ACCOUNTING FOR GREENHOUSE GAS EMISSIONS AND TOXIC AIR POLLUTANTS IN TRUCKING EFFICIENCY AND PRODUCTIVITY

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ACCOUNTING FOR GREENHOUSE GAS EMISSIONS AND TOXIC AIR

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

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ABSTRACT

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Air pollution is a threat to the environment and human health. Freight trucking in particular is the main source of freight transportation emissions. Heavy-duty trucks emit large amounts of toxic air pollutants that cause serious diseases and harm public health. In addition, heavy-duty trucks emit great amounts of greenhouse gas (GHG), which is the leading cause of global warming.

Despite increased environmental restrictions on air pollution and rising trucking greenhouse gas emissions in the past decades, no economic study has examined the potential GHG and air pollution reductions in the trucking sector and the associated private abatement costs to the industry. This study accounts for GHG emissions and toxic air pollutants in measuring and evaluating efficiency and productivity for the trucking industry in the 48 contiguous states. Moreover, the private costs of abatement to the industry were also estimated.

When only GHG was incorporated in the production model, the results showed that each state could expand desirable output and reduce GHG by an average of 11 percent per year between 2000 and 2007. The Malmquist-Luenberger productivity indexes showed that omitting or ignoring GHG in trucking service production yielded biased estimates. On the other hand, due to increased environmental regulations, most of the toxic air pollutants decreased dramatically between 2002 and 2005. The analytical results showed that inefficiency decreased during this period. The private costs of abatement averaged $73

million per state in 2005. When GHG and six toxic air pollutants were incorporated in the production model, the estimated private abatement cost was $76 million per state, which was equivalent to 0.7 percent of the industry output in 2005.

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CHAPTER 1. PROBLEM STATEMENT

Freight transportation is a driving force behind the U.S. economy, and the trucking industry is a crucial element of the freight transportation system and dominates the sector in terms of both volume and value.[1] From 2002 to 2007, the total truck tonnage increased 14.2 percent to 9.0 billion tons, which represented 69 percent of all freight tonnage in the U.S. The shipment value increased 9.1 percent to $ 8.4 trillion worth of goods during this period, which represented 71 percent of the total value of all shipments of goods (Bureau of Transportation Statistics, 2009a).

Since deregulation in the early 1980s, the trucking industry has shown increased efficiency and productivity. Deregulation reduced carriers' rates and cost, improved service quality, and led to a considerable increase in technical efficiency (Ying, 1990a; Ying, 1990b). Furthermore, the increasingly intense competition in this industry since deregulation pressed trucking firms to adopt new technologies, such as on-board computers and Internet-based communication, which have improved efficiency and productivity considerably for trucking firms (Hubbard, 2003; Nagarajan *et al.*, 2000; Schulz, 2009).

While the trucking industry has shown increased efficiency, freight transportation has experienced a decline in energy efficiency and produced negative environmental impacts. According to the U.S. Environmental Protection Agency (Environmental Protection Agency, 2009a), the transportation sector was responsible for 28 percent of all greenhouse gas (GHG) emissions in the U.S. in 2006 and 47 percent of the net increase in

[1] According to the U.S. Department of Transportation, heavy-duty vehicles are defined as vehicles of gross vehicle weight rating of above 10,000 lbs (DOT, 2009).

total GHG emissions between 1990 and 2006. The emissions of GHG from freight transportation are due mostly to fossil fuel combustion. Within the transportation sector, heavy-duty trucks make up only 4 percent of the on-road vehicles, but use more than 20 percent of the fuel in the U.S. (Department of Energy, 2009). As a result, trucking sector alone was the fifth largest CO_2 emitter in the U.S. and contributed to 27 percent of GHG emissions in 2005. In addition, due to the growth in freight demand and energy consumption, and an overall decline in energy efficiency within the industry, trucking GHG emissions increased by 69 percent between 1990 and 2005 (Facanha and Ang-Olson, 2009; American Trucking Associations, 2008).

In 2007, the U.S. Supreme Court held that GHG emissions were air pollutants under the Clean Air Act (CAA) and should be regulated by the U.S. Environmental Protection Agency (EPA). In order to control GHG emissions from transportation, the EPA launched the SmartWay program which aims to reduce diesel emissions and improve fuel economy (EPA, 2009c). Furthermore, some state and regional governments, such as California, Arizona, and New Mexico, have developed GHG regulations to reduce emissions from heavy-duty vehicles (California Environmental Protection Agency, 2010; Abraham, 2009). In addition, on May 21th, 2010, President Obama signed a Presidential Memorandum to direct the EPA and the Department of Transportation (DOT) to create a first-ever national policy to increase fuel efficiency and reduce GHG emissions for medium- and heavy-duty trucks for model years 2014-2018. The new policy is expected to protect the environment and reduce dependence on foreign oil (The White House, 2010).

Freight trucking is also a major emitter of toxic air pollutants, such as nitrogen oxides (NOx), particulate matter (PM) and air toxins, which post serious threats to human health (EPA, 2009d). According to the EPA (2000a), heavy-duty vehicles accounted for more than 30 percent of NOx emissions and 25 percent of PM emissions in the transportation sector.

To reduce diesel emissions from heavy-duty trucks throughout the United States, the EPA established the Clean Diesel Truck and Bus Program and set tighter clean diesel standards for new diesel engines. The EPA also developed the National Clean Diesel Campaign (NCDC) to promote diesel emissions reduction devices to the existing diesel engines (EPA, 2009e). Many states, such as New York and New Hampshire, implement smoke opacity testing programs to identify vehicle engines that emit excess smoke and need to be repaired (New Hampshire Department of Environmental Services, 2008; New York State Department of Environmental Conservation, 2010).

Traditional efficiency and productivity measures ignore air pollution or assume strong disposability of air pollution, which means that pollution can be disposed of without private costs. However, due to the current regulatory environment, traditional measures would lead to bias in evaluating performance of trucking firms, and weak disposability assumption, which implies that air pollutants cannot be disposed of for free, is imposed in this study.

Following Chung, Färe and Grosskopf (1997), directional output distance functions are used in this study to measure efficiency and productivity changes in the trucking industry and account for air pollutants in measures for the 48 contiguous states for 2000-2007. The objectives of this study are to evaluate each state's trucking performance and assess the private abatement costs to the trucking industry as a result of increased environmental constraints. This benchmarking study allows comparisons of states' abilities to simultaneously reduce air pollution and increase trucking services; the abatement cost is measured in terms of good output foregone. This analysis identifies the gap between the states and their peers and enables policy makers to devise appropriate policy tools to improve the environment and human health via improved trucking environmental efficiency.

CHAPTER 2. TRUCKING INDUSTRY BACKGROUND

Pre-deregulation Era

The trucking industry underwent a long period of regulations. The federal government began regulating railroads to prevent unfair prices and competition in the late 1800s. In 1935, Congress passed the Motor Carrier Act, which authorized the Interstate Commerce Commission (ICC) to decide which companies could become trucking firms, and the ICC regulated trucking firms and drivers involved in interstate commerce. The ICC also granted operating permits and approved trucking routes, types of commodities carried, and the regions in which trucking firms served (Stratton, 2006). The primary purpose of the 1935 Act was to protect the regulated railroads from trucking's competition and to keep the transportation industry stable by rate regulation, entry and operating restrictions, and limited competition (Wong, 2001).

The Motor Carrier Act (MCA) of 1935 set many restrictions on trucking business. New trucking companies were required to obtain a "certificate of public convenience and necessity" from the ICC.[2] However, incumbent trucking firms did not need the certificates. Consequently, new trucking firms suffered severe restrictions and barriers to entry due to the regulations, which in turn also restricted incumbent firms from market expansion. Under this situation, trucking firms incurred extra costs and delivery delays due to additional mileage, and they also had empty backhauls if they only had a one-way permit. Thus, many firms had to purchase the permits of existing carriers to obtain the rights to

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[2] According to Edles (2004), the "Certificate of public convenience and necessity" is approved based on three factors: (i) whether the operation serves "a useful public purpose, responsive to a public demand or need," (ii) whether the operation "could be served as well by existing firms or carriers," and (iii) whether the service could be operated "without endangering or impairing the operations of existing companies."

transport certain commodities through certain regions in order to save costs. The restriction on types of commodities also prevented trucking firms from filling their hauls completely (Moore, 1993; Ying, 1990a).

The Act required the rates charged by trucking firms to be "just and reasonable" and prohibited price discrimination (Edles, 2004). The ICC required trucking firms to post rates thirty days before they could be effective, and anyone, including the competitors, were allowed to protest. In 1948, Congress passed the Reed-Bulwinkle Act which authorized the "rate bureaus" to set rates. The rate bureaus represented a group of trucking firms and could agree on the uniform rates applied to all its members, and the carrier cartels ruined price competition (Stratton, 2006).

Additionally, the trucking industry was more heavily unionized than other sectors during the regulation period, and high payments to union workers were burdens to trucking firms (Ying, 1990a). Moreover, due to regulatory and union imposed constraints on operations, unionized trucking firms were less efficient than non-union firms (McMullen and Lee, 1999).

Deregulation Era

Economists argued that regulations distorted economic behavior and competition in the trucking industry and caused inefficiency in operations and resource allocation. In 1980, Congress passed the Motor Carrier Act of 1980 to deregulate the trucking industry. The Act eliminated barriers to entry and rate restrictions. The requirements to obtain a certificate of public convenience and necessity were reduced, and this made it much easier for new trucking firms to receive a certificate. The MCA of 1980 restricted the authority of rate bureaus and allowed trucking firms to set rates individually. The Act also gave trucking firms more freedom to choose routes and commodities (Moore, 1993). Winston *et al.* (1990) concluded that deregulation reduced shipping rates and trucking cost, improved firms' service quality, and led to a considerable increase in technical efficiency and productivity.

Competition and Service

As deregulation made it much easier for firms to enter or exit the trucking industry, the number of trucking firms increased dramatically through the decades following deregulation, and competition became more intense. In 2004, the number of members of the American Trucking Association (ATA), which is the largest trade association for the trucking industry, had more than doubled the number licensed by the ICC in 1978 (Moore, 2008). The number of trucking firms in truckload sector (TL) increased from 20,000 in 1980 to 55,000 in 1995.[3] Wang Chiang and Friedlaender (1984) believed that the deregulated environment required a large number of small and efficient firms to serve in the industry. However, due to adjustment failures and mergers in this industry, the number of firms of the less-than-truckload (LTL) sector declined to only 273 at the end of 1987 compared to 614 firms in 1976 (Wong, 2001). Moreover, Silverman, Nickerson and Freeman (1997) found that there were 2,669 large carriers in 1977 while only 1,588 firms were left in the ICC's large carrier population by the end of 1989. They indicated that large trucking firms suffered more pressure and fewer survival chances after deregulation. Just a few of the top 50 trucking firms that existed in 1979 are still operating (Schulz, 2009). A trucking industry profile study by Corsi and Infanger (2004) showed that firms that

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[3] According to Winston (1998), truckload (TL) trucking provides point-to-point service for one shipper's goods which fill an entire truck; less-than-truckload (LTL) trucking consolidates different shippers' goods on a truck by a network of terminals.

survived deregulation and some new entrants who adapted to the new deregulated environment achieved great improvements in performance and productivity gains. The average annual miles per truck increased from 65,700 in 1987 to 83,563 in 2002. However, due to intense competition, trucking companies had to pass along most efficiency gains to shippers in the forms of lowered rates and improved services. As a consequence, the overall industry suffered low profit margins and high employee turnover (Corsi and Infanger, 2004).

Labor

Engel (1998) found that payments for labor in the trucking industry declined significantly due to cost cutting of trucking firms. The real average hourly salary of for-hire truck drivers declined by 40 percent between 1978 and 1996, while the average earnings of private sector workers also declined by 13 percent. Nickerson, Silverman and Freeman (1997) pointed out that inappropriate management of labor and capital increased carriers' failure rate.

The trucking industry had more union members than other transport sectors before deregulation. Union members had significant bargaining power and captured a great share of monopoly rents under regulation. Rose (1987) found that the Teamsters Union was the primary beneficiary in this regulated industry. However, as rate competition, free entry, and non-union companies increased in the industry after deregulation, union density and bargaining power were reduced significantly (Hirsch, 1988). In 1973, 62 percent of for-hire truck drivers were unionized. Union carriers were always considered to operate more efficiently, but non-union carriers won business after deregulation because they had lower costs. Real hourly wage for union truckers fell considerably from \$12.45 in 1979 to \$11.15

in 1985, whereas the decline in nonunion earnings was less. In addition, wage differential between union and nonunion truck drivers were narrowing significantly. As a consequence, the percentage of unionized truckers declined to 30 percent by 1984, and only 23 percent of truckers were union members by 1996. Increased workload due to service quality requirements and less-attractive wages resulted in high labor turnover in this industry (Hirsch, 1993; Engel, 1998).

Costs

The estimate of savings due to deregulation was about $10 billion (in 1990 dollars) annually. If inventory cost saving were added, total savings amounted to be more than $60 billion per year (Engel, 1998). Moore (1986) wrote that trucking costs decreased by 12-25 percent while service quality did not decline after deregulation.

Daughety and Nelson (1988) studied the change of cost and production structure in the trucking industry before and after deregulation using panel data from 1953 to 1982. They found strong similarities between the estimated cost functions for the 1950s and those for 1982. The only differences between the early period of regulation and the post-regulation period were elasticities of substitution and choices of levels of inputs and outputs.

Ying (1990a) estimated a translog cost function with data for 1975-1984 and found that total cost savings increased from less than 1 percent in 1981 to 23 percent in 1984. In his study, the result showed that after a short period of adjustment, deregulation improved productivity growth significantly in the trucking industry. The direct effect of deregulation on costs could attribute to output, input, operating characteristics and time. The results showed that a less valuable commodity mix and a lower percentage of LTL traffic helped improve productivity. He also found that deregulation made utilizing capital and purchased transportation more efficient and led to a decrease in the utilization of labor and fuel, which caused an incentive for firms to accelerate technological progress in order to operate efficiently.

In another paper, Ying (1990b) concluded that the regulatory reform led to lower costs in the trucking industry and increased substitution of capital and purchased transportation for fuel and labor for the years 1975-1984. As showed by Keeler (1989) and McMullen and Stanley (1988), Ying found that the trucking industry has tended toward scale economies since deregulation. Ying (1990b) also showed that deregulation gave trucking firms, particularly large firms, freedom to organize more flexibly and operate more efficiently, and enabled larger firms to cut costs further in the future.

Using a profit function and cross-sectional data for years 1976 and 1984, Adrangi, Chow and Raffiee (1995) examined the economies of scale and productive efficiency in the trucking industry after deregulation. They concluded that the industry was under constant returns to scale (CRS) before and after 1980, and mergers and expansions did not substantially reduce the costs of trucking firms. These findings were in contrast with Ying (1990b), who concluded that this industry was under increasing returns to scale. Adrangi, Chow and Raffiee (1995) concluded that deregulation restored efficiency in the trucking industry.

Although most transportation economists considered deregulation to have positive impacts on the industry and economy, Keeler (1986), using a translog cost function for 1966-1983, found that costs increased after deregulation, but he also pointed out that it was possibly due to improved service quality. Boyer (1993) held that deregulation improved efficiency and productivity in the trucking industry by 1987, but the improvements were due to factors outside the industry such as technology improvements, cost efficient locations, lower transaction costs for shippers, and more service types (private and for-hire trucking). He also believed that the benefits obtained from deregulation were due to increased small carriers that strived to optimize, and they made the industry competitive.

McMullen and Lee (1999) applied a stochastic cost frontier approach to analyze the efficiency in the trucking industry from 1976 to 1987. They found an overall inefficiency in the industry and suggested that unionization in this industry was the major reason for inefficiency before and after deregulation, and higher service quality which tended to raise costs might have been one of the factors as well. They also pointed out that firms that survived deregulation were more efficient than those that exited the industry.

Another study by Wong (2001) examined the impact of deregulation in the trucking industry from 1976 to 1987, and he argued that deregulation increased costs and reduced productivity in the industry. He reported that this may have resulted from poor adjustments to deregulation or over expansion of services. He also found that deregulation led to a reduction in fuel cost, which may be caused by the elimination of route restriction.

Post-deregulation Era

Technological Improvements

Hubbard (2003) examined how information technologies impact capacity utilization in the trucking industry. On-board computers helped managers monitor trucks and drivers. For example, the electronic vehicle management system (EVMS) provided information on trucks' locations, facilitated communication between dispatchers and drivers, and enabled dispatchers to optimize use of trucks and trailers, and allocate matching capacity and demand more efficiently. The technology improved capacity utilization and productivity in the industry. Estimation in this study showed that advanced on-board computers increased capacity utilization of adopting firms by 13 percent in 1997. Hubbard concluded that productivity gains from new technology were quite substantial.

The Internet has changed the operation of the trucking business. Nagarajan *et al.* (2000a; 2000b) investigated the impact of the Internet on the industry and concluded that Internet-based communication resulted in "both potential for greater efficiency in traditional transportation activities and in the creation of demand for new types of transportation activities" (2000b, p. 10). They found that the Internet had both direct impacts on freight brokers and indirect impacts on competition environment of shippers and consignees in the industry. The productivity gains from the trucking industry came from fewer empty miles and higher cargo space usage and less idle time. Freight brokers provided load-matching services that offered information of available shipments and available cubic space of trucks, and the matching information was crucial to increase trailers' utilization and decrease waiting time as well as empty backhauls. Nagarajan *et al.* suggested that Internet-based intermediaries had advantages over traditional freight brokers. Because of using the technology, the new brokers combined load matching and competitive pricing, which enabled shippers to receive lower costs and truckers to reduce empty miles. Moreover, the new intermediaries also enabled small shippers to aggregate loads and obtain volume discounts. The indirect influence of the Internet on shippers was reflected by the new service and demand requirements for trucking firms from shippers and consignees since e-commerce created more intense competitions in their market environments. For example, manufacturing firms adopting just-in-time delivery require timely shipment of raw materials and finished products. Nagarajan *et al.* (2000b) also found that the benefits from the use of the Internet were more likely attributable to better information for shippers on their shipments rather than to the lower costs of trucking services.

A recent trucking firms' efficiency study report by the Federal Motor Carrier Safety Administration (2008) found inefficiencies in the industry after deregulation. These include underutilization of equipment and assets, fuel waste, loss and theft, equipment failure and safety problems. The report suggested that applying wireless technologies, such as on-board computer and communications systems, remote vehicle monitoring systems, and GPS, could improve efficiency within the industry. Currently, trucking industry should focus on improving fuel economy. For instance, a 20 percent improvement in fuel economy could cause a $14,000 to $25,000 cost saving per year per truck (U.S. Department of Energy, 2009).

Recent Developments

Since the current recession began in late 2007, freight demand slumped sharply, and even some of the best performing trucking firms started to lay off employees and reduce capacity in order to survive. The industry has cut 208,000 jobs between January 2007 and November 2009. The economic recession has slowed trucking activities. Diesel fuel price fluctuations also contributed to the industry slowdown. Although fuel prices have decreased from the peak in 2008, high and volatile fuel prices still affect financial returns. Many small firms spend a large portion of their total operating costs on diesel fuel, and high diesel fuel prices would drive some small companies out of business (Bureau of Labor Statistics, 2010).

From 2000 to 2009, among the top 100 trucking firms, nearly 22 percent of them closed and 8 percent were acquired. A survey of more than 100 TL carriers conducted in 2009 showed most carriers considered current freight downturn as the worst one since the mid-1970s, before deregulation. Since the deregulation, increasing competition, just-in-time delivery system, Internet-based communication, new technologies and the recent economic recession, those survivors in the trucking industry must be more efficient and definitely stronger (Schulz, 2009).

GHG Emissions and Trucking

Greenhouse gas emissions have been a serious global problem, and policy makers are giving more attention to this environmental issue. California has proposed state regulations to reduce GHG emissions from new vehicles; New York has developed the State Energy Plan; seven other states have set their targets to reduce GHG; and forty-two states and Puerto Rico developed GHG inventories by January 2006 (ICF Consulting, 2006).[4] Forty-four states and Puerto Rico completed inventories by March 2008. Inventories from states are used to develop State Climate Change Action Plans and to implement policies and programs to reduce GHG (EPA, 2009c).

According to the Environmental Protection Agency (EPA, 2009c), the transportation sector is responsible for 28 percent of all GHG emissions in the U.S. in 2006 and 47 percent of the net increase in total GHG emissions between 1990 and 2006. Generally, GHG includes water vapor, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), ozone (O_3), chlorofluorocarbons (CFCs), perfluorocarbons (PFCs) and sulfur

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[4] As of January 2006, the seven states that had set targets to reduce GHG were Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, Rhode Island, and Vermont

hexafluoride (SF_6). Transportation sources emit CO_2, CH_4, N_2O, and hydrochlorofluorocarbons (HFCs). The majority of GHG in the U.S. is CO_2, which contributes to approximately 85.4 percent of the total emission and over 95 percent of transportation emission (EPA, 2009c).

The emissions of GHG from freight transportation are due mostly to fossil fuel combustion. Although some technologies can reduce air pollution (e.g. CO) by achieving a more complete combustion of fuel, no technology is capable of reducing CO_2 emissions. Moreover, even a more complete fuel combustion increases CO_2 emissions. Thus, the single solution to reduce CO_2 by transportation is to reduce fuel consumption. The more fuel efficient a vehicle is, the less fuel it uses, and the less CO_2 it emits.

Under the Clean Air Act (CAA), the EPA is required to address air pollution and set emission standards for air pollutants from motor vehicles. [5] However, the role of GHG as an air pollutant has long been debatable. In 2003, the EPA denied a petition for making rules to regulate GHG emissions from transportation.[6] On April 2, 2007 the U.S. Supreme Court issued a decision in Massachusetts v. EPA, stating that the EPA violated the CAA by not regulating GHG emissions. The U.S. Supreme Court held that GHG emissions were air pollutants under the CCA and should therefore be regulated by the EPA (The Supreme Court, 2007).

The concern for GHG emissions and discussion about addressing this problem with policy tools have been hot-button issues. Emissions tax and tradable permit systems have

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[5] Section 202(a) of the CAA holds: "The Administrator shall by regulation prescribe (and from time to time revise) in accordance with the provisions of this section, standards applicable to the emission of any air pollutant from any class or classes of new motor vehicles or new motor vehicle engines, which in his judgment cause, or contribute to, air pollution which may reasonably be anticipated to endanger public health or welfare."

[6] According to the EPA (2003a), this petition was filed by International Center for Technology Assessment and other organizations.

been proposed. A cap-and-trade system sets the total allowable emissions quantity (cap) and creates permits which are equivalent to unit allowable emissions and can be traded in a market (trade). While the government would capture the value of emissions as tax revenue, regulated industries would obtain the value of emissions in the form of free distributed permits under a cap-and-trade system. The distinction between the two policies is that a tax sets the price for emissions and the quantity of emissions is determined within the regulated industries, while a trade permit system fixes the total quantity of emissions and leaves the price of emissions to the permit market (Keohane, 2009; Murray, Newell and Pizer; 2009).

The American Clean Energy and Security Act of 2009 (ACES), which is also known as the Waxman-Markey climate and energy bill after its sponsors, is an energy bill in the 111th United States Congress (H.R.2454) that aims to establish comprehensive solutions for addressing GHG emission. The bill was passed by the House of Representatives on June 26, 2009 (EPA, 2009g). The bill would create new energy efficiency programs, require the EPA to promulgate GHG standards for new heavy duty vehicles and engines, and put a limit (cap) on the total emissions of GHG nationally; the cap would be decreased over time to reduce total carbon emission gradually. The bill, if passed, would be implemented in 2012 and cover 85 percent of the overall economy. The goals of the cap-and-trade for total GHG emission reductions of all regulated companies based on their 2005 level are to cut emissions by 3 percent by 2012, 17 percent by 2020, 42 percent by 2030, and more than 80 percent by 2050 (Pew Center in Global Climate Change, 2009d).

