An economic model for sustainable harbor trucking

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An economic model for sustainable harbor trucking

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ABSTRACT

Truck emissions at a port may have a severe impact on neighbors, resulting in a politically sensitive sustainability issue for the port management. Strict emissions controls may adversely affect throughput whereas the lack of strict controls will be unacceptable to local citizens and environmental interests. We develop an economic model minimizing cost of truck emissions control and collateral production changes and apply it to decision making for a port seeking to meet a throughput goal while also attempting to satisfy an emissions constraint. Outcomes predicted by the model allow informed decisions about the impact of controls.

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1. Introduction

Instituting sustainable practices in a supply chain has recently emerged as an important goal. Maritime ports have come under pressure to control emissions from ships, trucks, and other equipment used in landing containers and other products. Many maritime ports still use diesel trucks to bring containers to and from them. These trucks are large sources of nitrogen oxide (NO_X) and particulate matter (PM) which have been shown to be injurious to the local population, and add to the emissions load generated by the port, causing consternation in US ports over the economic effects of emissions control policies.

Various mechanisms of reducing emissions around transport facilities have been proposed. Drury et al. (1999), for example, looks at pollution trading's failure in the Los Angeles basin, Liao et al. (2010) found that container traffic in Taiwan will switch ports if emissions requirements change, and Berechman (2009) assessed the marginal costs of port related truck traffic at Port of New York–New Jersey, including congestion and safety as well as emissions.

Our model minimizes the cost of implementing an emissions control initiative while jointly satisfying constraints of meeting a production goal and reducing emissions to a specific level, using a simple constrained nonlinear economic production model. The initiative specifies an emissions level at the port and uses per-container fees to obtain capital for subsidies to truckers to induce a percentage of trucks to be upgraded. This has been the most recent strategy attempted at the Ports of Los Angeles (POLA) and Long Beach (POLB). The majority of other US maritime ports have developed Clean Truck Plans that are patterned after the POLA and POLB but less restrictive and expansive.

2. The model

We begin by adapting a basic cost minimization model from microeconomics. The economic agent is the port operator, who has the objective of meeting a forecasted production goal for container throughput. Denoting by Q the production,

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measured in 20 foot equivalent container units (TEU) moved per period; we assume variables are flows on a per year basis. The forecasted production requirement is Q_0.

In addition, the port wishes to control emissions; our example deals with diesel particulate matter (DPM), but any factor could be used. The production of Q generates E units of emissions; there is an increasing functional relationship. The US Environmental Protection Agency (2011) states that the general relation is linear;

$$E = A \times \text{EF} \times (1 - \text{ER}/100)$$

where E is emissions, A is activity rate, EF is emission factor, and ER is overall emission reduction efficiency. Denote the targeted level of emissions by E_0.

In the case of harbor trucking, reducing emissions can be accomplished by upgrading trucks, or by replacing them with versions that pollute less. This expense will raise the cost borne by the truckers, and they will try to pass on this increased transaction cost to their customers. This will ultimately result in a rise in the cost to a shipper to bring a container through the port, and will raise freight rates through the port. Demand will be reduced which may result in a loss of business; fewer containers may pass through the port, reducing Q. The port must balance emissions reduction with the need to meet its throughput goal. One option for the ports is to raise capital C to devote to emissions control, such as by granting subsidies to truckers for upgrading trucks. Such capital would cost r per unit, in interest or opportunity value. It might be obtained by a loan or bond issue, a federal or state grant, or a container fee, resulting in a per container burden. In addition, trucking labor costs per unit w are raised by the introduction of the emissions constraint, and these affect the amount of truck labor L employed.

Our model minimizes capital and labor costs attributable to the controls subject to a throughput constraint and an emissions constraint. It is not necessary to include other capital and labor costs of the port in the model, because we consider the levels of these inputs independent of those directly related to the truck emissions.

$$\begin{aligned}
\min \quad & Z = rC + wL \\
\text{s.t.} \quad & Q \geqslant Q_0 \\
& E \leqslant E_0
\end{aligned} \tag{1}$$

Harbor trucks typically haul 20 or 40 foot standard ocean containers. The unit of transfer is a twenty-foot equivalent unit (TEU). A truck may haul more than one TEU in a trip, but each container will need one truck trip at the port. Therefore we can measure the unit of labor as one TEU trip. The cost of a trip in labor will be constant except for the cost of the time spent by the driver. Fuel consumed will be proportional to the number and average length of trips, but is not relevant to the cost of emissions reduction.

