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DISSERTATION

POLLUTION CONTROL POLICY AND SOCIAL WELFARE: A THEORETICAL AND EMPIRICAL ANALYSIS

Submitted by

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In partial fulfillment of the requirements

for the degree of Doctor of Philosophy

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Fort Collins, Colorado

Fall 1999

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY DOUGLAS SLOAN WHITE ENTITLED "POLLUTION CONTROL POLICY AND SOCIAL WELFARE: A THEORETICAL AND EMPIRICAL ANALYSIS" BE ACCEPTED AS FULFILLING IN PART THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

Committee on Graduate Work

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ABSTRACT OF DISSERTATION

POLLUTION CONTROL POLICY AND SOCIAL WELFARE: A THEORETICAL AND EMPIRICAL ANALYSIS

The impact of pollution control policy upon social welfare is a central theme to the discipline of environmental economics. Theoretical analyses focus on minimizing social welfare losses when selecting a policy instrument. The efficiency of a price or quantity policy depends on the nature of the marginal benefit and marginal cost curves. Their relative slopes are key to the selection of the more efficient instrument.

In addition, uncertainty of the curve estimates can affect policy instrument choice. Since policymakers and even polluters rarely have accurate estimates of the abatement benefits and costs, the nature of the marginal curves is not well known. Such complications and how to account for them can affect the choice of the more efficient policy instrument. Typically theoretical analysis assumes an additive and symmetric distribution about the marginal curves. While these assumptions provide ease of use, they can lead to the use of the improper instrument.

In the first two chapters of this dissertation, the influence of these error assumptions is examined. Chapter 1 compares a simple additive error structure with a more complex and realistic multiplicative error. When the marginal benefit and marginal cost curved are relatively flat, the difference between selection criteria can be substantially different. The ability of the price instrument to efficiently minimize welfare losses is compromised with the multiplicative error assumption. Chapter 2 focuses upon the role of informational bias upon policy instrument choice. With biased estimates, the assumption of a symmetric distribution about the marginal curves becomes invalid.

Chapter 3 is an empirical analysis of air pollution in forty metropolitan areas of the United States. The criteria pollutant ozone is used as the dependent variable. Two hypotheses are tested: that 1) automobile use and 2) economic sector composition affect ambient ozone levels. Econometric results strongly support the first hypothesis and weakly support the second.

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CHAPTER 1

UNCERTAINTY AND POLICY INSTRUMENT CHOICE: DOES THE INVISIBLE HAND HAVE BUTTERFINGERS?

INTRODUCTION

Government policies enacted to restrict polluting activities are becoming more pervasive and stringent. Not only are government policymakers at local and national levels limiting pollution emissions, but also recent coordinated efforts aim at international environmental protection. These global endeavors include the regulation of CFC manufacture and negotiations to reduce carbon emissions. In addition to these examples of geographically extensive legislation, policymakers continue to develop more intensive restrictions against criteria pollutants. For example in the United States, new legislation and amendments call for further curbs upon pollution emissions since the original Clean Air and Water act of 1970. Such trends follow the improving understanding of the cause and effect relationship between pollution levels and subsequent environmental damages.

Yet while the scope of these policies expands, so grows the potential for detrimental effects upon economic activity. Costs to reduce pollution fall primarily upon private manufacturers, whereby their international competitiveness is compromised by higher production costs. In attempt to minimize the negative repercussions of pollution legislation, the discipline of economics has examined, both theoretically and empirically, how government pollution abatement policies impact social welfare (Lerner 1971, Weitzman 1974, Adar and Griffin 1976, Yohe 1978, Watson and Ridker 1984, Helfand 1991).

While empirical benefit-cost studies typically determine optimal levels of pollution abatement, theoretical economic analyses examine the consequences of selecting price or quantity policy instruments to control pollution. Theoretical analyses often focus upon central issue of how marginal social benefit and marginal social cost curves influence the relative welfare efficacy of a policy instrument.

As the reach of environmental legislation extends, so does the need for a better understanding of how theoretical and modeling assumptions affect the conclusions regarding proper policy instrument choice in a social welfare context. For reasons of clarity and ease of calculation, early theoretical analyses employed an independent additive error term to represent uncertainty of both the benefit and cost estimates. In this paper, we briefly review the methods and principal results of theoretical analyses that employ 1) standard additive and 2) complex multiplicative error structures. Departing from this base, we next compare how assumptions regarding the error structure affect the decision criteria of pollution policy instruments. Finally, we conclude by discussing the implications of the results upon pollution abatement policy.

STANDARD ADDITIVE ERROR AND POLICY INSTRUMENT CHOICE

Social welfare analysis of pollution policy instruments often employs an additive error term to represent the inherent uncertainty of benefit and cost estimates. In this section, we review the findings of two principle papers by Weitzman (1974) and Adar and Griffin (1976). Of interest, these two papers take distinct approaches yet arrive at the same conclusion of how the slopes of the marginal curves affect the selection of the efficient policy instrument.[1] Specifically, the price instrument considered is an effluent fee or Pigouvian tax and the quantity instrument is a tradable permit.[2] The nature of marginal benefit and marginal cost curves and the subsequent effect upon policy instrument choice can be presented with both graphical and mathematical analyses. To illustrate the social welfare analysis, we begin with a graphical presentation.

Uncertainty about the optimal level of pollution control can be common as central regulating authorities attempt to estimate the social marginal damages and private sector's marginal cost of abatement. Since there exists uncertainty about the true location of the marginal cost (MC) curve, the selection of the more efficient control instrument depends upon the relative slopes of the marginal benefit and cost curves. In Figure 1.1 the relative slope of the MC curve are less than the MB curve. If a quota were to be used, the level of the abatement would be too high at q_q, where the MB is equal to the estimated MC. Since the intersection of the MB and real MC curves is at a lower abatement level, $q*$ is the actual optimal level of abatement. The darker shaded triangle on the right depicts the welfare inefficiency produced by the quantity instrument.

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[1] In general, we maintain the notation employed in the original papers.

[2] For further detail regarding different types of quantity instruments see (Helfand 1991).

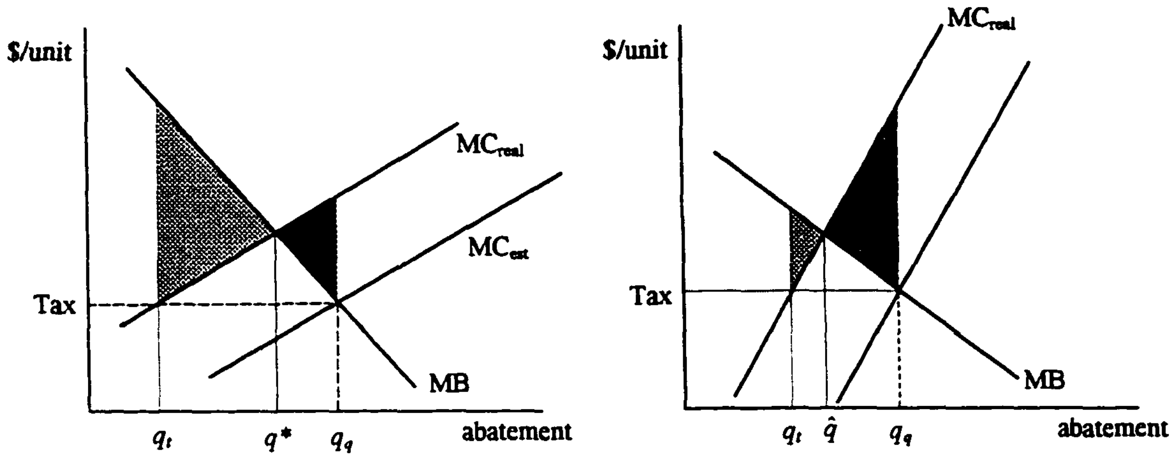

Figure 1.1

Figure 1.2

Figures 1.1 and 1.2. Example Welfare Losses with Price and Quantity Policy Instruments Under Uncertain Marginal Cost Estimates

If instead a price instrument were employed, the resulting level of abatement would be at q_t. At this level, the polluter abates until point where the real MC is equal to the cost of polluting (the tax). In Figure 1.1, the abatement level is too low, lying to the left of optimal q^*. In this example, the relative inefficiency of the tax is greater that that of the quota as can be seen with the larger size of the welfare loss triangle.

The relative efficiency of the respective price and quantity policy instruments is reversed when the slope of the MC is steeper than the MB. In Figure 1.2, a tax is more efficient than a quota as can be seen by their welfare loss triangles.

Besides graphical interpretations, mathematical rigor can be used to demonstrate the efficiency of policy instruments. In a principal environmental economics paper, Weitzman (1974) provides an elegant microeconomic justification for selecting either price or quantity restrictions. The approach employs a third-order Taylor series approximation of the total cost $C(q,\theta)$ and benefit $B(q,\eta)$ curves where q is the abatement level and uncertainty is represented by η and θ for the benefit and cost estimates respectively. The following restrictions of the benefit and cost curves are also employed: $B''(q) < 0$, $C''(q) > 0$, $B''(0) > C''(0)$ and $B'(q) < C'(q)$ for q sufficiently large.

$$C(q,\theta) \cong a(\theta) + (C' + \alpha(\theta))(q - \hat{q}) + \frac{C''}{2}(q - \hat{q})^2$$

$$B(q,\eta) \cong b(\eta) + (B' + \beta(\eta))(q - \hat{q}) + \frac{B''}{2}(q - \hat{q})^2$$

where $(q- q)$ is the neighborhood about abatement level q.

The first terms of the expansion, $a(\theta)$ and $b(\eta)$, represent vertical shifts of the total cost and benefits curves respectively and are not of consequence for the marginal analysis. However the stochastic terms, $\alpha(\theta)$ and $\beta(\eta)$ within the second order expansion, represent vertical shifts of the marginal cost and marginal benefits. Note that the second order expansion implicitly assumes that the marginal curves are linear. Letting $E[\alpha(\theta)] = E[\beta(\eta)] = 0$, where $E[\cdot]$ is the expectation operator, and assuming that benefit and cost uncertainty are independent, the fundamental result for policy instrument selection is summarized in the below equation. Δ_{pq} represents the comparative advantage of price over quantity instruments.

$$\Delta_{pq} = \frac{\sigma_C^2 B''}{2C''^2} + \frac{\sigma_C^2}{2C''} \qquad \text{or} \qquad \Delta_{pq} = \frac{\sigma_C^2}{2C''^2}(B'' + C'')$$

where B'' and C'' are respectively the slopes of the marginal benefit and marginal costs curves, and $\sigma_c^2 = (\alpha(\theta))^2$ is the variance of the marginal cost curve. Positive (negative) Δ_{pq} values imply greater welfare efficiency under price (quantity) instruments. Using the reformulated equation on the right, interpretation is straightforward. The comparative advantage of quantity instrument is greater as either the slope of the marginal benefit curve steepens (recall B'' is negative) or the slope of the marginal cost curve flattens. The variance of the marginal cost curve has no influence upon the policy choice but merely determines the magnitude of difference between the two instruments. Also note that since η is not present, benefit uncertainty has no effect.

Employing an algebraic approach, Adar and Griffin (1976) arrive at the same fundamental result by directly comparing the relative welfare gains under a price instrument versus those of a quantity instrument. Again, the relative slopes of the marginal curves, assumed to be linear, determine the selection of the policy instrument. Their approach is as follows.

Let $B' = a - bq + v$ and $C' = \alpha + \beta q + u$ where $\mathrm{E}[u] = \mathrm{E}[v] = 0$. Using quantitative controls the expected welfare gain, $\mathrm{E}(WG_q)$ is not stochastic.

$$\mathrm{E}(WG_q) = \frac{(\alpha - a)^2}{2(b + \beta)}$$

Calculation of the expected welfare gain with a price instrument is more complicated. Since the optimal price instrument depends upon a stochastic marginal cost function, the optimal abatement level and hence the expected welfare gain from the price instrument, $\mathrm{E}(WG_p)$, is therefore stochastic.

$$\mathrm{E}(WG_p) = \frac{(\alpha - a)^2}{2(b + \beta)} - \frac{\beta - b}{2\beta^2} \underset{u}{\mathrm{E}} u^2$$

where $\mathrm{E}[u^2]$ is the variance of the marginal cost curve. The fundamental result of price versus quantity instruments is:

$$\Delta_{pq} = \underset{u}{\mathrm{E}} u^2 \left(\frac{\beta - b}{2\beta^2} \right)$$

The equivalence to the Weitzman result can be seen by noting that $E(u^2)$ represents variance of the marginal cost curve and b is the negative of the slope of the marginal benefit curve.

COMPLEX ERROR ASSUMPTIONS AND POLICY INSTRUMENT CHOICE

Despite the computational and presentational ease associated with using an additive error term, there could exist shortcomings by employing such a simplification. Use of an additive error term is well justified where pollution policy restrictions abide by the Taylor theoretic context of being merely marginal changes or according to Adar and Griffin, if factor price variations are subject to Leontif production technology. Yet as the intensive and extensive scope of environmental legislation continues, marginal changes are unlikely to be common. Furthermore the Leontif production technology assumption, which forgoes the possibility of substituting inputs, is restrictive and may not be appropriate. Uncertainty of the marginal cost estimate undoubtedly increases as abatement levels rise. For example, if the mis-estimation of costs is 10%, the magnitude of the error increases absolutely with the level of abatements. Furthermore as abatement levels increase, unproven technologies often have little or poorly estimated cost data.

The potential influence that complex error structures may have upon the proper selection of the more efficient policy instrument was recognized both by Weitzman and later by Adar and Griffin. Their papers provide distinct approaches that follow their respective methodologies. To create a more complex error structure, Weitzman generalizes the total benefit and cost curves by adding stochastic terms to the third order of the Taylor series. In addition to the stochastic terms $\alpha(\theta)$ and $\beta(\eta)$, which represent *vertical shifts* of the marginal curves, stochastic terms $f(\theta)$, $g(\eta)$ model uncertainty with respect to the *slope changes* of the marginal curves.[3]

$$C(q,\theta) \cong a(\theta) + (C' + \alpha(\theta))(q - \vec{q}) + \frac{C''}{2f(\theta)}(q - \vec{q})^2$$

$$B(q,\eta) \cong b(\eta) + (B' + \beta(\eta))(q - \vec{q}) + \frac{B''g(\eta)}{2}(q - \vec{q})^2$$

Letting $\mathrm{E}[f(\theta)] = \mathrm{E}[g(\eta)] = 1$ and for simplicity also assuming that $\alpha(\theta)$ and $f(\theta)$ are independent, leads to a generalization of Weitzman's fundamental result.

$$\overline{\Delta}_{pq} = \frac{B''\sigma_C^2}{2C''^2}\left(1+\delta^2\right) + \left(\frac{\sigma_C^2}{2C''}\right) \qquad \text{or} \qquad \overline{\Delta}_{pq} = \frac{\sigma_C^2}{2C''^2}\left(B'' + B''\delta^2 + C''\right)$$

where δ^2 is the variance of $f(\theta)$. According to the above generalization ($\overline{\Delta}_{pq}$), any marginal cost slope uncertainty *ceteris paribus*, increases the comparative advantage of the quantity instrument. The multiplicative manner of the MC slope uncertainty, δ^2, can greatly affect the decision rule ($\overline{\Delta}_{pq}$), especially when B'' is large. While it appears counterintuitive to have this generalization depend upon the marginal benefit curve, the result is logical. Since the effectiveness of the price instrument depends greatly upon the slope of the marginal cost curve, any additional slope error of MC reduces their efficacy. The above generalized equation ($\overline{\Delta}_{pq}$) demonstrates the enhanced welfare efficiency loss of price instruments as either δ^2 or B'' becomes large.