The bill requires the regulated companies to acquire "emission permits" (also referred to as "carbon credits" or "pollution allowances") to emit GHG, primarily CO_2. If a company reduces its emissions so much that it has more permits than it needs, it can sell excess permits to other companies or save them for future use. On the contrary, if a company uses up its permit and needs more, it has to buy more or borrow its future permits and pay interest. If a company exceeds its permitted emission, it would be fined twice the fair market value of permits. The EPA estimates that a permit to emit one ton of CO_2 or its equivalent would be worth \$11 to \$15 (in 2005 dollars) in 2012. This provides an incentive for companies to reduce GHG emissions. Non-regulated entities would also be allocated permits and could trade permits. Some permits would be distributed to states to establish State Energy and Environmental Development (SEED) Accounts to promote renewable energy and energy efficiency, transportation planning and transmission programs. Almost 80 percent of emission permits would be distributed free at the beginning of the program and about 20 percent of permits would be auctioned off, and the percentage of auction would increase to about 70 percent by 2030 and beyond. The portion of revenue of permits auctioned would be transferred to low and moderate income households by a refundable tax credit or rebate (Congressional Research Service, 2009).

The bill also establishes offset credits as an additional way for companies to comply with the requirement of holding emission credits to emit GHG. As an alternative of emission permits, regulated industries would also purchase offset credits that demonstrate reducing GHG emissions from non-covered sources, like decreasing CO_2 emission by afforestation. The bill limits up to a total of 2 billion tons of offset credits to be used both domestically and internationally (EPA, 2009g).

The counterpart proposal in the Senate is the Clean Energy Jobs and American Power Act of 2009 (also as known as the Kerry-Boxer Climate Bills), which was introduced by Senators John Kerry and Barbara Boxer on September 30, 2009. Another similar bill is the American Power Act introduced in May 2010, and the bill is also known as the Kerry-Lieberman bill after its sponsors (Massachusetts Senator John Kerry's Online Office, 2009).

There are a few minor differences among these three bills. For example, by 2020, the Kerry-Boxer climate bill requires a 20 percent emission reduction from the 2005 emission level, while the Waxman-Markey climate and energy bill and the Kerry-Lieberman bill require a 17 percent reduction based on the 2005 emission level. However, these bills are consistent with each other for the transportation section (EPA, 2009f). These bills seek to amend the Clean Air Act (CAA) to require the EPA to establish GHG emission standards for new heavy-duty vehicles and engines and to expand the SmartWay program to help American trucks to become more fuel efficient and less polluting vehicles. State and local governments are required to submit emission reduction targets and implementation plans to the EPA and to revise them every four years (Congressional Research Service, 2009).

Programs to Control GHG Emissions from Heavy-Duty Trucks

The American Trucking Association (ATA) provides several recommendations to achieve GHG reduction in the trucking industry. First, the ATA recommends regulating trucking speed at no more than 65 miles per hour (mph) since a truck driving at 75 mph consumes 27 percent more fuel than one traveling at 65 mph. Governing speed limits at 65 mph for trucks would save 2.8 billion gallons of diesel fuel in a decade and reduce 31.5 million tons of CO_2 emissions. Furthermore, both non-discretionary and discretionary idling of highway vehicles consume nearly 1.1 billion gallons of diesel fuel each year.[7] The ATA proposes pursuing a federal solution for reducing non-discretionary idling through highway infrastructure improvements and for decreasing discretionary idling by offering incentives for new technology in order to reduce GHG emissions. Improving highway infrastructures and reducing congestion are also important for reducing GHG emissions. The estimation by the ATA reveals that the reduction of GHG emissions would be 45.2 million tons over a decade if all congestion was eliminated in urban areas. Combinations of trucking companies would achieve more productivity and reduce the number of trucks needed in the industry, which means a smaller number of trucks with larger volumes of freight could reduce the fuel usage and CO_2 emissions. Another way to lower emissions and fuel consumption is to improve fuel economy through engineering innovations, driving techniques, aerodynamic features, and lightweight design options. In addition, the ATA recommends that shippers and carriers participate in the EPA SmartWay program (ATA, 2008b).

The SmartWay program is an innovative program whose chief purpose is to reduce diesel emissions and improve fuel efficiency through innovative and cost effective approaches to increase the amount of distance trucks can travel per gallon of fuel. The program involves shippers, truckers, rail carriers, and truck stops in the trucking industry. Technologies verified by the SmartWay program, such as low rolling resistance tires, idle reduction devices and aerodynamic technologies, help reduce GHG. The SmartWay is projected to conserve up to 6.6 billion gallons of diesel fuel per year, which is equivalent to 150 million barrels of oil (ATA, 2008b; EPA, 2009e). According to the EPA (2010a), the

[7] Non-discretionary idling is idling while stuck in congested traffic. Discretionary idling is idling when drivers idle their engines to provide heat or air conditioning.

SmartWay program partners have saved nearly 1.5 billion gallons of diesel fuel and have reduced 14.7 million metric tons of CO_2 and its equivalent since the program launched in 2004.

Recent Legislative Developments

The California Air Resources Board (CARB) in December 2008 developed the heavy-duty greenhouse gas regulations to reduce GHG emissions produced by heavy-duty vehicles through improving fuel efficiency. The regulations are projected to reduce GHG emissions by nearly 1 million metric tons of CO_2 equivalents within the state by 2020. Over the first 11 years from 2010, California estimates that truckers and trucking firms will save approximately $8.6 billion as diesel fuel consumption is reduced by 750 million gallons in California and 5 billion gallons across the nation. All affected vehicles subject to the new regulations must use EPA SmartWay certified vehicles, or retrofit their existing fleet with the SmartWay program verified technologies (California Environmental Protection Agency, 2010).

Southwestern states, including Arizona, New Mexico, Utah, and Colorado have created plans to achieve statewide GHG emission reductions from commercial heavy-duty vehicles between 2005 and 2007. Arizona and New Mexico recommended reducing idling when drivers wait, heat, cool and use electricity, and several technologies, such as fuel operated heaters, battery air conditioning systems, and thermal storage systems for cooling, have been available to meet these needs without idling the truck's large diesel engine. These options are estimated to reduce emissions between 2007 and 2020 by more than 11 million metric tons of CO_2 equivalents and would save fuel costs up to $23 million in New Mexico and up to $260 million in Arizona. Policy makers in the southwestern states also suggest reducing the speed limit for commercial trucks to 60 mph. Other options for reducing emissions from heavy-duty trucks include incentives to retrofit or replace inefficient trucks and create and strengthen the "buy local" program that could reduce GHG emissions associated with the transportation of goods (Abraham, 2009).

Toxic Air Emissions from the Trucking Industry

Heavy-duty trucks not only emit large amounts of GHG emissions, but also emit large quantities of harmful pollutants. As diesel vehicles, heavy-duty trucks emit large amounts of nitrogen oxides (NO_X), particulate matter (PM) and air toxins, which cause serious diseases like lung cancer, asthma, and other cardiac problems and jeopardize public health (EPA, 2009d).

The CAA requires EPA to set national Amebient Air Quality Standards (NAAQS) to reduce toxic pollutants, including CO, NO_2, PM, and SO_2. The EPA designates areas of a state as meeting or not meeting the standards, and the state must develop a general plan to meet and maintain the standards and a specific plan to each area designated not meeting the standards (nonattainment). States not meeting the standards also risk losing federal highway funds (EPA, 2010b; Thornton, Kagan, Gunningham, 2009).

The EPA has adopted several emission standards to reduce diesel emissions from heavy-duty trucks throughout the United States. In October 1997, the EPA scheduled new emission standards for heavy-duty diesel truck engines for model year 2004, which were implemented on schedule, to reduce toxic air pollutants, like NO_X and non-methane hydrocarbons (NMHC). In June 2000, the EPA signed the Clean Diesel Truck and Bus Program of 2001 and set new clean diesel standards for diesel engines to take full effect in 2006. The program also requires refiners to produce diesel fuel with much lower sulfur content.[8] This program is projected to reduce 2.6 million tons of NO_x, 115,000 tons NMHC and 109,000 tons of PM by model year 2030. This is equivalent to reducing 90 percent of particulate matter and 95 percent of NO_x, compared to year 2000 level (EPA, 2000a). The most recent standards of emissions from heavy-duty diesel trucks were set in 2007 and require 2010 model year engines to reduce more than 90 percent toxic air pollutants from 1990 levels.

However, more than 11 million old diesel engines, which do not meet the EPA's new clean diesel standards, are still operating, and their average lifetime is 20 to 30 years. Due to this problem, the EPA established the National Clean Diesel Campaign (NCDC), which regulates diesel engines and promotes diesel emissions reduction devices. Diesel retrofit technology could reduce diesel emissions by decreasing up to 90 percent of particulate matter and 50 percent of NO_X from current diesel engines in use (EPA, 2009e).

[8] The EPA requires refiners to reduce the sulfur content of highway diesel fuel by 97 percent.

CHAPTER 3. REVIEW OF METHODOLOGY

Traditional Efficiency Measures

Modern efficiency measures began from Farrell (1957), who defined efficiency of a firm in terms of technical efficiency and allocative efficiency. Technical efficiency measures the maximum possible output level for a given input level, and allocative efficiency reflects the optimal input usage at given input prices and production technology.

Using radial efficiency measurement, Farrell (1957) calculated the technical efficiency by the distance from the origin to a production frontier over the distance from the origin to the measured observation. There are two ways to gauge the efficiency of a firm: an input-oriented measure and an output-oriented measure.

Following Farrell (1957), the difference between output-oriented and input-oriented measures can be described in one simple graph with a single input (x) and a single output (y) in Figure 3.1.

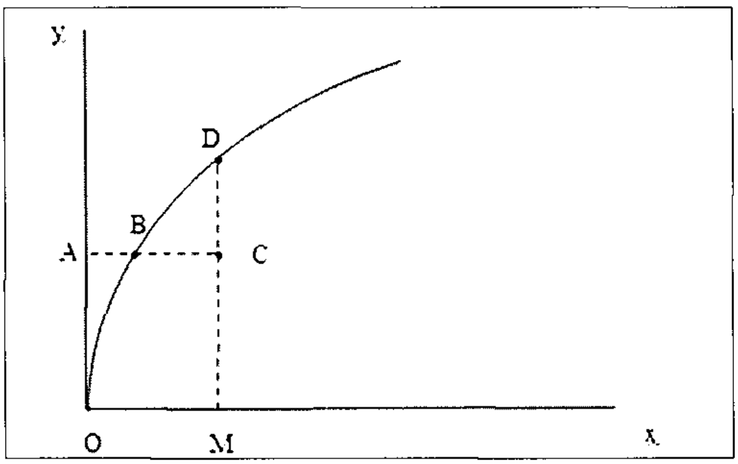

Figure 3.1. Output-Oriented and Input-Oriented Technical Efficiency Measures

In Figure 3.1, output-oriented measure of technical efficiency for the firm operating at point C is defined by TE_o=MD/MC. Input-oriented measure of technical efficiency at point C is defined by TE_i=AB/AC.

Output-Oriented and Input-Oriented Measurements

An output-oriented efficiency measurement is illustrated in Figure 3.2, which assumes a given firm produces two outputs (y_1 and y_2) with one input (x) under constant returns to scale (CRS) technology. The production possibility frontier is represented by MM′, all points on this curve are technically efficient, and point S is an inefficient firm. AA′ represents the isorevenue, and its slope reflects the output price ratio.

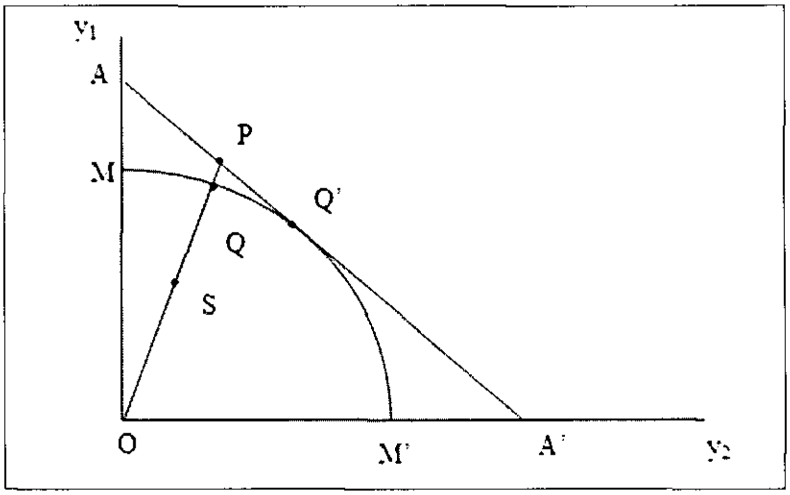

Figure 3.2. Output-Oriented Efficiencies

According to Farrell (1957), output-oriented technical efficiency (TE) is measured by TE_o=OQ/OS. The distance SQ reflects the amount of the outputs that could be increased without additional input. Allocative efficiency (AE) is defined by AE=OP/OQ. The distance PQ reflects the amount of output revenue that could be expanded if the firm is allocatively efficient. Both values of TE and AE are greater than or equal to one.

Alternatively, input-oriented efficiency measures the input that could be proportionally decreased at a given output level. Assuming two inputs (x_1, x_2) are used to produce output (y) under CRS, the details of an input-orientated measurement are illustrated in Figure 3.3. Point S represents the quantities of the two inputs used by a given firm. The curve MM' is the isoquant. AA' represents the isocost, and its slope reflects the input price ratio.

Technical efficiency of a given firm at S is measured by TE=OQ/OS. The distance QS reflects the amount of inputs that could be shrunk proportionally without reducing output, and if the ratio value equals to one, the firm is technically efficient. Allocative efficiency is defined by AE=OP/OQ. The distance of PQ reflects the production costs that could be reduced if a firm is both technically and allocatively efficient. Both values of TE and AE are between zero and one.

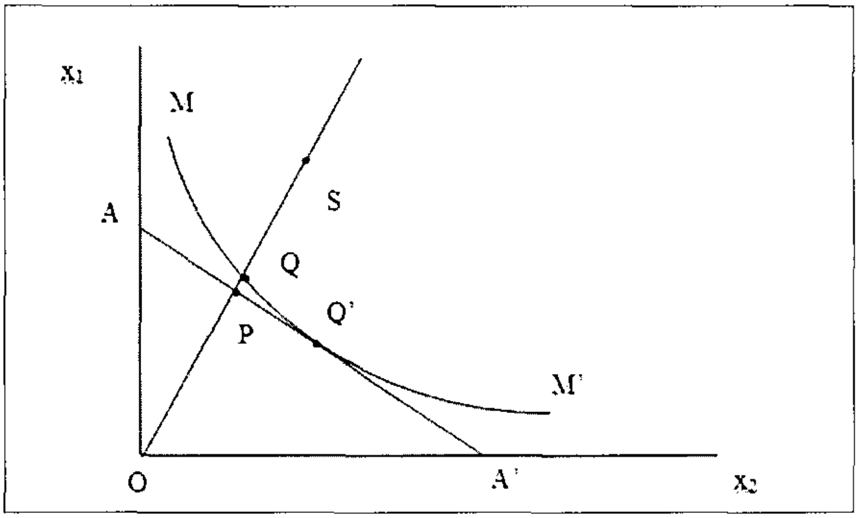

Figure 3.3. Input-Oriented Efficiencies

Scale Efficiency

Another important concept related to efficiency is scale efficiency. If a firm's production exhibits variable returns to scale (VRS) technology, it is possible for this firm to be both technically and allocatively efficient, but not scale efficient. Scale inefficiency indicates that the firm may improve its efficiency by changing its operating scale, and the inefficiency is the amount of productivity that can be increased if a firm is operating at the most productive scale size. The point of scale efficiency is where technical efficiency under

CRS is equal to that under VRS. In Figure 3.4, a simple case with a single input (x) and a single output (y) is used to illustrate scale efficiency. The firms at points A, B, and C are all on the production possibility frontier NN' and have achieved technical efficiency, but their productivities, which can be represented by the slope of a ray from the origin through the firm point, are different. OM is a CRS frontier, and NN' is a VRS frontier. The most productive scale is represented by point B, where a firm cannot increase its production by changing its scale.

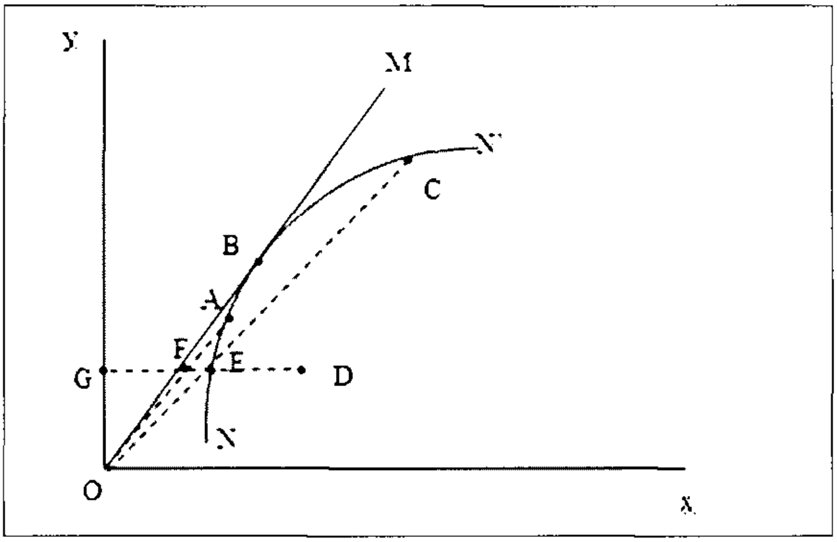

Figure 3.4. Scale Efficiency

The firm at point D is neither technically nor allocatively efficient. The technical efficiency of firm D under VRS is obtained by TE_{VRS}= GE/GD. The technical efficiency of firm D under CRS is defined as TE_{CRS}= GF/GD. Thus, the ratio of these two measures of technical efficiency is the scale efficiency score, which can be calculated by SE = TE_{CRS} /TE_{VRS} = GF/GE

Distance Function

Coelli *et al.* (2005) maintained that the Farrell's input- and output-oriented technical efficiency measurements are equivalent to input and output distance functions developed by Shephard (1953). Distance functions have been widely used to measure productivity and efficiency. The output distance function measures the amount of outputs to be increased to reach the production frontier for a firm, and input distance function reflects the minimal input vector for a given output level. The Shephard's output distance function can be defined as:

$$d_o(\mathbf{x}, \mathbf{y}) = \min\left\{\delta: \left(\frac{\mathbf{y}}{\delta}\right) \in P(\mathbf{x})\right\}, \tag{3.1}$$

where P(**x**) represents the output set of output vector **y** which can be produced by the input vector **x**.

Output distance function $d_0(\mathbf{x}, \mathbf{y})$ has several properties: zero inputs generate zero outputs; **y** is non-decreasing and convex; **x** is non-increasing and quasi-convex; **y** is homogenous of degree one; $d_0(\mathbf{x}, \mathbf{y}) \leq 1$, and it equals to one when the outputs are on the production possibility frontier. Figure 3.5 shows the details using an example including two outputs (y_1, y_2) at a given input vector **x**. The production possibility set, P(**x**), is represented by the area bounded by production possibility frontier AA′.

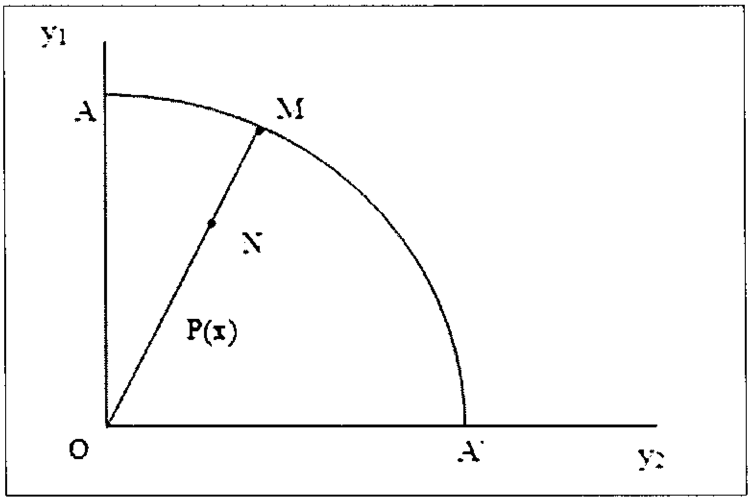

Figure 3.5. Output Distance Function

A given technically inefficient firm is reflected by point N under the production possibility frontier. The output distance function value of firm N can be calculated by δ= ON/OM. Point M, which is on the production possibility frontier, has a distance function value equal to 1.

Farrell's output oriented technical efficiency measure can be represented by Shephard's output distance function as: $F_o(\mathbf{x}, \mathbf{y}) = \max\{\varphi: \varphi \mathbf{y} \in P(\mathbf{x})\}$. The duality shows that $F_o(\mathbf{x}, \mathbf{y}) = 1/d_0(\mathbf{x}, \mathbf{y})$. A firm is technically efficient when the value of output distance function is equal to 1.

Alternatively, the input distance function is defined by Shephard as:

$$d_i(\mathbf{x}, \mathbf{y}) = \max\left\{\rho: \left(\frac{\mathbf{x}}{\rho}\right) \in L(\mathbf{y})\right\}, \tag{3.2}$$

where the input set $L(\mathbf{y})$ represents all the input vectors $\mathbf{x}$ used to produce $\mathbf{y}$.

Input distance function $d_i(\mathbf{x}, \mathbf{y})$ has a few properties: $\mathbf{y}$ is non-increasing and quasi-concave; $\mathbf{x}$ is non-decreasing and concave; $\mathbf{x}$ is homogenous of degree one; $1 \leq d_i(\mathbf{x}, \mathbf{y}) < \infty$, and it equals one when the inputs are on the isoquant.

In Figure 3.6, two inputs (x_1, x_2) are used to produce an output vector ($\mathbf{y}$). The isoquant is represented by curve AA′. Point M reflects a given technically inefficient firm. The input distance function of firm M can be calculated by ρ= OM/ON. Point N is on the frontier of the isoquant, and its value of distance function equals 1. Under CRS, the output distance function is the reciprocal of the input distance function for all $\mathbf{x}$ and $\mathbf{y}$.

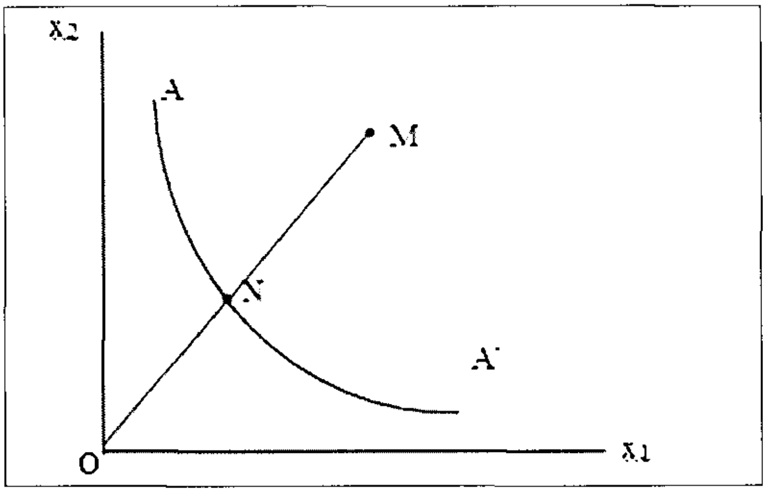

Figure 3.6. The Input Distance Function

Farrell's input-oriented measure of technical efficiency can be expressed by the Shephard's input distance function as: $F_i(\mathbf{x}, \mathbf{y}) = \min \{\theta, \theta\mathbf{x} \in L(\mathbf{y})\}$. The duality shows that $F_i(\mathbf{x}, \mathbf{y}) = 1/ d_i(\mathbf{x}, \mathbf{y})$. Technical efficiency is achieved when the distance function is equal to 1 and leads to a technical efficiency score of 1. Also, following Färe, Grosskopf and Roos (1998), the scale efficiency can be defined by distance function as:

$$SE = \frac{d_i(\mathbf{x}, \mathbf{y}|VRS)}{d_i(\mathbf{x}, \mathbf{y}|CRS)}. \tag{3.3}$$

Data Envelopment Analysis

Data envelopment analysis (DEA) is a piecewise linear programming approach to construct a non-parametric frontier, and efficiency of units could be measured based on the frontier.

