases permit price, $\partial p_e / \partial \overline{E} < 0$.*

Proof. See Appendix. ■

The intuition of the rising permit price as the permit cap falls follows exactly the same as in the closed economy. It still has no detailed information about the changing aggregate permit auction revenue in response to the cap. Whereas, responses of productivity cutoffs to the lower emission cap vary with the factor-biased feature. The relations are expressed in the next Proposition.

Proposition 4 *A lower emission permit cap ($d\overline{E}^* = d\overline{E} < 0$),*

(i) if the clean technology is labor-biased, $\partial\varphi_d/\partial\overline{E} < 0$, $\partial\varphi_x/\partial\overline{E} < 0$, $\partial\varphi_c/\partial\overline{E} > 0$;

(ii) if the clean technology is emission-biased, $\partial\varphi_d/\partial\overline{E} > 0$, $\partial\varphi_x/\partial\overline{E} > 0$, $\partial\varphi_c/\partial\overline{E} < 0$;

(iii) if the clean technology is Hicks-neutral, $\partial\varphi_d/\partial\overline{E} = 0$, $\partial\varphi_x/\partial\overline{E} = 0$, $\partial\varphi_c/\partial\overline{E} = 0$;

Proof. See Appendix. ■

Figure 2.4 depicts the impacts of the stringent environmental policy on the productivity cutoffs in the open economy. The intuition directly comes from the general equilibrium implications for the permit input market. A reduction in the permit cap puts upward pressure on the input prices, affecting all operating firms with different magnitudes across technologies. When the clean technology is labor-biased, the clean firms suffer relatively less pressure from the factor market compared with the dirty firms. The cost-saving advantage of adopting the clean technology becomes more prominent, thereby creating profitable incentives of adopting it even for less productive dirty firms, illustrated by a falling φ_c. Competition in the factor markets causes the least productive dirty firms which serve only the domestic market to drop out, since they are unable to earn enough revenue to cover their fixed production costs, represented by a rising φ_d. For the least productive exporting firms, while the increasing permit price stops them from entering the export market due to negative profits. But they still can keep operating in the domestic market, expressed by a rising φ_x.

When the clean technology is emission-biased, on the other hand, the clean firms bear more pressure from the rising permit price than the dirty firms. The less productive clean firms are forced to downgrade to the dirty technology, while the less productive dirty firms enter the export market because of profitable incentives. When the clean technology is Hicks-neutral, all types of firms are facing the same proportional increasing environmental costs. Resource is not reallocated either between exporters and non-exporters, or between clean firms and dirty firms.

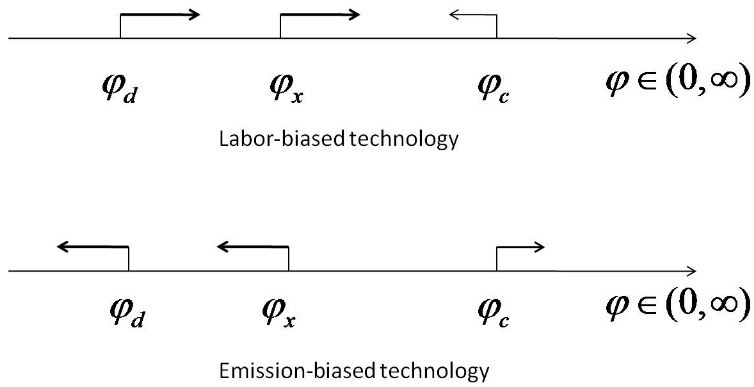


Figure 2.4: Impacts of a Stringent Environmental Policy in the Open Economy

Directly from Proposition 4 coupled with the relationship between the relative cutoffs and the *ex post* fractions in equation (2.35), one can easily inspect changes of the *ex post* fractions of firms in response to a reduction in the permit cap.

Corollary 3 *A lower emission permit cap ($d\overline{E}^* = d\overline{E} < 0$),*

(i) if the clean technology is labor-biased, $\partial\lambda_d/\partial\overline{E} > 0$, $\partial\lambda_c/\partial\overline{E} < 0$, $\partial\lambda_x/\partial\overline{E} = 0$;

(ii) if the clean technology is emission-biased, $\partial\lambda_d/\partial\overline{E} < 0$, $\partial\lambda_c/\partial\overline{E} > 0$, $\partial\lambda_x/\partial\overline{E} = 0$;

(iii) if the clean technology is Hicks-neutral, $\partial\lambda_d/\partial\overline{E} = 0$, $\partial\lambda_c/\partial\overline{E} = 0$, $\partial\lambda_x/\partial\overline{E} = 0$.

The *ex post* fractions of dirty firms (λ_d) and of clean firms (λ_c) vary with the factor-biased feature, and the intuition follows exactly the same as one in the closed economy. While the reason why the *ex post* fraction of exporting firms does not respond to the permit cap reduction lies in the same proportional burdens of rising permit prices for all dirty firms across exporting status.

When the clean technology is labor-biased, the expected profit rises as φ_d increases. As a consequence, the weighed average revenue rises due to the increasing expected profit, the *ex post* fraction of exporting firms, and that of clean firms, using the rewritten free entry condition $\bar{r} = \sigma(\bar{\pi} + wf_d + wf_x\lambda_x + wf\lambda_c)$. Conversely, when the clean technology is emission-biased, both the expected profit and weighted average revenue drop as the permit cap goes down because of the non-increasing φ_d, λ_c, and λ_x. When the clean technology is Hicks-neutral, neither the expected profit nor the weighted revenue change as the permit cap.

2.3.5.2 Trade Cost Reduction

The exposure to trade could occur in the way of lowering the variable trade cost or fixed cost. The fixed cost structure plays an essential role in generating the partitioning of firms by exporting status. As long as a small change in the fixed trade cost does not violate the assumed cost structure in Assumption 4, it has economic implications that are similar to the impacts of a reduction in the variable trade cost. Here, I only consider changes in the variable trade cost, which also capture the stylized facts that cross-border transportation costs have been declining overtime.

The effect of the exposure to trade driven by a reduction in the variable trade cost ($d\tau < 0$) differs substantially from a reduction in the emission permit cap. Trade costs are exogenous, hence are not affected by environmental policy instruments. The variable trade cost reduction, on the other hand, has an indirect impact on the emission permit price. This indirect impact is stated as follows,

Proposition 5 *A reduction in the variable trade cost ($d\tau < 0$),*

(i) if the clean technology is labor-biased, $\partial p_e / \partial \tau > 0$;

(ii) if the clean technology is emission-biased, $\partial p_e / \partial \tau < 0$;

(iii) if the clean technology is Hicks-neutral, $\partial p_e / \partial \tau = 0$.

Proof. See Appendix. ■

A reduction in the variable trade cost brings with an increasing demand from the foreign market for exporters, and creates profitable incentives even for less productive dirty firms, which originally did not select to export. This market expansion, if the technology is labor-biased, increases the competition in labor inputs relative to emission permits, hence bids up the wage rate relative to the permit price. Conversely, if the technology is emission-biased, the factor demand for emission permits increases more than that for labor, thereby driving up the permit price relative to the wage rate. If the clean technology is Hicks-neutral, the factor demand for emission permits rises as the same as for labor, henceforth leaving no influence on the relative factor rewards.

The last research question of this paper is to investigate how the productivity cutoffs vary with variable trade costs. Before addressing this point, I define two indices measuring the openness to trade and the technology adoption effect. The trade literature regards $\tau^{1-\sigma}$ as a measure of the openness to trade (Okubo, 2009). Here I introduce $T \equiv \left(1+\tau^{\sigma-1}\right)^{1/(1-\sigma)}$ as a similar measure. The openness to trade index is decreasing in τ given $\sigma > 1$. When the trade barrier is prohibitive ($\tau \to \infty$), $T \to 0$ implying the autarky. $\frac{\partial T}{\partial \tau}\frac{\tau}{T} < 0$ then denotes the trade cost elasticity of the openness to trade, representing a positive effect on the openness to trade from the lower τ, which is favorable for exporting.

Define $\Delta \equiv \left[(c_d/c_c)^{\sigma-1} - 1\right]^{1/(1-\sigma)}$ as an index of the advantage of adopting the clean technology, where c_d/c_c denotes the marginal costs of adopting the dirty technology relative to the alternative one. When $c_d = c_c$, there is no cost-saving advantage of adopting the clean technology. Then $\Delta \to \infty$ given $\sigma > 1$, capturing that no firms would have any profitable incentives to adopt the clean technology. Given permit price and $\sigma > 1$, Δ is inversely related with the relative marginal cost. The larger Δ is, the less the advantage of adopting the clean technology will be.

As stated in Proposition 5, a reduction in the variable trade cost reduces permit price if the technology is labor-biased, otherwise increases permit price. Combined with the feature of factor-biased technical change that $\partial(c_d/c_c)/\partial p_e > 0$ if the technology is labor-biased, $\partial(c_d/c_c)/\partial p_e < 0$ if the technology is emission-biased, $\partial(c_d/c_c)/\partial \tau > 0$ always hold, implying that the advantage of adopting the clean technology always falls as the variable trade cost falls, $\partial\Delta/\partial\tau < 0$. Therefore, regardless of the factor-biased technology feature, the variable trade cost reduction has an indirectly negative impact on the clean technology adoption, which is not favorable for adopting the clean technology, reflected by $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} < 0$.

Proposition 6 *A reduction in the variable trade cost ($d\tau < 0$):*

(i) $\partial\varphi_x/\partial\tau > 0$*;*

(ii) $\partial\varphi_d/\partial\tau < 0$, $\partial\varphi_c/\partial\tau < 0$, *if* $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial(\tau T)}{\partial \tau}\frac{\tau}{\tau T} = 0$*;*

(iii) $\partial\varphi_c/\partial\tau < 0$, *but the sign of* $\partial\varphi_d/\partial\tau$ *is ambiguous, if* $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial(\tau T)}{\partial \tau}\frac{\tau}{\tau T} < 0$*;*

(iv) $\partial\varphi_d/\partial\tau < 0$*, but the sign of* $\partial\varphi_c/\partial\tau$ *is ambiguous, if* $\frac{\partial\Delta}{\partial\tau}\frac{\tau}{\Delta} + \frac{\partial(\tau T)}{\partial\tau}\frac{\tau}{\tau T} > 0$.

Proof. See Appendix. ■

A reduction in the variable trade cost makes export profitable even for less productive dirty firms, so that the relative cutoff between exporting and adopting the dirty technology falls, $\varphi_x/\varphi_d \downarrow$, when examining the relative equilibrium cutoff in equation (2.29). The variable trade cost reduction also squeezes out profitable incentives of adopting the clean technology through both a direct impact on the openness to trade and an indirect impact on the clean technology adoption. Hence the cutoff gap between adopting the clean technology and exporting rises, $\varphi_c/\varphi_x \uparrow$. These two opposite forces ($\varphi_x/\varphi_d \downarrow$ & $\varphi_c/\varphi_x \uparrow$) together push the less productive dirty firms to select to trade, illustrated by a falling φ_x. When examining the effect of the variable trade cost reduction on φ_c/φ_d in equation (2.31), there exists a negative effect on the clean technology adoption ($\frac{\partial\Delta}{\partial\tau}\frac{\tau}{\Delta}$) but a positive effect on the openness to trade ($\frac{\partial(\tau T)}{\partial\tau}\frac{\tau}{\tau T}$). The relative strength of these two opposing effects jointly determine the productivity cutoffs φ_d and φ_c.

2.4 Conclusion

The feature of heterogeneous productivity in the Melitz framework plays a significant role in modeling firms's decisions of exporting and adopting technology. This paper is the first study of applying and extending this framework into environmental economics. I incorporate a technology choice of dirty or clean and pollution externality into the Melitz model. Heterogeneous firms make decisions of entry, exit, and export. More importantly, they decide to adopt either dirty or clean technology. The latter is considered as factor-biased technical change compared with the former but incurs higher fixed costs. The objective of this study is to examine the impact of stringent environmental policy and openness to trade on heterogeneous firms' dynamic decisions, thereby making inferences about the aggregate productivity and composition of the entire industry.

I investigate the implications concerning reductions in emission permit cap, and show that how these implications vary with the factor-biased technology feature. When the clean technology is labor-biased technical change relative to the alternative dirty technology, a lower permit cap reallocates market share and resource from the dirty firms to the clean ones, encouraging firms to adopt the emission-saving clean technology, but discouraging the least productive firms to enter the market. The entire industry is composed of more clean firms but less dirty ones. It also experiences an gain of improved aggregate productivity by driving out the least productive firms. When the clean technology is emission-biased technical change, the reallocation of resource induced by the lower permit cap runs in the opposite direction.

This paper sheds light on the environmental impact of the openness to trade in terms of a variable trade cost reduction. When the clean technology is labor-biased compared with the dirty technology, the trade cost reduction raises the factor demand of labor more than emission permits, and thus lowers down the permit price relative to the wage rate. When the clean technology is emission-biased, however, the excess demand for emission permits rather than labor inputs drives up the relative emission permit price. When it comes to the impact of the further exposure to trade on firm dynamics, the lower variable trade costs leaves a positive effect on the selection to trade, but an indirectly negative impact on the clean technology adoption. The relative strength of these two opposing forces jointly determines the intra-industry firm decisions.

The paper represents a push toward understanding the comprehensive climate legislation in the context of an open economy with costly trade. An appealing research agenda is to calibrate the model to capture some salient features of U.S. data on firm distribution and dynamics. The parameterized model can be employed to explore the impacts of unilateral or multilateral climate policy change in an asymmetric setting on the inter- and intra-industry firm dynamics.

CHAPTER 3. ARE EXPORTERS MORE ENVIRONMENTALLY FRIENDLY THAN NON-EXPORTERS? THEORY AND EVIDENCE

3.1 Introduction

With the increasing availability of micro-level data sets, the differences between exporters and non-exporters have been receiving widespread attention in many dimensions, e.g., productivity growth, price markup, etc (Bernard and Jensen, 1999; Tybout, 2003; Loecker, 2007). However, the variations of firm-level environmental performance across exporting status have received scant attention. Neither theoretical nor empirical studies provide a clear-cut answer as to the relationship among export, productivity, and pollution. Part of the reason is the lack of longitudinal micro-level data sets containing both emissions and export. This is unfortunate because environmental variations between exporters and non-exporters are arguably of growing importance from the government's point of view. For instance, policies targeting various types of firms (either exporters or non-exporters) might have unintended differential environmental consequences, thereby generating ambiguous impacts on curbing global warming pollution.

In this paper, we explore the firm-level relationship between export status and environmental pollution from both theoretical and empirical approaches. To guide the empirical work, we incorporate a technology upgrading choice and pollution externality into a trade model with heterogeneous firms, using the approach of the so-called Melitz model (Melitz, 2003). The upgraded technology is assumed to be an emission-saving technical change relative to the initial technology.[1] Upgrading the technology requires extra fixed costs but provides lower marginal

[1] The upgraded emission-saving technology could be process/equipment modification or redesign including in-process recycling and pollution control devices to reduce pollution from the manufacturing process. The technology varies with pollutants that must be removed. For example, spray towers applied in food processing and foundries industries remove gaseous pollutants and particulates; thermal oxidizer used in chemical industries destroys hazardous air pollutants and volatile organic compounds from industrial air emissions.

costs. The augmented model predicts that a continuum of heterogeneous firms is partitioned by technology upgrade choice and export status. Productive firms can earn enough revenues to cover the fixed costs of entering the export market and thus select to be exporters. Moreover, only the most productive exporters upgrade to the emission-saving technology because they are the only ones with profitable incentives. The paper provides this technology upgrading mechanism to explain a negative correlation between the export status of a firm and its emission intensity. An analytic expression of the relative emission intensity across export status derived from the model gives rise to two testable predictions: (i) facility productivity is inversely related to the emission intensity; and (ii) export status is negatively correlated with the emission intensity.

To test the model, we compiled a unique detailed facility-level dataset of the U.S. manufacturing industry in years 2002 and 2005. The dataset is assembled from a variety of sources. The National Emission Inventory (NEI) of the U.S. Environmental Protection Agency (EPA) provides the facility-level criteria air pollution data, i.e., Ammonia (NH_3), Sulfur Dioxide (SO_2), Carbon Monoxide (CO), Ozone (O_3), and Total Suspended Particulates (TSPs). The facility-level economic characteristics data are obtained from the National Establishment Time Series database (NETS). These two databases are matched through the Data Universal Number System (DUNS), which is a unique facility identifier. To measure facility's exposure to environmental compliance costs, we further augment the dataset with pollutant-specific county nonattainment/attainment designations under the Clean Air Act Amendments (CAAA) legislation.

The endogeneity of the export decision is a common problem in the empirical literature on trade and the environment. To address this endogeneity issue, the empirical strategy employed in this paper involves two main steps. First, facility productivity is measured by total factor productivity (TFP), which is estimated as a Cobb-Douglas production function residual. Second, with the estimated facility TFP, we explore the correlation between exporting status and emission intensity using a two-stage estimation for each pollutant. In the first stage, we estimate the impacts of facility attributes on the probability of selection to export via a logistic regression of export status on measures of trade costs and facility TFP, as well as a facility's exposure to environmental regulations (i.e., the CAAA). Two measures of trade variable costs are used as instrumental variables for export decisions. One is facility-specific geographical distance to the nearest U.S. port, the other is industry-specific freight rate. In the second stage, an OLS regression is employed to investigate the impact of predicted likelihood of exporting on emission intensity, while controlling for facility-level productivity and industry characteristics.

Empirical findings presented in this paper are overall supportive of the theoretical predictions. For each criteria air pollutant, i.e., NH_3, SO_2, CO, O_3, and TSPs, we find a significantly negative correlation between the estimated facility productivity and emission intensity. Conditional on a facility's estimated productivity and exposure to the CAAA, facilities with high probability of exporting emit less emissions per value of sales than those with relatively low probability within the same industry. The impact of the predicted export likelihood on emission intensity is highly significant (1 percent level) for all pollutants we track. To take advantage of the variation of the environmental regulation across space and time, we also provide estimates of the impact of the CAAA on facility emission intensity. There is some evidence that polluters located in CO, O_3, or TSPs nonattainment counties have lower emission intensity than those residing in attainment areas.

The paper contributes to a growing literature in trade and the environment. With a theoretical foundation from Copeland and Taylor (1994, 1995), the existing studies document the mixed environmental impacts of trade at the aggregate (e.g., country) level (Antweiler, Copeland, and Taylor, 2001; Jeffrey and Rose, 2005; Managi, Hibiki, and Tsurumi, 2009). These studies, however, do not account for firm heterogeneity and fail to capture the firms' dynamic decisions of entry and exit. To remedy this, Cui (2011) incorporates technology adoption and environmental pollution into the Melitz framework. The analysis by Cui (2011) is theoretical in nature, aiming at the impacts of openness to trade and stringency of an environmental policy on the induced clean technology adoption and firm dynamics. In this paper, we apply the basic model setup in Cui (2011) to provide a theoretical guide for the empirical investigation on the firm-level relationship between export status and environmental performance.

The empirical evidence found in this paper contributes to the recent trade literature on the differences between exporters and non-exporters, in particular on the role of exporters in environmental performance. The literature has addressed the question using micro-level data sets from different countries and various measures of environmental behavior, and has identified robust findings in favor of exporters' environmental advantage over non-exporters. Girma, Hanley, and Tintelnot (2008) use a measure of a four-point ordinal response, ranging from not at all important to very important, to two surveyed questions concerning the environmental impacts of innovation for UK firms. They find that exporters are more likely to denote innovation as having "high" or "very high" environmental effects than non-exporters. Batrakova and Davies (2010) adopt fuel consumption as a proxy for firms' environmental behavior, and show a negative correlation between exporting status and fuel expenditures for high fuel intensity firms for a panel of Irish manufacturing firms. Similarly, Forslid, Okubo, and Ulltveit-Moe (2011) construct firm-level CO_2 emissions using data on all type of fuel use together with emission coefficients from Swedish firms. Their findings also suggest a negative correlation between export dummy and CO_2 emission intensity at the firm level. However, the self-reported answers to survey and fuel input consumption, on which these three papers focus, may not truly reflect firms' environmental performance.

Another recent paper by Holladay (2010) investigates toxic pollution emissions from the United States' manufacturing establishments over the years 1990-2006. His main results show that exporters emit less toxic emissions than non-exporters when controlling for establishment output and industry characteristics. One aspect our work shares in common with Holladay (2010) is the utilization of the NETS database. He matches plant-level toxic pollution emitters reported in the Toxic Release Inventory of the EPA with those covered in the NETS, while our paper sheds light on criteria air polluters collected in the NEI of the EPA. One departure of the present paper from his study is the empirical implementation in our paper, which controls for the estimated facility TFP and facility's exposure to the CAAA. In addition, our paper attempts to address the endogeneity issue of export decision using measures of trade costs as instrumental variables.

This paper also relates to a handful of empirical studies on the impacts of the Clean Air Act (CAA) and CAAA on industrial activities. Greenstone (2002) finds negative impacts of the CAA on the growth of polluting manufactures in nonattainment counties during the 1967-

1987 period, i.e., the growth of employment, capital stock, and shipments. Additionally, it has been further pointed out that the CAAA nonattainment designation is associated with drops in TFP for surviving polluting plants (Becker, 2010; Greenstone, List, and Syverson, 2010). Both studies use the plant/establishment level data from the U.S. Census Bureaus. Moreover, there is a long-lasting debate on whether the CAAA causes firms to reallocate within the country or even flee the country. Henderson (1996) and his follow-up study with Becker (Becker and Henderson, 2000) show that the O_3 nonattainment regulation leads to the reallocation of polluting plants from more to less polluted areas during 1963-1992. Hana (2010), on the other hand, finds robust findings that the CAAA causes regulated U.S. based multinational firms to increase their foreign assets and outputs. When it comes to the impact of the regulation on pollution cleanup, Greenstone (2004) documents evidence that the SO_2 nonattainment designation plays a minor role in the dramatic decline of county-level ambient concentrations of SO_2 during the 1969-1997 period. However, the main departure of the present paper from the foregoing studies is to explore the link among productivity, export status, and environmental pollution, controlling for facility's environmental regulatory pressure.