---

[3] Implicitly both $f(\theta)$ and $g(\eta)$ must remain positive or the convexity conditions would be violated.

The comparative welfare efficiency approach of Adar and Griffin also permits generalizations regarding uncertainty of the marginal curves. They employ a multiplicative error term to generalize the variance of the marginal cost curve yet provide little interpretation as to the results.

Adar and Griffin let $B' = a - bq + v$ and $C' = (\alpha + \beta q)u$ where $E[u] = E[v] = 1$. Note that the random variable u affects both the intercept and slope parameters, so that the expected welfare gains from a quantity instrument are:

$$\breve{\Delta}_{pq} = \frac{a\beta + \alpha b}{2\beta}\left[\underset{u}{E}\left(\frac{P}{\beta u} - \frac{\alpha}{\beta}\right) - \frac{a - \alpha}{b + \beta}\right]$$

As can be seen in the above result, it is not easily comparable to the result, Δ_{pq} using the additive error term . Furthermore, the multiplicative nature of the parameters makes comparative statics generalizations problematic.

COMPARING THE ASSUMPTIONS OF ADDITIVE AND MULTIPLICATIVE ERROR

By presenting the additive and multiplicative approaches above, our objective is now to contrast the their effect upon policy instrument choice. Since additive and multiplicative measures of variance are not analogous, results of the two welfare efficiency approaches are not easily comparable. Therefore, we use conditional variances to contrast the additive (homoskedastic) with the multiplicative (heteroskedastic) error structure of marginal curves. Below, we first present a graphical approach and then the numerical analysis.

A Graphical Exposition

As seen in the above multiplicative error analysis of Adar and Griffin, $\hat{\Delta}_{pq}$, multiplicative representations of uncertainty are not easily generalizable. In addition to the slopes of the marginal curves determining the more efficient policy instrument, the criterion is conditional upon both the distribution of error and the abatement level. To develop generalizable results, we assume that the error term is conditional upon the level of abatement. In other words, the error term affects only the slope parameter of the marginal cost curve (as opposed to the random variable u affecting both slope and intercepts with the Adar and Griffin approach). At the expected optimal abatement level, q^*, let the conditional variance of the multiplicative error structure equal the traditional additive variance(Figure 1.3). For abatement levels below (above) the optimal level, the variance about the marginal cost estimate is lower (higher). As $q \rightarrow 0$, the variance of the marginal costs is equal to zero, since when there is no abatement, it is certain that marginal abatement costs are nil.

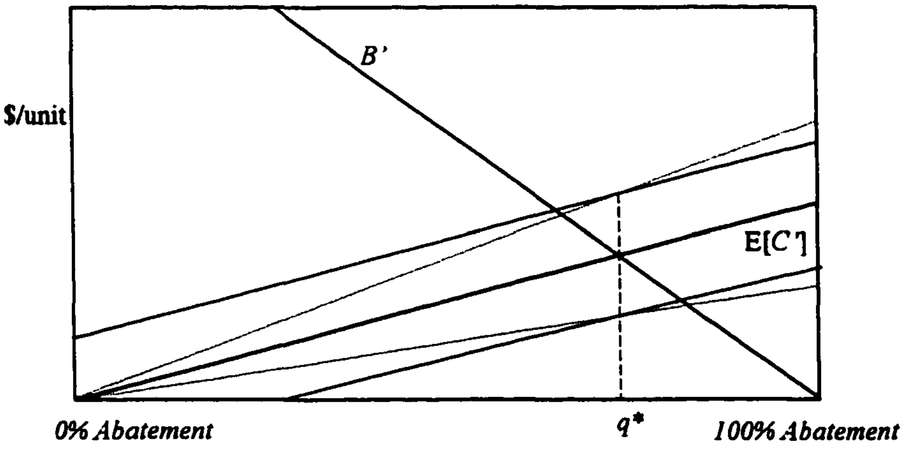

Figure 1.3. Multiplicative (Heteroskedastic) Error versus Additive Error of the Estimated Marginal Cost Curve

Uncertainty about the MC curve increases *ceteris paribus* as the MB becomes steeper. For example in Figure 1.4, C_1' and C_2' represent the error about MC curve and E[C'] is the mean MC. Where the marginal benefit curve is relatively flat B_1' there is less than error (a < b) than where the marginal benefit curve is steep B_2'. This result thus implies that *ceteris paribus*, at higher optimal abatement levels, q_2, quantity instruments become the more efficient policy tool.

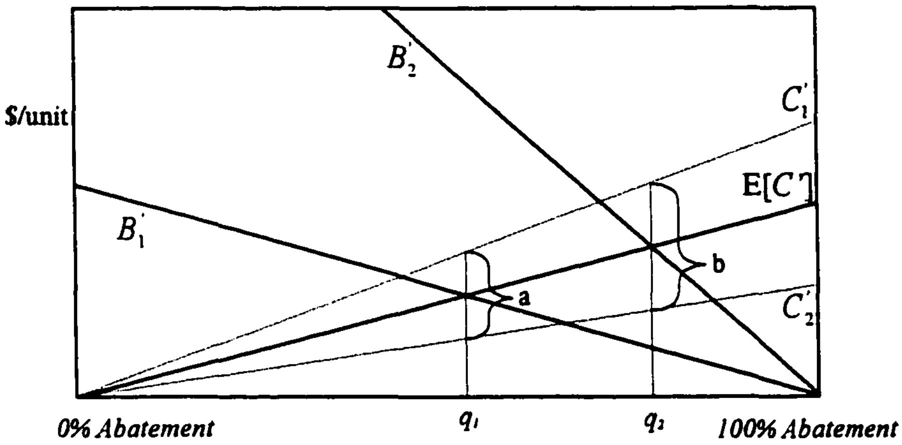

Figure 1.4. Slope of Marginal Benefit and Changing Uncertainty about the Marginal Cost

A Numerical Simulation

Let $B' = a + bq$ and $C' = \alpha + \beta q(u(q))$ and for the purposes of the below comparison, let $a = \alpha$. With results of an additive versus multiplicative error structure, Δ_{pq}, being difficult to generalize, we resort to numerical methods. Two factors influence the relationship 1) the absolute slopes of the marginal curves, and 2) the distribution of the error term u representing uncertainty of the marginal cost curve. The numerical analysis varies the slopes of the marginal curves (B'' and C'') to determine the relative efficiencies of the two policy instruments. The error is assumed to be normally distributed.

Appropriate shifting of the marginal cost curve to represent additive error term, and rotating the *MC* curve for the multiplicative error, is accomplished by using the quantiles of a specified distribution. The quantile function $Q(u) = CDF^{-1}(u)$ computes the percentage points of the distribution. By using quantiles, locations and associated probabilities of the marginal curves are equally likely but the spacing of the curves follow the characteristics of the assumed distribution. In the numerical analysis, forty quantiles characterize the distribution of marginal costs.[4] The computer algebra system, Maple V (Waterloo Maple Software and the University of Waterloo 1994), was used for the analysis (code can be found in Appendix 1). The degree of movement is determined by the distribution quantiles for both the marginal benefit curve (i = 1 to m) and the marginal cost curve (j =1 to n).

To examine the effect uncertainty has upon the expected welfare gains of using a price instrument $E(WG_p)$ versus that of a quantity instrument, $E(WG_q)$, a normal distribution ($N \sim (\mu = f(q), \sigma^2 = 8)$) is used, where the mean is conditional upon the stochastic nature of the assumed distributions about the marginal curves. The respective welfare inefficiencies of the policy instruments, $E(WG_q)$ and $E(WG_p)$, are the summed probability-adjusted triangles of the marginal curves represented by quantile location.

---

[4] For greater potential accuracy, more quantiles were also employed with little resulting difference.

$$\mathrm{E}(WG_q) = \sum_{i}^{m}\sum_{j}^{n}\left|\int_{q^*}^{q_{ij}}\left[MC_j(q) - MB_i(q)\right]du\right|$$

$$\mathrm{E}(WG_p) = \sum_{i}^{m}\sum_{j}^{n}\left|\int_{q^*}^{MC_j(q)=\overline{tax}}\left[MC_j(q) - MB_i(q)\right]du\right|$$

While the expected welfare gain with a quantity instrument, $\mathrm{E}(WG_q)$, is known to be non-stochastic if an additive error term is used, $\mathrm{E}(WG_q)$ with a multiplicative error is influenced by the assumed distribution of the marginal cost curve. Let $\tilde{\Delta}_{pq} = \mathrm{E}(WG_p) / \mathrm{E}(WG_q)$. The following section presents the results of the numerical analysis.

RESULTS

Results of the following numerical analyses reinforce those of the above theoretical approaches. Namely, there are potentially severe welfare efficiency losses when price instruments miss their mark. Figures 1.5 through 1.8 illustrate the relative welfare efficiency of price and quantity instruments under numerous slope scenarios of marginal benefit and marginal cost. The curved lines represent the ratio of the welfare loss of created by the policy instruments: Pigouvian taxes over marketable permits.

To track the welfare efficiency changes, the lines are constructed so that C'' is held constant while B'' varies in Figures 1.5 and 1.7. The constant and variable switch for Figures 1.6 and 1.8, where B'' remains fixed and C'' changes. The four figures also differ according to error structure. Additive uncertainty is assumed in Figures 1.5 and 1.6 corresponding to Δ_{pq}. With the assumption of multiplicative error, $\tilde{\Delta}_{pq}$ represents the ratio of welfare losses created by the price over quantity instruments (Figures 1.7 and 1.8). Tabular results can be found in Table 1.1 (Appendix 1).

There are similarities in the behavior of the performance of price and quantity instruments for both additive and multiplicative errors. When C'' (B'') is held constant, the efficiency of the price instrument decreases (increases) monotonically as B'' (C'') increases as depicted in Figure 1.5 (Figure 1.6). This result reflects the above theoretical outcomes.

More important is the magnitude of the welfare efficiency loss when price instruments are inaccurately employed. Even though a price instrument can be two times more efficient that of a quantity instrument, with C'' steep and B'' flat, price instruments rapidly lose efficiency when C'' is flat and B'' becomes steeper. To illustrate using Figure 1.5 when $C'' = B'' = 0.25$, both instruments are equally efficient. Yet holding C'' constant and when $B''= 0.5$, price instruments become only 40% as efficient as quantity instruments. Examining the ratio of welfare losses holding B'' constant, in Figure 1.6, once again the sensitivity to changes in C'' are evident especially when B'' is small. For example, price instruments rapidly gain efficiency as C'' increases.

Since contrasting the welfare losses using ratios can be deceptive, one crucial comparison between the efficiency of the two instruments can be best made by examining two vertical regions. The abscissa between 1 and 2 reflects the advantage of the price instrument. Yet the y-axis between 0.5 and 1 represents the same amount of advantage (0.5 implies that quantity instruments are twice as efficient) in one-half the linear space. Hence the region below the horizontal line at 1, represents a severe penalty attributable to price instruments.

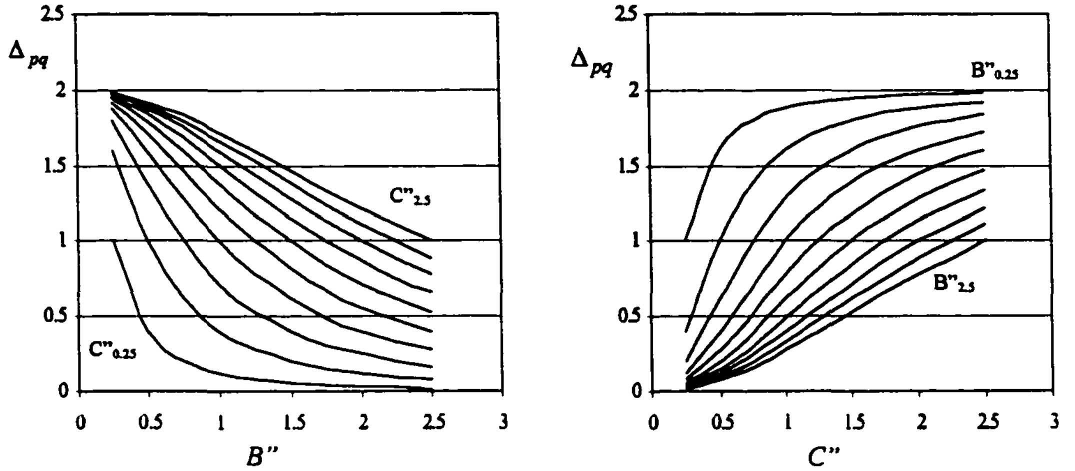

Figure 1.5: Marginal Cost (C'') constant

Figure 1.6: Marginal Benefit (B'') constant

Figures 1.5 and 1.6: Ratio of Welfare Losses, Price over a Quantity Instrument with an Additive Error Assumption ($N\sim(\mu = f(q), \sigma^2(q^*) = 4)$)

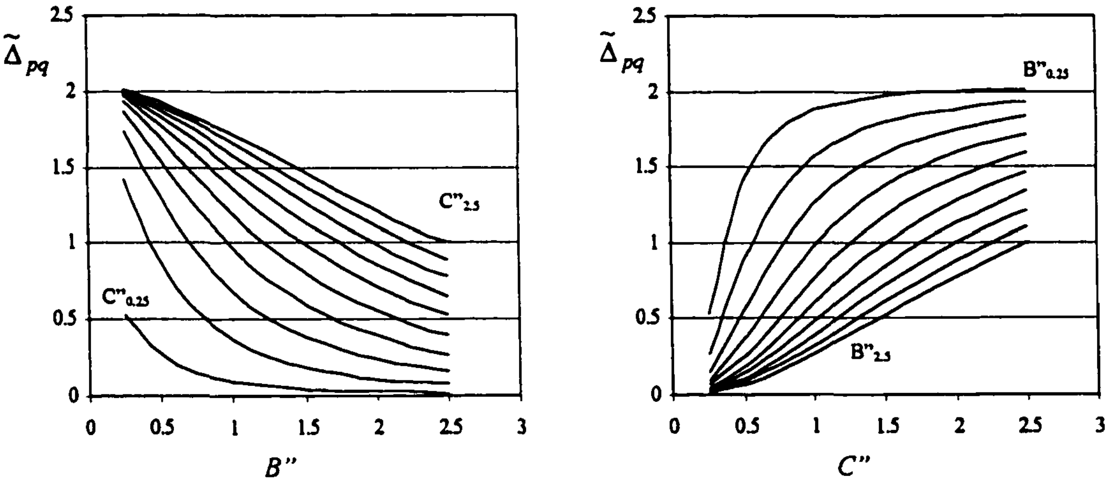

Figure 1.7: Marginal Cost (C'') constant

Figure 1.8: Marginal Benefit (B'') constant

Figures 1.7 and 1.8: Ratio of Welfare Losses, Price over a Quantity Instrument with a Multiplicative Error Assumption ($N\sim(\mu = f(q), \sigma^2(q^*) = 4)$)

The performance of the price instrument worsens under the assumption of a multiplicative error term in almost all instances. Figure 1.9 compares the constant *C"* cases (Figure 1.5 with Figure 1.7) and Figure 1.10 relates the constant *B"* scenarios (Figure 1.6 with Figure 1.8). When the marginal cost curve is held constant representing a relatively flat position, the price instrument even more inefficient under the multiplicative error assumption. The same gross inefficiency is evident when the *B"* is constant in a relatively flat position but only when the *C"* curve is a correspondingly flat (Figure 10). For few instances do quantity instruments lose favor when multiplicative errors are employed and if there is more loss, it is minimal.

