Credit-Based Congestion Pricing: A Policy Proposal and the Public's Response

by

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Introduction

Congestion is a pervasive problem in nearly all urban areas, impacting many facets of urban life. Schrank and Lomax (2002) estimated that congestion in 75 major U.S. urban areas amounts to $68 billion per year in fuel and time losses to the traveling public, or $1,160 per peak-period traveler in those areas. American commuters consistently rank traffic among the top three regional policy issues together with the economy, education, and/or crime. (See, e.g., Scheibal, 2002 and Knickerbocker, 2000.) Fimrite (2002) quotes a San Francisco Bay Area Council survey of California residents where transportation ranks as the primary public concern, even ahead of a struggling economy. Accordingly, finding a solution to traffic congestion has captured the attention of engineers, economists, policy makers and the public for quite sometime.

With demand for automobile travel regularly outstripping roadspace provision[1], many solutions propose demand management. Congestion pricing (CP), now also often called "value pricing", is a rather obvious market concept with a long history of attention. Pigou (1920), Knight (1924), Walters (1961) and Vickrey (1963, 1969) provided seminal works exploring pricing mechanisms to allocate scarce roadspace. In the absence of pricing or regulation, the demand-supply equilibrium for roadspace settles at a suboptimal point where users recognize only average travel time rather than the true marginal (social) cost of their travel. This negative externality results in over-consumption and excessive roadway congestion. Such inefficiency, due to an absence of a demand moderating policy, pervades many road networks at peak periods.

Vickrey (1969) developed the first (two-link, single-OD pair) dynamic model of vehicle congestion, with flexible departure and arrival times, where individuals seek to minimize the sum of travel time and schedule delay costs. Vickrey derived socially optimal tolls for this situation. Arnott et al. (1990) also considered two parallel routes and demonstrated how social cost savings from altering departure time patterns could exceed route-shift savings, under pricing. Arnott et al. (1993) later compared four distinct pricing regimes[2] on a route with a single Vickrey-type bottleneck and concluded that there are substantial benefits to be derived from employing technologically sophisticated pricing systems.

Congestion Pricing Applications and Issues

CP has found application in many places around the world, notably in South East Asia (e.g., Singapore's toll-tag-collected variable prices and Seoul's Nam Sam tunnels) and Western Europe (e.g., Trondheim, Norway's toll ring and downtown London's cordon toll). Gómez-Ibáñez and Small (1994) describe various applications. In 1998 in the United States, Orange County, California's State Route 91 (S.R.91) was the first Pilot study commissioned under federal legislation.[3] The results of this variable pricing experiment were explored by Sullivan et al. (2000) who found that priced-lane use was defined by "highly selective travel behavior"[4]. Poole and Orski (2003).noted that High Occupancy Toll (HOT)[5] lanes represented only 33 percent of the SR-91's capacity but were carrying 40 percent of the traffic during the busiest peak hours, at speeds of 65 mi/h versus 10 to 20 mi/h in the other lanes. Also in 1998, a fully automated dynamic pricing pilot project was implemented on San Diego's I.H. 15 with tolls capable of changing every 6 minutes at $ 0.50 increments and variable message signs informing drivers of current tolls.[6]

In spite of many advantages, system-wide CP proposals have encountered considerable public resistance. (See, e.g., Jones, 1998, and Oberholzer-Gee and Weck-Hannemann, 2002.) Though marginal cost pricing is desirable from a market efficiency viewpoint (i.e., net benefits are maximized as travelers internalize/recognize the true marginal costs of their activities), it can have substantial equity impacts.

For example, both Small (1983) and Hau (1992) found that "average commuters" under CP would be somewhat worse off without special revenue redistribution policies. Arnott et al. (1994) employed Vickrey's (1969) bottleneck model and assumed fixed demand on a single link. Like Hau (1992) and Evans (1992), they concluded that road pricing without returning revenues generally would be regressive, with tolls primarily benefiting those with high values of travel time (VOTTs)[7]. Arnott et al. (1994) also briefly considered the possibility of an equal per-capita rebate and found that drivers with lower VOTTs could remain worse off, if they are relatively insensitive to travel time costs. Parry and Bento (1999) suggested that a "congestion tax" on commute travel could discourage labor force participation to such an extent that the resulting welfare losses in the labor markets exceed Pigouvian welfare gains (from internalizing the congestion externality).

