AN ABSTRACT OF THE DISSERTATION OF

Flavius Badau for the degree of Doctor of Philosophy in Applied Economics presented on December 12th, 2014.

Title: Climate Change and Trade in a Globalized World.

Abstract approved: ____

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Environmental sustainability and economic growth is at the forefront of international policy discussions. There is no question that climate change is happening, but also that countries all around the world aspire to continued economic growth. When it comes to climate change, scientists agree that increased carbon dioxide (CO_2) emissions in the atmosphere from human activity contribute to the current process of global climate change. Regarding economic growth, International Economics taught us that when countries engage in international trade, these countries benefit in terms of increased overall welfare, ceteris paribus. Finding additional avenues that would further stimulate growth in international trade, causing further increases in welfare, could be valuable. In this context, this dissertation examines the following research question: Could global standards of living continue to improve in the presence of global climate change and international trade resistance? This question will be addressed in this dissertation in two parts.

Addressing the first part of the research question in chapter two, this dissertation uniquely employs the theoretical and empirical tool known as the directional distance function to investigate the possibility of a global carbon dioxide (CO_2) market. The goal is to reduce or stabilize emissions without hindering global Real Gross Domestic Product (RGDP), and to achieve a uniform global price for CO_2, accomplishing environmental and economic global goals. First, this chapter looks at the Law of One Price for CO_2 and estimates shadow prices of CO_2 across countries. A joint production model with one desirable output and one undesirable output is presented. Drawing upon data from 141 countries spanning 18 years and exploiting the duality between the directional distance function and this production model, the parameters of a quadratic directional distance function are then estimated which yield country level shadow prices of CO_2. Results suggest an average country level price of $719.33 per metric ton of CO_2. Based on the relative shadow prices, a hypothetical CO_2 global market is simulated to investigate whether reduced emissions are possible without hindering RGDP. Simulation results suggest that it is possible for global emissions to stabilize while global RGDP increases, achieving environmental and economic global goals.

The second part of the research question is investigated in chapter three by uniquely employing Data Envelopment Analysis (DEA) techniques to estimate Johansen's Capacity Utilization notion with the goal of examining resistance to trade across trading partners. A trade resistance model is presented, where trade barriers are (undesirable) inputs used in the production of the (undesirable) output, trade resistance. Drawing upon United States manufacturing industries trade data, the impact that each trade barrier has on trade resistance is assessed. Results suggest that U.S. port logistics are the most limiting trade barrier, followed by the distance between trade partners, the U.S. imposed tariffs, and the trading partner's imposed tariffs.

Climate Change and Trade in a Globalized World

by

Flavius Badau

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of

the requirements for the

degree of

Doctor of Philosophy

Presented December 12th, 2014

Commencement June 2015

Doctor of Philosophy dissertation of Flavius Badau presented on December 12th, 2014.

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Flavius Badau, Author

ACKNOWLEDGEMENTS

I would like to express my sincere appreciation to my co-advisers Dr. Rolf Färe and Dr. Munisamy Gopinath for their continued assistance and support throughout my doctoral studies. I would like to thank my committee members, Dr. Steven Buccola, Dr. Susan Capalbo, and Dr. Adam Branscum for being part of my dissertation committee. I would like to thank Dr. Buccola and Dr. Capalbo for their helpful comments and suggestions on my research. I would also like to thank Dr. William Weber for his help with the data analysis in Chapter two. Thank you to the Applied Economics faculty, staff, and students. Thank you to my family and friends for their continued support and understanding during my demanding doctoral studies.

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CHAPTER 1

1. Introduction and Overview

Environmental sustainability and economic growth are at the forefront of international policy discussions. There is no question that climate change is happening, but also that countries all around the world aspire to continued economic growth. In terms of climate change, scientists agree that increased carbon dioxide (CO_2) emissions in the atmosphere from human activity contribute to the current process of global warming through an amplification of the greenhouse effect. The concern is that if human activity continues as is, global warming could potentially have adverse impacts on the world. For example, melting glacial ice all over the world would cause sea level rises, potentially displacing populations along coastal areas, but would also cause changes in agricultural patterns due to climate shifts, possibly distressing global agricultural markets, which could in turn affect jobs and incomes. Concerning economic growth, International Economics teaches that when countries engage in international trade, these countries benefit in terms of increased overall welfare, ceteris paribus. Although nations are increasingly dependent on each other for goods and services and some countries have drawn up trade agreements meant to be mutually beneficial, trade impediments still exist between them, making trade still relatively restrictive. Finding additional avenues that would further stimulate growth in international trade, causing further increases in welfare, could be valuable.

In this context, this dissertation examines the following research question: Could global standards of living continue to improve in the presence of global climate change and international trade resistance? This question will be addressed in this dissertation in two parts. The first part, presented in chapter two, will examine if global CO_2 emission could stabilize without restricting global incomes. The second part, presented in chapter three, will examine the factors contributing to international trade resistance. A desired end result of this work is to provide a benchmark, or a guide, from which international talks can begin or advance towards an agreement on how to mitigate the effects of global climate change without adverse effects on global standards of living, and how to reduce international trade resistance further.

Using established, theoretically grounded, and empirically tested tools this dissertation contributes three-fold to the Economics literature. Addressing the first part of the research question, this dissertation uniquely employs the theoretical and empirical tool known as the directional distance function to investigate the possibility of a global CO_2 market based on the relative differences in country level prices of CO_2. The objective is to reduce or stabilize global CO_2 emissions without hindering global Real Gross Domestic Product (RGDP) and to achieve a uniform price for carbon dioxide. A polluting production process is modeled using the directional distance function, which then allows computation of shadow prices for CO_2 at the country level, something performed for the first time at this scale and using these methods.

The main contribution stemming from the approach used in chapter two is that it allows for a model of optimal reallocation of pollution across markets, permitting the simulation of a CO_2 global market. The goal of the simulation is to examine how CO_2 emissions are optimally reallocated across countries based on their respective shadow prices, and what happens to shadow prices and RGDP once optimal reallocations are complete. From a policy perspective, the goal of chapter two is to provide policy makers with a guide on how global environmental and economic efficiency, i.e. equilibrium in the global CO_2 market without restricting global incomes, could be attained.

Addressing the second part of the research question, this dissertation contributes further to the Economics literature by using techniques from the Operational Research area to examine resistance to trade across trading partners. The main contribution here is that these techniques allow for Johansen's Capacity Utilization to be applied to international trade, with estimations yielding a ranking of trade barriers based on their impact on trade resistance. Knowing the ranking of trade resistance factors could help steer trade policy in the direction that could potentially stimulate trade the most, resulting in further increases in overall welfare.

One assumption being made in this dissertation is that countries around the world all have the common goal of increasing standards of living in the presence of global climate change and international trade resistance. It could be possible that certain countries around the world might have different objectives when it comes to addressing global climate change and trade resistance. The research in this dissertation also does not prescribe policy or address distributional issues, it only provides information, a benchmark, or guideline to policy makers, so that there is a basis for discussion in the policy setting environment related to the global issues investigated in this dissertation. After all, scientific research is only one of the components in the policy making process. Setting policy is a normative process and many more factors go into it beyond the research performed in the bench and social sciences.

This dissertation is organized as follows. Chapter two investigates the first part of the research question: Is global environmental stability possible without hindering global standards of living? The second part of the research question is addressed in chapter three: Is there potential for international trade to continue expanding, contributing further to increases in the standards of living? Chapter four summarizes the main findings of this dissertation, and then concludes.

Chapter 2

2. Towards a global carbon dioxide market: shadow pricing carbon dioxide across countries

2.1 Introduction

Pollution is a byproduct of many economic activities, i.e. production processes, transportation, and if not discarded and managed properly, reduced or eliminated, it could come into contact directly or indirectly with people and cause adverse health effects. As a nation grows economically, it is assumed that it passes a certain threshold beyond which citizens' preferences change towards assigning greater values to a cleaner natural environment and longer healthier lives for current and future generations. For example, countries reach a particular level of income per capita where certain human needs like food, water, shelter, sanitation are not the main concern and focus, but issues like a clean environment are. Of course, even wealthy nations still experience hunger, homelessness, and disease outbreaks, no matter the income per capita level. As a consequence, policy makers seek to mitigate the effects of pollution by discussing legislation that could help in this aspect but at the same time not be detrimental to future incomes. One such possible policy action is to implement pollution quotas and have a market for emissions trading. An industry can have an emissions cap but individual firms in that industry could then trade emission permits between themselves, i.e. less polluting firms could trade emissions permits with more polluting firms. The same scenario could be applied at a global scale.

For trading to take place at any level, a market place needs to exist for pollutants. In order for the market to exist, prices of the pollutant(s) need to be known, but such prices do not exist. That is where this paper comes in. Using established, theoretically grounded, and empirically tested tools this study investigates if the Law of One Price holds for carbon dioxide (CO_2) across countries, and if it does not, how could prices possibly equalize, achieving global environmental and economic goals. Employing the theoretical and empirical tool known as the directional distance function shadow prices for CO_2 at the country level are estimated. Further, the main contribution in this research is that the methods used will then allow for a model of optimal reallocation of pollution across countries, permitting for the investigation of a hypothetical global CO_2 market, where the goal is to achieve a global, uniform price for CO_2 with reduced or stable emissions and without limiting global incomes.

But why shadow price CO_2 and how could this help mitigate the effects of global climate change? Given the threat of global climate change, policy makers and economists are looking for an environmental and economic solution to this problem. A possible solution is to implement a global CO_2 market where countries could trade emission permits based on their respective shadow prices for CO_2. The goal is to achieve equilibrium in this market so that global CO_2 emission levels become stable at sustainable levels. As a result, there will be no further arbitrage opportunities in emissions trading which will then help countries to consider investing in, improving, or adopting additional abatement technologies in order to continue or move beyond current standards of living.

Therefore, the objective and main contribution in this study is to investigate the possibility of a global CO_2 market based on relative differences in country level prices of CO_2, where the goal is to reduce global emissions without hindering global Real Gross Domestic Product (RGDP). A joint production model with one desirable output (RGDP) and one undesirable output (CO_2) is presented. Then it is shown how the directional distance function represents the polluting production process presented, accommodating the global goal of reduced CO_2 emissions while increasing RGDP. Drawing upon data from 141 countries spanning 18 years and exploiting the duality between the directional distance function and the joint production model, the parameters of a quadratic directional distance function are then estimated which yield country level shadow prices of CO_2. Results suggest an average country level price of $719.33 per metric ton of CO_2, defined as the value of RGDP needed to be forgone in order to reduce CO_2 by one metric ton. Based on the relative shadow prices, a hypothetical CO_2 global market is then simulated. The goal of the simulation is to examine how CO_2 emissions are optimally reallocated across countries based on their respective shadow prices, and what happens to shadow prices and RGDP once optimal reallocations are complete. Simulation results suggest that it is possible for global emissions to decrease, global RGDP to increase, while shadow prices equalize.

Why choose the directional distance function approach? When production of a certain output is simultaneously associated with the production of a certain pollutant, here CO_2, the directional distance function models this process well by permitting increases in the good output while simultaneously allowing for reductions in the bad output, i.e. pollutant. In essence, the directional distance function will project towards the technical and environmental efficiency frontier in a multi-output production model with simultaneous production of a good and bad output. In contrast, Shephard's output distance function allows for only proportional increases in both outputs, hence the choice of the directional distance function as the theoretical and empirical tool for this study.

(Directional) Distance functions have been used to create indexes of efficiency and productivity especially when technology is characterized by multiple outputs, and to model technologies when prices of inputs or outputs are not observable. Single output technologies could be modeled using production functions given input quantities, while multi-output technologies could be modeled using cost functions given input prices and output quantities, but when prices are not available, distance functions could be used (Weber and Xia 2011). Similarly, in this study, prices of CO_2 are not observable. Further, (Directional) Distance functions also allow for computation of shadow prices, elasticity of substitution, technical change, and optimal reallocation models, outcomes desired in this study. The directional distance function has its roots in the shortage function that was first introduced by Luenberger (1992), and it has been extended to production theory by Chambers et al. (1996). Under certain conditions, Chambers et al. (1996) have shown that Shephard's input and output distance functions are just variants of directional distance functions.

Similar approaches have been used in previous studies of shadow pricing pollutants like SO_2 (Coggins and Swinton 1996; Swinton 1998) employing Shephard's output distance function (Shephard 1970). Lee and Zhang (2012) shadow priced CO_2 for a sample of Chinese manufacturing industries employing Shephard's input distance function, and found shadow prices ranging from $0/ton to $18.82/ton. Qi et al. (2004) investigated shadow prices across 44 countries during the 1980-2000 period using the distance function approach and found an average price of $308.5/ton. Salnykov and Zelenyuk (2005) looked at 96 countries for 1995 and found shadow prices for CO_2 ranging from $133.85/ton to $478.4/ton. In a working paper, Dang and Mourougane (2014) employ the output distance function for 19 OECD countries during the period 1990-2008 to obtain shadow prices for CO_2 that range from a low of $240/ton to a high of $786/ton.

In this paper, the approach will be similar to Färe et al. (2005) where directional distance functions have been used to obtain shadow prices of SO_2 for a sample of U.S. utility companies. More recently, directional distance functions have been used in Weber and Xia (2011) and Summary and Weber (2012) where a stochastic directional distance function has been estimated for thirty universities that participated in nanobiotechnology research and a stochastic directional distance function has been estimated for academic departments at Southeast Missouri University to analyze grade distribution and grade inflation, respectively. In Wang et al. (2011) marginal abatement costs of CO_2 for Chinese provinces were obtained employing non-parametric techniques which yielded a CO_2 price of 475.3yuan/ton. Marklund and Samakovlis (2007) looked at 15 European Union members for the period 1990-2000 using the directional distance function approach and found an average price of about €670/ton. In Wei et al. (2013), Chinese thermal enterprises' shadow prices for CO_2 were estimated using the directional distance function approach employing deterministic and stochastic methods for the year 2004. Estimated prices ranged from a low of \$0.04/ton to a high of \$496/ton. Based on the past and current studies presented here, shadow prices at the country level seem to be on the average higher relative to firm or industry level prices.

Estimates of shadow prices for CO_2 vary greatly across studies. Reasons include the methods used, i.e. output (input) distance functions vs. directional distance functions, stochastic vs. deterministic approach, the scope of the studies, i.e. firm vs. industry vs. country level analysis, what the policy goals are, i.e. simultaneous increase in emissions and the good output vs. simultaneous decrease in emissions and increase in the good output, and what theoretical and empirical tools are used that accommodate policy makers' goals.

One assumption being made in this study is that countries around the world all have the common goal of reducing CO_2 emissions and increasing RGDP, and that countries do not all operate on the efficiency frontier. This study does not prescribe policy, it provides information, a benchmark, or guideline to policy makers, so that there is a basis for discussion in the policy setting environment related to the global issues presented here.

This paper is organized as follows. In Section two, the theoretical model for a polluting industry is presented along with how the directional distance function accommodates such an industry.