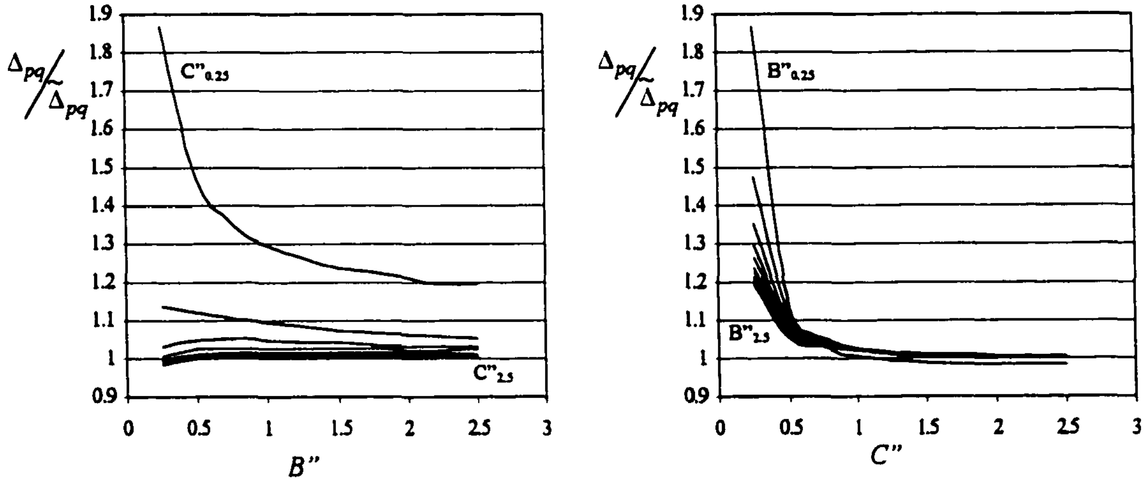

Figure 1.9. Marginal Cost (*C"*) constant

Figure 1.10. Marginal Benefit (*B"*) constant

Figures 1.9 and 1.10: The Difference Between Welfare Efficiency of Analyses Employing Additive and Multiplicative Error Structures
$(N\sim(\mu=f(q),\sigma^2(q^*)=4))$

CONCLUSION: IMPLICATIONS FOR POLLUTION ABATEMENT POLICY

According to Weitzman (1974), "(t)he average economist in the Western marginalist tradition has at least a vague preference toward indirect control by prices, just as the typical non-economist leans toward the direct regulation of quantities." Suspicions have continued to arise regarding the theoretical appropriateness of price instruments to control pollution emissions. For example, Stavins (1996) revisited a subtle point originally mentioned in a footnote by Weitzman (1974). At issue was how the presence of simultaneous correlated uncertainty of benefit and cost estimates can reverse the conventional identification of the more efficient policy instrument. Since historical evidence demonstrates that simultaneous correlated uncertainty is more often positively related, quantity instruments are more apt to be the more welfare efficient policy selection.

Our results, coupled with those of Weitzman and Stavins, reinforce the doubts regarding the efficacy price instruments to being able to minimize social welfare losses. These results are based upon the assumed modeling parameters, in practice there exists a variety of confounding factors such as administrative and transactions costs, that can blur the ability of this focused approach to select the more effective policy. Furthermore, there are other policy measures than the use of price and quantity instruments alone. For example, both instruments can be used in conjunction in order to reduce welfare losses (Roberts and Spence 1976).

While more simple modeling assumptions using additive errors provide concise theoretical relationships, they may lead to erroneous conclusions. To put into practice a comparison of additive versus multiplicative error structures and the implications therein, policymakers could empirically estimate the welfare effects of specific pollution control approaches and examine the sensitivity of the results to the existence of multiplicative error. Furthermore, these empirical analyses would be able to focus upon a relevant range of abatement rather than the generalized results given above. The results in this paper give further credence to the conclusion that the invisible hand of price instrument may not be as adept minimizing social welfare losses as the oft-maligned quantity instrument.

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APPENDIX 1

Maple V Code for Welfare Efficiency Analysis

```
> #Normal Distribution
> qq:=20;  # ----Number of Quantiles ----
> s := 2;   #MB slope
> t := 1.5;  #MC slope
> a := 0;  # MB distribution parameter [mean]
> b := 8;  # MB distribution parameter [variance]
> c := 0;  # MC distribution parameter [mean]
> d := 8;  # MC distribution parameter [variance]
> MBm:=(((s)*100) - ((s)*x));  #------Mean Marginal Benefit Function
> MCm:=t*x;                    #------Mean Marginal Cost Function
> with(student):
> with(stats):
> with(describe):
> with(statevalf):
> with(statplots):
> with(linalg):
> MBE :=  [seq(icdf[normald[a,b]]((1/(qq+1))*i),i=1..qq)];
> MBE:=convert(MBE,vector):
> MCE:=  [seq(icdf[normald[c,d]]((1/(qq+1))*i),i=1..qq)];
> MCE:=convert(MCE,vector):
> m:=1:#------------Marginal Benefit Curves Calculation
> x:= 'x':
> for m from 1 to qq do
> MB(m):= ((MBm)  + (MBE[m]))
> od;
> n:=1:#--------------Marginal Cost Curves Calculation
> for n from 1 to qq do;
> MC(n):= (MCm +(MCE[n]))
> od;
> quot:=solve(MBm=MCm): #    Quota value at intersection of mean
> MB & MC
> XX := matrix(qq,qq):   # Intersections of MB & MC
> for m from 1 to qq do
> for n from 1 to qq do
> XX[m,n]:=fsolve(MB(m)=MC(n),x=0..1000000);
> od;
> od;
> x:='x':
> m:=1:
> n:=1:
> spaceaq :=matrix(qq,qq):
> for m from 1 to qq do
```

```
>   for n from 1 to qq do
>   spaceaq[m,n]:=abs(int(MC(n)-MB(m), x = XX[m,n]..quot ))
>   od
> od:
> Vaq:= col(spaceaq, 1..qq):
> waq:= vector(qq):
> for i from 1 to qq do
> waq[i]:= norm(Vaq[i],1)
> od:
> Total[quota]:=(norm(waq,1)/(qq*qq));
> #Price instrument
> eTx:=solve(MBm=MCm); # to find tax value at intersection of mea
> n MB & MC
> x:=eTx:
> eTax:=evalf(MCm);
> x:='x':
> xT:=vector(qq):             # to find  tax rate intersection of MC[n]
> for n from 1 to qq do
> xT[n]:=solve(MC(n)=eTax)
> od:
> x:='x':
> spaceat :=matrix(qq,qq):
> m:=1:
> n:=1:
> for m from 1 to qq by 1 do
>   for n from 1 to qq by 1 do
>   spaceat[m,n]:=abs(int(MC(n)-MB(m), x = XX[m,n]..xT[n] ));
>   od;
> od;
> Vat:= col(spaceat, 1..qq):
> i:='i':
> wat:= vector(qq):
> for i from 1 to qq do
> wat[i]:= norm(Vat[i],1)
> od:
> Total[tax]:=(norm(wat,1)/(qq*qq)):
> #          MULTIPLICATIVE ERROR
> i:'1':
> obhy:=vector(qq):
> for i from 1 to qq do
> obhy[i]:=(eTax+(MBE[i]));
> slopeb[i]:=value(obhy[i]/(100-quot));
> od:
> n:='n':
> for n from 1 to qq do
>   MBo(n):=((100*slopeb[n])-(slopeb[n]*x))
> od:
> i:'1':
> ohy:=vector(qq):
> for i from 1 to qq do
>   ohy[i]:=(eTax+(MCE[i]));
>   slopec[i]:=value(ohy[i]/quot);
> od:
> n:='n':
```

```
> for n from 1 to qq do
>    MCo(n):=(x*slopec[n])
> od:
> m:='m':
> n:='n':
> XXo := matrix(qq,qq):    # Intersections of MB & MC
> for m from 1 to qq do
>    for n from 1 to qq do
>    XXo[m,n]:=fsolve(MBo(m)=MCo(n),x=0..1000000);
>    od;
> od;
> x:='x':
> m:=1:
> n:=1:
> spacemq :=matrix(qq,qq):
> for m from 1 to qq do
>    for n from 1 to qq do
>    spacemq[m,n]:=abs(int(MCo(n)-MBo(m), x = XXo[m,n]..quot ))
>    od
> od:
>  Vmq:= col(spacemq, 1..qq):
> wmq:= vector(qq):
> for i from 1 to qq do
>    wmq[i]:= norm(Vmq[i],1)
> od:
> xTo:=vector(qq):               # to find  tax rate intersection of MC[n]
> for n from 1 to qq do
>    xTo[n]:=solve(MCo(n)=eTax)
> od:
> x:='x':
> spacemt :=matrix(qq,qq):
> m:=1:
> n:=1:
> for m from 1 to qq by 1 do
>    for n from 1 to qq by 1 do
>    spacemt[m,n]:=abs(int(MCo(n)-MBo(m), x = XXo[m,n]..xTo[n] ));
>    od;
> od;
> Vmt:= col(spacemt, 1..qq):
> i:='i':
> wmt:= vector(qq):
> for i from 1 to qq do
>    wmt[i]:= norm(Vmt[i],1)
> od:
> Total[taxm]:=(norm(wmt,1)/(qq*qq)):
> Total[atax]:=(norm(wat,1)/(qq*qq));
> Total[aquota]:=(norm(waq,1)/(qq*qq));
> Total[mtax]:=(norm(wmt,1)/(qq*qq));
> Total[mquota]:=(norm(wmq,1)/(qq*qq));
> Total[atax]/Total[aquota];
> Total[mtax]/Total[mquota];
>
```

Table 1.1. Tabular Results of Welfare Efficiency Analysis: Ratio of Price over Quantity Instrument (Error~N($\mu = f(q), \sigma^2(q^*) = 4$)

Additive Error Assumption

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	1.00	0.40	0.20	0.12	0.08	0.05	0.04	0.03	0.02	0.02
0.5	1.60	1.00	0.62	0.40	0.28	0.20	0.15	0.12	0.09	0.08
0.75	1.80	1.39	1.00	0.72	0.53	0.40	0.31	0.25	0.20	0.17
1.0	1.88	1.60	1.28	1.00	0.78	0.62	0.49	0.40	0.33	0.28
1.25	1.92	1.72	1.47	1.22	1.00	0.82	0.68	0.56	0.47	0.40
1.5	1.95	1.80	1.60	1.39	1.18	1.00	0.85	0.72	0.62	0.53
1.75	1.96	1.85	1.69	1.51	1.32	1.15	1.00	0.87	0.75	0.66
2.0	1.97	1.88	1.75	1.60	1.44	1.28	1.13	1.00	0.88	0.78
2.25	1.98	1.90	1.80	1.67	1.53	1.39	1.25	1.12	1.00	0.89
2.5	1.98	1.92	1.83	1.72	1.60	1.47	1.34	1.22	1.10	1.00

Multiplicative Error Assumption

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	0.53	0.27	0.15	0.09	0.06	0.04	0.03	0.03	0.02	0.02
0.5	1.41	0.89	0.56	0.37	0.25	0.19	0.14	0.11	0.09	0.07
0.75	1.74	1.32	0.95	0.69	0.51	0.38	0.30	0.24	0.19	0.16
1.0	1.87	1.56	1.25	0.97	0.76	0.60	0.48	0.39	0.32	0.27
1.25	1.93	1.70	1.45	1.20	0.98	0.81	0.67	0.55	0.46	0.40
1.5	1.96	1.79	1.58	1.37	1.17	0.99	0.84	0.71	0.61	0.52
1.75	1.99	1.85	1.68	1.50	1.31	1.14	1.00	0.86	0.75	0.65
2.0	2.00	1.88	1.75	1.59	1.43	1.27	1.12	0.99	0.88	0.78
2.25	2.01	1.91	1.80	1.66	1.52	1.38	1.24	1.11	1.00	0.89
2.5	2.01	1.93	1.83	1.72	1.59	1.46	1.34	1.22	1.10	1.00

Ratio: Additive/Multiplicative

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	1.87	1.47	1.35	1.30	1.26	1.24	1.22	1.21	1.20	1.20
0.5	1.13	1.12	1.11	1.09	1.08	1.07	1.07	1.06	1.06	1.05
0.75	1.03	1.05	1.05	1.05	1.04	1.04	1.04	1.03	1.03	1.03
1.0	1.01	1.02	1.03	1.03	1.03	1.02	1.02	1.02	1.02	1.03
1.25	0.99	1.01	1.02	1.02	1.02	1.02	1.01	1.02	1.01	1.01
1.5	0.99	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
1.75	0.99	1.00	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.01
2.0	0.98	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01
2.25	0.98	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.00
2.5	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

CHAPTER 2

THE EFFECT OF INFORMATION BIAS UPON POLLUTION CONTROL POLICY AND WELFARE EFFICIENCY

INTRODUCTION

Policymakers face the challenge of protecting citizens from harmful pollution levels while minimizing controls placed upon the economy. Since the 1970s, economists have examined this inherent tradeoff between the benefits and costs of pollution control both theoretically and empirically. With the goal of minimizing losses in social welfare, economic research examines the relative efficiency of price and quantity policy instruments under different benefit and cost curve scenarios (Adar and Griffin 1976, Fishelson 1976, Weitzman 1974). In addition, these same analyses recognized the inherent difficulty of estimating cost and benefits and the role of uncertainty upon policy instrument choice to minimize social welfare losses.

Underlying the estimation of both costs and benefits are complex cause and effect relationships requiring informational input ranging from disciplines ranging from engineering to medicine. Therefore, neither economist nor policymaker will ever know the true cost or benefit of pollution abatement. Welfare analyses of policy instruments traditionally invoke strict assumptions regarding how uncertainty affects the marginal cost and benefit curves. The traditional result that policy instrument choice depends upon the relative slopes of the marginal curves has become a common presentation in many environmental economics texts (Baumol and Oates 1988). Yet achievement of this result requires that uncertainty be represented by symmetric distributions in an additive form. Hence the real world applicability of a conclusion found regarding the more efficient policy instrument may be suspect.

In this paper, we investigate the effect that uncertainty has upon policy instrument choice and more specifically, the role biased information. Policymakers receive data from numerous sources including pollution emitters. Strategic incentives of firms to provide inaccurate data along with other possible sources of bias such as damage assessment can affect the ability of a policymaker to correctly choose the more efficient policy instrument (e.g. Bulckaen 1997). In order to minimize welfare losses, inclinations would perhaps urge a reduction in the bias of the marginal estimates. Yet with the presence of simultaneous bias of the marginal benefit and cost curves, there are conditions where efforts to reduce potential bias may not be worthwhile.

The paper is organized as follows. The following section reviews the sources of uncertainty and bias within the regulatory framework. Next, a graphical and mathematical analysis methods of how bias affects policy instrument choice is presented. The final sections conclude by discussing the results and their policy implications.

SOURCES OF UNCERTAINTY AND BIAS

Inaccurate data from which policymakers estimate pollution control benefits and costs, can be the result of many factors. Yohe (1976) notes that unperceived bias in measurement, an insufficiently fine measurement grid or imprecise data reporting can cause inaccuracies. It is illustrative to separate the sources of uncertainty into two distinct categories: random uncertainty and systematic bias. The former category, uncertainty, is considered to be symmetrically distributed random error where the likelihood of overestimation is equal to that of underestimation. Many of the early theoretical investigations employed such symmetric errors to represent uncertainty (Adar and Griffin 1976, Fishelson 1976, Weitzman 1974). On the other hand, the second component of inaccuracy, systematic bias, skews the data so that the "true" cost or benefit of pollution abatement is either overestimated or underestimated.

