Non-Parametric Distributional Analysis of a Transportation Policy: The Case of Stockholm's Congestion Pricing Trial

Joel P. Franklin
Ph.D. Candidate
Urban Design & Planning
Box 355740
University of Washington
Seattle, WA 98195
(206) 616-4499
joelpf{at}u{dot}washington{dot}edu

Length: 6,754 effective words
(5,754 actual words + 4 tables & figures)

ABSTRACT

When public policies are expected to affect a population in complex ways, the normal evaluation measures, such as mean effect, may fail to capture all of the effects that are important to societal goals. As an example, if the policy is expected to be “regressive”, benefiting mainly those who are already in the best position or costing mainly those who are already in the worst position, then we might say that its poor equity overwhelms any advantage in average benefit. The converse is a policy that is “progressive”, redistributing welfare from richer to poorer members of society. This study demonstrates the application of some nonparametric distributional comparison tools in the evaluation of a transportation policy whose effects are simulated using a complex urban modelling system. We consider a case study of peak-period roadway tolls for Stockholm, Sweden. This case is particularly relevant because congestion pricing in general has been both lauded and criticized for its anticipated progressivity or regressivity. The results confirm earlier findings that the magnitudes of redistribution effects are small compared to estimated total welfare. The overall progressivity or regressivity that is present is strongly related to the reallocation scheme, with the most progressive scenario being a public transit subsidy and the least progressive being a reduction in the income tax rate. The results also suggest lower-tail regressivity in all reallocation schemes studied, most likely due to differences in the initial peak-hour trip modes among low-income households.

INTRODUCTION

When public policies are expected to affect a population in complex ways, the normal evaluation measures, such as mean effect, may fail to capture all of the effects that are important to societal goals. As an example, if the policy is expected to be “regressive”, benefiting mainly those who are already in the best position or costing mainly those who are already in the worst position, then we might say that its poor equity overwhelms any advantage in average benefit. The converse is a policy that is “progressive”, playing the Robin Hood role of redistributing welfare from richer to poorer members of society.

Another example of a complex policy effect is the emergence of dispersed outcomes for subgroups of a population. In many cases, it is of interest to evaluate the effects of a policy along socio-demographic dimensions such as gender. These effects are normally considered in the context of group means, with the implied assumption that within-group distributions are normal. Consequently, any heterogeneous effects within the groups, such as regressivity or bimodality, will be overlooked.

This study demonstrates the application of a small set of nonparametric distributional comparison tools in the evaluation of a transportation policy whose effects are simulated using a complex urban modelling system. As a case study, we consider a proposed system of peak-period roadway tolls for Stockholm, Sweden. This case is particularly relevant because congestion pricing in general has been both lauded and criticized for its anticipated progressivity or regressivity. While some have argued that congestion pricing burdens lower-income individuals who are least flexible to change travel patterns, others have argued that lower-income individuals are less likely to be tolled because they tend to use public transportation.

The nonparametric comparison tools used here include estimations of relative distribution functions and polarization indices. These estimations were conducted using travel demand modeling data that was produced for an earlier study on the distributional effects of Stockholm’s congestion pricing proposal (*1*).

BACKGROUND

This study generally builds on three existing bodies of theory: equity evaluation for public policies, roadway pricing theory, and non-parametric methods of measuring inequality. The first two of these are briefly summarized below, while the third is discussed in the Methodology section.

Equity Evaluation

In many social science questions, the total consumer welfare is not the only issue under consideration; also important is how consumer welfare is distributed among society’s members, or how equitable is that distribution. Equity questions are often considered with respect to two types, each of which can be linked to Rawlsian principles of justice (*2*). First, *horizontal* equity refers to the distribution of welfare among individuals who are otherwise identical, drawing from Rawls’s “principle of equal opportunity”. Second, *vertical* equity refers to the distribution of welfare among individuals who are unequal in other respects, drawing from Rawls’s “principle of difference”. Raux & Souche (*3*) identified an additional form of equity in the context of roadway pricing: *spatial* equity, which implements Rawls’s “principle of liberty” as providing the right of access to any location in space. In this study, we are exclusively considering vertical equity, where the individuals vary with respect to initial welfare, as indicated by household income. Consistent with Giuliano (*4*), we consider as equity the distribution of a policy’s effects, both positive and negative, in reference to household income as a baseline.

These approaches to equity implicitly suggest two notions that must be clarified: how to identify society’s members, and how to quantify the welfare that is distributed among them (*5*). The first question is an issue of the unit of analysis, but its importance is underscored by the fact that the chosen unit will affect how different kinds of members of society are weighted. For example, if each individual is a unit of analysis, the results may tend to favor large families over those who live alone. If the unit of analysis is all households, there may be the opposite tendency. In this study, we consider all adults in Greater Stockholm.

The second question concerns the quantification of welfare for society’s members. One of the most common measures of individual welfare is income; another is accumulated wealth. The situation is complicated by co-habitation of adults in, for example, domestic partnerships, marriages, and families. In these cases, the individuals may share resources to such an extent that to use the actual income generated by one of the individuals could be misleading, especially if only one of two adults is employed. A more representative estimate should account for the income of the household as a whole. In this study, we use total household income per adult. In effect, the total household earnings are considered pooled, then divided equally among the adults.

Some common methods of quantifying equity effects of transportation policies were reviewed by Levinson (*6*). Most common in the social sciences is the Lorenz Curve graphical tool and its associated summary statistic, the Gini Coefficient. It is important to note, first, that the Lorenz Curve only illustrates the progressivity or regressivity for a *single* population. Moreover, these tools often hide useful information about the tails of the distributions being compared, since nearly all Lorenz Curves tend asymptotically toward the 45-degree line at the two ends of the distribution, despite often large differences in density at the tails.

Also, quantile-quantile plots (Q-Q plot) are used frequently in evaluating econometric models' error distributions against a normal distribution, wherein the quantile function of one distribution is plotted against the quantile function of the other distribution. Because these quantiles are in the units of the variable's quantities, they are intrinsically scale dependent, and are therefore subject to inconsistencies in the scale of the variable, and different results can be found if any monotonic transformations, such as a log transformation, are applied.