Suppose there are M outputs ($\mathbf{y}$) and N inputs ($\mathbf{x}$) for each of i=(1,...,I) firms, consider an efficiency measure by a ratio $\boldsymbol{\mu}'\mathbf{y}_i/\mathbf{v}'\mathbf{x}_i$, where $\boldsymbol{\mu}$ is an M×1 vector of output weights and $\mathbf{v}$ is an N×1vector of input weights. The optimal weights $\boldsymbol{\mu}$ and $\mathbf{v}$ can be obtained by solving the following mathematical programming problem:

$$\text{Max}_{\mu,v} \ (\boldsymbol{\mu}'\mathbf{y}_i/\mathbf{v}'\mathbf{x}_i),$$

$$\text{s.t. } \boldsymbol{\mu}'\mathbf{y}_i / \mathbf{v}'\mathbf{x}_i \le 1,$$

$$\boldsymbol{\mu}, \mathbf{v} \ge 0 . \tag{3.4}$$

The programming problem (3.4) maximizes the efficiency of firm i, subject to the constraints that all efficiency measures must be less than or equal to one. One problem of the ratio form is that it has an infinite number of solutions, that is, if ($\boldsymbol{\mu}^*$, $\mathbf{v}^*$) is a solution, then ($\alpha\boldsymbol{\mu}^*$, $\alpha\mathbf{v}^*$) is another solution. One way to avoid this is to impose the constraint $\mathbf{v}'\mathbf{x}_i$ =1, which allows the model to be rewritten as:

$$\text{Max}_{\mu,\nu}\ (\mathbf{u}'\mathbf{y}_i),$$

$$\text{s.t. } \mathbf{v}'\mathbf{x}_i = 1,$$

$$\mathbf{u}'\mathbf{y}_i - \mathbf{v}'\mathbf{x}_i \le 0,$$

$$\mathbf{u}, \mathbf{v} \ge 0 . \tag{3.5}$$

The form of the DEA model (3.5) is called the multiplier form. The duality of (3.5) can be derived in an equivalent envelopment form of this linear programming problem:

$$\text{Max}_{\theta,\lambda}\ \theta$$

$$\text{s.t.} - \mathbf{y}_i + \mathbf{Y}\boldsymbol{\lambda} \ge 0,$$

$$\theta\mathbf{x}_i - \mathbf{X}\boldsymbol{\lambda} \ge 0,$$

$$\boldsymbol{\lambda} \ge 0, \tag{3.6}$$

where θ is a scalar, which presents the firm's efficiency score, and $0< \theta \le 1$; $\boldsymbol{\lambda}$ is a $I\times 1$ vector of constants; $\mathbf{Y}$ is an $M\times I$ output matrix and $\mathbf{X}$ is an $N\times I$ input matrix for all I firms. The linear programming problem (3.6) is an input-oriented DEA model.

Under CRS technology, all firms are operating at the optimal scale; otherwise, it is necessary to take VRS into consideration. The DEA model with CRS production technology can be adjusted to account for VRS production technology by imposing the constraint $\mathbf{I1}'\lambda = 1$ and rewriting (3.6) as:

$$\mathrm{Min}_{\theta,\lambda}\ \theta$$

$$\mathrm{s.t.} -\mathbf{y_i} + \mathbf{Y}\lambda \geq 0,,$$

$$\theta\mathbf{x_i} - \mathbf{X}\lambda \geq 0,$$

$$\mathbf{I1}'\lambda = 1$$

$$\lambda \geq 0, \tag{3.7}$$

where $\mathbf{I1}$ is an $I\times 1$ vector of ones. This approach provides a tighter envelopment of the data than does the CRS model.

Alternatively, the output-oriented DEA models are very similar to the input-oriented DEA models. Consider the output-oriented DEA model under VRS as following:

$$\mathrm{Max}_{\varphi,\lambda}\ \varphi,$$

$$\mathrm{s.t.} -\varphi\mathbf{y_i} + \mathbf{Y}\lambda \geq 0,$$

$$\mathbf{x_i} - \mathbf{X}\lambda \geq 0,$$

$$\mathbf{I1}'\lambda = 1,$$

$$\lambda \geq 0, \tag{3.8}$$

where φ is a scalar, and $1\leq \varphi<\infty$. Under CRS, $\theta = 1/\varphi$.

The DEA models discussed so far are based on the assumption that inputs and outputs are strongly disposable. This implies that firms can discard unwanted inputs or outputs without costs. If this is not true, some segments of the piece-wise linear frontier constructed by DEA would have a positive slope, as illustrated *in* Figure 3.7. The isoquant frontier MM′ reflects the assumption of strong disposability and the curve AM′ assumes weak disposability of x_1. The segment AP bends back and positive slopes.

Similarly, the production possibility frontier NN′ assumes strong disposability while curve BN′ assumes weak disposability of y_2 in Figure 3.8. The latter has a positively sloped segment BQ.

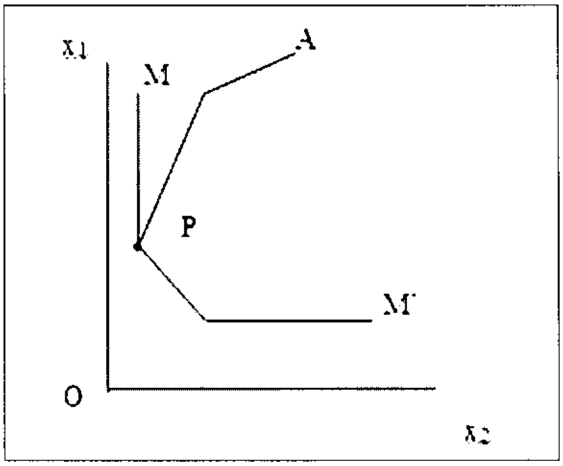

Figure 3.7. Input Disposability

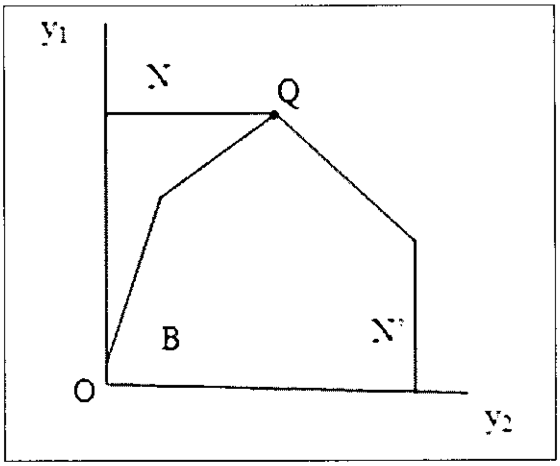

Figure 3.8. Output Disposability

Traditional Productivity Measures

Productivity represents a firm's performance and can be measured by a ratio of outputs produced over inputs consumed. A simple measurement for productivity is profitability ratios, which are defined as revenue over input cost. For example, one firm produces single output y with price p produced by single input x with price w, the profitability ratio is given by $\pi = \frac{py}{wx}$.

However, the measure of the productivity in the case involving multiple inputs and outputs is much more complicated. It is not appropriate to sum up all the outputs and inputs to form an output quantity and input quantity. To solve this problem, disaggregated data on the quantity of outputs and inputs are usually weighted by output and input prices to form output and input quantity indexes. Thus, multiple inputs and outputs have to be adjusted by input and output price indexes instead of being adjusted by a simple price ratio.

For multiple outputs and inputs across firms or over time, the total factor productivity (TFP) is commonly used, which can be defined as a ratio of aggregate outputs to aggregate inputs. The change in TFP is the change of total outputs relative to the change of total inputs:

$$\mathrm{TFP} = \frac{y^t/y^s}{x^t/x^s}\ , \tag{3.9}$$

where the superscripts t and s represent the associated quantities of output and input in period t and period s, respectively.

Laspeyres and Paasche Index Numbers

Denote p_{mj} and y_{mj} as the price and quantity of the m-th output (m=1,2,...,M), w_{nj} and x_{nj} as the price and quantity of the n-th input (n=1,2,...,N), in j-th period (j=s, t). Period s represents the base period, period t represents the current period.

The Laspeyres quantity index employs previous period prices as the base, and it is represented by the ratio of aggregate values of base period prices at current and base period quantities:

$$\text{Laspeyres output quantity index} = Q_{OL}^{st} = \frac{\sum_m^M p_m^s y_m^t}{\sum_m^M p_m^s y_m^s}\ . \tag{3.10}$$

$$\text{Laspeyres input quantity index} = Q_{IL}^{st} = \frac{\sum_n^N w_n^s x_n^t}{\sum_n^M w_n^s x_n^s}\ . \tag{3.11}$$

The Passche index is an alternative to Laspeyres index, and it uses the current period as the base. Passche quantity index employs current period prices as the base and is measured by the ratio of aggregate values of current-period prices at current- and base-period quantities:

$$\text{Passche output quantity index} = Q_{OP}^{st} = \frac{\sum_m^M p_m^t y_m^t}{\sum_m^M p_m^t y_m^s}\ . \tag{3.12}$$

$$\text{Passche input quantity index} = Q_{IP}^{st} = \frac{\sum_n^N w_n^t x_n^t}{\sum_n^M w_n^t x_n^s}. \tag{3.13}$$

The Laspeyres and Passche indexes are widely applied in practice since they are easy to calculate. But a clear drawback of the two indexes is that one must arbitrarily choose between two time periods as the base.

Fisher Index Number

The Fisher index is defined by the geometric mean of the Laspeyres and Passche indexes (Fisher, 1922). The Fisher quantity index is defined as:

$$\text{Fisher quantity index} = Q_F^{st} = \sqrt{Q_P^{st} \times Q_L^{st}}. \tag{3.14}$$

Diewert (1992) recommends using the Fisher index since it satisfies many more tests (axioms) than its competitors. Some basic axioms include positivity, which implies that the index should be positive; proportionality, which requires that if all quantities increase or decrease by the same proportion, the index should increase or decrease by the same proportion; time-reversal test, which implies that for periods s and t, the index going from period s to period t is the inverse of the index going from period t to period s; and factor-reversal test, which indicates that if interchange the factors (price and quantity) in a price index formula to obtain a quantity index of exactly the same functional form, the product of the indexes should equal the ratio of values of the aggregate.

The Fisher index satisfies all the four tests above, while both Laspeyres and Paasche indexes fail the time-reversal test, and the Törnqvist index fails factor-reversal test. The Fisher is also known as the ideal index. [9]

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[9] The Fisher ideal index satisfies the all tests except circularity test, which requires an index should be independent of a choice of a third period.

The Törnqvist Index

The Törnqvist index is another popular index that has been applied in many total factor productivity studies. The Törnqvist quantity index is the weighted geometric average of a relative quantity ratio, with the weight of simple average of the value shares in periods s and t. The Törnqvist output quantity index is given by:

$$\text{Törnqvist output quantity index} = Q_{OT}^{st} = \prod_{m=1}^{M} \left[\frac{y_m^t}{y_m^s}\right]^{\frac{\omega_m^s+\omega_m^t}{2}}, \tag{3.15}$$

where ω_{ms} is the value share of m-th output in period s, and $\omega_m^s = \frac{p_m^s y_m^s}{\sum_{m=1}^{M} p_m^s y_m^s}$, while ω_{mt} is the value share of m-th output in period t, and it is defined as $\omega_m^t = \frac{p_m^t y_m^t}{\sum_{m=1}^{M} p_m^t y_m^t}$.

Similarly, the Törnqvist input quantity index is given by:

$$\text{Törnqvist iutput quantity index} = Q_{st}^{IT} = \prod_{n=1}^{N} \left[\frac{x_n^t}{x_n^x}\right]^{\frac{\omega_n^s+\omega_n^t}{2}}, \tag{3.16}$$

where ω_{ns} is the value share of n-th input in period s, and $\omega_n^s = \frac{w_n^s x_n^s}{\sum_{n=1}^{N} w_n^s x_n^s}$, while ω_{nt} is the value share of n-th input in period t, and it is defined as $\omega_n^t = \frac{w_n^t x_n^t}{\sum_{n=1}^{N} w_n^t x_n^t}$.

The log-change form of the Törnqvist quantity index is generally applied since it is convenient for computation. The logarithmic of the Törnqvist output quantity index is defined as:

$$\ln Q_{OT}^{st} = \sum_{m=1}^{M} \left(\frac{\omega_m^s + \omega_m^t}{2}\right) [\ln y_m^t - \ln y_m^s]. \tag{3.17}$$

Similarly, the logarithmic of Törnqvist input quantity index is defined as:

$$\ln Q_{IT}^{st} = \sum_{n=1}^{N} \left(\frac{\omega_n^s + \omega_n^t}{2}\right) [\ln x_n^t - \ln x_n^s]. \tag{3.18}$$

Diewert (1992) showed that the Törnqvist index also provides proper approximations to the actual quantities of output and input as the Fisher index, and both of the two indexes yield very close results in defining the TFP index.[10]

Malmquist Index

Malmquist index was proposed by Sten Malmquist, and was applied popularly after introduced by Caves, Christensen and Diewert (1982b). Malmquist index accommodates multiple outputs and inputs, and it does not require price information. It is preferred to the Fisher and Törnqvist indexes when price information is not available.

The output-oriented Malmquist productivity index in period s under constant returns to scale technology can be calculated using the output distance functions based on period s reference technology as:

$$M_o^s(\mathbf{y}^s, \mathbf{y}^t, \mathbf{x}^s, \mathbf{x}^t) = \frac{d_o^s(\mathbf{y}^t, \mathbf{x}^t)}{d_o^s(\mathbf{y}^s, \mathbf{x}^s)}, \tag{3.19}$$

where $d_o^s(\mathbf{y}^t, \mathbf{x}^t)$ is a mixed-period distance function and thus may yield a value greater than, equal to, or less than one.

Similarly, the output-oriented Malmquist productivity index in period t under constant returns to scale technology as:

$$M_o^t(\mathbf{y}^s, \mathbf{y}^t, \mathbf{x}^s, \mathbf{x}^t) = \frac{d_o^t(\mathbf{y}^t, \mathbf{x}^t)}{d_o^t(\mathbf{y}^s, \mathbf{x}^s)}. \tag{3.20}$$

As the output-oriented Malmquist productivity index can use either period-s technology or period-t technology as the benchmark technology, one could define the

[10] The Törnqvist formula satisfies 12 of Diewert's (1992) desirable tests but fails the circularity test and time-reversal test. Diewert (1978) showed that only small differences exist between the Fisher and Törnqvist indexes.

Malmquist TFP index as the geometric mean of the two indexes based on period s and period t, which is given by:

$$M_o(y^s, y^t, x^s, x^t) = [M_o^s(y^s, y^t, x^s, x^t) \times M_o^t(y^s, y^t, x^s, x^t)]^{0.5}$$
$$= \left[\frac{d_o^s(y^t, x^t)}{d_o^s(y^s, x^s)} \times \frac{d_o^t(y^t, x^t)}{d_o^t(y^s, x^s)}\right]^{0.5}. \qquad (3.21)$$

If the value of the Malmquist measure is greater than one, it indicates productivity improvement, while a value less than one indicates a decrease in productivity.

According to Caves, Christensen and Diewert (1982b), under the assumptions of CRS technology and technical and allocative efficiency of the firm in both period s and period t, the Malmquist TFP index can be approximately computed as a ratio of a Törnqvist output index over a Törnqvist input index, which is given by:

$$M_o(y^s, y^t, x^s, x^t) = [M_o^s(y^s, y^t, x^s, x^t) \times M_o^t(y^s, y^t, x^s, x^t)]^{0.5}$$
$$= \frac{\text{Törnqvist output index}}{\text{Törnqvist input index}}. \qquad (3.22)$$

The Malmquist index which is defined as the geometric mean of distance functions based on current- and base- period technologies can be rearranged and defined in terms of the product of a technical change index and a technical efficiency change index under CRS. The output-oriented Malmquist quantity index can be rewritten as:

$$M_o(y^s, y^t, x^s, x^t) = \frac{d_o^t(y^t, x^t)}{d_o^s(y^s, x^s)}\left[\frac{d_o^s(y^t, x^t)}{d_o^t(y^t, x^t)} \times \frac{d_o^s(y^s, x^s)}{d_o^t(y^s, x^s)}\right]^{0.5} \qquad (3.23)$$

where the term $\frac{d_o^t(y^t,x^t)}{d_o^s(y^s,x^s)}$ is technical efficiency change and the term $\left[\frac{d_o^s(y^t,x^t)}{d_o^t(y^t,x^t)} \times \frac{d_o^s(y^s,x^s)}{d_o^t(y^s,x^s)}\right]^{0.5}$ represents technical change.

Technical efficiency change (EFFCH) measures the change in technical efficiency between the two periods, while the technical change (TECH) measures the geometric mean of the shifts in the production possibility frontier. This decomposition is illustrated in Figure 3.9 with a single input (x) and one single output (y) under CRS technology.

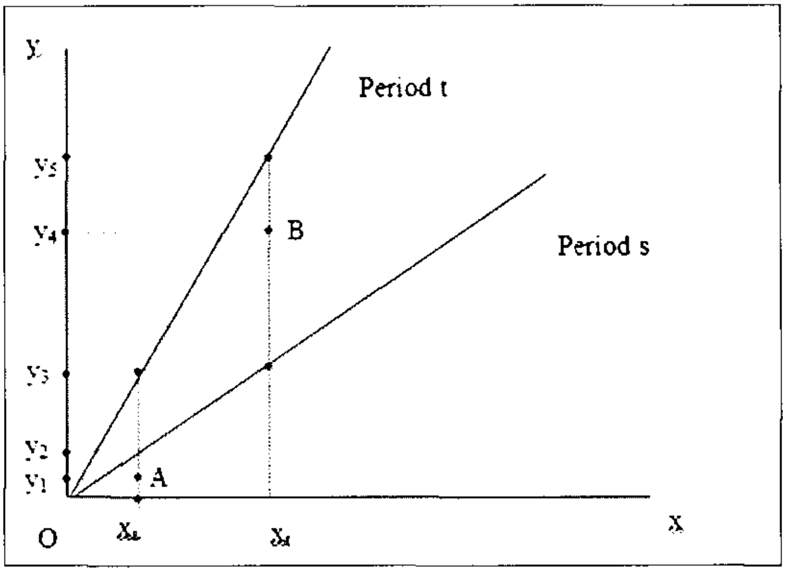

Figure 3.9. Technical Efficiency Change and Technical Change

A firm operates at point A in period s and at point B in period t. In each period, the firm is technically inefficient since point A and point B are both under the frontier which indicates technical efficiency for that period. Hence, the ratio $\frac{y_4/y_5}{y_1/y_2}$ represents the technical efficiency change for the firm between two periods. The technical change can be represented by $\left[\frac{y_4/y_3}{y_4/y_5} \times \frac{y_1/y_2}{y_1/y_3}\right]^{0.5}$.

If suitable panel data are available, the distance functions in equation (3.22) can be calculated by DEA-like linear programs. Following Färe *et al.* (1994), for the i-th firm, four distance functions are calculated using Farrell output-oriented technical efficiencies under CRS technology in their TFP measurements:

$$[d_o^t(\mathbf{y}^t, \mathbf{x}^t)]^{-1} = \max_{\varphi,\lambda}, \varphi$$

$$\text{s.t.} \ -\varphi \mathbf{y}_i^t + \mathbf{Y}^t \lambda \geq 0,$$

$$\mathbf{x}_i^t - \mathbf{X}^t \lambda \geq 0,$$

$$\lambda \geq 0, \tag{3.24}$$

$$[d_o^s(\mathbf{y}^s, \mathbf{x}^s)]^{-1} = \max_{\varphi,\lambda}, \varphi$$

$$\text{s.t.} \ -\varphi \mathbf{y}_i^s + \mathbf{Y}^s \lambda \geq 0,$$

$$\mathbf{x}_i^s - \mathbf{X}^s \lambda \geq 0,$$

$$\lambda \geq 0, \tag{3.25}$$

$$[d_o^t(\mathbf{y}^s, \mathbf{x}^s)]^{-1} = \max_{\varphi,\lambda}, \varphi$$

$$\text{s.t.} \ -\varphi \mathbf{y}_i^s + \mathbf{Y}^t \lambda \geq 0,$$

$$\mathbf{x}_i^s - \mathbf{X}^t \lambda \geq 0,$$

$$\lambda \geq 0, \tag{3.26}$$

and

$$[d_o^s(\mathbf{y}^t, \mathbf{x}^t)]^{-1} = \max_{\varphi,\lambda}, \varphi$$

$$\text{s.t.} \ -\varphi \mathbf{y}_i^t + \mathbf{Y}^s \lambda \geq 0,$$

$$\mathbf{x}_i^t - \mathbf{X}^s \lambda \geq 0,$$

$$\lambda \geq 0. \tag{3.27}$$

As equations (3.26) and (3.27) measuring mix-period distance function, the φ value may yield greater than, equal to, or less than one.

Accounting for Bad Outputs in Efficiency and Productivity Measures

Caves, Christensen and Diewert (1982b) derived multilateral superlative indexes for comparisons of outputs, inputs, and productivity across firms. Pittman (1983) pointed out that if undesirable outputs are produced with desirable output, desirable and undesirable outputs should be treated asymmetrically. When evaluating the performance of firms or industries, it makes sense to credit them for increased production of goods and reduction of undesirable outputs, such as air and water pollution. However, traditional productivity measures focus on desirable outputs but ignore undesirable outputs because bad outputs, such as pollution, usually do not have marketable prices. To address this problem, Pittman (1983) provided an enhanced multi-factor productivity index and constructed shadow prices for undesirable outputs from profit maximizing with exogenous constraints on the amount of undesirable outputs. However, Pittman (1983) noted that assigning shadow prices to undesirable output was difficult because the estimations of shadow prices were based on exogenous information of bads abatement costs from other studies and were likely to be subject to a wide range of errors.

Färe *et al.* (1989) modified Farrell (1957)'s traditional technical efficiency measures to allow asymmetrical treatments of desirable and undesirable outputs. Färe *et al.* (1989) used a non-parametric non-linear programming approach which only requires data on quantities and avoids shadow price estimations. Undesirable outputs were assumed to be weakly disposable rather than strongly disposable. Weak disposability implies that undesirable outputs cannot be disposed of without costs, while strong disposability implies that undesirable outputs can be disposed of for free. The weak disposability assumption is consistent with the fact that desirable and undesirable outputs are always produced jointly, and the reduction of undesirable outputs could cause a reduction of desirable outputs simultaneously. Färe *et al.* (1993) derived the negative shadow prices by Shephard's Lemma. Shadow prices reflect the opportunity cost of regulation and abatement activities faced by firms. This enables firms to measure whether it is optimal to pollute under environmental regulations.

Using the directional distance function, Chung, Färe and Grosskopf (1997) developed the Malmquist-Luenberger productivity index to incorporate both desirable and undesirable outputs in efficiency and productivity measurements. Weber and Domazlicky (1999) and Färe, Grosskopf and Pasurka (2001) applied the directional output distance function to measure how pollution influenced productivity growth in manufacturing. Domazlicky and Weber (2004) used this approach to account for toxic chemic releases in measuring chemical industry's productive efficiency. Färe *et al.* (2004) employed the directional output distance function to measure technical efficiency in electric utilities that produce electricity and SO_2. This model was used in transportation by Weber and Weber (2004) to measure state trucking producing accounting for traffic fatalities as an undesirable output. Pathomsiri *et al.* (2007) employed this model to study the impact of delays on airport productivity.

CHAPTER 4. METHODOLOGY AND DATA

Methodology

Following Chung, Färe and Grosskopf (1997), I denote desirable outputs as $\mathbf{y} \in R_{+}^{M}$, the undesirable outputs as $\mathbf{b} \in R_{+}^{K}$, and the inputs as $\mathbf{x} \in R_{+}^{N}$. The technology can be described by output sets:

$$P(\mathbf{x})=\{(\mathbf{y}, \mathbf{b}): \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{b})\}. \tag{4.1}$$

This means that input vector **x** produces the combinations of desirable and undesirable outputs (**y**, **b**). The technology is required to satisfy the following axioms:

$$\{0\} \in P(0). \tag{4.2a}$$

$$P(\mathbf{x}) \text{ is compact.} \tag{4.2b}$$

$$P(\mathbf{x}') \supseteq P(\mathbf{x}) \text{ if } \mathbf{x}' \geq \mathbf{x}. \tag{4.2c}$$

Axiom (4.2a) implies that null input vector yields zero output; (4.2b) implies that finite inputs can only produce finite outputs; (4.2c) implies that all inputs are strongly disposable and that an increase in inputs cannot lead to a reduction in outputs.