Operator wages are a major consideration in the model. In the US ports are served by drayage companies and owner-operators. Drayage companies use drivers as employees, and also hire owner-operators on a piecework basis. For trips made by drayage company employees, the employee wage is paid hourly or set by the union wage rate. Our research and that of Haveman and Monaco (2009) has shown that when drayage firms use contract workers with upgraded trucks they tend to pay them at the rate equivalent to the union wage. So, for all the upgraded truck trips, in our model the wage rate w_1 in $ per TEU applies, since the number of hours per trip and the TEU per trip used are averages.

The wage rates of owner-operators (w_0) are set by market forces with drayage providers paying only what the market requires; if there is an ample supply the wage may drop. It is the average price paid the owner operator for the trip divided by the average TEU moved per trip and the number of hours per trip; $w_1 > w_0$, because the union/employee wage is higher than the nonunion wage. In some ports, such as POLA, owner-operators of their own trucks make little over a minimum wage per hour, say $10; if the average TEU move takes 5 h their wage rate might be $50 per move. Union drivers might make $20 per hour, so on the same basis their wage rate could be $100. The differential $\Delta w = w_1 > w_0$ would then be $50.

The cost wL is the weighted average of the cost of the upgraded hauls and the cost of those made with trucks not upgraded. L can be measured in TEU-trips, and is essentially proportional to the number of TEUs moved at the port, or Q. It would be possible to include a correction factor for the average number of TEU per trip, to obtain a closer estimate of the number of trips; we do this in the example. Alternatively, we could adjust w_i, leaving the model intact.

The port can induce private truckers and drayage firms to upgrade their trucks to reduce emissions. One incentive mechanism, the Clean Truck Program, provides subsidies to truckers who upgrade to a chosen emissions control standard. Define ϕ as the percentage of trucks which have been upgraded to meet that standard. Clott and Hartman (forthcoming) suggest, using a game theory model, that the mandated policy should apply the same percentage of upgrades ϕ to both firm-owned and individually owned trucks.

The cost of labor due to the sustainability program is the traffic Q, multiplied by a convex combination with parameter ϕ, of the wages,

$$wL = (w_1\phi + w_0(1 - \phi))Q = (w_1 - w_0)\phi Q + w_0 Q = (w_0 + \phi\Delta w)Q \tag{2}$$

One expects the emission level E to decrease with ϕ, but to increase with Q. The amount of capital required is clearly proportional to the percentage of upgraded hauls, since we will pay for the upgraded trucks. Assume that c is the amortized amount per period paid for each upgraded truck. We take the cost of the upgrade specified, estimate its lifetime, and amortize over that number of periods, using say a straight line method. Such figures are available from many estimates, including

Environmental Protection Agency (2011), US Office of Transportation and Air Quality (2011), and from the specifications of the upgrade equipment. We divide it by the average number of TEU hauled per truck per year to get the capital share of the TEU moved. Then $C = c\phi Q$.

Emissions are approximately proportional to the number of hauls and therefore to Q. But since only some of the trucks have been upgraded, the amount of emission from the upgraded trucks per haul, k_1 is smaller than k_0, the amount of emission per haul from a non-upgraded truck. Thus $\Delta k = k_1 - k_0$ is negative. The emissions is therefore the convex combination,

$$E = k_1\phi Q + k_0(1 - \phi)Q = (k_1 - k_0)\phi Q + k_0 Q = (k_0 + \phi\Delta k)Q$$

The decision variables are Q and ϕ, the amount of traffic moved, and the percentage of trucks upgraded. We assume the amount of capital required per upgraded truck is chosen by the port based on some criterion, like what upgrade to specify; it is useful to think of it as a subsidy, though the port will decide whether to use it that way. It is independent of ϕ and Q. The optimization problem becomes

$$\min \quad Z = (rc + \Delta w)\phi Q + w_0 Q \tag{3}$$
$$\text{s.t.} \quad Q \geqslant Q_0 \tag{4}$$
$$\phi \in [0, 1] \tag{5}$$
$$E_0 \geqslant \Delta k\phi Q + k_0 Q \tag{6}$$