Relative distributions and polarization indices are the principle methods applied in this study. In contrast to the above methods, they are scale-invariant—meaning they show the same result regardless of any monotonic transformations of the variable of interest—and they capture differences in the tails as readily as they do differences in the center of the distribution.

The Effects of Congestion Tolls

Congestion tolls have long been proposed as a simple means of improving the economic efficiency of roadways. According to prevailing theories of roadway dynamics, as traffic demand approaches a roadway's capacity, overall traffic speeds decrease. The resulting increased travel times are externalities of individual motorists' decisions to take a particular roadway, since their decisions neglect the travel time costs on other users. Consequently, the user-equilibrium traffic distribution is distinct from the globally optimal traffic distribution. Congestion pricing systems have been proposed to charge motorists for the difference between the user cost and the full social cost of the decision to take a particular roadway, thereby bringing the user equilibrium and the global optimum into convergence. The literature largely agrees on the efficiency benefits of a theoretical first-best congestion pricing system, as well as of a more feasible second-best system that is subject to various unavoidable distortions in how the transportation system is priced. However, the theoretical arguments on the equity impacts of congestion have been varied.

"Congestion Pricing is Progressive"

As summarized in Eliasson & Mattsson (*1*), most arguments regarding the equity effects of congestion pricing have supported the notions that the positive and the negative effects of congestion pricing favor either higher-income individuals or lower-income individuals. Progressive effects have been supported by Foster (*7*), arguing that higher-income individuals are those most likely to be affected by a toll, since they choose to drive private cars more often and they tend to have a home-to-work trip originating in the suburbs and ending in the central city. This overall result was borne out in a study by Santos & Rojey (*8*), although they note that there are a small number of individual cases where low-income payer would experience regressive effects.

"Congestion Pricing is Regressive"

The literature supporting regressive effects of congestion pricing is much broader. For example, in several theoretical studies using a queue-based congestion model with commuters that are heterogeneous in their travel time and delay costs, Arnott et al found congestion pricing to be regressive, favoring those that value travel time the most and value taking the trip the most (*9-11*), confirming several earlier studies' findings of regressive effects (*12-14*). More recent work by Raux and Souche (*3*) also confirm these results. However, all of these studies disregarded the redistributive effects of toll revenue usage, which could significantly alter the equity results, as found by Small (*15*). Small's study found that benefits under several refund schemes could benefit all income levels, although once travel time benefits are accounted for (which may be equal across incomes), higher-income groups will continue to enjoy the greatest benefit, due to their higher value of time.

Eliasson & Mattsson (*1*) argue that the variation in the above evidence can be explained by differences in two key factors: the initial set of travel patterns, and the scheme used for redistributing collected tolls. This latter point is supported by the theoretical arguments set forth by Mayeres & Proost (*16*). However, Giuliano (*4*) argues that redistribution cannot resolve all equity concerns due to individual- and household-level variation in flexibility with respect to alternate modes or work schedules.

Eliasson & Mattsson (*1*) also note that the magnitudes of differences in effects for different income levels, as observed in past studies, is far surpassed by the magnitudes of incomes themselves, implying that whatever progressivity or regressivity exists would be quite small. Instead, they approach the question of equity by comparing average net effects on discrete or discretized demographic dimensions, regardless of the exact initial income level. These dimensions included gender, employment status, family type, geographic area of residence, and three income groups that represent equal proportions of the sample.

RESEARCH QUESTIONS

This study expands on the equity analysis conducted by Eliasson & Mattsson by revisiting the question of the Stockholm congestion pricing plan's progressivity/regressivity through the use of median polarization indices and relative distributions. The polarization indices can give us a more rigorous indication of whether a policy's redistributive effects, apart from its overall effects, tend to increase or decrease polarization between the best-off and worst-off individuals. These indices are of course useful because they summarize the polarization effect in a single number. However, this number may still fail to identify important features of the effect. To help us identify these, we will also examine the graphic estimates of the relative distributions' probability density functions.

This study is organized around a set of three research questions:

1. Will Stockholm's congestion pricing plan have the *same distribution of welfare levels* as that which is already exhibited in the distribution of prior incomes? Put another way, how does the plan change the distribution of individuals' *actual* welfare levels?
2. *After accounting for aggregate effects* (as represented by the distributions' medians), will Stockholm's congestion pricing plan will have the same distribution of welfare levels as that which is already exhibited in the distribution of prior incomes? Put another way, how does the plan redistribute individuals' welfare levels *relative to each other*?
3. When compared to prior welfare levels, will Stockholm's congestion pricing plan have neither a progressive nor a regressive effect on welfare levels of greater Stockholm residents? Put another way, how does the plan affect the objectively-measured polarization between high- and low-welfare individuals, relative to each other and regardless of overall improvements or diminishments?

Question 1 will be examined by estimating the relative distributions between *before* and *after* conditions for the entire sample. Question 2 will use the median-adjusted versions of these relative distributions. Finally, Question 3 will be examined using Mean Polarization Indices (MRPs).

CASE STUDY: STOCKHOLM'S CONGESTION PRICING PROPOSAL

The Municipality of Stockholm and the Swedish national government are planning a 12-month, full-scale test of congestion pricing for central Stockholm. While the proposal has changed as it progresses through planning stages, the one modeled here consists of time-differentiated toll levels during most of the day, collected along two cordon lines. Since the plan on how to use the collected revenues has still been under active discussion, three different reallocation plans were identified for analysis, along with a fourth hypothetical plan where no reallocation occurs.