In addition to the above axioms, I assume that bad outputs are weakly disposable and good outputs and bad outputs are together weakly disposable, which indicates that bad outputs cannot be reduced without reducing good outputs in a single period, that is:

$$(\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \text{ and } 0 \leq \theta \leq 1 \text{ imply } (\theta\mathbf{y}, \theta\mathbf{b}) \in P(\mathbf{x}), \tag{4.3}$$

This means that proportional reductions in (**y**, **b**) are possible with no change in **x**.
In addition, desirable outputs (**y**) are strong disposable, which means desirable outputs can be reduced without reducing undesirable outputs in a single period, that is:

$$(\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \text{ and } \mathbf{y}' \leq \mathbf{y} \text{ imply } (\mathbf{y}', \mathbf{b}) \in P(\mathbf{x}). \tag{4.4}$$

Equations (4.3) and (4.4) represent the asymmetry between desirable and undesirable outputs.

Finally, the assumption of null-jointness between goods and bads is imposed. This means that no desirable outputs can be produced unless undesirable outputs are also produced in a single period. The null-jointness is defined as:

$$(\mathbf{y}, \mathbf{b}) \in \mathrm{P}(\mathbf{x}) \text{ and } \mathbf{b} = 0 \text{ then } \mathbf{y} = 0. \quad (4.5)$$

However, desirable outputs could be increased while undesirable outputs are decreased over time due to production possibility frontier shift.

Chambers and Pope (1996) proposed the directional distance function is given by:

$$\overrightarrow{\mathrm{d_o}}(\mathbf{x}, \mathbf{y}, \mathbf{b};\ \mathbf{g}) = \max\{\beta\colon (\mathbf{y}, \mathbf{b}) + \beta\mathbf{g} \in \mathrm{P}(\mathbf{x})\}, \quad (4.6)$$

where $\mathbf{g}=(\mathbf{g_y}, -\mathbf{g_b})$ is a vector of directions, and desirable outputs are expanded in the $\mathbf{g_y}$ direction, and undesirable outputs are contracted in the $-\mathbf{g_b}$ direction. In this case, let $\mathbf{g}= (\mathbf{y},-\mathbf{b})$, which means the projected direction depends on individual trucking's good output as well as bad outputs. The maximum feasible proportion for desirable outputs expansion and undesirable outputs contraction is represented by β.

In Figure 4.1, reference technology $P_W(x)$ assumes weak disposability for **b** and its production frontier is OABCD. Producers A, B, C, and D are on the production possibility frontier, therefore, they are efficient. Producer E is below the frontier and operates inefficiently. On the contrary, reference technology $P_S(x)$ assumes strong disposability for bad; its frontier is OKBCD. The area OKBA reflects the possible production which is feasible under strong disposability of both outputs but not feasible when undesirable output is weak disposable. The product set $P_W(x)$ satisfies all the assumptions (4.2)-(4.5) that the segment OAB with positive slope reflects weak disposability of undesirable output, and

$P_W(x)$ begins from the origin reflects that desirable output is "null-joint" with undesirable output, which means the only method to produce no bad outputs is to produce no good outputs. I distinguish the traditional output distance function and the directional output distance function in Figure 4.1. Assuming strong disposability of both **y** and **b**, the technical efficiency of E is based on the Shephard's output distance function and calculated by the ratio OE/OL. That is, if both desirable and undesirable outputs expand by the factor OE/OL, the state could move to point L on the frontier and be technically efficient. However, it is not credible to improve efficiency by producing more bads. Alternatively, if bad outputs are weakly disposable, using a directional distance function, the technical efficiency can be defined as EH/Og. This means that the state would improve its efficiency and move in the direction **g** to point H on the frontier by increasing desirable output while decreasing undesirable output.

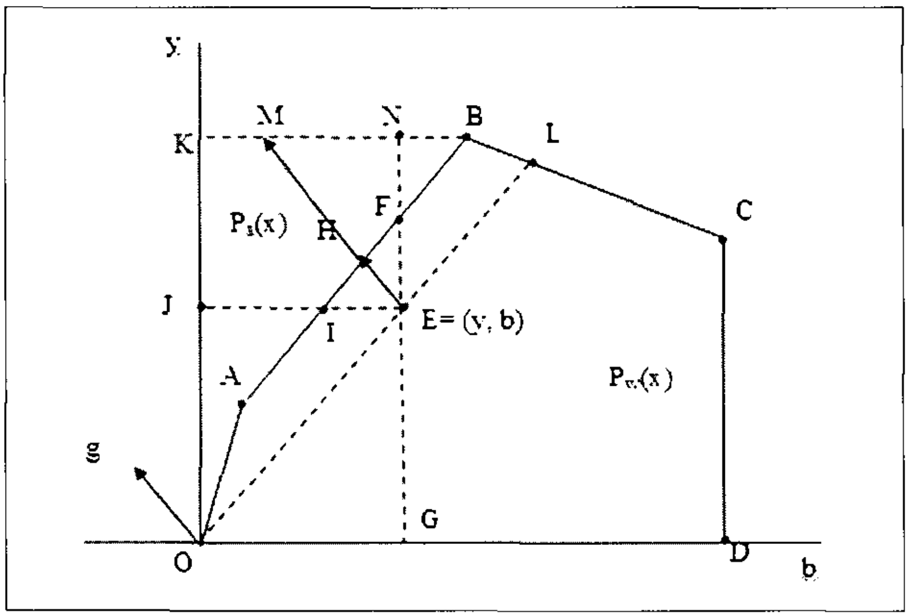

Figure 4.1. Directional Distance Function

To show the relation of the directional output distance function and Shephard's output distance function, let **g**=(**y**, **b**). Chung, Färe and Grosskopf (1997) showed that:

$$\overrightarrow{\mathrm{d_o}}(\mathbf{x},\mathbf{y},\mathbf{b};\mathbf{g}) = \frac{1}{\mathrm{d_o}(\mathbf{x},\mathbf{y},\mathbf{b})} - 1. \tag{4.7}$$

Based on directional distance functions, Chung, Färe and Grosskopf (1997) calculated the Malmquist- Luenberger (ML) productivity index. Let periods s and t represent the base period and the current period, respectively. The ML index is

$$\mathrm{ML_o}(\mathbf{y}^s,\mathbf{y}^t,\mathbf{x}^s,\mathbf{x}^t,\mathbf{b}^s,\mathbf{b}^t)$$

$$= \left[\frac{\left((1+\overrightarrow{\mathrm{d}_o^s}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s;-\mathbf{b}^s)\right)}{\left(1+\overrightarrow{\mathrm{d}_o^s}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;\mathbf{y}^t,-\mathbf{b}^t)\right)} \times \frac{\left(1+\overrightarrow{\mathrm{d}_o^t}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s;\mathbf{y}^s,-\mathbf{b}^s)\right)}{\left(1+\overrightarrow{\mathrm{d}_o^t}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;\mathbf{y}^t,-\mathbf{b}^t)\right)}\right]^{0.5}. \tag{4.8}$$

If the ML index in (4.8) is equal to one, it indicates no productivity change between periods s and t; an ML index greater than one implies productivity improvement, while an ML index less than one implies a productivity decline.

Following Färe *et al.* (1994), the index can also be decomposed into technical efficiency change (EFFCH) and technical change (TECH), where

$$\mathrm{EFFCH} = \frac{1+\overrightarrow{\mathrm{d}_o^s}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s;-\mathbf{b}^s)}{1+\overrightarrow{\mathrm{d}_o^t}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;-\mathbf{b}^t)}\text{, and} \tag{4.9}$$

$$\mathrm{TECH} = \left[\frac{\left(1+\overrightarrow{\mathrm{d}_o^t}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s;-\mathbf{b}^s)\right)}{\left(1+\overrightarrow{\mathrm{d}_o^s}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s;-\mathbf{b}^s)\right)} \times \frac{\left(1+\overrightarrow{\mathrm{d}_o^t}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;\mathbf{y}^t,-\mathbf{b}^t)\right)}{\left(1+\overrightarrow{\mathrm{d}_o^s}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;\mathbf{y}^t,-\mathbf{b}^t)\right)}\right]^{0.5}. \tag{4.10}$$

Technical efficiency change (EFFCH) measures the change in technical efficiency between the two periods. If EFFCH = 1, production exhibits no efficiency change between periods s and t. If EFFCH > (<) 1, production exhibits technical efficiency improvement (decline). On the other hand, technical change (TECH) measures the geometric mean of the shift in the production possibility frontier, which reflects the technical progress (or regress) in producing the good and bad outputs. If TECH = 1, production exhibits no technical change between periods s and t. If TECH > (<) 1, production exhibits technological progress (regress).

Figure 4.2 illustrates the EFFCH and TECH components. Suppose under CRS technology, a firm operates at point E in period s and at point L in period t. The firm is technical inefficient in both periods. The technical efficiency change can be represented by $\frac{1+LI/Og}{1+EH/Og}$. The technical change can be represented by $\left[\frac{1+LG/Og}{1+LI/Og} \times \frac{1+EH/Og}{1+HF/Og}\right]^{0.5}$.

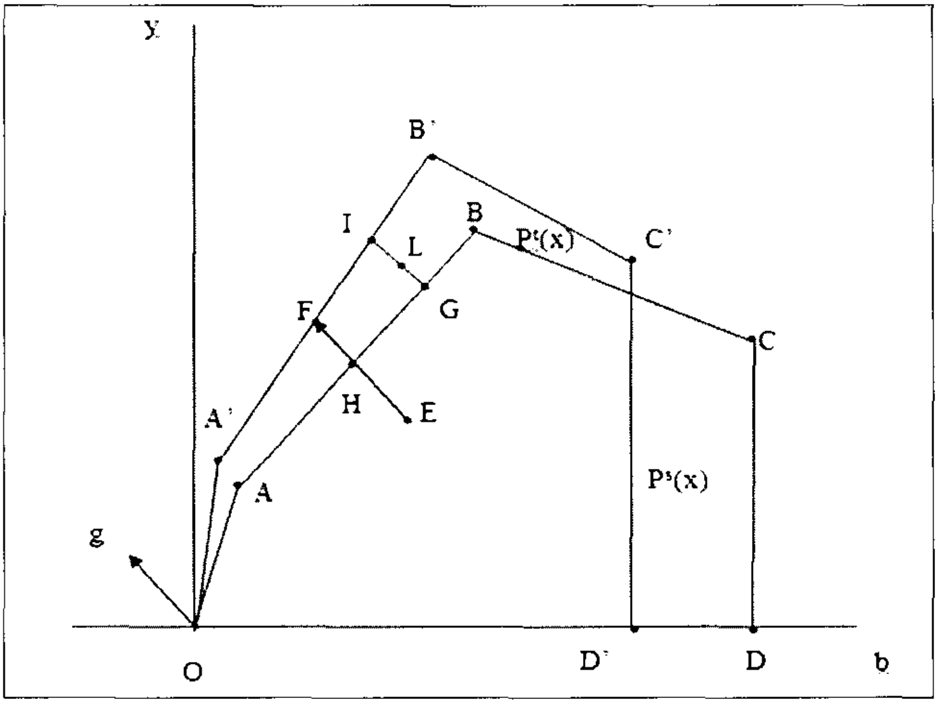

Figure 4.2. A Mixed-Period Distance Function

In this study, the directional output distance function can be estimated non-parametrically by solving liner programming problems. Suppose in period t=1,…,T, there are i=1,…,I observations operate under CRS technology, I construct the non-parametric piecewise linear production possibility set P(**x**) as follows:

$$P(\mathbf{x}) = \{(\mathbf{y}, \mathbf{b}): \sum_{i=1}^{I} \lambda_i \, y_{im}^t \geq y_{im}^t, \qquad m = 1, \dots, M,$$

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{t} = b_{ik}^{t}, \qquad k = 1, \dots, K,$$

$$\sum_{i=1}^{I} \lambda_i x_{in}^{t} \leq x_{in}^{t}, \qquad n = 1, \dots, N,$$

$$\lambda_i \geq 0, \qquad i = 1, \dots, I\}, \tag{4.11}$$

where λ_i are the weights assigned to each observation when constructing the production possibility frontier.

The inequality on input and desirable output constraints assume strongly disposable, whereas the equality on undesirable outputs assume weakly disposable. This production set satisfies the assumption that both desirable and undesirable outputs are null-joint, that is:

$$\sum_{i=1}^{I} b_{ik}^{t} > 0, \qquad k = 1, \dots, K, \tag{4.12a}$$

$$\sum_{k=1}^{K} b_{ik}^{t} > 0, \qquad i = 1, \dots, I. \tag{4.12b}$$

Condition (4.12a) indicates that each bad output is produced by at least one observation, and condition (4.12b) indicates that each observation produces at least one bad output.

Thus, the single-period directional distance function incorporating air pollutants as weakly disposable bad outputs can be estimated by solving the following linear programming problems:

$$\overrightarrow{d_o^t}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t; \mathbf{y}^t, -\mathbf{b}^t) = \max \beta$$

$$\text{s.t.} \sum_{i=1}^{I} \lambda_i y_{im}^{t} \geq (1+\beta) y_{im}^{t}, \qquad m = 1, \dots M,$$

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{t} = (1-\beta) b_{ik}^{t}, \qquad k = 1, \dots K,$$

$$\sum_{i=1}^{I} \lambda_i x_{in}^{t} \leq x_{in}^{t}, \qquad n = 1, \dots N,$$

$$\lambda_i \geq 0, \qquad i = 1, \dots I, \tag{4.13}$$

$$\overrightarrow{d_o^s}(\mathbf{x}^s, \mathbf{y}^s, \mathbf{b}^s; \mathbf{y}^s, -\mathbf{b}^s) = \max \beta$$

$$\text{s.t.} \sum_{i=1}^{I} \lambda_i y_{im}^{s} \geq (1+\beta) y_{im}^{s}, \qquad m = 1, \dots M,$$

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{s} = (1-\beta) b_{ik}^{s}, \qquad k = 1, \dots K,$$

$$\sum_{i=1}^{I} \lambda_i x_{in}^{s} \leq x_{in}^{s}, \qquad n = 1, \dots N,$$

$$\lambda_i \geq 0, \qquad i = 1, \dots I. \tag{4.14}$$

The mixed-period directional distance function whereby the observed $(\mathbf{x}_i^s, \mathbf{y}_i^s, \mathbf{b}_i^s)$ for producer i in period s compared to the reference technology at time period t can be estimated by solving the following linear programming problem:

$$\overrightarrow{d_o^t}(\mathbf{x}^s, \mathbf{y}^s, \mathbf{b}^s; \mathbf{y}^s, -\mathbf{b}^s) = \max \beta$$

$$\text{s.t.} \sum_{i=1}^{I} \lambda_i y_{im}^{t} \geq (1+\beta) y_{im}^{s}, \qquad m = 1, \dots M,$$

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{t} = (1-\beta) b_{ik}^{s}, \qquad k = 1, \dots K,$$

$$\sum_{i=1}^{I} \lambda_i x_{in}^{t} \leq x_{in}^{s}, \qquad n = 1, \dots N,$$

$$\lambda_i \geq 0, \qquad i = 1, \dots I. \tag{4.15}$$

The mixed-period directional distance function whereby the observed $(\mathbf{x}_i^t, \mathbf{y}_i^t, \mathbf{b}_i^t)$ for producer i in period t compared to the reference technology at time period s can be estimated by solving the following leaner programming problem:

$$\overrightarrow{d_o^s}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t; \mathbf{y}^t, -\mathbf{b}^t) = \max \beta$$

$$\text{s.t.} \sum_{i=1}^{I} \lambda_i y_{im}^{s} \geq (1+\beta) y_{im}^{t}, \qquad m = 1, \dots M,$$

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{s} = (1-\beta) b_{ik}^{t}, \qquad k = 1, \dots K,$$

$$\sum_{i=1}^{I} \lambda_i x_{in}^{s} \leq x_{in}^{t}, \qquad n = 1, \dots N,$$

$$\lambda_i \geq 0, \qquad i = 1, \dots I \tag{4.16}$$

The equality constrains in (4.13) through (4.16) impose the weak disposability assumption on bads. The values obtained from (4.13) through (4.16) are used to calculate the ML productivity index defined by (4.8), the EFFCH index defined by (4.9), and the TECH index defined by (4.10).

Alternatively, one could assume bads to be strongly disposable by replacing the equality constraint in (4.13) with

$$\sum_{i=1}^{I} \lambda_i b_{ik}^{t} \geq (1-\beta) b_{ik}^{t}, \qquad k = 1, \ldots K,$$

The same strong disposability constraint can be imposed in (4.14) through (4.16) by changing the time superscripts accordingly.

Traditionally, bad outputs tended to be omitted from the production process, which means **b**= 0. If so, one would drop the constraints on bads from equations (4.13)-(4.16). For comparison purpose, I consider bad outputs to be weakly disposable in Model 1, strongly disposable in Model 2 or non-existent in Model 3 in the production process. I summarize the treatments of bads in Table 4.1 below. The sign "W" and "S" represent weak and strong disposability, respectively. The sign "-" denotes omission of bads. Inputs and desirable output are assumed strong disposable in the three models.

Table 4.1. Overview of Models

Variables	Model 1	Model 2	Model 3
Desirable output	S	S	S
Inputs	S	S	S
Bads	W	S	-

Data

A set of balanced panel data covering years 2000 through 2007 for the 48 contiguous states was used for this analysis. Data were obtained from multiple sources: Bureau of Economic Analysis, U.S. Environmental Protection Agency, U.S. Census Bureau, Federal Highway Administration, and U.S. Energy Information Administration. The trucking industry (classified by NAICS 484) produces one desirable output measured in terms of state trucking gross domestic product (GDP) (y), and eight undesirable byproducts GHG (b_1), particles less than 10 micrometers in diameter (PM10) (b_2), particles less than 2.5 micrometers in diameter (PM2.5) (b_3), carbon monoxide (CO) (b_4), nitrogen oxides (NO_X) (b_5), sulfur dioxide (SO_2) (b_6), and volatile organic compounds (VOC) (b_7). Among these outputs, the data of bad outputs b_1-b_7 are only available for years 2002 and 2005. The trucking industry uses seven inputs including labor (x_1), interstate highway (x_2), non-interstate highway (x_3), trailers and semi-trailers (x_4), fuel (x_5), heavy-duty trucks (x_6), and interstate highways in adjoining states (x_7). Variable definitions are displayed in Table 4.2.

Table 4.2. Variable Definitions

Variables	Definitions	Units of Measurement
Desirable Output		
y	Real GDP	Million dollars of state trucking GDP
Undesirable Output		
b1	GHG emissions	Thousand metric tons of CO_2-equivalents
b2	PM 10 emission	Metric tons of PM 10 emission
b3	PM 2.5 emission	Metric tons of PM 2.5 emission
b4	CO emission	Metric tons of CO emission
b5	NO_X emission	Metric tons of NO_X emission
b6	SO2 emission	Metric tons of SO2 emission
b7	VOC emission	Metric tons of VOC emission
Inputs		
x1	Labor	Number of employees in trucking
x2	Interstate Highway	Miles of interstate highway
x3	Non-interstate Highway	Miles of non-interstate highway
x4	Trailers and Semi-Trailers	Numbers of registered trailers and semi-trailers
x5	Fuel	Thousands of barrels of diesel fuel
x6	Trucks	Numbers of registered heavy-duty trucks
x7*	Interstate Highway in Adjoining State*	Miles of adjoining states interstate highway

* Miles of interstate highway in adjoining states are calculated based on the interstate highway data from the Highway Statistics Series.

Real trucking GDP (y) is measured in millions of chained 2000 dollars; GHG (b_1) is measured in thousand tons of CO_2-equivalent emitted by heavy-duty trucks annually; toxic air pollutants, including PM10 (b_2), PM2.5 (b_3), CO (b_4), NO_X (b_5), SO_2 (b_6), and VOC (b_7), are measured in tons of pollutants emitted by heavy-duty trucks annually; labor (x_1) is measured by the annual average number of employees in the trucking industry; interstate highway (x_2), non-interstate highway (x_3) and interstate highway in adjoining states (x_4) are all measured in miles; trucks (x_5), trailers and semi-trailers (x_6) are measured by annual registered heavy-duty trucks, trailers and semi-trailers, and fuel (x_7) is measured by thousands of barrels of diesel fuel used. Table 4.3 displays the descriptive statistics.

Table 4.3. Descriptive Statistics

Variables	Definition	Mean	St Dev.	Minimum	Maximum
y	Real GDP	1977.56	1862.671	164	9851
b1	GHG	7763.59	8325.91	665.18	49603.71
b2*	PM 10	1993.15	2403.03	67.30	15195.10
b3*	PM 2.5	1726.96	2108.09	56.87	13422.48
b4*	CO	17839.61	18036.03	493.52	93212.57
b5*	NO_X	61578.44	64690.47	1927.40	339792.77
b6*	SO_2	1329.18	1236.54	69.75	7459.11
b7*	VOC	3432.42	3776.34	100.35	21879.12
x_1	Labor	29767	25978.60	2241	120014
x_2	Interstate Highway	945.76	584.26	41	3234
x_3	Non-interstate Highway	2372.17	1518.753	192	10202
x_4	Trailers and Semi-Trailers	106256	147134.50	4105	818997
x_5	Fuel	20509.28	18591.08	1245.08	119276.08
x_6	Trucks	37644	41928.65	1404	286024
x_7	Interstate Highway in Adjoining States	4523.21	1980.93	224	8876

*Data are available for years 2002 and 2005 only.

The trucking industry achieved an average GDP of $1.98 billion per state per year during 2000-2007. Rhode Island generated the least trucking output in 2001 while California generated the most in 2007; California also emitted the most GHG at nearly 50 million metric tons in 2007, while state trucking sector emitted an average of 7.8 million metric tons. Additionally, California emitted the most of all toxins except SO_2 (Texas emitted the most SO_2), while Rhode Island emitted the least toxic air pollutants. On average, more than 37 thousand heavy-duty trucks and more than 106 thousand trailers and semi-trailers were registered in a state, and each state employed roughly an average of

30,000 workers, and owned about 946 miles of interstate highway, more than 2.2 thousand miles of non-interstate highways and more than 4.5 thousand miles of adjoining states interstate highway on average. Tucking industry fuel averaged 205 million barrels of diesel. Among the states, Texas consumed most diesel fuel while Vermont consumed the least.

The total state consumption of diesel in the trucking industry was about 878 million barrels in 2000 and increased to nearly 1.1 billion barrels in 2007, which increased almost by 25 percent. The percentage increase in fuel consumption is consistent with the increase in GHG emissions. As showed in Figure 4.3, total trucking GHG emissions were 330 million metric tons in 2000 and increased to 409 million metric tons in 2007, up by 24 percent. GHG emissions were increased along with the increase of trucking GDP expect a decrease of GDP occurred during 2000 and 2002. Total real trucking GDP in 2000 was $92 billion and increased by 14 percent to 105 billion in 2007.