This section continues by showing how shadow prices of the pollutant will be obtained through the use of the directional distance function. Section two concludes by presenting the functional form chosen for the directional output distance function used in this study. Section three discusses the estimation procedure employed in this paper, while section four discusses the data. The estimation results are presented in section five which include directional distance function parameter estimates, technical inefficiencies estimates, technical change estimates, and shadow prices for CO_2. Section six presents a simulated carbon dioxide quota global market based on the shadow price information from section five. Section seven summarizes and concludes.

2.2 Theoretical Framework

2.2.1 The Output Set

The study begins by presenting the theoretical framework that is used to model a certain country's polluting production process. It will be assumed that for every country, there is a single aggregate good output (*y*), and a single aggregate bad output (*b*), where (*b*) is a by-product of the production process of (*y*). Representing the polluting technology is a standard output set P(*x*), where the good output (*y*) and the bad, polluting output (*b*) are produced jointly from the input vector (**x**):

$$P(x) = \{(y,b) : x\, can\ produce\, (y,b)\} \tag{2.1}$$

Following Färe et al. (2005), certain assumptions and properties about the output set P(*x*) as well as the good output (*y*) and the bad output (*b*) are presented, assumptions that are relevant for a polluting technology scenario. Firstly, the output set P(*x*) is assumed to be a compact set, implying it is a closed and bounded set, an assumption that any traditional output set possesses.

In intuitive, economic terms, compactness of a set implies scarcity-there is a finite amount of inputs that can produce a finite amount of outputs (Färe and Primont 1995).

A standard assumption being made is that inputs are strongly disposable, signifying that inputs will not congest outputs (increasing inputs will not decrease production, or that expanding inputs will not decrease productivity, or increasing inputs does not contract the output set).

$$if\ x' \geq x\ then\ P(x') \supseteq P(x) \tag{2.2}$$

The following assumption is the first departure from a traditional output set, assumption that is illustrative of a polluting production process. Assume that good and bad outputs are null-joint (Shephard and Färe 1974), meaning that one output cannot occur without the other, i.e. production of the good output comes with the simultaneous production of the bad output, the latter being a byproduct of the production process of the first. If a certain country produced good (*y*), then it must have also produced pollution (*b*). Mathematically,

$$if\ (y,b) \in P(x)\ and\ b = 0\ then\ y = 0 \tag{2.3}$$

Assuming the goal of any society and therefore policy makers is to reduce pollution as much as possible, we impose the condition that the good output (*y)* and the bad output (*b*) are together weakly disposable (proportional reductions in both are feasible), i.e. if it is mandated by law that the bad output is to be reduced by a certain amount, then the production of the good output must be reduced also, and both reduction are possible, meaning production can always be reduced. Intuitively, this condition says that reductions in pollution are costly, either by having to reduce production of the good output that will automatically reduce pollution, by diverting inputs towards cleanup of the bad output, inputs that would have gone towards the good output production otherwise, or by having to pay certain pollution fees. Mathematically, weak disposability of the good output (y) and the bad output (b) is:

$$if\ (y,b) \in P(x)\ and\ 0 \le \theta \le 1\ then(\theta y, \theta b) \in P(x) \tag{2.4}$$

A standard assumption that good outputs (y) are strongly disposable is maintained also, implying that good outputs can always be tossed out without any cost (an output vector with less of the good output but the same level of the bad output is feasible-it is part of the output set):

$$if\ (y,b) \in P(x)\ and\ (y',b) \le (y,b)\ then(y',b) \in P(x) \tag{2.5}$$

The disposability assumptions imply that there are no holes (or gaps, or jumps) in the output set ensuring that the output set can be fully characterized by the directional output distance function (presented in the next section). The strong disposability of the inputs (x) and the good outputs (y), can also be interpreted as ensuring that marginal products are positive (i.e. $dy/dx>0$) and that the marginal rate of technical substitution and marginal rate of product transformation are negative, i.e. $dx_i/dx_j<0$ and $dy_i/dy_j<0$ (FØrsund 2008). These are standard conditions in the neoclassical framework of production theory.

Figure 2.1, shows an output set that satisfies the assumptions outlined above. The output set P(x) outlined by 0AC0 characterizes the polluting technology presented in this study where null-jointness and weak disposability of both good and bad outputs are imposed. The output set outlined by 0DAC0 represents a traditional output set where strong disposability of both the good and bad output is imposed, while null-jointness is not-production of the good output (y) can occur without any bad output (b), as illustrated by the line segment OD in Figure 2.1.

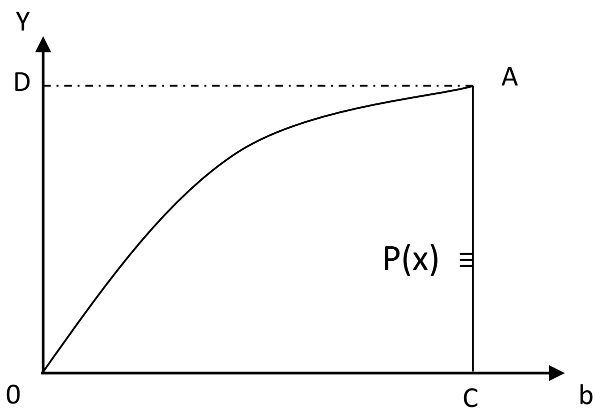

Fig. 2.1 Output set of a polluting technology

2.2.2 The Directional Output Distance Function

To be able to engage in an empirical exercise, the polluting technology presented above needs to be represented by a function. Following Färe et al. (2005), this function will be the directional output distance function, which accommodates this polluting technology and the goal of simultaneously reducing the bad output while increasing the good output. The directional output distance function is defined as follows:

$$\vec{D}_o(x, y, b; g_y, -g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{2.6}$$

where $g=(g_y,-g_b)$ is a directional vector . The directional vector is usually chosen by the researcher, given the nature of the research question. This directional distance function seeks to simultaneously increase the production of the good output (in the g_y direction) while at the same time it seeks the maximum reduction in the bad output (in the - g_b direction), by moving production to the technical and environmental efficiency frontier (in Figure 2.1 the outer boundary of the output set spanned by OAC), given the directional vector (g_y, -g_b). For a country to be on the technical and environmental efficiency frontier, the value of the directional distance function has to be zero. Values divergent from zero will be indicative of the country not operating at the efficiency frontier.

Figure 2.2 illustrates the directional output distance function given our output set P(*x*). For a given point (y_1, b_1) and directional vector represented by OA, the directional distance function will seek expansion to the boundary of P(*x*)-at point C- in the direction OA. The resulting value of the directional output distance function will be OB/OA (or the value of inefficiency).

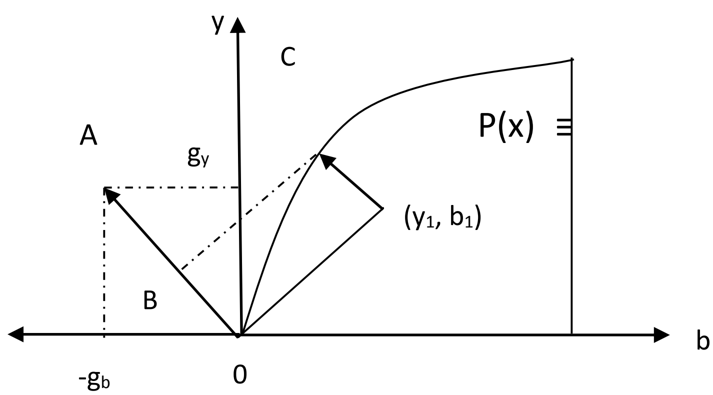

Fig. 2.2 Directional Output Distance Function

Given the output set P(*x*) and its properties outline in the previous section, the directional distance function displays certain properties which are outlined in Appendix A. The one property of this function that is worth mentioning in the body of this paper is the translation property, which is a property analogous to the homogeneity property of Shephard's output distance function:

$$\vec{D}_o(x, y+\Omega g_y, b-\Omega g_b; g_y, -g_b) = \vec{D}_o(x, y, b; g_y, -g_b) - \Omega, \Omega \in \Re \qquad (2.7)$$

If the good output is expanded by Ωg_y and the bad output is contracted by Ωg_b then efficiency will improve by Ω, or the value of the directional distance function will be reduced by Ω. As the value of the directional distance function gets smaller, efficiency increases, and when the value equals zero, then maximum efficiency is achieved, given current inputs and technology. The translation property will be important when it comes to choosing functional forms for the directional output distance function.

2.2.3 Shadow Pricing of the Bad Output

Seeing how the directional output distance function completely characterizes technology (see Appendix A), we can recover the shadow price of CO_2 from the revenue maximization problem as portrayed in Färe et al. (2005). The revenue function can be specified as follows:

$$R(x, p, s) = \max_{y,b} \left\{ py - sb : \vec{D}_o(x, y, b; g_y, -g_b) \geq 0 \right\} \tag{2.8}$$

where s is the price of the bad output, and p is the price of the good output.

The Lagrangian multiplier for this problem has been shown to be $\lambda = pg_y - sg_b$ by Chambers et al. (1998). Therefore the Lagrangian for this problem becomes:

$$L = py - sb + \left[(pg_y - sg_b)\vec{D}_o(x, y, b; g_y, g_b) \right] \tag{2.9}$$

First order conditions (FOC) yield:

$$\frac{dL}{dy} = p + (pg_y - sg_b)\frac{d\vec{D}_0(x, y, b; g_y, -g_b)}{dy} \overset{set}{=} 0 \tag{2.10}$$

$$\frac{dL}{db} = -s + (pg_y - sg_b)\frac{d\vec{D}_0(x, y, b; g_y, -g_b)}{db} \overset{set}{=} 0 \tag{2.11}$$

$$\frac{dL}{d\lambda} = \vec{D}_0(x, y, b; g_y, -g_b) \overset{set}{=} 0 \tag{2.12}$$

Conditions (2.10), (2.11), (2.12) will give us the optimal good output y^* and optimal bad output b^* allocations, where technical and environmental efficiency are achieved (given by equation (2.12)-recall that efficiency is reached when the value of the directional distance function is zero). Taking the ratio of (2.10) and (2.11) gives us:

$$-\frac{p}{s} = \frac{d\,\vec{D}_0(\mathrm{x, y, b; g_y, \text{-}g_b})/d\mathrm{y}}{d\,\vec{D}_0(\mathrm{x, y, b; g_y, \text{-}g_b})/d\mathrm{b}} \tag{2.13}$$

Equation (2.13) gives the tangency point between the isorevenue line and the output set P(x), represented by the directional output distance function, at optimal points y^* and b^* (Figure 2.3 presents an illustration). It follows that the shadow price (s) of the pollutant can be recovered by solving equation (13) for s as follows:

$$s = -p\,\frac{d\,\vec{D}_0(\mathrm{x, y, b; g_y, \text{-}g_b})/d\mathrm{b}}{d\,\vec{D}_0(\mathrm{x, y, b; g_y, \text{-}g_b})/d\mathrm{y}} \tag{2.14}$$

Equation (2.14) says that as long as the researcher knows the price (p) of the good output (y) and is employing a differentiable directional distance function in the analysis, the shadow price (s) of the pollutant (b) can be obtained using the above method.

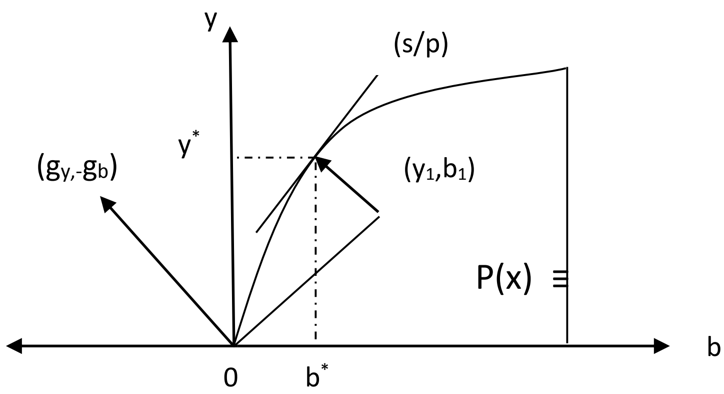

Fig. 2.3 Revenue Maximization Illustration

2.3 Empirical Specification of the Directional Output Distance Function

In the previous sections, the theoretical model of a polluting technology, the directional output distance function and the derivation of shadow prices using the directional output distance function have been presented. In what follows, a functional form for the directional output distance function needs to be chosen in order to engage in an empirical exercise. In doing so, the researcher needs a functional form that will retain the translation property of the directional distance function and that is also differentiable to be able to derive shadow prices of CO_2.

To begin, functional forms for directional distance functions have been restricted to those functions that are linear in parameters and they are referred to as the class of transformed quadratic functions (Färe et al. 2010).   Färe and Lundberg (2005) solved for functions that satisfies the directional distance function's translation property and that are simultaneously linear in parameters and have found as one of the two solutions the quadratic function. The quadratic function has been suggested as a functional form that can accommodate the translation property earlier by Chambers (1998).

Let the directional vector **g** equal g= (1,-1). Then, the directional distance function will give the maximum simultaneous expansion and contraction in the good and bad outputs, respectively, given the inputs. Other directional vectors could be chosen by the researcher such as g=(1,0), which gives the maximum feasible expansion in the good output while holding the bad output constant, or, g=(0,-1), which gives the maximum feasible contraction in the bad output, holding the good output fixed. Given the directional vector g= (1,-1), the two outputs (*y*, *b*), and the inputs (**x**) labor and capital (l, k), the quadratic function for the directional output distance function for a certain country and a particular point in time is:

$$\vec{D}_0(x,y,b;1,-1) = \alpha_0 + \sum_{n=1}^{2}\alpha_n x_n + \beta_1 y + \gamma_1 b + \frac{1}{2}\sum_{n=1}^{2}\sum_{n'=1}^{2}\alpha_{nn'}x_n x_{n'} + \\ + \frac{1}{2}\beta_2 y^2 + \frac{1}{2}\gamma_2 b^2 + \sum_{n=1}^{2}v_n x_n y + \sum_{n=1}^{2}\delta_n x_n b + \mu y b \tag{2.15}$$

For the translation property to hold, the following restrictions need to be imposed on the quadratic function presented above:

1. $\beta_1 - \gamma_1 = -1$

2. $\beta_2 = \gamma_2 = \mu$

3. $\delta_n = v_n, n = 1,2$

In addition symmetry is also imposed and implied by the above formulation of the directional output distance function:

$$\alpha_{nn'} = \alpha_{n'n}, n, n' = 1,2$$

Given the quadratic function for the directional output distance function above, the shadow price of CO_2 (s) can then be recovered using equations (2.14) and (2.15) as:

$$s = -p\,\frac{\gamma_1 + \gamma_2 \mathrm{b} + \delta_1 \mathrm{L} + \delta_2 \mathrm{k} + \mu \mathrm{y}}{\beta_1 + \beta_2 \mathrm{y} + \mathrm{v}_1 \mathrm{L} + \mathrm{v}_2 \mathrm{k} + \mu \mathrm{b}} \qquad (2.16)$$

2.4 Estimation Method

Estimation of equation (2.15) will take place via stochastic frontier methods. Usually the methods follow Kumbhakar and Lovell (2000), and Green (2008). The basic specification for a fixed effects stochastic frontier model is:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it} \qquad (2.17)$$

where

$$\varepsilon_{it} = v_{it} - u_{it}$$

y_{it} is output of country i at time t,

x_{it} represents input of country i at time t,

α_i represents country specific fixed effects,

v_{it} represents an error term capturing stochastic elements specific to each country and time period, and

$$\mathrm{v}_{\mathrm{it}} \sim \mathrm{N}(0, \sigma_{\mathrm{v}}^2)$$

u_{it} captures each country's departure from the stochastic frontier $y_{it} = \alpha_i + \beta x_{it} + \upsilon_{it}$ and therefore representing inefficiency , with

$$u_{it} = |U_{it}| and U_{it} \sim N(0, \sigma_u^2)$$

In the formulation above $\alpha_i + v_{it} - u_{it}$ captures both country specific heterogeneity and inefficiency.