Toll Collection Scheme

The proposal defines two cordon lines: the first around the central city area, crossing several major entrances where fees would be collected, and to charge a toll that varies among multiple fee levels depending on fixed time periods in the day, and the second along the Lake Mälaren/Baltic Sea waterway that separates the north side from the south side. The exception to this is that no tolls would be collected on the Essingeleden highway, which is the westernmost crossing over Lake Mälaren and constitutes a segment of the partial ring highway surrounding the central city. The level of the tolls would vary between 15 Swedish Crowns (SEK) during peak hours (7-9 a.m. and 4-7 p.m.) and 10 SEK during midday hours (9 a.m. to 4 p.m.). No tolls would be collected during the nighttime hours of 7 p.m. to 7 a.m.

Reallocation Scenarios

Some of the disagreement in the literature regarding congestion pricing's distributional effects may be attributable to whether, and how, collected revenues are reallocated to the population. To investigate this further, the effects of the congestion pricing scheme were analyzed both in isolation and with one of three allocation plans. The four scenarios are summarized in Table 1, along with how they were operationalized and what progressivity or regressivity we should expect to come from the reallocation itself. Note that we are considering travel demand to be inelastic to the reallocation scheme.

Data Summary

In an earlier study (*17*), travel choice probabilities and costs were computed using a travel model for a sample of 2,893 adult travelers residing within Greater Stockholm, of whom 1,423 were male and 1,470 were female. The sample had an overall median household income per adult of 165,700 Swedish Crowns (SEK) per year and a maximum of 2,732,000 SEK per year. At June, 2004 exchange rates, these translate to approximately US$22,000 and US$363,000 per year, respectively. The median incomes per adult for males and females, respectively, were 187,200 SEK per year and 149,900 SEK per year.

It is worth noting that 173 individuals in the sample, or 6.0%, had a zero household income per adult. Since the reason for this is unknown, we cannot say whether these individuals actually have an extremely low initial welfare level. It may be that they actually do have zero income; conversely, it may be that they simply report a zero income for tax reasons, and in fact receive substantial income from unconventional sources. In either case, we cannot consider income to be a reliable indicator of welfare for these individuals. Consequently, those data are excluded from the analyses below that depend on estimates of total welfare.

METHODOLOGY

Transportation Modeling

The data on each individual's predicted welfare, both with and without congestion pricing, were generated using the SAMPERS travel demand model for Greater Stockholm (*18*) as a means of computing travel times, together with a separate system of logit models for decisions on travel mode and destination choice, estimated separately for men and for women, and for work trips and non-work trips (*17*). Sample enumeration was used to produce a population-weighted sample of estimated choice probabilities, travel costs, and travel times for each combination among five travel modes and 20 destinations (one destination as observed and 19 others sampled from the entire set of transportation analysis zones). Individuals' welfare calculations included changes in travel costs and travel times for each mode, subject to the probability of taking each mode, where the value of time varied by gender, income, and purpose of the trip.

The "Rule of Half" was used to estimate the changes in welfare levels for each individual between the two scenarios, with and without the congestion pricing program. This estimation procedure uses the assumption that travel demand changes approximately linearly at small changes in prices and travel costs, such that the welfare change can be estimated by computing the trapezoidal area under the demand (or choice probability) curve. This reduces the data requirements from knowing the entire shape of the demand curve, to only knowing its locations for the two scenarios being compared. The net welfare, under each of the reallocation scenarios, was added to the baseline welfare level, for which reported income was used as a proxy.

Relative Distributions

The fundamental comparison tool used in this study is the *relative distribution*, which is treated thoroughly by Handcock & Morris (*19*) for application to the social sciences, but has roots as early as Parzen's closely related *comparison distribution* (*20, 21*). We begin by considering two random variables, Y_0 and Y, which represent the probability distributions for some attribute, such as welfare, of two distinct populations. Those populations may actually be the same individuals, but under different conditions, such as a different policy scenario. The first, Y_0, represents a *reference* distribution, and acts as a base for comparison. The second, Y, represents the *comparison* distribution. Respectively, these two random variables have cumulative distribution functions (CDFs) given by F_0 and F, and probability density functions (PDFs) given by f_0 and f.

Using these two probability distributions, we can define the relative distribution as a random variable generated by a transformation of the comparison random variable *Y* through the CDF of the reference random variable:

$$R = F_0(Y), \tag{1}$$

where: *R* = the relative distribution,
F_0 = the CDF of the reference distribution, and
Y = the comparison distribution.

The relative distribution's random variable can be interpreted as producing quantile levels that data drawn from the comparison group would have if they had come from the reference group. Hence, with *R*'s output being quantiles, they can hold values from 0 to 1.

The relative distribution's CDF can be expressed as:

$$G(r) = F(F_0^{-1}(r)) = F(Q_0(r)) \quad 0 \le r \le 1, \tag{2}$$

where: $F(y)$ = the CDF of the comparison distribution,
$Q_0(r)$ = the reference distribution's quantile function, and
r = a quantile level from the reference distribution.

We obtain the relative distribution's PDF by deriving Equation 2, giving us:

$$g(r) = \frac{f(y_r)}{f_0(y_r)} \quad y_r = Q_0(r) \ge 0, \tag{3}$$

where: $g(r)$ = the relative distribution's PDF,
$f(r)$ = the comparison distribution's PDF,
$f_0(r)$ = the reference distribution's PDF, and
y_r = values of the reference distribution at quantile *r*.

The PDF of the relative distribution will be the focus of our results. As suggested by Equation 3, the shape of *g* can be interpreted as a density ratio, between the probability density functions of some characteristic of two distinct populations. The ratio is evaluated as a function of the quantiles, *r*, of the reference distribution. Its support includes quantiles of the reference distribution from zero to one, and it can take on values ranging from zero to, asymptotically, $+\infty$. Values of zero arise where the comparison distribution has zero density. High positive values above arise where the comparison distribution has positive density but the reference distribution has nearly zero density. The relative density takes on values of one where the probability densities of the two distributions are equal. For two probability distributions that are completely identical, the relative distribution takes on a value of one across its entire support from 0 to 1.

The relative distributions were estimated from the simulated sample data using a weighted local likelihood density estimation with kernel weighting of the observed data. See Handcock & Janssen (*22*) for more details.