Application issues and potential for regressive impacts have led researchers to seriously consider other forms of CP. These include Dial's (1999) "minimal revenue pricing"[8] and other forms second-best pricing (e.g., Verhoef 2002 and Verhoef et al. 1996[9]), Viegas' (2001) "mobility rights", and the FHWA's "Fast and Intertwined Regular (FAIR) Lanes"[10] (DeCorla-Souza, 1995). Daganzo (1995) proposed a strategy to reduce the size of money transfers and possibly achieve a Pareto-improving solution (i.e., with positive difference in utilities for all traveler classes [Varian 1999]) by tolling certain groups only on certain days, while recognizing the value of time of the lowest income travelers. Nakamura and Kockelman (2002) applied this idea to the San Francisco-Oakland Bay Bridge to assess whether one might arrive at a Pareto-improving "toll-plus-rationing strategy" without redistribution, under a variety of pricing-policy and speed-flow (i.e., performance-function) assumptions.

All these investigations underscore the fact that CP raises serious equity issues. Though there has been much excellent research in the area of CP, an efficient and equitable policy to tackle the congestion externality has yet to be developed.

A Credit-Based Congestion Pricing (CBCP) Policy

This paper explores a substantially different approach to congestion pricing based on "credit allowances" similar in many respects to the "tradable" emission credits set up by the 1990 Clean Air Act Amendments (CAAA1990). Under a CBCP policy, drivers receive an allowance of monetary travel credits, to use on the roads. Time- and link-varying prices recognize variable demands and their associated negative externalities. Drivers do not pay money "out of pocket" unless they exceed their allowance. They save the value of unused credits and can spend these elsewhere. For drivers with special, socially desirable travel needs (e.g., welfare-to-work participants, and single parent low-income household heads), extra credits may be allotted.

A CBCP policy has the potential to achieve optimal network use while addressing the primary impediments to congestion pricing policies, namely equity, welfare, and revenue-distribution. This paper investigates initial perceptions of CBCP in Austin, Texas, and describes various application details. A survey was undertaken to predict public response to CBCP in Austin. With 61 hours of estimated annual traffic delays and 104 gallons wasted fuel per peak-period road traveler, Austin ranks 16th among US urban areas in Schrank and Lomax's (2002) studies. The associated annual time and fuel costs are estimated to be $1190 per peak-period road user. (Shrank and Lomax 2002) To add capacity in a time of declining funding, the Texas DOT recently raised billions in bond monies for Austin region toll roads.[11] Such factors make Austin an appealing choice for this study.

Survey Design and Administration

The CBCP survey was designed to illuminate constraints on traveler choices (such as work times and child care locations), public support for and perception of CBCP and other transportation policies, and behavioral response to such policies. The survey was the result of a semester-long assignment for a diverse set of graduate students enrolled in the Transport Data Acquisition and Analysis course at the University of Texas at Austin (UT). Surveys in both English and Spanish were conducted across a wide spectrum of Austin residents, to recognize the diversity of Austin residents and their travel preferences with particular attention to equity issues.

The survey design consisted of three sections and a total of 31 questions. The first section collected general information on demographics, locations and trip-making behaviors of respondents. The second section described CBCP scenarios in order to glean information helpful for predicting behavioral response. The third section sought respondent opinions about congestion and strategies to reduce it.

Respondents were recruited through personal visits to Austin dwelling units, telephone calls, intercept surveys at public places, and online (and other media) advertisements of the web-based survey. Locations for household surveys were selected to obtain a wide spatial distribution of respondents. Austin's 1074 traffic assignment zones (TAZs) were grouped into 6 districts of almost equal population. In every district, a TAZ was sampled (for survey distribution) in proportion to its population. Both single-household dwelling units and apartments were approached along various streets within each zone.