In order to recover estimated technical inefficiencies the approach of Atkinson et al. (2003a) will be followed. Inefficiency will be modeled in a second stage regression as,

$$u_{it} = \kappa_{1i} C_i + \kappa_{2i} C_i * T + \kappa_{3i} C_i * T^2 \tag{2.18}$$

where C is a dummy variable for each country, and T is a time trend. The first term's coefficient in equation (2.18) captures time invariant, country specific differences in the technology, while the coefficients of the second and third terms capture time variant, country specific differences in the technology. More details on recovering the technical inefficiencies will be given once the first stage regression equation will be presented.

The stochastic frontier specification of the directional distance function will be:

$$o = \vec{D}_o(x, y, b; 1, -1) + \varepsilon \tag{2.19}$$

where

$\varepsilon = (v - u)$ and v, u are as described previously,

and $\vec{D}_o(x, y, b; 1, -1)$ represents equation (2.15).

To estimate equation (2.19), recall the directional output distance function's translation property:

$$\vec{D}_o(x, y+\Omega g_y, b-\Omega g_b; g_y, -g_b) = \vec{D}_o(x, y, b; g_y, -g_b) - \Omega, \Omega \in \Re$$

Given the chosen directional vector g = (1,-1):

$$\vec{D}_o(x, y+\Omega, b-\Omega; 1, -1) + \Omega = \vec{D}_o(x, y, b; 1, -1) \tag{2.20}$$

Substituting (2.20) into equation (2.19), (2.19) becomes:

$$-\Omega = \vec{D}_o(x, y+\Omega, b-\Omega; 1, -1) + \varepsilon \tag{2.21}$$

Given (2.15), (2.21) becomes:

$$\begin{aligned} -\Omega &= \alpha_0 + \alpha_1 L + \alpha_2 K + \beta_1(y+\Omega) + \gamma_1(b-\Omega) + \frac{1}{2}\alpha_{11}L^2 + \\ &+ \frac{1}{2}\alpha_{22}K^2 + \frac{1}{2}\alpha_{12}LK + \frac{1}{2}\alpha_{21}LK + \frac{1}{2}\beta_2(y+\Omega)^2 + \frac{1}{2}\gamma_2(b-\Omega)^2 + \\ &+ v_1 L(y+\Omega) + v_2 K(y+\Omega) + \delta_1 L(b-\Omega) + \delta_2 K(b-\Omega) + \mu(y+\Omega)(b-\Omega) + \varepsilon \end{aligned} \tag{2.22}$$

Therefore, the directional output distance function's translation property allows estimation of equation (2.22) by choosing a Ω that will give variation on the left hand side of equation (2.22).

Following Färe et al. (2005), *b* is chosen for Ω. Substituting for Ω in equation (2.22), the main first stage regression equation becomes

$$\begin{aligned} -b_{it} &= c_i C_i + \alpha_1 L_{it} + \alpha_2 K_{it} + \beta_1 \tilde{y}_{it} + \frac{1}{2}\alpha_{11}L_{it}^2 + \frac{1}{2}\alpha_{22}K_{it}^2 + \alpha_{12}L_{it}K_{it} + \\ &+ \frac{1}{2}\beta_2 \tilde{y}_{it}^2 + v_1 L_{it}\tilde{y}_{it} + v_2 K_{it}\tilde{y}_{it} + t_t T_t + \varepsilon_{it} \end{aligned} \tag{2.23}$$

where $\tilde{y}_{it} = y_{it} + b_{it}$; i=1,..,141; t=1,...,18, and $\varepsilon_{it} = v_{it} - u_{it}$

This specification controls for country and time effects through the dummy variables C(ountry) and T(ime).

Technical Inefficiency will be recovered as follows. First step is to recover the predicted residuals of equation (2.23), $\hat{\varepsilon}_{it}$, and then use them as the dependent variable in equation (2.18). Once (2.18) is estimated, fitted values, $\tilde{\varepsilon}_{it}$, are obtained for the dependent variable. Recall, $\varepsilon_{it} = v_{it} - u_{it}$, therefore identifying the minimum $\tilde{\varepsilon}_{it}$ identifies the most technically efficient country (u_{it} is the smallest). Technical inefficiencies, TI, for every country will then be calculated as $TI = (\tilde{\varepsilon}_{it} - \min \tilde{\varepsilon})$.

2.5 Data

For this study, data on the good output (*y*), inputs (**x**) and bad output (*b*) are needed for each country. For the good output (*y*), each country's Real Gross Domestic Product (RGDP) will be used. For the inputs (**x**), total capital stock (K) and total labor force (L) will be used. For the bad output (*b*), CO_2 emissions levels will be used for each country that is part of this study. There are 141 countries included in this study covering the period from 1992 through 2009, with a mix of low income, middle income, and high income countries. As of July 2013, according to the World Bank, a country is classified as low income if it has an income per capita of $1,035 or less, middle income if income per capita is between $1,036 and $12,615, and high income if above $12,616.

Data on carbon dioxide was obtained from the World Bank. The World Bank gathered the data from the Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory in Tennessee, United States. According to the World Bank, the data reflects estimates of carbon dioxide from the burning of fossil fuels and cement production, which includes emissions produced during consumption of solid, liquid, and gas fuels and gas flaring. According to the Carbon Dioxide Information Analysis Center, it is difficult to trace emissions back to the source. Hence, it is possible for some countries to exhibit higher than expected CO_2 levels, i.e. flights originating in a different country have to fuel and refuel, and the emissions of CO_2 created are recorded in the native country, and not in the country where the flight originated. According to the Carbon Dioxide Information Analysis Center, this could influence especially small, island states, where foreign military bases exist and where tourism from other countries is prevalent. A possible consequence of this accounting process is that some portion of the shadow price estimates for certain countries might be due to this.

Although shadow prices might be in part influenced by the accounting process described above, I do not feel that it would create great distortions in shadow prices across most countries because for instance, emissions from international transportation are but a small, negligible percentage of total emissions. For example, according to the United States Environmental Protection Agency, during 2012, U.S. CO_2 emissions stemming from transportation, which includes cars, trucks, ships, trains and planes, accounted for 28% of total U.S. CO_2 emissions. Further, according to the United States Bureau of Transportation Statistics, about 10% of total departure flights in the U.S. in 2012 were international departures.

Data on RGDP, capital and labor was obtained from the Penn World Table, Version 8.0. RGDP is measured in millions of 2005 USD, as well as capital, and labor is measured as millions of persons employed. For the purposes of this study, a brief description of capital is given here. For more detailed information on the capital variable, the Penn World Table, Version 8.0 literature should be consulted. The capital variable was calculated using the perpetual inventory method (PIM). Six asset categories were considered in the construction of capital: structures, transport equipment, computers, communication equipment, software, and other machinery and assets. It is assumed that the geometric depreciation rates are constant over countries and time. Overall, data quality is a function of the accuracy of the national income and product accounts across countries and of the methods used to collect, report, and compile the data.

Table 2.1 presents descriptive statistics of the data for the entire time span of the study, while table two presents descriptive statistics by time periods. It can be seen from table one that all variables display great variation and from table 2.2 that all variables exhibit growth over time as expected. Over the time span of this study, world population did increase, pollution is higher, world income has increased, and capital is higher.

Following Summary and Weber (2012), all outputs and inputs were normalized by their respected pooled averages, and Tables one, two and three reflect this. As a result of this normalization, the average country uses one unit of labor and one unit of capital to produce one unit of RGDP and one unit of carbon dioxide. An additional consequence of this normalization is that all the variables are now free of the units of measurement seeing how interaction terms need to be created in the quadratic function specification of the directional distance function.

Table 2.1 Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
CO_2 (b)	2538	154273.40	625820.20	14.67	7687114.00
Labor (l)	2538	17.16	70.46	0.03	777.38
RGDP (y)	2538	322773.30	1139303.00	157.30	13100000.00
Capital (k)	2538	1004075.00	3590308.00	204.23	40300000.00

Table 2.2 Descriptive Statistics over Time

1992-1997	N	Mean	Std. Dev.	Min	Max
CO_2 (b)	846	136499.50	531491.00	14.67	5501365.00
Labor (l)	846	15.64	65.14	0.03	693.85
Capital (k)	846	790365.40	2801947.00	204.23	29900000.00
RGDP (y)	846	256298.30	884729.40	157.30	9783200.00
1998-2003	N	Mean	Std. Dev.	Min	Max
CO_2 (b)	846	147253.30	580443.20	73.34	5713450.00
Labor (l)	846	17.05	70.21	0.04	740.86
Capital (k)	846	981898.90	3446797.00	648.92	35700000.00
RGDP (y)	846	314856.00	1102018.00	174.20	11800000.00
2004-2009	N	Mean	Std. Dev.	Min	Max
CO_2 (b)	846	179067.30	745319.70	102.68	7687114.00
Labor (l)	846	18.80	75.69	0.04	777.38
Capital (k)	846	1239960.00	4343754.00	736.58	40300000.00
RGDP (y)	846	397165.50	1374732.00	210.37	13100000.00

2.6 Estimation Results

One common production possibilities frontier is estimated for the entire data set. Therefore, one production unit (observation) is equivalent to one country for one year. Table 2.3 presents the parameter estimates of the directional distance function based on equation (2.23). There are six specifications presented in this table. The first three and the sixth one present estimates based on the ordinary least squares (OLS) estimation, while the fourth and fifth specifications present estimates based on the instrumental variables (IV) estimator. The reason for IV estimations stems from Weber and Xia (2011) and Summary and Weber (2012) where directional distance functions were estimated using generalized method of moments (GMM) to allow for the possibility of endogenous outputs and inputs. Although I do not suspect endogeneity in this paper, the IV estimations are undertaken as additional checks. I believe that the country and time fixed effects will capture any additional unobservable effects that could possibly affect coefficient estimates.

Specification OLS3 and OLS2 include country and time effects and country effects only, respectively. To notice in Table 2.3 is that the coefficient estimates do not vary statistically from one OLS specification to the next. Specifications four and five present estimates based on the IV estimator. Labor, capital and RGDP are instrumented by the labor, capital and RGDP variables interacted with a time trend. Relative to the OLS specifications, the magnitude of some coefficient estimates change. Employing the IV coefficient estimates into the calculations of shadow prices changes the actual levels of shadow prices, increases them, but the relative differences between shadow prices across countries stay the same, which is what this study is after. For the reasons outlined in the beginning paragraph of this section and since the relative differences in shadow prices across countries matter, specification OLS3 will be chosen as the preferred specification, and all subsequent estimations and calculations will be based on this specification unless specified otherwise. Directional distance function coefficient estimates are presented in Table 2.3.

Before proceeding with calculations based on these parameter estimates it is worthy to note that the directional distance function's monotonicity properties, i.e. $\frac{d\vec{D}_o}{dy} \leq 0, \frac{d\vec{D}_o}{db} \geq 0$, have been satisfied by all the observations in the data set. Also, a test of the null-jointness property was undertaken by calculating the value of the directional distance function when the bad output is set to zero, i.e. $\vec{D}_o(x, y, 0; 1, -1)$. If $\vec{D}_o(x, y, 0; 1, -1) < 0$, then this will signify a violation of the null-jointness property. Recall, $\vec{D}_o(x, y, 0; 1, -1) \geq 0$ if and only if $(y, b) \in P(x)$. It was found that 74% of the data satisfies the null-jointness property.

Table 2.3 Directional Distance Function Parameter Estimates

Parameter	Variable	OLS1	OLS2	OLS3	IV1	IV2	OLS4
α_1	l	.0874***	-0.0164	-.0512**	-.1816**	-.1813**	-.0477**
α_2	k	.4380***	.5841***	.5669***	.5382***	.5384***	.5672***
β_1	y	-.6814***	-.7463***	-.7506***	-.6055***	-.6042***	-.7483***
$\gamma_1 = \beta_1 + 1$	b	0.3186	0.2494	0.2494	0.3945	0.3958	0.2517
α_{11}	l^2	-.01***	.0159***	.0180***	.0163***	.0162***	.0177***
α_{22}	k^2	-.1261***	-.0782***	-.0764***	-.0837***	-.0838***	-.0765***
$\alpha_{12} = \alpha_{21}$	l*k, k*l	-.0341***	-.025***	-.0249***	-.0229**	-.0228**	-.0248***
$\beta_2 = \gamma_2 = \mu$	y^2,b^2,y*b	-.0428***	-.0181***	-.0176***	-.0214***	-.0215***	-.0177***
$v_1 = \delta_1$	l*y, l*b	.0097***	-0.0002	-0.0003	-0.0011	-0.0012	-0.0003
$v_2 = \delta_2$	k*y, k*b	.0733***	.0403***	.0395***	.0435***	.0435***	.0396***
t_2	period 2					0.0043	.0093**
t_3	period 3					.0087*	.0240***
Time Effects		no	no	yes	yes	no	no
Fixed Effects		no	yes	yes	yes	yes	yes
N		2538	2538	2538	2538	2538	2538
R^2		0.9978	0.9998	0.9998	0.9998	0.9998	0.9998

*Indicates p<.05; **Indicates p<.01; ***Indicates p<.001

2.6.1 Technical Efficiency

With directional distance function parameter estimates in hand, the first step is to recover technical efficiency estimates based on the specification OLS3. Following the methods outlined in section 2.4, a second stage regression is undertaken, equation 18, and technical inefficiencies are obtained. The results are presented in Table 2.4. The table presents overall directional distance function values, but also values when extreme outliers are left out. Eliminating extreme outliers removes about 11% of the data, i.e. when TI<2. Recall that the property of null-jointness did not hold for about 26% of the data, and that could be reflected in the technical efficiency scores presented here. Therefore, I interpret the results based on the TI<2 scores.

The average technical inefficiency over all countries and the entire time period of the study is 0.2349, meaning the average country needed to increase RGDP and decrease CO_2 emissions by about 24% in order to achieve efficiency. Given the normalization of the data employed earlier, the average observation could have increased RGDP by 0.2349*322,773.3= 75,819.45million USD or about 75.82 billion USD and decreased carbon dioxide by 0.2349*154,273.4= 36,238.82 kilotons or about 36.24 million metric tons, in order to achieve environmental and technical efficiency, or to reach the frontier of the output set. To give these numbers some perspective, in 2009, the U.S. had a value of RGDP of about 12.69 trillion and CO_2 emissions of about 5.29 billion metric tons. The most efficient observation (i.e. TI=0) is Ethiopia in 1992, and the most inefficient observation is Brazil in 2000.