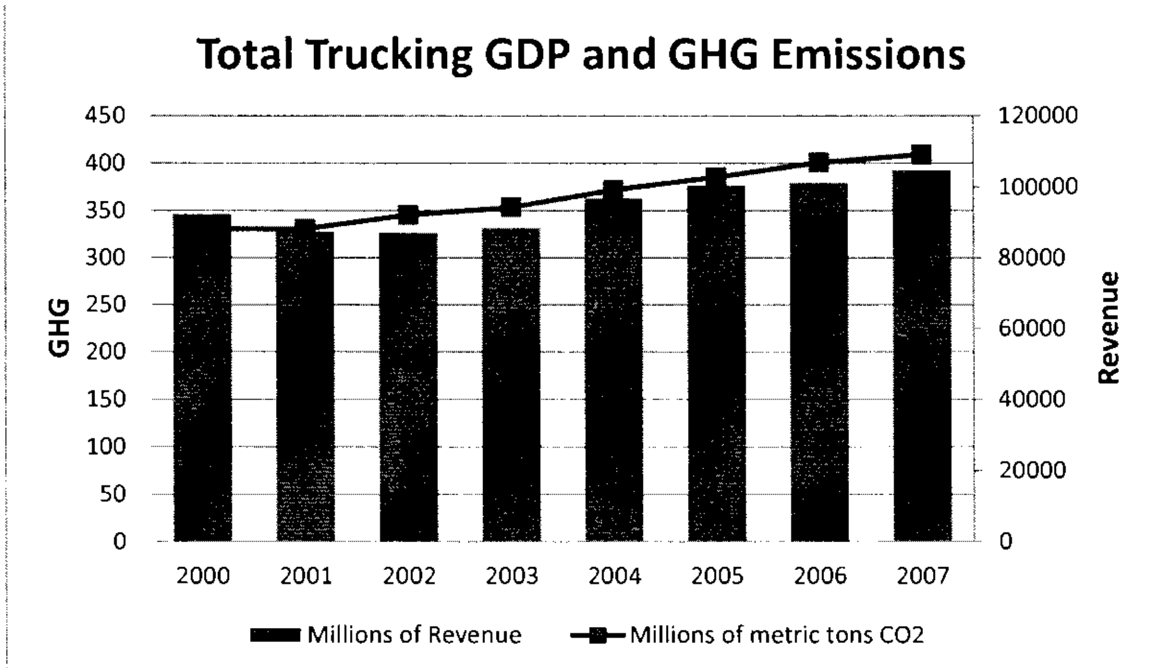

Figure 4.3. Total Trucking GDP and GHG Emissions

The utilization of inputs and production of desirable output and GHG increased between 2000 and 2007 generally, but the quantities of toxic air pollutants except SO_2 declined significantly from 2002 to 2005. In Figure 4.4, total NO_X emission from heavy-duty trucks reduced by nearly 21 percent to 2.6 million thousand tons from 2002 to 2005. PM10 and PM 2.5 also decreased by more than 12 percent between 2002 and 2005, but SO_2 increased slightly by 4.8 percent to 67 thousand tons during the same period. The reductions of toxic air pollutants were mainly caused by increasingly stringent emission standards since 1990. For example, according to the DOT (2005), due to the stricter new emission standards (2007 level), the 2010 NOx factor for combination diesel trucks is 67 percent lower than that in 2002 (2004 level standards). The EPA also estimated that air toxic emissions would reduce by 60 percent between 1999 and 2020 due to national and local emission controls (EPA, 2006).

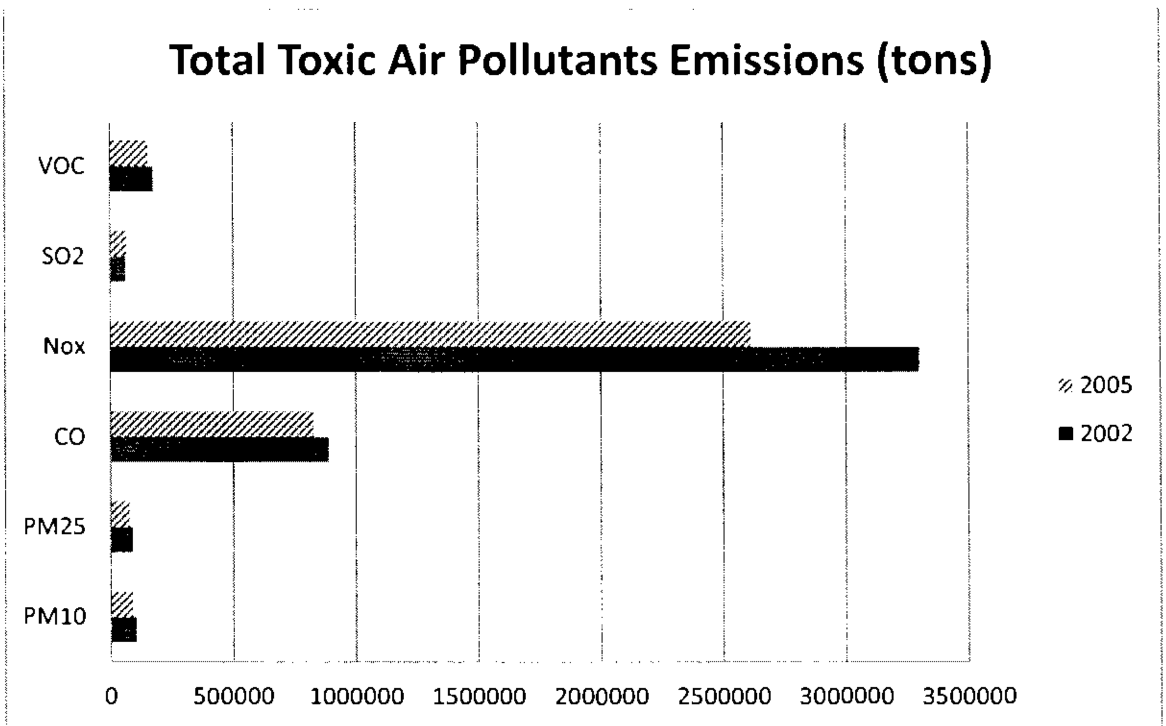

Figure 4.4. Total Toxic Air Pollutants Emissions in 2002 and 2005

CHAPTER 5. RESULTS AND DISCUSSION

Incorporating GHG in Trucking Efficiency and Productivity

Using production and GHG data for 2000 through 2007, trucking efficiency and productivity were estimated in three models. In Model 1, GHG is included as a bad output and assumed to be weakly disposable, while GHG is assumed to be a strongly disposable bad output in Model 2. Model 3 ignores GHG when constructing the reference technology.

For each model, the value generated by a single-period directional distance function (4.13) represents the distance from an observation to the production possibility frontier. Thus if $\beta = 0$, the observation is efficient. If $\beta > 0$, the observation is inefficient, and higher scores indicate higher levels of inefficiency. The descriptive statistics of the inefficiency scores obtained by solving the linear programming problems in Models (1) – (3) are displayed in Table 5.1.

Table 5.1. Average Inefficiency Scores by Year (2000-2007)

	2000	2001	2002	2003	2004	2005	2006	2007
Model 1								
Mean	0.087	0.099	0.108	0.131	0.121	0.119	0.117	0.087
SD	0.104	0.113	0.125	0.134	0.127	0.125	0.128	0.103
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Max	0.341	0.438	0.425	0.404	0.400	0.362	0.430	0.344
Model 2								
Mean	0.105	0.127	0.142	0.184	0.159	0.153	0.153	0.105
SD	0.128	0.155	0.171	0.193	0.149	0.151	0.163	0.127
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Max	0.517	0.836	0.796	0.990	0.430	0.455	0.567	0.509
Model 3								
Mean	0.107	0.137	0.158	0.190	0.167	0.162	0.165	0.107
SD	0.127	0.153	0.172	0.192	0.148	0.152	0.162	0.126
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Max	0.517	0.836	0.796	0.990	0.437	0.455	0.567	0.509

In all three models, average inefficiency was incurred for 2000-2007. For example, for year 2000, the average inefficiency score in Model 1 was 0.087, which implies that after accounting for GHG as a weakly disposable bad output, states could expand good output and contract GHG by an average of 8.7 percent at a given input level; the average inefficiency score in Model 2 was 0.105, which means that states could expand their good output and contract GHG by an average of 10.5 percent; the average score in Model 3 for was 0.107, which implies that states could expand good output by 10.7 percent at a given input level in that year. The inefficiency scores were the largest in Model 3 because the model ignores bad output. This relaxation of (4.11) in Model 3 failed to account for GHG and state's effort to control pollution. As a result, Models 3 allows a larger technology set and higher inefficiency scores compared to Models 1 and 2. Also, the inefficiency scores were greater in Model 2 in which GHG was strongly disposable compared to those in Model 1 in which bad output is weakly disposable because the technology set for a weakly disposable GHG (defined by Model 1) was nested within the technology set for a strongly disposable GHG (defined by Model 2), and Model 1 credits states with tighter emission standards. In all three models, the average inefficiency was the largest in 2003, and this might be due to the lowest fuel efficiency that year.[11]

Table 5.2 presents the average annual technical inefficiency scores by state. The average inefficiency score in Model 1 was 0.109, which indicates that states could, on average, expand good output and contract GHG by 10.9 percent when bad output was weakly disposable. Model 3 generated higher average annual inefficiency scores, which reflects the higher inefficiency of the industry for each state, and inefficiency scores generated by Model 2 were also greater than those generated by Model 1. Different rankings of states' performances were found in the three models. For instance, the five least

[11] The estimations of average miles traveled per gallon of fuel consumed come from Highway Statistics of FHWA (2001-2008).

efficient states in Model 3 were Arizona, Utah, Louisiana, North Dakota, and Alabama, while the five least efficient states in Model 1 were Arizona, North Dakota, Louisiana, Virginia, and West Virginia, and the most inefficient states were Arizona, Utah, North Dakota, Alabama, and Georgia in Model 2. In this sample, most of the states experienced lower inefficiency in Model 1 than in Model 2, which means that more states were located interior of the frontier in Model 2. Referring to Figure 4.1 and comparing Models 1 and 2, eight states (California, Florida, Maine, Nebraska, New Jersey, New York, Texas, and Wisconsin) operated on the production possibility frontier; they were located on the production possibility frontier segment BCD. Five states (Arkansas, Illinois, Indiana, Ohio, and Tennessee) operated inefficiently in Model 2 but efficiently in Model 1. These states were located on the production possibility frontier segment OAB.

Table 5.2. Average Annual Inefficiency Scores by State (2000-2007)

State	Model 1	Model 2	Model 3
AL	0.254	0.340	0.340
AZ	0.342	0.532	0.534
AR	0.000	0.163	0.163
CA	0.000	0.000	0.000
CO	0.121	0.137	0.138
CT	0.000	0.000	0.001
DE	0.000	0.000	0.071
FL	0.000	0.000	0.000
GA	0.238	0.324	0.324
ID	0.222	0.245	0.245
IL	0.000	0.011	0.011
IN	0.000	0.011	0.011
IA	0.114	0.256	0.256
KS	0.250	0.290	0.290
KY	0.016	0.018	0.018
LA	0.309	0.310	0.363
ME	0.000	0.000	0.000
MD	0.158	0.161	0.164
MA	0.000	0.000	0.016
MI	0.087	0.091	0.092
MN	0.072	0.089	0.092
MS	0.098	0.133	0.135

Table 5.2. Continued

MO	0.072	0.116	0.116
MT	0.176	0.176	0.222
NE	0.000	0.000	0.000
NV	0.000	0.000	0.038
NH	0.121	0.122	0.147
NJ	0.000	0.000	0.000
NM	0.222	0.222	0.288
NY	0.000	0.000	0.000
NC	0.132	0.224	0.224
ND	0.313	0.349	0.349
OH	0.000	0.044	0.044
OK	0.213	0.274	0.274
OR	0.186	0.278	0.278
PA	0.002	0.016	0.016
R1	0.202	0.204	0.221
SC	0.141	0.176	0.176
SD	0.095	0.097	0.124
TN	0.000	0.005	0.005
TX	0.000	0.000	0.000
UT	0.234	0.468	0.468
VT	0.046	0.048	0.059
VA	0.290	0.310	0.310
WA	0.024	0.026	0.033
WV	0.276	0.314	0.314
WI	0.000	0.000	0.000
WY	0.185	0.185	0.197
Mean	0.109	0.141	0.149

Most states experienced inefficiency between 2000 and 2007. This may be due to high driver turnover, information technology mismanagement, and the lack of skilled labor to take advantage of new technology (Lim and Condon, 2009). The more efficient states generally have lower trucking speed limits and implement state no-idling laws (EPA, 2003b; Carr, 2010; American Transportation Research Institute, 2010). For example, California has trucking speed limit at 55 mph and requires no more than five minutes idling for heavy-duty trucks. New York and New Jersey regulate trucking speed limit to be 65 mph, and the two states require no more than five minutes and three minutes idling, respectively. On the contrary, the speed limit for North Dakota, Louisiana, and West

Virginia is 70 mph, and the three states did not set no-idling laws during the study period.[12] These laws are consistent with the requirements and recommendations of the EPA and ATA that lower highway speed limit and reduce idle to control trucking GHG emissions. Moreover, some states, which operated inefficiently in Model 2 but were efficient in Model, generally have lower trucking speed limits. For example, Arkansas's speed limit is 65 mph, and Illinois's speed limit is 55 mph. This result implies that states with regulations that help to reduce emissions tend to be more efficient accounting for GHG.

Table 5.3 presents the geometric mean of the Malmquist-Luenberger (ML) index and its technical change (TECH) and efficiency change (EFFCH) components by year.[13] A greater than one index value indicates improvements in productivity growth, technical change and efficiency change, while a value less than one indicates a decline. Productivity improvements were observed in 2003-2004, 2004-2005, and 2006-2007, and productivity declines were observed in other years in Model 1. Productivity decreased in 2000-2001, 2002-2003, and 2005-2006, and productivity increased in other years in Model 3 without incorporating GHG. The most significant productivity regress was occurred in 2000-2001, and this may be due to the September 11 attack and the economic recession that year (Apostolides, 2009). Trucking experienced an overall productivity growth from 2001 to 2007 with an average increasing employment of inputs, including labor, trucks, and fuel. Productivity declined slightly in 2002-2003 and 2005-2006 with increasing output and inputs except decreasing number of trucks in the former. This decline with increasing output may be a result of inefficiency of utilization of resources, which can be presented by the negative efficiency change during the periods.

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[12] West Virginia has set state no-idling law in June, 2010.

[13] The mean growth is measured by geometric means.

Table 5.3. Mean Productivity Change and Decomposition (2000-2007)

Year	00-01	01-02	02-03	03-04	04-05	05-06	06-07
Model 1							
ML	0.961	0.996	0.983	1.041	1.019	0.981	1.027
EFFCH	0.990	0.993	0.981	1.008	1.002	1.002	1.026
TECH	0.971	1.003	1.003	1.032	1.017	0.979	1.001
Model 2							
ML	0.847	1.127	0.964	1.144	1.008	0.979	1.091
EFFCH	0.983	0.989	0.966	1.018	1.005	1.002	1.039
TECH	0.893	1.140	0.997	1.124	1.003	0.977	1.046
Model 3							
ML	0.891	1.029	0.972	1.071	1.015	0.987	1.047
EFFCH	0.975	0.984	0.975	1.015	1.005	0.998	1.049
TECH	0.914	1.046	0.997	1.055	1.010	0.989	0.997

In Model 1, state trucking productivity was improved by an average of 4.1 percent in 2003-2004. But for the same period, Model 2 estimated an average growth of 14.4 percent, and Model 3 estimated a 7.1 percent average growth. This shows that different assumptions about bad in constructing the technology sets create different estimates. Although no consistent pattern is observed, the environmentally sensitive ML indexed derived from Model 1 were different from those derived from Model 2 and the conventional ML indexes in Model 3 in the time periods studied, suggesting that ignoring GHG emissions in freight trucking leads to biased productivity indexes. The periods of improvement and decline in productivity and its components were slightly different in all three models. In Model 1, a 0.3 percent improvement in technical change was observed in 2002-2003, while technical regresses were observed in Models 2 and 3.[14] In the same model, technical progress was observed in all years except 2000-2001 and 2005-2006, while technical regresses were also observed in 2002-2003 in Models 2 and 3. In all three

[14] The ML index and the decomposition for all the 48 states are presented in Appendix A.

models, states experienced decreased efficiency until 2003, but became more efficient from 2004 to 2007.

An ANOVA F-test and a series of nonparametric tests are used to examine the differences of productivity change among three models and present the results in Table 5.4. From the results, the null hypothesis that no significant differences of ML in three models was failed to reject for years 2002-2003, 2004-2005, and 2005-2006, but was rejected in other years.

Table 5.4. ANOVA F-test and Nonparametric Tests

Year	00-01	01-02	02-03	03-04	04-05	05-06	06-07
ANOVA-F	9.412	2.156	1.641	5.131	2.080	0.273	3.340
(Prob > F)	(0.000)	(0.120)	(0.198)	(0.007)	(0.129)	(0.762)	(0.038)
Kruskal-Wallis	18.738	24.567	3.248	21.276	1.208	0.180	5.889
(Prob > χ^2)	(0.000)	(0.000)	(0.197)	(0.000)	(0.547)	(0.914)	(0.053)
Median	8.635	23.001	3.651	20.523	0.267	0.166	7.694
(Prob > χ^2)	(0.013)	(0.000)	(0.161)	(0.000)	(0.876)	(0.921)	(0.021)
Van der Waerden	18.051	20.251	2.601	19.132	2.044	0.162	5.160
(Prob > χ^2)	(0.000)	(0.000)	(0.271)	(0.000)	(0.360)	(0.922)	(0.076)
Savage	13.425	14.924	0.735	14.769	1.781	0.293	7.720
(Prob > χ^2)	(0.001)	(0.001)	(0.692)	(0.001)	(0.411)	(0.864)	(0.021)

The ratio of cumulated ML index in Model 1 over cumulated ML index in Model 2 was calculated to see the differences in productivity due to the lack of strong disposability over time. The results show that ML differences existed between Model 1 and Model 2, which are displayed in Table 5.5. The ratio measures the extent of environmental compliance. If the ratio is greater than 1, the conventional ML understates productivity and is therefore biased downward. If the ratio is less than 1, weak disposability results in a loss in productivity. If the ratio is one, the two productivity measures are equal. The results indicate that the conventional ML understated productivity in 18 states by conventional ML, and 22 states experienced productivity losses under the weak disposability assumption. In addition, the productivity of each state was improved by an average of 7 percent over time under the weak disposability assumption of GHG.

Table 5.5. The Ratio of (Cumulated ML 1)/ (Cumulated ML 2)

State	cumulated ML1	cumulated ML2	(cumulated ML 1)/ (cumulated ML 2)
AL	0.974	0.995	0.979
AZ	0.987	1.035	0.954
AR	0.983	0.990	0.993
CA	0.952	na	na
CO	1.019	0.927	1.099
CT	1.017	na	na
DE	1.094	27.593	0.040
FL	0.978	na	na
GA	0.999	0.989	1.010
ID	0.997	0.968	1.030
IL	0.987	1.020	0.968
IN	1.000	1.042	0.959
IA	0.988	0.972	1.016
KS	0.995	1.012	0.983
KY	1.008	0.989	1.019
LA	1.119	0.725	1.543
ME	1.036	0.854	1.213
MD	1.009	1.172	0.861
MA	0.995	1.123	0.886
MI	1.024	1.022	1.002
MN	1.052	1.043	1.009
MS	0.983	0.836	1.176
MO	0.987	na	na
MT	1.062	na	na
NE	0.988	1.011	0.978
NV	1.045	na	na
NH	1.087	na	na
NJ	0.976	na	na
NM	1.142	0.956	1.194
NY	0.980	1.288	0.761
NC	0.992	0.977	1.015
ND	0.972	1.009	0.964
OH	1.013	1.007	1.006
OK	0.984	1.009	0.975
OR	0.961	0.998	0.964
PA	1.004	0.987	1.017
RI	0.909	2.647	0.343
SC	0.982	0.995	0.987
SD	1.021	1.021	1.000

Table 5.5. Continued

TN	1.032	1.033	0.999
TX	1.023	1.173	0.872
UT	1.011	0.948	1.067
VT	1.007	0.874	1.152
VA	0.994	1.000	0.993
WA	0.966	1.171	0.825
WV	0.966	0.991	0.974
WI	1.012	1.016	0.996
WY	1.009	0.974	1.036
Mean	1.007	1.710	0.971

*na: infeasible solution

Finally, GHG abatement costs were estimated for each state. According to Färe, Grosskopf and Pasurka (2003), pollution abatement costs are calculated by the difference between the maximum feasible productions of the good output under strongly disposable technology and weakly disposable technology. In Figure 4.1, the pollution abatement cost for point E is represented by distance FN, which indicates the amount of good output that must be reduced as a result of lack of free disposability. Thus, the amount of good output foregone is an abatement cost to producers. Denote the distance between an observation and the frontier defined by strongly disposable technology as $\overrightarrow{D_o^s}$, and the distance between an observation and the frontier defined by weakly disposable technology as $\overrightarrow{D_o^w}$. If the good output is y, then the pollution abatement costs can be defined by $(\overrightarrow{D_o^s} - \overrightarrow{D_o^w}) \times y$.

Table 5.6 displays the abatement costs for each state in each year. Within each year, most states suffered no abatement costs. The mean abatement costs ranged between \$26.23 million and \$94.47 million between 2000 and 2007, and the average abatement cost per state per year was \$56.45 million. A total of 13 states (California, Colorado, Delaware, Florida, Maine, Massachusetts, Nebraska, Nevada, New Jersey, New York, Texas, Wisconsin, and Wyoming) did not incur any good output losses for between 2000 and 2007 compared to their peers, which implies regulations did not constrain their efficiency. On the contrary, five states (Arkansas, North Carolina, Georgia, Utah, and Iowa) incurred an average of more than $200 million losses per year due to regulations. The average abatement cost was the largest in 2004 at $94.47 million per state. The highest abatement cost, $751.29 million, was incurred by Arizona in 2003. On average, the average abatement cost accounts for only 0.6 percent of the average trucking GDP.

Table 5.6. GHG Abatement Costs by State ($ millions, 2000-2007)

	2000	2001	2002	2003	2004	2005	2006	2007
AL	12.35	107.08	71.50	282.22	160.47	309.73	257.87	13.53
AZ	76.60	468.89	454.60	751.29	0.00	20.23	15.87	99.94
AR	143.48	240.86	515.89	505.90	498.57	268.87	201.59	180.78
CA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CO	5.66	36.18	0.00	0.00	0.00	59.93	48.43	6.85
CT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GA	182.62	86.58	139.10	267.68	413.84	335.07	480.21	205.97
ID	7.96	1.35	0.24	9.16	25.60	29.46	15.64	9.84
IL	0.00	0.00	0.00	366.06	52.25	0.00	0.00	0.00
IN	0.00	4.98	86.97	138.97	35.03	0.00	0.00	0.00
IA	210.27	194.22	197.49	271.39	313.76	325.24	263.47	148.33
KS	23.60	4.46	15.28	19.65	60.96	71.47	143.99	25.23
KY	0.00	21.24	0.00	0.00	0.00	0.00	0.00	0.00
LA	0.81	0.00	0.00	0.00	0.00	0.00	0.00	1.03
ME	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MD	0.00	0.00	2.52	0.00	0.00	0.96	31.02	0.37
MA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MI	0.00	1.04	0.00	30.54	16.07	2.90	32.90	0.00
MN	74.47	0.00	11.93	0.00	0.00	26.94	44.61	86.33
MS	0.00	26.32	7.68	72.31	103.86	97.13	16.32	0.00
MO	12.53	137.59	70.06	257.34	241.76	135.72	137.42	13.64
MT	1.04	0.00	0.00	0.00	0.00	0.00	0.00	1.13
NE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NH	0.00	0.00	0.00	0.00	0.00	0.00	1.53	0.00
NJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NM	0.67	0.00	0.00	0.00	0.00	0.00	0.00	0.84
NY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NC	102.00	234.30	202.45	458.58	496.86	344.02	260.89	103.78
ND	5.77	3.04	19.75	8.72	3.08	12.22	43.65	7.40
OH	0.00	314.43	203.25	375.11	335.34	189.96	203.35	0.00
OK	63.60	57.59	58.69	26.86	78.10	118.42	108.90	75.63

Table 5.6. Continued

OR	13.61	22.25	96.96	245.74	254.18	213.70	67.44	14.72
PA	0.00	75.22	0.00	0.00	147.47	160.78	123.21	0.00
RI	0.00	0.00	0.00	0.00	1.57	0.03	0.00	0.00
SC	3.64	7.33	4.81	43.83	129.43	102.11	79.27	4.21
SD	1.79	0.00	0.00	0.00	0.00	0.00	0.00	2.14
TN	0.00	0.00	0.00	99.33	63.73	0.00	0.00	0.00
TX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UT	286.36	145.68	255.51	206.93	181.83	154.65	364.16	348.41
VT	0.09	1.25	2.02	0.00	0.00	0.00	0.00	0.10
VA	0.00	10.49	0.00	62.73	22.80	73.25	145.56	1.44
WA	15.54	0.00	0.00	0.00	0.00	0.00	0.00	19.00
WV	14.50	13.03	26.82	34.14	12.02	24.36	25.06	15.35
WI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	26.23	46.15	50.91	94.47	76.01	64.11	64.84	28.87

Accounting for Toxic Air Pollutants in Efficiency and Productivity

Now apply the three models to measure efficiency and productivity change in the face for 6 toxic air pollutants: PM10, PM2.5, CO, NO_X, SO_2, and VOC. In Model 1, toxic air pollutants are included as six bad outputs and assumed to be weakly disposable. In Model 2, toxic air pollutants are assumed to be strongly disposable bad outputs. In Model 3 toxic air pollutants are ignored when constructing the reference technology.