The remainder of the paper is organized as follows. The next section presents the theoretical framework and derives the firm-level relationship among productivity, exporting status, and emission intensity. Section 3 introduces the CAAA regulation. Section 4 describes the facility-level dataset constructed from a variety of data sources. Section 5 provides the empirical strategy and results. The last section concludes.

3.2 Theoretical Model

This section extends the Melitz framework by incorporating environmental pollution and a choice of technology upgrade. The augmented model considers a world of two countries, home and foreign, with labor endowment $\overline{L}$ and emission permit cap $\overline{E}$. Each economy consists of a single monopolistically competitive industry. The government implements a domestic emission permit cap-and-trade program. Firms are heterogeneous in terms of productivity. They produce differentiated products using labor as a primary input and generate emissions as byproducts. The notation uses an asterisk to denote foreign country variables to distinguish them from home country variables when necessary. Equations for the foreign country are omitted but could be derived analogously.

3.2.1 Setup of the Model

3.2.1.1 Entry and Exit

The timeline is depicted in Figure 3.1. At the beginning of each time period, there is a large pool of identical firms prior to entry. To enter the market, each firm pays a time-invariant entrance fee of $f_e > 0$ as an initial investment. The new entrant then draws the firm-specific productivity φ from a common density distribution $g(\varphi)$ with a positive support on $(0, \infty)$. Upon observing φ, each firm decides to either stay or exit the market immediately. If the firm stays, production requires fixed production costs of $f_d > 0$. In addition, the firm chooses whether to upgrade to an emission-saving production technology or not. Upgrading the technology requires extra fixed costs of $f > 0$. Export entails additional fixed costs of $f_x > 0$ and the standard iceberg form of variable cost (e.g., transportation cost) whereby $\tau > 1$ units of a good must be shipped in order for one unit to arrive at the destination. In the end of the period, the firm faces a constant probability $\delta \in (0, 1)$ of an idiosyncratic shock that forces it to exit regardless of the technology upgrading choice and exporting status. All fixed costs, measured in labor units and thereafter sunk, are known to all potential entrants.

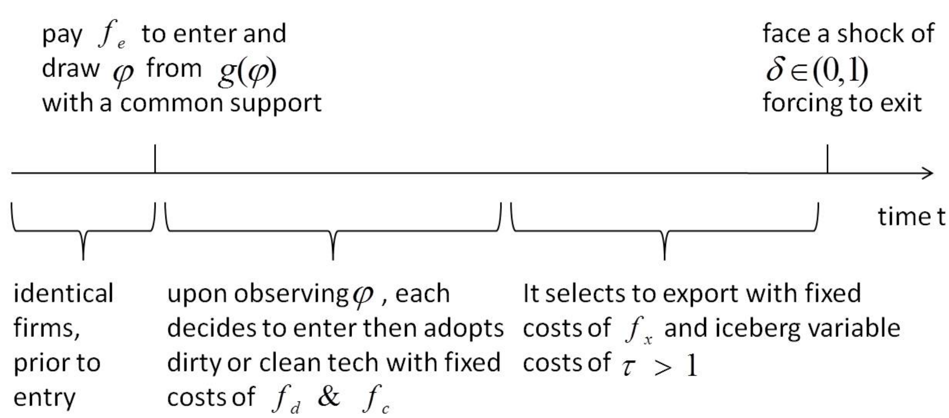


Figure 3.1: Timeline

3.2.1.2 Technology Upgrade

The technology upgrade is modeled as a choice between two different technologies dirty and clean. The initial production technology is labeled as the dirty technology. The upgraded technology is assumed to be an emission-saving technical change, and is thus labeled as the clean technology. These two technologies differ in the fixed production cost and cost share of emission permit. The production with the upgraded clean technology requires total $f_c = f_d + f$ amount of fixed costs but reduce the cost shares of emission permits. The latter is due to the emission-saving feature of the clean technology.

3.2.1.3 Production

Output produced using technology j employs labor as a primary input and generates emissions as byproducts, which are treated as production inputs following Copeland and Taylor's technique (1994), where $j \in \{c, d\}$ refers to the clean and dirty technology, respectively. The production function is written as:[2]

$$q_j = \varphi F_j(e, l) \tag{3.1}$$

where l is variable labor input; e denotes pollution emissions; φ indexes the firm-specific productivity. The production function $F_j(e, l)$ is increasing, concave, and homogeneous of degree one in e and l. Concavity is a conventional curvature assumption on the production function. The property of homogeneous of degree one allows us to derive the equivalent expression between the marginal cost and unit cost functions, which in turn guarantees that the relative input demand across productivity preserves the same structure as the relative revenue across productivity. This nice feature makes derivation tractable.

Each firm must purchase emission permits from the domestic government to emit the equivalent amounts of pollution. Given the common wage rate w and permit price p_e, the variable cost function corresponding to the production function (3.1) is:

$$C_j(\varphi, w, p_e) = \frac{q_j c_j(w, p_e)}{\varphi} \tag{3.2}$$

[2]There exists a pollution abatement technology behind the production technology. Let the production technology be, $q_j = \varphi(1-\theta)Q_j(l)$, pollution byproducts $e_j = A(\theta)Q_j(l)$, where $\theta \in [0, 1]$ denotes an endogenous faction of resources to abatement activity, $A(\theta)$ represents an abatement technology with $A(0) = 1$, $A(1) = 0$, and $\partial A/\partial\theta < 0$. Thus, the joint production technology is given by $q_j = \varphi[1 - A^{-1}(e_j/Q_j)]Q_j$.

where $c_j(w, p_e)$ is the marginal cost of production adopting technology j. As always, $c_j(w, p_e)$ is increasing and concave in input prices.

3.2.1.4 Consumption

Preferences across differentiated varieties produced in the single industry have the standard Constant Elasticity of Substitution (CES) form, with an elasticity of substitution of $\sigma = 1/(1-\rho) > 1$ and we assume that $\rho \in (0, 1)$. As a result of Dixit-Stiglitz monopolistic competition, for any varieties produced by technology j in home country, the iso-elastic form of residual demand in the home market, denoted by q_{jh}, and that in the export market, denoted by q_{jx}, can be written as functions of aggregate price indices (P, P^*), aggregate expenditure indices (R, R^*), as well as individual variety's prices (p_{jh}, p_{jx}):

$$q_{jh} = \frac{RP^{\sigma-1}}{(p_{jh})^{\sigma}}; \qquad q_{jx} = \frac{R^*(P^*)^{\sigma-1}}{(p_{jx})^{\sigma}} \tag{3.3}$$

where the first subscript $j \in \{c, d\}$ denotes technology choice, clean or dirty, respectively; the second subscript (h, x) represents the home and export market, respectively. (p_{jh}, p_{jx}) index the variety prices in the home market and in the export market, respectively.

3.2.2 Firm Behavior

Each firm with the firm-specific productivity φ faces the home and export residual demand functions with a constant elasticity of $\sigma > 1$ defined in equation (3.3). Under CES preferences the profit maximizing price is a constant markup over marginal costs. The optimal prices and outputs across markets are given by:

$$p_{jh}(\varphi) = \frac{c_j}{\rho\varphi}; \qquad p_{jx}(\varphi) = \frac{\tau c_j}{\rho\varphi} \tag{3.4a}$$

$$q_{jh}(\varphi) = RP^{\sigma-1}\left(\frac{\rho\varphi}{\tau c_j}\right)^{\sigma}; \qquad q_{jx}(\varphi) = R^*(P^*)^{\sigma-1}\left(\frac{\rho\varphi}{\tau c_j}\right)^{\sigma} \tag{3.4b}$$

Firms charge a higher price in the export market than the home market due to the extra trade variable costs. Note that $c_j \equiv c_j(w, p_e)$ is a function of endogenous input prices. Revenues earned from each market are:

$$r_{jh}(\varphi) = RP^{\sigma-1}\left(\frac{\rho\varphi}{c_j}\right)^{\sigma-1}; \qquad r_{jx}(\varphi) = R^*(P^*)^{\sigma-1}\left(\frac{\rho\varphi}{\tau c_j}\right)^{\sigma-1} \tag{3.5}$$

Using Shephard's Lemma, firm's variable labor and emission permit input demands across markets are:

$$l_{jh}(\varphi) = \frac{\rho s_j^l}{w} r_{jh}(\varphi); \qquad l_{jx}(\varphi) = \frac{\rho s_j^l}{w} r_{jx}(\varphi) \tag{3.6a}$$
$$e_{jh}(\varphi) = \frac{\rho s_j^e}{p_e} r_{jh}(\varphi); \qquad e_{jx}(\varphi) = \frac{\rho s_j^e}{p_e} r_{jx}(\varphi) \tag{3.6b}$$

where ($s_j^e \equiv \frac{\partial c_j}{\partial p_e}\frac{p_e}{c_j}, s_j^l \equiv \frac{\partial c_j}{\partial w}\frac{w}{c_j}$) denote the cost shares of emission permits, and of labor, respectively.[3] By the cost function's properties, $s_j^e + s_j^l = 1$, $\forall j \in \{c, d\}$.

We separate each firm's profits into components from sales in the home and export markets to make the derivation tractable. The entire fixed production cost and fixed export cost are apportioned to the home profit $\pi_{jh}(\varphi)$ and to the export profit $\pi_{jx}(\varphi)$, respectively. So the profit earned from each market is given by:

$$\pi_{jh}(\varphi) = \frac{r_{jh}(\varphi)}{\sigma} - wf_j; \qquad \pi_{jx}(\varphi) = \frac{r_{jx}(\varphi)}{\sigma} - wf_x \tag{3.7}$$

3.2.3 Sorting Pattern

There exist three productivity cutoffs: (i) the zero-profit productivity cutoff of adopting the dirty technology, denoted by φ_d, above which firms enter the market and adopt the dirty technology; (ii) the zero-profit productivity cutoff of exporting, denoted by φ_x, above which firms select to export; and (iii) the equivalent-profit productivity cutoff of upgrading to the clean technology, denoted by φ_c, above which firms choose to upgrade the technology. They are defined as follows:

$$\pi_{dh}(\varphi_d) = 0 \Rightarrow \frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_d)^{\sigma-1} = wf_d \tag{3.8a}$$
$$\pi_{dx}(\varphi_x) = 0 \Rightarrow \frac{R^*}{\sigma}\left(\frac{P^*\rho}{\tau c_d}\right)^{\sigma-1}(\varphi_x)^{\sigma-1} = wf_x \tag{3.8b}$$
$$\pi_{ch}(\varphi_c) + \pi_{cx}(\varphi_c) = \pi_{dh}(\varphi_c) + \pi_{dx}(\varphi_c) \Rightarrow$$
$$\left(1 + \tau^{1-\sigma}\Lambda\right)\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]\frac{R}{\sigma}\left(\frac{P\rho}{c_d}\right)^{\sigma-1}(\varphi_c)^{\sigma-1} = wf \tag{3.8c}$$

We assume that: $\Lambda\tau^{1-\sigma}f_d < f_x < f\left\{(1+\Lambda^{-1}\tau^{\sigma-1})\left[(c_d/c_c)^{\sigma-1} - 1\right]\right\}^{-1}$, such that the partitioning of firms by technology upgrade choice and export status occurs. As depicted in

[3] $s_j^e \equiv \frac{\partial c_j}{\partial p_e}\frac{p_e}{c_j} = \frac{\partial c_j}{\partial p_e}\frac{p_e q_j \varphi}{c_j q_j \varphi} = \frac{\partial(q_j c_j/\varphi)}{\partial p_e}\frac{p_e}{q_j c_j/\varphi} = \frac{\partial C_j}{\partial p_e}\frac{p_e}{C_j}$. By Shephard's Lemma, $\frac{\partial C_j}{\partial p_e}\frac{p_e}{C_j} = \frac{p_e e_j}{C_j}$, which is the cost share of emission permit. Likewise for the cost share of labor, s_j^l.

Figure 3.2, all clean firms serve both the home and export markets, only a fraction of dirty firms select to export, that is $\varphi_d < \varphi_x < \varphi_c$.[4] As a consequence, the *ex post* distribution of productivity, denoted by $\mu(\varphi)$, is conditional on successful entry, and is thus truncated at φ_d:

$$\mu(\varphi) = \begin{cases} \dfrac{g(\varphi)}{1 - G(\varphi_d)} & \text{if } \varphi > \varphi_d \\ 0 & \text{otherwise} \end{cases} \tag{3.9}$$

where $G(\varphi)$ is the cumulative distribution function for $g(\varphi)$.

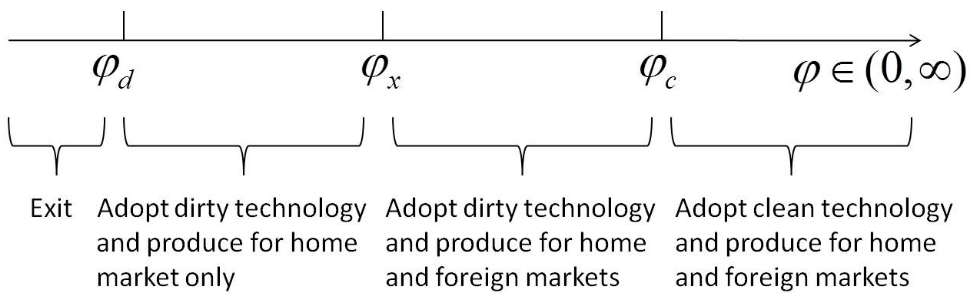


Figure 3.2: Technology and Exporting Choices

Given an unbounded pool of potential new entrants, in any equilibrium with unrestricted entry, the expected value of entry, the *ex ante* probability of successful entry $(1 - G(\varphi_d))$ multiplied by the expected profitability of producing the good and until hit by the bad shock $(\bar{\pi}/\delta)$, must equal its sunk entry cost wf_e. This defines the free entry condition:

$$\frac{\bar{\pi}\left[1 - G(\varphi_d)\right]}{\delta} = wf_e \tag{3.10}$$

where the expected profit conditional on successful entry, denoted by $\bar{\pi}$, is defined as:

$$\bar{\pi} = \int_{\varphi_d}^{\varphi_c} \pi_{dh}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} \pi_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} \left[\pi_{ch}(\varphi) + \pi_{cx}(\varphi)\right]\mu(\varphi)d\varphi \tag{3.11}$$

The expected profit consists of three components: one from adopting the dirty technology and serving only the domestic market; another from adopting the dirty technology but serving both the domestic and export markets; and the other from upgrading the clean technology and serving both markets.

In the end, the steady-state equilibrium is characterized by a constant mass of firms entering in each period, M_e, and a constant mass of operating firms, M. The mass of successful new

[4] By assumptions on parameters and cost structure, one could also have $\varphi_d < \varphi_c < \varphi_x$.

entrants exactly replaces the mass of incumbents who are hit by the bad shock and exit:

$$\delta M = [1 - G(\varphi_d)]\, M_e \tag{3.12}$$

3.2.4 Equilibrium

The paper focuses on a steady-state equilibrium. The equilibrium is defined as a vector of eight variables in each country $\{\varphi_d, \varphi_x, \varphi_c, w, p_e, R, M, M_e\}$ subject to the following eight equilibrium conditions: two equilibrium relationships between cutoff values (3.8) (any two conditions could derive the third one), free entry condition (3.10), law of motion (3.12), aggregate revenue index (3.17), emission permit market clear condition (3.13), labor market clear condition (3.16), and the equivalent aggregate expenditure condition (3.18). One of the conditions is redundant by Walras' Law.

Total emissions generated during the production process are the mass of firms multiplied by emissions aggregated from the home and export markets and from the dirty and upgraded clean technology. Thus the emission permit market clearing condition is:

$$\overline{E} = M\left\{\int_{\varphi_d}^{\varphi_c} e_{dh}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} e_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} \left[e_{ch}(\varphi) + e_{cx}(\varphi)\right]\mu(\varphi)d\varphi\right\} \tag{3.13}$$

Similarly, the aggregate variable labor input demand is given by:

$$L^v = M\left\{\int_{\varphi_d}^{\varphi_c} l_{ch}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} l_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} \left[l_{ch}(\varphi) + l_{cx}(\varphi)\right]\mu(\varphi)d\varphi\right\} \tag{3.14}$$

The aggregate fixed labor inputs used in the domestic production, export, and initial investment as entry costs are:

$$L^f = M\left\{\int_{\varphi_d}^{\varphi_c} f_d\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} f_x\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} (f_c + f_x)\mu(\varphi)d\varphi\right\} + M_e f_e \tag{3.15}$$

The aggregate labor demand is then given by the sum of the above two aggregate variable labor input demand L^v and fixed labor input demand L^f. The labor market clearing condition satisfies,

$$\overline{L} = L^v + L^f \tag{3.16}$$

The aggregate expenditure equals the aggregate revenue, which is the mass of firms multiplied by the weighted average revenue expressed as the term in the curly bracket:

$$R = M\left\{\int_{\varphi_d}^{\varphi_c} r_{dh}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} r_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty}\left[r_{ch}(\varphi)+r_{cx}(\varphi)\right]\mu(\varphi)d\varphi\right\} \tag{3.17}$$

In equilibrium, the aggregate expenditure is the sum of total payments to labor and emission permits,

$$R = w\overline{L} + p_e\overline{E} \tag{3.18}$$

3.2.5 Environmental Performance

Differences in emission intensity, measured by emissions per output, between exporters and non-exporters is the primary focus of this paper. The relative emission intensity across export status and technology upgrading choice is derived as follows:

$$\frac{\left[e_{ch}(\varphi')+e_{cx}(\varphi')\right]/\left[q_{ch}(\varphi')+q_{cx}(\varphi')\right]}{e_{dh}(\varphi)/q_{dh}(\varphi)} = \underbrace{\left(\frac{1+\tau^{1-\sigma}\Lambda}{1+\tau^{-\sigma}\Lambda}\right)}_{\text{Market Size Effect}}\underbrace{\left(\frac{c_c s_c^e}{c_d s_d^e}\right)}_{\text{Technology Effect}}\underbrace{\left(\frac{\varphi}{\varphi'}\right)}_{\text{Productivity Effect}} \tag{3.19}$$

where $\Lambda \equiv R^*(P^*)^{\sigma-1}/\left(RP^{\sigma-1}\right)$ denotes the relative foreign market potential, the ratio of foreign market potential to home market potential. The market potential index is decreasing in the market crowding ($P^{1-\sigma}$) but increasing in the aggregate expenditure (Okubo, 2009). The right hand side of the above equation can be decomposed into the following three effects.

The *market size effect* (in the first parenthesis) is reflected by the production expansion as a result of the export decision. *Ceteris paribus*, an increase in the relative foreign market potential Λ raises the market size effect. This effect is always greater than one as long as the iceberg trade cost exceeds one, that is $\tau > 1$. If $\tau = 1$, implying that accessing to the export market is no more costly than accessing to the home market, a partitioning of a continuum of firms across export status will not be induced, thus the market size effect equals one. If the two countries are identical, the aggregate variables would be same across countries. As a consequence, the market size effect only depends upon the trade variable cost τ.

The *technology effect* (in the middle parenthesis) is represented by the emission-saving benefit from the upgraded clean technology. The clean technology has lower marginal cost relative to the dirty technology, the inequality of $c_c < c_d$ always holds because of the factor-augmenting feature. This effect is less than one ($c_c s_c^e < c_d s_d^e$), if the clean technology is the emission-saving technique change relative to the dirty technology.[5]

The *productivity effect* (in the last parenthesis) is associated with the relative productivity gains. The higher the productivity, the lower the emission intensity is. Both the technology and productivity effects contribute to emission intensity reductions, but the market size effect leads to more emissions.

The firm-level relationship between export status and pollution intensity in equation (3.19) provides theoretical guidance for the empirical investigation. Due to a lack of detailed trade and technology information at the firm level, the available data do not allow us to directly estimate the decomposed effects of the market size, technology, and productivity. Alternatively, there are two main testable predictions implied by the theoretical model: (i) the productivity effect, measured by the relative productivity, is inversely related to the emission intensity; and (ii) exporting status is negatively correlated with the emission intensity if the technology and productivity effects together dominate the market size effect. Before turning to the empirical implementation, we discuss the related environmental regulation and the data in next two sections.

3.3 The Clean Air Act

In this section, we discuss environmental regulations, i.e., the Clean Air Act. The data and analysis in the paper relate to implementation and changes in this regulation.

3.3.1 Background

The Clean Air Act, initially passed in 1970 and amended in 1977 and 1990 (the CAAA thereafter), regulated that the EPA should classify each county in the United States into pollutant-specific nonattainment and attainment categories based upon the ambient concentrations of four criteria air pollutants: i.e., SO_2, CO, O_3, and TSPs. Under the 1977 amendments, each

[5] As shown in Cui (2011), the technology effect is emission-saving, that is $s_c^e < s_d^e$, if the clean technology is a labor-biased technique change relative to the dirty technology. The technology effect is labor-saving, that is $s_c^e > s_d^e$, if the clean technology is an emission-biased technique change relative to the dirty technology.

July, the pollutant-specific nonattainment/attainment designation is officially reclassified for every U.S. county under the national standards for each criteria pollutant.

When a county is designated as nonattainment, the state of the county is required to develop a State Implementation Plan (SIP), which lays out specific regulations for every major source of each pollutant for which the county is in nonattainment. Existing facilities located in the county are subject to reasonably available control technology which usually involves retrofitting existing equipment, whereas new facilities are exposed to the lowest achievable emission rate (LAER), requiring the installation of the cleanest available technology. The 1977 amendments added the requirement that new facilities could be required to purchase pollution offsets from existing facilities. In contrast, when a county is in attainment, existing facilities are not subject to any technological standards. Only those new facilities with the potential to emit over 100 tons per year of a criteria pollutant, classified as class A polluters, have to comply with best available control technology control standard, a weaker standard than the LAER. New small facilities in attainment counties are exempt from the regulation.

In summary, new and existing facilities are each exposed to more stringent regulations in nonattainment counties relative to attainment ones, while new small facilities in attainment counties are exempt from the regulation. Additionally, non-polluters are free from the regulation in both sets of counties.