Table 2.4 Technical Inneficiency (TI) Estimates

Variable	N	Mean	Std. Dev.	Min	Max
TI	2538	1.0126	4.0520	0.0000	50.7383
TI<10	2498	0.5470	1.1645	0.0000	9.6508
TI<5	2448	0.4204	0.7430	0.0000	3.6907
TI<2	2258	0.2349	0.3661	0.0000	1.9997

2.6.2 Technical Change

An added benefit of the directional distance approach is that estimations can be made to investigate whether technical change has occurred. Due to improvements in technology, holding everything else constant, i.e. input use, did the output set presented in this study experience technical progress or technical regress? Did the frontier shift outwards or inwards? Or, did the good outputs increase and bad outputs decrease due to technological improvements? Figure four illustrates this graphically for the case of technical progress.

Given an observation located at point A in Figure four, the first step is to eliminate any inefficiencies and move to point B (along the directional vector) on the technological and environmental frontier of the output set at time period t^o. Technical progress has occurred if in the next time period, t^1, the observation that was located at point B, has moved outside the output set P(x,t^0), to a point like C which is part of the output set P(x,t^1).

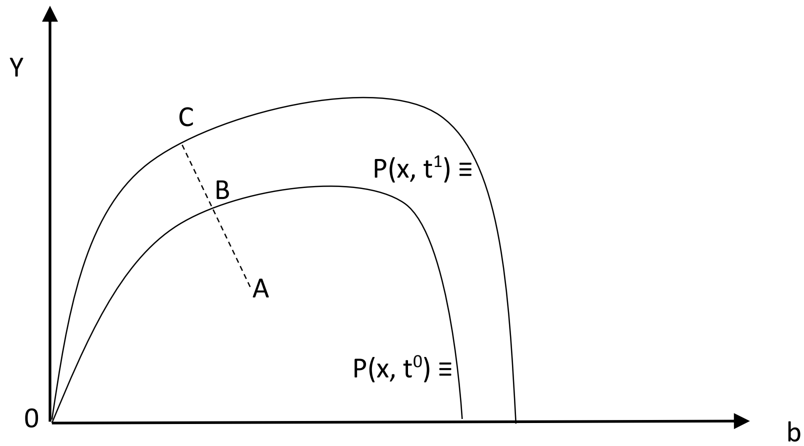

Fig. 2.4 Technical Change

Empirically, Weber and Xia (2011) have included a technical change component in their study based on the directional distance function. Theoretically, the directional measures of technical change have been thoroughly outlined by Färe and Karagiannis (2014). Applying that theoretical framework in this study, assuming efficiency, adding a time index, t, and allowing technical change to occur in the direction (zg_y, $-ug_b$), where z and u are the good output and the bad output translation factors, respectively, the total differential of $\vec{D}_o(x, y+zg_y, b-ug_b, t; g_y, g_b) = 0$ yields:

$$(\nabla_y \vec{D}_o)' g_y dz - (\nabla_b \vec{D}_o)' g_b du + \frac{d\vec{D}_o}{dx} dx + \frac{d\vec{D}_o}{dt} dt = 0 \tag{2.24}$$

Allowing for common marginal changes in the translation factors induced by technical change, i.e. dz=du=d$\hat{a}$, using $(\nabla_y \vec{D}_o)' g_y - (\nabla_b \vec{D}_o)' g_b = -1$ from Chambers (2002), and dx=0 (from the definition of technical change), the total differential of the directional distance function reduces to:

$$-d\hat{a} + \frac{d\vec{D}_o}{dt}dt = 0 \tag{2.25}$$

Therefore the rate of technical change along a predetermined directional vector with common marginal changes in the translation factors will be given by:

$$\frac{d\hat{a}}{dt} = \frac{d\vec{D}_o}{dt} \tag{2.26}$$

which, according to Färe and Karagiannis (2014), gives the common number of times the good output and bad output vectors (g_y and g_b) can be added to the good outputs and subtracted from the bad outputs as a result of technical change.

Based on the theoretical framework outlined above and the empirical strategy outlined in section 2.4, specification OLS4 in table 2.3 was used to investigate whether technical change has occurred. This specification includes country fixed effects and three time period indicator variables-time1 (t_1), time2 (t_2) and time3 (t_3) corresponding to the time periods 1992 through 1997, 1998 through 2003, and 2004 through 2009. The coefficients on these variables will signal whether technological progress or regress occurred from one time period to the next. Coefficients t_2 and t_3 are both positive signifying that technological progress has occurred in time period 2 and time period 3 relative to time period 1. The average observation in time period 2 and time period 3 lies further away from its respective frontier (implying more good output and less bad output with everything else constant), relative to the same average observation in time period 1.

2.6.3 Shadow Prices of CO_2

Given the directional distance function's coefficient estimates based on specification OLS3, the shadow prices of carbon dioxide are calculated and presented next. Recall the shadow price formula as

$$s = -p\,\frac{\gamma_1 + \gamma_2 \mathrm{b} + \delta_1 \mathrm{L} + \delta_2 \mathrm{k} + \mu \mathrm{y}}{\beta_1 + \beta_2 \mathrm{y} + \mathrm{v}_1 \mathrm{L} + \mathrm{v}_2 \mathrm{k} + \mu \mathrm{b}}$$

Table 2.5 presents the shadow price estimates based on the above formula. In the calculation of the shadow prices, the price (*p*) of the good output (RGDP) is set to one, seeing how RGDP takes into account the price deflator of GDP in its calculation. Due to the normalization of the data and to obtain shadow price in terms of USD/ton of CO_2, the final shadow price calculations are as follows:

$$s = -\frac{\gamma_1 + \gamma_2 \mathrm{b} + \delta_1 \mathrm{L} + \delta_2 \mathrm{k} + \mu \mathrm{y}}{\beta_1 + \beta_2 \mathrm{y} + \mathrm{v}_1 \mathrm{L} + \mathrm{v}_2 \mathrm{k} + \mu \mathrm{b}} * \frac{1{,}000{,}000}{1{,}000} * \frac{322773.3}{154273.4} * \frac{USD}{CO_2} \tag{2.27}$$

where the second ratio reflects the fact that the good output is in millions USD while the bad output in kilotons (1 kiloton=1000 tons), and the third ration is the ratio of the pooled average of RGDP to the pooled average of CO_2.

Table 2.5 Carbon Dioxide Shadow Price Estimates

Shadow Price	N	Mean	Std. Dev.	Min	Max
s	2538	719.33	165.65	61.18	3049.28
0<s<1000	2458	697.18	59.93	61.18	999.54
s>1000	80	1400.01	533.90	1002.20	3049.28

The average shadow price across all observations is \$719.33, with a minimum price of \$61.18 corresponding to China for the year 1995, and a maximum of \$3,049.28 corresponding to Japan for the year 2009. What this shadow price implies is that, on the average, in order to reduce country level CO_2 emissions by one metric ton, \$719.33 has to be forgone in RGDP. Therefore, one metric ton of country level CO_2 emissions would cost Japan \$3,049.28 in 2009, while it would cost China \$61.18 in 1995, in terms of RGDP.

The next section discusses what could be done with the knowledge of shadow prices of CO_2 across countries in the context of curbing global CO_2 emissions in an effort to mitigate the environmental effects of global climate change.

2.7 Extension of Results

Once country-level shadow prices of CO_2 are known, how could this information be used to guide policy makers towards achieving an environmental and economic solution to the global warming problem? One option for reducing or stabilizing emissions of CO_2 and having shadow prices of CO_2 equalize across countries is by setting up a quota system and by trading emission permits based on each country's shadow price information.

In the introduction, it was presented why knowing country level shadow prices for CO_2 could be relevant for mitigating the effects of global climate change. Assuming the goal is to reduce or keep CO_2 emissions stable at a certain level, countries could trade emission credits based on each country's shadow price for CO_2. Relative differences in prices across countries will incentivize trading of credits based on arbitrage opportunities. Eventually, prices will reach an equilibrium, achieving efficiency in this market, with emissions levels stabilizing. As a result, countries would then be incentivized to invest in new abatement technologies and improve knowledge, in order for incomes to increase further without extra CO_2 emissions. In this section, a simulation of this example is presented using nonlinear programming techniques.

2.7.1 Simulation of a CO_2 quota market

A hypothetical example is presented to show what could happen to shadow prices of CO_2 when a quota on the bad output is imposed between three countries. The countries are characterized as having free trade between them, one good output (y-RGDP), one bad output (b-CO_2), and labor (x_1) and capital (x_2) as inputs to production. This hypothetical example of a quota will be set up as a nonlinear programming problem. The goal is to maximize the joint amount of the good output between these countries, with the restriction that the total amount of the bad output between these countries cannot go above a set quota level, with everything else kept constant, i.e. the inputs to production.

A three country (i=1, 2, 3) problem is set up as follows:

$$\max\left\{\begin{array}{l}\sum_{i=1}^{3} y_i : \\ (y_i, b_i) \in P(\bar{x}_{1i}, \bar{x}_{2i}), \\ \sum_{i=1}^{3} b_i \leq \bar{b},\ \ where\ i = 1,2,3\end{array}\right\} \tag{2.28}$$

The bars above any variable signifies that the variable is fixed. The CO_2 quota, $\bar{b}$, will be set as the summation of the currently observed levels of CO_2 between the countries. Therefore, everything else the same, this investigation asks what could happen to the level of combined RGDP between the countries when the combined CO_2 level stays at current levels or below?

It was shown earlier that the directional distance function is a functional representation of the output set. Therefore, the above maximization problem can be written as:

$$\max\left\{\begin{array}{l}\sum_{i=1}^{3} y_i : \\ \vec{D}_{oi}(\bar{x}_{1i}, \bar{x}_{2i} y_i, b_i; 1, -1) \geq 0, \\ \sum_{i=3}^{3} b_i \leq \bar{b}, \; where\, i = 1,2,3 \end{array}\right\} \tag{2.29}$$

The quadratic functional form was shown to accommodate directional distance functions. Given the quadratic functional form, (2.29) can be written as follows:

$$\max\left\{\begin{array}{l}\sum_{i=1}^{3} y_i : \\ \alpha_0 + \alpha_1 \bar{L}_i + \alpha_2 \bar{K}_i + \beta_1 y_i + \gamma_1 b_i + \frac{1}{2}\alpha_{11}\bar{L}_i^{\;2} + \frac{1}{2}\alpha_{22}\bar{K}_i^{\;2} + \alpha_{12}\bar{L}_i\bar{K}_i + \\ + \frac{1}{2}\beta_2 y_i^2 + \frac{1}{2}\gamma_2 b_i^2 + v_1\bar{L}_i y_i + v_2\bar{K}_i y_i + \delta_1\bar{L}_i b_i + \delta_2\bar{K}_i b_i + \mu y_i b_i \geq 0, \\ \sum_{i=1}^{3} b_i \leq \bar{b}, \; where \; i = 1,2,3 \end{array}\right\} \tag{2.30}$$

All of the coefficients of the quadratic function in (2.30) have been estimated earlier in equation (2.23) and will be used as constants in (2.30), as well as the fixed levels of labor and capital. The solution to (2.30) will yield optimal values for the good outputs (RGDP) and the optimal allocations of the bad output, CO_2, between the two countries. Once the optimal values of CO_2 and RGDP are obtained, these optimal values are plugged into the shadow price formula from earlier, equation (2.16), and new shadow prices of CO_2 will be obtained for these countries based on the model formulation above.

Recall equation (2.16), the shadow price formula, as:

$$s_i = -p_i \frac{\gamma_1 + \gamma_2 \mathrm{b}_\mathrm{i}^* + \delta_1 \overline{\mathrm{L}}_\mathrm{i} + \delta_2 \overline{\mathrm{k}}_\mathrm{i} + \mu \mathrm{y}_\mathrm{i}^*}{\beta_1 + \beta_2 \mathrm{y}_\mathrm{i}^* + \mathrm{v}_1 \overline{\mathrm{L}}_\mathrm{i} + \mathrm{v}_2 \overline{\mathrm{k}}_\mathrm{i} + \mu \mathrm{b}_\mathrm{i}^*} \quad where \ i = 1,2,3 \tag{2.31}$$

The variables with stars represent optimal levels of the bad and good output obtained as the solutions to (2.30).

2.7.2 Simulation results

Two simulation examples are presented. One example includes the countries Canada, Mexico and the United States, while the second one includes the countries India, China, and Japan. The simulation results are illustrated in tables 2.6 and 2.7. Included in the tables are the initial starting (normalized by the pooled averages) values for all countries, along with the estimated shadow prices of CO_2 for each country. The optimal values of RGDP (y^*), CO_2 (b^*) along with the new shadow prices (s^*) calculated based on the optimal value of outputs are presented as well in tables 2.6 and 2.7. The optimal *y** also include the revenue or cost associated with selling or purchasing emission credits or permits at the equilibrium shadow price. The difference between *b* and *b** multiplied by *s** is added to y*, and that is what is presented in the results tables.

Table 2.6 Extension Estimation Results 1

Country	Year	l	k	b	y	b*	y*	s	s*
Canada	2000	0.8514	2.2759	3.4645	3.1345	2.8070	2.8044	601	676
Mexico	2000	2.2176	2.6600	2.4730	3.5855	3.3400	2.6158	688	676
U.S.A.	2000	8.0623	32.9434	37.0346	34.5695	36.8260	37.2574	841	676
Totals				42.9721	41.2895	42.9730	42.6780		

Table 2.6 presents the simulation results for Mexico, Canada and the United States. All three countries start with a combined level of CO_2 of 42.9721 (which will be the emissions quota level) and a combined level of RGDP of 41.2895. The most CO_2 emitting country is the United States, followed by Canada, and then Mexico. U.S. has the highest RGDP, followed by Mexico,

and then Canada. After the simulation, the three country combined emissions levels stay at the quota level, combined RGDP increases, and shadow prices equalize. To note in table 2.6 is that CO_2 optimally reallocates from the relatively low shadow price country, Canada, to the higher shadow price Mexico. As a result, the shadow prices equalize at a level somewhere between the original shadow price starting levels of these countries, which in theory should disincentives any further reallocations of pollution. To note, is that the global level of RGDP, *y**, has increased but not for every country in this example. Reasons could be due to initial starting conditions. For example, U.S. has relatively higher levels of CO_2 emissions with the highest shadow price. Therefore, in this particular market, there might be no economic incentives for trading to occur. There still are environmental incentives, i.e. stabilizing emissions and a uniform shadow price, but policy discussions on the redistribution of the global income would have to come into play.