The descriptive statistics of the annual inefficiency scores for 2002 and 2005 obtained in Models (1) – (3) are displayed in Table 5.7. Between 2002 and 2005, inefficiency decreased in Model 1, while inefficiency increased in Model 2 and 3. As Model 1 defines the smallest technology set, and Model 3 defines the largest one, the inefficiency scores were the smallest in Model 2 and the largest in Model 3. Also, the technology set defined by Model 1 was nested within the technology set defined by Model 2, and Model 1 credits states with tighter emission standards. Thus, the inefficiency scores were larger in Model 1 than Model 2.

Table 5.7. Inefficiency Scores in 2002 and 2005

	2002	2005
Model 1		
Mean	0.009	0.008
SD	0.016	0.013
Min	0.000	0.000
Max	0.082	0.046
Model 2		
Mean	0.030	0.039
SD	0.033	0.027
Min	0.000	0.000
Max	0.134	0.107
Model 3		
Mean	0.037	0.039
SD	0.031	0.027
Min	0.000	0.000
Max	0.134	0.107

Table 5.8 presents the average technical inefficiency scores by state in 2002 and 2005. The results show that 21 states were defined efficient in Model 1 which assumes weak disposability for toxic air pollutants, while only four states were efficient in Model 2 which assumes strong disposability for bads. This implies that most truck firms relocate their inputs from producing good output to reducing toxic air pollutants, which reflects the increasingly stringent standards for truck engines since 1990.

Table 5.8. Average Inefficiency Scores by State in 2002 and 2005

State	Model 1	Model 2	Model 3
AL	0.016	0.048	0.048
AZ	0.000	0.000	0.000
AR	0.000	0.000	0.000
CA	0.000	0.041	0.041
CO	0.000	0.000	0.021
CT	0.014	0.032	0.032
DE	0.000	0.037	0.037
FL	0.000	0.034	0.034
GA	0.000	0.027	0.031
ID	0.000	0.014	0.047
IL	0.006	0.026	0.026
IN	0.013	0.054	0.054
IA	0.000	0.022	0.027
KS	0.023	0.044	0.046

Table 5.8. Continued

KY	0.013	0.046	0.046
LA	0.017	0.034	0.037
ME	0.000	0.022	0.042
MD	0.000	0.041	0.041
MA	0.000	0.037	0.039
MI	0.003	0.018	0.018
MN	0.021	0.046	0.046
MS	0.024	0.042	0.042
MO	0.021	0.046	0.046
MT	0.019	0.038	0.038
NE	0.019	0.031	0.032
NV	0.000	0.067	0.067
NH	0.000	0.016	0.021
NJ	0.000	0.034	0.034
NM	0.020	0.054	0.054
NY	0.000	0.028	0.030
NC	0.012	0.039	0.048
ND	0.025	0.044	0.044
OH	0.023	0.036	0.036
OK	0.012	0.027	0.027
OR	0.000	0.053	0.054
PA	0.024	0.046	0.046
RI	0.000	0.053	0.053
SC	0.005	0.019	0.019
SD	0.013	0.033	0.033
TN	0.000	0.048	0.048
TX	0.000	0.056	0.056
UT	0.000	0.045	0.045
VT	0.000	0.000	0.026
VA	0.000	0.024	0.049
WA	0.000	0.051	0.051
WV	0.002	0.014	0.014
WI	0.025	0.046	0.046
WY	0.041	0.061	0.061
Mean	0.009	0.035	0.038

Different rankings of states' performances were also found in the three models. The five least efficient states in Model 1 were Wyoming, Wisconsin, Pennsylvania, Mississippi, and Kansas, while the five least efficient states in Model 2 were Nevada, Wyoming, Texas, New Mexico, and Oregon, the most inefficient states were Nevada, Wyoming, Texas, Oregon, and Indiana in Model 3. Moreover, three of the five least efficient states in Model

2, which were Nevada, Texas, and Oregon, operated efficiently in Model 1. Within the three states, Nevada and Texas had already implemented no-idling laws in 2002. Texas and Oregon provided financial incentives for encouraging emission control equipment, which imply environmental policies could improve technical efficiency accounting for toxic air pollutants.

Without considering state's effort to reduce toxic air pollutants, many states appeared inefficient. For example, the inefficiency score for California was 0.041 in Model 2 compared to zero inefficiency in Model 1. However, the California Air Resources Board set the Diesel Risk Reduction Plan to reduce diesel emissions from in-use and off-road diesel engines since 2000, and California also has the no-idling law and lower speed limits. The inefficiency result of California in Models 2 and 3 failed to credit the state for its efforts to improve environmental performance and reduce bad outputs.

Table 5.9 presents the Malmquist-Luenberger (ML) index and its technical change (TECH) and efficiency change (TECH) components derived from the three models in 2002 and 2005. Productivity change and its components are different in three models. In Model 1, a productivity decline, technical regress, and efficiency stagnant were observed in 2002-2005, while a productivity growth, technical progress, and efficiency decline were observed in Model 2 and Model 3.

Table 5.9. Mean Productivity Change and Decomposition in 2002-2005

	Model 1			Model 2			Model 3		
Year	ML	EFFCH	TECH	ML	EFFCH	TECH	ML	EFFCH	TECH
02-05	0.979	1.001	0.978	1.174	0.991	1.186	1.104	0.997	1.107

Table 5.10 represents the productivity growth and its EFFCH and TECH components by state. An average productivity decline, technical regress, and stagnant efficiency change were observed in Model 1, which assumes weakly disposability for toxic

air pollutants. Within the sample, 35 states experienced productivity decline, and 10 states had productivity growth in Model 1. The productivity decline could be explained by a technical regress possibly resulting from in-use old diesel trucks that had not been phased out. The trucking industry is not currently mandated to apply latest diesel engines or to retrofit old engines with pollution control equipment. Even for California, the state government did not enact regulations to modernize on-road trucks until December 2008 (Thornton, Kagan and Gunningham, 2009). Thus, Model 1 with declined technical change seems more consistent with the current regulatory environment and trucking operations. In addition, productivity change and its components varied in different states. For example, when the weak disposability assumption is made, the variation range of productivity decline ranged from 0.1 percent for New Mexico to 34.6 percent for Arizona. Productivity change and its components also vary greatly in different models. For example, Colorado's productivity decreased by 3.1 percent in Model 1 while productivity improved by 23.2 percent in Model 2 and by 28.6 percent in Model 3.

Table 5.10. Productivity Change and Its Decompositions by State in 2002 and 2005

	Model 1			Model 2			Model 3		
State	ML	EFFCH	TECH	ML	EFFCH	TECH	ML	EFFCH	TECH
AL	0.951	0.969	0.982	1.070	0.945	1.131	1.042	0.945	1.102
AZ	0.654	1.000	0.654	1.340	1.000	1.340	1.092	1.000	1.092
AR	1.419	1.000	1.419	0.973	1.000	0.973	1.145	1.000	1.145
CA	na	1.000	na	1.176	0.984	1.195	1.078	0.984	1.096
CO	0.969	1.000	0.969	1.232	1.000	1.232	1.286	1.043	1.233
CT	0.890	0.973	0.915	1.049	0.940	1.116	1.023	0.940	1.089
DE	0.901	1.000	0.901	na	0.931	na	0.897	0.931	0.964
FL	0.919	1.000	0.919	0.958	0.936	1.023	1.025	0.936	1.095
GA	0.973	1.000	0.973	1.117	0.953	1.173	1.062	0.960	1.107
ID	1.077	1.000	1.077	1.053	0.973	1.081	1.123	1.038	1.082
IL	0.984	1.013	0.971	2.963	1.018	2.911	1.122	1.018	1.103
IN	0.984	1.025	0.960	1.182	1.033	1.144	1.126	1.033	1.090
IA	1.002	1.000	1.002	1.210	0.959	1.262	1.087	0.968	1.123
KS	0.936	0.956	0.979	1.042	0.933	1.116	1.024	0.938	1.092
KY	0.972	1.025	0.948	1.175	1.030	1.140	1.123	1.030	1.090

Table 5.10. Continued

LA	0.954	0.968	0.986	1.075	0.977	1.101	1.072	0.983	1.090
ME	1.041	1.000	1.041	1.060	0.958	1.106	1.092	0.997	1.095
MD	na	1.000	na	na	0.935	na	1.029	0.934	1.102
MA	0.948	1.000	0.948	1.040	0.931	1.117	1.028	0.934	1.100
MI	1.477	1.006	1.469	na	1.036	na	1.195	1.036	1.154
MN	0.961	0.998	0.963	1.178	1.023	1.152	1.119	1.023	1.094
MS	0.966	0.997	0.969	1.290	0.994	1.297	1.100	0.994	1.106
MO	0.984	1.006	0.979	1.139	1.008	1.130	1.105	1.008	1.097
MT	0.919	0.964	0.954	1.070	0.929	1.152	1.027	0.929	1.106
NE	0.935	0.963	0.971	1.125	0.946	1.189	1.046	0.948	1.103
NV	na	1.000	na	na	1.134	na	1.258	1.134	1.110
NH	0.995	1.000	0.995	1.315	1.032	1.274	1.173	1.042	1.126
NJ	0.924	1.000	0.924	0.870	0.937	0.929	1.031	0.937	1.101
NM	0.999	1.039	0.962	1.217	1.049	1.160	1.152	1.049	1.098
NY	0.947	1.000	0.947	1.077	0.952	1.131	1.049	0.957	1.097
NC	0.976	0.976	1.000	1.046	0.927	1.128	1.040	0.944	1.101
ND	0.967	1.007	0.960	1.194	1.031	1.158	1.127	1.031	1.092
OH	0.982	1.008	0.975	1.180	1.018	1.159	1.115	1.018	1.095
OK	0.990	1.024	0.966	3.656	1.054	3.470	1.154	1.054	1.095
OR	0.903	1.000	0.903	1.125	0.993	1.133	1.090	0.995	1.095
PA	0.970	0.993	0.976	1.123	0.992	1.132	1.089	0.992	1.097
RI	0.903	1.000	0.903	0.994	0.904	1.100	0.983	0.904	1.088
SC	1.048	1.011	1.037	1.572	1.039	1.513	1.590	1.039	1.530
SD	0.978	1.014	0.965	1.163	1.026	1.133	1.122	1.026	1.093
TN	0.970	1.000	0.970	1.123	0.994	1.129	1.092	0.994	1.098
TX	0.937	1.000	0.937	1.235	1.035	1.194	1.137	1.035	1.099
UT	1.150	1.000	1.150	1.215	1.028	1.182	1.128	1.028	1.097
VT	0.907	1.000	0.907	1.145	1.000	1.145	1.148	1.051	1.092
VA	1.036	1.000	1.036	1.082	0.954	1.134	1.098	1.002	1.096
WA	0.974	1.000	0.974	1.168	1.018	1.147	1.112	1.018	1.092
WV	0.921	0.996	0.925	0.563	0.974	0.579	1.078	0.974	1.108
WI	1.016	1.029	0.987	1.143	1.035	1.105	1.126	1.035	1.088
WY	1.050	1.082	0.971	1.309	1.122	1.167	1.233	1.122	1.099
Mean	0.986	1.001	0.985	1.228	0.992	1.234	1.108	0.999	1.109

*na: infeasible solution

I use an ANOVA F-test and a series of nonparametric tests to examine the differences in productivity indexes in the three models. The results are displayed in Table 5.11. The null hypothesis that no significant difference between Model 1 and Model 2 for 2002 and 2005 was rejected, implying that the productivity indexes were statistically significantly different for the two models.

Table 5.11. ANOVA F-test and Nonparametric Tests

Year	ANOVA-F (Prob > F)	Kruskal-Wallis (Prob > χ^2)	Median (Prob > χ^2)	Van der Waerden (Prob > χ^2)	Savage (Prob > χ^2)
02-05	10.433	36.083	46.934	28.805	23.798
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)

Toxic air pollutants abatement costs for each state were also estimated. Table 5.12 displays the abatement costs for each state in 2002 and 2005. The mean abatement costs increased from \$44.96 million in 2002 to \$72.78 million in 2005. Unlike GHG emissions, toxic air pollutants abatement costs were incurred for most states, since they are subject to the environmental requirements and standards under the Clean Air Act amendments of 1990.

Table 5.12. Toxic Air Pollutants Abatement Costs by State in 2002 and 2005 (\$ millions)

	2002	2005
AL	29.05	84.35
AZ	0.00	0.00
AR	0.00	0.00
CA	276.78	473.72
CO	0.00	0.00
CT	0.00	21.00
DE	0.00	16.69
FL	0.00	238.06
GA	5.29	163.73
ID	0.00	15.70
IL	105.57	93.87
IN	141.56	134.05
IA	0.00	86.36
KS	8.22	38.72
KY	50.67	48.95
LA	23.58	15.05
ME	0.00	18.23
MD	6.03	91.02
MA	0.00	95.42
MI	79.37	0.00
MN	63.40	24.30
MS	16.92	23.70
MO	68.75	73.64
MT	0.00	14.42
NE	3.25	35.41
NV	51.25	0.00

Table 5.12. Continued

NH	8.06	0.00
NJ	0.00	226.66
NM	15.84	13.88
NY	7.69	157.94
NC	0.00	168.40
ND	9.89	2.61
OH	81.57	37.38
OK	31.69	0.00
OR	56.58	77.36
PA	90.94	108.62
RI	0.00	18.37
SC	32.75	0.00
SD	9.62	5.61
TN	160.65	210.62
TX	482.70	305.33
UT	53.19	32.36
VT	0.00	0.00
VA	0.00	100.18
WA	96.80	76.42
WV	0.00	13.05
WI	69.30	59.49
WY	8.20	0.00
Mean	44.96	72.78

Abatement Cost Estimation Accounting for GHG and Other Air Pollutants

Finally, Model 1 and Model 2were used to estimate the abatement costs. Table 5.13 displays the abatement costs for each state for 2002 and 2005. [15] The mean abatement costs increased from $48.63 million in 2002 to $75.56 million in 2005. The abatement costs for Arizona, Arkansas, Colorado, and Vermont were zero, while Texas, California, Tennessee, and Indiana each incurred over $100 million losses of output resulting from environmental regulations.

[15] The results of inefficiency scores and productivity index and its decompositions are displayed in Appendix B.

The abatement costs estimation implies that the costs of regulating both GHG and toxic air pollutants are not substantially higher than the costs of regulating only toxic pollutants from heavy-duty trucks, since these gases are all directly resulted from diesel fuel consumption. On average, the average abatement cost of all pollutants accounts for only 0.7 percent of the average trucking GDP.

Table 5.13. Bad Outputs Abatement Costs by State in 2002 and 2005 ($ millions)

	2002	2005
AL	29.05	112.78
AZ	0.00	0.00
AR	0.00	0.00
CA	276.78	473.72
CO	0.00	0.00
CT	0.00	22.58
DE	0.00	16.69
FL	0.00	238.06
GA	5.29	163.73
ID	0.00	15.70
IL	163.66	0.00
IN	141.56	134.05
IA	0.00	86.36
KS	8.01	68.02
KY	53.70	48.95
LA	23.58	46.11
ME	0.00	18.23
MD	6.03	91.02
MA	0.00	95.42
MI	94.35	0.00
MN	73.20	35.42
MS	40.27	49.98
MO	70.58	97.98
MT	0.00	16.63
NE	3.25	54.32
NV	51.25	0.00
NH	0.00	0.00
NJ	0.00	226.66
NM	15.84	13.88
NY	7.69	157.94
NC	0.00	188.16
ND	11.16	6.84
OH	113.31	63.66
OK	32.33	0.00

Table 5.13. Continued

OR	56.58	77.36
PA	101.84	158.86
RI	0.00	18.37
SC	40.86	0.00
SD	10.12	8.02
TN	160.65	210.62
TX	482.70	305.33
UT	53.19	32.36
VT	0.00	0.00
VA	0.00	100.18
WA	96.80	76.42
WV	0.00	15.72
WI	96.20	80.59
WY	14.58	0.00
Mean	48.63	75.56

CHAPTER 6. CONCLUSION

Air pollution is a threat to the environment and human health. Freight trucking is the main source of freight transportation emissions. Heavy-duty trucks emit large amounts of toxic air pollutants, such as nitrogen oxides and particulate matter, which cause serious diseases and harm public health. Also, heavy-duty trucks emit large amounts of greenhouse gas (GHG) emissions, which is the leading cause of global warming.

Despite increased environmental restrictions on trucking air pollution and rising trucking GHG emissions in the past decades, no economic study had examined the potential GHG and air pollution reductions in the trucking sector and the associated private abatement costs to the industry. This study introduced air pollution (GHG emissions and toxic air pollutants) into the measurements of trucking productivity and efficiency. I conducted a benchmarking analysis of states' performance with and without air pollutants. The benchmarking analysis allows comparisons of the extent of emission control on performance and measures the private costs of abatement. This study estimated environmentally sensitive efficiency and productivity for the trucking industry in the 48 contiguous states.

First, I measured states' performance with and without GHG. The analytic results indicated that average inefficiency peaked in 2003. On average, each state could expand good output and reduce GHG emissions by 10.9 percent per year, if they operate efficiently. Positive productivity growths were found in 2003-2004, 2004-2005, and 2006-2007 accounting for GHG. I found that productivity was understated for 20 states and 21 states experienced productivity declines by conventional productivity measure. The average abatement cost was between \$26.23 million and \$94.47 million per state over the study period, and the highest abatement cost ($751 million) was incurred by Arizona in 2003. The states of Arkansas, North Carolina, Georgia, Utah and Iowa would incur high abatement costs for GHG reduction. On the contrary, 13 states (California, Colorado, Delaware, Florida, Maine, Massachusetts, Nebraska, Nevada, New Jersey, New York, Texas, Wisconsin, and Wyoming) incurred no good output loss in the face of pollution control; this suggests that these states could serve as industry benchmarks to their peers.

Second, I incorporated six toxic air pollutants into the measurements of efficiency and productivity. Due to increased environmental regulatory constraints, most of the toxic air pollutants decreased dramatically between 2002 and 2005. The results showed that environmental inefficiency decreased during this period, and 21 states operated efficiently. Productivity indexes derived from the three models showed that omitting or ignoring toxic air pollutants in trucking production yielded statistically significant biased estimates. Between 2002 and 2005, productivity decline was observed during the study period and the main source of productivity change was technical regress. The average decline of technical change may be due to a large number of existing old trucks that have yet to meet the more stringent environmental standards. The average abatement cost was estimated to be $44.96 million in 2002 and $72.78 million in 2005. The trucking industry in Texas incurred a private abatement cost $482 million in 2002, which was the highest among all states, followed by California, Tennessee, Indiana, and Illinois.

Finally, I accounted for GHG and six other air pollutants to estimate the abatement costs for the trucking industry in each of the 48 states. The average abatement costs were $48.63 million in 2002 and $75.56 million in 2005. Thus, the costs of abating both GHG and toxic air pollutants were slightly higher than the costs of abating only the 6 toxic air pollutants. In fact, the costs of restricting all emissions accounted for 0.7 percent of the industry GDP.

Since GHG, NO_x, CO, and other toxic pollutants are all direct results of fossil fuel combustion and diesel truck operations, devising policies to improve fuel economy and enhance operational performance could improve environmental quality and living conditions.

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APPENDIX A

Tables A.1-A.3 present the results of geometric means of state ML index and its components based on Model 1 accounting for GHG. Tables A.5-A.7 and A.9-A.11 present the results of geometric means of ML index and its components for Models 2 and 3.

In Model 1, 23 states experienced productivity decline, and 22 states had productivity growth over the sample period. On average, a productivity decline ranged between 0.1 percent and 1.3 percent. Table A.2 shows that most states experienced stagnant average efficiency change. In Table A.3, technical regresses were observed in 23 states, while technical progresses were observed in 21 states. On average, a productivity decline, technical regress and stagnant efficiency change were observed in Model 2 and Model 3. Technical change was the main source of productivity growth. Productivity change and its components varied in different models.