Sources of systemic bias can be divided into three general types. The first, *measurement* bias is the result of the inherent difficulty associated with determining the cause and effect relationship of pollution emissions and subsequent damages. One source of measurement inaccuracy is the methodological tools used to measure the effects, which in turn influences the benefit estimate of pollution abatement. For example, the human response to pollution is not well understood nor easily measured. It is quite possible that damages to health may be underestimated since only a portion of illnesses are reported and pollution may exacerbate existing diseases (Bates 1992).

The work of Viscusi (1993) presents another important source of potential bias: the valuation of risks to life and health. While the metric of the dollar enables to economists to place monetary values on life, these estimates range greatly from $3 million to $7 million and may be dependent upon non-economic factors such as jury sentiments. Furthermore, the techniques used to assess non-market goods damages such as travel cost method, hedonic pricing and contingent valuation have been plagued with a lack of consensus amongst the economics profession and could also be a source of bias (c.f. McFadden 1996).

The second type of bias is *strategic*. Two conflicting agents, the emitter and the recipient, both attempt to influence the decisions of the policymaker. Information supplied by the agents is used by the policymaker to determine an optimal level of abatement. The informational asymmetry between the regulator and agents, termed adverse selection, is the result of incentives to over-estimate the reported values. Information supplied to agencies need not be merely false. According to Owen and Braeutigam (1978), the ability to control the flow of information to the regulatory agency is crucial in affecting decisions. Agencies can be guided by making carefully selected facts available or withholding information merely to achieve delays.

Static bias is the third category. Butler and Maher (1982) challenged the implicit assumption that the marginal benefit and marginal cost curves are fixed. They claim growth of the economy or population causes a movement of the marginal curves. For example, as population grows any fixed level of pollution abatement produces increased benefits. Thus the traditional conclusions regarding the selection more effective policy instrument may be spurious.

Input price and technology changes are also common sources of static bias. As technology advances, abatement costs often decline precipitously yet regulators may continue using the earlier high estimates. The strategic tactic of firms to delay pertinent information regarding pollution control costs can also be considered static bias albeit a staged one. Input prices such as energy, are notorious difficult to forecast and can greatly affect abatement cost estimates. For example, the current relatively low price of petroleum was not foreseen years ago.

The three bias sources that often affect the benefit and cost estimates are summarized in Table 2.1. Along with an example, the sign of the bias source refers to the likely bias of the information supplied by the agent to the regulator or other potential biases from unrecognized factors.

Table 2.1. Types of Bias Affecting Marginal Benefits and Marginal Costs

CATEGORY	EXAMPLE	LIKELY BIAS
MARGINAL BENEFITS		
Measurement		
	Morbidity	+/-
	Mortality	+/-
	Valuation	+/-
Strategic		
	Damage estimates	+
Static		
	Population	-
MARGINAL COSTS		
Measurement		
	Sensor readings	+/-
Strategic		
	Foregone production	+
	Abatement costs	+/-
Static		
	Technology change	+
	Energy prices	+/-

Few welfare analyses either theoretical or empirical have explored the potential effects of biased data upon policy instrument choice. In an extensive empirical investigation, Watson and Ridker (1980, 1984) employed skewed distributions in a welfare analysis. At issue were the environmental consequences of alternative pollution policies and economic development growth paths. Within the welfare analysis, the frequency distributions of both the marginal benefit and marginal cost distributions were assumed to be skewed since estimates of control and damage costs are usually conservative.

Recognizing the difference between the symmetric and asymmetric distributions and the forces behind them, permits the policymaker to take appropriate action if necessary. In the quest of attaining unbiased and hence "true" measures of marginal benefits and costs, the regulator can 1) demand more accurate data where penalties threaten against non-compliance, 2) dedicate government resources to obtain unbiased information, 3) note the incentives behind the information suppliers (agents) and adjust estimates accordingly, or 4) use policy instruments which are less affected by uncertainty and potential bias.

ANALYTICAL FRAMEWORK

With the goal of minimizing the welfare losses created by policy instruments, the subdiscipline of environmental economics has long stressed the importance of marginal analysis. Typically kept within a theoretical framework, such analysis provides insights regarding the relative welfare efficiency of the tax and quota policy tools. To control pollution, policymakers use price instruments (a tax or charge), a quantity instrument (a license or quota) or a combination of both (Roberts and Spence 1976). An efficient level of pollution abatement occurs where the marginal control costs are equal to the marginal damages, thus minimizing welfare loss.

However, under conditions of uncertainty and bias, where the estimated curves have a high probability of not representing their true location, the relative advantages of one policy instrument can become evident. The following sections analyze the effect of uncertainty and bias upon policy instrument choice. First, we review traditional approaches taken by the literature to model uncertainty and next present how biased information can impact a regulator's decision criteria. Both graphical and mathematical approaches to welfare analysis are presented.

Traditional Analysis with Symmetric Uncertainty

Traditional environmental analysis (c.f. Baumol and Oates, 1988) examines the welfare efficiency of policy instruments by measuring the relative welfare losses created under conditions of uncertainty. Within a graphical analysis, the policy instrument that produces a smaller triangle is preferred to the other. Underlying the analysis of welfare losses are the relative slopes of the marginal cost and marginal benefit curves.

Since the pollution emitters will typically produce without regard to shape or position of the marginal benefit function, tax and quota policies result in the same level of abatement under conditions of benefit uncertainty. Figure 2.1 presents a case where the firm abates too little under both price and quantity instruments. Firms abate pollution at the level q_{qt} for either policy instrument; hence the welfare losses are equivalent.

On the other hand, uncertainty of the marginal cost curve has implications for policy instrument selection. For example in Figure 2.2, inaccuracy of the marginal cost curve creates a situation where a price instrument (tax) produces less of a welfare loss than the quantity instrument.[5] Using the supplied biased information, regulators set the quantity pollution control instrument where estimated marginal benefits are equal to estimated marginal costs. However, since the real marginal cost curve is greater than the

---

[1] Ironically, graphical representations much like Figure 2.3 are commonly (and erroneously) used to depict relative welfare losses under conditions of symmetric random error (e.g. Stavins 1996). Figure 2.3 actually presents a condition where inaccurate data is *biased.* For an illustration of symmetric random error, see Watson and Ridker (1984).

estimated, firms actually abate too much at level q_q. The welfare loss due to the inaccurate (biased) estimate is the lighter triangle on the right.

Workings of the price instrument are somewhat more subtle. Regulators impose a tax based on the price level where $MB_{est} = MC_{est}$, yet in reality the firm abates where MC_{real} = tax and hence in the example of Figure 2.2, abates too little (q_t is to the left of optimal $\tilde{q}$). The resulting social welfare loss from over-polluting is the darkly shaded left triangle. Hence the example depicted in Figure 2.2, is one where the price instrument is more efficient that the quantity instrument.

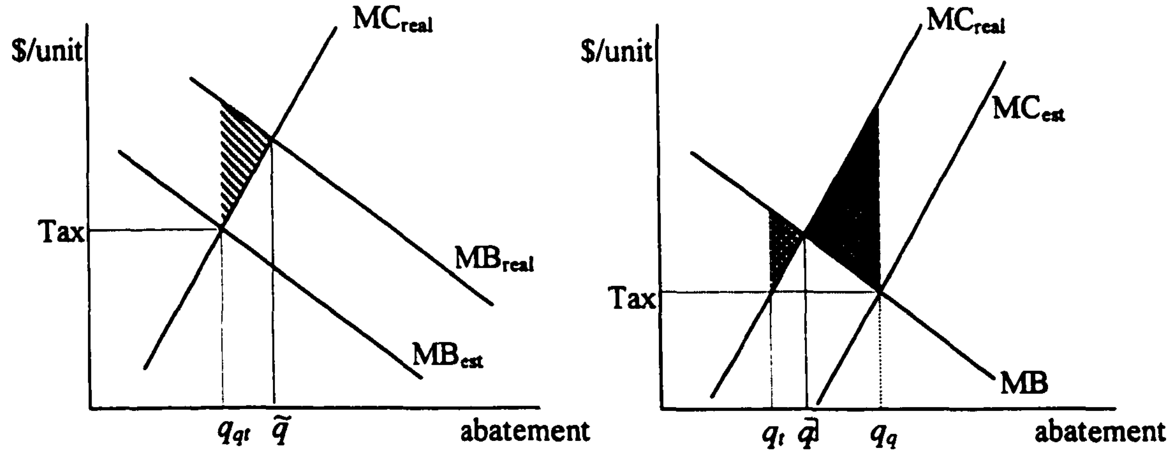

Figure 2.1 Figure 2.2

Figures 2.1 and 2.2. Welfare Losses Created by Price and Quantity Instruments

Traditional mathematical policy choice analyses use the first two central moments to demonstrate the relationship between the policy instrument choice and the nature of the benefit and cost curves. Weitzman (1974) uses a second-order Taylor series approximation of the total benefit and total cost curves in deriving the following equation: $\Delta_{pq} \approx \left[\frac{\sigma_C^2 B''}{2C''^2} + \frac{\sigma_C^2}{2C''}\right]$ where: Δ_{pq} is the net welfare advantage of the tax method relative to the quota; B'', C'' are the second derivatives of the total benefit and total cost functions (i.e. the slopes of the MB, MC curves) and σ^2_c is the variance of the estimated marginal cost. As with the conclusion of the graphical analysis, the magnitude of benefit uncertainty, σ^2_b does not enter the equation.

Incorporating Simultaneous Bias

Does benefit uncertainty, especially bias, affect policy instrument choice? In the case developed by Weitzman (1974) and later by Stavins (1996) with the presence of correlated uncertainty of the marginal curves, marginal benefit uncertainty can either reinforce or reverse selection of the more efficient policy instrument. We argue that correlated uncertainty need not be required for benefit uncertainty to affect policy instrument selection, since simultaneous bias of benefit and cost estimates can also play a role.

For example, suppose that both marginal benefits and costs are underestimated. Thus the estimated curves lie below the real marginal benefit and cost curves. As depicted in Figure 2.3, the use of a quantity instrument results in an abatement level at q_q where the estimated MB is equal to the estimated MC. However, the real MB and MC curves indicate that an optimal level of abatement q^* is less than q_q. The relative inefficiency of the quantity instrument is depicted by the shaded triangle on the right. However, if a tax were employed as the policy instrument, the level of abatement would be at q_t. At this level, the polluter produces at the point where the real MC is equal to the cost of polluting (the tax). Hence the abatement level is too low, lying to the left of q^*. In this example, the relative inefficiency of the tax is greater than that of the quota as can be seen with the larger size of the welfare loss triangles.

The example depicted in Figure 2.3 demonstrates that negative bias of both the marginal benefit and marginal cost curves switches the selection of the more efficient policy instrument as compared to the example of Figure 2.2. Yet the proper instrument choice may simply be reinforced if the biases of the curves are not in the same direction, i.e. one is positive and the other negative. Say that the marginal costs are overestimated and marginal benefits are underestimated. Thus, in Figure 2.4, the marginal benefit and marginal cost curves move in opposite directions. A quantity instrument would force the polluter to abate at level q_q , yet the bias of the marginal cost curve make the optimal abatement level much higher level q^*. The resulting welfare loss of the quantity instrument is represented by the lighter triangle on the left. In this case, the use of the price instrument results in a much smaller welfare loss.

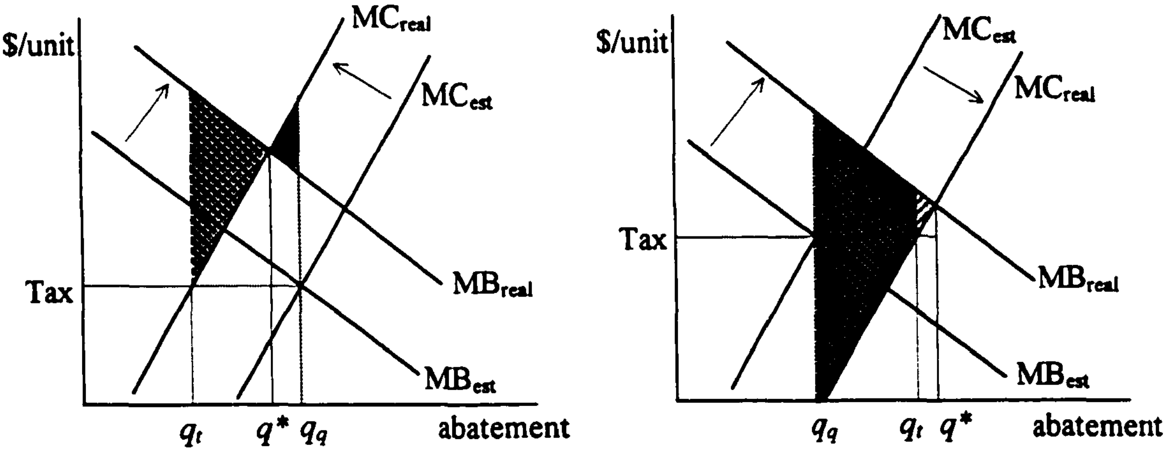

Figure 2.3 Figure 2.4

Figures 2.3 and 2.4. Relative Welfare Losses of Price and Quantity Instruments with Simultaneous Bias of the Marginal Benefit and Marginal Cost Curves

The above graphical results however are special cases. A comprehensive welfare analysis needs take into account the magnitude of bias along with the slopes of the marginal curves. A more accurate representation of the forces that affect policy instrument choice is summarized in the following equation:

$\Delta_{pq} \approx \left[\frac{\sigma_C^2 B''}{2C''^2} + \frac{\sigma_C^2}{2C''} \right] + (B'' + C'')(\Delta_B + \Delta_c)$ where Δ_B and Δ_C are respectively, the bias of the marginal benefit and marginal cost estimates. The latter terms in parentheses refer to the relative slopes of the marginal curves and the "shift" or bias of the distribution about the curves. As seen above, these terms can either accentuate or cancel each the effect of upon policy instrument choice, depending upon relative slopes and the direction of bias of the marginal curves.

EMPIRICAL METHODS

While graphical analysis is illustrative in demonstrating the effects of bias, empirical estimation of bias and its effects upon policy instrument choice is more problematic. For this purpose, we employ numerical methods. Skewed parametric distributions permit a modeling of the impact that positive and/or a negative biases of the marginal curves have upon welfare efficiency. Adar and Griffin (1976) hinted at the importance of examining the underlying distribution of the marginal control cost curve:

> Admittedly, the difference in the expected welfare gains is the more cumbersome to calculate for policy analysis than the simple case where the disturbance term is additive and we need only measure the relative elasticities, or slopes and the variance [of the cost disturbance term]. Policy analysts definitely have some knowledge about the parameters of [the marginal damage function and marginal control cost function]...since this is presumably the basis for current decision making. [W]e feel that policy analysts can distinguish the types of uncertainty ... most relevant to

> the case at hand. Finally, as for the frequency distribution of [the cost disturbance term], ...our suggestion is simply to test for sensitivity using several alternative distributions as the policy implications may turn out to be quite robust to the distributional changes.