Random digit dialing (RDD) telephone recruitment[12] and public intercept surveys also were used. Intercept surveys were much more successful than RDD recruitment and took place at a UT women's soccer game and a popular grocery store with children's play area and café. Surveys were handed out to persons who appeared to be of driving age and collected back after the game or shopping.

While over 36 percent of the 480 responses were obtained in paper form from intercept and neighborhood surveys, the great majority came from a user-friendly web-survey. IP addresses of survey-submitting computers were stored so that no repeated entries were received. The internet link to the web-survey was widely circulated through pamphlets delivered to residences and intercepted individuals, over telephone (since telephone surveys were tedious), articles in the *Austin American Statesman* and UT's *Daily Texan* (campus newspaper), links from City of Austin, Capital Metro (the region's transit agency) and Austin neighborhood association websites, and finally by sending e-mails to random lists of Austin residents.

The web survey contributed about two thirds of the final sample. Public intercept surveys contributed over 21% of the sample. Around 10% of responses came from the household surveys, and the remainder came from telephone surveys. Over 480 responses were obtained between October 2002 and February 2003.

Data Analysis

The following sections describe the models resulting from the returned surveys. Due to non-completion of income data (9.79% of respondents) and gender data (1.46%), only 426 responses out of 480 are used for analysis. Upon comparison with Austin's 1996 region-wide travel survey, sample weights were developed for three age classes (16 to 24, 25 to 44, and over 45 years), gender, and four household income classes (less than \$15,000, \$15,000 to \$30,000, \$30,000 to \$50,000, and over \$50,000, in 2002 dollars).[13] Only 39.27% of the survey respondents were women, and just 5.4%

were from the lowest income group. The weighted adjustments alter these initially-biased percentages to population-representative values of 49.6% and 7.4%, respectively. Additional demographic comparisons of the weighted sample are shown in Table 1a. A list of all variables considered in the data analysis (along with their means and standard deviations) is given in Table 1b. The following statistics and regression model results are weighted to reflect the true population.

Perceptions of Congestion and Traveler Response

The survey asked respondents for their peak and off-peak commute times. The (weighted) mean of the ratio of these two times is 1.96, illustrating how congested Austin roads tend to be. The survey also asked people how problematic they feel congestion in Austin to be, by ranking it on a 4-point scale (from "not a problem" to "a major problem"). 84.3% responded that congestion is a problem in Austin and almost half felt congestion to be a major problem. An ordered probit model (Greene, 2000) was used to predict this four-level response, and results are shown in Table 2. Initially 407 valid weighted responses were grouped for analysis out of which 49 responses had to be excluded since they did not provide information on critical variables such as peak-hour travel distances and times. Perceptions tend to be rather uniform across gender and income group. However, people who have lived in Austin longer are predicted to perceive the congestion problem to be much worse than newer residents, even when faced with the same delays over similar distances. One reason for this may be that newer residents have lived in more congested cities than Austin. Students (both high school and college) are the least concerned. Employed persons find congestion to be less frustrating than retired or unemployed people. With increasing education and income, people seem less inclined to perceive congestion as a problem.

Table 3 gives ordered probit model results for frequency of trip modification in response to congestion. Controlling for a variety of individual (and household) characteristics (including peak-hour trip-making frequency and congestion experience [measured as lost time per mile traveled during daily commute]), it can be inferred that older persons more frequently modify trip choices in order to avoid congestion, as do higher-income individuals[14]. Men have a marginally higher tendency to modify trips to avoid congestion, when compared to women. Such tendencies diminish with additional children (which may be due to greater child care responsibilities) and vehicle ownership (per household member). Those sensing greater total delays in peak-hour congestion and those presently making fewer peak-period trips are more likely to modify travel plans. Students seem the least inclined to modify travel, whereas unemployed and retired people are the most inclined.