3.3.2 Regulation Variation

County nonattainment designation is adopted as a proxy for a facility's exposure to stringent environmental regulation. There exist three sources of variations, in which facilities are affected by the nonattainment designation. First, the regulation is pollutant-specific and only applies to polluting facilities located in nonattainment counties. The comparison across facilities but within the same industry removes industry-specific shock, hence identifies the regulation effect from the shock. Second, every year, each county's attainment/nonattainment designations are reclassified. Consequently, the variation of an individual facility's exposure to regulation is traceable over time. The comparison within a facility across the attainment and nonattainment regimes ensures that firm-specific factors (e.g., heterogeneous productivity) do not drive the results. However, the facility fixed effect cannot be implemented in the econometric estimation that follows (because such an effect cannot be identified separately from the parameter of an export indicator, which is time-invariant in the dataset). Third, the exposure to a regulatory program within nonattainment counties varies across facilities, only those emitting the relevant pollutant are subject to the regulation. Accounting for the intra-county variations by adding county by year effects ensures that time-varying factors common to all facilities within a county are not confounded with the effects of regulation.

3.4 Data

We compiled the unique detailed facility-level emission data on criteria air pollutants and facility characteristics in the U.S. manufacturing industry in years 2002 and 2005. This section describes data sources and how we match the data from two different facility-level databases.

3.4.1 Data Sources

A facility is a place where economic activities resulting in air emissions occur. In general, facility emission data come from the NEI of the U.S. EPA, and facility economic characteristics are taken from the NETS Database. These two databases are matched through the DUNS number assigned by Dun and Bradstreet to identify unique business establishments. The regulatory attainment/nonattainment county status information is obtained from the Green Book Nonattainment Areas for Criteria Pollutants reported by the EPA.[6] A list of variables and data sources used in the paper is summarized in Table C.3 in the Appendix.

For each criteria air pollutant we track, the Green Book indicates whether only part of a county or the whole county is in nonattainment. We assign a county to the nonattainment category for each of four criteria pollutants, i.e., CO, SO_2, O_3,[7] and TSPs,[8] if the entire county

[6]For detailed information, see http://www.epa.gov/air/oaqps/greenbk/index.html.

[7]The formation of ground-level ozone is a complicated chemical process that involves volatile organic compounds (VOCs) and oxide of nitrogen (NO_x) when these two react in the presence of sunlight. There are separate standards for nitrogen dioxide, 1-hour ozone, and 8-hour ozone. We classify a county as nonattainment for ozone if it is in nonattainment for nitrogen dioxide or ozone including both 1-hour and 8-hour standards. Therefore, the pollution of VOCs and NO_x is associated with this combined O_3 nonattainment designation.

[8]TSPs is defined as the sum of Particulate Matter-10 (PM-10) and Particulate Matter-2.5 (PM-2.5). There exist separate standards for PM-10 and PM-2.5 (There exists 1997 standard and 2006 standard. Only 2006 standard is effective during the sample period). We classify a county as nonattainment for TSPs if it is in

or part of the county is designated as nonattainment status.

We now turn to an introduction of two primary facility-level databases. The NETS database, developed through a joint venture with Dun and Bradstreet by Walls and Associates, is a truly unique business establishment database covering over 300 fields and 40 million unique establishments on a national basis for every year since 1990. The data acquired for this study include number of employee, value of sale, export indicator, DUNS number, geographic location (i.e., latitude and longitude), five-digit zip code, and five-digit Federal Information Processing Standard (FIPS) county code.

The EPA's NEI database contains information about facilities that emit criteria air pollutants for all areas of the United States.[9] It releases an updated version of the NEI database every three years since 2002. The facility-level emission data in the NEI database acquired for this empirical study includes emissions of six criteria air pollutants: i.e., SO_2, CO, VOCs, NO_x, TSPs, and NH_3, in years 2002 and 2005.[10]

3.4.2 Data Matching

The data matching work consists of two main procedures. First, we retrieve DUNS numbers for polluting facilities in the NEI database from the Facility Registry System (FRS) of the EPA. Second, we match them with those appearing in the NETS database through the DUNS number.

The NEI database assigns each polluting facility a unique NEI site ID, which we use to retrieve facility geographic information and facility registry ID from the FRS of the EPA. The FRS is a centrally-managed database that identifies facilities, sites, or places subject to environmental regulations or of environmental interests. Facility geographic information and DUNS numbers are obtained from the FRS through two different channels. Specifically, EZ

nonattainment for at least one of these standards.

[9]For a detailed discussion on the facility-level NEI database, please see the Appendix.

[10]The EPA has been collecting facility-level criteria air emissions since 1990. It has emission reports for years 1990, 1996 through 2002, and 2005. Because of changes in EPA emission inventory procedures, emissions for 1999 and later years may not be directly comparable with prior years, especially with regard to particulate matter emissions. Some facility IDs and names changed in the 1999 data, so it may not be possible to identify unambiguously the corresponding 1999 data and data in years prior to 1999 for some facilities. In addition, facility IDs are not uniquely assigned and not well organized in years 1999 through 2002, therefore making the facility data matching work across years less promising.

Query in the FRS provides data download options for a customized list of facilities, which are associated with the NEI program.[11] The data obtained from the EZ Query include: facility registry ID uniquely assigned by the FRS, NEI site ID assigned by the NEI, FIPS county code, zip code, latitude, longitude, and four-digit Standard Industry Classification (SIC) code.[12] For each polluting facility in the NEI database, we obtain two different IDs assigned uniquely by each source, i.e., the facility NEI ID and facility registry ID. With the facility registry ID, facility DUNS numbers are retrieved separately through Facility Registry System Query.[13] In the end, the facility-level emission dataset we compiled contains criteria air emissions, facility name, FIPS county code, zip code, geographic location (i.e., latitude and longitude), SIC code, facility NEI ID, facility registry ID, and DUNS number.

In the next step, we match polluting facilities in the NEI database with those that appear in the NETS Database through the DUNS number. The EPA does not provide further information about how DUNS numbers are reported for polluting facilities and why some of them have missing DUNS numbers in the dataset.[14] A pair of facilities from each source is considered as a match if the following series of criteria are satisfied. They share the same DUNS number and are located in the same area in terms of five-digit zip code and five-digit FIPS county code.[15] More importantly, for each pair, we compare their facility names from each source to ensure the match.

In the matched dataset, we count the number of facilities with the missing values and zeros for emission estimates by pollutant and year. For each pollutant, the number of polluting facilities with zero emissions drops dramatically from year 2002 to year 2005, while the number of polluting facilities with the missing estimates increases accordingly. This pattern still exists in the original facility-level NEI database prior to matching. We drop those polluting facilities with either zeros or the missing values of emission estimates because of incapable of distinguishing

[11]For EZ Query, see http://www.epa.gov/enviro/html/fii/ez.html.

[12]Given the NEI site ID contained in the FRS, we are able to match all polluting facility in the NEI database with those in the FRS through the NEI site ID.

[13]For Facility Registry System Query, http://www.epa.gov/enviro/html/fii/fii_query_java.html.

[14]Due to an incomplete report on DUNS numbers in the FRS, approximately 80 percent of polluting facilities in the manufacturing industry collected in the NEI database have associated DUNS numbers.

[15]In the NEI database, a small fraction of polluting facilities does not report a complete five-digit zip code. In that case, we will only match their FIPS county codes.

non-emitting facilities from emitting ones.

Finally, this matching procedure narrows down our dataset to 15,604 polluting facilities in year 2002 and 15,006 polluting facilities in year 2005, all in the U.S. manufacturing industry as determined by having a four-digit SIC code between 2000 and 4000. That is roughly half of polluting facilities with DUNS numbers in the manufacturing industry reported in the NEI database.

3.4.3 Descriptive Statistics

The merged dataset in this study consists of an unbalanced panel of polluting facilities in years 2002 and 2005. The analysis uses 30,610 facility-by-year observations from 17,594 facilities located among 2,025 U.S. counties. There are 13,016 facilities surviving throughout the study period. Table 3.1 provides summary statistics on a number of variables. It is worth to note that each facility emits at least one pollutant, but not all facilities have emissions reports for all five criteria air pollutants. In many cases, facilities only have estimates for one pollutant in the NEI database. In addition, the dataset contains some observations with extremely low emissions, which are dropped in the two-stage estimation. As listed at the bottom of Table 3.1, these outliers only account for a small fraction of total relevant observations.[16]

Table 3.2 summarizes the differences between exporters and non-exporters across facility characteristics. Exporters are larger than non-exporters in terms of sale and number of employee. This result is in line with the growing empirical trade literature on heterogeneous firms. When it comes to the environmental performance, exporters emit more SO_2 and TSPs, but less CO, O_3, and NH_3 than non-exporters. Pollution intensity, measured by emissions per value of sales (tons per thousand dollars), is lower for exporters relative to non-exporters for all criteria air pollutants. As shown in column 4 of Table 3.2, simple two-group mean-comparison tests (T-test) do not present any significant mean differences in the pollution intensity across export status. The differences are persistent for sample years 2002 and 2005 separately.

Figures C.1-C.5 in the Appendix present a series of U.S. maps indicating geographic loca-

[16] For each pollutant, a fraction of observations with annual emissions less than 0.001 tons are listed as follows: i.e., 6.55 percent for SO_2, 0.45 percent for CO, 0.15 percent for O_3, 1.01 percent for TSPs, and 3.79 percent for NH_3.

Table 3.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Sales (thousand $)	30,610	23387.0	41257.5	8	3,130,369
Employees	30,610	147.0	179.5	1	998
NH_3 (tons)	6,998	10.9	92.2	0.001	3,280.3
SO_2 (tons)	14,823	128.3	1319.3	0.001	96,822.7
CO (tons)	17,803	133.8	1386.3	0.001	56,727.5
O_3 (tons)	27,421	95.6	460.1	0.001	20,592.5
TSPs (tons)	22,405	63.3	475.4	0.001	36,211.4
Export Indicator	30,610	0.24	0.43	0	1
Any NA	30,610	0.50	0.50	0	1
SO_2 NA	30,610	0.01	0.08	0	1
CO NA	30,610	0.08	0.27	0	1
O_3 NA	30,610	0.48	0.50	0	1
TSPs NA	30,610	0.23	0.42	0	1

Note: NA stands for Nonattainment.

tions of polluting exporters and non-exporters on a pollutant-by-pollutant basis.[17] The pink points indicate polluting non-exporters, the light green points refer to polluting exporters, and the yellow areas represent pollutant-specific nonattainment counties. According to the Green Book reported by the EPA, in year 2002, only a small number of the total 3,143 U.S. counties are designated as nonattainment: 21 counties in SO_2 nonattainment, 19 counties in CO nonattainment, 251 counties in O_3 nonattainment, and 64 counties in TSPs nonattainment. In year 2005, the number of counties with SO_2 or CO nonattainment designations declines to 12 and 11, respectively, while the number of counties with O_3 or TSPs nonattainment status increases drastically to 431 and 259, respectively. Most of nonattainment counties, shown in Table 3.3, are covered in our merged dataset. Additionally, the EPA has not regulated NH_3 emissions under the CAAA. However, industries heavily emitting the other four criteria air pollutants are usually also dirty polluters of NH_3, as shown in Table C.2 in the Appendix (e.g., Industrial Organic Chemicals with three-digit SIC codes 286, 287, and 289).[18] To capture NH_3 polluters'

[17]Polluting facilities located in the State of Alaska and State of Hawaii are not shown in the figures, but do exist in the merged dataset.

[18]As reported in Table C.2 in Appendix, shares of total emissions from these three industries to aggregate

Table 3.2: Exporter and Non-Exporter Differences

	Year 2002 and 2005			
	Exporter Mean	Non-Exporter Mean	Mean Difference	T-Stat
Variable	(1)	(2)	(3)	(4)
Sales (thousand $)	31291.6	20910.6	10381.0	18.87***
Employees	194.9	132.0	62.9	26.44***
NH_3(tons)	10.8	10.94	-0.141	-0.06
SO_2(tons)	136.5	125.5	10.9	0.45
CO (tons)	122.8	137.4	-14.7	-0.61
O_3 (tons)	95.2	95.7	-0.5	-0.07
TSPs (tons)	66.7	62.2	4.5	0.60
NH_3 per sale	0.001	0.004	-0.004	-1.13
SO_2 per sale	0.010	0.067	-0.057	-1.63
CO per sale	0.019	0.075	-0.056	-1.22
O_3 per sale	0.023	0.038	-0.015	-1.43
TSPs per sale	0.016	0.022	-0.006	-0.76

Note: *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

exposure to additional environmental compliance costs, a NH_3 polluter is considered regulated if it resides in a county which is nonattainment for at least one criteria air pollutant. This regulation indicator, denoted as any nonattainment throughout the paper, equals one if the county is designated as nonattainment status for one or more criteria air pollutants, and equals zero otherwise.[19]

Table 3.4 summarizes the number of polluting facilities across the exporting status and pollutant-specific county status for each criteria air pollutant. The first two rows of the table present the number of NH_3 polluting facilities across any nonattainment/attainment designation and export status, while the remaining rows report the number of other polluting exporters and non-exporters. For example, there are 941 NH_3 polluting exporters located in counties, which are designated for at least one criteria air pollutants. There are 152 SO_2 polluters residing in the SO_2-specific nonattainment counties in the sample period.

emissions from the entire manufacturing sector are: 14.7 percent for SO_2, 10.3 percent for CO, 8.6 percent for VOC, 13.7 percent for NO_x, 7.6 percent for TSPs, and 38.1 percent for NH_3.

[19]The indicator of any nonattainment was first defined by Greenstone, List, and Syverson (2011). They adopted this regulation indicator to estimate the impact of nonattainment designations on productivity.

Table 3.3: Number of Nonattainment Counties

	SO_2	CO	O_3	TSPs
number of counties in nonattainment status				
2002	21	19	251	64
2005	12	11	431	259
number of counties in nonattainment status covered in the dataset				
2002	17	18	231	52
2005	9	11	402	219

Source: The Green Book Nonattainment Areas for Criteria Pollutants reported by the EPA.

Several key patterns arise from both Table 3.4 and the location figures. First, around half of NH_3 emitters are located in any nonattainment counties, and the number of these emitters increases substantially from year 2002 to year 2005. Such drastic changes are likely driven by the substantial increases in the number of O_3 and TSPs nonattainment counties during the study period. Second, only a very small fraction of SO_2 emitters are subject to extra environmental compliance costs associated with the SO_2-specific pollution abatement activities. Similarly, a small number of CO emitters are located in counties, which are in CO nonattainment, and roughly one-tenth of exporting CO emitters reside in CO nonattainment counties during the study period. Finally, a substantial fraction of O_3 and TSPs polluters, however, are located in the relevant pollutant-specific nonattainment counties, and are thus exposed to the corresponding regulation requiring considerable efforts in abating the pollution.

Table 3.5 summarizes the variation in nonattainment designations across counties between years 2002 and 2005. It is a Markov transition matrix of counties' lagged and current nonattainment status by pollutant. The number in the table is the probability of going from one status to the other. For example, 89.07 percent of any pollutant attainment counties in 2002 still remain attainment in 2005. While the rest 10.93 percent fall into attainment in 2005. For any pollutant nonattainment designations, counties fall into nonattainment and come back into attainment at roughly the same rates. Looking at specific pollutants, counties with either CO or SO_2 attainment status in 2002 still retain that attainment status in 2005, while roughly 40 percent of counties with CO or SO_2 nonattainment status in 2002 are reclassified as attainment

Table 3.4: Number of Polluting Facilities

	Year 2002 and 2005		Year 2002		Year 2005	
	Exporter	Non-Exporter	Exporter	Non-Exporter	Exporter	Non-Exporter
Any Nonattainment	941	2,569	350	868	591	1,701
Any Attainment	902	2,586	523	1,513	379	1,073
SO_2 Nonattainment	32	120	27	98	5	22
SO_2 Attainment	3,694	10,977	1,875	5,658	1,819	5,319
CO Nonattainment	290	1,193	147	609	143	584
CO Attainment	4,199	12,121	2,145	6,229	2,054	5,892
O_3 Nonattainment	3,293	10,173	1,473	4,511	1,820	5,662
O_3 Attainment	3,512	10,443	2,002	6,061	1,510	4,382
TSPs Nonattainment	1,200	3,882	370	1,283	830	2,599
TSPs Attainment	4,210	13,113	2,366	7,315	1,844	5,798

Note: The indicator of any nonattainment is defined as a county-level dummy which equals one if the county is designated as nonattainment status for at least one criteria air pollutant, and zero otherwise. The first two rows report the number of NH_3 polluters.

in 2005. Changes in attainment status are similar for TSPs and O_3. Around 10 percent of counties change their status from one to the other. It is worth mentioning that theses variations only reflect counties covered in the merged dataset and but not the annual status changes through years 2002 to 2005.

3.5 Empirics

In this section, we would like to test the two main predictions derived from the theoretical model: first, whether productivity is inversely related to emission intensity; second, whether there exists a negative correlation between export status and emission intensity. We begin by estimating the facility productivity as a residual of the production function. Given the estimated facility productivity, we then employ a two-stage estimation procedure on a pollutant-by-pollutant basis. The first stage estimates the probability of selecting to export conditional

Table 3.5: Changes in Attainment Status between Years 2002 and 2005

Any NA			
		Status in 2005	
		Attainment	Nonattainment
Status in 2002	Attainment	89.07	10.93
	Nonattainment	8.66	91.34
SO_2 NA			
		Status in 2005	
		Attainment	Nonattainment
Status in 2002	Attainment	100.00	0.00
	Nonattainment	43.75	56.25
CO NA			
		Status in 2005	
		Attainment	Nonattainment
Status in 2002	Attainment	100.00	0.00
	Nonattainment	38.89	61.11
O_3 NA			
		Status in 2005	
		Attainment	Nonattainment
Status in 2002	Attainment	89.99	10.01
	Nonattainment	8.12	91.88
TSPs NA			
		Status in 2005	
		Attainment	Nonattainment
Status in 2002	Attainment	91.63	8.37
	Nonattainment	15.09	84.91

Note: NA stands for Nonattainment. Changes in county nonattainment status only reflect counties covered in the dataset.

on facility productivity and measures of trade variable costs. The second stage investigates the impact of predicted exporting probability on emission intensity controlling for facility and industry characteristics.

3.5.1 Productivity Measures

The productivity estimate is measured by TFP, which is calculated as a production function residual. The production function is assumed to take a Cobb-Douglas form with two inputs: capital and labor. Pollution byproducts are omitted in measuring productivity. All facilities within the same industry share the same structure of production technology in terms of identical input cost shares, but they differ in heterogeneous firm-specific productivity. Facilities across industries display differences in both input cost shares and productivity. A facility i with productivity φ_i in industry j at time t has the following production technology:

$$q_{ijt} = \varphi_i (l_{ijt})^{\alpha_j} (k_{ijt})^{\beta_j} \tag{3.20}$$

where l_{ijt} and k_{ijt} are labor and capital inputs, respectively. q_{ijt} represents output, and φ_i indexes the facility-specific productivity. α_j and β_j denote the input cost shares of labor and capital, respectively. The input cost shares also reflect the technology variation across industries.

The facility-level capital or investment data are not provided in the merged dataset. To implement the TFP estimation, we assume that the input price ratio is the same within industry but differs across industries. Given the iso-elastic residual demand curves, each facility with a heterogeneous productivity parameter φ_i in industry j chooses the profit-maximizing labor and capital inputs facing the common wage rate (w_j) and capital rent (r_j). Consequently, the optimal input ratio of capital to labor is proportional to the ratio of capital rent to wage rate, that is $k_{ijt}/l_{ijt} \propto r_j/w_j$. Assuming cost minimization, the production function can be rewritten as:

$$q_{ijt} \propto \varphi_i \left(\frac{w_j}{r_j}\right)^{\beta_j} (l_{ijt})^{\alpha_j+\beta_j} \tag{3.21}$$

With the assumption of the input price equalization within the same industry, we use three-digit SIC industry dummies to proxy the input price ratio, w_j/r_j. The estimation is conducted by first taking the logarithm of the above production function (3.21), and is then carried out with the following specification:

$$\log(q_{ijt}) = \text{Constant} + (\alpha_j + \beta_j)\log(l_{ijt}) + \sum_j \beta_j \text{SIC}_j + \text{Residual}_{ijt} \tag{3.22}$$

where q_{ijt} denotes output measured by values of sales and l_{ijt} is measured by numbers of employees. SIC_j indexes a set of three-digit SIC dummies, which equals one if the facility belongs to industry j. Residual_{ijt} is an error term containing the unobserved heterogeneous productivity φ_i and other possible explanatory factors, which are not covered in the regression.

Finally, given the estimated coefficients of $(\hat{\alpha}_j + \hat{\beta}_j)$ and $\hat{\beta}_j$ from the above specification (3.22), we recover the (exogenous) heterogeneous productivity φ_i of facility i in industry j at time t as follows:

$$\log(\hat{\varphi}_{it}) \equiv \widehat{\text{Residual}}_{ijt} = \log(q_{ijt}) - (\widehat{\text{Constant}}) - (\hat{\alpha}_j + \hat{\beta}_j)\log(l_{ijt}) - \sum_j \hat{\beta}_j \text{SIC}_j \tag{3.23}$$

where $\log(\hat{\varphi}_{it})$ is the estimated facility TFP.

3.5.2 Two-Stage Estimation

To estimate the impact of exporting status on emission intensity, an endogeneity problem regarding the export indicator arises. According to the theoretical model aforementioned, the exporting status is endogenous, depending upon trade variable costs, environmental compliance costs, and other cost parameters. Aiming at correcting for the endogeneity, we look for proxies of trade variable costs serving as instrument variables for the export dummy. Two proxies employed in the study are facility-specific and industry-specific trade variable costs. The former is measured by the geographical distance of each polluting facilities to its nearest U.S. port, and the latter is measured by the *ad valorem* freight rate at the four-digit SIC industry level.[20] The geographic distance reflects the costs associated with transportation of goods from manufacturing sites to the port of shipment. The freight rate, constructed by Bernard, Jensen, and Schott (2006), is the markup of the Cost-Insurance-Freight (CIF) value over the Free-on-Board (FOB) value relative to the FOB. This industry-specific freight rate only serves as a proxy of the iceberg trade costs associated with ocean or inland waterway transport of the goods to the port of destination. These two measures together are considered as proxies of trade variable costs. Given that facilities have made their location decisions prior to the sample year 2002, these geographic variable and product freight rate are exogenous yet highly correlated with export decisions, thus making valid instrumental variables.