The beta is a convenient parametric distribution with which to model the effects of skewness upon policy instrument choice. Two parameters, *a* and *b*, enter the probability distribution function (pdf) as follows:

$f_x(x;a,b) = \dfrac{\Gamma(a+b)}{\Gamma(a)\cdot\Gamma(b)} x^{a-1}(1-x)^{b-1} I_{(0,1)}(x)$ where Γ is the gamma function and *I* is an indicator function (i.e. the continuous random variable *x* ranges from 0 to 1). Parameters *a* and *b* are both greater than zero. Figure 2.5 presents alternative forms of the beta with the positive or negative skewness depending upon the values of the *a* and *b* parameters. A linear transformation $y = \alpha + \beta x$ of the random variable *x* produces a probability density over the interval α to $\alpha+\beta$, thus enabling the beta distribution to relocated and scaled accordingly.

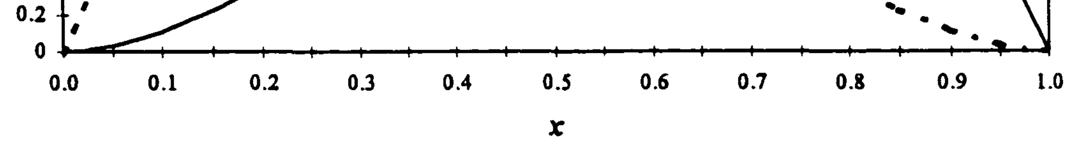

Figure 2.5. Sample Beta Distributions with Corresponding Skewness

In the numerical analysis, the welfare loss of the price instrument is compared to that of the quantity instrument under different assumptions of the distributional properties of the marginal curves. The marginal benefit and marginal costs curves are functions of the level of abatement (q) and a random error term ε. The first three central moments are used to describe the characteristics of the distribution (parameters: μ = location, σ^2 = variance and κ = skewness). Uncertainty is assumed to affect the marginal curves additively.

$$MB(q)=f(q) + \varepsilon_B(\mu_B,\sigma_B^2,\kappa_B)$$

$$MC(q)=f(q) + \varepsilon_C(\mu_C,\sigma_C^2,\kappa_C)$$

Two primary factors influence policy instrument choice 1) the slopes of the marginal curves, and 2) the distribution of the error terms, ε_B and ε_C representing uncertainty of the marginal curves. Appropriate shifting of the marginal cost curve to represent the effect of additive error, is accomplished by defining quantiles of the specified distribution. The quantile function $Q(u)=CDF^{-1}(u)$ computes the percentage points of the distribution. By using quantiles, locations of the marginal curves are equally likely but the spacing of the curves follow the characteristics of the assumed distribution. In the numerical analysis, twenty quantiles characterize the distribution for each marginal curve. The computer algebra system, Maple V, was used to conduct the numerical analysis (Waterloo Maple Software and the University of Waterloo 1994).

To calculate the effect of uncertainty upon the expected welfare gain by using a price instrument, E(WG_p), and quantity instrument, E(WG_q), a similar procedure characterizes the assumed probability distributions. Quantiles determine the shifts of both the marginal benefit curve (i = 1 to m) and the marginal cost curve (j =1 to n). The welfare inefficiencies of the policy instruments, E(WG_q) and E(WG_p), are summed probability sized welfare loss triangles.

$$\mathrm{E}(WG_q) = \sum_{i}^{m}\sum_{j}^{n}\left|\int_{q^*}^{q_{ij}}\left[MC_j(q) - MB_i(q)\right]du\right|$$

$$\mathrm{E}(WG_p) = \sum_{i}^{m}\sum_{j}^{n}\left|\int_{q^*}^{MC_j(q)=\overline{tax}}\left[MC_j(q) - MB_i(q)\right]du\right|$$

In order to facilitate comparability amongst the empirical simulations, appropriate linear transformations maintain the same variance of the Beta distributions.

RESULTS

The effect of biased estimates of the marginal curves upon policy instrument choice can be summarized as follows. Biased data resulting in skewed distributions in the same direction, either both positive or both negative, tends to improve the efficacy of quantity instruments. The same-direction bias results in "vertical shift" of the marginal curve intersections (Figure 2.3). Yet when the data used to estimate the marginal curves are biased in opposite directions, one positive and the other negative, price instruments become more effective. One could consider this type of inaccuracy as a "horizontal shift" of the intersections (Figure 2.4).

The results of the numerical analysis, depicted in Figures 2.6 and 2.7, demonstrate the relative impact of estimating welfare losses assuming skewed distributions about the marginal curves. The surfaces represent the change in efficiency of a price instrument over quantity instrument due to the effect of the skewed versus symmetric error assumptions (Δ_s/Δ_b, where s: symmetric; b: bias). In other words, the surfaces demonstrate how bias of the marginal curve estimates affects the performance of a policy instruments. The comparison is a ratio between the symmetric and biased welfare loss estimates at a range of marginal curve slope scenarios. Figure 2.6 depicts the difference in the relative welfare efficiency assuming same-direction bias of both marginal curves, whereas Figure 2.7 presents results where the bias is of opposite-direction.

Under modeling assumptions with same-direction bias, the comparative advantage of quantity instruments improves over price instruments. This can be seen in Figure 2.6, by the surface being located below the threshold value, which is equal to one. The price instrument becomes less able to minimze welfare loss under conditions of bias, as the slopes of the marginal curves (their absolute value) be more similar. This can be seen by surface having a valley where the slopes of the marginal curves are equal. The difference in the bias effect decreases as the relative slopes of the marginal curves differ, represented by the "hillsides"of the surface.

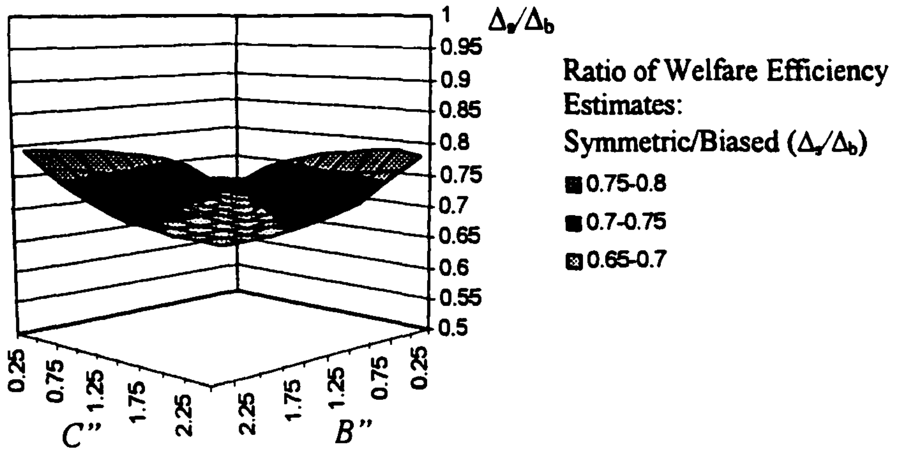

Figure 2.6. Change in Welfare Efficiency Assuming Same-Direction Skew Versus Symmetric Distributions About the Estimated Marginal Curves (Δ_s/Δ_b) ~Beta(a=c=3; b=d=2) $\kappa = 0.207$, ~Beta(a=c=3; b=d=3) $\kappa = 0$

However, when the biases of estimated marginal curves are of opposite direction, price instruments gain favor (Figure 2.7). The entire surface lies above the threshold of

$\Delta_a/\Delta_b = 1$. As the slopes of the marginal curves become more similar, the advantage of the price instruments increases. The ridge of the surface is along where the absolute value of the marginal curves slopes are equal. The magnitude of impact upon policy instrument choice becomes more pronounced as bias increases. Tabular results of these simulations and those for other Beta distribution parameters appear in Appendix 2 (Table 2.2 through Table 2.20).

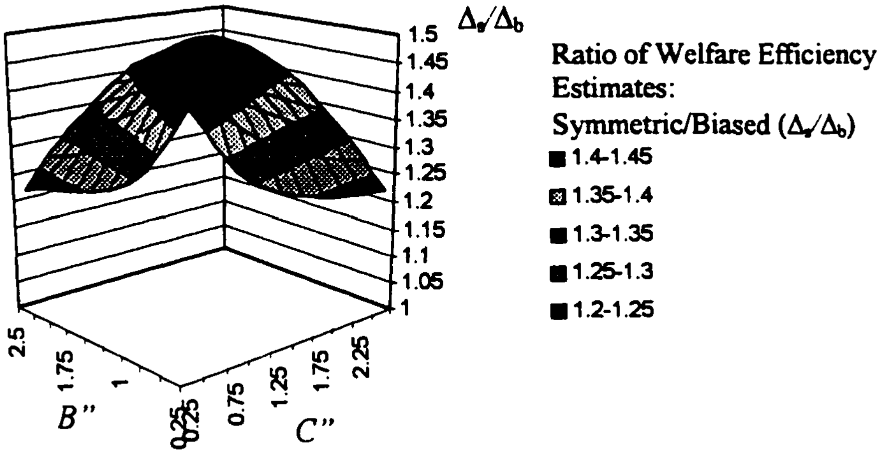

Figure 2.7. Change in Welfare Efficiency Assuming Opposite-Direction Skew Versus Symmetric Distributions About the Marginal Curves (Δ_a/Δ_b) ~Beta(a=d=3; b=c=2) $\kappa = -0.207$, ~Beta(a=c=3; b=d=3) $\kappa = 0$

Our results mirror those of Weitzman (1974) and Stavins (1996) where the existence of simultaneous correlated uncertainty of the marginal benefit and cost curves can lead to a change in the optimal policy instrument. Their primary result: positive correlation tended to increase the efficiency of quantity instruments whereas negative correlation improved price instruments. Hence, uncertainty of the marginal benefit curve has effect upon policy instrument choice when there is simultaneous correlated uncertainty or when data is biased.

POLICY IMPLICATIONS AND CONCLUSION

An important issue regarding the analysis is the one of applicability to real world situations. Thus we must address the question of whether bias of benefit and cost data is discernible or is the inaccurate data randomly and symmetrically distributed. One way to make the skewness parameter function operational is to let κ_c represent industry concentration.[2] Supplied cost information from industries that have fewer players is more likely to be biased upward. On the benefits side, a regulator can recognize that not all pollution damages may be accounted, thus the benefits are apt to be biased downward. Such a situation would result in oppositely skewed distributions representing the uncertainty of the marginal curves; hence price instruments would gain favor.

The impact of bias upon the marginal curve estimates need be considered on a case by case basis. It may be likely that for some pollutants, damages may be overestimated due to confounding factors. A policymaker who takes note of the strategic measurement and static biases, can realize welfare efficiency gains. Furthermore, increased expenses to reduce biases information may be unnecessary. By selecting the policy control instrument that is least affected by the purported bias, a policymaker is able to minimize the influence an agent exerts.

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[2] The optimal tax for a polluting monopoly is less than that for perfect competition, since the monopolist optimal tax varies with its price elasticity of demand. Nevertheless, there is empirical evidence that the welfare loss due to monopolistic distortions is very small (Oates and Strassmann 1984).

Incorrectly assuming that the uncertainty about the marginal curve estimates is unbiased and therefore symmetrically distributed can lead to the selection of a less efficient policy instrument. Traditional welfare analyses which presume that inaccurate data is unbiased, thus concluding that the influence of marginal benefit uncertainty as having no influence upon the policy selection criteria, can lead to fallacious conclusions. In order to empirically estimate the effect of bias, the potential sources could be identified, attributed with the more likely positive or negative sign, and if possible categorized given their relative order of magnitude. Sensitivity analysis of the case would then lead to a more clear understanding of the effect of information bias and hence aid policymakers choose the more efficient pollution control instrument.

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APPENDIX 2

Tables 2.2. through 2.6. Tabular Results of Welfare Efficiency Analysis: Ratio of Price over Quantity Instrument (Error~$\beta(\mu = 0, \sigma^2 = 24)$) (a,b; and c,d are parameters of Beta distributions about MB, MC curves)

Table 2.2. Symmetric Beta (a=b=c=d=3)$\kappa = 0$

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	1	2.5	5	8.5	13	18.5	25	32.5	41	50
0.5	0.625	1	1.625	2.5	3.62	5	6.62	8.5	10.6	13
0.75	0.556	0.722	1	1.39	1.89	2.5	3.22	4.06	5	6.06
1.0	0.531	0.625	0.781	1	1.28	1.63	2.03	2.5	3.03	3.62
1.25	0.52	0.58	0.68	0.82	1	1.22	1.48	1.78	2.12	2.5
1.5	0.514	0.556	0.625	0.722	0.847	1	1.18	1.39	1.62	1.89
1.75	0.51	0.541	0.592	0.663	0.755	0.867	1	1.15	1.33	1.52
2.0	0.508	0.531	0.57	0.625	0.695	0.781	0.883	1	1.13	1.28
2.25	0.506	0.525	0.556	0.599	0.654	0.722	0.802	0.895	1	1.12
2.5	0.505	0.52	0.545	0.58	0.625	0.68	0.745	0.82	0.905	1

Table 2.3. Same-Direction Skew of Marginal Curves; Beta (a=c=3; b=d=2) $\kappa = 0.207$

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	1.44	3.5	6.77	11.3	17	23.9	32.1	41.5	52.1	63.9
0.5	0.874	1.44	2.32	3.5	5	6.77	8.87	11.3	14	16.98
0.75	0.752	1.03	1.44	2	2.68	3.5	4.45	5.54	6.77	8.13
1.0	0.704	0.874	1.12	1.44	1.84	2.32	2.87	3.5	4.2	5
1.25	0.679	0.797	0.963	1.18	1.44	1.76	2.12	2.53	3	3.5
1.5	0.665	0.752	0.874	1.03	1.22	1.44	1.7	1.99	2.32	2.68
1.75	0.655	0.723	0.818	0.937	1.08	1.24	1.44	1.66	1.9	2.17
2.0	0.648	0.704	0.78	0.874	0.988	1.12	1.27	1.44	1.63	1.84
2.25	0.642	0.69	0.752	0.83	0.922	1.03	1.15	1.29	1.44	1.61
2.5	0.639	0.679	0.732	0.797	0.874	0.963	1.06	1.18	1.3	1.44

Table 2.4. Opposite-Direction Skew of Marginal Curves; Beta (a=d=2; b=c=3) $\kappa = -0.207$

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	0.693	1.81	3.77	6.58	10.24	14.74	20.1	26.29	33.33	41.22
0.5	0.452	0.693	1.15	1.81	2.69	3.77	5.07	6.58	8.3	10.24
0.75	0.419	0.509	0.693	0.971	1.34	1.81	2.37	3.02	3.77	4.62
1.0	0.411	0.452	0.546	0.693	0.893	1.15	1.45	1.81	2.22	2.69
1.25	0.41	0.43	0.483	0.571	0.693	0.849	1.04	1.26	1.52	1.81
1.5	0.409	0.419	0.452	0.509	0.589	0.693	0.82	0.971	1.146	1.34
1.75	0.41	0.414	0.435	0.474	0.53	0.603	0.693	0.801	0.926	1.07
2.0	0.411	0.411	0.425	0.452	0.493	0.546	0.613	0.693	0.786	0.893
2.25	0.411	0.41	0.419	0.439	0.469	0.509	0.56	0.621	0.693	0.775
2.5	0.412	0.409	0.415	0.43	0.452	0.484	0.523	0.571	0.628	0.693

Table 2.5. Same-Direction Skew of Marginal Curves; Beta (a=c=2; b=d=4) $\kappa = 0.326$