Table 2.7 Extension Estimation Results 2

Country	Year	l	k	b	y	b*	y*	s	s*
China	2000	41.8020	13.0757	22.0724	13.1715	14.7230	17.6940	320	586
India	2000	22.8305	3.9734	7.6919	6.2575	4.1800	7.0980	381	586
Japan	2000	3.7707	15.6047	7.9054	11.5832	18.7670	15.1170	2283	586
Totals				37.6697	31.0122	37.6700	39.6390		

Table 2.7 presents simulation results for China, India, and Japan. Combined CO_2 emissions level stays at quota level, combined RGDP increases, and shadow prices equalize. Emissions reallocate from the low shadow price countries of India, and China to the higher shadow price country of Japan. In this particular example, every country gains in terms of RGDP, and an economic and environmental solution towards a uniform shadow price of carbon dioxide is possible. Relative to the Table 2.6 example, the initial conditions differ. For example, China has the most emissions with the lowest shadow price, implying an economic incentive to trade exists

in this market. Redistributions of global income discussions are not needed for this particular case.

Based on the set up of this quota simulation problem, and given the results in tables 2.6 and 2.7, in a world with one good output (RGDP) and one bad (polluting) output (CO_2), two inputs of production (labor and capital), free trade between countries in the CO_2 allowances market, imposing a CO_2 quota yields results in line with theoretical expectations. Combined RGDP increases after the quota and CO_2 is optimally redistributed between the countries, where the redistribution happens based on the arbitrage opportunities in this market for CO_2. The reallocation flows from relatively lower CO_2 shadow price countries to higher CO_2 shadow price countries. As a result, shadow prices equalize as predicted eliminating further arbitrage opportunities. Given the models presented in this study, it could be possible to institute a global CO_2 market, where global emissions levels would be in equilibrium and are optimally reallocated across the world with global RDGP increasing and a uniform price for carbon dioxide. To note is that initial starting conditions might matter, and policy interventions might be necessary in certain cases in order to achieve both an environmental and economic solution to curbing global warming.

2.8 Remarks

Concerned with the effects of pollution across the world, policy makers are taking part in international talks at the United Nations in hopes of mitigating these effects. The goal of these talks would be to reduce pollution levels across the globe while at the same time not sacrificing standards of living for future generations. One of the ways this goal could possibly be achieved would be to set up an international quota level for CO_2 or set up a trading scheme of CO_2

emission credits based on the prices of CO_2 across countries. With time, trading will induce the prices of carbon dioxide to equalize, eliminating any additional arbitrage opportunities and as a result pollution levels would stabilize. Since carbon dioxide is a non-market good (or bad in this case), its prices are not known. In order for exchanges to take place in a market place, prices need to be known. This is where this study comes in. In order to guide policymakers in their international goals, in this chapter shadow prices of carbon dioxide are estimated across countries, to investigate the Law of One Price for CO_2 and a possible global CO_2 market.

Estimating shadow prices first began by setting up a theoretical framework in the context of an output set that has countries producing two outputs, one good (RGDP) and one bad (CO_2), with two inputs of production, labor and capital. The goal in this model is to increase RGDP while at the same time reduce CO_2. For the model to be estimated and shadow prices recovered, a functional representation of the output set is needed, one that accommodates the goal of the problem. The directional distance function is such a functional representation of the output set. One advantage of this function is that it allows for simultaneous increases in RGDP and reductions in CO_2. A second advantage is that a functional form (the quadratic) arises out of the theoretical framework of directional distance functions, functional form that can be easily estimated which would yield the needed shadow prices. Through the directional distance function shadow prices of CO_2 are therefore estimated across countries. Results suggested an average country-level price of $719.33 per metric ton of CO_2.

Once shadow prices were estimated across countries, in order to show how this information could be useful to policy makers, this study turned to using the information on shadow prices in a pollution quota simulation problem, where the goal would be to increase world income while at the same time keeping CO_2 levels to a set quota limit or below it. The results from this simulation revealed that emissions of CO_2 optimally reallocate across the world, fleeing from low shadow price countries to higher shadow price countries, with increased global income at the same time. The most notable outcome of this simulation is that shadow prices of CO_2 across countries equalize as predicted, therefore eliminating any further arbitrage opportunities (or emissions reallocation) based on the shadow prices of CO_2. As a result, world pollution levels would be in equilibrium (at or below the quota level) with global income at relatively higher levels of RGDP.

Possible future directions that the research in this chapter could take include disaggregating the data to reflect polluting units at the industry and possibly firm level. Shadow prices will then be calculated at the industry/firm level across countries. This way, the analysis could move closer to the source of pollution, and shadow prices would reflect a more detailed story. Going even further, the model could possibly be expanded to reflect polluting, intermediate inputs that could be consumed and produced during a production process (some inputs are used in the production of an output, which in turn could be used as an input in the final production of a different output), intermediate inputs that could also be traded in the international market. Another possibility is to set up a model that would consider the carbon content of goods that are traded internationally. Shadow prices would then reflect the different countries' export and import levels of different carbon content goods. The model in section six could also be expanded to allow for time substitution. What that entails is investigating when the optimal economic time would have been for a particular country to reduce emissions based on its shadow prices across time, shadow prices recovered based on optimal emission and income levels, levels calculated as described in section 2.7.

Could a world with less pollution and higher income for current and future generations be possible? According to this study, it could be possible. Given the theoretical model and estimations laid out in this chapter, the goal of an environmentally friendlier and richer world could be possible. The benefits could be even greater assuming that abatement technologies, production processes, peoples' skills, and knowledge in general will continue to improve. Nevertheless, even in world characterized by scarcity, progress is still possible, especially when economic theory and estimation techniques evolve to accommodate current issues, issues that arise as a result of scarcity.

CHAPTER 3

3. Ranking trade resistance variables using data envelopment analysis

3.1 Introduction

Globalization is a phenomenon that is not new anymore. Technological improvements in transportation and communication systems have facilitated an increased interconnection between countries around the world. Evident to this is that the size of cargo ships is increasing, and as a result there are talks about the construction of a second canal in Central America that would link the Pacific and Atlantic Oceans. According to a recent article in The Economist (2013), a canal is being proposed in Nicaragua, one that will be able to accommodate more traffic and larger ships relative to the Panama Canal. World Trade Organization statistics show world merchandise exports' value varying from about \$2 trillion in 1980 to over \$18 trillion in 2012. When it comes to the United States (U.S.), according to the Census Bureau's Foreign Trade Division, U.S. exports' value has increased from approximately \$271 billion in 1980 to about \$2.2 trillion in 2012 while the value of imports has increased from about \$291 billion in 1980 to \$2.7 trillion in 2012. The above statistics provide support for the fact that trade around the world is at an all-time high and continues to rise.

Although the U.S. is increasingly dependent on trade with other countries, impediments to trading goods and services still exist. There are trade agreements between the U.S. and other countries around the world (i.e. North American Free Trade Agreement) which are drawn up to economically benefit participating countries. Nevertheless, trade resistance between the U.S. and its trading partners still persist.

Trade resistance as an international trade concept has its roots in the gravity equation. The gravity equation itself has its beginnings in Tinbergen (1962). The author specified bilateral trade flows as a function of country sizes (given by their gross national product) and trade resistance between the countries in question (Helpman et al. 2008). Therefore, trade resistance can be seen as all other factors besides country sizes that influence bilateral trade flows. Trade resistance factors include the distance between countries, geographic variables, i.e. common borders, island, landlocked, political and institutional variables, and any other factors that could influence bilateral trade flows.

Drawing upon trade data for U.S. manufacturing industries, this chapter seeks to investigate which trade resistance variable, if not regulated, i.e. left to vary freely, will impact trade resistance the most between the U.S. manufacturing industries and their trading partners. A desired outcome is to rank the trade resistance variables from the most limiting to the least limiting in terms of trade resistance, in an effort to shed light on how international trade flows could possibly be increased even further.

Knowing which trade resistance variable is the most restrictive is important because U.S. trade policy could then be appropriately targeted. For example, previous studies (Anderson and van Wincoop 2004; Novy 2006; Novy 2009) have found that the trade resistance variable, tariff, does not affect trade resistance greatly. Wu (2012) found similar results for tariffs, but the trade resistance variable distance was found to be impactful on trade resistance. As a result, it would be unwise to direct policy efforts towards tariffs, when other trade resistance variables have greater economic impacts.

The research in this chapter could also benefit institutions in the world trade arena devoted to reducing trade resistance. For example, if distance between the U.S. and its trading partners is a major factor influencing bilateral trade, then Research & Development efforts can be directed to things such as improvements in infrastructure, and advances in transportation technologies, i.e. fuel efficiency. At the same time, this paper’s findings can also steer academic research in a new direction, by incentivizing university research to focus on areas with the greatest potential impact on reducing trade resistance, research that can be immediately employed by policy makers.

To further substantiate this research, according to the International Trading Centre, there are some interesting trade patterns to notice around the world. India's exports to the United States are 13% of its total exports, to Brazil 2%, to the United Kingdom 3%, but to Pakistan, Myanmar, Nepal, Bhutan (some neighboring countries) exports are a total of 2% combined. In India's case, distance does not seem to be an important trade resistance factor. In contrast, Mexico's exports to the United States are 78% of its total exports, while exports to Western Europe less than 4%. In these cases, and possibly others, the patterns of trade could be associated with the history between nations. For example, India's colonial ties to the United Kingdom and its historical relationship with Pakistan are no mystery, and its trade patterns may be a reflection of that. Inducing India to trade with relatively closer nations might be better addressed through political and social avenues, rather than policy instruments such as tariffs. Therefore, it is important for policy makers to know which trade resistance variable is the most restrictive, so that trade policy can then be formulated in a way that it could have the greatest potential impact on trade.

In this chapter a theoretical model of (undesirable) trade resistance is formulated. Trade resistance variables are being specified as (undesirable) inputs into the (undesirable) production of the output, trade resistance. Then, in the spirit of Justus von Liebig's Law of the Minimum, Johansen's notion of capacity is injected into this framework which will theoretically predict certain results. Estimation takes place via non-parametric Data Envelopment Analysis (DEA), which will allow the research question to be addressed: which trade resistance variable increases trade resistance the most? Using DEA, a ranking of the trade resistance variables is obtained by allowing them to take values from zero up to their observed values, something that cannot be accomplished using statistical techniques (problems will be encountered such as omitted variable bias, etc.). Before proceeding to the main body of this paper, Justus von Liebig's Law of the Minimum and Johansen's concept of Capacity will be explained in the context of this paper.

This research is in the spirit of Justus von Liebig's Law of the Minimum which states that growth (of a biological plant) is given by the scarcest or limiting factor, or alternatively, that increases in abundant nutrients do not affect growth as much as increases in the scarcest nutrient do. This "law" is applied here but in the international trade arena, where an inquiry is conducted to explore which trade resistance variable ("nutrient") is the most limiting in terms of trade resistance ("plant growth"), or which variable increases trade resistance the most.

This paper makes use of the concept of capacity which is defined by Johansen (1987) as "…the maximum amount that can be produced per unit of time with the existing plant and equipment provided that the availability of variable factors is not restricted." This says that, in a production framework, inputs will be divided into two categories-fixed and variable. The maximum potential output will therefore be given by the variable inputs, which can vary to any level. In a Law of the Minimum context, variable inputs can be seen as the limiting factors, the ones that can cause increases in output growth the most. In a similar fashion, in this paper, trade resistance variables are split up into fixed and variable. For example, the distance variable could be held fixed, while tariffs would be variable, and DEA estimation will take place to see how tariffs impact trade resistance. Then the roles will be reversed to investigate distance's impact. In the end, a ranking of trade resistance variables will be established based on the impact each of these variables have on trade resistance.

Past studies investigating trade resistance included Hausman et al. (2005) and Wu (2012). These papers have analyzed the impacts of trade resistance variables on calculated trade costs indexes. Econometric estimates in these papers yield statistically significant results in line with theoretical predictions, i.e. positive relationships between trade costs and these variables. Wu (2012) calculates elasticities of the impacts on trade costs, which show the economic significance of the statistical results, but a ranking of trade resistance variables free of statistical assumptions is not obtained. As previously stated, omitting a variable in an econometric model induces certain statistical problems. Therefore, this study, by employing Data Envelopment Analysis, will obtain a ranking of U.S. trade resistance variables, free of statistical assumptions.

This chapter is organized as follows. Section II introduces the theoretical model. The estimation procedure is laid out in section III. The data used in this study is presented in section IV. Section V presents the estimation results and discusses them, while section VI summarizes and concludes.

3.2 Theoretical Framework

3.2.1 Trade Resistance Function

Trade resistance will be specified as a function of the trade resistance variables, meaning these variables will generate the level of trade resistance present. The trade resistance level will be represented by $r \in \Re_+$, and the trade resistance variables will be represented by a vector $q, (q_1,..., q_n)$, *with* $q \in \Re_+^N$. A trade resistance function, *T(q)*, can then be specified as a function of the trade resistance variables as follows,

$$T(q) = \max_r \{ r : q \ \textit{generates} \ r, \ \ q \in \Re_+^N, \ \ r \in R_+ \} \tag{3.1}$$

This function therefore represents the bilateral trade resistance level given by the trade resistance variables. Also, the set bounded from above by *T(q)* can be defined as,

$$S = \{(q,r) : T(q) \geq r, q \in \Re^N_+,\ \ r \in R_+\} \tag{3.2}$$

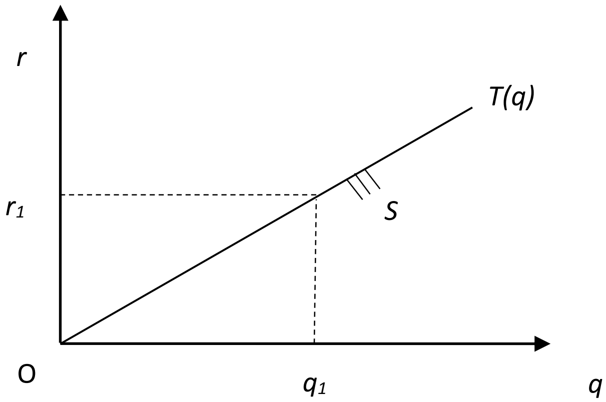

Figure 3.1 Trade Resistance Function T(q) and S

As an illustration and assuming a linear trade resistance function, figure 3.1 portrays the relationship between trade resistance, *r*, and the trade resistance variable, *q*. In the figure, r_1 is the level of trade resistance given by the q_1 level of the resistance variable *q*. Set *S* (given by *q* and *r*) is also portrayed in this figure as all the *r* values lower than or equal to the *T(q)* line. Certain properties are imposed on this framework. These properties, are outlined next as follows:

(i) The set *S* is convex and nonempty

Convexity implies averages are possible in this set. Non-emptiness says that trade resistance exists or that it is feasible.

(ii) Doing nothing is feasible: $0 \in S$

A customs district can always choose to remain in the state of autarky and incur no trade resistance.

(iii) No free lunch: $if\ r > 0, then\ q > 0$

Trade resistance cannot be positive without the trade resistance variables being positive. For example, the distance between customs districts and their trading partners will always be positive; hence trade resistance will be positive.

(iv) Trade resistance variables are freely disposable:

$$if\,(q,r) \in S\ and\,(q',r) \geq (q,r)\,then(q',r) \in S$$

A higher level of trade resistance variables will generate a higher level of trade resistance, but the old level of trade resistance is achievable given the higher level of the resistance variables. For example, distance generates a certain level of trade resistance, but also all lower levels. This property rules out congestion in the system.