With the estimated TFP as a measure of heterogeneous productivity, for each pollutant, we employ a two-stage estimation to investigate the impact of exporting status on emission intensity. Using a logit model, the first stage estimates the probability of selecting to export

[20] According to IHS Global Services, U.S. seaborne trade with the rest of the world accounts for 78.05% by volume (millions of metric tons), and 48.47% by value of total U.S. trade (billions of dollars) in year 2008.

conditional on the estimated facility TFP, two measures of trade variable costs, and exposure to environmental regulations controlling for industry characteristics. The first-stage logistic regression is specified as follows:

$$\begin{aligned}\Pr(\text{Exp}_i = 1) = &F(\gamma_0^{1st} + \gamma_1^{1st}\text{Distance}_i + \gamma_2^{1st}\text{Freight}_{jt} + \gamma_3^{1st}\text{Prod}_{it} \\ &+ \gamma_4^{1st}\text{Size}_{it} + \gamma_5^{1st}\text{Reg}_{cpt} + \theta_j + \lambda_t + \varepsilon_{ijt})\end{aligned} \tag{3.24}$$

where i indexes a facility, j indicates an industry, c denotes a county, p refers to a pollutant, and t references a year. θ_j is an industry-specific coefficient that control for the variations of production and pollution abatement technologies across three-digit SIC industry. λ_t is a year-specific coefficient, and ε_{ijt} is the stochastic error term. $F(\cdot)$ indexes a logistic function.

Exp_i is a time-invariant export indicator that equals one if the facility exports and zero otherwise. Prod_{it} denotes facility productivity measured as the TFP residual estimated in equation (3.23). The estimated TFP is in a logarithmic fashion in the regression. We also include a measure of facility size, denoted by Size_{it}, by the number of employees, as this has been found to influence facility decisions of becoming exporters (Bernard, Jensen, and Schott, 2006).[21]

Distance_i denotes the distance of a polluting facility to its nearest U.S. port.[22] The World Port Source online database provides geographic locations (i.e., latitude and longitude) of a total of 548 U.S. ports including harbor, river port, seaport, off-shore terminal, and pier, jetty or wharf.[23] For each polluting facility, we compute its distance to all 548 U.S. ports based on the "Haversine" formula, given the latitude and longitude of two points,[24] then pick the shortest distance as the distance to the nearest port. Freight_{jt} indexes the freight rate at four-digit SIC industry level. The industry-level data on CIF and FOB are acquired from the online data source of U.S. Manufacturing Exports and Imports compiled by Peter Schott.

Reg_{cpt} is a county-level indicator of nonattainment status, measuring a facility's environ-

[21]In the regression, the size variable is converted to number of thousand employees.
[22]In the regression, the distance variable is converted to thousand miles.
[23]The locations of a total of 548 U.S. ports, which are denoted as blue triangles, are shown in Figures C.1-C.5 in the Appendix. For detailed information, please refer to the website http://www.worldportsource.com/states.php.
[24]The "Haversine" formula calculates the great-circle distance between two points, that is, the shortest distance over the earth's surface.

mental regulatory pressure. The construction of Reg_{cpt} varies with types of polluting facilities examined in the first-stage specification. For each pollutant p, it equals one if the facility emits that pollutant and is located in the pollutant p-specific nonattainment county at time t, and zero otherwise. p belongs to the set of four criteria air pollutants $\{SO_2, CO, O_3, TSPs\}$. When NH_3 polluters are of interest, we adopt an indicator of any pollutant nonattainment defined earlier to proxy NH_3 polluters' exposure to environmental compliance costs.

The main interest of this paper is to capture the relationship between exporting status and emission intensity. With the likelihood of selecting to export predicted after the first-stage estimation, denoted by $\text{Pr}(\widehat{\text{Exp}_{it}})$, we then turn into the second-stage estimation. In the second stage, an OLS regression is employed to explore the impact of the predicted exporting likelihood on emission intensity conditional on facility-level productivity and industry characteristics. The regression is given by:

$$\text{E}_{ipt} = \gamma_0^{2nd} + \gamma_1^{2nd}\text{Pr}(\widehat{\text{Exp}_{it}}) + \gamma_2^{2nd}\text{Prod}_{it} + \gamma_3^{2nd}\text{Reg}_{cpt} + \theta_j + \lambda_t + \varepsilon_{ijt} \tag{3.25}$$

where E_{ipt} is the facility's emission intensity measured by emissions per value of sales (tons per thousand dollars). The dependent variable is implemented in a logarithmic fashion. To test the model pollutant-by-pollutant, the emission intensity is computed for each criteria air pollutant. This pollutant-specific regression examines the relationship between exporting likelihood and emission intensity among facilities emitting the same pollutant and within the same industry, which is captured by the main parameter of interest γ_1^{2nd}.

Another interest of this paper lies in γ_2^{2nd}, the coefficient of the estimated facility productivity that indicates whether facility productivity is inversely related to emission intensity as predicted by the productivity effect in the theoretical model. Moreover, it has a clear economic interpretation, i.e., the estimated coefficient reflects the elasticity of emission intensity with respect to productivity.

3.5.3 Results

We start with presenting the empirical results including the estimated TFP measures. Using the data on 30,610 facility-by-year observations from 17,594 facilities, we obtain the following estimation based on the specification in (3.22):

$$\widehat{\log(\text{sales})} = \underset{(0.363)}{11.767} + \underset{(0.003)}{1.027} \log(\text{employees}), \quad R^2 = 0.89$$

where the quantities in parenthesis are the heteroskedasticity-robust standard errors. The coefficient estimates of SIC dummies are omitted to save space. The F-statistic of $F(134, 30475) = 1868.73$ shows a statistical joint significance. The estimate of log(employees) is statistically significant at the 1 percent level, suggesting that an one percent increase in the number of employees leads to 1.027 percent increase in the value of sales.

Table 3.6 presents the results of the first-stage estimation in equation (3.24) on a pollutant-by-pollutant basis. The columns correspond to various pollutants. The sample size of polluting facilities varies with pollutant type.[25] All columns include a set of three-digit SIC dummies and a year dummy as noted at the bottom of the table. The standard errors are robust.[26] The regulatory variable Reg_{cpt} in column 1 captures the impact of any nonattainment regulation on NH_3 emission intensity, while in the remaining columns it reflects the impact of a pollutant-specific nonattainment designation on the relevant polluting facilities.

The empirical findings concerning the decisions to export are in favor of our theoretical model. First of all, as expected, an estimated coefficient of distance to port is negative, and significant at the 1 percent level for four criteria air pollutants, i.e., O_3, SO_2, CO, and TSPs, and at the 5 percent level for NH_3. These negative location effects suggest that facilities residing closer to ports have lower costs associated with transporting the goods from manufacturing sites to the ports of shipment, and thus appear to be more likely to engage in the export market. When it comes to the impact of freight rates on the export decisions, facilities in industries with lower freights rates tend to be more likely to export for NH_3 emitters as shown by a negative and significant coefficient of γ_2^{1st} in column 1. However, the impact of industry freight rates is not statistically significant and changes sign in column 4, suggesting that the selection effect is not more pronounced for the remaining pollutants than for NH_3.

[25] The number of observations drops as compared with the number in Table 3.1, since Peter Schott's online data source does not provide data for all four-digit SIC industries.

[26] Alternative specifications of standard errors (i.e., cluster at industry level, county level, or facility level) are considered but not reported in the paper. These specifications do not alter the estimates in any significant ways.

Table 3.6: First-Stage Estimation: Export Status

Variable \ Pollutant	NH_3	SO_2	CO	O_3	TSPs
	(1)	(2)	(3)	(4)	(5)
Distance to Port	-0.672**	-0.537***	-0.502***	-0.457***	-0.618***
	(0.313)	(0.197)	(0.178)	(0.123)	(0.150)
Freight Rate	-2.981**	-0.927	-0.979	0.721	-0.199
	(1.332)	(0.989)	(0.922)	(0.824)	(0.878)
Productivity	0.184***	0.131***	0.180***	0.146***	0.134***
	(0.059)	(0.042)	(0.039)	(0.032)	(0.035)
Size	1.228***	1.111***	1.152***	1.243***	1.158***
	(0.156)	(0.111)	(0.101)	(0.087)	(0.095)
Any NA	0.023				
	(0.069)				
SO_2 NA		-0.092			
		(0.232)			
CO NA			-0.249***		
			(0.082)		
O_3 NA				-0.030	
				(0.035)	
TSPs NA					-0.033
					(0.046)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,744	12,520	14,844	22,595	18,696
R^2	0.093	0.099	0.096	0.086	0.105

Note: the dependent variable is a binary export decision. All regressions include a set of three-digit SIC dummies and a year dummy. Robust standard errors are reported in parenthesis. NA stands for Nonattainment. Coefficients for the regression constant and variables of industry and year dummies are suppressed. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Second, a positive coefficient of productivity indicates that the higher productivity a facility is, the more likely it is to engage in the export market. The positive productivity effect is statistically significant at the 1 percent level for all five pollutants. In addition, we find evidence that the larger the size of a facility, the higher the probability of selecting to export is, as documented by positive and statistically significant coefficients on the size variable. These two empirical findings also match results from a substantial body of empirical research on export decisions (Bernard, Jensen, and Schott, 2006, etc).

Last but not least, we find a negative and statistically significant impact of CO nonattainment designation. This evidence suggests that CO polluters subject to strict regulatory controls might have additional environmental burdens, are thus less likely to export than those exempt from environmental charges associated with CO emissions. However, there is no evidence supporting that the remaining pollutant-specific nonattainment designations have regulatory influences on the export decisions.

Table 3.7 reports the second-stage estimation results based on the specification in equation (3.25). Columns in the table correspond to various pollutants of interest. All regressions incorporate industry and year fixed effects as noted at the bottom of the table. The robust standard errors are reported in parenthesis.

The estimated effect of nonattainment designations on pollution intensity is negative and significant at the 1 percent level for all pollutants in the paper except for SO_2 nonattainment designation. These negative impacts of pollutant-specific designations suggest that strict regulatory controls have beneficial effects on reducing emission intensity. The estimated coefficients show that polluters located in nonattainment counties have approximately from 22 percent (NH_3) to overwhelmingly 77 percent (CO) less pollution intensity than those in attainment areas. There is some evidence that any nonattainment regulations contribute to the clean-up of NH_3 emission intensity. It is plausible that as enforced by the pollutant-specific nonattainment regulations, abating criteria air pollutants other than NH_3 may share pollution abatement technologies, therefore having unintentionally beneficial consequences on curbing NH_3 emission intensity. Surprisingly, a positive and significant SO_2 regulatory impact suggests that SO_2 emitters located in the pollutant-specific nonattainment counties pollute roughly 66

Table 3.7: Second-Stage Estimation: Emission Intensity

Variable \ Pollutant	NH_3	SO_2	CO	O_3	TSPs
	(1)	(2)	(3)	(4)	(5)
Export Status	-12.290***	-9.744***	-7.061***	-8.303***	-8.429***
	(0.635)	(0.675)	(0.461)	(0.296)	(0.419)
Productivity	-0.521***	-0.801***	-0.625***	-0.667***	-0.549***
	(0.071)	(0.056)	(0.040)	(0.027)	(0.038)
Any NA	-0.252***				
	(0.070)				
SO_2 NA		0.509*			
		(0.301)			
CO NA			-1.465***		
			(0.077)		
O_3 NA				-0.872***	
				(0.028)	
TSPs NA					-0.585***
					(0.046)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,744	12,520	14,844	22,595	18,696
R^2	0.303	0.413	0.390	0.286	0.396

Note: the dependent variable is log of emissions per value of sales (tons per thousand dollars). "Export Status" is the estimated likelihood of selecting to export. "Productivity" is the estimated facility TFP. All regressions include a set of three-digit SIC dummies and year dummy. Robust standard errors are reported in parenthesis. NA stands for Nonattainment. Coefficients for the regression constant and variables of industry and year dummies are suppressed. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

percent more SO_2 per unit sales than those free from the regulation. This finding should be interpreted with caution, since the merged dataset contains insufficient observations of SO_2 polluters located in SO_2-specific nonattainment counties.[27]

Of greater interest is the relationship between productivity and emission intensity. The estimated coefficient on the productivity is negative and highly significant at the 1 percent level for all pollutants, confirming the theoretical prediction that productivity is inversely related to the emission intensity. The estimated elasticity of emission intensity with respect to productivity, reflected by γ_2^{2nd}, ranges from -0.52 to -0.80, depending upon the pollutant type. Among all pollutants reported in the paper, SO_2 has the highest elasticity, suggesting that an one percent increase in productivity of SO_2 polluters leads to approximately 0.80 percent decrease in SO_2 emissions per value of sales.

The central interest of this paper is γ_1^{2nd}, the coefficient on the predicted likelihood of selecting to export. The estimates consistently show negative correlations between the predicted export likelihood and emission intensity for all five criteria air pollutants. These negative impacts are highly significant at the 1 percent level. The empirical findings are in line with the aforementioned theoretical prediction that exporting status is negatively correlated with emission intensity. Facilities with a high probability of selecting to the export market tend to be more environmentally friendly than than those with a relatively low exporting probability in terms of lower emission intensity.

3.6 Conclusion

In this paper, a model is proposed to provide the theoretical guide for the empirical investigation on the differences between exporters and non-exporters in the environmental dimension. A productive firm is more likely to export and upgrade the emission-saving clean technology than a less productive firm. The analytic expression of relative emissions per output across exporting status predicts two negative correlations: one is between productivity and emissions

[27] A small number of U.S. counties are in SO_2 nonattainment status in the study period (21 counties in 2002, 12 counties in 2005), and only a very small fraction of SO_2 polluting facilities residing in these nonattainment counties are covered in the merged dataset (131 out of 8,184 in year 2002, 27 out of 7,714 in year 2005) as shown in Table 3.4.

per output, and the other is between export status and emissions per output.

The evidence provided in the paper supports the theoretical predictions. Using a two-stage estimation, we find robust evidence of a negative correlation between the estimated facility productivity and emissions per value of sales. The negative impact of productivity is statistically significant for each criteria air pollutant we track. More importantly, we find that facilities with high probability of selecting to export tend to emit less emissions per value of sales than their competing non-exporters within the same industry conditional on estimated TFP and exposure to the CAAA. Additionally, the paper provides evidence of negative impacts of pollutant-specific nonattainment designations on the relevant polluters in the case of CO, O_3, and TSPs regulations.

These empirical results, coupled with a substantial body of identified findings on the growth of productivity due to engaging in the export market (Benard, Jensen, and Schott, 2006, Loecker, 2007), shed some light on policy implications. The environmental advantage of exporters could be cited as an argument for active export promotion. Policies oriented to facilitate access to foreign markets would contribute to reducing emissions per output, and might be able to clean up the aggregate emissions by driving the least efficient firms out of the market. Alternatively, policy makers should be aware of unintentionally negative environmental consequences of policies, which are aimed at protecting the least productive local polluters.

APPENDIX A. WELFARE IMPACTS OF ALTERNATIVE BIOFUEL AND ENERGY POLICIES

Sensitivity Analysis

Tables A.1 to A.9 provide a few more details on the sensitivity analysis carried out. In these tables we concentrate on the main four scenarios discussed in the text: the first best solution with border policies and the carbon tax; the second best solution without border policies but where the fuel tax and the ethanol subsidy are optimally chosen; the case when the only active policy instrument is an ethanol subsidy; and the case in which the active policy instrument is the ethanol mandate. For each case only one parameter at a time is changed from the set of baseline values, and for each of these tables we report the results of the baseline parameters (middle column) along with the lower and upper ends of the parameter ranges postulated (as reported in Table 1.7).

The elasticity of the foreign oil export supply $\bar{\varepsilon}_o$ plays a predictable, but crucial, role. Naturally, the optimal oil import tariff varies inversely with this elasticity. The second best policy with the optimal fuel tax and ethanol subsidy also varies inversely with this parameter's values. But note that even a fairly elastic supply of foreign oil ($\bar{\varepsilon}_o = 5.0$) provides scope for a fairly large fuel tax and ethanol subsidy (\$0.69/gallon and \$0.77/gallon, respectively), and the second best solution still achieves over 83% of the gain achievable with the first best policy. Perhaps the most noticeable effect is that, as the export supply elasticity increases, the relative performance of the ethanol-only policy (compared to the first and second best) improves, because the higher foreign supply elasticity means that the gains obtained from taxing foreign oil become less important.

Altering the elasticity of foreign corn import demand $\bar{\eta}_c$ over the range considered has predictable results. Hardly surprising, the first best corn export tariff varies inversely with this elasticity, but the impact on the optimal oil tariff is minimal (and the first best carbon tax is unaffected). The most notable result, perhaps, is that the second best instruments do not perform as well, in a relative sense, when the foreign corn demand is very inelastic. This is not a surprise because, whereas the fuel tax does a good job of approximating an import tariff (given the low domestic oil supply elasticity), the ethanol subsidy-or mandate-is not a very good substitute for the corn export tariff. Thus, when foreign corn demand is inelastic, the second best policies, and ethanol policies alone, are not as effective. Still, ethanol policies are useful, and in the case when fuel taxes are not endogenous, the optimal mandate can exceed 18 billion bushels.

Varying the elasticity of domestic demand for fuel and petroleum byproducts, η_f and η_h does not have very dramatic results. As one would expect, the oil import tariff, or, in the case of the second best, the fuel tax, is (marginally) higher when fuel demand is inelastic. Also, given the fuel tax, the optimal ethanol subsidy, or ethanol mandate, is higher when domestic fuel demand is inelastic. The basic result that the fuel tax/ethanol subsidy regime is a close substitute for first best policy still holds.

When the cost of CO_2 is reduced to \$5/tCO_2, the first best gasoline tax is only 6c per gallon, and the relative attractiveness of ethanol because of its lower pollution emissions is negligible. Nevertheless, the first best policies - which include a very modest ethanol subsidy - not only deliver significant welfare gains compared to the *status quo*, but they also result in sharp increases in ethanol production and-despite a \$1.21/bushel tax on corn exports-an increase in the U.S. corn price. This outcome is driven by the \$18/barrel oil import tariff, which drives up domestic fuel prices and increases the competitiveness of ethanol. In the second best case, the high fuel tax proxies for the oil import tariff and the ethanol subsidy (the net ethanol subsidy is \$0.19/GEEG) partly proxies for a corn export tariff. Because of these two policies, the second best price of corn is considerably higher than in the first best situation (though the world price of corn is lower than in the first best case); and the world price of oil in the second best case is only slightly higher than in the first best case, indicating that the fuel tax is a much better proxy for an oil import tariff than is the ethanol subsidy for a corn export tariff. Finally, given an exogenous fuel tax of \$0.39/GEEG, the optimal subsidy is larger than the *status quo* level, and thus a binding ethanol mandate can improve upon both the *status quo* and an ethanol subsidy. Note that, even without a carbon-pollution rationale for ethanol mandates, the impact of the mandate on world oil and corn prices is such that ethanol production under the mandate exceeds the current mandated level for 2015 by about 2.5 billion gallons.

Raising the cost of CO_2 to \$80/tCO_2 has predictable effects on first and second best policies and outcomes. The first best fuel tax increases to \$0.90/gallon - reflecting the costs of emissions - and due to the assumption that ethanol releases less pollution, a gross subsidy of \$0.44/gallon is part of the first best solution. The higher fuel tax, by itself, would reduce U.S. imports and this, in turn, means that tariffs will be lower than under the case where the pollution tax was minimal. Note that in this case the second best policy, while still a good proxy for first best policies, far outperforms the case in which only ethanol policy is discretionary. Indeed, given the existing fuel tax, the optimal subsidy - and the welfare outcome - is only slightly above the *status quo* level. In this case, the ethanol mandate leads to a considerable improvement over the ethanol subsidy and to considerably more ethanol output than the subsidy. The reason for the dominance of the mandate is because the tax on fuel is very low compared to its second best level (\$0.39 versus \$1.56), and hence the implicit fuel tax embodied in the mandate is more important than the implicit ethanol subsidy. One less transparent result, perhaps, is that ethanol production - under either the optimal subsidy or the optimal mandate - is lower when pollution costs are high. That is, while more ethanol on the market crowds out some gasoline, total fuel consumption expands as ethanol production increases, and the efficiency gain of using ethanol is not sufficient to offset the pollution costs of the expanded fuel consumption. Thus, the argument for an ethanol mandate is not really because of ethanol's relative pollution efficiency, but rather because of both the implicit tax on fuel and also the terms-of-trade effect. Clearly, then, in the logic of this model, combining an ethanol subsidy with the mandate is very poor policy.

Variations in the relative efficiency of ethanol in terms of pollution emissions - from $\lambda = 0.5$ to $\lambda = 2$ - have predictable results in terms of the ethanol subsidy/tax but don't otherwise overturn other patterns with the exception that, in the case when ethanol pollutes more than gasoline, optimal ethanol mandates lead to more pollution than optimal ethanol subsidies (not a surprising result). Nevertheless, mandates still deliver higher welfare, and the largest use of ethanol still occurs under mandates. Despite the significant subsidies to ethanol, *status quo* policies - even when ethanol is more polluting - still deliver higher welfare than *laissez faire*, and the *status quo* subsidy is remarkably close to the optimal subsidy, given the fuel tax. The story remains that the case for ethanol is not largely about pollution, but rather it is about the policy's impact on the U.S. gains from trade (through the impact on the terms of trade).

The effects of changing, one at a time, the elasticities of domestic corn demand, of domestic corn supply and of domestic oil supply are fairly minimal for the variables reported in Tables A.7-A.9, at least over the range of these parameters that is being considered.