Median-Adjusted Relative Distributions

To examine redistributive effects independently from aggregate changes in magnitude, it is useful to decompose the relative distribution into two comparisons: one that represents changes in *location*, and another representing location-controlled changes in *shape*. To do this, we denote an intermediate random variable, Y_{0L}, which produces values identical to the reference distribution, except that the values are all shifted upward or downward by some constant value such that the distribution's median matches the comparison distribution. In other words, the random variable, its CDF, and its PDF, respectively, can be defined as:

$$Y_{0L} = Y_0 + \delta, \tag{4}$$

$$F_{0L}(y) = F_0(y - \delta), \text{ and} \tag{5}$$

$$f_{0L}(y) = f(y - \delta), \tag{6}$$

where: $\delta = Q\left(\tfrac{1}{2}\right) - Q_0\left(\tfrac{1}{2}\right)$ = the difference in medians between the two distributions.

Using Y, Y_0, and Y_{0L}, we can now define two intermediate relative distributions, the first representing differences in location and the second representing residual changes in shape:

$$R_0^{0L} = F_0(Y_{0L}) = F_0(Y_0 + \delta) \text{ and} \tag{7}$$

$$R_{0L} = F_{0L}(Y) = F_0(Y - \delta) \tag{8}$$

The first of these, R_0^{0L}, represents the relative distribution between the *original* reference distribution and the *median-adjusted* reference distribution. In other words, it captures the changes in density due only to an overall shift in magnitude. The second of these, R_{0L}, represents the remaining differences in shape.

The three relative distributions we have now defined (R_0, R_{0L}, and R_0^{0L}) can be related to each other in terms of probability density functions, as defined in Equation 3:

$$g_0(r) = g_0^{0L}(r) \times g_{0L}(p) \tag{9}$$

$$= \frac{f(y_r)}{f_0(y_r)} = \frac{f_{0L}(y_r)}{f_0(y_r)} \times \frac{f(y_r)}{f_{0L}(y_r)}, \tag{10}$$

where r = the quantile in the reference group for a given value y_r, and
p = the quantile in the location-adjusted reference group for the same value y_r.

In this study's results, we will focus only on the complete relative distribution, R_0, and the median-adjusted relative distribution, R_{0L}. Changes in location will be reported simply as the differences in medians (δ).

Polarization Indices

While the graphical estimates of relative distributions are instructive on a policy's redistribution patterns, it remains useful to summarize regressive or progressive tendencies using a single metric. To do this, we use indices of relative polarization (*19*). The polarization indices are computed based on the median-adjusted relative distribution. Consequently, they indicate the relative polarization that results only from changes in the distribution's shape, regardless of any aggregate changes in welfare. We start with the Median Relative Polarization (MRP) Index of a distribution Y, relative to a baseline distribution Y_0, which indicates the polarization across the entire distribution. It can be expressed either using expected values of the distribution's distances from one-half, or using an integral area calculation for the distribution's PDF:

$$\mathrm{MRP}(F;F_0) = 4\,\mathrm{E}\left(\left|R_{0L} - \tfrac{1}{2}\right|\right) - 1 = 4\int_0^1 \left|r - \tfrac{1}{2}\right| g_{0L}(r)\,dr - 1 \tag{11}$$

where: $\mathrm{E}(\ )$ = the expected value function,
$R_{0L} = F_{0L}(Y) = F_0(Y - \delta) =$ the median-adjusted relative distribution of the comparison distribution, Y, to the reference distribution, Y, and
$g_{0L}(r)$ = the PDF of the median-adjusted relative distribution.

As suggested by the integral form above, relative polarization indices are essentially weighted measures of the area underneath the relative distribution's density curve. The weighting is such that areas near the center of the curve are weighted the least, and areas near the tails are weighted the greatest. As a result, the polarization index will be high when the tails are high but the center is low, indicating a probability density that is dispersing from the median in the comparison distribution, when compared to the reference distribution. In the case of changing incomes, this would be analogous with "the rich getting richer, the poor getting poorer". The polarization index will be low when the tails are low but the center is high, indicating convergence of values in the population, or increasing equity.

The polarization indices indicate the level of polarization in the comparison distribution, relative to the reference distribution. An MRP value between 0 and 1 indicates greater polarization, while a value between -1 and 0 indicates less polarization. In the social sciences, greater polarization can be interpreted as indicating a regressive difference between the distributions, while lower polarization can be interpreted as indicating a progressive difference.

We can also consider the two tails of the relative distribution curve in isolation by conditioning our definitions on the quantile levels. Using this approach, the Lower and Upper Relative Polarization Indices (LRP and URP) are:

$$\begin{aligned} \mathrm{LRP}(F;F_0) &= 4\mathrm{E}\left(\left|R_{0L} - \tfrac{1}{2}\right| \mid R_{0L} < \tfrac{1}{2}\right) - 1 = 8\int_0^{\frac{1}{2}} \left|r - \tfrac{1}{2}\right| g_{0L}(r)\,dr - 1 \\ \mathrm{URP}(F;F_0) &= 4\mathrm{E}\left(\left|R_{0L} - \tfrac{1}{2}\right| \mid R_{0L} > \tfrac{1}{2}\right) - 1 = 8\int_{\frac{1}{2}}^{1} \left|r - \tfrac{1}{2}\right| g_{0L}(r)\,dr - 1 \end{aligned} \quad (12)$$

The tail-specific indices, LRP and URP, indicate the degree to which the upper and lower halves of the distributions contribute to the overall polarization or de-polarization effect. As with the MRP, their values range from -1 to 1, and are interpreted similarly with regard to progressivity and regressivity. The three indices have the useful property that they can be related to each other by a simple linear average:

$$\mathrm{MRP}(F;F_0) = \frac{1}{2}\mathrm{LRP}(F;F_0) + \frac{1}{2}\mathrm{URP}(F;F_0) \quad (13)$$

The MRP is estimated using a set of quasi-relative data generated for a comparison between the reference group and the estimated-median-adjusted comparison group. For more details, see Handcock & Janssen (*22*).