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	2.45	5.75	10.78	17.54	26.02	36.22	48.14	61.79	77.16	94.25
0.5	1.44	2.45	3.88	5.75	8.05	10.79	13.95	17.54	21.56	26.02
0.75	1.2	1.73	2.45	3.36	4.46	5.75	7.24	8.92	10.78	12.85
1.0	1.1	1.44	1.89	2.45	3.11	3.88	4.77	5.75	6.85	8.05
1.25	1.04	1.29	1.61	2	2.45	2.97	3.56	4.22	4.95	5.75
1.5	1.01	1.2	1.44	1.73	2.06	2.45	2.88	3.36	3.88	4.46
1.75	0.982	1.14	1.33	1.56	1.82	2.11	2.45	2.81	3.22	3.65
2.0	0.965	1.1	1.25	1.44	1.65	1.89	2.15	2.45	2.77	3.11
2.25	0.953	1.06	1.2	1.35	1.53	1.73	1.95	2.19	2.45	2.73
2.5	0.943	1.04	1.156	1.3	1.44	1.61	1.79	1.99	2.21	2.46

Table 2.6. Opposite-Direction Skew of Marginal Curves; Beta (a=d=4; b=c=2) $\kappa = -0.326$

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	0.409	1.17	2.64	4.8	7.68	11.26	15.54	20.53	26.2	32.61
0.5	0.292	0.409	0.701	1.17	1.81	2.64	3.63	4.8	6.15	7.68
0.75	0.293	0.312	0.409	0.584	0.837	1.17	1.58	2.07	2.64	3.28
1.0	0.3	0.292	0.329	0.409	0.533	0.701	0.913	1.17	1.47	1.81
1.25	0.307	0.29	0.302	0.341	0.409	0.505	0.629	0.781	0.961	1.17
1.5	0.313	0.293	0.292	0.312	0.35	0.409	0.487	0.584	0.701	0.838
1.75	0.317	0.296	0.29	0.298	0.321	0.358	0.409	0.474	0.554	0.649
2.0	0.321	0.3	0.291	0.292	0.305	0.329	0.363	0.409	0.465	0.533
2.25	0.324	0.304	0.293	0.291	0.297	0.312	0.335	0.368	0.409	0.459
2.5	0.326	0.307	0.295	0.29	0.292	0.302	0.318	0.341	0.371	0.409

Tables 2.7 through 2.10. Ratio of Welfare Loss Created by Price over Quantity Instruments assuming the Symmetric Error Distribution over that of the Skewed Error Distribution

Table 2.7 Ratio of Symmetric Beta (a=b=c=d=3)$\kappa = 0$ Results and Same-Direction Skew of Marginal Curves; Beta (a=c=3; b=d=2) $\kappa = 0.207$ (Table 2.2/Table 2.3)

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	0.694	0.714	0.739	0.752	0.765	0.774	0.779	0.783	0.787	0.782
0.5	0.715	0.694	0.700	0.714	0.724	0.739	0.746	0.752	0.757	0.766
0.75	0.739	0.701	0.694	0.695	0.705	0.714	0.724	0.733	0.739	0.745
1.0	0.754	0.715	0.697	0.694	0.696	0.703	0.707	0.714	0.721	0.724
1.25	0.766	0.728	0.706	0.695	0.694	0.693	0.698	0.704	0.707	0.714
1.5	0.773	0.739	0.715	0.701	0.694	0.694	0.694	0.698	0.698	0.705
1.75	0.779	0.748	0.724	0.708	0.699	0.699	0.694	0.693	0.700	0.700
2.0	0.784	0.754	0.731	0.715	0.703	0.697	0.695	0.694	0.693	0.696
2.25	0.788	0.761	0.739	0.722	0.709	0.701	0.697	0.694	0.694	0.696
2.5	0.790	0.766	0.745	0.728	0.715	0.706	0.703	0.695	0.696	0.694

Table 2.8. Ratio of Symmetric Beta (a=b=c=d=3)$\kappa = 0$ Results and Opposite-Direction Skew of Marginal Curves; Beta (a=d=2; b=c=3) $\kappa = -0.207$ (Table 2.2/Table 2.4)

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	1.443	1.381	1.326	1.292	1.270	1.255	1.244	1.236	1.230	1.213
0.5	1.383	1.443	1.413	1.381	1.346	1.326	1.306	1.292	1.277	1.270
0.75	1.327	1.418	1.443	1.432	1.410	1.381	1.359	1.344	1.326	1.312
1.0	1.292	1.383	1.430	1.443	1.433	1.417	1.400	1.381	1.365	1.346
1.25	1.268	1.349	1.408	1.436	1.443	1.437	1.423	1.413	1.395	1.381
1.5	1.257	1.327	1.383	1.418	1.438	1.443	1.439	1.432	1.414	1.410
1.75	1.244	1.307	1.361	1.399	1.425	1.438	1.443	1.436	1.436	1.421
2.0	1.236	1.292	1.341	1.383	1.410	1.430	1.440	1.443	1.438	1.433
2.25	1.231	1.280	1.327	1.364	1.394	1.418	1.432	1.441	1.443	1.445
2.5	1.226	1.270	1.313	1.349	1.383	1.405	1.424	1.436	1.441	1.443

Table 2.9. Ratio of Symmetric Beta (a=b=c=d=3) $\kappa = 0$ Results and Same-Direction Skew of Marginal Curves; Beta (a=c=4; b=d=2) $\kappa = 0.326$ (Table 2.2/Table 2.5)

MC slope	*MB slope*									
	0.25	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	2.445	2.137	1.894	1.771	1.693	1.643	1.609	1.583	1.565	1.533
0.5	2.140	2.445	2.318	2.137	2.000	1.894	1.824	1.771	1.724	1.693
0.75	1.898	2.314	2.445	2.380	2.258	2.137	2.038	1.961	1.894	1.848
1.0	1.770	2.140	2.374	2.445	2.402	2.325	2.223	2.137	2.061	2.000
1.25	1.694	2.000	2.252	2.405	2.445	2.416	2.353	2.279	2.206	2.137
1.5	1.642	1.898	2.140	2.314	2.420	2.445	2.423	2.380	2.311	2.255
1.75	1.609	1.828	2.041	2.225	2.352	2.422	2.445	2.426	2.401	2.342
2.0	1.583	1.770	1.959	2.140	2.279	2.374	2.433	2.445	2.430	2.402
2.25	1.562	1.727	1.898	2.058	2.202	2.314	2.394	2.432	2.445	2.440
2.5	1.549	1.694	1.847	2.000	2.140	2.252	2.343	2.405	2.439	2.445

Table 2.10. Ratio of Symmetric Beta (a=b=c=d=3)$\kappa = 0$ Results and Opposite-Direction Skew of Marginal Curves; Beta (a=d=4; b=c=2) $\kappa = -0.326$ (Table 2.2/Table 2.6)

	MB slope									
MC slope	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**	**2.5**
0.25	0.408	0.435	0.464	0.485	0.500	0.511	0.519	0.526	0.531	0.531
0.5	0.434	0.408	0.419	0.435	0.450	0.463	0.475	0.485	0.492	0.500
0.75	0.463	0.417	0.408	0.414	0.424	0.435	0.445	0.455	0.464	0.472
1.0	0.483	0.434	0.413	0.408	0.412	0.420	0.426	0.435	0.442	0.450
1.25	0.500	0.450	0.422	0.410	0.408	0.411	0.416	0.422	0.428	0.435
1.5	0.509	0.463	0.434	0.417	0.411	0.408	0.410	0.414	0.418	0.424
1.75	0.519	0.475	0.445	0.425	0.415	0.411	0.408	0.409	0.413	0.416
2.0	0.526	0.483	0.456	0.434	0.421	0.413	0.411	0.408	0.408	0.412
2.25	0.531	0.495	0.463	0.444	0.427	0.417	0.411	0.409	0.408	0.410
2.5	0.536	0.500	0.471	0.446	0.434	0.422	0.416	0.412	0.410	0.407

CHAPTER 3

DETERMINANTS OF OZONE LEVELS IN CITIES OF THE UNITED STATES: AN ECONOMETRIC ANALYSIS

INTRODUCTION

Despite years of environmental regulation and technology improvements, air pollution continues to adversely affect many city dwellers throughout the United States. In addition, even rural areas suffer from contaminated air, as a result of being downwind from neighboring urban zones. Despite a myriad of government regulations attempting to control emissions, a few urban areas persistently fail to meet national standards. This study focuses upon the determinants of ozone levels, O_3, one of the six primary criteria pollutants monitored by the Environmental Protection Agency (EPA 1997).

The root causes of poor air quality are many. While different sectors of the overall economy contribute to the air pollution problem, transportation, manufacturing, and power generation facilities are perceived as being the primary offenders. Since the Clean Air Act of 1970, high ozone levels continue to plague many urban areas. In 1995, nearly 71 million people lived in counties where air quality levels exceeded national ozone standards. Of all the criteria pollutants, ozone is the most common reason for an area to receive non-attainment status. (EPA 1995)

This paper tests two hypotheses regarding the determinants of ozone levels in United States cities. First, is whether the use of the automobile within urban areas is a major contributor to the presence of high ozone concentrations. Second, is whether the type economic activity within a city can lead to higher ozone levels. For the purpose of this paper, the economy is divided into two major sectors: a "dirty" sector (construction and manufacturing) and a "clean" sector (service, retail and government). To test these two hypotheses, we employ a panel data set for 40 metropolitan statistical areas (MSAs)[7] covering a twenty-one year time frame (specifically the years of 1974, 1978, 1982, 1986, 1990, 1994).

THE ROLE OF OZONE

At natural ambient levels, ozone is a colorless and tasteless gas. The pollutant is not emitted from any specific source. Rather ozone is formed from volatile organic compounds (VOCs) and nitrogen oxides (NOx). In urban regions, there are many origins of VOCs: automotive exhaust, vapors from gasoline refueling, industrial solvents, degreasing agents, etc. The second component of ozone, nitrogen oxides, is typically created when nitrogen and oxygen combine during high temperature combustion processes.

The highest ozone levels usually occur during the summer season. Stronger sunlight during those months facilitates the chemical production process. Damages due to ozone are many. Its high reactivity causes health problems especially to the pulmonary system. Lung tissue damage and associated decreases of functionality, and can make the lungs even more sensitive to other irritants. Chest pain, coughing, sneezing and pulmonary

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[7] MSAs are US government designations of urban and related suburban areas used to compare metropolitan areas.

congestion often result, especially for those people of decreased lung capacity such as asthmatics.

THE ECONOMY, OZONE AND AUTOMOBILES

Consequences to an urban area of not receiving attainment status can greatly affect future economic activity. State Implementation Plans (SIPs) developed by each state as part of the 1970 Clean Air Act, require control of new emission sources if an air quality region does not meet established standards. Specifically, permits and stringent pollution control technologies are mandated for new and expanding emitters. The EPA standard for ozone requires that for each day, that the second highest hourly reading not exceed a maximum concentration of 0.12 parts per million (ppm). All urban counties in the United States are examined each July to determine if pollution standards are properly attained.

If a city is found to not be in attainment, strict regulations can be imposed. These regulations often have a bias against new pollution sources, which can negatively affect a growing local economy. Since only new firms are typically subject to higher pollution control costs, existing firms can earn economic rents by not facing new competition (Maloney and McCormick 1982). This economic gain to existing firms from pollution regulation often extends the time existing facilities are operated before retirement. (Maloney and Brady 1982)

The perverse effect of pollution regulation has been traced by numerous studies. McConnell and Schwab (1990) examined the impact of environmental regulation on decision process of industry location. Firms were found, at the margin, to be deterred from locating plants in the most polluted non-attainment areas. In addition to evading regulations in spatial terms, Henderson (1996) found evidence that emitters respond to the temporal nature of the restrictions and hence avoid peak ozone levels by rescheduling production with its associated pollution emission.

The transportation sector is also affected by environmental regulation. If a MSA receives a non-attainment status, vehicles need to pass annual inspections and often fuel mixtures are reformulated to be cleaner burning. In the worst offending MSAs, e.g. the Los Angeles area, the introduction of electric cars has been mandated.

With additional regulation, come higher pollution control costs. On one hand, perhaps there is a loss of economic competitiveness, but a cleaner environment and positively associated city amenities attract a higher quality, healthier and thus productive labor force. Such a potential trade-off leads to the question: is there a relationship between pollution and per capita income? This question has been examined using various indicators of environmental quality (e.g. air and water). Employing an international panel data set, studies have determined that there exists an inverted U shape relation between income and such air quality measures as particulates and SO_2. Results show that ambient concentrations of these pollutants rise until approximately $5000 GDP then decline as affluence increases (World Bank 1992, Grossman and Krueger 1993, 1994). For the United States, Grossman and Krueger (1994) examined the inverted U shape relation and despite the fact that there is less inherent variation, there exists such a relation for many of the criteria pollutants.

There are two primary explanations for the existence of the inverted U relation. One line of thought asserts that pollution emissions follow the natural evolution of economic activity. The early stages of economic development, starting with agrarian societies, pollute relatively little. Economic development progresses into polluting industrial societies that eventually evolve into cleaner service-oriented or high-technology economies. The second viewpoint claims that environmental quality is a luxury good. As societies become more wealthy, they are able to demand environmental quality improvements through increasing government regulations and technological advances (Radetzski 1991, Grossman and Krueger 1994)

Grossman and Krueger (1993) maintain that the inverted U relation can be divided into three distinct effects: *scale* where more economic activity leads to more pollution, *composition* effect (similar to the evolution concept above) refers to a shifting of production from dirty to clean economic sectors, and *technique* effect where new technologies enable pollution reductions per unit of economic output.

Yet not all pollutants follow the inverted U pattern. Some ambient pollutant levels continue to increase as the economy prospers. For example, in many areas of the United States, criteria pollutants such as ozone continue to exceed standards despite years of regulatory efforts. Perhaps notions of environmental quality as being a luxury are superseded by increased wealth leading to worsening ambient concentrations of pollutants.

One potential contributor to the ozone problem is the automobile and its increasing use and popularity. For instance, despite a relatively slow population growth rate of 28% from 1975 to 1995, miles traveled by US citizens increased 116% over the same time period (EPA 1997). However previous environmental economic analyses of ozone have not accounted for automobile use. (Henderson 1996, Grossman, Krueger and Laity 1994)

With the consistent south and westward growth of the United States both demographically and economically, regional descriptive statistics can provide insights regarding the factors contributing to ozone levels. The forty MSAs of the study are divided into four regions per Table 3.1. Region 1 refers to the northeast, Region 2 is the north central, Region 3 is the southern and Region 4 refers to the western portion of the United States. To create regions crudely based upon temperatures, Regions 1 and 2 can be considered the "Frost Belt" whereas Regions 3 and 4 comprise the "Sun Belt."

Table 3.1. Geographic Regions and Associated Metropolitan Statistical Areas

Region 1	*Region 2*	*Region 3*	*Region 4*
Baltimore	Akron	Atlanta	Albuquerque
Boston	Chicago	Austin	Denver
Buffalo	Cincinnati	Baton Rouge	Los Angeles
Newark	Cleveland	Birmingham	Phoenix
New York City	Detroit	Charlotte	Portland
Norfolk	Indianapolis	Dallas	Sacramento
Philadelphia	Kansas City	Houston	San Diego
Pittsburgh	Milwaukee	Memphis	San Francisco
Rochester	Minneapolis	Miami	Seattle
Washington	St. Louis	Tampa	Tucson

For all regions, the maximum daily levels of ozone decreased for most of the years used in the analysis (Figure 3.1). Perhaps the relatively lower ozone levels of 1974 can be attributed to an oil embargo effect when the amount of per capita miles traveled decreased. Despite being restricted by environmental regulations for the establishment of new industrial facilities, the faster growing regions of the south and west have similar ozone levels to the Frost Belt through the years. These higher ozone concentrations in the south and west may be due to more days with sunshine and high temperatures.