As an additional sensitivity analysis exercise we carried out a Monte Carlo simulation meant to represent our uncertainty about the model's true parameters. Specifically, we carried out our policy calculations a large number of times, each time using a randomly drawn vector of parameters. The parameters were drawn from independent beta distributions, with the shape parameters of the beta distribution calibrated with the so-called PERT (Program Evaluation and Review Technique) methodology (Davis, 2008). More precisely, each beta distribution has a finite support on $[a, b]$, where the extreme of this interval are the minimal and maximal parameter values reported in Table 1.7. Given $[a, b]$, the shape parameters of the beta distribution are picked so that the standard deviation satisfies $\sigma^2 = (b - a)/6$ and the mean is equal to the baseline value as reported in Table 1.7. The Monte Carlo simulation relied on 100,000 randomly drawn parameter vector. The results from this exercise are summarized in Table A.10, which reports the 10% and 90% percentile points (as well as the mean) of the resulting empirical distribution of a number of variables of interest, for the same four scenarios covered in Tables A.1-A.9. One way to interpret the results of this Monte Carlo experiment is as a robustness check on the magnitude of the policy tool parameters that we computed in our baseline. Within this perspective, some of our main conclusions are re-emphasized by the Monte Carlo simulation. For example, for the first best scenario the critical role of the terms of trade are reflected in the substantial level of border policies: the optimal oil tariff that we compute ranges from \$14/barrel to \$23.67/barrel, and the optimal corn tariff ranges form \$0.93/bushel to \$1.70/bushel. Similarly, for the second best scenario, the fuel tax ranges from \$0.75/gallon to \$1.27/gallon, whereas the ethanol subsidy ranges from \$0.86/gallon to \$1.28/gallon. When the only active policy instrument is the ethanol subsidy, with the fuel tax held at its current value of \$0.39/gallon, the optimal subsidy range is fairly compact, ranging from \$0.60/gallon to \$0.77 gallon. Similarly, if the ethanol mandate is the only active policy instrument, with the fuel tax held at its current value, the optimal ethanol quantity is shown to range from 15.51 to 20.32 billion gallons.

Table A.1: Sensitivity Analysis: Elasticity of Foreign Oil Export Supply

	$\bar{\varepsilon}_0 = 1.0$	$\bar{\varepsilon}_o = 3.0$	$\bar{\varepsilon}_o = 5.0$
Laissez Faire			
Ethanol quantity (billion gallons)	6.88	6.03	5.77
CO_2 emission (million tCO_2)	1495.21	1508.97	1513.21
Social welfare ($ billion)	753.05	759.47	761.47
Status Quo			
CO_2 emission changes (million tCO_2)	-37.10	-50.87	-55.11
Social welfare changes ($ billion)	13.12	6.70	4.70
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	43.71	17.53	11.21
Corn tariff ($/bushel)	0.95	1.26	1.39
Ethanol quantity (billion gallons)	18.30	13.94	12.25
CO_2 emission changes (million tCO_2)	-197.79	-128.70	-100.92
Social welfare changes ($ billion)	40.88	11.48	6.84
Tax & Subsidy			
Fuel tax ($/gallon)	2.00	0.96	0.69
Ethanol subsidy ($/gallon)	2.01	1.02	0.77
CO_2 emission changes (million tCO_2)	-208.56	-128.71	-99.34
Social welfare changes ($ billion)	34.72	9.92	5.72
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.96	0.67	0.59
CO_2 emission changes (million tCO_2)	-6.97	-41.11	-49.91
Social welfare changes ($ billion)	16.90	7.46	4.99
Mandate only (with existing fuel tax)			
Ethanol quantity (billion gallons)	28.21	17.45	14.70
CO_2 emission changes (million tCO_2)	-25.05	-54.24	-60.44
Social welfare changes ($ billion)	21.36	8.19	5.28

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.2: Sensitivity Analysis: Elasticity of Foreign Corn Import Demand

	$\bar{\eta}_c$ = -3.0	$\bar{\eta}_c$ = -1.5	$\bar{\eta}_c$ = -1.0
Laissez Faire			
Ethanol quantity (billion gallons)	4.87	6.03	6.45
CO_2 emission (million tCO_2)	1506.89	1508.97	1509.73
Social welfare ($ billion)	759.23	759.47	759.56
Status Quo			
CO_2 emission changes (million tCO_2)	-48.78	-50.87	-51.63
Social welfare changes ($ billion)	6.94	6.70	6.61
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.53	17.53	17.53
Corn tariff ($/bushel)	0.64	1.26	1.89
Ethanol quantity (billion gallons)	13.90	13.94	13.95
CO_2 emission changes (million tCO_2)	-126.70	-128.70	-129.43
Social welfare changes ($ billion)	11.14	11.48	11.98
Tax & Subsidy			
Fuel tax ($/gallon)	0.96	0.96	0.96
Ethanol subsidy ($/gallon)	0.96	1.02	1.05
Ethanol quantity (billion gallons)	15.00	15.51	15.80
CO_2 emission changes (million tCO_2)	-127.78	-128.71	-128.80
Social welfare changes ($ billion)	9.97	9.92	9.94
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.61	0.67	0.71
Ethanol quantity (billion gallons)	15.59	16.02	16.29
CO_2 emission changes (million tCO_2)	-40.09	-41.11	-41.68
Social welfare changes ($ billion)	7.50	7.46	7.48
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	17.01	17.45	17.76
CO_2 emission changes (million tCO_2)	-51.10	-54.24	-55.64
Social welfare changes ($ billion)	8.16	8.19	8.27

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.3: Sensitivity Analysis: Elasticity of Fuel Demand

	$\bar{\eta}_f$ = -0.9	$\bar{\eta}_f$ = -0.5	$\bar{\eta}_f$ = -0.2
Laissez Faire			
Ethanol quantity (billion gallons)	6.71	6.03	5.16
CO_2 emission (million tCO_2)	1523.30	1508.97	1490.76
Social welfare ($ billion)	612.87	759.47	1252.60
Status Quo			
CO_2 emission changes (million tCO_2)	-65.19	-50.87	-32.65
Social welfare changes ($ billion)	7.47	6.70	5.75
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.20	17.53	17.99
Corn tariff ($/bushel)	1.34	1.26	1.16
Ethanol quantity (billion gallons)	12.85	13.94	15.43
CO_2 emission changes (million tCO_2)	-164.79	-128.70	-80.66
Social welfare changes ($ billion)	12.71	11.48	9.91
Tax & Subsidy			
Fuel tax ($/gallon)	0.94	0.96	0.98
Ethanol subsidy ($/gallon)	1.01	1.02	1.02
Ethanol quantity (billion gallons)	14.55	15.51	16.83
CO_2 emission changes (million tCO_2)	-163.49	-128.71	-82.07
Social welfare changes ($ billion)	11.10	9.92	8.39
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.62	0.67	0.74
Ethanol quantity (billion gallons)	15.05	16.02	17.22
CO_2 emission changes (million tCO_2)	-52.66	-41.41	-31.68
Social welfare changes ($ billion)	7.94	7.46	6.98
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	16.99	17.45	17.96
CO_2 emission changes (million tCO_2)	-65.72	-54.24	-40.95
Social welfare changes ($ billion)	8.83	8.19	7.44

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.4: Sensitivity Analysis: Elasticity of Petroleum Byproduct Demand

	$\bar{\eta}_h$ = -0.9	$\bar{\eta}_h$ = -0.5	$\bar{\eta}_h$ = -0.2
Laissez Faire			
Ethanol quantity (billion gallons)	5.22	6.03	7.40
CO_2 emission (million tCO_2)	1522.12	1508.97	1486.76
Social welfare ($ billion)	671.89	759.47	1052.28
status quo			
CO_2 emission changes (million tCO_2)	-64.01	-50.87	-28.65
Social welfare changes ($ billion)	8.30	6.70	4.09
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.15	17.53	18.25
Corn tariff ($/bushel)	1.21	1.26	1.36
Ethanol quantity (billion gallons)	14.66	13.94	12.60
CO_2 emission changes (million tCO_2)	-155.51	-128.70	-81.02
Social welfare changes ($ billion)	13.56	11.48	7.96
Tax & Subsidy			
Fuel tax ($/gallon)	0.94	0.96	0.98
Ethanol subsidy ($/gallon)	0.99	1.02	1.06
Ethanol quantity (billion gallons)	16.22	15.51	14.16
CO_2 emission changes (million tCO_2)	-156.84	-128.71	-78.33
Social welfare changes ($ billion)	12.09	9.92	6.21
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.70	0.67	0.61
Ethanol quantity (billion gallons)	16.93	16.02	14.38
CO_2 emission changes (million tCO_2)	-57.36	-41.41	-17.20
Social welfare changes ($ billion)	9.31	7.46	4.46
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	18.60	17.45	15.31
CO_2 emission changes (million tCO_2)	-75.81	-54.24	-22.33
Social welfare changes ($ billion)	10.25	8.19	4.87

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.5: Sensitivity Analysis: Cost of CO_2 Pollution ($/t$CO_2$)

	$\sigma'(\cdot) = 5$	$\sigma'(\cdot) = 20$	$\sigma'(\cdot) = 80$
Laissez Faire			
Ethanol quantity (billion gallons)	6.03	6.03	6.03
CO_2 emission (million tCO_2)	1508.97	1508.97	1508.97
Social welfare ($ billion)	782.10	759.47	668.93
Status Quo			
CO_2 emission changes (million tCO_2)	-50.87	-50.87	-50.81
Social welfare changes ($ billion)	5.94	6.70	9.76
First Best			
Fuel tax ($/gallon)	0.06	0.23	0.90
Ethanol subsidy ($/gallon)	0.03	0.11	0.44
Oil tariff ($/barrel)	17.97	17.53	15.79
Corn tariff ($/bushel)	1.21	1.26	1.46
Ethanol quantity (billion gallons)	14.62	13.94	11.20
CO_2 emission changes (million tCO_2)	-104.39	-128.70	-225.94
Social welfare changes ($ billion)	9.74	11.48	22.12
Tax & Subsidy			
Fuel tax ($/gallon)	0.81	0.96	1.56
Ethanol subsidy ($/gallon)	0.94	1.02	1.30
Ethanol quantity (billion gallons)	16.14	15.51	12.98
CO_2 emission changes (million tCO_2)	-104.61	-128.71	-225.12
Social welfare changes ($ billion)	8.17	9.92	20.53
Subsidy-only (with existing fuel tax)			
Fuel tax Ethanol subsidy ($/gallon)	0.69	0.67	0.59
Ethanol quantity (billion gallons)	16.51	16.02	14.03
CO_2 emission changes (million tCO_2)	-40.52	-41.41	-44.98
Social welfare changes ($ billion)	6.84	7.46	10.05
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	17.46	17.45	17.44
CO_2 emission changes (million tCO_2)	-54.24	-54.24	-54.24
Social welfare changes ($ billion)	7.38	8.19	11.45

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.6: Sensitivity Analysis: Ethanol Pollution Efficiency Parameter

	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 2.0$
Laissez Faire			
Ethanol quantity (billion gallons)	6.03	6.03	6.03
CO_2 emission (million tCO_2)	1497.41	1508.97	1567.95
Social welfare ($ billion)	759.70	759.47	758.29
Status Quo			
CO_2 emission changes (million tCO_2)	-59.93	-50.87	-4.59
Social welfare changes ($ billion)	6.89	6.70	5.78
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.15	0.11	-0.09
Oil tariff ($/barrel)	17.47	17.53	17.83
Corn tariff ($/bushel)	1.21	1.26	1.55
Ethanol quantity (billion gallons)	14.71	13.94	10.01
CO_2 emission changes (million tCO_2)	-143.60	-128.70	-98.72
Social welfare changes ($ billion)	11.80	11.48	10.32
Tax & Subsidy			
Fuel tax ($/gallon)	0.96	0.96	0.97
Ethanol subsidy ($/gallon)	1.04	1.02	0.87
Ethanol quantity (billion gallons)	16.21	15.51	11.90
CO_2 emission changes (million tCO_2)	-146.63	-128.71	-79.56
Social welfare changes ($ billion)	10.30	9.92	8.42
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.70	0.67	0.52
Ethanol quantity (billion gallons)	16.72	16.02	12.42
CO_2 emission changes (million tCO_2)	-60.65	-41.41	14.64
Social welfare changes ($ billion)	7.85	7.46	5.85
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	18.18	17.45	13.68
CO_2 emission changes (million tCO_2)	-77.56	-54.24	19.83
Social welfare changes ($ billion)	8.65	8.19	6.33

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.7: Sensitivity Analysis: Elasticity of Domestic Corn Demand

	$\bar{\eta}_c$ = -0.5	$\bar{\eta}_c$ = -0.2	$\bar{\eta}_c$ = -0.1
Laissez Faire			
Ethanol quantity (billion gallons)	4.98	6.03	6.41
CO_2 emission (million tCO_2)	1507.09	1508.97	1509.65
Social welfare ($ billion)	712.44	759.47	837.70
Status Quo			
CO_2 emission changes (million tCO_2)	-48.98	-50.87	-51.55
Social welfare changes ($ billion)	6.82	6.70	6.66
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.54	17.53	17.53
Corn tariff ($/bushel)	1.26	1.26	1.27
Ethanol quantity (billion gallons)	13.88	13.94	13.96
CO_2 emission changes (million tCO_2)	-126.96	-128.70	-129.33
Social welfare changes ($ billion)	11.60	11.48	11.44
Tax & Subsidy			
Fuel tax ($/gallon)	0.96	0.96	0.96
Ethanol subsidy ($/gallon)	0.98	1.02	1.03
Ethanol quantity (billion gallons)	15.64	15.51	15.43
CO_2 emission changes (million tCO_2)	-126.53	-128.71	-129.57
Social welfare changes ($ billion)	9.93	9.92	9.93
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.64	0.67	0.68
Ethanol quantity (billion gallons)	16.30	16.02	15.89
CO_2 emission changes (million tCO_2)	-39.03	-41.41	-42.32
Social welfare changes ($ billion)	7.47	7.46	7.46
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	1.94	17.45	17.24
CO_2 emission changes (million tCO_2)	-51.17	-54.24	-55.43
Social welfare changes ($ billion)	8.19	8.19	8.20

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.8: Sensitivity Analysis: Elasticity of Domestic Corn Supply

	$\varepsilon_c = 0.1$	$\varepsilon_c = 0.3$	$\varepsilon_c = 0.5$
Laissez Faire			
Ethanol quantity (billion gallons)	7.28	6.03	4.93
CO_2 emission (million tCO_2)	1511.22	1508.97	1507.00
Social welfare ($ billion)	764.53	759.47	754,42
Status Quo			
CO_2 emission changes (million tCO_2)	-53.12	-50.87	-48.89
Social welfare changes ($ billion)	6.57	6.70	6.83
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.53	17.53	17.54
Corn tariff ($/bushel)	1.27	1.26	1.26
Ethanol quantity (billion gallons)	14.01	13.94	13.87
CO_2 emission changes (million tCO_2)	-130.78	-128.70	-126.87
Social welfare changes ($ billion)	11.35	11.48	11.61
Tax & Subsidy			
Fuel tax ($/gallon)	0.96	0.96	0.96
Ethanol subsidy ($/gallon)	1.07	1.02	0.98
Ethanol quantity (billion gallons)	15.17	15.51	15.64
CO_2 emission changes (million tCO_2)	-131.73	-128.71	-126.44
Social welfare changes ($ billion)	9.97	9.92	9.93
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.72	0.67	0.64
Ethanol quantity (billion gallons)	15.51	16.02	16.31
CO_2 emission changes (million tCO_2)	-44.57	-41.41	-38.92
Social welfare changes ($ billion)	7.49	7.46	7.47
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	16.65	17.45	17.96
CO_2 emission changes (million tCO_2)	-58.35	-54.24	-51.03
Social welfare changes ($ billion)	8.26	8.19	8.19

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.9: Sensitivity Analysis: Elasticity of Domestic Oil Supply

	$\eta_o = 0.1$	$\eta_o = 0.2$	$\eta_o = 0.5$
Laissez Faire			
Ethanol quantity (billion gallons)	6.04	6.03	5.99
CO_2 emission (million tCO_2)	1508.78	1508.97	1509.52
Social welfare ($ billion)	765.27	759.47	742.05
Status Quo			
CO_2 emission changes (million tCO_2)	-50.67	-50.87	-51.41
Social welfare changes ($ billion)	6.80	6.70	6.43
First Best			
Fuel tax ($/gallon)	0.23	0.23	0.23
Ethanol subsidy ($/gallon)	0.11	0.11	0.11
Oil tariff ($/barrel)	17.73	17.53	17.00
Corn tariff ($/bushel)	1.25	1.26	1.29
Ethanol quantity (billion gallons)	14.08	13.94	13.54
CO_2 emission changes (million tCO_2)	-131.29	-128.70	-121.70
Social welfare changes ($ billion)	11.23	11.48	12.17
Tax & Subsidy			
Fuel tax ($/gallon)	0.97	0.96	0.93
Ethanol subsidy ($/gallon)	1.03	1.02	0.99
Ethanol quantity (billion gallons)	15.56	15.51	15.33
CO_2 emission changes (million tCO_2)	-129.75	-128.71	-125.68
Social welfare changes ($ billion)	10.14	9.92	9.31
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.62	0.67	0.66
Ethanol quantity (billion gallons)	16.10	16.02	15.78
CO_2 emission changes (million tCO_2)	-41.00	-41.41	-42,54
Social welfare changes ($ billion)	7.58	7.46	7.12
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	17.57	17.45	17.11
CO_2 emission changes (million tCO_2)	-53.94	-54.24	-55.10
Social welfare changes ($ billion)	8.34	8.19	7.78

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

Table A.10: Sensitivity Analysis: Monte Carlo on Selected Nine Parameters

	10%	Mean	90%
Laissez Faire			
Ethanol quantity (billion gallons)	5.17	6.09	6.98
CO_2 emission (million tCO_2)	1490.58	1507.32	1527.05
Social welfare ($ billion)	670.38	799.59	946.80
Status Quo			
CO_2 emission changes (million tCO_2)	-64.17	-49.25	-32.97
Social welfare changes ($ billion)	4.98	6.78	8.81
First Best			
Fuel tax ($/gallon)	0.08	0.23	0.43
Ethanol subsidy ($/gallon)	0.03	0.11	0.23
Oil tariff ($/barrel)	14.00	18.32	23.67
Corn tariff ($/bushel)	0.93	1.31	1.71
Ethanol quantity (billion gallons)	12.35	14.06	15.80
CO_2 emission changes (million tCO_2)	-173.72	-129.18	-87.82
Social welfare changes ($ billion)	7.98	12.34	17.80
Tax & Subsidy			
Fuel tax ($/gallon)	0.75	0.99	1.27
Ethanol subsidy ($/gallon)	0.86	1.05	1.28
Ethanol quantity (billion gallons)	14.01	15.63	17.31
CO_2 emission changes (million tCO_2)	-175.55	-129.28	-85.55
Social welfare changes ($ billion)	6.60	10.60	15.60
Subsidy-only (with existing fuel tax)			
Ethanol subsidy ($/gallon)	0.60	0.68	0.77
Ethanol quantity (billion gallons)	14.45	16.18	18.11
CO_2 emission changes (million tCO_2)	-62.86	-40.94	-14.24
Social welfare changes ($ billion)	5.52	7.67	10/14
Mandate-only (with existing fuel tax)			
Ethanol quantity (billion gallons)	15.51	17.69	20.32
CO_2 emission changes (million tCO_2)	-80.71	-53.73	-21.08
Social welfare changes ($ billion)	5.91	8.48	11.51

Notes: CO_2 emission changes and welfare changes are relative to *laissez faire*.

APPENDIX B. INDUCED CLEAN TECHNOLOGY ADOPTION AND INTERNATIONAL TRADE WITH HETEROGENEOUS FIRMS

Proof of Proposition

Proof of Remark1.

The relationship between the relative marginal costs (c_d/c_c) and permit price could be related to the cost shares,

$$\frac{\partial(c_d/c_c)}{\partial p_e} = \frac{p_e c_d}{c_c}\left(\frac{\partial c_d}{\partial p_e}\frac{p_e}{c_d} - \frac{\partial c_c}{\partial p_e}\frac{p_e}{c_c}\right) = \frac{c_d}{p_e c_c}\left(s_d^e - s_c^e\right)$$

Thus, $\text{sign}(\partial(c_d/c_c)/\partial p_e) = \text{sign}(s_d^e - s_c^e)$. If the clean technology is labor-biased ($s_d^e > s_c^e$), then $\partial(c_d/c_c)/\partial p_e > 0$; if it is emission-biased ($s_d^e < s_c^e$), then $\partial(c_d/c_c)/\partial p_e < 0$; if it is Hicks-neutral, then $\partial(c_d/c_c)/\partial p_e = 0$. ■

Proof of Proposition 1.

Recall revenue functions $r_j(\varphi) = \tilde{r}_j\varphi^{\sigma-1}$, where $\tilde{r}_j \equiv RP^{\sigma-1}\left(\rho/c_j\right)^{\sigma-1}$. Use the definition of φ_d, $\tilde{r}_d = wf_d\sigma(\varphi_d)^{1-\sigma}$ and $\tilde{r}_c = \tilde{r}_d\left(c_d/c_c\right)^{\sigma-1}$. Recall emission input demand functions $e_i(\varphi) = \rho s_j^e r_j(\varphi)/p_e = \rho s_j^e \tilde{r}_j\varphi^{\sigma-1}/p_e$. Use $M = R/\bar{r}$, the emission permit market clear condition is,

$$\begin{aligned}\overline{E} =& M\left\{\int_{\varphi_d}^{\varphi_c} e_d(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty} e_c(\varphi)\mu(\varphi)d\varphi\right\}\\ =& \frac{R}{p_e}\frac{\rho s_d^e\tilde{r}_d\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \rho s_c^e\tilde{r}_c\int_{\varphi_c}^{\infty}\varphi^{\sigma-1}\mu(\varphi)d\varphi}{\tilde{r}_d\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \tilde{r}_c\int_{\varphi_c}^{\infty}\varphi^{\sigma-1}\mu(\varphi)d\varphi}\end{aligned}$$

Define $A \equiv \left(\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)(c_c/c_d)^{\sigma-1}/\left(\int_{\varphi_c}^{\infty}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)$, recall the Pareto distribution assumption for φ, $A = \left[H(\varphi_c) - H(\varphi_d)\right](c_c/c_d)^{\sigma-1}/\left[1 - H(\varphi_c)\right]$, further simplification yields $A = \left[(\varphi_c/\varphi_d)^{\gamma} - 1\right](c_c/c_d)^{\sigma-1}$, where $\gamma = c + \sigma - 1 > 0$. Using the equilibrium relative cutoffs φ_c/φ_d in equation (2.10) and Assumption 1, it comes immediately that $\text{sign}(\frac{\partial A}{\partial p_e}) = \text{sign}(\frac{\partial(c_c/c_d)}{\partial p_e}) = \text{sign}(\frac{\partial(\varphi_c/\varphi_d)}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$. In addition, $A > 0$ provided with Lemma 1.