(v) Trade resistance levels are freely disposable:

$$if\,(q,r) \in S\ and\,(q,r') \leq (q,r), then(q,r') \in S$$

This property states that lower levels of trade resistance are part of the set given by a certain level of trade resistance variables.

For illustrative purposes, the free disposability properties in (iv) and (v) are presented in figure 3.2. Property (iv) says that q_2 which is greater than q_1 generates r_2 but could also generate r_1. Property (v) says that q_2, which gives r_2 can also give r_1, a lower level than r_2. Monotonicity is a result of the disposability properties. Based on trade theory and the disposability properties, monotonicity, $dT(q)/dq_n \geq 0$, can be incorporated into this paper's theoretical formulation, as long as *T(q)* is assumed to be differentiable. Therefore, this model can be interpreted as an undesirable output production model, where the undesirable inputs yield an output that is undesirable, i.e. more undesirable inputs yield more undesirable output. There is a positive relationship between the trade resistance variables and the trade resistance level. Given the aforementioned properties of this model, Shephard (1970) showed that DEA accommodates these properties. Estimation employing DEA will be discussed in a later section.

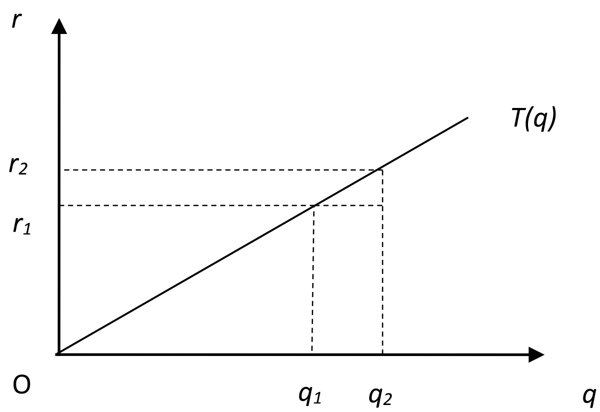

Figure 3.2. Disposability Properties

3.2.2. Capacity Framework

To answer the research question, the concept of capacity is integrated into this framework. Recall capacity being defined by Johansen (1987) as "…the maximum amount that can be produced per unit of time with the existing plant and equipment provided that the availability of variable factors is not restricted." In the spirit of capacity, the vector *q* will be partitioned in two, a fixed part and a variable part, as $q = (q_f, q_v)$ following Färe et al. (1989). Given figure 3.3, the level of trade resistance will therefore be given by the variable trade resistance component as follows,

$$r_1 = \max\left\{ r_1 : (r_1, q) \in S \right\} \tag{3.3}$$

which portrays the situation before allowing one component to be free (variable), and

$$r_2 = \hat{T}(q_f) = \max\left\{r_2 : (r_2, q_{-1}) \in S_{q_{-1}}\right\} \tag{3.3'}$$

which portrays the state after allowing one of the components to be free (variable).

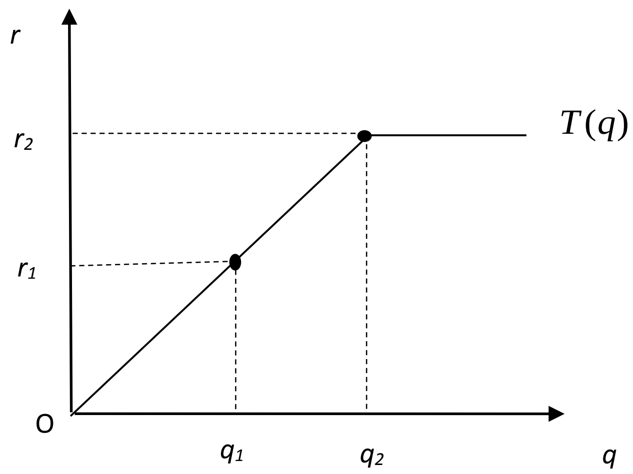

Figure 3.3 Capacity Utilization

Graphically, the capacity utilization notion is presented in figure 3.3. The graph illustrates the example of one trade resistance variable, q, while keeping the others fixed. There is an initial situation where for example q_1 generates r_1. Then, allowing the trade resistance variable q to fluctuate to any level, the optimal level of q that yields the highest trade resistance r is estimated. In figure 3.3 the optimal level is q_2 with a new trade resistance level of r_2. Additional increases in q beyond q_2 will not generate additional trade resistance. Repeating this process for every available trade resistance variable, a ranking could then be obtained. The trade resistance variables could then be ranked based on the following (capacity utilization) formula,

$$CU_i = \frac{r_{i1}}{r_{i2}} \leq 1 \tag{3.4}$$

where i represents a particular trade resistance variable, r_{i1} represents the current (observed) trade resistance level given by variable i, and r_{i2} represents the maximal trade resistance level given by the optimal level of trade resistance variable i, holding all the others fixed. The trade resistance variable that yields the lowest value in equation (3.4) will be interpreted as the most restrictive, or the one that induces the most trade resistance.

3.3 Estimation Procedure

Answering the research question will be done through the use of Data Envelopment Analysis (DEA) following Färe et al. (2013). To note is that the analysis here should not to be confused with negative DEA models. First, for every observation k', the maximal trade resistance level is calculated given that the trade resistance variables are at their observed values, as follows

$$\hat{r}_{k'} = \max_{r} \ s.t. \tag{3.5}$$

$$\sum_{k=1}^{K} z_k r_k \geq r \ ,$$

$$\sum_{k=1}^{K} z_k q_{k1} \leq q_{k'1}, \ n = 1,$$

$$\sum_{k=1}^{K} z_k q_{kn} \leq q_{k'n}, \ n = 2,\ldots, N,$$

$$z_k \geq 0, \ k = 1,\ldots, K$$

where the first three inequalities represent the disposability properties outlined earlier, while the last inequality represents $S(q, r)$ characterized by constant returns to scale. Given each observation's trade resistance variables (q), equation (3.5) seeks to estimate which observation has the highest trade resistance ($\hat{r}_{k'}$), or which one is technically efficient based on the properties of this model. A departure from traditional interpretations of efficiency is in order here. In this paper, because trade resistance is interpreted as an undesirable output, the observation that the calculations yield as the most efficient is actually interpreted as the least efficient. Efficiency will be given by a Farrell Output-Oriented Measure of Technical Efficiency as,

$$F_o = \frac{\hat{r}_{k'}}{r_{k'}} \geq 1 \tag{3.6}$$

If (3.6) equals one, then *k'* is relatively doing the worst it can in terms of trade resistance level, i.e. it is technically the most inefficient. Potential for improvements, i.e. reductions in trade resistance, exist. If (3.6) is greater than one, then *k'* is technically more efficient, or doing better, relative to an observation for which (3.6) has values less than the value for *k'*.

The second step is to calculate the denominator of equation (3.4). For every observation, k', the maximal trade resistance level is calculated given that one of the trade resistance variables is not at its observed value, i.e. it is allowed to freely vary or take any value, as follows:

$$\bar{r}_{k'} = \max_{r} \ s.t. \tag{3.7}$$

$$\sum_{k=1}^{K} z_k r_k \geq r \ ,$$

$$\sum_{k=1}^{K} z_k q_{k1} \leq q_1 \, , \ n = 1,$$

$$\sum_{k=1}^{K} z_k q_{kn} \leq q_{k'n} \, , \ n = 2,\dots, N,$$

$$z_k \geq 0, \ k = 1,\dots, K$$

By choosing different trade resistance variables to freely vary in (3.7), a ranking of the trade resistance variables could then be established. The trade resistance variable that generates the highest values for (3.7) or lowest values for (3.4) will signify that that variable is the most limiting.

As an illustration, figure 3.4 presents the estimation procedure graphically. For example, point *A* represents $\bar{r}_{k'}$, point *B* represents $\hat{r}_{k'}$, while point *C* represents $r_{k'}$. Point *A* represents the capacity notion, which is the highest level of trade resistance that could be achieved as a result of varying a certain trade resistance variable for a particular observation. Before estimating point *A*, estimating point *B* will represent an observation that is relatively the most technically inefficient, i.e. has the highest trade resistance level, while point *C* represents a more technically efficient customs district relative to *B*.

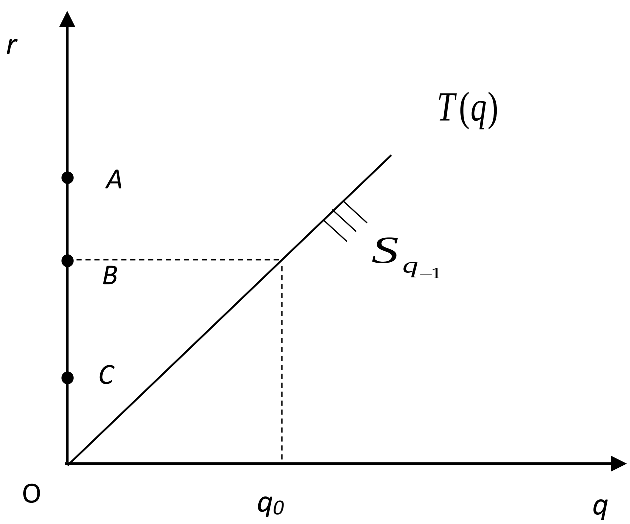

Figure 3.4 Estimating the most restrictive trade resistance variable

The first step in the estimation procedure is to calculate the distance between points *B* and *C*, which will signify how much more technically efficient the customs district located at point *C* is relative to the one at point *B*. The second step is to calculate point *A* to see how high trade resistance levels could go as a result of varying a certain trade resistance variable.

3.4 Data

This study uses data collected and compiled in Wu (2012). For the purpose of this study, a quick exposition of the data is given here. For greater detail on the sources of the data and the computation of variables Wu (2012) should be consulted. There is data for one time period on 25 three-digit North American Industry Classification System (NAICS) level industries trading with 72 countries out of 38 U.S. customs districts. One observation represents a particular manufacturing industry, trading with a particular country, out of a particular U.S. customs district. In Wu (2012), the author derived a bilateral trade resistance index (TRI) by industry. The index represents the international trade resistance that an industry trading out of a particular U.S. customs port with a certain country is facing relative to domestic trade resistance. The trade resistance index (the average for the time period 2005-2009) is being specified as a function of the following trade resistance variables:

- distance between the U.S. customs district and the trading partner (in miles)
- U.S. domestic tariffs by industry (in percentages, for year 2004)
- trading partner's tariffs by industry (in percentages, for year 2004)
- whether or not there is a common border between trading partners (indicator variable)
- whether or not there is a common language between trading partners (indicator variable)
- whether the trading partner is landlocked (indicator variable)
- time required to import goods (in calendar days, for year 2006)

Wu (2012) estimated the following econometric specification with the trade resistance index as the dependent variable and the trade resistance variables as independent variables as follows:

$$TRI_{ijs} = \alpha_0 + \beta_1 * Dist_{ij} + \beta_2 * USTariff_{is} + \beta_3 * TradingPartnerTariff_{js} +$$
$$+ \beta_4 * Border_{ij} + \beta_5 * CommonLanguage_{ij} + \beta_6 * LandLocked_j + \beta_7 * IMportTime_j + \varepsilon_{ijs}$$

where i stands for U.S. customs district, j for U.S. trade partners, and s stands for industry. Wu (2012) found distance, trading partner's tariffs and importer's time to have a statistically positive relationship with the trade resistance index, meaning reductions in any of these variables could lower bilateral trade resistance. The trade resistance variables specified above, excluding the indicator variables border, common language, and landlocked, will be used in this paper along with the trade resistance index.

Before estimation, the data was inspected and some inconsistencies, i.e. negative values for the trade resistance index, the distance variable, and extreme outliers were found. This could have been a result of data entry error or calculation of variables especially for the negative values just mentioned. As a result, observations with negative values associated with the trade resistance index and distance variable were deleted as well as observations with extreme tariff values (based on the density of tariffs, tariff rates for both U.S. and trading partners fluctuate generally between 0 to 20 percent). This deletion of observations reduced the dataset by less than 0.4% of the original size. All estimations, including calculating equation (3.6) and equation (3.7) were performed using the software OnFront2.

Table 3.1 displays summary statistics for all variables used in the estimation process. Overall, average international trade resistance (TRI) is 158.05 percent of domestic trade resistance, with a high of 981.22 percent that corresponds to the Crop Production industry (NAICS 111) trading out of Houston, Texas with South Africa and a low of 0.64 percent corresponding to the Electrical Equipment and Appliances industry (NAICS 335) trading out of Miami, FL to Mexico, The average U.S. tariff (TariffUS) is 2.16 percent with a high of 51.31 percent corresponding to the Crop Production Industry trading out of Baltimore, M.D., New York City, N.Y., and Houston, TX with South Africa. The average trading partner's tariff (TariffCty) is 5.39 percent with a high of 20 percent corresponding to the Leather and allied product industry (NAICS 316) for Senegal, Australia, and Egypt. The average distance (Distance) between U.S. industries and their trading partners is 5417.71 miles, while the average time required to import goods (TimeImp) is 17.69 days.

Table 3.1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
TRI	23289	1.5805	0.9701	0.0064	9.8122
TariffCty	23289	0.0539	0.0527	0.0000	0.2000
TariffUs	23289	0.0216	0.0358	0.0000	0.5131
Distance	23289	5417.71	2061.43	546.00	10610.00
TimeImp	23289	17.6959	10.4346	0.0000	76.0000

Additional descriptive statistics (only means) by industry, trading country, and U.S. customs districts are presented and discussed in Appendix B.

3.5 Estimation Results

Table 3.2 presents estimation results for equation 3.6. It also includes results for equation 3.5 and the trade resistance index (TRI) for comparison purposes. The average Farrell Output-Oriented Measure of Technical Efficiency, F_o, is 13.51, which says that the average observation (average industry trading out of the average port with the average trading partner) is 13.51 times more efficient (or has less trade resistance) than the least efficient observation, which equals one.

The most efficient observation, or the best one in terms of lowest trade resistance for which F_o=959.05, corresponds to the Electrical Equipment and Appliances industry (NAICS 335) trading out of Miami, FL to Mexico. In Table five, the average $\hat{r}$ (Rhat) or maximal trade resistance level given F_o, is 15.79. That means that for the average observation to become the least efficient observation the average trade resistance level would have to increase from 1.5805 to 15.79.

Table 3.2. Equation 3.6 Results

Variable	Obs	Mean	Std. Dev.	Min	Max
F_o	23289	13.51	12.64	1.00	959.05
$\hat{r}$	23289	15.79	6.64	1.15	47.24
TRI	23289	1.5805	0.9701	0.0003	9.8122

Table 3.3. Equation 3.7 Results

Variable	Obs	Mean	Std. Dev.	Min	Max
Distance	23289	6.19	6.42	0.01	102.29
TimeImp	23289	6.96	6.62	0.01	106.23
TariffUS	23289	1.75	1.12	0.01	11.13
TariffCty	23289	1.61	1.00	0.01	9.81

Table 3.4. Equation 3.4 Results

Variable	Obs	Mean	Median	Skeweness	Min	Max
Distance	23289	0.37	0.38	0.26	0.01	1.00
TimeImp	23289	0.28	0.26	1.15	0.02	1.00
TariffUS	23289	0.92	0.96	-1.16	0.24	1.00
TariffCty	23289	0.98	1.00	-4.51	0.60	1.00

Equation 3.7 results, or $\bar{r}$ calculated for every trade resistance variable, are presented in Table 3.3. Recall, that the largest increase amongst the variables will represent that that variable will be the most restrictive in terms of trade resistance, i.e. it increases trade resistance the most. By

allowing the trade resistance variables to take any value, the most restrictive variable comes out to be the time to import, or port logistics, variable (it raises trade resistance to an average level of 6.96), followed by the distance variable (average level of 6.19), the U.S. tariff (average level of 1.75), and the least restrictive variable being the tariff of the trading partner (average level of 1.61). Therefore, table 3.3 results indicate that, on average, bilateral trade resistance is affected most by the time it takes to import goods, or port logistics, followed by distance, with relatively and considerably lower effects by tariffs.