Support for Congestion-Mitigating Policies

The various congestion-mitigation policy options proposed in the survey can be broadly grouped as "Pricing-related" and "Infrastructure-related". Pricing-related policies include credit-based congestion pricing, flat tolls and parking charges. Infrastructure-related policies include providing a light rail system, more buses, more roads, and high occupancy vehicle (HOV) lanes. While 87.9% of (population-weighted) respondents supported infrastructure-related policies, a healthy 47.1% supported at least one pricing-related policy. 24.9% supported a policy of CBCP, 24.2% supported flat tolls, and 11.1% supported parking charges (at more than $5/day). Light rail garnered 57.2% support. This is not surprising considering that Austin went through a recent high-profile campaign for light rail before this was narrowly defeated[15]. Also of interest is the fact that 23% of the (population-weighted) sampled respondents had heard about CP, over 90% (91.8%) had driven on toll roads, and 12.2% had used a transponder.

Logit models were developed to study support for pricing policies and support for infrastructure related policies. The results are shown in Tables 4 and 5, respectively. There appears to be greater support for pricing among long-term residents of Austin, but also among young persons. Higher-income individuals appear more inclined to support pricing policies, along with those having higher levels of education (after controlling for income, age, and other variables, of course). Students, volunteers, retired, and unemployed persons, also appear more supportive, as compared to employed people. As expected, people with greater flexibility in their work schedules and those traveling larger distances during peak hours are less supportive of pricing policies. People with greater vehicle ownership per person were surprisingly less welcoming of a pricing policy, which could be because they may be making more trips on average and also travel alone on many trips.

It is interesting to explore the link between support for pricing-related policies and exposure to congestion pricing. While support for flat tolls did not vary much based on exposure to CP, 50% of people who had heard of CP supported a policy of CBCP – in contrast to only 26.5% of those who had not heard of CP. Parking charges were advocated by 28.8% of those who had heard of CP, compared to 11.7% of those who had not. Clearly, education on the merits of CP may make a substantial difference in public perception of CBCP policies.

Support for infrastructure related policies was higher among newer residents in Austin and also among men as compared to women. Support for infrastructure related policies declined with age, income levels, higher education, vehicle ownership, and number of children in household which could indicate the tax-payer's sensitivity to greater infrastructure spending. People with highly flexible work schedules and those traveling larger distances during peak hours were less likely to support infrastructure improvement policies.

Specific Responses related to CBCP

As part of the survey, respondents were asked to rate ease of use, fairness, cost to users, and privacy as "very important", "somewhat important", or "not important" for implementation of CBCP policies. Almost 70% (68.6% [weighted for gender, age, and income]) felt that user costs (i.e., tolls) are very important, 58.1% were very concerned with implementation issues (i.e., ease of use), and 56.2% believed fairness to be a pressing issue. The issue of privacy appears much less controversial: only 32.3% felt it to be very important (25.8% rated it somewhat important, 31.7% rated it unimportant, and 11.2% did not respond to this question). Nevertheless, a CBCP policy will have to address the privacy issue in order to win support from all quarters. Central maintenance of travel data for purposes of account charges permits much less expensive on-board technology (e.g., \$15 passive transponders) and reduces opportunities for fraud (since active read-write second-generation transponders may be "reverse engineered" to misreport true accumulated charges). However, it also requires third-party protections of data and legislative action to ensure such privately held data are not abused.

Stated Responses to Congestion Pricing Policies

In response to a peak-hour distance-based toll of 25¢ per mile on all freeways in Austin, 21% (weighted proportion) said that would not alter their driving patterns, 29.4% predicted they would drive less, 9.9% said they actually would drive more, 29.4% said they would change the time of arrival or departure, and 40.2% said they would try changing routes to avoid the peak-period toll. 12.1% said they would try carpooling, while only 9.2% said they would take the bus and 1.7% would bike more often. 5% predicted they would alter their home location, while 1% would change jobs or telecommute. 3.9% said CBCP would not impact them since they do not drive on Austin freeways Finally, 3% of the weighted responses appeared wholly resistant to CBCP[16], with 1.1% saying they would leave Austin altogether.