Use the equilibrium $R = p_e\overline{E} + w\overline{L}$ and $\tilde{r}_c = \tilde{r}_d\,(c_d/c_c)^{\sigma-1}$, the emission market clear condition is,

$$p_e\overline{E} = w\overline{L}\frac{\rho s_c^e + \rho s_d^e A}{(1-\rho s_c^e) + (1-\rho s_d^e)A}$$

Rewrite the above equation and define an implicit function $F(\cdot) = 0$:

$$F(\cdot) \equiv \left[p_e\overline{E}(1-\rho s_c^e) - w\overline{L}\rho s_c^e\right] + \left[p_e\overline{E}(1-\rho s_d^e) - w\overline{L}\rho s_d^e\right] A$$

Using the implicit function $F(\cdot) = 0$, it is easy to check that

$$\left[p_e\overline{E}(1-\rho s_d^e) - w\overline{L}\rho s_d^e\right] \begin{cases} > 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

Combined with $\text{sign}(\frac{\partial A}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$, the term $\left[p_e\overline{E}(1-\rho s_d^e) - w\overline{L}\rho s_d^e\right]\frac{\partial A}{\partial p_e}$ is always nonnegative.

To show monotonicity, applying the implicit function theorem, $\frac{\partial \overline{E}}{\partial p_e} = -\frac{\partial F(\cdot)/\partial p_e}{\partial F(\cdot)/\partial \overline{E}}$,

$$\begin{aligned} \frac{\partial F(\cdot)}{\partial \overline{E}} &= p_e\left[1-\rho s_c^e + (1-\rho s_d^e)A\right] > 0 \\ \frac{\partial F(\cdot)}{\partial p_e} &= \underbrace{\overline{E}\left[1-\rho s_c^e + (1-\rho s_d^e)A\right]}_{>0} - \rho R\left(\frac{\partial s_c^e}{\partial p_e} + \frac{\partial s_d^e}{\partial p_e}A\right) + \underbrace{\left[p_e\overline{E}(1-\rho s_d^e) - w\overline{L}\rho s_d^e\right]\frac{\partial A}{\partial p_e}}_{\geq 0} \end{aligned}$$

Because the last term is always nonnegative, $\frac{\partial \overline{E}}{\partial p_e} < 0$ can be determined if the sum of the first two terms in $\frac{\partial F(\cdot)}{\partial p_e}$ is positive.

Recall the CES production technology $\left[(\beta_j e)^{(\eta-1)/\eta} + (\alpha_j l)^{(\eta-1)/\eta}\right]^{\eta/(\eta-1)}$ and its dual unit cost function $c_j(w, p_e) = \left[(p_e/\beta_j)^{1-\eta} + (w/\alpha_j)^{1-\eta}\right]^{1/(1-\eta)}$. Hence, the cost share of the emission permit is given by,

$$s_j^e \equiv \frac{\partial c_j(w,p_e)}{\partial p_e}\frac{p_e}{c_j(w,p_e)} = \left[\frac{\beta_j c_j(w,p_e)}{p_e}\right]^{\eta-1};\ \frac{\partial s_j^e}{\partial p_e} = (1-\eta)\frac{s_j^e(1-s_j^e)}{p_e}\begin{cases} < 0 & \text{if } \eta > 1 \\ = 0 & \text{if } \eta = 1 \\ > 0 & \text{if } \eta < 1 \end{cases}$$

When the factors are gross substitutes ($\eta > 1$) or ($\eta = 1$), $\frac{\partial s_j^e}{\partial p_e} \leq 0$, $\forall j \in \{c, d\}$, the sum of the first two terms in $\frac{\partial F(\cdot)}{\partial p_e}$ is positive, thus $\frac{\partial \overline{E}}{\partial p_e} < 0$. When the factors are gross complements

$(\eta < 1)$, $\frac{\partial s_j^e}{\partial p_e} > 0$, $\forall j \in \{c, d\}$, the proof of $\frac{\partial \overline{E}}{\partial p_e} < 0$ can be finished by plugging $\frac{\partial s_j^e}{\partial p_e}$ into $\frac{\partial F(\cdot)}{\partial p_e}$ and using the definition of $F(\cdot)$.

$$\begin{aligned}
&\overline{E}\left[1 - \rho s_c^e + (1 - \rho s_d^e)A\right] - \rho R\left[\frac{\partial s_c^e}{\partial p_e} + \frac{\partial s_d^e}{\partial p_e}A\right] \\
=&\rho\left\{\frac{w}{p_e}\overline{L}\left[\eta(s_c^e + s_d^e A) + (1-\eta)(s_c^e)^2 + (1-\eta)(s_d^e)^2 A\right] - \overline{E}(1-\eta)\left[s_c^e(1 - s_c^e) + s_d^e(1 - s_d^e)A\right]\right\} \\
=&\frac{\overline{E}}{s_c^e + s_d^e A}\left\{(1-\rho)\left[(s_c^e)^2 + (s_d^e A)^2\right] + A\left[(s_d^e)^2 + (s_c^e)^2 - 2\rho s_c^e s_d^e\right]\right. \\
&\left. + \eta(1 + A)\left[s_c^e(1 - s_c^e) + s_d^e(1 - s_d^e)A\right]\right\} > 0
\end{aligned}$$

The last inequality holds, since $A > 0$, $\rho < 1$, $s_c^e < 1$, $s_d^e < 1$, and $(s_d^e)^2 + (s_c^e)^2 \geq 2 s_c^e s_d^e$.

In summary, $\frac{\partial \overline{E}}{\partial p_e} < 0$ holds for all CES functions regardless of the factor-biased feature. ■

Proof of Proposition 2.

Define $J(\varphi^*) \equiv \int_{\varphi^*}^{\infty}\left[\left(\frac{\varphi}{\varphi^*}\right)^{\sigma-1} - 1\right] g(\varphi)d\varphi$, so $J'(\varphi^*) < 0$, $\forall \varphi^*$. The free entry condition (2.13) and the equilibrium relative cutoff condition (2.10) are rewritten as:

$$f_d J(\varphi_d) + f J(\varphi_c) = \delta f_e; \qquad \frac{\varphi_c}{\varphi_d} = \Delta\left(\frac{f}{f_d}\right)^{1/(\sigma-1)}$$

where $\Delta \equiv \left[(c_d/c_c)^{\sigma-1} - 1\right]^{1/(1-\sigma)}$, $\text{sign}(\frac{\partial \Delta}{\partial p_e}) = \text{sign}(\frac{\partial c_c/c_d}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$ given $\sigma > 1$.

Total differentiation of the above two equations with respect to p_e yields:

$$f_d J'(\varphi_d)\frac{\partial \varphi_d}{\partial p_e} + f J'(\varphi_c)\frac{\partial \varphi_c}{\partial p_e} = 0; \qquad \frac{\partial \varphi_c}{\partial p_e} = \frac{\partial \varphi_d}{\partial p_e}\frac{\varphi_c}{\varphi_d} + \frac{\partial \Delta}{\partial p_e}\frac{\varphi_c}{\Delta}$$

The comparative statics results are:

$$\frac{\partial \varphi_d}{\partial p_e} = -\frac{\varphi_d}{\Delta}\frac{f\varphi_c J'(\varphi_c)}{f_d\varphi_d J'(\varphi_d) + f\varphi_c J'(\varphi_c)}\frac{\partial \Delta}{\partial p_e}\begin{cases} > 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

$$\frac{\partial \varphi_c}{\partial p_e} = \frac{\varphi_c}{\Delta}\frac{f_d\varphi_d J'(\varphi_d)}{f_d\varphi_d J'(\varphi_d) + f\varphi_c J'(\varphi_c)}\frac{\partial \Delta}{\partial p_e}\begin{cases} < 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ > 0 & \text{if } s_d^e < s_c^e \end{cases}$$

In summary, when the technical change is labor-biased $(s_d^e > s_c^e)$, $\frac{\partial \varphi_d}{\partial p_e} > 0$ and $\frac{\partial \varphi_c}{\partial p_e} < 0$; when the technical change is emission-biased $(s_d^e < s_c^e)$, $\frac{\partial \varphi_d}{\partial p_e} < 0$ and $\frac{\partial \varphi_c}{\partial p_e} > 0$; when the technical change is Hicks-neutral $(s_d^e = s_c^e)$, $\frac{\partial \varphi_d}{\partial p_e} = 0$ and $\frac{\partial \varphi_c}{\partial p_e} = 0$. ■

Proof of Proposition 3.

From this proposition onward, I assume that the two countries (home and foreign) are identical. Thus, the relative foreign market potential is unit, $\Lambda = 1$.

Recall revenue functions $r_{jh}(\varphi) = \tilde{r}_{jh}\varphi^{\sigma-1}$, where $\tilde{r}_{jh} \equiv RP^{\sigma-1}(\rho/c_j)^{\sigma-1}$. Use the definition of φ_d, $\tilde{r}_{dh} = wf_d\sigma(\varphi_d)^{1-\sigma}$, and $\tilde{r}_{ch} = \tilde{r}_{dh}(c_d/c_c)^{\sigma-1}$. Recall $r_{jx}(\varphi) = \tilde{r}_{jx}\varphi^{\sigma-1}$, where $\tilde{r}_{jx} \equiv R^*(P^*)^{\sigma-1}(\rho/(\tau c_j))^{\sigma-1}$. Use the definition of φ_x, $\tilde{r}_{dx} = \sigma w f_x(\varphi_x)^{1-\sigma}$, $\tilde{r}_{cx} = \tilde{r}_{dx}(c_d/c_c)^{\sigma-1}$. Recall emission permit input demand functions $e_{jh}(\varphi) = \rho s_j^e \tilde{r}_{jh}\varphi^{\sigma-1}/p_e$ and $e_{jx}(\varphi) = \rho s_j^e \tilde{r}_{jx}\varphi^{\sigma-1}/p_e$. Use $M = R/\bar{r}$, the emission permit market clear condition is:

$$\begin{aligned}\overline{E} =& M\left\{\int_{\varphi_d}^{\varphi_c} e_{dh}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_x}^{\varphi_c} e_{dx}(\varphi)\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty}\left[e_{ch}(\varphi) + e_{cx}(\varphi)\right]\mu(\varphi)d\varphi\right\}\\ =& M\left\{\frac{\rho s_d^e \tilde{r}_{dh}}{p_e}\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \frac{\rho s_d^e \tilde{r}_{dx}}{p_e}\int_{\varphi_x}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \frac{\rho s_c^e}{p_e}\int_{\varphi_c}^{\infty}\left[\tilde{r}_{ch}\varphi^{\sigma-1} + \tilde{r}_{cx}\varphi^{\sigma-1}\right]\mu(\varphi)d\varphi\right\}\\ =& \frac{R\rho}{p_e}\frac{\left\{s_d^e\tilde{r}_{dh}\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + s_d^e\tilde{r}_{dx}\int_{\varphi_x}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + s_c^e\int_{\varphi_c}^{\infty}\left[\tilde{r}_{ch}\varphi^{\sigma-1} + \tilde{r}_{cx}\varphi^{\sigma-1}\right]\mu(\varphi)d\varphi\right\}}{\left\{\tilde{r}_{dh}\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \tilde{r}_{dx}\int_{\varphi_x}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi + \int_{\varphi_c}^{\infty}\left[\tilde{r}_{ch}\varphi^{\sigma-1} + \tilde{r}_{cx}\varphi^{\sigma-1}\right]\mu(\varphi)d\varphi\right\}}\end{aligned}$$

Recall $A \equiv \left(\int_{\varphi_d}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)(c_c/c_d)^{\sigma-1}/\left(\int_{\varphi_c}^{\infty}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)$, $\text{sign}(\frac{\partial A}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$. Similarly, define $B \equiv \left(\int_{\varphi_x}^{\varphi_c}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)(c_c/c_d)^{\sigma-1}/\left(\int_{\varphi_c}^{\infty}\varphi^{\sigma-1}\mu(\varphi)d\varphi\right)$. Use the Pareto distribution of φ, $B = [H(\varphi_c) - H(\varphi_x)](c_c/c_d)^{\sigma-1}/[1 - H(\varphi_c)] = [(\varphi_c/\varphi_x)^{\gamma} - 1](c_c/c_d)^{\sigma-1}$. Using the relative cutoffs of φ_x/φ_c and technology cost assumption, $\text{sign}(\frac{\partial B}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$. Recall $\tilde{r}_{jh} = \tilde{r}_{jh}(c_d/c_c)^{\sigma-1}$ and $\tilde{r}_{jx} = \tilde{r}_{jh}\tau^{1-\sigma}$. The above emission market clear condition is rewritten as,

$$p_e\overline{E} = R\rho\frac{s_d^eA + s_d^e\tau^{1-\sigma}B + s_c^e + s_c^e\tau^{1-\sigma}}{A + \tau^{1-\sigma}B + 1 + \tau^{1-\sigma}}$$

Plug in $R = w\overline{L} + p_e\overline{E}$ and express the permit auction revenue ($p_e\overline{E}$) as a function of the rest of variables:

$$p_e\overline{E} = w\overline{L}\frac{\rho s_c^e(1+\tau^{1-\sigma}) + \rho s_d^e(A+\tau^{1-\sigma})B}{(1-\rho s_{p_e}^c)(1+\tau^{1-\sigma}) + (1-\rho s_d^e)(A+\tau^{1-\sigma})B}$$

Define $C \equiv (A+\tau^{1-\sigma})B/(1+\tau^{1-\sigma})$, $\text{sign}(\frac{\partial C}{\partial p_e}) = \text{sign}(\frac{\partial A}{\partial p_e}) = \text{sign}(\frac{\partial B}{\partial p_e})$, then the above equation returns back to the one in the proof of Proposition 1,

$$p_e\overline{E} = w\overline{L}\frac{\rho s_c^e + \rho s_d^e C}{(1-\rho s_c^e) + (1-\rho s_d^e)C}$$

The remaining proof follows exactly as the one in Proposition 1. Therefore, $\frac{\partial \overline{E}}{\partial p_e} < 0$ still holds in the open economy. ■

Proof of Proposition 4.

Recall $J(\varphi^*) \equiv \int_{\varphi^*}^{\infty} \left[\left(\frac{\varphi}{\varphi^*} \right)^{\sigma-1} - \right] g(\varphi) d\varphi$, $J'(\varphi) < 0, \forall \varphi$, the free entry condition (2.33), and the equilibrium cutoff relationship condition (2.29)-(2.31) are rewritten as:

$$f_d J(\varphi_d) + f_x J(\varphi_x) + f J(\varphi_c) = \delta f_e$$

$$\begin{aligned}
\left(\frac{\varphi_x}{\varphi_d}\right)^{\sigma-1} &= \tau^{\sigma-1}\frac{f_x}{f_d} && \Rightarrow \frac{\varphi_x}{\varphi_d} = \tau\left(\frac{f_x}{f_d}\right)^{1/(\sigma-1)} \\
\left(\frac{\varphi_c}{\varphi_x}\right)^{\sigma-1} &= \frac{1}{1+\tau^{\sigma-1}}\frac{f}{f_x}\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]^{-1} && \Rightarrow \frac{\varphi_c}{\varphi_x} = \Delta T\left(\frac{f}{f_x}\right)^{1/(\sigma-1)} \\
\left(\frac{\varphi_c}{\varphi_d}\right)^{\sigma-1} &= \frac{1}{1+\tau^{\sigma-1}}\frac{f}{f_d}\left[\left(\frac{c_d}{c_c}\right)^{\sigma-1} - 1\right]^{-1} && \Rightarrow \frac{\varphi_c}{\varphi_d} = \Delta\tau T\left(\frac{f}{f_d}\right)^{1/(\sigma-1)}
\end{aligned}$$

where $\Delta \equiv \left[(c_d/c_c)^{\sigma-1} - 1\right]^{1/(1-\sigma)}$, $T \equiv \left[1/(1+\tau^{\sigma-1})\right]^{1/(\sigma-1)}$, and $\tau T \equiv \left[1/(1+\tau^{1-\sigma})\right]^{1/(\sigma-1)}$. It is easy to see that $\frac{\partial T}{\partial \tau} < 0$, and $\frac{\partial(\tau T)}{\partial \tau} > 0$. Then total differentiation with respect to p_e yields:

$$\begin{aligned}
&f_d J'(\varphi_d)\frac{\partial \varphi_d}{\partial p_e} + f_x J'(\varphi_x)\frac{\partial \varphi_x}{\partial p_e} + f J'(\varphi_c)\frac{\partial \varphi_c}{\partial p_e} = 0 \\
&\frac{\partial \varphi_x}{\partial p_e} = \frac{\partial \varphi_d}{\partial p_e}\frac{\varphi_x}{\varphi_d}; \frac{\partial \varphi_c}{\partial p_e} = \frac{\varphi_c}{p_e}\left(\frac{\partial \varphi_x}{\partial p_e}\frac{p_e}{\varphi_x} + \frac{\partial \Delta}{\partial p_e}\frac{p_e}{\Delta}\right); \frac{\partial \varphi_c}{\partial p_e} = \frac{\varphi_c}{p_e}\left(\frac{\partial \varphi_d}{\partial p_e}\frac{p_e}{\varphi_d} + \frac{\partial \Delta}{\partial p_e}\frac{p_e}{\Delta}\right)
\end{aligned}$$

The comparative statics results are:

$$\frac{\partial \varphi_d}{\partial p_e} = -\frac{\varphi_d}{\Delta}\frac{f J'(\varphi_c)\varphi_c}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c}\frac{\partial \Delta}{\partial p_e}\begin{cases} > 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

$$\frac{\partial \varphi_x}{\partial p_e} = -\frac{\varphi_x}{\Delta}\frac{f J'(\varphi_c)\varphi_c}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c}\frac{\partial \Delta}{\partial p_e}\begin{cases} > 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

$$\frac{\partial \varphi_c}{\partial p_e} = \frac{\varphi_c}{\Delta}\frac{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c}\frac{\partial \Delta}{\partial p_e}\begin{cases} < 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

In summary, when the technical change is labor-biased ($s_d^e > s_c^e$), $\frac{\partial \varphi_d}{\partial p_e} > 0$, $\frac{\partial \varphi_x}{\partial p_e} > 0$, and $\frac{\partial \varphi_c}{\partial p_e} < 0$; when the technical change is emission-biased ($s_d^e < s_c^e$), $\frac{\partial \varphi_d}{\partial p_e} < 0$, $\frac{\partial \varphi_x}{\partial p_e} < 0$, and

$\frac{\partial \varphi_c}{\partial p_e} > 0$; when the technical change is Hicks-neutral ($s_d^e = s_c^e$), $\frac{\partial \varphi_d}{\partial p_e} = 0$, $\frac{\partial \varphi_x}{\partial p_e} = 0$, and $\frac{\partial \varphi_c}{\partial p_e} = 0$

■

Proof of Proposition 5.

Recall the expression of permit auction revenue as a function of the rest of variables in the proof of Proposition 3.

$$p_e \overline{E} = w\overline{L} \frac{\rho s_d^e (A + \tau^{1-\sigma} B) + \rho s_c^e (1 + \tau^{1-\sigma})}{(1 - \rho s_d^e)(A + \tau^{1-\sigma} B) + (1 - \rho s_c^e)(1 + \tau^{1-\sigma})}$$

where $A \equiv (c_c/c_d)^{\sigma-1} [H(\varphi_c) - H(\varphi_d)]/[1 - H(\varphi_c)]$, $B \equiv (c_c/c_d)^{\sigma-1} [H(\varphi_c) - H(\varphi_x)]/[1 - H(\varphi_c)]$, as defined above. Thus, $\text{sign}(\frac{\partial A}{\partial p_e}) = \text{sign}(\frac{\partial B}{\partial p_e}) = \text{sign}(\frac{\partial (c_c/c_d)}{\partial p_e}) = \text{sign}(s_c^e - s_d^e)$. Rewrite the above equation, and define an implicit function $F(\cdot) = 0$,

$$F(\cdot) \equiv \left[p_e \overline{E}(1 - \rho s_d^e) - w\overline{L}\rho s_d^e\right](A + \tau^{1-\sigma} B) + \left[p_e \overline{E}(1 - \rho s_c^e) - w\overline{L}\rho s_c^e\right](1 + \tau^{1-\sigma})$$

Using the definition of $F(\cdot) \equiv 0$, it is easy to check that

$$p_e \overline{E}(1 - \rho s_d^e) - w\overline{L}\rho s_d^e \begin{cases} < 0 & \text{if } s_d^e > s_c^e \\ = 0 & \text{if } s_d^e = s_c^e \\ < 0 & \text{if } s_d^e < s_c^e \end{cases}$$

By the implicit function theorem, $\frac{\partial p_e}{\partial \tau} = -[\partial F(\cdot)/\partial \tau]/[\partial F(\cdot)/\partial p_e]$, the denominator is,

$$\frac{\partial F(\cdot)}{\partial p_e} = \left[p_e \overline{E}(1 - \rho s_d^e) - w\overline{L}\rho s_d^e\right]\left(\frac{\partial A}{\partial p_e} + \tau^{1-\sigma}\frac{\partial B}{\partial p_e}\right) - \left[(A + \tau^{1-\sigma} B)\frac{\partial s_d^e}{\partial p_e} + \rho R(1 + \tau^{1-\sigma})\frac{\partial s_c^e}{\partial p_e}\right]$$
$$+ \overline{E}\left[(1 - \rho s_d^e)(A + \tau^{1-\sigma} B) + (1 - \rho s_c^e)(1 + \tau^{1-\sigma})\right]$$

The first term is always nonnegative, $\left[p_e \overline{E}(1 - \rho s_d^e) - w\overline{L}\rho s_d^e\right]\left(\frac{\partial A}{\partial p_e} + \tau^{1-\sigma}\frac{\partial B}{\partial p_e}\right) \geq 0$. When $s_d^e > s_c^e$, the term in the square bracket is negative, the term in the parenthesis is negative as well since $\frac{\partial A}{\partial p_e} < 0$, $\frac{\partial B}{\partial p_e} < 0$; vice-versa. If $\frac{\partial s_j^e}{\partial p_e} \leq 0$, $\forall j$, it is easy to see that $\frac{\partial F(\cdot)}{\partial p_e} > 0$. If $\frac{\partial s_j^e}{\partial p_e} > 0$, $\forall j$, one still can show $\frac{\partial F(\cdot)}{\partial p_e} > 0$ using the similar proof of Proposition 1.