Table 3.5. Results by U.S. Region

Region	Distance	TimeImp	F_o
East Coast	0.36	0.30	14.77
West Coast	0.39	0.26	13.95
Gulf Coast	0.38	0.29	14.23
Midwest	0.36	0.28	11.53
Southwest	0.37	0.29	11.10

With the results of equation (3.7) in hand, the results for equation (3.4) will be presented next in Table 3.4. Recall, equation (3.4) will be less than or equal to one. The trade resistance variable that yields the lowest values for this equation is interpreted as the most restrictive. Evidently, the same conclusions can be drawn from Table 3.4 as they were in Table 3.3.

Given that trade policy could possibly be directed at certain regions of the U.S., industries or customs districts depending on policy makers' goals, the results are therefore also presented by U.S. region, by industry and by customs district. Due to distance and time to import goods being found as the most limiting variables, with tariffs having relatively negligible impacts, the subsequent discussion will focus on the former variables. The results are presented based on equation (3.4).

Table 3.5 presents results by U.S. regions. From an efficiency perspective, the most efficient (highest F_o) region is the East Coast, followed by the Gulf Coast, West Coast, Midwest and then Southwest. This is as expected, seeing how the coast regions have ports where large, ocean transport ships have relatively easy access. Also, the Midwest is more efficient than the Southwest and this is as expected as well. The Midwest includes the ports of Chicago, Detroit and Cleveland, which are all located on the Great Lakes where big transport ships from all over the world have access to these ports through the St. Lawrence River, Niagara River, Detroit River and other connecting waterways that can accommodate large ships.

Distance is the most restrictive trade resistance variable for the Midwest, the East Coast, and the Southwest, and the least restrictive for the Gulf Coast and the West Coast. It makes sense seeing how the Midwest, the East Coast and the Southwest are relatively further away from trade routes from Eastern Asia and U.S. trade with Eastern Asia, especially China, has increased greatly in the past decade according to the U.S. Census. The time it takes to import goods is the most restrictive trade resistance variable for the West Coast and the Midwest and the least restrictive for the East Coast. It could be argued that the East Coast ports have a longer history of operation implying more experience in port procedures, which could be also reflected in the East Coast being the most efficient region given the results in Table 3.5.

Table 3.6 presents the results by industry. Crop production, Animal production, Forestry and Logging, Fishing, Hunting and Trapping, and Paper manufacturing seem to be the least efficient industries in terms of trade resistance, while Fabricated Metal Product, and Machinery Manufacturing seem to be the most efficient industries. Distance seems to be the most restrictive variable for Food Manufacturing and Apparel Manufacturing, and least restrictive for the Forestry and Logging and the Petroleum and Coal Products industries. Time to import goods is the most restrictive variable for the Forestry and Logging, Petroleum and Coal Products, and the Furniture and Related Product industries, and least restrictive for the Crop Production, and Food Manufacturing industries. Although the overall results identified the time to import goods variable as the most restrictive, to note in table 3.6 is that distance is more restrictive than time to import for the Crop Production, Food Manufacturing, Textile Mills, Textile Product Mills, Apparel Manufacturing, Leather and Allied Product, Plastics and Rubber Products, and Nonmetallic Mineral Product industries.

Lastly, the estimation results are presented by U.S. customs districts in table 3.7. The most efficient ports include Nogales, AZ, Norfolk, VA, Savannah, GA, Miami, FL, Detroit, MI and Seattle, WA, while the most inefficient ports include St. Louis, MO, Minneapolis, MN, and Providence, RI. Distance is the most restrictive variable for Pembina, ND, New York City, NY, Ogdensburg, NY, Portland, ME, and St. Louis, MO and the least restrictive for the ports of Detroit, MI, El Paso, TX, Port Arthur, TX, and Providence, RI. The time to import goods is the most restrictive for Columbia/Snake, OR, Laredo, TX, and San Francisco, CA, and the least restrictive for Providence, RI, Boston, MA, Port Arthur, TX, and St. Albans, VT. Worthy to note in table 3.7 as well is that there were a few exceptions where distance is more restrictive than the time to import goods for the ports of Boston, MA, New York, NY, Portland, ME, Pembina, ND, Ogdensburg, NY, and St. Albans, VT.

Overall, the estimation results showed that the ranking of trade resistance variables consists of the time to import, or port logistics, as the most limiting variable in terms of the impact on the level of trade resistance, followed by distance, the tariff imposed by the U.S., and the tariff imposed by the trading partner. If the results are presented by industry or by port, the distance variable emerges as being more restrictive than the time to import goods for a few industries and ports.

Table 3.6. Results by Industry

NAICS	Industry	Distance	TimeImp	F_o
111	Crop Production	0.30	0.33	6.59
112	Animal Production	0.50	0.27	5.22
113	Forestry and Logging	0.57	0.25	5.95
114	Fishing, Hunting and Trapping	0.43	0.30	6.63
311	Food Manufacturing	0.18	0.33	17.91
312	Beverage and Tobacco product	0.32	0.30	11.76
313	Textile Mills	0.21	0.30	16.55
314	Textile Product Mills	0.19	0.30	16.88
315	Apparel Manufacturing	0.16	0.30	18.96
316	Leather and Allied Product	0.19	0.31	12.90
321	Wood Product	0.46	0.29	10.97
322	Paper Manufacturing	0.46	0.27	6.74
323	Printing and Related Activities	0.48	0.27	12.00
324	Petroleum and Coal Products	0.55	0.26	12.50
325	Chemicals Manufacturing	0.35	0.30	10.39
326	Plastics and Rubber Products	0.27	0.29	11.40
327	Nonmetallic Mineral Product	0.29	0.30	11.08
331	Primary Metal Manufacturing	0.45	0.28	15.46
332	Fabricated Metal Product	0.31	0.29	20.53
333	Machinery Manufacturing	0.44	0.28	23.41
334	Computer and Electronic Product	0.51	0.27	11.20
335	Electrical Equipment, Appliances	0.38	0.28	11.70
336	Transportation Equipment	0.40	0.28	12.49
337	Furniture and Related Product	0.52	0.26	12.68
339	Miscellaneous Manufacturing	0.42	0.28	15.51

Table 3.7. Results by U.S. Port District

District	F_o	Distance	TimeImp	District	F_o	Distance	TimeImp
Baltimore, MD	13.66	0.24	0.23	New Orleans, LA	10.29	0.26	0.22
Boston, MA	11.26	0.24	0.25	New York City	15.58	0.23	0.24
Buffalo, NY	10.50	0.24	0.23	Nogales, AZ	20.64	0.28	0.22
Charleston, SC	15.24	0.26	0.23	Norfolk, VA	16.76	0.25	0.24
Chicago, IL	13.52	0.25	0.23	Ogdensburg, NY	9.49	0.23	0.24
Cleveland, OH	11.19	0.24	0.23	Pembina, ND	8.68	0.22	0.24
Columbia/Snake,OR	11.62	0.27	0.21	Philadelphia, PA	11.58	0.24	0.24
Dallas/Fort Worth	10.81	0.25	0.22	Port Arthur, TX	9.71	0.33	0.25
Detroit, MI	15.83	0.29	0.22	Portland, ME	11.56	0.23	0.24
Duluth, MN	7.43	0.24	0.23	Providence, RI	7.74	0.32	0.32
El Paso, TX	9.75	0.29	0.22	San Diego, Ca	9.16	0.28	0.22
Great Falls, MT	9.75	0.26	0.23	San Francisco, CA	12.12	0.28	0.21
Houston, TX	8.67	0.26	0.22	Savannah, GA	16.22	0.25	0.23
Laredo, TX	15.42	0.26	0.21	Seattle, WA	15.88	0.27	0.22
Los Angeles, CA	13.38	0.27	0.22	St. Albans, VT	12.87	0.22	0.25
Miami, FL	16.41	0.28	0.22	St. Louis, MO	6.96	0.23	0.23
Milwaukee, WI	15.68	0.24	0.24	Tampa, FL	11.22	0.26	0.23
Minneapolis, MN	6.88	0.25	0.23	Washington, D.C.	12.88	0.28	0.24
Mobile, AL	8.78	0.26	0.23	Wilmington, N.C.	9.28	0.25	0.24

3.6 Remarks

United States' trade volume with the world has increased over time and continues to rise. Although trade with other countries has become relatively less costly due to trade agreements, improvements and advancements in technology, communication, transportation and infrastructure, trade impediments still exist. In an effort to identify how trade resistance can further be ameliorated and trade costs reduced further so that the welfare benefits from trade continue to rise for the U.S. and its trading partners, this chapter set out to investigate which trade resistance variable has the greatest impact on the level of trade resistance. The goal of the study was to produce a ranking of trade resistance variables from the most restrictive to the least restrictive based on their impact on the level of trade resistance.

In this chapter, a model for trade resistance was presented where a trade resistance function was specified as a function of trade resistance variables. Then, in the spirit of the Law of the Minimum, the concept of capacity utilization was applied to this model. Using Data Envelopment Analysis, the trade resistance variables were allowed to vary to any level one by one and the impact of each on the level of trade resistance was noted. The estimation results revealed that, for the average U.S. industry trading out of the average U.S. customs port with the average foreign trading partner, the time to import goods was the most restrictive trade resistance variable, followed by the distance between U.S. and its trading partners, the tariffs imposed by the U.S., and lastly the tariffs imposed by the trading partner.

From a policy perspective, these findings suggest that policy instruments, i.e. tariffs, are not as impactful on bilateral trade resistance as port logistics (in terms of moving imported goods to the market), infrastructure, and transportation and communication systems/technology are. Ceteris paribus, the results in this study suggest that in order for U.S. bilateral trade volumes to increase even further, U.S. international trade policy should be directed at improving port logistics and reducing the distance between trading partners. The ladder goal could be possibly accomplished by implementing additional improvements in infrastructure for better traffic flow, improvements in fuel efficiency, increasing the capacity of transport vessels, and ensuring safe waterways free of pirating activity. The former goal could be possibly accomplished by expediting the bureaucratic process of releasing imported goods to the market, perhaps through a type of certification system for importers and exporters and their suppliers so that certain steps in the bureaucratic process could then be expedited. Based on the results in this study, more specific policy actions could be further directed at certain regions, industries, or U.S. customs ports, based on what the policy makers' goals are.

This study could be extended in several ways. The binary variables including whether trading partners share a common language, common border, whether a country is landlocked or an island, were excluded from the estimation process. Data envelopment analysis could perhaps be improved upon to accommodate binary variables. As a result, additional trade resistance variables could be investigated based on this paper's framework. Another possible extension would be to shadow price the trade resistance variables. Using the trade cost variable from Wu (2012) which was employed as a proxy for trade resistance in this study, the trade resistance variables could be seen as characteristics of trade costs. In a hedonic or non-market valuation context, these characteristics could be then shadow priced by employing a directional distance function approach which will take into account customs ports' inefficiencies, inefficiencies that are traditionally assumed away in hedonic pricing models.

Moving beyond the production possibilities frontier (PPF) signals improvements in welfare. International trade theory suggests that when countries engage in trade with each other based on their respective comparative advantages, as a result, these countries move beyond their PPF and increase their welfare. Given that the goal of policy makers is to improve social welfare, increasing trade volumes is one avenue to that end. In support of this goal, this study delved into this area and identified certain factors that influence trade volumes the most. Future research will hopefully investigate further this and other avenues through which benefits from trade will continue to accumulate for all trading countries.

CHAPTER 4

4. Summary and Conclusion

Advances in communication and transportation systems have brought about a global interconnectedness in a relatively short time period. As a result, thinking at all levels, i.e. business, academic, political, has a global perspective. This is especially true in the policy setting arena. In today's world, policy should be formulated with consideration to the global implications. In this context, this dissertation investigated the following global research question: Could global standards of living continue to rise in the presence of global climate change and international trade resistance? The research question was addressed in two parts. The first part was addressed in chapter two, while the second part in chapter three.

The first part of the research question investigated whether an environmental and economic solution is possible to the global climate change problem. The objective was to employ theoretical and empirical tools that model the global goal of reduced CO_2 emissions while simultaneously increasing RGDP, to shadow price CO_2 at country levels, and to simulate a global market for CO_2. The tool used was the directional distance function. Exploiting the duality between this function and the polluting technology, country level shadow prices for CO_2 were estimated and a global CO_2 market was simulation based on the country level shadow price information. Results suggest an average country level price of $719.33 per metric ton of CO_2. Market simulation results suggest that it is possible for global emissions to decrease, global RGDP to increase, while shadow prices equalize. The end goal is to achieve equilibrium in this market, where in order for countries to continue or go beyond current standards of living, there would have to be improvements in abatement technologies so that CO_2 levels remain at equilibrium, sustainable levels.

The goal of the second part of the research question was to rank the factors that restrict trade between trading partners in terms of their respective impacts on trade resistance, so that trade policy could then be steered in the direction that could potentially stimulate trade the most, resulting in relatively higher increases in overall welfare. To this end, this dissertation used techniques from the Operational Research field, i.e. DEA. These techniques allowed for a unique way of looking at trade resistance between trade partners, and allowed for a ranking of trade barriers to be established based on their impacts on trade resistance. In the context of Justus von Liebig's Law of the Minimum and using Johansen's notion of Capacity, a trade resistance model was presented, where trade barriers are (undesirable) inputs used in the production of the (undesirable) output, trade resistance. DEA was then employed to assess the impact that each trade barrier has on trade resistance. Results suggest that U.S. port logistics are the most limiting trade barrier, followed by the distance between trade partners, the U.S. imposed tariffs, and the trading partner's imposed tariffs.

Since this dissertation employs some unique theoretical and empirical tools and applies them to new areas of research, future directions in these areas are abundant. For example, the analysis in chapter two could be extended to link the market simulation with country level efficiency measures, investigating how the global CO_2 market might affect the efficiency performance of individual countries. The analysis in chapter three could be extended to include policy variables to investigate how policy might influence trade, i.e. trade agreements, or even shadow price trade barriers in an effort to establish a ranking of trade barriers based on a new methodology.