The objective function (3) has isocost contours which are hyperbolic in ϕ, Q space. A level cost curve with cost Z_0 has the form,

$$Q = Z_0 / \{\phi(rc + \Delta w) + w_0\} \tag{7}$$

The emissions constraint (6) is also hyperbolic,

$$Q = E_0 / \phi\Delta k + k_0 \tag{8}$$

This is a nonlinear optimization problem over ϕ and Q, with three constraints. Constraint (4) says that any decision must meet forecasted demand for container moves; we must produce output greater than Q_0 TEU per period. Constraint (5) identifies ϕ as a proper fraction, a convex combination parameter. Constraint (6) assures the amount of emissions generated by the choice does not exceed the emissions target E_0. The boundary is nonlinear in form, being hyperbolic in (ϕ, Q). Δk is negative, because upgraded trucks have lower emissions per trip than non-upgraded ones. So the emissions hyperbola opens toward the left rather than toward the right. Constraints (4) and (5) limit the feasible set to a truncated strip in the first quadrant whose lower boundary occurs at $Q = Q_0$, and whose width is unity because ϕ is a fraction. Table 1 sets out the parameters of the model and typical units of measurement.

The optimal value of ϕ is obtained by solving $\phi\Delta k + k_0 = E_0/Q_0 \rightarrow \phi = [(E_0/Q_0) - k_0]/\Delta k$. Fig. 1 portrays a typical situation. The Q-constraint is a horizontal line, and the emissions E-constraint is a leftward opening hyperbola given by Eq. (8). There are three possibilities for the feasible set: A the E-constraint cuts the Q-constraint for a legal value of $\phi \in [0, 1]$; B the E-constraint is always below the Q-constraint for those values; and C the E-constraint is entirely above the Q-constraint for those values. In case A, since the E-constraint is upward sloping, the minimum will always be where the two constraints bind, at their intersection. In case B, we have an emissions requirement so strict (low emissions) that we cannot meet it even by upgrading all trucks. There is an empty feasible set; to make this E-level feasible, we must accept lower production. In case C, the E-constraint is so weak (high emissions allowed) that we need not upgrade any of the trucks; the E-constraint does not limit the solution, and can always be met by current trucks. The isocost curve is given by Eq. (7) with the optimal cost at the intersection of the isocost line and the left end of the Q-constraint.

Table 1
Parameters of the cost model and example units of measure.

| Parameter	Description	Typical units
Q_0	Target production	million TEU
c	Upgrade unit cost	$ per TEU trip
r	Capital interest rate	Per year
w_1	Labor cost, employee/union driver	$ per TEU trip
w_0	Labor coat, independent owner operator	$ per TEU trip
E_0	Emissions target	million tons per year
k_1	Emissions rate, upgraded truck	Ton per TEU trip
k_0	Emissions rate, standard truck	Ton per TEU trip
Δw	Wage difference $w_1 - w_0$	$ per TEU trip
Δk	Emissions difference $k_1 - k_0$	Ton per TEU trip
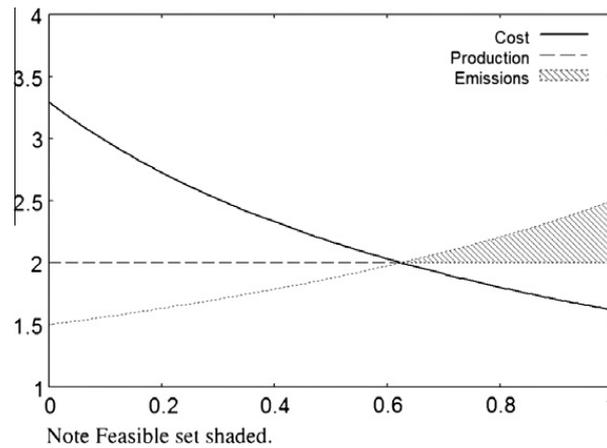
Fig. 1. Minimum cost attained at approximately (0.625, 2) in the (ϕ, Q) plane.

3. Lagrangean formulation and shadow prices

A nonlinear optimization problem with constraints can be rewritten using Lagrangean duality, which yields additional insight. The problem is stated as

$$\min \quad Z = (A\phi + B)Q \tag{9}$$
$$\text{s.t.} \quad E_0 \leqslant (C\phi + D)Q \tag{10}$$
$$Q \geqslant Q_0 \tag{11}$$
$$\phi \in [0, 1] \tag{12}$$

We associate $A = rc + \Delta w$; $B = w_0$ with $\Delta w > 0$, and $C = \Delta k$; $D = k_0$ with $0 > \Delta k$.