The numerator is then given by,

$$\frac{\partial F(\cdot)}{\partial \tau} = \left[p_e \overline{E}(1 - \rho s_d^e) - w\overline{L}\rho s_d^e\right]\left[\frac{\partial A}{\partial \tau} + \tau^{1-\sigma}\frac{\partial B}{\partial \tau} + \frac{(\sigma - 1)\tau^{-\sigma}}{1 + \tau^{1-\sigma}}(A - B)\right]$$

Combined with $\frac{\partial F(\cdot)}{\partial p_e} > 0$, one could sign $\frac{\partial p_e}{\partial \tau}$,

$$\text{sign}\left(\frac{\partial p_e}{\partial \tau}\right) = \begin{cases} \text{sign}\left\{\frac{\partial A}{\partial \tau} + \tau^{1-\sigma}\frac{\partial B}{\partial \tau} + \frac{(\sigma-1)\tau^{-\sigma}}{1+\tau^{1-\sigma}}(A-B)\right\} & \text{if } s_d^e > s_c^e \\ 0 & \text{if } s_d^e = s_c^e \\ -\text{sign}\left\{\frac{\partial A}{\partial \tau} + \tau^{1-\sigma}\frac{\partial B}{\partial \tau} + \frac{(\sigma-1)\tau^{-\sigma}}{1+\tau^{1-\sigma}}(A-B)\right\} & \text{if } s_d^e < s_c^e \end{cases}$$

Given Assumption 3 on the Pareto distribution function, recall the relative equilibrium cutoffs (2.30) and (2.31), and plug into the previously defined terms A and B:

$$A = \left(\frac{c_c}{c_d}\right)^{\sigma-1}\left[(\Delta\tau T)^{\gamma}\left(\frac{f}{f_d}\right)^{\gamma/(\sigma-1)} - 1\right]; B = \left(\frac{c_c}{c_d}\right)^{\sigma-1}\left[(\Delta T)^{\gamma}\left(\frac{f}{f_x}\right)^{\gamma/(\sigma-1)} - 1\right]$$

$$A - B = \left(\frac{c_c}{c_d}\right)^{\sigma-1}(\Delta T)^{\gamma}\left[\tau^{\gamma}\left(\frac{f}{f_d}\right)^{\gamma/(\sigma-1)} - \left(\frac{f}{f_x}\right)^{\gamma/(\sigma-1)}\right]$$

Substituting $\frac{\partial T}{\partial \tau} = -\tau^{\sigma-2}T/(1+\tau^{\sigma-1}) < 0$ and $\frac{\partial(\tau T)}{\partial \tau} = \tau^{1-\sigma}T/(1+\tau^{1-\sigma}) > 0$ yields:

$$\frac{\partial A}{\partial \tau}\left(\frac{c_d}{c_c}\right)^{\sigma-1} = \left(\frac{f}{f_d}\right)^{\gamma/(\sigma-1)}(\Delta\tau T)^{\gamma}\frac{\gamma\tau^{-\sigma}}{\tau^{1-\sigma}+1}; \quad \frac{\partial B}{\partial \tau}\left(\frac{c_d}{c_c}\right)^{\sigma-1} = \left(\frac{f}{f_x}\right)^{\gamma/(\sigma-1)}(\Delta T)^{\gamma}\frac{-\gamma\tau^{-1}}{\tau^{1-\sigma}+1}$$

Further simplification gives rise to:

$$\left(\frac{\partial A}{\partial \tau} + \tau^{1-\sigma}\frac{\partial B}{\partial \tau}\right) + \frac{(\sigma-1)\tau^{-\sigma}}{1+\tau^{1-\sigma}}(A-B)$$
$$= \left(\frac{c_c}{c_d}\right)^{\sigma-1}\left\{\frac{(\Delta T)^{\gamma}}{1+\tau^{1-\sigma}}f^{\gamma/(\sigma-1)}\left[\gamma\tau^{-\sigma} + (\sigma-1)\tau^{-\sigma}\right]\left[(f_d)^{\gamma/(1-\sigma)} - (f_x)^{\gamma/(1-\gamma)}\right]\right\} > 0$$

To show the above inequality, recall $\tau^{1-\sigma}f_d < f_x$ in Lemma 2 which guarantees the partitioning of firms,

$$\frac{f_d}{f_x} < \tau^{\sigma-1} \Rightarrow \left(\frac{f_d}{f_x}\right)^{1/(\sigma-1)} < \tau \Rightarrow \left(\frac{f_d}{f_x}\right)^{\gamma/(\sigma-1)} < \tau^{\gamma} \Rightarrow (f_x)^{\gamma/(1-\sigma)} < \tau^{\gamma}(f_d)^{\gamma/(1-\sigma)}$$

In summary, when the technical change is labor-biased ($s_d^e > s_c^e$), $\frac{\partial p_e}{\partial \tau} > 0$; when the technical change is emission-biased ($s_d^e < s_c^e$), $\frac{\partial p_e}{\partial \tau} < 0$; when the technical change is Hicks-neutral, $\frac{\partial p_e}{\partial \tau} = 0$. ■

Proof of Proposition 6.

Recall $J(\varphi^*) \equiv \int_{\varphi^*}^{\infty}\left[\left(\frac{\varphi}{\varphi^*}\right)^{\sigma-1} - 1\right]g(\varphi)d\varphi$, $J'(\varphi^*) < 0$, $\forall\varphi^*$. Then the free entry condition (2.33), and the equilibrium cutoff relationship conditions (2.29)-(2.31) are simplified to:

$$f_dJ(\varphi_d) + f_xJ(\varphi_x) + fJ(\varphi_c) = \delta f_e$$

$$\frac{\varphi_x}{\varphi_d} = \tau\left(\frac{f_x}{f_d}\right)^{1/(\sigma-1)}; \frac{\varphi_c}{\varphi_x} = \Delta T\left(\frac{f}{f_x}\right)^{1/(\sigma-1)}; \frac{\varphi_c}{\varphi_d} = \Delta\tau T\left(\frac{f}{f_d}\right)^{1/(\sigma-1)}$$

where $\Delta \equiv \left\{(c_d/c_c)^{\sigma-1} - 1\right\}^{1/(1-\sigma)}$, $T \equiv \left(1+\tau^{\sigma-1}\right)^{1/(1-\sigma)}$, $\tau T \equiv \left(1+\tau^{1-\sigma}\right)^{1/(1-\sigma)}$.

$$\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} = -\frac{\partial (c_d/c_c)}{\partial \tau}\tau\Delta^{\sigma-1}; \frac{\partial \tau T}{\partial \tau}\frac{1}{T} = T^{\sigma-1}; \frac{\partial T}{\partial \tau}\frac{\tau}{T} = -(\tau T)^{\sigma-1}$$

$$\frac{\partial c_d/c_c}{\partial \tau} = \frac{\partial c_d/c_c}{\partial p_e}\frac{\partial p_e}{\partial \tau} \geq 0 \begin{cases} \text{if } \frac{\partial c_d/c_c}{\partial p_e} > 0 (s_d^e > s_c^e) & \text{then } \frac{\partial p_e}{\partial \tau} > 0 \\ \text{if } \frac{\partial c_d/c_c}{\partial p_e} = 0 (s_d^e = s_c^e) & \text{then } \frac{\partial p_e}{\partial \tau} = 0 \\ \text{if } \frac{\partial c_d/c_c}{\partial p_e} < 0 (s_d^e < s_c^e) & \text{then } \frac{\partial p_e}{\partial \tau} < 0 \end{cases}$$

Total differentiation with respect to τ yields:

$$\begin{aligned} & f_d J'(\varphi_d)\frac{\partial \varphi_d}{\partial \tau} + f_x J'(\varphi_x)\frac{\partial \varphi_x}{\partial \tau} + f J'(\varphi_c)\frac{\partial \varphi_c}{\partial \tau} = 0 \\ & \frac{\partial \varphi_x}{\partial \tau} = \frac{\varphi_x}{\tau}\left(\frac{\partial \varphi_d}{\partial \tau}\frac{\tau}{\varphi_d} + 1\right) \\ & \frac{\partial \varphi_c}{\partial \tau} = \frac{\varphi_c}{\tau}\left[\frac{\partial \varphi_x}{\partial \tau}\frac{\tau}{\varphi_x} + \frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial T}{\partial \tau}\frac{\tau}{T}\right] \\ & \frac{\partial \varphi_c}{\partial \tau} = \frac{\varphi_c}{\tau}\left[\frac{\partial \varphi_d}{\partial \tau}\frac{\tau}{\varphi_d} + \frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{(\tau T)}\right] \end{aligned}$$

The comparative statics results are:

$$\begin{aligned} \frac{\partial \varphi_x}{\partial \tau} &= \frac{\varphi_x}{\tau}\frac{f_d J'(\varphi_d)\varphi_d - f J'(\varphi_c)\varphi_c\left(\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial T}{\partial \tau}\frac{\tau}{T}\right)}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c} \\ \frac{\partial \varphi_d}{\partial \tau} &= -\frac{\varphi_d}{\tau}\frac{f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c\left[\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{\tau T}\right]}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c} \\ \frac{\partial \varphi_c}{\partial \tau} &= \frac{\varphi_c}{\tau}\frac{f_x J'(\varphi_x)\varphi_x\left(\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial T}{\partial \tau}\frac{\tau}{T}\right) + f_d J'(\varphi_d)\varphi_d\left[\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{\tau T}\right]}{f_d J'(\varphi_d)\varphi_d + f_x J'(\varphi_x)\varphi_x + f J'(\varphi_c)\varphi_c} \end{aligned}$$

In summary, $\frac{\partial \varphi_x}{\partial \tau} > 0$ since $J'(\cdot) < 0$, $\partial \Delta/\partial \tau < 0$ and $\partial T/\partial \tau < 0$. the possible signs for the rest of two cutoffs are discussed as follows:

- If $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{\tau T} = 0$, then $\partial \varphi_d/\partial \tau < 0$, $\partial \varphi_c/\partial \tau < 0$;
- If $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{\tau T} < 0$, then $\partial \varphi_c/\partial \tau < 0$, but the sign of $\partial \varphi_d/\partial \tau$ is indeterminate;
- If $\frac{\partial \Delta}{\partial \tau}\frac{\tau}{\Delta} + \frac{\partial (\tau T)}{\partial \tau}\frac{\tau}{\tau T} > 0$, then $\partial \varphi_d/\partial \tau < 0$, but the sign of $\partial \varphi_c/\partial \tau$ is indeterminate.

■

APPENDIX C. ARE EXPORTERS MORE ENVIRONMENTALLY FRIENDLY THAN NON-EXPORTERS? THEORY AND EVIDENCE

Description of the NEI Database

This section provides a detailed introduction of the NEI facility level emission database. We first introduce the background of emission reporting rule. Then we conduct some data comparison among several aggregate-level emission databases used in related literature, i.e., National Emission Trends (NET) of the EPA,[1] and Annual Industrial Sector Pollutant Release by Industry in Greenstone (2002).[2]

The NEI database includes estimates of annual criteria and hazardous air pollutant emissions from point, non-point, and mobile sources in the 50 States, the District of Columbia, Puerto Rico, and the Virgin Islands. The compilation includes emission estimates submitted by State, Local, and Tribal air pollution control agencies. The collection and updating of emission inventory information follow with the Consolidated Emissions Reporting Rule (CERR) published by the EPA in 2002. The CERR requires the reporting emissions for all facilities sites that emit above certain thresholds, determined by pollutant and depending upon whether the facility site is located in a nonattainment area. State or local pollution control agencies have to comply with the CERR requirement. They will continue to report emissions from larger point sources annually, and have a choice to report smaller point sources every three years or one-third of the sources each year.[3]

The NEI database reports estimates for the following facility-level criteria air pollutants: i.e., NH_3, SO_2, CO, NOx, VOCs, and TSPs. For each of six pollutants, we aggregate annual

[1]For National Emission Trends database, please see: http://www.epa.gov/ttnchie1/trends/.

[2]For the table of Annual Industrial Sector Pollutant Release by Industry, please see Table A2 in Greenstone (2002).

[3]For the CERR Final Rule, please see http://www.epa.gov/ttn/chief/cerr/cerr.pdf.

emissions across all facilities and compare them to the national aggregate emission level provided by the NET of the EPA. As shown in Table C.1, the magnitude of total emissions for each criteria air pollutant (except VOCs) aggregated from the NEI facility level database comes close to the national aggregate emission level reported in the NET of the EPA. The latter is the sum of the following source categories classified in the NET: fuel combustion electric utility, fuel combustion industrial, chemical & allied product manufacturing, metals processing, petroleum & related industries, other industrial process, solvent utilization, storage & transport, waste disposal & recycling. Columns 2 and 3 in Table C.1 show the comparison between aggregate emissions from the manufacturing sector with emissions from all industrial activities within the same NEI database. Since fuel combustion electric utility (SIC code 4911, not in the manufacturing industry thus excluded in this study) releases roughly 80 percent of total SO_2 emissions, SO_2 emitted from the manufacturing sector only accounts for one-tenth of total emissions. Moreover, TSPs emissions, aggregated from the facility-level NEI database, increase substantially from year 2002 to year 2005. Part of the reason is due to the enforcement of PM2.5 reporting rule started effectively on June 1, 2004.[4] Such drastic increase cannot reflect its real change.

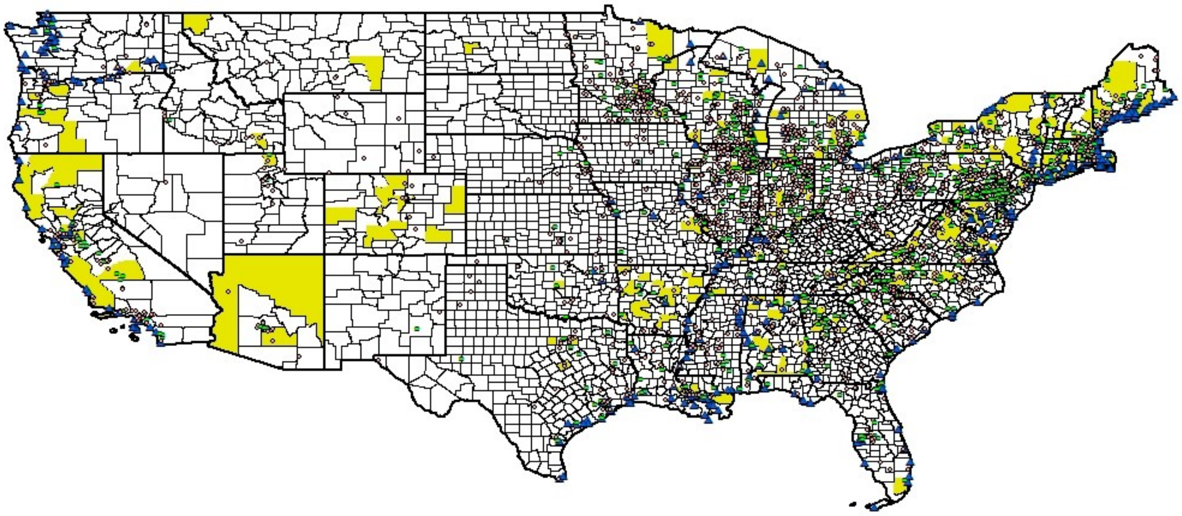
Furthermore, we aggregate the industrial emissions from the NEI database by pollutant type, and compare them with the Annual Industrial Sector Pollutant Release by Industry, which Greenstone (2002) constructed using the EPA Sector Notebook Project (1995). Note that the magnitude of the industrial emissions from each data source cannot directly compare since they reflect the annual emissions during the different periods. In particular, there exists a drastic reduction in air pollution in the U.S. manufacturing industry during the 1980-2000 period (Greenstone, 2004; Levinson, 2009). Despite that, we seek some similarities in identifying dirty industries between these two databases. Table C.2 presents the annual industrial emissions in major polluting industries between year 2002 and 2005. We define the major polluting industries as those which emit at least one percent of total emissions from the manufacturing sector. For each pollutant, the industrial emission is calculated by total emissions of a three-digit SIC industry, within which emissions of the pollutant are aggregated across all relevant

[4]Please see the CERR Final Rule: http://www.epa.gov/ttn/chief/cerr/cerr.pdf.

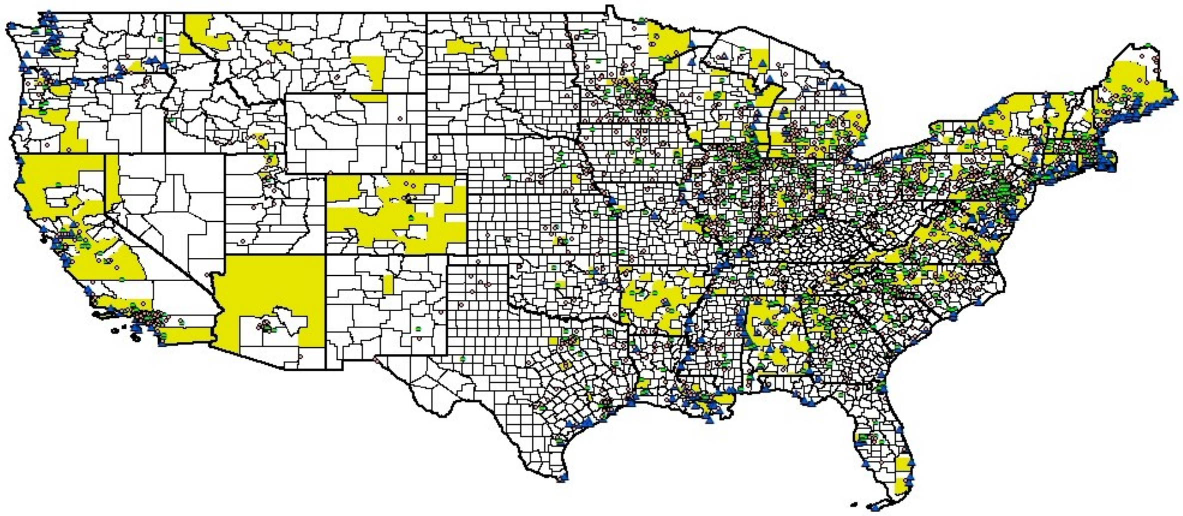
polluting facilities. Total emissions from the manufacturing sector are aggregated from all facilities within that sector. The following industries are defined as pollutant-specific dirty polluters in both tables: Sawmill and Planning Mills (242, 243): TSPs; Paper and Allied Products (261-263, 267): SO_2, CO, O_3, and TSPs; Industrial Inorganic Chemicals (281): SO_2; Industrial Organic Chemicals (286, 287, 289): SO_2, CO, O_3, and TSPs; Petroleum Refining and Related Industries (291, 295, 299): SO_2, O_3, and TSPs; Stone, Clay, Glass, and Concrete Products (321-329): SO_2, CO, O_3, and TSPs.[5]

[5] The number in parenthesis is three-digit SIC code range.