Table A.1. State Malmquist-Luenberger Productivity Index in Model 1

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.907	0.988	1.002	1.021	1.009	0.996	1.057	0.996
AZ	0.893	0.998	1.011	1.231	0.925	0.986	0.977	0.998
AR	1.080	0.935	1.012	0.996	0.987	0.968	1.011	0.998
CA	1.139	0.918	0.989	1.005	0.987	0.948	0.981	0.993
CO	0.910	1.056	0.917	1.034	1.122	0.988	1.009	1.003
CT	1.082	0.906	0.963	1.002	1.068	1.017	0.992	1.002
DE	1.094	0.961	1.051	1.043	1.024	0.907	1.022	1.013
FL	1.079	0.950	1.060	0.922	1.095	0.978	0.913	0.997
GA	0.968	0.990	0.987	1.017	1.005	0.980	1.055	1.000
ID	1.023	1.055	0.977	1.077	0.967	0.952	0.955	1.000
IL	0.952	1.005	0.975	1.046	1.005	0.987	1.020	0.998
IN	0.891	0.966	1.001	1.071	1.041	1.004	1.037	1.000
IA	0.939	0.992	1.033	1.031	1.003	0.974	1.018	0.998
KS	0.959	1.002	0.972	1.039	1.011	0.971	1.045	0.999
KY	0.879	1.165	1.003	0.988	1.024	0.977	0.993	1.001
LA	0.937	1.154	0.792	1.121	1.064	0.956	1.147	1.016
ME	1.092	0.931	0.944	1.047	1.011	0.982	1.038	1.005
MD	0.994	0.998	1.020	1.059	0.949	0.935	1.062	1.001
MA	1.058	0.966	0.988	1.013	1.004	0.976	0.992	0.999

Table A.1. Continued

MI	0.854	1.091	0.892	1.085	1.066	0.962	1.109	1.003
MN	1.023	0.987	1.040	1.068	0.986	0.966	0.985	1.007
MS	0.862	1.021	0.977	1.053	1.024	0.987	1.073	0.998
MO	0.894	1.001	0.998	1.051	1.019	1.000	1.033	0.998
MT	0.754	1.104	0.985	1.146	0.988	1.138	1.007	1.009
NE	0.949	1.056	0.956	1.032	1.025	1.017	0.959	0.998
NV	0.986	1.012	1.063	0.997	1.016	0.967	1.006	1.006
NH	1.024	1.001	0.833	1.086	1.017	0.932	1.237	1.012
NJ	1.175	0.944	1.031	0.954	0.952	0.977	0.963	0.996
NM	0.784	1.126	0.850	1.085	1.121	1.064	1.178	1.019
NY	1.165	0.915	1.001	0.979	0.974	0.965	1.000	0.997
NC	0.994	0.970	1.008	1.021	0.996	0.994	1.011	0.999
ND	0.840	0.999	1.011	1.054	1.028	0.999	1.058	0.996
OH	0.932	1.007	0.997	1.040	1.032	0.974	1.037	1.002
OK	0.813	1.011	1.022	1.059	0.999	1.002	1.107	0.998
OR	0.944	0.979	0.985	1.040	1.007	1.013	0.997	0.994
PA	0.906	1.022	0.999	1.035	1.021	0.994	1.033	1.001
RI	1.112	1.004	0.828	0.991	0.991	0.996	1.006	0.986
SC	1.008	1.023	0.965	0.964	1.026	0.972	1.026	0.997
SD	0.862	1.025	1.008	1.121	1.029	1.018	0.975	1.003
TN	0.991	0.989	0.987	1.054	1.022	0.985	1.006	1.005
TX	1.047	0.922	1.061	1.001	1.035	0.944	1.021	1.003
UT	1.066	0.924	0.984	1.019	1.021	0.977	1.026	1.002
VT	0.871	0.982	1.035	1.144	1.049	0.966	0.982	1.001
VA	0.915	1.000	0.990	1.047	0.973	0.967	1.114	0.999
WA	1.041	0.979	0.975	1.029	1.027	0.967	0.952	0.995
WV	0.909	0.951	1.032	1.028	1.048	0.969	1.037	0.995
WI	0.967	1.009	1.055	0.999	1.083	0.905	1.004	1.002
WY	0.809	0.908	1.027	1.075	1.075	1.042	1.111	1.001

Table A.2. State Efficiency Change Index in Model 1

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.969	0.970	1.007	0.989	0.997	1.015	1.057	1.000
AZ	0.932	1.009	1.029	1.166	0.913	0.993	0.976	1.000
AR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CO	0.959	1.007	0.922	0.970	1.134	1.018	1.003	1.000
CT	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
GA	1.043	0.969	0.995	0.968	0.985	1.012	1.030	1.000
ID	1.113	0.974	0.992	1.032	0.954	0.957	0.987	1.000
IL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
IN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
IA	0.959	1.007	1.035	1.011	0.984	1.004	1.004	1.000

Table A.2. Continued

KS	1.051	0.948	0.986	0.987	0.992	0.994	1.046	1.000
KY	0.887	1.127	1.000	1.000	1.000	1.000	1.000	1.000
LA	0.990	1.302	0.712	1.003	1.028	0.952	1.110	1.000
ME	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MD	1.038	0.969	0.995	1.020	0.965	0.957	1.062	1.000
MA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MI	0.913	1.031	0.902	1.016	1.064	0.983	1.110	1.000
MN	1.135	0.929	1.076	0.954	0.971	0.979	0.973	1.000
MS	0.875	1.010	0.961	1.045	1.034	1.021	1.067	1.000
MO	0.951	0.985	1.003	1.022	0.998	1.018	1.025	1.000
MT	0.868	1.002	0.999	1.080	0.953	1.107	1.011	1.000
NE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NV	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NH	1.000	1.000	0.801	1.017	1.019	0.934	1.289	1.000
NJ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NM	0.876	1.073	0.829	1.023	1.076	1.063	1.098	1.000
NY	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NC	1.045	0.974	1.002	0.994	0.974	1.015	0.997	1.000
ND	0.896	0.974	1.025	1.009	0.994	1.030	1.082	1.000
OH	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
OK	0.864	0.991	1.009	1.042	0.993	1.037	1.080	1.000
OR	1.005	0.975	0.994	1.015	0.978	1.040	0.995	1.000
PA	1.000	1.000	1.000	0.982	1.018	1.001	1.000	1.000
RI	1.232	0.947	0.835	0.986	1.000	1.008	1.032	1.000
SC	1.054	1.000	0.945	0.964	1.029	0.995	1.018	1.000
SD	0.948	0.926	1.032	1.057	0.994	0.961	1.093	1.000
TN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
UT	1.042	0.967	0.979	1.003	1.005	0.999	1.016	1.001
VT	0.961	0.932	1.054	1.065	1.020	1.000	0.976	1.000
VA	1.029	0.960	0.994	0.987	0.962	0.979	1.098	1.000
WA	1.095	1.000	1.000	1.000	1.000	1.000	0.914	1.000
WV	0.981	0.919	1.034	0.991	1.036	0.983	1.064	1.000
WI	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
WY	0.916	0.854	1.036	1.013	1.053	1.066	1.086	1.000

Table A.3. State Technical Change Index in Model 1

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.936	1.019	0.996	1.033	1.012	0.981	1.000	0.996
AZ	0.958	0.988	0.982	1.056	1.013	0.993	1.002	0.998
AR	1.080	0.935	1.012	0.996	0.987	0.968	1.011	0.998
CA	1.139	0.918	0.989	1.005	0.987	0.948	0.981	0.993
CO	0.949	1.049	0.995	1.065	0.990	0.971	1.006	1.003
CT	1.082	0.906	0.963	1.002	1.068	1.017	0.992	1.002
DE	1.094	0.961	1.051	1.043	1.024	0.907	1.022	1.013

Table A.3. Continued

FL	1.079	0.950	1.060	0.922	1.095	0.978	0.913	0.997
GA	0.928	1.021	0.992	1.051	1.020	0.968	1.023	1.000
ID	0.919	1.083	0.985	1.044	1.013	0.994	0.968	1.000
IL	0.952	1.005	0.975	1.046	1.005	0.987	1.020	0.998
IN	0.891	0.966	1.001	1.071	1.041	1.004	1.037	1.000
IA	0.979	0.986	0.999	1.019	1.019	0.971	1.014	0.998
KS	0.912	1.057	0.986	1.052	1.019	0.977	1.000	0.999
KY	0.990	1.034	1.003	0.988	1.024	0.977	0.993	1.001
LA	0.947	0.886	1.111	1.118	1.035	1.004	1.033	1.016
ME	1.092	0.931	0.944	1.047	1.011	0.982	1.038	1.005
MD	0.958	1.031	1.025	1.039	0.983	0.976	1.000	1.001
MA	1.058	0.966	0.988	1.013	1.004	0.976	0.992	0.999
MI	0.936	1.058	0.989	1.068	1.002	0.978	0.999	1.003
MN	0.902	1.063	0.966	1.120	1.016	0.987	1.013	1.007
MS	0.986	1.012	1.017	1.008	0.990	0.967	1.006	0.998
MO	0.940	1.016	0.995	1.028	1.021	0.982	1.007	0.998
MT	0.869	1.102	0.986	1.061	1.037	1.028	0.996	1.009
NE	0.949	1.056	0.956	1.032	1.025	1.017	0.959	0.998
NV	0.986	1.012	1.063	0.997	1.016	0.967	1.006	1.006
NH	1.024	1.001	1.040	1.068	0.998	0.998	0.960	1.012
NJ	1.175	0.944	1.031	0.954	0.952	0.977	0.963	0.996
NM	0.895	1.050	1.025	1.060	1.042	1.001	1.074	1.019
NY	1.165	0.915	1.001	0.979	0.974	0.965	1.000	0.997
NC	0.951	0.996	1.006	1.027	1.023	0.979	1.013	0.999
ND	0.938	1.026	0.987	1.045	1.033	0.970	0.978	0.996
OH	0.932	1.007	0.997	1.040	1.032	0.974	1.037	1.002
OK	0.942	1.020	1.013	1.016	1.006	0.966	1.025	0.998
OR	0.939	1.004	0.991	1.025	1.030	0.974	1.003	0.994
PA	0.906	1.022	0.999	1.055	1.002	0.993	1.033	1.001
RI	0.903	1.060	0.991	1.005	0.991	0.988	0.975	0.986
SC	0.957	1.024	1.022	1.000	0.997	0.977	1.008	0.997
SD	0.909	1.107	0.977	1.061	1.035	1.059	0.892	1.003
TN	0.991	0.989	0.987	1.054	1.022	0.985	1.006	1.005
TX	1.047	0.922	1.061	1.001	1.035	0.944	1.021	1.003
UT	1.024	0.955	1.005	1.016	1.016	0.978	1.010	1.000
VT	0.906	1.054	0.982	1.075	1.028	0.966	1.006	1.001
VA	0.890	1.041	0.997	1.061	1.012	0.988	1.015	0.999
WA	0.951	0.979	0.975	1.029	1.027	0.967	1.041	0.995
WV	0.927	1.034	0.998	1.038	1.012	0.986	0.976	0.995
WI	0.967	1.009	1.055	0.999	1.083	0.905	1.004	1.002
WY	0.884	1.063	0.991	1.061	1.021	0.978	1.023	1.001

Table A.4 displays the cumulated productivity growth of each state over 2000-2007 in Model 1. Clearly, efficiency change remained stagnant, while technical change was driving a productivity growth (decline) over time. This suggests that technological factors were crucial for environmental productivity enhancements.

Table A.4. Model 1: State Cumulated Productivity Growth, 2000-2007

State	ML	EFFCH	TECH
AL	0.974	1.000	0.974
AZ	0.987	0.998	0.989
AR	0.983	1.000	0.983
CA	0.952	1.000	0.952
CO	1.019	1.000	1.019
CT	1.017	1.000	1.017
DE	1.094	1.000	1.094
FL	0.978	1.000	0.978
GA	0.999	1.000	0.999
ID	0.997	1.000	0.997
IL	0.987	1.000	0.987
IN	1.000	1.000	1.000
IA	0.988	1.002	0.986
KS	0.995	1.000	0.995
KY	1.008	1.000	1.007
LA	1.119	1.000	1.119
ME	1.036	1.000	1.036
MD	1.009	1.000	1.009
MA	0.995	1.000	0.995
MI	1.024	1.000	1.024
MN	1.052	1.000	1.052
MS	0.983	1.000	0.983
MO	0.987	1.000	0.987
MT	1.062	1.000	1.062
NE	0.988	1.000	0.988
NV	1.045	1.000	1.045
NH	1.087	1.000	1.087
NJ	0.976	1.000	0.976
NM	1.142	1.000	1.142
NY	0.980	1.000	0.980
NC	0.992	1.000	0.992
ND	0.972	1.000	0.972
OH	1.013	1.000	1.013
OK	0.984	1.000	0.984
OR	0.961	1.000	0.961
PA	1.004	1.000	1.004

Table A.4. Continued

RI	0.909	1.000	0.909
SC	0.982	1.000	0.983
SD	1.021	1.000	1.021
TN	1.032	1.000	1.032
TX	1.023	1.000	1.023
UT	1.011	1.009	1.002
VT	1.007	1.000	1.007
VA	0.994	1.001	0.993
WA	0.966	1.000	0.966
WV	0.966	1.000	0.966
WI	1.012	1.000	1.012
WY	1.009	1.000	1.009

GHG was assumed to be strongly disposable in Model 2. The results showed that 24 states experienced productivity growth, while 21 states experienced productivity decline. Delaware showed a larger growth than others. Table A.6 shows that most states also experienced stagnant efficiency change in Model 2. In Table A.7, 21 states experienced technical regress, while 24 states experienced technical progress.

Table A.5. State Malmquist-Luenberger Productivity Index in Model 2

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.829	1.037	0.924	1.125	0.945	1.022	1.153	0.999
AZ	0.705	1.045	0.922	1.768	0.913	0.984	0.960	1.005
AR	0.978	0.912	1.022	1.011	1.072	1.003	0.999	0.999
CA	0.951	1.002	0.792	1.336	0.989	0.967	na	0.994
CO	0.807	1.086	0.917	1.035	1.086	0.984	1.043	0.989
CT	na	1.031	0.952	0.940	1.025	0.885	na	0.965
DE	1.225	8.158	0.880	1.121	0.939	0.807	3.695	1.606
FL	0.885	1.002	1.040	1.471	1.035	0.984	na	1.055
GA	0.936	1.001	0.960	1.020	1.008	0.961	1.114	0.998
ID	1.005	1.061	0.969	1.063	0.956	0.982	0.940	0.995
IL	0.954	1.023	0.910	1.129	1.018	0.979	1.022	1.003
IN	0.881	0.970	1.010	1.111	1.039	1.010	1.036	1.006
IA	0.922	1.039	1.010	1.012	1.013	0.964	1.017	0.996
KS	0.954	1.014	0.966	1.035	1.005	0.959	1.086	1.002
KY	0.609	1.538	1.027	1.014	1.023	0.987	1.006	0.998
LA	0.830	1.279	0.484	1.144	1.064	0.956	1.213	0.955
ME	0.669	1.099	1.008	1.050	1.043	1.010	1.042	0.978
MD	0.922	0.999	1.023	1.336	0.949	0.913	1.076	1.023
MA	0.837	1.201	1.024	1.134	0.965	0.977	1.020	1.017
MI	0.855	1.092	0.886	1.091	1.067	0.959	1.109	1.003

Table A.5. Continued

MN	1.029	0.990	1.043	1.072	0.976	0.959	0.978	1.006
MS	0.670	1.055	0.937	1.088	1.024	1.048	1.080	0.975
MO	0.827	1.062	0.951	1.099	1.027	1.007	1.052	1.000
MT	0.746	1.105	0.985	1.146	0.988	1.138	1.007	1.008
NE	0.945	1.089	0.947	1.036	1.028	1.020	0.956	1.001
NV	0.801	na	1.535	9.760	na	0.904	0.980	1.604
NH	na	1.872	0.790	1.086	1.017	0.930	1.633	1.163
NJ	1.039	0.988	1.045	0.978	0.784	0.971	na	0.963
NM	0.641	1.151	0.850	1.085	1.121	1.064	1.179	0.994
NY	0.962	0.995	1.262	1.050	0.963	0.989	1.066	1.037
NC	0.945	1.015	0.950	1.034	0.999	1.003	1.036	0.997
ND	0.812	1.015	1.028	1.093	1.008	0.985	1.096	1.001
OH	0.849	1.054	0.988	1.089	1.020	0.968	1.061	1.001
OK	0.798	1.009	1.024	1.066	0.989	1.001	1.160	1.001
OR	0.912	0.978	0.911	1.090	1.004	1.120	1.001	1.000
PA	0.856	1.055	0.998	1.022	1.024	0.986	1.061	0.998
RI	1.112	2.928	0.828	0.988	0.993	0.996	1.006	1.149
SC	0.983	1.031	0.946	0.976	1.025	0.980	1.060	0.999
SD	0.862	1.025	1.008	1.121	1.029	1.018	0.975	1.003
TN	1.009	0.983	0.987	1.061	0.997	0.995	1.003	1.005
TX	0.827	0.999	0.958	1.063	1.064	1.006	1.304	1.023
UT	1.117	0.882	1.018	1.025	1.010	0.866	1.054	0.992
VT	0.750	0.985	1.039	1.144	1.049	0.966	0.983	0.981
VA	0.898	1.010	0.975	1.078	0.956	0.938	1.171	1.000
WA	0.984	1.291	0.896	1.112	0.988	0.991	0.945	1.023
WV	0.890	0.942	1.003	1.088	1.060	0.974	1.049	0.999
WI	0.964	1.022	1.064	0.988	1.095	0.892	1.004	1.002
WY	0.781	0.908	1.027	1.075	1.075	1.042	1.111	0.996

*na: infeasible solution

Table A.6. State Efficiency Change Index in Model 2

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.925	0.987	0.915	1.052	0.945	1.036	1.163	1.000
AZ	0.765	1.023	0.902	1.675	0.903	0.995	0.940	1.000
AR	0.953	0.894	1.000	1.020	1.107	1.029	1.011	1.000
CA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CO	0.936	1.037	0.922	0.970	1.087	1.026	1.034	1.000
CT	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
GA	1.067	0.956	0.962	0.942	1.006	0.980	1.096	1.000
ID	1.124	0.976	0.977	1.007	0.952	0.978	0.995	1.000
IL	1.000	1.000	0.929	1.066	1.010	1.000	1.000	1.000
IN	0.998	0.974	0.984	1.034	1.010	1.000	1.000	1.000
IA	0.969	1.008	1.002	1.008	0.986	1.030	1.000	1.000

Table A.6. Continued

KS	1.065	0.941	0.983	0.962	0.985	0.951	1.127	1.000
KY	0.875	1.143	1.000	1.000	1.000	1.000	1.000	1.000
LA	0.990	1.302	0.712	1.003	1.028	0.952	1.109	1.000
ME	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MD	1.038	0.967	0.997	1.020	0.964	0.938	1.084	1.000
MA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MI	0.912	1.031	0.893	1.021	1.068	0.974	1.121	1.000
MN	1.177	0.923	1.084	0.954	0.958	0.972	0.957	1.000
MS	0.856	1.025	0.915	1.026	1.039	1.081	1.081	1.000
MO	0.912	1.007	0.944	1.034	1.031	1.017	1.064	1.000
MT	0.870	1.002	0.999	1.080	0.953	1.107	1.008	1.000
NE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NV	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NH	1.000	1.000	0.801	1.017	1.019	0.931	1.295	1.000
NJ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NM	0.877	1.073	0.829	1.023	1.076	1.063	1.096	1.000
NY	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NC	1.000	0.983	0.933	0.995	1.017	1.037	1.040	1.000
ND	0.902	0.938	1.050	1.023	0.977	0.972	1.159	1.000
OH	0.932	1.025	0.964	1.015	1.030	0.997	1.041	1.000
OK	0.870	0.989	1.032	1.008	0.972	1.044	1.103	1.000
OR	0.998	0.927	0.906	1.025	1.007	1.127	1.027	1.000
PA	0.982	1.018	1.000	0.952	1.016	1.009	1.025	1.000
RI	1.232	0.947	0.835	0.979	1.007	1.008	1.032	1.000
SC	1.050	1.002	0.920	0.918	1.047	1.010	1.065	1.000
SD	0.953	0.926	1.032	1.057	0.994	0.961	1.087	1.000
TN	1.000	1.000	0.973	1.011	1.016	1.000	1.000	1.000
TX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
UT	1.135	0.884	1.021	1.035	1.030	0.886	1.038	1.001
VT	0.955	0.929	1.065	1.065	1.020	1.000	0.975	1.000
VA	1.024	0.965	0.968	1.004	0.945	0.955	1.155	1.000
WA	1.104	1.000	1.000	1.000	1.000	1.000	0.906	1.000
WV	0.982	0.901	1.024	1.025	1.019	0.983	1.076	1.000
WI	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
WY	0.916	0.854	1.036	1.013	1.053	1.066	1.086	1.000

Table A.7. State Technical Change Index in Model 2

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.897	1.051	1.011	1.069	1.000	0.986	0.992	0.999
AZ	0.921	1.022	1.022	1.056	1.010	0.988	1.021	1.005
AR	1.026	1.020	1.022	0.992	0.969	0.975	0.988	0.999
CA	0.951	1.002	0.792	1.336	0.989	0.967	na	0.994
CO	0.862	1.047	0.995	1.067	0.999	0.959	1.009	0.989
CT	na	1.031	0.952	0.940	1.025	0.885	na	0.965
DE	1.225	8.158	0.880	1.121	0.939	0.807	3.695	1.606

Table A.7. Continued

FL	0.885	1.002	1.040	1.471	1.035	0.984	na	1.055
GA	0.877	1.048	0.998	1.082	1.002	0.981	1.016	0.999
ID	0.894	1.087	0.992	1.056	1.004	1.004	0.945	0.995
IL	0.954	1.023	0.980	1.059	1.008	0.979	1.022	1.003
IN	0.883	0.996	1.026	1.074	1.029	1.010	1.036	1.006
IA	0.951	1.030	1.008	1.004	1.028	0.937	1.017	0.996
KS	0.896	1.078	0.983	1.075	1.020	1.008	0.964	1.002
KY	0.696	1.346	1.027	1.014	1.023	0.987	1.006	0.998
LA	0.838	0.982	0.679	1.141	1.035	1.004	1.093	0.955
ME	0.669	1.099	1.008	1.050	1.043	1.010	1.042	0.978
MD	0.889	1.033	1.026	1.310	0.984	0.973	0.992	1.023
MA	0.837	1.201	1.024	1.134	0.965	0.977	1.020	1.017
MI	0.937	1.058	0.992	1.068	1.000	0.984	0.989	1.003
MN	0.874	1.073	0.963	1.124	1.019	0.987	1.022	1.006
MS	0.783	1.029	1.024	1.061	0.985	0.969	0.999	0.975
MO	0.907	1.054	1.007	1.064	0.996	0.990	0.989	1.000
MT	0.858	1.103	0.986	1.061	1.037	1.028	0.998	1.007
NE	0.945	1.089	0.947	1.036	1.028	1.020	0.956	1.001
NV	0.801	na	1.535	9.760	na	0.904	0.980	1.604
NH	na	1.872	0.986	1.068	0.998	1.000	1.261	1.163
NJ	1.039	0.988	1.045	0.978	0.784	0.971	na	0.963
NM	0.731	1.073	1.025	1.060	1.042	1.001	1.076	0.994
NY	0.962	0.995	1.262	1.050	0.963	0.989	1.066	1.037
NC	0.945	1.033	1.019	1.039	0.982	0.968	0.996	0.997
ND	0.900	1.083	0.979	1.069	1.032	1.014	0.946	1.001
OH	0.911	1.028	1.024	1.073	0.990	0.970	1.019	1.001
OK	0.917	1.021	0.993	1.058	1.018	0.959	1.052	1.001
OR	0.914	1.056	1.006	1.064	0.997	0.993	0.975	1.000
PA	0.872	1.036	0.998	1.074	1.008	0.978	1.035	0.998
RI	0.903	3.091	0.991	1.009	0.986	0.988	0.975	1.149
SC	0.936	1.029	1.029	1.062	0.980	0.970	0.995	0.999
SD	0.905	1.107	0.977	1.061	1.035	1.059	0.896	1.003
TN	1.009	0.983	1.015	1.049	0.981	0.995	1.003	1.005
TX	0.827	0.999	0.958	1.063	1.064	1.006	1.304	1.023
UT	0.984	0.998	0.997	0.990	0.981	0.977	1.015	0.992
VT	0.786	1.061	0.976	1.075	1.028	0.966	1.007	0.981
VA	0.877	1.047	1.007	1.074	1.011	0.983	1.014	1.000
WA	0.891	1.291	0.896	1.112	0.988	0.991	1.044	1.023
WV	0.907	1.045	0.980	1.062	1.040	0.992	0.974	0.999
WI	0.964	1.022	1.064	0.988	1.095	0.892	1.004	1.002
WY	0.853	1.063	0.991	1.061	1.021	0.978	1.023	0.996

*na: infeasible solution

Table A.8 displays the cumulated productivity growth of each state over the sample period in Model 2. Technical change was the major source driving productivity change over time.

Table A.8. Model 2: State Cumulated Productivity Growth, 2000-2007

State	ML	EFFCH	TECH
AL	0.995	1.000	0.995
AZ	1.035	1.000	1.035
AR	0.990	1.000	0.990
CA	0.000	1.000	0.000
CO	0.927	1.000	0.927
CT	0.000	1.000	0.000
DE	27.593	1.000	27.593
FL	0.000	1.000	0.000
GA	0.989	0.998	0.991
ID	0.968	1.000	0.968
IL	1.020	1.000	1.020
IN	1.042	1.000	1.042
IA	0.972	1.001	0.971
KS	1.012	1.000	1.012
KY	0.989	1.000	0.989
LA	0.725	1.000	0.725
ME	0.854	1.000	0.854
MD	1.172	1.000	1.172
MA	1.123	1.000	1.123
MI	1.022	1.000	1.022
MN	1.043	1.000	1.043
MS	0.836	1.000	0.836
MO	0.999	1.000	0.999
MT	1.054	1.000	1.054
NE	1.011	1.000	1.011
NV	0.000	1.000	0.000
NH	0.000	1.000	0.000
NJ	0.000	1.000	0.000
NM	0.956	1.000	0.956
NY	1.288	1.000	1.288
NC	0.977	1.000	0.977
ND	1.009	1.000	1.009
OH	1.007	1.000	1.007
OK	1.009	1.000	1.009
OR	0.998	1.000	0.998
PA	0.987	1.000	0.987
RI	2.647	1.000	2.648
SC	0.995	1.000	0.996

Table A.8. Continued

SD	1.021	1.000	1.020
TN	1.033	1.000	1.033
TX	1.173	1.000	1.173
UT	0.948	1.005	0.943
VT	0.874	1.000	0.874
VA	1.000	1.001	1.000
WA	1.171	1.000	1.171
WV	0.991	1.000	0.991
WI	1.016	1.000	1.016
WY	0.974	1.000	0.974

In Model 3, 18 states experienced an average of 3.5 percent productivity growth over the sample period. In this sample, 17 states experienced productivity decline, and the average declines in productivity ranged between 0.1 percent and 1.1 percent. The stagnant efficiency change was also observed for each state, and the results are shown in Table A.10. In Table A.11, technical regress was experienced by 19 states, while technical progress was experienced by 25 states. Technical change was the main source of productivity change.