Note on Inference for Simulated Model Results

When applying these methods to empirical data, it is appropriate to quantify the uncertainty associated with their estimates, giving an indication of what the probability is that the variation observed is due not to the theorized relationship, but rather to the effects of unobserved factors. In this application, however, we are simulating data using a known, albeit complex, modeling system. While we may not know what the full set of results will be, we can say that those results will be based on factors under our observation.

Because of this, we can interpret the results of the relative distribution and polarization index estimates without concern for random disturbances, since the two samples in each of those cases have identical members, and it is only the scenario that is different between the two distributions. Hence, no confidence measures are shown. There is indeed uncertainty in these estimations, but that uncertainty is embedded in the travel model's internal stochasticity, in the uncertainty of its behavioral parameters, and thus in the estimated welfare values. Due to the complexity of the travel model, confidence intervals are not directly obtainable for the estimated welfare values through analytical means, and computational means have not yet been used due to processing time demands. Consequently, we can make useful observations about the shapes of these relative distributions and the values of the polarization indices, but we cannot yet reject null hypotheses with any specific level of certainty.

RESULTS

The overall results are shown in Table 2. We start by examining the proportion of the sample with a net gain or a net loss. The first scenario, in which there is no reallocation of collected toll revenue, has a median at zero but has asymmetric tails: the tail below zero is thicker than the tail above zero, suggesting there are fewer winners (27%) than losers (73%). Since revenue is disappearing in this scenario, this result makes sense; it is only when collected revenue is redistributed in some way that the winners outnumber the losers.

In the second scenario, each individual receives an equal share of the toll revenues. This moves the probability density function to the right by a fixed amount, preserving its shape but making most Stockholmers winners (73%) instead of losers (27%) – the opposite proportions as in the No Refund scenario. The third scenario's transit subsidy benefits individuals bi-modally, probably reflecting the divergence between benefits for those who predominantly use transit versus those who predominantly use automobiles to take trips. The last scenario's reallocation according to income has a broader distribution of impacts, since the refund in that case is proportional to an individual's prior income level, thus varying from person to person.

Question 1: Redistribution of Welfare

To start examining the redistributive effects of the congestion pricing plan on actual welfare levels, we graph the estimated relative distribution curves for each scenario, as shown in Figure 1. These curves show us how each scenario's probability density compares to the probability density without congestion pricing – which parts of the original distribution's range has been made more dense with individuals, and which parts less dense. Note first that the *y*-axis includes only a very narrow range of values, all in close vicinity with unity. This is because the relative distribution line itself is very close to unity across its entire range, suggesting that the welfare distributions are nearly equal across the four scenarios. However, even at this narrow range the results have interesting properties.

First, the No Refund scenario has a decreasing function over its entire length, indicating that the overall distribution of total welfare is more concentrated at the low end and less concentrated at the high end, when compared to the total welfare values without congestion pricing. As expected, because tolls are being collected but not returned in any way to the population, welfare values decrease.

The Lump Sum and Transit Subsidy scenarios both show concave functions with a slightly upward tilt. This suggests a combination of an increase in overall welfare and a concentration of welfare, or decreased polarization. The Tax Reduction scenario, on the other hand, exhibits a slightly upward-tilting *convex* curve, which an overall increase in welfare but also increase polarization.

Question 2: Median-Adjusted Redistribution of Welfare

To assess whether the four scenarios are progressive or regressive, it is useful to separate the overall changes in magnitude across the population from redistributions around the central tendency. This allows us to observe the redistribution of welfare levels relative to each other, rather than relative to any absolute base levels. To accomplish this, we produce a comparison between the comparison distribution and the *median-adjusted* reference distribution, which is identical to the reference distribution in *shape* but has its values adjusted in magnitude such that its median matches the comparison distribution. The resulting relative distributions, as shown in Figure 2, show the residual changes in shape, independent of magnitude changes.

Here, the first two scenarios, No Refund and Lump Sum, show the same results: a decreasing, nearly flat line. It is expected that these two scenarios would be identical to each other, since the only difference between them is that the Lump Sum scenario pays a fixed amount to each individual. Since these results are adjusted by such fixed effects, that difference disappears. Notice also that there is little concavity exhibited in these curves, except for possibly a slight concave-down curve. This suggests that the de-polarizing effects noticed in the curves without median-matching may have been overstated. The polarization indices computed below may help resolve this.

The other two scenarios show clear but opposite concavities. The Transit Subsidy scenario is concave, suggesting decreased polarization, while the Tax Reduction scenario is convex, suggesting increased polarization. These findings are consistent with the expectations set forth in Table 1.

Question 3: Polarization Effects

To evaluate progressivity and regressivity more objectively, we compute the Mean Relative Polarization indices, shown in the last set of rows of Table 2, which are based on comparisons using median-matched reference distributions in Figure 2.

As with the median-matched relative distribution curve results, the No Refund and Lump Sum scenarios have identical polarization indices, a result expected for the same reason: that these scenarios are only different with respect to a fixed payment, which is absorbed in the median-matching process. The polarization indices also agree with respect to the shape of the median-matched curves. The overall index's value very close to zero (relative to the other scenarios) agrees with the observation that the median-matched curves do not exhibit strong concavity of any kind. Interestingly, however, the tail-specific indices are not so close to zero but have opposite signs. These results suggest some redistributive effects within each tail that cancel each other out in the overall index and in the smoothed relative distribution curves. Without a larger sample, however, it is difficult to discern these smaller redistributive effects.

The third scenario, Transit Subsidy, has the lowest (i.e. most negative) median polarization index, suggesting that this scenario is the most progressive of the four overall. As with the first two scenarios, however, the tail-specific indices are opposite and larger in magnitude than the overall median polarization index, suggesting some other redistributive effects within each tail.