Dualizing the emissions constraint 10 by assigning penalty μ to an excess of emissions, and assign penalty λ to a failure to meet the production constraint 11, forms the Lagrangean to get

$$\min \quad L = (A\phi + B)Q + \mu\{(C\phi + D)Q - E_0\} + \lambda(Q_0 - Q) \tag{13}$$

We apply the Karush–Kuhn–Tucker conditions to determine optima:

$$\partial L / \partial Q = A\phi + B + (C\phi + D)\mu - \lambda = 0 \tag{14}$$
$$\partial L / \partial \phi = AQ + \mu CQ = 0 \tag{15}$$
$$\partial L / \partial \mu = (C\phi + D)Q - E_0 = 0 \tag{16}$$
$$\partial L / \partial \lambda = Q_0 - Q = 0 \tag{17}$$

From (15) we obtain

$$AQ + \mu CQ = 0 \rightarrow \mu = -A/C \tag{18}$$

Now $\lambda = 0 \rightarrow BC = AD$, by substituting for μ in Eq. (14). In our case, $C < 0 \rightarrow BC < 0$, but $A, D > 0 \rightarrow AD > 0$, so λ is never zero. Therefore the constraint for production is always binding; we can meet the production goal at optimality whenever the problem is feasible, so $0 \leqslant \phi \leqslant 1$, and $Q = Q_0$. Considering $\mu = -A/C$, we see that because $\Delta k < 0$

$$\mu = -(rc + \Delta w)/\Delta k > 0 \tag{19}$$

Therefore the emissions constraint binds at an interior minimum and we have, because $Q = Q_0$,

$$E_0 = (C\phi + D)Q_0 \rightarrow E_0 = Q_0/(C\phi + D)$$

Then we have at optimality

$$\phi^* = E_0/Q_0 - D/C = [E_0/Q_0 - k_0]\Delta k \tag{20}$$

From this we find that whenever the emission target and production are related so that $k_0 < E_0/Q_0 < k_1$, we have a feasible optimal policy. ϕ^* is the ratio of the goal improvement of the target emissions level per unit of targeted production to the maximum improvement per unit of targeted production, when this ratio is between zero and one. This result summarizes the optimality story for our scenario. It derives from the specific proportional dependence on Q we have assumed for the labor cost and the emissions created. If it were relaxed to another increasing functional form, results would differ.

We can derive from the model and data for a port an interesting result on the implied price of emissions offsets. From Eq. (19), $\mu = -(A/C)$; notice that C is negative; this is a price per unit of emissions. If the port could sell emissions credits for a

larger sum than this it would pay them to reduce their emissions target E_0. Each unit of increase would cost them μ; a reservation price for emission credits for the port is established. It depends only on the cost and amount of subsidy, the wage increase, and the technological factors of the upgrade chosen (under the assumptions of the model). A brief informal survey of values of emissions upgrades for carbon, for instance, shows them ranging for $3–10 per ton; but of course buying would not fix the external effects such as health problems in the local community. There is no corresponding market for DPM emissions, as in the example. Given the limits of technology, the structure of μ shows the principal role unions and the labor market have on the ability of the port to impose emissions standards. The Δw term has a large effect, and Δk is a long-term effect since technology does not change so quickly.

The effect of the capital investment c is typically secondary; at normal interest rates and amounts of capital per TEU trip per period allocated at many ports, the effect on μ will quite probably be much smaller. In that case the ability of the port to raise capital to subsidize upgrades is not a major mover of the reservation price. This may partially explain why subsidy programs have had little support such as the state of California initiative to impose a $35 per TEU movement fee to offset the cost of pollution control (Mongelluzzo, 2011).