Table A.9. State Malmquist-Luenberger Productivity Index in Model 3

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.829	1.037	0.924	1.125	0.945	1.022	1.153	0.999
AZ	0.705	1.045	0.922	1.730	0.919	0.984	0.960	1.003
AR	0.978	0.912	1.022	1.011	1.072	1.003	0.999	0.999
CA	0.933	1.005	0.850	1.244	0.989	0.967	1.053	1.000
CO	0.876	1.072	0.921	1.033	1.087	0.984	1.043	1.000
CT	0.924	0.999	0.991	1.042	1.040	0.954	1.087	1.004
DE	0.967	1.141	0.871	1.072	0.966	0.982	1.065	1.006
FL	0.883	1.017	1.031	0.975	1.036	0.982	1.066	0.997
GA	0.936	1.001	0.960	1.020	1.008	0.961	1.114	0.998
ID	1.009	1.053	0.969	1.063	0.956	0.982	0.940	0.995
IL	0.954	1.022	0.910	1.129	1.018	0.979	1.022	1.003
IN	0.881	0.970	1.010	1.111	1.039	1.007	1.036	1.006
IA	0.922	1.039	1.010	1.012	1.013	0.964	1.017	0.996
KS	0.954	1.014	0.966	1.035	1.005	0.959	1.086	1.002
KY	0.609	1.627	1.042	1.033	0.994	0.987	1.006	1.007
LA	0.862	1.081	0.895	1.084	1.044	0.972	1.096	1.001
ME	0.913	0.992	0.989	1.038	1.029	1.006	1.042	1.000
MD	0.970	0.999	1.022	1.081	0.953	0.913	1.073	1.000
MA	0.950	1.036	0.997	1.061	0.980	0.980	1.004	1.000
MI	0.849	1.084	0.894	1.089	1.068	0.959	1.109	1.002

Table A.9. Continued

MN	1.026	0.988	1.038	1.054	0.980	0.959	0.978	1.003
MS	0.803	1.055	0.937	1.088	1.024	1.048	1.074	0.999
MO	0.829	1.062	0.951	1.099	1.027	1.007	1.052	1.000
MT	0.788	1.077	0.973	1.111	0.987	1.063	1.014	0.997
NE	0.945	1.083	0.953	1.032	1.028	1.013	0.956	1.000
NV	0.858	1.058	1.126	1.007	1.035	0.947	0.996	1.001
NH	0.830	1.040	0.865	1.079	1.009	0.944	1.290	0.999
NJ	1.042	1.000	1.027	0.976	0.971	0.969	0.995	0.997
NM	0.766	1.065	0.929	1.069	1.083	1.029	1.114	1.001
NY	0.780	1.020	0.973	1.067	1.058	1.156	1.062	1.010
NC	0.945	1.015	0.950	1.034	0.999	1.003	1.036	0.997
ND	0.817	1.015	1.028	1.093	1.008	0.985	1.096	1.002
OH	0.849	1.054	0.988	1.089	1.020	0.968	1.061	1.001
OK	0.798	1.009	1.024	1.066	0.989	1.001	1.160	1.001
OR	0.912	0.978	0.911	1.090	1.004	1.120	1.001	1.000
PA	0.856	1.055	0.998	1.022	1.024	0.986	1.061	0.998
RI	1.030	1.049	0.872	0.989	0.993	0.995	1.009	0.989
SC	0.985	1.031	0.946	0.976	1.025	0.980	1.060	0.999
SD	0.869	1.011	1.012	1.103	1.026	1.015	0.980	1.000
TN	1.008	0.983	0.987	1.061	0.997	0.995	1.003	1.005
TX	0.827	0.997	0.994	1.063	1.064	1.009	1.070	1.000
UT	1.117	0.882	1.018	1.025	1.010	0.866	1.054	0.992
VT	0.879	0.976	1.039	1.105	1.051	0.976	0.984	0.999
VA	0.907	1.010	0.975	1.078	0.956	0.938	1.158	1.000
WA	0.965	1.054	0.979	1.076	1.014	0.993	0.953	1.004
WV	0.893	0.942	1.003	1.088	1.060	0.974	1.049	0.999
WI	0.967	1.013	1.036	1.003	1.075	0.916	1.002	1.001
WY	0.812	0.921	1.020	1.072	1.070	1.041	1.097	1.000

Table A.10. State Efficiency Change Index in Model 3

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.925	0.987	0.915	1.052	0.945	1.036	1.163	1.000
AZ	0.765	1.023	0.902	1.659	0.912	0.995	0.940	1.000
AR	0.953	0.894	1.000	1.020	1.107	1.029	1.011	1.000
CA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CO	0.936	1.034	0.923	0.970	1.089	1.026	1.034	1.000
CT	1.000	1.000	1.000	0.989	1.011	1.000	1.000	1.000
DE	0.942	1.070	0.871	1.052	0.966	1.019	1.100	1.000
FL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
GA	1.067	0.956	0.962	0.942	1.006	0.980	1.096	1.000
ID	1.124	0.976	0.977	1.007	0.952	0.978	0.995	1.000
IL	1.000	1.000	0.929	1.066	1.010	1.000	1.000	1.000
IN	0.998	0.974	0.984	1.034	1.010	1.000	1.000	1.000
IA	0.969	1.008	1.002	1.008	0.986	1.030	1.000	1.000
KS	1.065	0.941	0.983	0.962	0.985	0.951	1.127	1.000

Table A.10. Continued

KY	0.875	1.143	1.000	1.000	1.000	1.000	1.000	1.000
LA	0.976	1.011	0.918	0.990	1.029	0.971	1.115	1.000
ME	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MD	1.042	0.967	0.994	1.018	0.969	0.938	1.079	1.000
MA	1.022	1.000	0.983	0.999	0.993	1.001	1.004	1.000
MI	0.912	1.027	0.897	1.021	1.068	0.974	1.121	1.000
MN	1.169	0.929	1.070	0.959	0.965	0.972	0.957	1.000
MS	0.862	1.025	0.915	1.026	1.039	1.081	1.073	1.000
MO	0.912	1.007	0.944	1.034	1.031	1.017	1.064	1.000
MT	0.863	0.990	1.003	1.038	0.957	1.005	1.170	1.000
NE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NV	0.930	1.014	1.089	0.971	1.030	0.978	0.996	1.000
NH	0.939	0.973	0.870	1.016	1.007	0.949	1.295	1.000
NJ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NM	0.832	0.970	0.961	1.001	1.043	1.009	1.226	1.000
NY	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NC	1.000	0.983	0.933	0.995	1.017	1.037	1.040	1.000
ND	0.902	0.938	1.050	1.023	0.977	0.972	1.159	1.000
OH	0.932	1.025	0.964	1.015	1.030	0.997	1.041	1.000
OK	0.870	0.989	1.032	1.008	0.972	1.044	1.103	1.000
OR	0.998	0.927	0.906	1.025	1.007	1.127	1.027	1.000
PA	0.982	1.018	1.000	0.952	1.016	1.009	1.025	1.000
RI	1.141	0.992	0.865	0.980	1.007	1.007	1.028	1.000
SC	1.050	1.002	0.920	0.918	1.047	1.010	1.065	1.000
SD	0.938	0.909	1.052	1.030	0.995	0.951	1.144	1.000
TN	1.000	1.000	0.973	1.011	1.016	1.000	1.000	1.000
TX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
UT	1.135	0.884	1.021	1.035	1.030	0.886	1.038	1.001
VT	0.955	0.929	1.065	1.039	1.025	0.978	1.017	1.000
VA	1.025	0.965	0.968	1.004	0.945	0.955	1.153	1.000
WA	1.080	1.023	0.984	1.005	1.004	1.004	0.908	1.000
WV	0.982	0.901	1.024	1.025	1.019	0.983	1.076	1.000
WI	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
WY	0.888	0.881	1.031	1.008	1.053	1.055	1.106	1.000

Table A.11. State Technical Change Index in Model 3

State	00-01	01-02	02-03	03-04	04-05	05-06	06-07	Mean
AL	0.897	1.051	1.011	1.069	1.000	0.986	0.992	0.999
AZ	0.921	1.022	1.022	1.043	1.008	0.988	1.021	1.003
AR	1.026	1.020	1.022	0.992	0.969	0.975	0.988	0.999
CA	0.933	1.005	0.850	1.244	0.989	0.967	1.053	1.000
CO	0.937	1.037	0.998	1.065	0.999	0.959	1.009	1.000
CT	0.924	0.999	0.991	1.053	1.029	0.954	1.087	1.004
DE	1.027	1.066	1.000	1.020	1.000	0.964	0.968	1.006
FL	0.883	1.017	1.031	0.975	1.036	0.982	1.066	0.997

Table A.11. Continued

GA	0.877	1.048	0.998	1.082	1.002	0.981	1.016	0.999
ID	0.898	1.078	0.992	1.056	1.004	1.004	0.945	0.995
IL	0.954	1.022	0.980	1.059	1.008	0.979	1.022	1.003
IN	0.883	0.996	1.026	1.074	1.029	1.007	1.036	1.006
IA	0.951	1.030	1.008	1.004	1.028	0.937	1.017	0.996
KS	0.896	1.078	0.983	1.075	1.020	1.008	0.964	1.002
KY	0.696	1.423	1.042	1.033	0.994	0.987	1.006	0.998
LA	0.882	1.070	0.975	1.095	1.015	1.001	0.983	0.955
ME	0.913	0.992	0.989	1.038	1.029	1.006	1.042	0.978
MD	0.931	1.033	1.028	1.062	0.984	0.973	0.995	1.023
MA	0.930	1.036	1.014	1.062	0.988	0.979	1.000	1.017
MI	0.930	1.056	0.997	1.067	1.000	0.984	0.989	1.003
MN	0.877	1.063	0.970	1.099	1.015	0.987	1.022	1.006
MS	0.931	1.029	1.024	1.061	0.985	0.969	1.001	0.975
MO	0.909	1.054	1.007	1.064	0.996	0.990	0.989	1.000
MT	0.914	1.089	0.970	1.071	1.031	1.058	0.867	1.007
NE	0.945	1.083	0.953	1.032	1.028	1.013	0.956	1.001
NV	0.923	1.044	1.033	1.037	1.005	0.969	1.000	1.604
NH	0.884	1.068	0.995	1.062	1.002	0.996	0.996	1.163
NJ	1.042	1.000	1.027	0.976	0.971	0.969	0.995	0.963
NM	0.921	1.099	0.967	1.068	1.038	1.020	0.909	0.994
NY	0.780	1.020	0.973	1.067	1.058	1.156	1.062	1.037
NC	0.945	1.033	1.019	1.039	0.982	0.968	0.996	0.997
ND	0.906	1.083	0.979	1.069	1.032	1.014	0.946	1.001
OH	0.911	1.028	1.024	1.073	0.990	0.970	1.019	1.001
OK	0.917	1.021	0.993	1.058	1.018	0.959	1.052	1.001
OR	0.914	1.056	1.006	1.064	0.997	0.993	0.975	1.000
PA	0.872	1.036	0.998	1.074	1.008	0.978	1.035	0.998
RI	0.903	1.057	1.008	1.009	0.986	0.988	0.982	1.149
SC	0.937	1.029	1.029	1.062	0.980	0.970	0.995	0.999
SD	0.927	1.113	0.962	1.071	1.031	1.067	0.857	1.003
TN	1.008	0.983	1.015	1.049	0.981	0.995	1.003	1.005
TX	0.827	0.997	0.994	1.063	1.064	1.009	1.070	1.023
UT	0.984	0.998	0.997	0.990	0.981	0.977	1.015	0.992
VT	0.921	1.051	0.976	1.063	1.025	0.998	0.967	0.981
VA	0.885	1.047	1.007	1.074	1.011	0.983	1.004	1.000
WA	0.893	1.031	0.995	1.071	1.010	0.989	1.050	1.023
WV	0.909	1.045	0.980	1.062	1.040	0.992	0.974	0.999
WI	0.967	1.013	1.036	1.003	1.075	0.916	1.002	1.002
WY	0.914	1.045	0.989	1.063	1.016	0.987	0.992	0.996

Table A.12 displays the cumulated productivity growth of each state over the sample period. The results also indicate that technical change was the factor that drove productivity growth (decline) over time.

Table A.12. Model 3: State Cumulated Productivity Growth, 2000-2007

State	ML	EFFCH	TECH
AL	0.995	1.000	0.995
AZ	1.020	1.000	1.020
AR	0.990	1.000	0.990
CA	0.999	1.000	0.999
CO	0.997	1.000	0.998
CT	1.027	1.000	1.027
DE	1.041	1.000	1.041
FL	0.978	1.000	0.978
GA	0.989	0.998	0.991
ID	0.966	1.000	0.965
IL	1.019	1.000	1.019
IN	1.039	1.000	1.039
IA	0.972	1.001	0.971
KS	1.012	1.000	1.012
KY	1.051	1.000	1.051
LA	1.005	1.000	1.005
ME	1.002	1.000	1.002
MD	0.998	1.000	0.998
MA	1.003	1.000	1.004
MI	1.017	1.000	1.017
MN	1.018	1.000	1.018
MS	0.996	1.000	0.996
MO	1.001	1.000	1.001
MT	0.976	1.000	0.976
NE	1.001	1.000	1.001
NV	1.004	1.000	1.004
NH	0.991	1.000	0.991
NJ	0.978	1.000	0.978
NM	1.005	1.000	1.005
NY	1.071	1.000	1.071
NC	0.977	1.000	0.977
ND	1.014	1.000	1.015
OH	1.007	1.000	1.007
OK	1.009	1.000	1.009
OR	0.998	1.000	0.998
PA	0.987	1.000	0.987
RI	0.928	1.000	0.928
SC	0.996	1.000	0.996
SD	1.001	1.000	1.001
TN	1.032	1.000	1.032
TX	1.000	1.000	1.000
UT	0.948	1.005	0.943
VT	0.994	1.000	0.994
VA	0.999	1.000	0.999

Table A.12. Continued

WA	1.028	1.000	1.028
WV	0.994	1.000	0.994
WI	1.005	1.000	1.005
WY	0.999	1.000	0.999

APPENDIX B

I applied three models to measure efficiency and productivity change in trucking in 2002 and 2005 accounting for both GHG emissions and toxic air pollutants. Table B.1 presents the descriptive statistics of the inefficiency scores obtained in Models (1) – (3).

Trucking inefficiency decreased in Model 1, but increased in Model 2 and 3. In Model 1, the average inefficiency scores were 0.007 in 2002 and 0.005 in 2005; this means that under the assumption of weak disposability of GHG and toxic air pollutants, states could expand good output and contract GHG and toxic air pollutants by an average of 0.7 percent and 0.5 percent in 2002 and 2005, respectively. Since the technology set was largest in Model 3, the inefficiency scores in Model 3 were higher.

Table B.1. Average Inefficiency Scores in 2002 and 2005

	2002	2005
Model 1		
Mean	0.007	0.005
SD	0.012	0.009
Min	0.000	0.000
Max	0.051	0.032
Model 2		
Mean	0.030	0.039
SD	0.034	0.028
Min	0.000	0.000
Max	0.134	0.107
Model 3		
Mean	0.037	0.039
SD	0.031	0.027
Min	0.000	0.000
Max	0.134	0.107

Table B.2 presents the average technical inefficiency scores by state in 2002 and 2005. Different rankings of states' performances were found in the three models. The five least efficient states in Model 1 were Wyoming, New Mexico, Wisconsin, Pennsylvania, and North Dakota, while the five least efficient states in Model 2 are Nevada, Wyoming, Texas, Indiana, and New Mexico, and the most inefficient states were Nevada, Wyoming, Texas, Oregon, and Indiana in Model 3.

Table B.2. Average Annual Inefficiency Scores by State in 2002 and 2005

State	Model 1	Model 2	Model 3
AL	0.008	0.048	0.048
AZ	0.000	0.000	0.000
AR	0.000	0.000	0.000
CA	0.000	0.041	0.041
CO	0.000	0.000	0.021
CT	0.013	0.032	0.032
DE	0.000	0.037	0.037
FL	0.000	0.034	0.034
GA	0.000	0.027	0.031
ID	0.000	0.014	0.047
IL	0.000	0.018	0.026
IN	0.013	0.054	0.054
IA	0.000	0.022	0.027
KS	0.010	0.044	0.046
KY	0.011	0.046	0.046
LA	0.004	0.034	0.037
ME	0.000	0.022	0.042
MD	0.000	0.041	0.041
MA	0.000	0.037	0.039
MI	0.000	0.018	0.018
MN	0.015	0.046	0.046
MS	0.002	0.042	0.042
MO	0.016	0.046	0.046
MT	0.016	0.038	0.038
NE	0.014	0.031	0.032
NV	0.000	0.067	0.067
NH	0.000	0.000	0.021
NJ	0.000	0.034	0.034
NM	0.020	0.054	0.054
NY	0.000	0.028	0.030
NC	0.009	0.039	0.048
ND	0.017	0.044	0.044
OH	0.017	0.036	0.036
OK	0.012	0.027	0.027
OR	0.000	0.053	0.054
PA	0.018	0.046	0.046
RI	0.000	0.053	0.053
SC	0.002	0.019	0.019
SD	0.009	0.033	0.033
TN	0.000	0.048	0.048

Table B.2. Continued

TX	0.000	0.056	0.056
UT	0.000	0.045	0.045
VT	0.000	0.000	0.026
VA	0.000	0.024	0.049
WA	0.000	0.051	0.051
WV	0.000	0.014	0.014
WI	0.018	0.046	0.046
WY	0.026	0.061	0.061
Mean	0.006	0.034	0.038

Table B.3 presents the geometric mean of the Malmquist-Luenberger (ML) index and its technical change (TECH) and efficiency change (TECH) components in 2002 and 2005. Productivity change and its components were different in three models. In Model 1, an average productivity decline, technology regress and efficiency improvement were observed in 2002-2005, while a productivity growth, technology progress and efficiency decline were observed in Model 2 and Model 3.

Table B.3 Mean Productivity Change and Decomposition in 2002-2005

	Model 1			Model 2			Model 3		
Year	ML	EFFCH	TECH	ML	EFFCH	TECH	ML	EFFCH	TECH
02-05	0.956	1.002	0.954	1.129	0.991	1.148	1.104	0.997	1.107

Table B.4 represents the productivity growth and it decompositions by state. An average productivity decline, technical regress, and efficiency improvement were observed in Model 1, which assumes weak disposability for GHG and toxic air pollutants. On the contrary, a productivity growth, technical progress and efficiency decline were observed in Model 2, which assumes strong disposability for GHG and toxic air pollutants, and Model 3, which ignores GHG and toxic air pollutants. Furthermore, 37 states experienced productivity decline, and eight states had productivity growth in Model 1, and technical change was the main source of productivity change. In addition, productivity change and its components varied in different states.

Table B.4. Productivity Change and Decompositions by State in 2002-2005

	Model 1			Model 2			Model 3		
State	ML	EFFCH	TECH	ML	EFFCH	TECH	ML	EFFCH	TECH
AL	0.958	0.984	0.974	1.068	0.945	1.130	1.042	0.945	1.102
AZ	0.654	1.000	0.654	1.333	1.000	1.333	1.092	1.000	1.092
AR	0.817	1.000	0.817	0.969	1.000	0.969	1.145	1.000	1.145
CA	na	1.000	na	1.176	0.984	1.195	1.078	0.984	1.096
CO	0.971	1.000	0.971	1.232	1.000	1.232	1.286	1.043	1.233
CT	0.891	0.975	0.914	1.064	0.940	1.132	1.023	0.940	1.089
DE	0.776	1.000	0.776	0.852	0.931	0.915	0.897	0.931	0.964
FL	0.919	1.000	0.919	1.233	0.936	1.317	1.025	0.936	1.095
GA	0.973	1.000	0.973	1.169	0.953	1.227	1.062	0.960	1.107
ID	1.077	1.000	1.077	1.095	0.973	1.125	1.123	1.038	1.082
IL	0.977	1.000	0.977	1.241	1.036	1.198	1.122	1.018	1.103
IN	0.984	1.025	0.960	na	1.033	na	1.126	1.033	1.090
IA	1.002	1.000	1.002	1.063	0.959	1.109	1.087	0.968	1.123
KS	0.948	0.980	0.967	1.042	0.933	1.116	1.024	0.938	1.092
KY	0.971	1.023	0.949	na	1.030	na	1.123	1.030	1.090
LA	0.966	0.993	0.974	na	0.977	na	1.072	0.983	1.090
ME	1.041	1.000	1.041	1.120	0.958	1.169	1.092	0.997	1.095
MD	na	1.000	na	1.212	0.935	1.297	1.029	0.934	1.102
MA	0.948	1.000	0.948	1.054	0.931	1.132	1.028	0.934	1.100
MI	0.978	1.000	0.978	na	1.036	na	1.195	1.036	1.154
MN	0.961	0.998	0.963	1.178	1.023	1.151	1.119	1.023	1.094
MS	0.966	0.996	0.970	1.114	0.994	1.120	1.100	0.994	1.106
MO	0.988	1.013	0.975	na	1.008	na	1.105	1.008	1.097
MT	0.922	0.969	0.951	1.076	0.929	1.159	1.027	0.929	1.106
NE	0.940	0.973	0.966	1.058	0.946	1.118	1.046	0.948	1.103
NV	na	1.000	na	1.911	1.134	1.686	1.258	1.134	1.110
NH	0.995	1.000	0.995	1.332	1.000	1.332	1.173	1.042	1.126
NJ	0.924	1.000	0.924	0.885	0.937	0.945	1.031	0.937	1.101
NM	0.999	1.039	0.962	na	1.049	na	1.152	1.049	1.098
NY	0.947	1.000	0.947	1.072	0.952	1.126	1.049	0.957	1.097
NC	0.979	0.982	0.997	1.076	0.927	1.160	1.040	0.944	1.101
ND	0.971	1.015	0.957	na	1.031	na	1.127	1.031	1.092
OH	0.981	1.006	0.976	1.145	1.018	1.125	1.115	1.018	1.095
OK	0.989	1.023	0.967	1.178	1.054	1.118	1.154	1.054	1.095
OR	0.903	1.000	0.903	1.135	0.993	1.143	1.090	0.995	1.095
PA	0.973	1.001	0.972	1.126	0.992	1.134	1.089	0.992	1.097
RI	0.903	1.000	0.903	0.994	0.904	1.100	0.983	0.904	1.088
SC	1.042	1.004	1.037	1.572	1.039	1.513	1.590	1.039	1.530
SD	0.980	1.018	0.963	na	1.026	na	1.122	1.026	1.093
TN	0.970	1.000	0.970	1.117	0.994	1.124	1.092	0.994	1.098
TX	0.937	1.000	0.937	na	1.035	na	1.137	1.035	1.099
UT	1.150	1.000	1.150	1.213	1.028	1.180	1.128	1.028	1.097
VT	0.907	1.000	0.907	1.308	1.000	1.308	1.148	1.051	1.092

Table B.4. Continued

VA	1.036	1.000	1.036	1.137	0.954	1.191	1.098	1.002	1.096
WA	0.974	1.000	0.974	1.178	1.018	1.157	1.112	1.018	1.092
WV	0.923	1.000	0.923	0.530	0.974	0.544	1.078	0.974	1.108
WI	1.014	1.026	0.988	1.152	1.035	1.113	1.126	1.035	1.088
WY	1.035	1.051	0.985	1.330	1.122	1.186	1.233	1.122	1.099
Mean	0.959	1.002	0.957	1.147	0.992	1.162	1.108	0.999	1.109

*na: infeasible solution

An ANOVA F-test and a series of nonparametric tests were applied to examine productivity index variations between Model 1 and Model 2. The statistical results are presented in Table B.5. The results show that the productivity indexes in Model 1 and Model 2 were statistically significantly different.

Table B.5. ANOVA F-test and Nonparametric Tests

Year	ANOVA-F (Prob > F)	Kruskal-Wallis (Prob > χ^2)	Median (Prob > χ^2)	Van der Waerden (Prob > χ^2)	Savage (Prob > χ^2)
02-05	32.811	37.968	39.773	31.628	32.943
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)