The last scenario, Tax Reduction, has a positive Median Polarization Index, suggesting increased polarization of high and low welfare individuals. This is exactly what we expected of a reallocation plan that benefits individuals in proportion to their incomes, thereby intensifying the existing dispersions of income. The same opposite results in the tail-specific indices exists here as in the other three scenarios, but now the magnitudes are reversed: the lower tail's regressivity is greater than the upper tail's progressivity.

CONCLUSIONS

This study set out to examine three questions concerning the overall redistributive effects, median-matched redistributive effects, and objective polarizations of the overall population under each of four reallocation scenarios. While no confidence levels could be established due to technical limitations of the travel model system, we can make two general comments about the aggregate-level progressivity or regressivity. First, the magnitude of redistribution of welfare due to congestion pricing is very small compared to the total welfare levels for the vast majority of the population. Second, the progressivity or regressivity that is present is strongly related to the method of reallocating collected tolls to the general public, with the most progressive scenario being the public transit subsidy and the least progressive scenario being the reduction in the income tax rate. Both of these conclusions are consistent with earlier conclusions by Eliasson & Mattsson (*1*) and by an earlier Swedish-language report (*17*).

An additional interesting result is that the redistributive effects within the tails are different in each of the scenarios. One explanation for that that is supported by the reviewed literature is that low-income households are affected quite differently depending on whether they currently tend to use transit or use automobiles for peak-hour trips. This finding certainly warrants further investigation of the effects of the congestion pricing plan on mode-specific sub-populations.

These results must be qualified by several important limitations:

? The travel modelling system cannot predict scheduling decisions in the face of congestion pricing. This limitation means that individuals are modeled has having fewer options for how to respond than they would in reality. With additional options, such as taking an auto trip at a late hour to avoid a toll, individuals would in general be better off, although the distribution of this flexibility is fairly unknown. It is particularly disconcerting to exclude this effect, since one of the primary criticisms of congestion pricing is that wealthier individuals have greater travel flexibility. This limitation suggests that the above results are conservative in their conclusions of regressivity, and liberal in their conclusions of progressivity.

? The absence of uncertainty estimates for the travel model's travel cost and choice probability estimates means that we cannot fully quantify the uncertainty of the relative distributions and polarization indices, which are themselves computed based on the travel model's outputs. Hence, none of the conclusions above can be supported with a specific level of confidence.

? The specifics of the congestion pricing program, as modeled, is different in important ways from the plan that is now being considered by the Swedish Parliament. The latest proposal has no bisection cordon line, it excludes charges for trips on Essingeleden that do not stop in the central city, and it treats trips to and from the island community of Lidingö (whose only land connection is through the central city) quite the opposite as they were modeled. Instead of treating Lidingö as part of the central city, such that its trips are free to the central city but charged elsewhere, in the latest proposal those trips would be charged for entering the central city but given a refund if they exit the central city in some other way within a 30-minute period.

While the limitations above inhibit the validity of the results in judging Stockholm's actual congestion pricing proposal, the results remain informative on what kinds of conclusions about equity can be drawn using non-parametric methods.

ACKNOWLEDGEMENTS

The author thanks Jonas Eliasson of Transek AB for his generosity in providing simulation data and for his assistance with its interpretation; Lars-Göran Mattsson of the Royal Institute of Technology, Stockholm, for his invaluable guidance and feedback; Paul Waddell and Mark Handcock of the University of Washington, Seattle, for guidance on the methodological and theoretical issues preconditioning this study; and the University of Washington's Valle Fellowship and International Exchange Program for making possible this research.

REFERENCES

1. Eliasson, J. and L.-G. Mattsson. *Equity effects of congestion pricing: quantitative methodology and a case study for Stockholm*. Transek AB & Royal Institute of Technology (KTH), 2004.
2. Rawls, J. *A Theory of Justice*. Revised. Belknap Press, Cambridge, MA, 1999.
3. Raux, C. and S. S. Souche. The Acceptability of Urban Road Pricing: A Theoretical Analysis Applied to Experience in Lyon. *Journal of Transport Economics and Policy*, Vol. 38, No. 2, 2004, pp. 191-216.
4. Giuliano, G. Equity and Fairness Considerations of Congestion Pricing. In *Special Report 242: Curbing Gridlock: Peak-Period Fees to Relieve Traffic Congestion, Volume 2*. Transportation Research Board, Washington, DC, 1994.
5. Cowell, F. A. *Measuring Inequality*. Philip Allan, Oxford, 1977.
6. Levinson, D. M. Identifying Winners and Losers in Transportation. In *Transportation Research Record 1812*. TRB, National Research Council, Washington, DC, 2002, pp. 179-185.
7. Foster, C. The Regressiveness of Road Pricing. *International Journal of Transport Economics*, Vol. 1, No. 133-41, 1974.
8. Santos, G. and L. Rojey. Distributional Impacts of Road Pricing: The Truth Behind the Myth. *Transportation*, Vol. 31, 2004, pp. 21-42.
9. Arnott, R., A. de Palma, and R. Lindsey. A Structural Model of Peak-Period Congestion: A Traffic Bottleneck with Elastic Demand. *The American Economic Review*, Vol. 83, No. 1, 1993, pp. 167-179.
10. Arnott, R., A. de Palma, and R. Lindsey. The Welfare Effects of Congestion Tolls with Heterogeneous Commuters. *Journal of Transport Economics and Policy*, Vol. 28, No. 2, 1994.
11. Arnott, R., A. de Palma, and R. Lindsey. Recent developments in the bottleneck model. In *Road Pricing, Traffic Congestion, and the Environment*, K. J. Button and E. T. Verhoef, Editors. Edward Elgar, Cheltenham, UK, 1998, pp. 79-110.
12. Layard, R. The Distributional Effects of Congestion Taxes. *Economica*, Vol. 44, 1977, pp. 297-304.
13. Cohen, Y. Commuter Welfare Under Peak-Period Congestion Tolls: Who Gains and Who Loses? *International Journal of Transport Economics*, Vol. 14, 1987, pp. 239-266.
14. Evans, A. Road Congestion Pricing: When Is It A Good Policy? *Journal of Transport Economics and Policy*, Vol. 26, No. 3, 1992, pp. 213-243.
15. Small, K. A. The Incidence of Congestion Tolls on Urban Highways. *Journal of Urban Economics*, Vol. 13, 1983, pp. 90-111.
16. Mayeres, I. and S. Proost. Optimal Tax and Public Investment Rules for Congestion Type Externalities. *Scandinavian Journal of Economics*, Vol. 99, No. 2, 1997, pp. 261-279.
17. Transek. *Fördelningeffekter av trängselavgifter: en utredningsmetod samt fallstudie i Stockholm (Distributional Effects of Congestion Fees: An Investigation Method and Case Study in Stockholm)*, 2003.
18. Algers, S., M. Beser, and G. J. Sveder. *SAMPERS – Erfarenheter av komplexa modeller i ett komplext utvecklingsprojekt*. Transek AB, 2000.
19. Handcock, M. S. and M. Morris. *Relative Distribution Methods in the Social Sciences*. Springer-Verlag, New York, 1999.
20. Parzen, E. Nonparametric statistical data modeling. *Journal of the American Statistical Association*, Vol. 74, No. 105-131, 1979.
21. Parzen, E. Comparison Change Analysis. In *Nonparametric Statistics and Related Topics*, A. Saleh, Editor. Elsevier, Holland, 1992, pp. 3-15.
22. Handcock, M. S. and P. L. Janssen. Statistical Inference for the Relative Density. *Sociological Methods & Research*, Vol. 30, No. 3, 2002, pp. 394-424.