Within each region, certain metropolitan areas had persistently high levels of ozone. In Region 1, for the areas examined, Philadelphia and Newark were the worst offenders. For Region 2, Cincinnati, Akron and St. Louis were often ranked poorly. The MSAs of Houston and Los Angeles representing Regions 3 and 4 respectively reported some of the highest ozone levels of the entire nation for all study years.

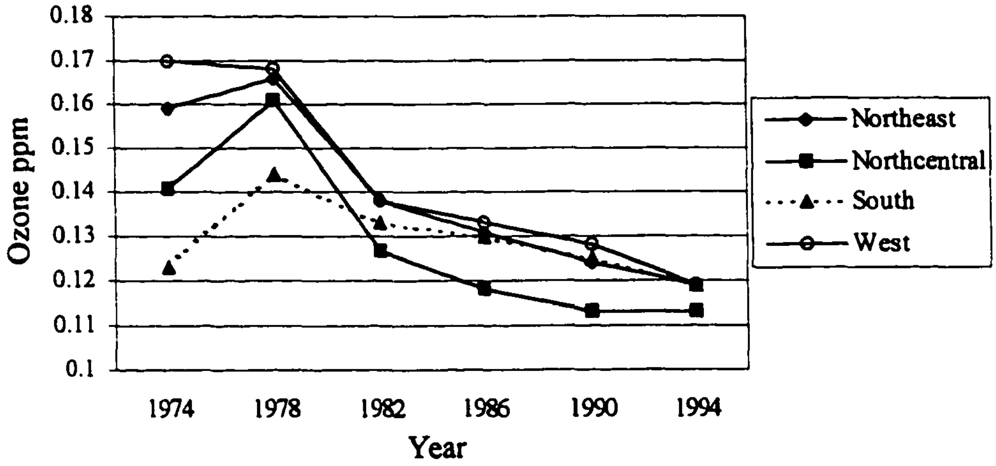

Figure 3.1. Average of Annual Daily Maximum Ozone Levels (ppm)

Since the 1970s, average gasoline consumption has increased only slightly in all regions (Figure 3.2). Yet, this is not to say that Americans are driving less. With fuel economy levels of the automobile fleet increasing each year, the relatively constant consumption figures reveal that more miles are being traveled. Even though urban regions of the south and western regions have less developed mass transit systems, average gasoline consumption does not appear to be greater in the Sun Belt than more established Frost Belt cities.

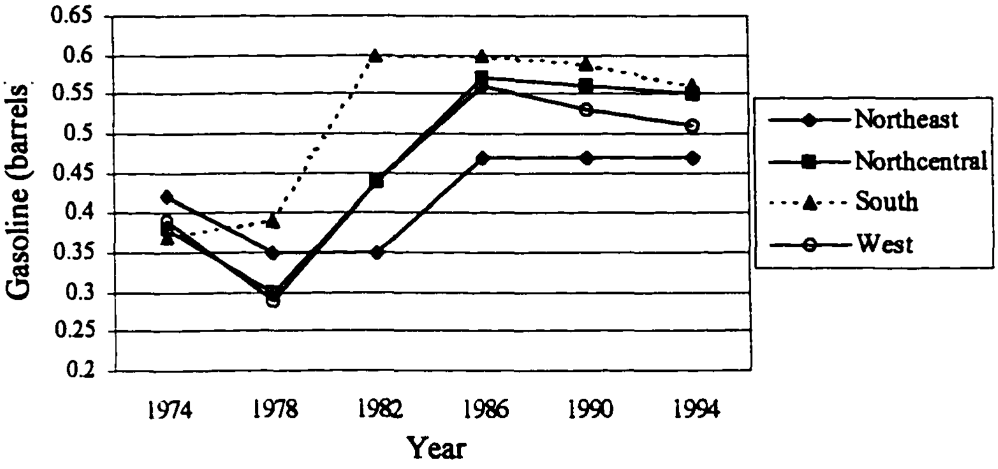

Figure 3.2. Average Gasoline Consumption per Region (barrels per capita)

HYPOTHESES

In this paper, we examine two socio-economic issues regarding the how personal transportation and predominant economic sectors affect ambient ozone concentrations.

Hypothesis One: the use of the automobile within urban areas is a major contributor to the presence of high ozone concentrations.

Hypothesis Two: "clean" economic activity (retail, service and government sectors) within a city leads to higher ozone levels than supposed the "dirty" economic sector (manufacturing and construction).

These two hypotheses can be considered inter-related. For example, the while the clean sector economic activity with its service focus may contribute less directly to the production of ozone, employees of the sector commonly enjoy greater personal incomes. Thus indirectly, the greater earnings within the clean sector can permit employees to live further from work and lead to more automobile use. Overall and for each of the four analyzed regions, there is a higher correlation between per capita income and the clean sector than so for the dirty sector (in Appendix 3). Furthermore, more disposable income permits clean sector employees to use less fuel-efficient luxury automobiles.

In attempt to capture, and if possible distinguish, the spatial aspect of pollution emissions within a MSA versus the economic sector composition of a MSA that may affect personal incomes, the following estimation methods employ both per capita measures and density measures of the principle explanatory variables.

DATA

To examine the spatial and economic relationships of ambient ozone levels requires use of both density and economic sector data. Unlike other air pollution studies, Grossman, Krueger and Laity (1994) and Kahn (1997) that use county level data from air quality monitoring stations, this analysis employs data compiled for metropolitan statistical areas similar to the approach taken by Duffy-Deno (1992) using monitoring stations in city centers. Since the dataset spans twenty-one years (1974, 1978, 1982, 1986, 1990 and 1994), federal government data sources often change the ranking of urban areas and hence the provision of data at the MSA level. The forty urban regions were also chosen based upon the criteria of data completeness, even though a random sample of MSAs would prevent problems of selection bias. The data used in the below analysis come from a variety of government sources.

Measures of ambient ozone concentrations are from the Air Quality Subsystem of the EPA Airs database in North Carolina, which was accessed remotely. Population, sectoral employment and earnings level data came from the U.S. Department of Commerce Regional Economic Information System (REIS). For the purposes of this study, economic sectors at one-digit level of the Standard Industry Classification (SIC codes) were employed. If more disaggregated data were used, a problem of incomplete information would have resulted since data reporting restrictions of the Census Bureau are commonly enacted when a few businesses comprise the sector.

The US Census Bureau provided data on pollution control compliance costs according to metropolitan statistical area for the years 1974-1982. These data include total expenditures by the private sector and expenditures for all types of emissions (i.e. solid water and air). Gasoline expenditure and per capita tax data was supplied by Statistical Abstract of the United States and the State and Metropolitan Area Data Book. The maximum annual temperature weather data was provided by EarthInfo NCDC Summary of the Day.

ANALYTICAL METHODS

Previous air quality studies typically employ fixed effects models where the pollutant level was the dependent variable (Grossman Krueger and Laity 1994, Kahn 1996, Henderson 1996). To examine the determinants of urban ozone levels, we estimated a pollution production function: $OZ_{it} = \beta X_{it} + \varepsilon$ where OZ is the dependent variable ozone, X is a vector of explanatory variables and ε is a random error term; the subscripts *i* and *t* refer to the MSA and time period respectively. The vector of estimated parameters β contains the intercept and slope coefficients of the regression model.

The structure of the error term ε is distinct depending upon the estimation method employed. In the following analysis, we employ three basic models (pooled, fixed effects and random effects) each of which assumes different structures of the error term. The classical pooled model, the error term is assumed to be independent and randomly distributed across time (t) and space (i). The fixed effects (or covariance) model recognizes that omitted variables may lead to changing cross-sections (MSAs), thus dummy variables are added to allow for specific spatially associated intercepts. The random effects (or error components) model accounts for both cross-section and time series disturbances of the panel data. We compare the results of these models since the each have their own particular limitations. For example, the random effects model may suffer from inconsistent parameter estimates due to the omitted variables (Greene 1993). Table 3.2 presents a summary of the model variables and expected signs of the estimated coefficients.

Table 3.2. Model Variables

Expected Sign	*Variable*
	OZ : Ozone level : average of four highest July readings (ppm)
-	PCTAX : Per capita taxes: state and local ($/person)
+	TEMP : Temperature July maximum (degrees Fahrenheit)
-	APOLCV: Air pollution control operational costs (abatement cost/ $1000 of Value added)
+	GASPOP : Gasoline consumption density (barrels per capita)
+	GASDEN : Gasoline consumption density (barrels per square mile)
+	AREA : Area of MSA (square miles)
+	POPDEN: Population density: (population/square mile)
+	DIRTY: Dirty sector : construction and manufacturing (employment/MSA population)
+	CLEAN: Clean sector : retail, services, government (employment/MSA population)
-	PCINC: per capita earnings ($/year)
+	OZ(-1) : lagged ozone level
-	APOLCV(-1): lagged air pollution control operational costs
	i : Metropolitan Statistical Area (total 40) t : Year (1974, 1978, 1982, 1986, 1990, 1994)

To account for the effect of ozone upon a MSA population, there are a variety of ways to measure ambient concentrations. For its standard, the EPA uses the second-highest daily maximum reading. Since humans typically respond to peak exposures but are also affected by prolonged exposure at lower concentrations, we use a composite measure that is an average of the four highest daily readings in ppm from the typically warmest month of July.[8] The variable OZ represents these ozone concentration levels in a MSA.

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[8] Henderson (1996) examined the effect of using mean annual reading, mean July reading, second highest daily maximum and median of July reading.

Explanatory economic variables examined are per capita income (PCINC) and the average amount of per capita tax within a MSA (PCTAX). The hypothesized sign of the estimated parameter of PCINC is negative. As the population of a MSA becomes more wealthy, environmental quality can be more adequately addressed. Similarly, PCTAX is hypothesized to be of negative sign. Regions that pay more in taxes represent not only wealthier regions, but those that would be inclined to fund public improvements and demand higher environmental quality.

In addition, proxies for economic sector activities are employed. CLEAN and DIRTY represent the percent of a MSA population employed in the dirty and clean sectors of the economy respectively. The manufacturing and construction sectors comprise the dirty sector, whereas the clean sector contains retail, services and government sectors (minus the military). As the economic sector variables suggest, the DIRTY sector is expected to be positively associated with ozone levels and more so than CLEAN. The variable APOLCV represents the total costs of air pollution control by the manufacturing sector per level of value added output. Since this variable is does not reflect investment but rather operating costs, it is expected to negatively related to ozone levels.

A potentially important factor contributing to high ozone levels is transportation. Two variables GASDEN and GASPOP reflect the use of automobiles within a MSA. By dividing gasoline expenditure data by the associated annual price, quantity data for gasoline consumption were calculated. GASPOP is per capita gasoline consumption and GASDEN is a measure of gasoline use per MSA land area. Both gasoline variables are expected to be positively related with ozone levels.

Population within a MSA and population density, respectively POP and POPDEN, are both hypothesized to be positively related to ozone levels. Since the ozone chemical reaction is enhanced by warm temperatures and sunlight, we include maximum annual temperature, TEMP, as a proxy for MSA weather conditions. The hypothesized sign of TEMP is positive. In addition, both APOLCV and OZ variables were lagged since their cause-effect relationship would not be only be contemporaneous. Where past levels of ozone have been high, readings in subsequent years are also expected to be high. Therefore, the lagged value of the dependent value is hypothesized to be positive. In addition, the lagged value of APOLCV is expected to be negative since past operating cost of pollution control would likely lead to lower ozone levels in the future.

RESULTS

Explaining the conduct of ozone levels in cities throughout the United States requires the use of meteorological, transportation, economic and social data. Hence a concise cause and effect theory to explain ambient ozone levels does not exist. Nevertheless, the use of a variety of data sources, many of them proxies, permits inferences to be made. Since there is no evident manner with which to examine the relationship between the explanatory variables of ozone, a range of model specifications and functional forms were developed and examined. While it may be desirable to merely select one and claiming it a "best" representation, a number of alternative specifications and approaches are presented not only for comparison, but also to validate the testing of key hypotheses.

Other functional forms besides linear were examined with mixed results. For example, a log-log specification, which may be useful to minimize the effects of heteroskedasticity, leads to extremely high R^2 values, possibly signaling multicolinearity problems.[9] In order to examine the correlation amongst the variables, correlation matrices were elaborated for the entire sample and the four regions (Tables 3.8 to 3.12 in Appendix 3). Of interest is the high correlation (0.995) between CLEAN and PCINC in all the tables, implying that performance of the clean sector drives per capita income growth. Also of note is a low correlation between population density, POPDEN, and gas consumption density, GASDEN, in the northeast (Region 1) and high correlation in all other regions ranging from 0.788 to 0.939. This result suggests that the northeast with its more established public transport and higher population densities leads to less of a connection with gasoline use.

Four model specifications: two pooled models (one corrected for heteroskedasticity and one employing cross-sections weights), a fixed-effects and a random-effects model are presented in Tables 3.4 to 3.7 (in Appendix 3). While a few of the estimated coefficients are not statistically significant, most are of expected sign. Such outcomes of air pollution analyses are not uncommon (Grossman, Krueger and Laity 1994, Kahn 1996, Henderson 1996). Table 3.3 presents a summary of the model results of the statistically significant variables.

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[9] In the Duffy-Deno paper, the log-log specification was used producing adjusted R^2 values above 0.9 for all equations estimated. No autocorrelation test results were reported.

Table 3.3. Summary of Econometric Modeling Results
(only estimated coefficients with P-value < 0.06 reported)

Expected Sign	*Actual Sign*	*Estimated Coefficient*	*Pooled*	*Pooled (weighted)*	*Fixed Effects*	*Random Effects*
		C	-4.4			
-	ns	PCTAX				
+	+	TEMP	0.9	0.8	0.6	0.7
-	+	APOLCV	1154.7	1167.4	461.4	1160.5
+	+	APOLCV (-1)	-867.2	-819.6	-504.0	-918.6
+	-	GASPOP	-107.0	-88.4	-145.5	-92.9
	-	GASPOP ^2	97.8	82.1	101.1	84.7
+	ns	GASDEN				
+	ns	AREA				
+	ns	POPDEN				
+	+	DIRTY	0.81	0.4	1.4	0.8
+	+	CLEAN	0.76	0.5	0.7	0.7
-	-	PCINC	-0.006	-0.003	-0.007	-0.005
+	+	OZ (-1)		0.6		0.7

ns = not significant

The similarity of some of the explanatory variables prevented their simultaneous inclusion in the models. For example the spatial- and demographic- based gasoline consumption variables, GASPOP and GASDEN did not produce the expected statistically significant results when employed together. Since the former measure provided more statistically significant results, its use was maintained in all four model representations.

By examining various functional forms, resulting estimated parameters demonstrate that there exists a statistically significant non-linear relationship between GASPOP and OZ. The levels term GASPOP is positive while the quadratic term GASPOP^2 is of negative sign signaling an inverted U shape (c.f. World Bank 1992, Grossman and Krueger 1993, 1994). At low and high gasoline use per person ozone levels are relatively low. However in intermediate gasoline use areas, ozone levels are more elevated. At mean levels of GASPOP and OZ (.447 barrels per capita, 140.2 ppm) a 1 % increase in per capita gasoline use would reduce ambient ozone levels by 0.09 %. (Recall that the mean values are within the intermediate region, where a change in the explanatory variable has more relative impact.