Figures and Tables

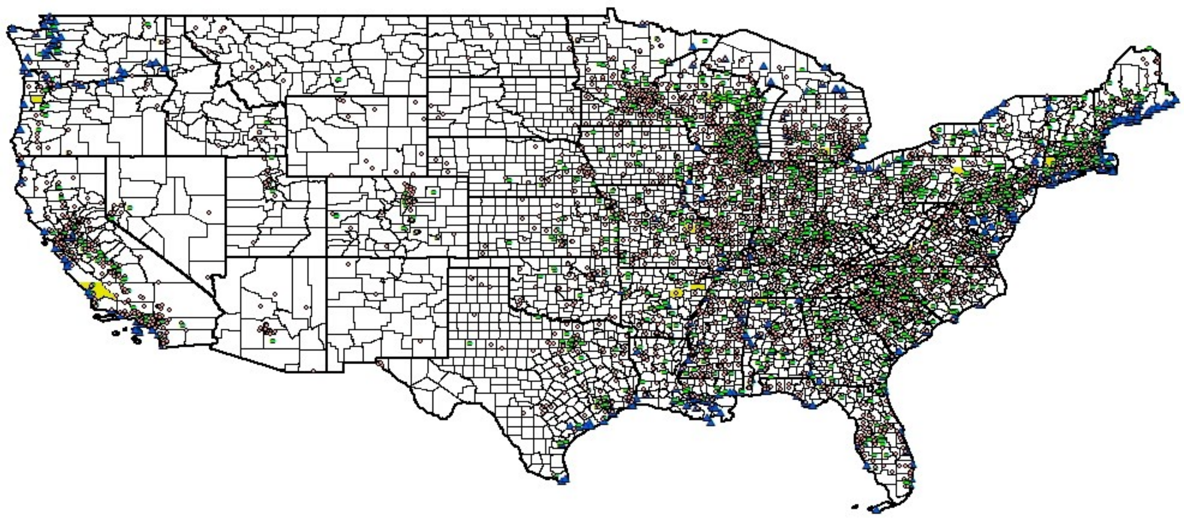


(a) Year 2002

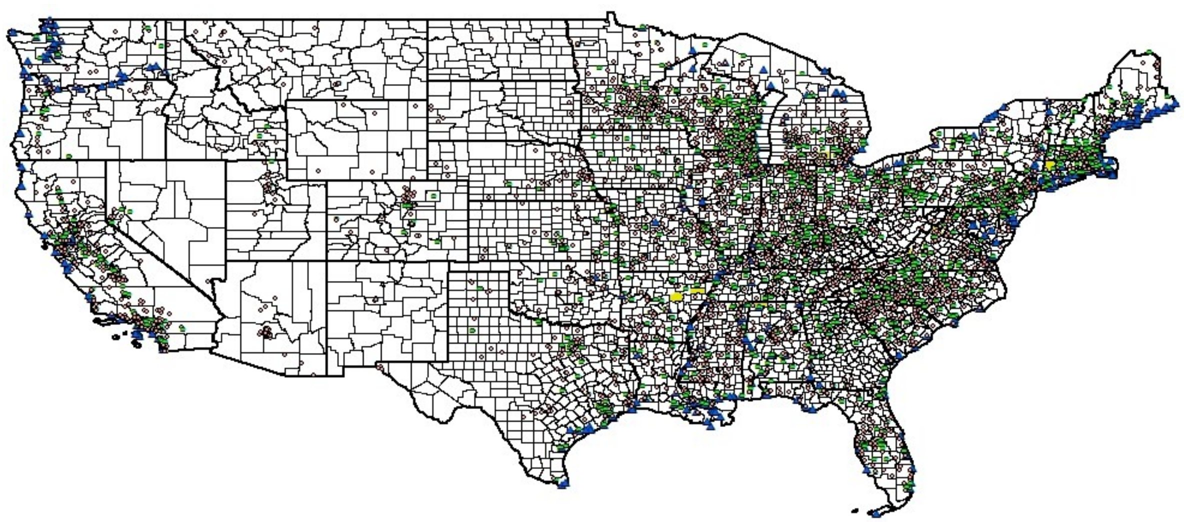


(b) Year 2005

Figure C.1: NH_3 Polluting Facilities. Source: NEI database. Yellow areas refer to any nonattainment counties, green points are exporters, pink points denote non-exporters, and blue triangles represent ports.

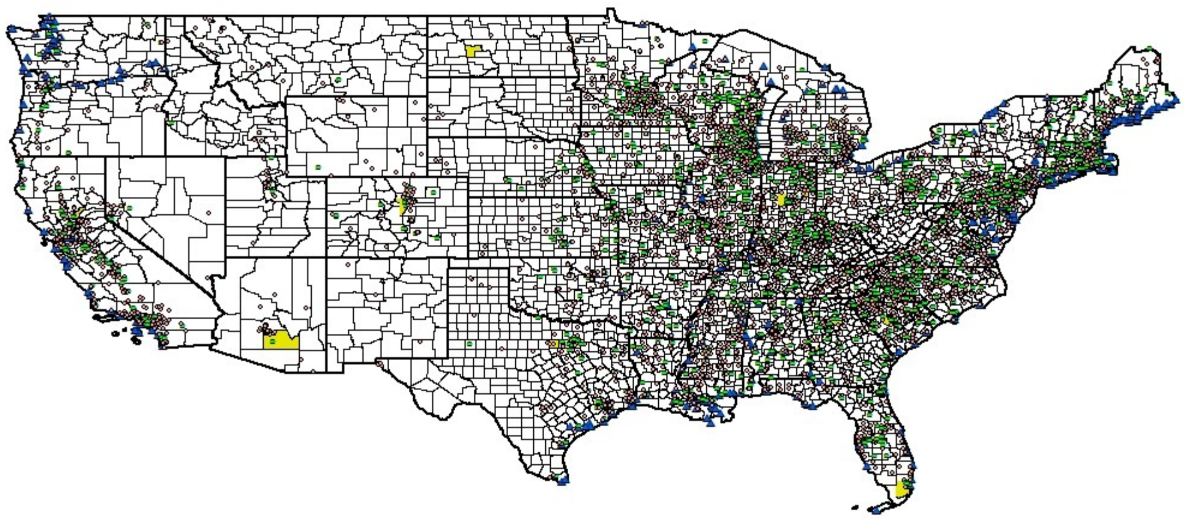


(a) Year 2002

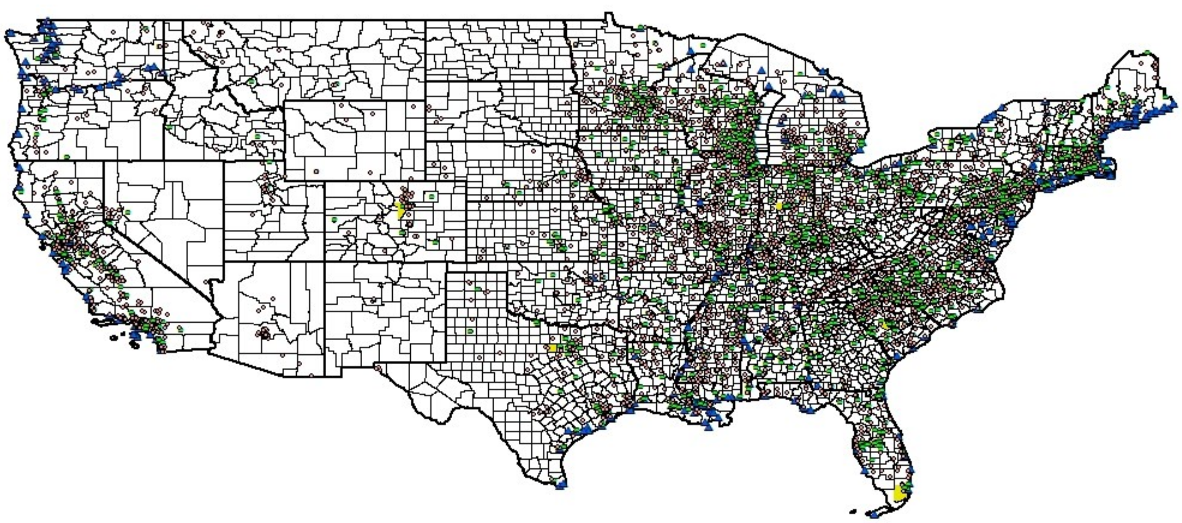


(b) Year 2005

Figure C.2: SO_2 Polluting Facilities. Source: NEI database. Yellow areas refer to SO_2-specific nonattainment counties, green points are exporters, pink points denote non-exporters, and blue triangles represent ports.

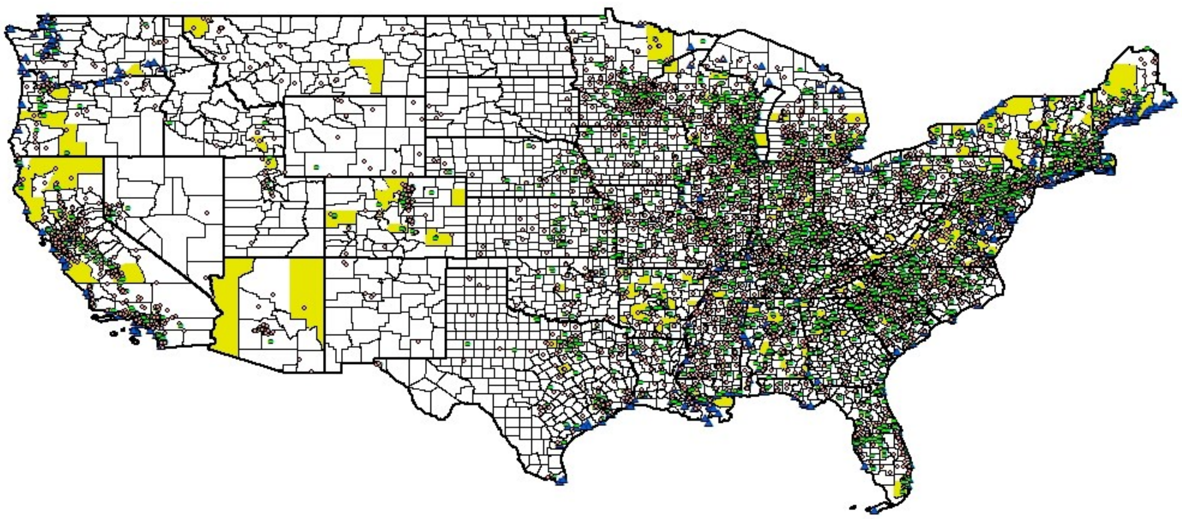


(a) Year 2002

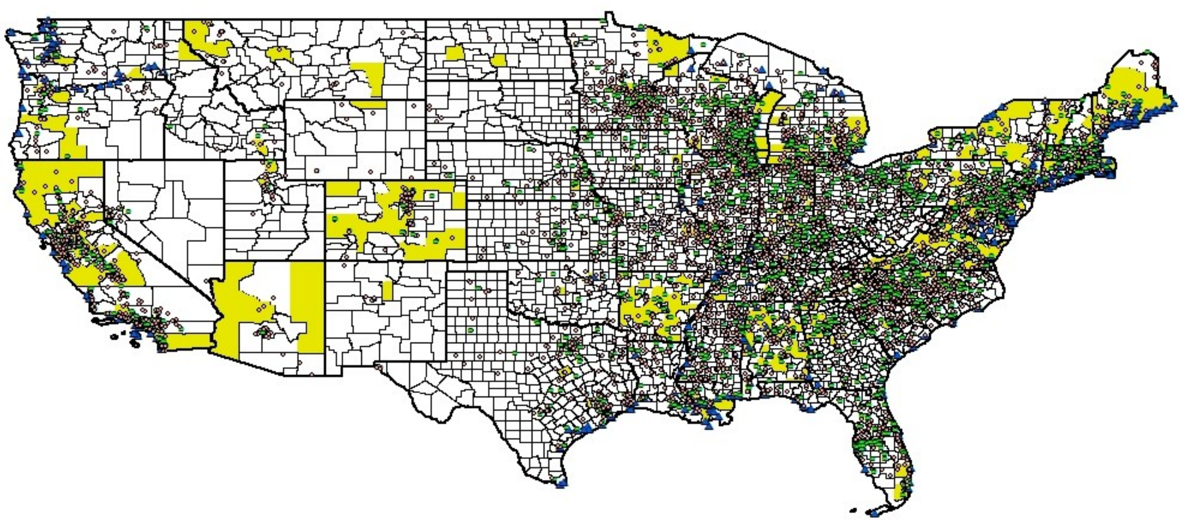


(b) Year 2005

Figure C.3: CO Polluting Facilities. Source: NEI database. Yellow areas refer to CO-specific nonattainment counties, green points are exporters, pink points denote non-exporters, and blue triangles represent ports.

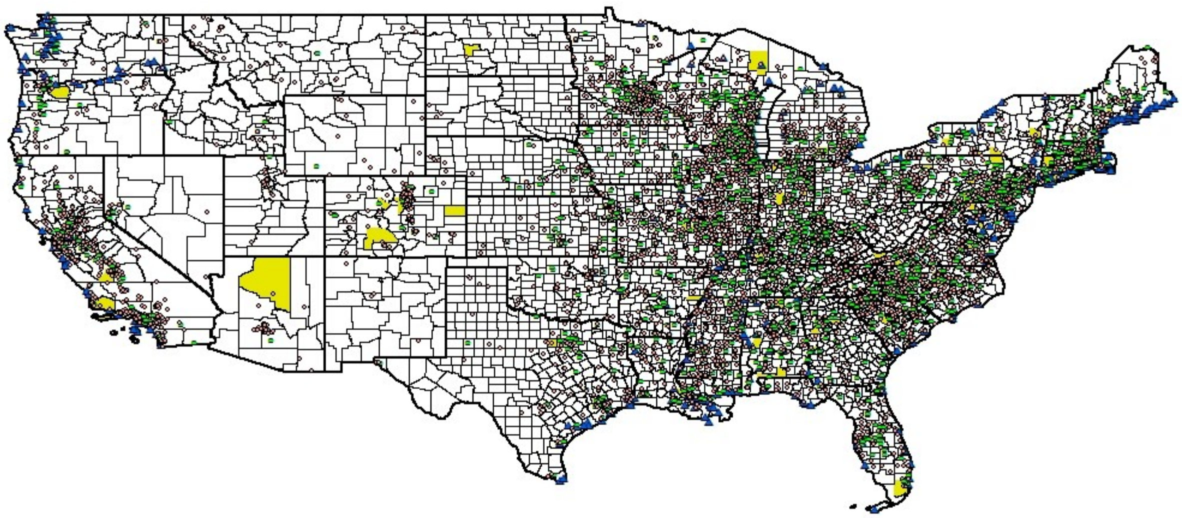


(a) Year 2002

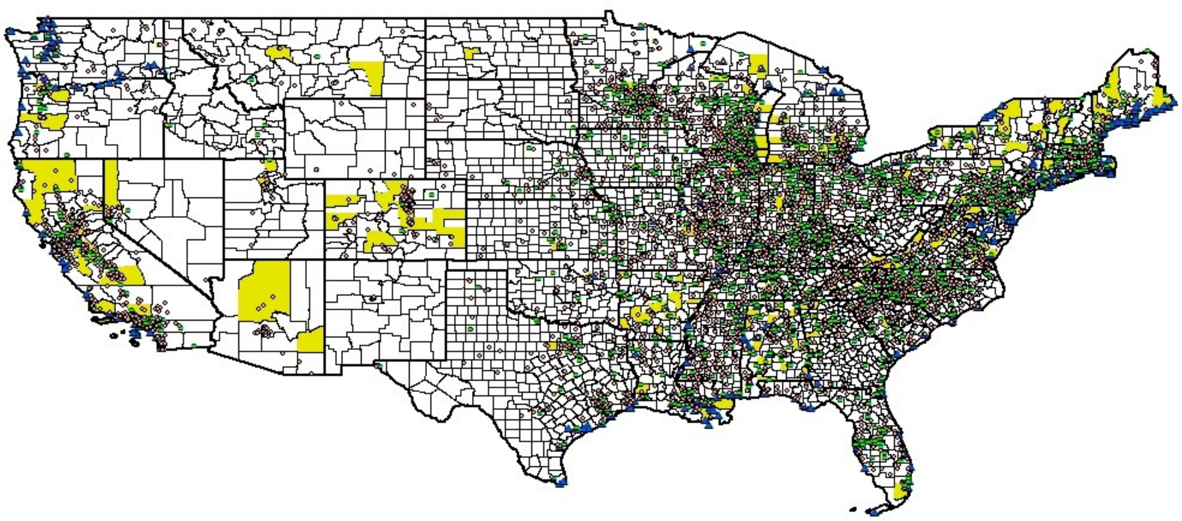


(b) Year 2005

Figure C.4: O_3 Polluting Facilities. Source: NEI database. Yellow areas refer to O_3-specific nonattainment counties, green points are exporters, pink points denote non-exporters, and blue triangles represent ports.



(a) Year 2002



(b) Year 2005

Figure C.5: TSPs Polluting Facilities. Source: NEI database. Yellow areas refer to TSPs-specific nonattainment counties, green points are exporters, pink points denote non-exporters, and blue triangles represent ports.

Table C.1: Aggregate Emission Comparison

	Year 2002				Year 2005			
	National Emission	National Emission Inventory			National Emission	National Emission Inventory		
	Trends	All Industry	Manufacturing	Merged Manufacturing	Trends	All Industry	Manufacturing	Merged Manufacturing
Column	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
SO_2	12,072,110	12,637,803	1,982,949	906,395	11,935,123	12,497,875	1,860,094	916,539
VOCs	6,981,811	1,472,397	1,089,903	562,966	6,861,154	1,413,782	1,011,276	490,815
NO_x	7,084,325	7,081,272	1,404,672	661,978	6,115,435	6,145,396	1,282,455	603,387
CO	5,221,843	3,833,746	2,637,738	1,187,171	4,880,736	3,966,641	2,325,981	941,782
TSPs	5,845,090	2,116,880	735,775	374,134	5,682,701	3,640,838	1,737,972	890,330
NH_3	253,109	184,884	66,213	38,614	251,294	181,613	60,107	31,558

Source: National Emission Trends, and National Emission Inventory of the EPA.
Note: Emissions in the National Emission Trends are converted from short tons to metric tons. All emissions are converted to thousand metric tons. Emissions in the merged manufacturing industry are calculated after merging the NEI database with the NETS database.

Table C.2: Annual Industrial Emissions by Pollutant between Years 2002 and 2005

	SO_2		CO		VOCs		NO_x		TSPs		NH_3	
	Emissions	Share	Emissions	Share	Emissions	Share	Emissions	Share	Emissions	Share	Emissions	Share
Industry (3-digit SIC)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Food industry (203-4,206-209)	106617.1	5.6%	92207.6	3.7%	79503.1	7.6%	62240.9	4.6%	107177.9	9.0%	4997.2	7.9%
Sawmill and planning mills, wood products (242-3,249)	5246.3	0.3%	107348.3	4.3%	100579.5	9.6%	33166.1	2.5%	120735.6	9.9%	513.9	0.8%
Household furniture (251)	470.2	0.0%	2225.7	0.1%	24535.6	2.3%	1670.0	0.1%	8545.1	0.8%	3.0	0.0%
Paper and allied products (261-3,267)	370228.2	19.3%	342872.7	13.9%	140386.0	13.4%	250296.9	18.7%	206329.2	16.4%	10408.2	16.6%
Commercial printing (275)	215.8	0.0%	1235.6	0.0%	37495.9	3.6%	1331.2	0.1%	1361.8	0.1%	84.2	0.1%
Industrial inorganic chemicals, plastic materials (281-2)	147339.0	7.7%	164574.7	6.7%	50085.6	4.8%	73361.2	5.4%	55682.9	4.5%	2623.7	4.1%
Industrial organic chemicals (286-7,289)	282418.0	14.7%	258070.9	10.3%	90538.1	8.6%	184888.2	13.7%	95226.8	7.6%	24129.8	38.1%
Petroleum refining and related industries (291,295,299)	380650.8	19.8%	159243.2	6.4%	122406.3	11.6%	190706.6	14.2%	109084.7	8.9%	5506.1	8.7%
Miscellaneous plastics (308)	2665.0	0.1%	1529.4	0.1%	59019.4	5.6%	2752.7	0.2%	7293.7	0.6%	303.2	0.5%
Stone, clay, glass, and concrete products (321-9)	249885.1	13.0%	254527.2	10.3%	23547.0	2.2%	362047.2	27.0%	237404.9	18.6%	6018.8	9.6%
Primary metal industries (331-5)	279044.6	14.5%	1035814.5	41.7%	59812.2	5.7%	103780.5	7.7%	188597.6	15.4%	3554.1	5.6%
Fabricated metal products (341,344)	105.6	0.0%	787.9	0.0%	28830.1	2.7%	1457.0	0.1%	3480.3	0.3%	14.4	0.0%
Electrical machinery, equipment, and supplies (371-3)	5177.6	0.3%	9627.9	0.4%	76024.5	7.2%	9444.8	0.7%	14103.7	1.1%	357.4	0.6%
Photographic equipment and supplies (386)	22781.5	1.2%	1022.4	0.0%	1590.0	0.2%	5341.6	0.4%	1870.5	0.2%	103.9	0.2%
Percent of industrial emissions accounted for	1852845.0	96.4%	2431087.9	97.9%	894353.1	85.2%	1282485.0	95.5%	1156894.7	93.5%	58617.9	92.8%

Source: National Emission Inventory of the EPA.

Note: for each pollutant, column (1) lists metric tons of emissions per year; column (2) reports the share of industrial sector emissions to manufacturing sector emissions.

Table C.3: Variable List

Variable	Definition	Source/Explaination
Facility Level		
Sales	Value of sales ($)	NETS
Employees	Number of employees	NETS
Export Dummy	Export indicator, = 1 if exports, = 0 otherwise	NETS
Distance	Distance of a facility to its nearest port (miles)	Calculated
SO_2	Sulfur Oxide (tons)	NEI
CO	Carbon Monoxide (tons)	NEI
VOCs	Volatile Organic Compounds (tons)	NEI
NO_x	Oxide of Nitrogen (tons)	NEI
NH_3	Ammonia (tons)	NEI
PM10-PRI	Primary particulate matter less than 10 microns (tons)	NEI
PM10-FIL	Filterable particulate matter less than 10 microns (tons)	NEI
PM25-PRI	Primary particulate matter less than 25 microns (tons)	NEI
PM25-FIL	Filterable particulate matter less than 25 microns (tons)	NEI
PM-Con	Condensible particulate matter (tons)	NEI
TSPs	Total Suspended Particulates, sum of the above PMs (tons)	Calculated
O_3	Ozone, sum of VOCs and NO_x (tons)	Calculated
NH_3 Intensity	NH_3 per value of sales	Calculated
SO_2 Intensity	SO_2 per value of sales	Calculated
CO Intensity	CO per value of sales	Calculated
O_3 Intensity	O_3 per value of sales	Calculated
TSPs Intensity	TSPs per value of sales	Calculated
County Level		
SO_2 NA	SO_2 Nonattainment, = 1 if nonattainment, = 0 otherwise	EPA
CO NA	CO Nonattainment, = 1 if nonattainment, = 0 otherwise	EPA
O_3 NA	O_3 Nonattainment, = 1 if nonattainment, = 0 otherwise	EPA
TSPs NA	TSPs Nonattainment, = 1 if nonattainment, = 0 otherwise	EPA
Any NA	Any Pollutant Nonattainment, = 1 if nonattainment for at least one pollutant, = 0 otherwise	Calculated
Industry Level at Four-Digit SIC		
CIF	Cost-Insurance-Freight value of U.S. imports	Schott (2010)
FOB	Free-on-Board value of U.S. imports	Schott (2010)
Freight Rate	(CIF - FOB)/FOB	Calculated

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