LIST OF TABLES

LIST OF FIGURES

TABLE 1 Reallocation Scenarios

Scenario	Description	Implementation	Expectations for Progressivity vs. Regressivity
No Refund	A purely theoretical scenario where none of the toll revenue is returned to the population.	Rebates for all are set to zero.	Since there is no reallocation of revenue, this should reflect the character of the congestion pricing system itself, in addition to a general worsening of welfare due to the disappearing revenue.
Lump Sum	Toll revenues are divided evenly among all adults living in Greater Stockholm.	Rebates are set to total revenue, divided by the total population.	Since payments are equal for all individuals, there should be no effect from the reallocation. Hence, this should be just as progressive or regressive as the No Refund scenario.
Public Transit Subsidy	Toll revenues are used to improve public transportation throughout Stockholm.	Rebates are allocated to individuals in proportion to the number of trips they take on public transportation.	If, as expected, lower income individuals take public transportation more than high income individuals, then this plan should be more progressive than the No Refund scenario.
Income Tax Reduction	Toll revenues enter into the general fund and the income tax rate for Greater Stockholmers is reduced accordingly.	Rebates are allocated to individuals in proportion to their income level.	This scenario should be more regressive than the No Refund scenario, since it will send larger rebates to those with greater incomes.

TABLE 2 Summary of Aggregate Results

Statistics	Reallocation Scenario			
	No Refund	**Lump Sum**	**Transit Subsidy**	**Tax Reduction**
Welfare Changes (SEK/year)				
Minimum Change	-5,301	-4,872	-5,006	-5,301
Mean Change	-304	+125	+145	+286
Median Change	-56	+373	+180	+272
Maximum Change	+4,079	+4,509	+4,270	+11,160
Winners vs. Losers				
Share with a Net Loss	73.3%	27.1%	38.3%	29.0%
Share with a Net Gain	26.7%	72.9%	61.7%	71.0%
Polarization Indices				
Lower Polarization	+0.0045	+0.0045	+0.0026	+0.0095
Median Polarization	-0.0001	-0.0001	-0.0007	+0.0035
Upper Polarization	-0.0047	-0.0047	-0.0039	-0.0025

Note: Positive indices indicate regressivity; negative indices indicate progressivity.