This dissertation uses a utilitarian approach, and distributional issues are not investigated here. It is assumed that addressing distributional issues is a normative process that goes beyond what this research produces, and it is left in the hands of policy makers. Moreover, the research in this dissertation is meant to provide information, a benchmark, or guideline to policy makers, so that there is a basis for discussion in the policy setting environment related to the global issues investigated in this dissertation. A desired goal of this dissertation is for policy makers to utilize the information herein towards the formulation of policy that will advance the wellbeing of people all over the world. Global climate change is a real threat and if its effects could be mitigated by the formulation of a global CO_2 market without impeding standards of living, then the world could benefit. International Trade and the availability of goods to people all over the world improves global welfare, therefore finding ways to reduce trade resistance between trading partners could have positive global welfare implications.

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APPENDICES

Appendix A. Additional Properties of the Directional Distance Function

Presented in Färe et al. (2005), the properties of the directional distance function are inherited from the polluting technology's output set. They are as follows:

(AA.1) $\vec{D}_o(x, y, b; g_y, -g_b) \geq 0 \; if \; and \; only \; if \; (y, b) \in P(x)$

The function will either be zero if (y, b) is on the boundary of the output set, or some other positive value if (y, b) is on the inside of the output set.

(AA.2) G-Disposability :

$$if \; g = (g_y, -g_b), (y, b) \in P(x), and \; 0 \leq \theta \leq 1, then (y + \theta g_y, b - \theta g_b) \in P(x)$$

Properties 1 and 2 ensure that our output set P(x) can be recovered from the directional output distance function, or that the directional output distance function fully characterizes the technology represented by P(x).

(AA.3) $\vec{D}_o(x, y', b; g_y, -g_b) \geq \vec{D}_o(x, y, b; g_y, -g_b) \; for (y', b) \leq (y, b) \in P(x)$

This property comes from the assumption of strong disposability of the good output (y). It says that using the same amount of inputs, and producing the same level of the bad output (b), but producing more of the good output (y), will not decrease efficiency. Or, producing more of the good output (y), while all else is held constant, can only increases efficiency.

(AA.4) $\vec{D}_o(x, y, b'; g_y, -g_b) \geq \vec{D}_o(x, y, b; g_y, -g_b) \; for (y, b') \geq (y, b) \in P(x)$

Similarly, using the same level of inputs and producing the same level of the good output (y), but producing more of the bad output (b), will not increase efficiency. It can only signal decreases in efficiency.

Properties (AA.3) and (AA.4) can be viewed as monotonicity properties.

(AA.5) $\vec{D}_o(x, \theta y, \theta b; g_y, -g_b) \geq 0 \; for \, (y,b) \in P(x) \, and \, 0 \leq \theta \leq 1$

This property reflects the joint weak disposability assumption of the good and bad outputs. Proportional contraction of both good and bad outputs is always feasible, and the directional output distance function will be non-negative.

(AA.6) $\vec{D}_o(x, y, b; g_y, -g_b) \, is \, concave in \; (y,b) \in P(x)$

Property (AA.6) comes in handy when taking second order derivatives of the directional output distance function in order to determine the curvature of the output set. For an application see Färe et al. (2005), where the shadow price output elasticity of substitution was estimated.

Appendix B. Additional Chapter 3 Summary Statistics

Table AB.1. Descriptive Statistics by Industry

NAICS	Industry	TRI	TariffCty	TariffUs	Distance	TimeImp
111	Crop Production	3.4350	0.0521	0.0706	5080.6880	19.2895
112	Animal Production	3.4727	0.0433	0.0039	5412.3570	17.0152
113	Forestry and Logging	2.8162	0.0206	0.0018	5507.2450	16.6094
114	Fishing, Hunting and Trapping	2.9830	0.0703	0.0050	5122.1860	17.0380
311	Food Manufacturing	1.1821	0.1202	0.0684	5485.9750	19.5819
312	Beverage and Tobacco product	1.2965	0.0717	0.0255	4760.8210	14.7816
313	Textile Mills	1.1905	0.0777	0.0462	5389.5900	17.4954
314	Textile Product Mills	1.1385	0.0841	0.0478	5334.5550	17.4768
315	Apparel Manufacturing	0.9957	0.0981	0.0840	5287.4910	16.9313
316	Leather and Allied Product	1.5551	0.0835	0.0588	5402.5200	17.9264
321	Wood Product	1.6301	0.0356	0.0104	5377.4930	17.5228
322	Paper Manufacturing	2.8130	0.0420	0.0088	5519.3530	17.0786
323	Printing and Related Activities	1.3710	0.0322	0.0053	5394.1670	17.4325
324	Petroleum and Coal Products	1.2496	0.0279	0.0063	4988.6660	15.9631
325	Chemicals Manufacturing	2.0886	0.0460	0.0161	5501.7160	18.8000
326	Plastics and Rubber Products	1.6921	0.0712	0.0249	5374.6600	17.5208
327	Nonmetallic Mineral Product	1.7214	0.0571	0.0273	5453.6560	17.8294
331	Primary Metal Manufacturing	1.2058	0.0414	0.0051	5457.1870	18.2602
332	Fabricated Metal Product	0.8957	0.0565	0.0176	5489.4180	17.9357
333	Machinery Manufacturing	0.8140	0.0357	0.0051	5513.8250	18.6281
334	Computer and Electronic Product	1.5973	0.0247	0.0042	5606.3050	17.7474
335	Electrical Equipment, Appliances	1.8032	0.0471	0.0135	5508.4420	17.2630
336	Transportation Equipment	1.5266	0.0438	0.0093	5498.8480	17.6096
337	Furniture and Related Product	1.2427	0.0560	0.0021	5300.7140	16.5687
339	Miscellaneous Manufacturing	1.2093	0.0454	0.0137	5580.0630	18.2064

Table AB.2. Descriptive Statistics by Trading Country

Country	TRI	TariffCty	TariffUs	Distance	TimeImp
Argentina	1.6192	0.0662	0.0223	4960.9070	12.1748
Armenia	1.3621	0.0680	0.0287	6012.6950	36.2655
Australia	1.6823	0.0663	0.0174	7401.8490	18.2797
Austria	1.6842	0.0349	0.0294	4873.6460	14.6389
Azerbaijan	1.5247	0.0884	0.0180	6070.5590	32.9804
Belgium	1.5246	0.0373	0.0277	4466.0110	11.9288
Bolivia	1.3305	0.0375	0.0064	4861.9540	25.5525
Brazil	1.6642	0.1011	0.0250	4770.8860	19.3633
Bulgaria	1.5286	0.0494	0.0217	6064.3640	21.6640
Canada	1.5692	0.0126	0.0041	1966.3230	14.6521
Chile	1.3989	0.0647	0.0183	4830.4320	21.1712
China	1.5422	0.0658	0.0301	6750.7900	16.9790
Colombia	1.4722	0.1125	0.0030	3078.3150	35.6019
Cyprus	1.2364	0.0224	0.0120	6563.1860	12.1947
Czech Republic	1.6968	0.0361	0.0305	4975.3990	20.7865
Denmark	1.4521	0.0362	0.0287	4150.7830	7.4440
Ecuador	1.4945	0.1059	0.0031	3652.1670	33.6718
Egypt	1.7269	0.1009	0.0115	5951.3870	29.7956
Estonia	1.5942	0.0342	0.0307	4761.2620	10.0359
Germany	1.6107	0.0319	0.0246	4781.7150	10.3303
Finland	1.5401	0.0367	0.0294	4408.5250	6.7677
France	1.4455	0.0327	0.0266	4552.6920	11.3458
Georgia	1.4495	0.0440	0.0178	5446.9800	38.5714
Ghana	1.6450	0.1003	0.0041	7372.0190	39.4167
Greece	1.7733	0.0755	0.0275	5780.9450	21.5115
Hungary	1.6752	0.0353	0.0300	4931.4490	13.6313
India	1.6414	0.1163	0.0220	8143.5240	26.3735
Indonesia	1.3554	0.0737	0.0290	7819.0940	24.3790
Iran	0.8976	0.0098	0.0002	6175.3750	12.0000
Ireland	1.4639	0.0309	0.0206	4170.5330	8.9689
Israel	1.5930	0.0610	0.0079	7024.4800	20.2731
Italy	1.7164	0.0410	0.0272	5477.6580	19.9505
Japan	1.6142	0.0342	0.0220	7233.0990	12.1172
Jordan	1.4811	0.0921	0.0172	7586.8420	25.9928
Kazakhstan	1.5724	0.0479	0.0345	5080.7740	33.7799
South Korea	1.6238	0.0419	0.0272	6622.8520	11.5503
Kyrgyzstan	1.4209	0.0371	0.0355	4962.4120	22.2549

Table AB.3. Descriptive Statistics by Trading Country (Continued)

Country	TRI	TariffCty	TariffUs	Distance	TimeImp
Latvia	1.5783	0.0362	0.0277	4906.3690	15.6560
Lithuania	1.7952	0.0370	0.0283	4874.4260	20.3062
Macedonia	1.6603	0.0526	0.0887	5501.0630	24.5625
Malawi	1.6322	0.0008	0.0003	1672.0000	11.3333
Malaysia	1.5221	0.0381	0.0176	9101.3980	11.2363
Malta	1.5195	0.0353	0.0325	5187.8550	14.2077
Mexico	1.5066	0.0500	0.0060	2326.7660	18.2317
Moldova	1.4901	0.0281	0.0250	4426.4800	10.0000
Morocco	1.6274	0.0830	0.0125	5803.1330	25.0533
Netherlands	1.4815	0.0337	0.0216	4405.8400	8.4997
Nigeria	1.6703	0.0778	0.0040	8150.6480	36.0432
Norway	1.5691	0.0256	0.0221	4397.3010	7.5721
Oman	1.2452	0.1314	0.0217	8114.3470	31.5612
Pakistan	1.6163	0.1116	0.0304	8438.9950	22.7846
Panama	1.3407	0.0970	0.0067	2425.5760	22.8259
Peru	1.5812	0.0758	0.0042	4357.5120	27.3043
Poland	1.7342	0.0701	0.0239	5039.2130	28.2280
Portugal	1.6597	0.0339	0.0345	4865.6990	13.3306
Qatar	1.3689	0.0877	0.0228	7653.7500	26.0046
Romania	1.7001	0.0905	0.0143	5763.2860	21.2379
Russia	1.7784	0.0868	0.0243	5393.3890	34.1069
Senegal	1.7641	0.1084	0.0051	6834.9270	39.4606
Singapore	1.5358	0.0356	0.0173	8872.6940	16.7968
Slovakia	1.7385	0.0356	0.0288	5023.0220	20.1507
Slovenia	1.7234	0.0403	0.0260	5482.6440	22.3915
South Africa	1.6561	0.0381	0.0099	4714.6770	22.4609
Spain	1.6877	0.0286	0.0289	4615.1790	14.0411
Sri Lanka	1.3945	0.1052	0.0210	8713.9110	20.6436
Sweden	1.5478	0.0229	0.0174	4356.7200	6.6499
Thailand	1.6625	0.0880	0.0224	8668.9590	18.2014
Trinidad Tobago	1.3042	0.1184	0.0044	2537.7960	32.4626
Turkey	1.6722	0.0414	0.0309	6445.4200	15.7972
Ukraine	1.6601	0.0607	0.0219	5638.4890	32.1894
United Kingdom	1.5434	0.0334	0.0226	4015.9700	9.7927
Uruguay	1.3845	0.1166	0.0268	5294.6310	19.8750
Vietnam	1.4822	0.0723	0.0235	8974.5250	16.6952

Table AB.4. Descriptive Statistics by U.S. Port District

District	TRI	TariffCty	TariffUs	Distance	TimeImp
Baltimore, MD	1.4171	0.0590	0.0218	5231.9270	18.6169
Boston, MA	1.6144	0.0531	0.0220	4989.3970	17.2973
Buffalo, NY	1.8830	0.0466	0.0214	5129.4960	16.3152
Charleston, SC	1.3165	0.0584	0.0226	5293.2280	18.6533
Chicago, IL	1.5772	0.0594	0.0243	5492.8780	18.6803
Cleveland, OH	1.7903	0.0552	0.0240	5342.7440	17.5270
Columbia/Snake, OR	1.6401	0.0466	0.0211	5821.7890	16.2863
Dallas/Fort Worth, TX	1.8947	0.0526	0.0230	5991.0800	17.0961
Detroit, MI	1.4884	0.0476	0.0173	5241.6290	16.7768
El Paso, TX	2.2013	0.0331	0.0146	5270.5750	15.3664
Great Falls, MT	2.3252	0.0335	0.0189	5045.5700	15.3835
Houston, TX	1.3827	0.0597	0.0225	5842.6960	19.4111
Laredo, TX	2.0598	0.0439	0.0169	5502.1570	16.0803
Los Angeles, CA	1.4688	0.0599	0.0231	6055.5060	19.3295
Miami, FL	1.5269	0.0598	0.0189	5471.2610	18.8174
Milwaukee, WI	2.2632	0.0375	0.0185	4743.4870	13.5812
Minneapolis, MN	1.9184	0.0438	0.0200	5192.3670	15.1845
Mobile, AL	1.7302	0.0426	0.0166	5170.9540	16.4212
New Orleans, LA	1.3420	0.0583	0.0213	5709.9270	18.5032
New York City, NY	1.0660	0.0648	0.0261	4986.8900	19.9886
Nogales, AZ	1.8867	0.0374	0.0152	5660.8280	15.9373
Norfolk, VA	1.1894	0.0597	0.0228	5284.0550	18.7235
Ogdensburg, NY	1.9445	0.0424	0.0213	4727.2240	14.4829
Pembina, ND	2.7567	0.0209	0.0341	4612.2610	15.2464
Philadelphia, PA	1.6806	0.0553	0.0227	5076.7240	17.8806
Port Arthur, TX	1.6814	0.0319	0.0079	4822.5000	17.0417
Portland, ME	1.5411	0.0413	0.0184	4684.3810	14.6285
Providence, RI	1.8800	0.0182	0.0097	3060.7600	11.3867
San Diego, Ca	2.1673	0.0435	0.0158	5629.1130	16.7179
San Francisco, CA	1.7566	0.0551	0.0224	6057.3730	17.6484
Savannah, GA	1.3329	0.0608	0.0230	5508.7290	18.7657
Seattle, WA	1.4320	0.0553	0.0238	5703.7900	17.5763
St. Albans, VT	1.3489	0.0375	0.0211	4324.0630	14.0119
St. Louis, MO	2.2192	0.0369	0.0189	5027.8770	13.7536
Tampa, FL	1.7381	0.0544	0.0196	5397.2690	17.7237
Washington, D.C.	1.2523	0.0490	0.0169	4983.6700	15.9425
Wilmington, N.C.	1.9621	0.0468	0.0211	5404.5000	16.3239

Based on Table AB.1, the largest trade resistance is in the Animal Production industry (NAICS 112) and Crop Production (NAICS 111), while the lowest is in the Machinery Manufacturing industry (NAICS 333) and the Fabricated Metal industry (NAICS 332). Averages by trading country are presented in Tables AB.2 and AB.3, while averages by U.S. customs district are presented in Table AB.4. To notice in Table AB.4 is that U.S. ports located in the middle of the country have on average the highest trade resistance, while the U.S. ports on the East Coast have on average the lowest trade resistance. This should not come as a surprise. The East Coast ports are located in relatively more accessible areas by big container ships.