The estimated coefficient of the economic sector variable DIRTY validates hypothesis two: that increased activity in the manufacturing and construction sectors results in higher levels of ozone. The same is true for the CLEAN sector but to a perhaps lesser extent (the difference in estimated parameters is statistically insignificant). PCINC reveals a slight negative relationship between per capita income and ozone level. At mean OZ and PCINC levels (140 ppm and $14,311 respectively) a 1 % increase in PCINC leads to a 0.6 % decrease in a MSA ozone level. Thus the notion that wealthier MSAs have or demand better air quality appears to be true.

Some non-economic explanatory variables were also of expected sign and magnitude. Higher annual maximum temperatures, TEMP, indeed do lead to higher ozone concentrations confirming the standard scientific conclusions. Past ozone levels OZ(-1) are positively related with current ozone levels. Thus past performance leads to the same good or bad. Regional dummy variables, which reflect the four national regions in Table 3.1 did not prove to be statistically significant. It appears that hot regional weather was adequately captured in the temperature variable TEMP.

POLICY IMPLICATIONS AND CONCLUSIONS

The above econometric analysis reveals that there exists a statistically significant relationship between socio-economic activity and ambient ozone levels in MSAs. Results support the first hypothesis that automobiles use, proxied by GASPOP, can be a major contributor to ozone levels. The inverted U shape between GASPOP and ambient ozone levels leads to the conclusion that in MSAs with either low or high gasoline use per capita have less impact upon ozone concentrations. It is rather MSAs with intermediate gasoline use per capita that are more troublesome. Low gasoline per capita MSAs could be described as those with more public transportation use whereas high gasoline per capita MSAs are larger and have relatively low population densities. Therefore the ozone production is over a larger area and not concentrated.

As for the role of economic sectors upon ozone production, the above results reveal that growth in both clean and dirty sectors lead higher ozone levels. While the estimated parameter of the dirty sector is greater than that of the clean sector, the difference was statistically insignificant. Thus the second hypothesis is weakly supported.

In sum, policymakers may wish to concentrate efforts on those MSAs where there is intermediate gasoline per capita consumption. Characterized by more dense populations but with less used public transportation, these MSAs are more prone to having higher ozone concentrations. By focusing efforts upon these regions, more citizens could benefit from lower ozone concentrations.

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APPENDIX 3

Table 3.4. Classical Pooled Model Regression Results

Dependent Variable: OZ
Method: Pooled Least Squares
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-4.397037	36.18390	-0.121519	0.9034
TEMP	0.866402	0.329823	2.626871	0.0093
APOLCV	1154.654	296.0460	3.900252	0.0001
APOLCV (-1)	-867.1736	297.3983	-2.915866	0.0040
GASPOP	-107.0236	38.95143	-2.747616	0.0066
GASPOP ^2	96.79777	35.83918	2.700893	0.0076
PCINC	-0.005580	0.001349	-4.136244	0.0001
DIRTY	0.819648	0.233929	3.503830	0.0006
CLEAN	0.760076	0.205508	3.698523	0.0003
OZ (-1)	0.621462	0.073788	8.422327	0.0000

R-squared	0.732772	Mean dependent var	136.8500
Adjusted R-squared	0.719772	S.D. dependent var	43.67764
S.E. of regression	23.12146	Sum squared resid	98901.32
F-statistic	56.36584	Durbin-Watson stat	2.217256
Prob(F-statistic)	0.000000		

Table 3.5. Classical Pooled Model Regression Results with Cross Section Weights

Dependent Variable: OZ
Method: GLS (Cross Section Weights)

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	6.05444	26.9757	0.22444	0.8227
TEMP	0.79477	0.25430	3.12521	0.0021
APOLCV	1167.44	225.720	5.17210	0.0000
APOLCV (-1)	-819.613	233.490	-3.51027	0.0006
GASPOP	-88.3968	25.7627	-3.43118	0.0007
GASPOP ^2	82.1498	23.5688	3.48552	0.0006
PCINC	-0.00377	0.00108	-3.49234	0.0006
DIRTY	0.39378	0.19372	2.03269	0.0435
CLEAN	0.51247	0.17437	2.93901	0.0037
OZ (-1)	0.56285	0.04170	13.4948	0.0000

Weighted Statistics			
R-squared	0.93602	Mean dependent var	169.807
Adjusted R-squared	0.93291	S.D. dependent var	87.2830
S.E. of regression	22.6066	Sum squared resid	94545.8
F-statistic	300.771	Durbin-Watson stat	2.09070
Prob(F-statistic)	0.00000		

Unweighted Statistics			
R-squared	0.72197	Mean dependent var	136.850
Adjusted R-squared	0.70845	S.D. dependent var	43.6776
S.E. of regression	23.5839	Sum squared resid	102897.
Durbin-Watson stat	1.98022		

Table 3.6. Fixed Effects Model Regression Results with Cross Section Weights

Dependent Variable: OZ
Method: GLS (Cross Section Weights)

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
TEMP	0.63747	0.33336	1.9122	0.057
APOLCV	461.396	214.645	2.1495	0.033
APOLCV (-1)	-504.048	194.411	-2.5926	0.010
GASPOP	-145.464	37.3398	-3.8956	0.000
GASPOP ^2	101.081	36.5791	2.7633	0.006
PCINC	-0.00731	0.00171	-4.2628	0.000
DIRTY	1.44274	0.35254	4.0924	0.000
CLEAN	0.73102	0.28985	2.5220	0.012
Fixed Effects				
1--C	110.038		21--C	137.284
2--C	136.128		22--C	122.722
3--C	144.509		23--C	132.882
4--C	97.6995		24--C	94.1337
5--C	158.368		25--C	152.164
6--C	152.133		26--C	163.754
7--C	136.053		27--C	115.300
8--C	116.711		28--C	165.646
9--C	105.300		29--C	120.496
10--C	118.341		30--C	136.388
11--C	136.657		31--C	126.717
12--C	137.989		32--C	97.7454
13--C	126.708		33--C	164.009
14--C	127.053		34--C	144.490
15--C	148.960		35--C	202.707
16--C	138.858		36--C	97.1543
17--C	131.861		37--C	118.450
18--C	210.958		38--C	140.038
19--C	117.933		39--C	105.279
20--C	304.379		40--C	156.704

Weighted Statistics			
R-squared	0.97981	Mean dependent var	195.748
Adjusted R-squared	0.97353	S.D. dependent var	114.828
S.E. of regression	18.6819	Sum squared resid	52701.5
F-statistic	1047.04	Durbin-Watson stat	2.11277
Prob(F-statistic)	0.00000		

Unweighted Statistics			
R-squared	0.85713	Mean dependent var	137.770
Adjusted R-squared	0.81266	S.D. dependent var	44.1723
S.E. of regression	19.1189	Sum squared resid	55195.8
Durbin-Watson stat	1.75356		

Table 3.7. Random Effects Model Regression Results

Dependent Variable: OZ
Method: GLS (Variance Components)

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-2.534385	28.62834	-0.088527	0.9296
TEMP	0.737231	0.283177	2.603430	0.0100
APOLCV	1160.525	237.5579	4.885228	0.0000
APOLCV (-1)	-917.6298	247.7396	-3.704008	0.0003
GASPOP	-92.87213	36.35547	-2.554558	0.0114
GASPOP ^2	83.72262	37.99959	2.203251	0.0288
PCINC	-0.005201	0.001383	-3.759659	0.0002
DIRTY	0.764559	0.230634	3.315034	0.0011
CLEAN	0.707024	0.222817	3.173122	0.0018
OZ (-1)	0.671536	0.034344	19.55341	0.0000
Random Effects				
1--C	1.196123		21--C	0.304759
2--C	-2.829246		22--C	-4.354040
3--C	-2.354597		23--C	2.839819
4--C	6.647324		24--C	5.039079
5--C	-4.327132		25--C	-1.480354
6--C	-6.028486		26--C	0.129764
7--C	-2.471998		27--C	4.655460
8--C	3.358011		28--C	-3.089509
9--C	3.358409		29--C	6.458710
10--C	-1.050703		30--C	0.004082
11--C	7.322704		31--C	0.115849
12--C	-3.139618		32--C	2.172486
13--C	-0.124917		33--C	-2.781580
14--C	1.047135		34--C	-4.218289
15--C	-3.676010		35--C	-0.690052
16--C	6.618615		36--C	4.818971
17--C	-4.347837		37--C	2.990112
18--C	-0.837422		38--C	-2.168213
19--C	0.990247		39--C	3.351032
20--C	-13.07951		40--C	-0.047801

GLS Transformed Regression

R-squared	0.711742	Mean dependent var	136.8500
Adjusted R-squared	0.697719	S.D. dependent var	43.67764
S.E. of regression	24.01402	Sum squared resid	106684.5
Durbin-Watson stat	2.218399		

Unweighted Statistics including Random Effects

R-squared	0.684525	Mean dependent var	136.8500
Adjusted R-squared	0.669177	S.D. dependent var	43.67764
S.E. of regression	25.12215	Sum squared resid	116757.6
Durbin-Watson stat	2.027010		

Table 3.8. Correlation Matrix of Model Variables (All Regions)

	oz	*pctax*	*temp*	*apolcv*	*gaspop*	*gasd*	*area*	*tpinc*	*pop*	*popd*	*pcinc*	*dirty*	*clean*
oz	1.000												
pctax	0.033	1.000											
temp	0.073	0.001	1.000										
apolcv	0.336	-0.054	-0.110	1.000									
gaspop	-0.146	0.182	0.127	-0.073	1.000								
gasd	0.117	0.255	-0.148	0.372	0.172	1.000							
area	0.055	-0.069	0.589	-0.018	0.160	-0.343	1.000						
tpinc	0.168	0.239	-0.004	0.228	-0.217	0.466	-0.021	1.000					
pop	0.425	0.190	-0.065	0.336	-0.325	0.516	-0.019	0.853	1.000				
popd	0.152	0.107	-0.216	0.349	-0.328	0.782	-0.383	0.665	0.774	1.000			
pcinc	-0.258	0.233	0.076	-0.003	0.142	0.211	-0.023	0.594	0.232	0.179	1.000		
dirty	-0.142	-0.013	-0.146	0.124	0.167	0.218	-0.074	0.352	0.131	0.108	0.705	1.000	
clean	-0.211	0.347	0.149	-0.048	0.132	0.178	0.007	0.616	0.263	0.165	0.955	0.522	1.000

Table 3.9. Correlation Matrix of Model Variables (Region 1)

	oz	*pctax*	*temp*	*apolcv*	*gaspop*	*gasd*	*area*	*tpinc*	*pop*	*popd*	*pcinc*	*dirty*	*clean*
oz	1.000												
pctax	0.020	1.000											
temp	0.212	0.451	1.000										
apolcv	0.261	-0.331	-0.206	1.000									
gaspop	-0.286	0.449	0.236	-0.065	1.000								
gasd	-0.076	0.449	0.327	-0.186	0.761	1.000							
area	0.280	0.285	0.066	0.314	-0.119	-0.353	1.000						
tpinc	0.058	0.150	0.223	-0.200	-0.341	0.024	0.213	1.000					
pop	0.458	0.028	0.139	-0.115	-0.539	-0.076	0.275	0.803	1.000				
popd	0.325	-0.075	0.105	-0.274	-0.440	0.141	-0.212	0.706	0.872	1.000			
pcinc	-0.466	0.299	0.302	-0.235	0.215	0.264	0.058	0.635	0.180	0.164	1.000		
dirty	-0.581	-0.143	-0.173	-0.062	0.263	0.181	-0.124	0.076	-0.238	-0.152	0.581	1.000	
clean	-0.349	0.508	0.406	-0.312	0.163	0.200	0.171	0.674	0.260	0.177	0.925	0.282	1.000

Table 3.10. Correlation Matrix of Model Variables (Region 2)

	oz	*pctax*	*temp*	*apolcv*	*gaspop*	*gasd*	*area*	*tpinc*	*pop*	*popd*	*pcinc*	*dirty*	*clean*
oz	1.000												
pctax	-0.295	1.000											
temp	-0.305	0.230	1.000										
apolcv	0.181	0.374	0.206	1.000									
gaspop	-0.496	0.430	0.283	-0.207	1.000								
gasd	0.055	0.298	0.145	0.785	-0.031	1.000							
area	-0.354	0.188	0.369	-0.201	0.250	-0.391	1.000						
tpinc	-0.204	0.370	0.222	0.696	-0.105	0.728	-0.019	1.000					
pop	0.051	0.329	0.225	0.899	-0.233	0.827	-0.019	0.839	1.000				
popd	0.143	0.207	0.074	0.857	-0.255	0.939	-0.424	0.746	0.881	1.000			
pcinc	-0.505	0.297	0.203	0.064	0.198	0.147	0.031	0.553	0.146	0.105	1.000		
dirty	-0.399	0.326	0.217	0.094	0.170	0.042	0.048	0.466	0.103	-0.005	0.911	1.000	
clean	-0.522	0.315	0.239	0.059	0.233	0.166	0.092	0.560	0.160	0.121	0.982	0.840	1.000

Table 3.11. Correlation Matrix of Model Variables (Region 3)

	oz	*pctax*	*temp*	*apolcv*	*gaspop*	*gasd*	*area*	*tpinc*	*pop*	*popd*	*pcinc*	*dirty*	*clean*
oz	1.000												
pctax	0.082	1.000											
temp	0.092	-0.199	1.000										
apolcv	0.690	0.082	0.096	1.000									
gaspop	-0.053	0.094	0.052	-0.052	1.000								
gasd	-0.060	0.260	-0.229	0.100	0.483	1.000							
area	0.406	0.383	-0.139	0.284	0.103	0.026	1.000						
tpinc	0.196	0.460	-0.065	0.329	0.208	0.568	0.607	1.000					
pop	0.341	0.425	-0.246	0.403	0.156	0.557	0.782	0.892	1.000				
popd	-0.068	0.242	-0.313	0.155	0.078	0.895	-0.043	0.522	0.546	1.000			
pcinc	-0.071	0.438	0.200	0.114	0.285	0.440	0.148	0.697	0.397	0.349	1.000		
dirty	0.217	0.334	0.204	0.244	0.172	0.020	0.329	0.531	0.313	-0.087	0.755	1.000	
clean	-0.116	0.427	0.260	0.079	0.305	0.449	0.131	0.685	0.380	0.350	0.978	0.686	1.000

Table 3.12. Correlation Matrix of Model Variables (Region 4)

	oz	*pctax*	*temp*	*apolcv*	*gaspop*	*gasd*	*area*	*tpinc*	*pop*	*popd*	*pcinc*	*dirty*	*clean*
oz	1.000												
pctax	0.194	1.000											
temp	-0.009	-0.402	1.000										
apolcv	0.524	0.692	-0.366	1.000									
gaspop	-0.027	0.383	0.065	0.019	1.000								
gasd	0.569	0.341	-0.438	0.657	-0.004	1.000							
area	-0.065	-0.248	0.784	-0.303	0.207	-0.463	1.000						
tpinc	0.423	0.123	-0.098	0.423	-0.160	0.801	-0.185	1.000					
pop	0.729	0.093	-0.122	0.509	-0.180	0.854	-0.173	0.892	1.000				
popd	0.318	0.031	-0.506	0.414	-0.459	0.788	-0.531	0.721	0.737	1.000			
pcinc	-0.233	0.212	-0.069	0.051	0.004	0.313	-0.136	0.551	0.242	0.307	1.000		
dirty	0.015	0.256	-0.069	0.124	0.136	0.362	-0.013	0.594	0.409	0.249	0.811	1.000	
clean	-0.167	0.211	-0.077	0.073	0.000	0.370	-0.214	0.598	0.290	0.341	0.982	0.755	1.000