The shadow price λ gives information on the cost of a change in the production goal. Since

$$\lambda = B - AD/C = w_0 + (rc + \Delta w)k_0/\Delta k = w_0 + (rc + \Delta w)/[1 - (k_1/k_0)] \tag{21}$$

it is something more than the owner-operator wage, the cost of an additional unit if there were no upgrade and no capital employed. The cost of capital and the wage up-tick must be weighted by the proportion $\{1/(1 - k_1/k_0)\}$. Now k_1/k_0 is the fraction reduction in pollution from the upgrade of a truck due to the technology chosen. $\{(k_0 - k_1)/k_0\}$ is the percentage amount of pollution removed from the air based on the technology. Since for the shadow price we are dividing by that, a small percentage reduction adds a large cost per unit of output, where a large reduction produces lower extra cost per unit of output. In other words, if you need to raise production and you are only making a small emissions improvement on each vehicle, you will pay a greater amount extra in cost than if you are making a large improvement in emissions on each vehicle. Using λ one can estimate the impact on cost per TEU trip of a particular upgrade plan. If freight rates were raised above market this would suppress demand; if rates were already a bit below market, the impact on demand might not be significant.

4. Sensitivity to other parameters

The simple structure of this nonlinear program allows us to identify graphically the effect of varying other parameters. If E_0, the level of emissions allowed, is raised, the port operator can lower the percent of trucks upgraded to achieve lower cost, because the E-hyperbola shifts left and up so its intersection with the demand forecast target line shifts left. If E_0 is large enough, the hyperbola could cut the Q axis above the Q_0 demand line. In that case the port would not need to upgrade trucks. Since the left endpoint is defined by the ratio E_0/k_0, we would need to raise E_0 above it to make this corner optimal. Correspondingly if the emissions target is lowered, the right endpoint E_0/k_1 could be optimal. In case target demand changes, if Q_0 increases, the optimal point moves to the right along the graph of E so that the fraction ϕ must rise; more traffic increases emissions. Once $Q_0 > E_0/k_1$, it is no longer feasible to meet both demand and the emission standard. If Q_0 decreases, perhaps due to an economic slowdown, the optimal choice of ϕ moves left; once demand goes below E_0/k_0, even trucks which are not upgraded will not overrun the emission standard.

On the capital side, a lower interest rate r makes it possible to upgrade a higher percentage of trucks for the same money. It reduces the size of the coefficient of ϕ in the denominator of the isocost line, which shifts it up to the right. If the quantity $rc + (\Delta w) = 0$, we have a constant cost and this would happen if $r = (w_0 - w)/c < 0$. If the amount of subsidy c changes, only the cost curve is affected. If c goes down, the cost level curve rises to the right, so the cost of the optimal solution, which remains at the intersection of the Q-constraint and the E-constraint, goes down; vice versa if c increases. Wage or pay changes per TEU trip for union/employee drivers and owner-operator drivers also affect the cost graph through two means: the actual value of w_0, and the differential $\Delta w > 0$. A rise in either or both results in a higher cost at the optimal solution point.

The emissions parameters k_1, k_0 change as a result of technology choices and innovations. If a different sort of upgrade is chosen, they will change, affecting the emissions curve but not the cost curve. They therefore change the optimal solution point. It is the ratio k_1/k_0 that is important.

5. Port data example

Data from Haveman and Monaco (2009) for the Port of Oakland in 2007 were obtained to test the model. In that year, the port moved 2.4 million TEU; at their figure of 1.8 TEU moved per trip, there were 1.33 million trips. Data Table 2 includes estimates from drayage driver questionnaires of the length of trips, and the distribution of trips of different length; shuttle, short, regional, and long. From California Air Resources Board (2011) we obtained the figure for very heavy-duty trucks of 0.002309 lbs of diesel particulate matter 10micron (DPM10) emissions per mile of travel. Models used for emissions calculation do take into account idling and unloaded mileages (bobtailing), but those for open highways may be quite different than those experienced by drivers at the actual port. The average figure are used here.

Table 2
Data on trip lengths and DPM10 emissions. *Source*: Haveman and Monaco (2009)

Trip type	Miles Avg.	Trips (Pct)	Trips (M)	Miles (M)	DPM10 (M lb)	DPM10 (lb/trip)	Hours Avg.
Shuttle	10.9	21%	0.280	3.0520	0.0071	0.02517	1.6
Short	65.7	69%	0.920	60.440	0.1396	0.15170	3.2
Regional	179.8	4%	0.053	9.5893	0.0221	0.41516	5.5
Long	319.7	6%	0.080	25.5760	0.0591	0.73819	9.1
Totals			1.333	98.6613	0.2278	0.00000	
Average						0.17086	3.3