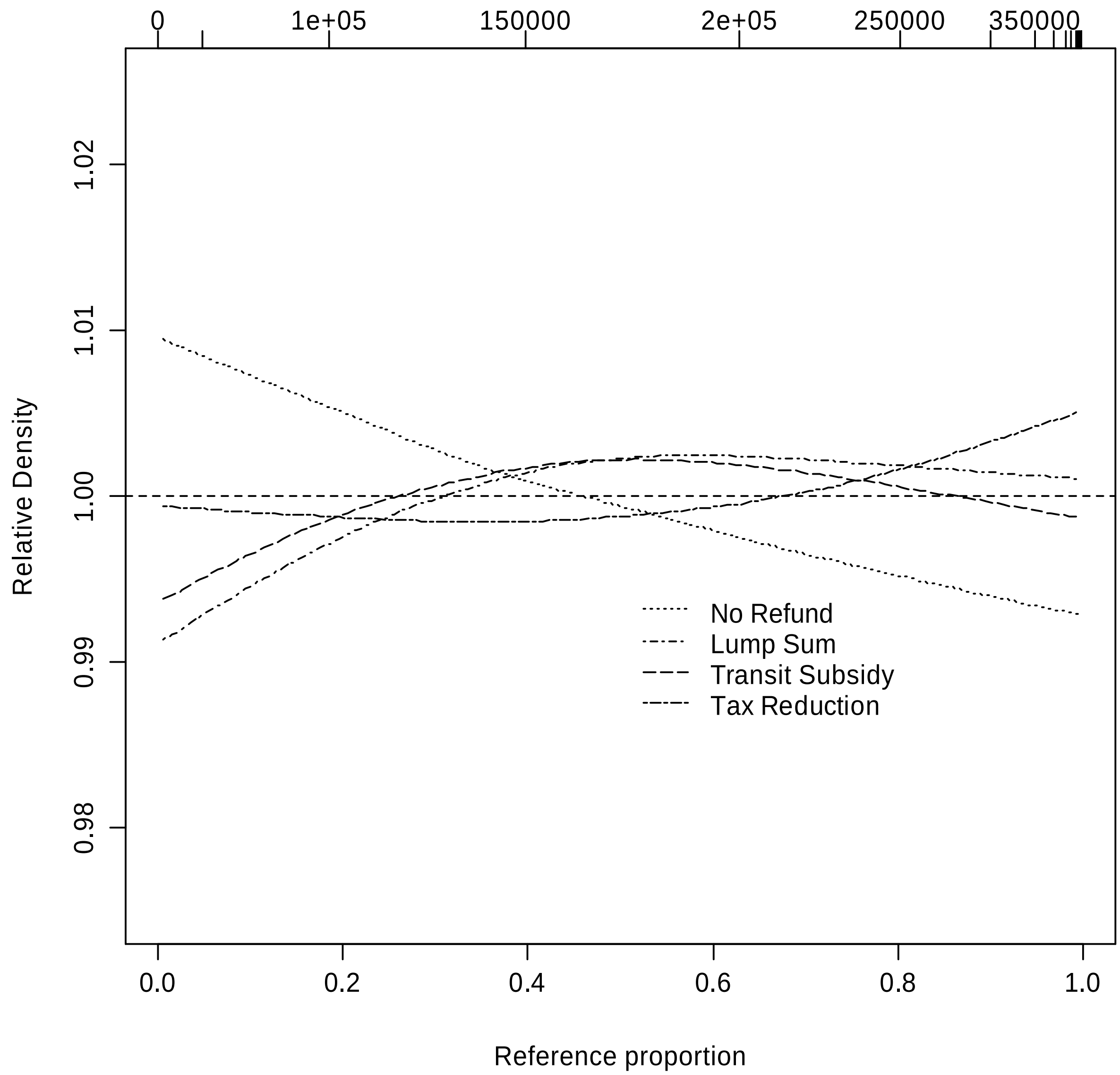

FIGURE 1 Relative PDFs of Total Net Welfare Compared to Prior Welfare

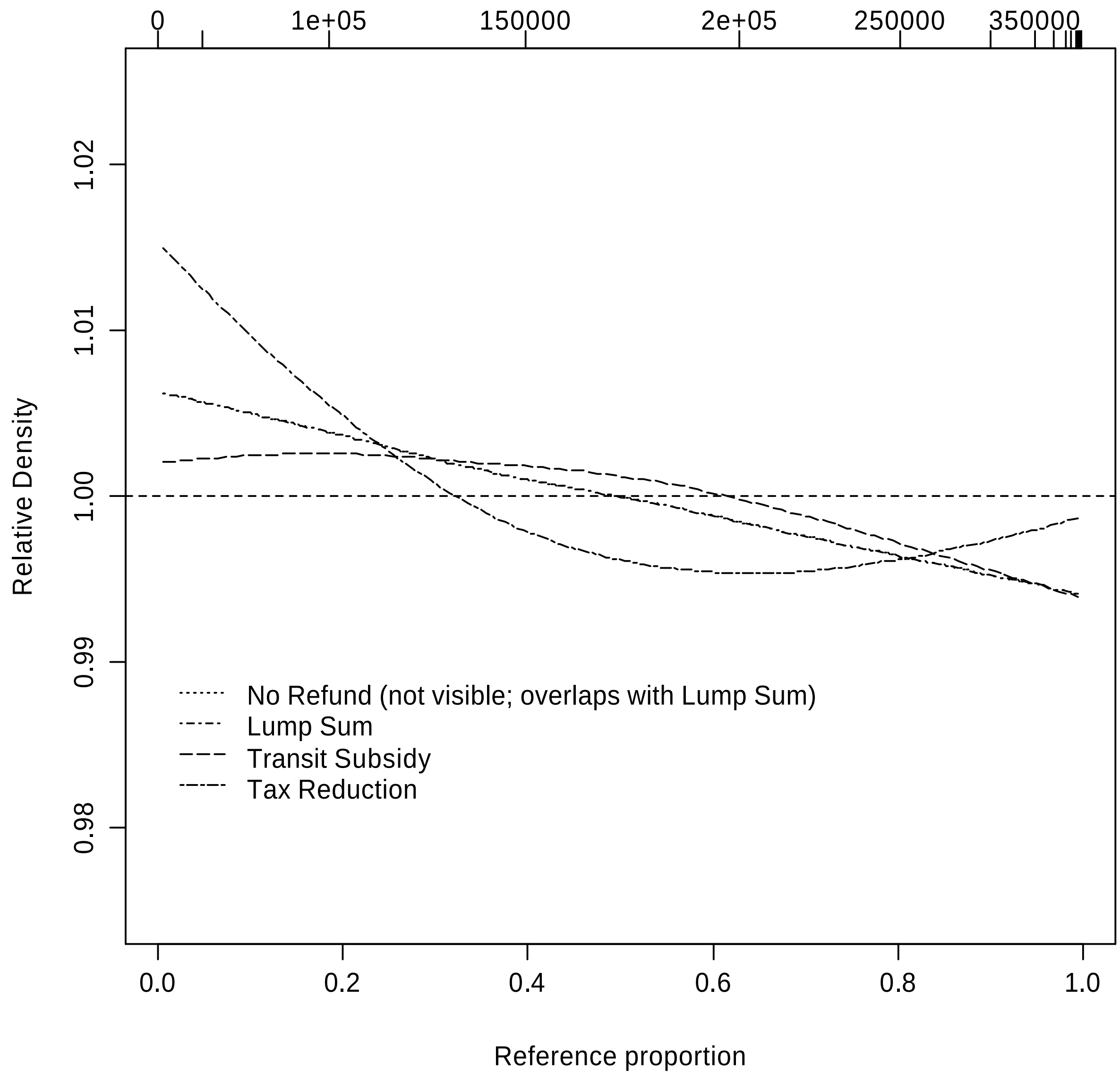

FIGURE 2 Median-Matched Relative PDFs of Total Net Welfare Compared to Prior Welfare