Table 3
Model value parameters. *Source*: Calculated from Haveman and Monaco (2009) and California Air Resources Board (2011)

Parameter	Study Value	Units
Demand	2.40	million TEU
Q_0	1.33	million TEU trips
c	40.70	$ per TEU trip
r	6%	per year
w_1	76.67	$ per TEU trip
w_0	40.00	$ per TEU trip
E_0	0.114	million lb per year
k_1	0.0142	lb per TEU trip
k_0	0.0949	lb per TEU trip
$\Delta w = w_1 - w_0$	36.67	$ per TEU trip
$\Delta k = k_1 - k_0$	−0.0807	lb per TEU trip

From this data the 2007 DPM10 emissions at Oakland were calculated as 0.228 million pounds per year. It would be desirable for the Clean Truck program to reduce this level by half for the purposes of the example. Using the weighted average of lb DPM10 per trip, we calculated $k_0 = 0.0949$, by dividing by the number of TEU per trip, 1.8 for Oakland. California Air Resources Board data on emissions control devices for heavy duty diesel trucks (California Air Resources Board, 2011) showed that all emissions control devices recommended and approved for installing under a rebate program reduced these emissions by 85%. Therefore we calculated $k_1 = 0.0142$. We have included figures on hours for each type of run based on the questionnaires. Table 3 gives the assumed values for each parameter of the model.

Fig. 2 shows the optimum. From Eq. (20), $\phi = .5873 \approx 59\%$, $Q = 2.4$ million TEU, and the optimal cost is then $Z = \$147.68$ million. The shadow price of the emissions level $\mu = 39.11/0.08 = \$484.63$, is a substantial cost per pound, which would radically affect freight rates. It is the social opportunity marginal cost or benefit of raising or reducing the emission level. The shadow price of throughput, from Eq. (21), is $\lambda = 40 + 39.11/(1 - 0.0142/0.0949) = \$85.99$ per TEU trip, a moderately large additional cost, which would certainly affect freight rates to some extent.
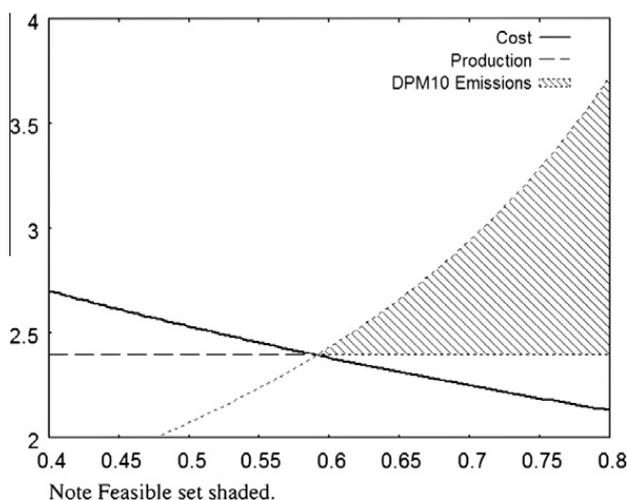

Fig. 2. Minimum cost for this port is $147.68 million, at (0.588, 2.4) in (ϕ, Q) plane.

6. Conclusion

We have modeled the port's decision of what percentage of trucks to upgrade to reduce pollution without adversely affecting the predicted level of throughput of TEUs. The problem is nonlinear in both constraints and objective, yet results in a very simple decision rule for the choice of a proportion of trucks to upgrade. If the ratio E_0/Q_0, the average per-TEU trip emissions for targeted production, is between the technologically determined emissions level per trip of the standard and that of the upgraded truck, we should choose that percentage of the maximum possible improvement. If the ratio is smaller than what can be obtained by the upgrade, the port will not be able to satisfy the emissions requirement at the production goal even if all trucks are upgraded; it would have to reduce production. If the ratio is larger than the emissions of a standard truck, one could raise production without reaching the emissions target.

The model also determines shadow prices of production and emission constraints. For emissions it indicates a price for additional emissions, which could be compared to a market if it exists. It also values the tradeoff between environmental health damage and the strict operational cost. The production shadow price tells how marginal increases in production would affect freight rates or costs through the controls. A simple graphical analysis allows one to assess the effects of changes or corrections in the parameters of the model set by policy.

Acknowledgments

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