A policy of CBCP was described, and various scenarios that could result were posed to the survey respondents. Respondents had to imagine themselves as drivers commuting every weekday during peak hours out and back on a ten-mile stretch upon which CBCP was implemented. The charge was to be 25¢ per mile; thus two peak-hour trips on the 10-mile stretch would cost $5 each day. Monthly credits worth $100 were allotted to the drivers so that they could meet all their regular work/school trips during peak hours on all 20 weekdays per month. Any further traveling during peak hours would require a driver to pay money out of pocket. These drivers had the opportunity to modify their trip making to save credits, and they would receive the dollar amount of any credits saved every month. Their responses permitted development of the following prediction models of behavior under a CBCP policy.

Travel Changes in the Face of CBCP

One question of great interest is how many days drivers will change their trip making (either by changing trip mode or time of day) so that they have monetary credits remaining at the end of the month. The average response was 3.58 days per month, with a generous standard deviation of 5.05; this corresponds to a credit savings of $17.90 per month (assuming a daily $5 toll on a 10 mile tolled section). A truncated negative binomial regression model (see, e.g., Greene, 1995, and Mishra and Sinha, 2001) with an upper bound of 20 for the number of weekdays (per month) was used for this analysis; the results are tabulated in Table 6.

The response models were developed with 344 responses. Though 368 responses were valid for weight calculations, 22 responses lacked information on the important trip-making characteristics of the respondent (concerning peak-hour distance and peak/off-peak travel times).

After controlling for various respondent characteristics, including income, age, vehicle ownership, and peak-hour trip-making (distances, and travel times), results indicate that trip-modification tendencies decrease with age, vehicle ownership and income. Thus, while older persons seemed more willing to modify trips to avoid congestion, they are more willing to pay tolls to continue driving at the same times of day. Furthermore, those more often willing to change their travel patterns tend to be those currently making trips in less congested conditions. (Evidently, those presently driving on more congested roads may have very little flexibility left for modifying their travel patterns.) People with more childcare responsibilities also were less willing to modify their trip making under CBCP. Clearly, there are important connections between need, constraints, and willingness to pay. A strong appreciation of these will enable more robust prediction of winners and losers under any form of CP policy and enhance formulation of credit distribution strategies.

Toll Levels for Travel Changes

It also is very valuable to appreciate how people react if they do not have sufficient credits to undertake all desired trips. One scenario provided only enough credits for three-quarters of all peak-hour commute trips (i.e., 15 per month) and queried respondents on the maximum amount per day that they are willing to pay (WTP) "out of pocket" so that they can continue driving alone during the peak periods. The average "out-of-pocket WTP" for the (weighted) sample was $4.96 per day ($\sigma =$ $5.66). Another scenario asked respondents for the "limiting toll" that would cause them to relinquish the car mode and use a slower bus mode (requiring 15 more minutes each way) for at least some of their peak-hour trips. The average value for this "limiting toll" was $4.90 per day ($\sigma =$ $5.43).

Table 7 presents the OLS results for log-linear models[17] estimated for maximum tolls Austinites are willing to pay to avoid shifting to transit (i.e., the limiting toll). One can expect an individual's response to be colored by his/her past travel experiences (e.g., average number, distance and delay of peak-period trips usually made), so, as before, these are included as control variables. Several key demographic variables (such as gender), are retained in the final models even if they are not statistically significant (p-value ≤ 0.10); this is done in order to facilitate inferences across models and avoid bias in other estimator values[18].

From Table 7, one observes that persons employed full time are willing to pay 30% more (than others) in daily tolls before shifting to the slower, transit mode. And men are prepared to pay 17% more on, an average, than women, before shifting. The impact of income and vehicle ownership on "limiting toll" were not statistically significant (after controlling for employment status and educational experience), but age was – with older people willing to pay higher tolls. People with highly flexible work hours were willing to pay 30% more than those without such flexibility. This may be because they expect to fewer peak-hour auto trips, and therefore are willing (and able) to pay more when they do.

Notably, the CBCP scenarios specified no travel time savings on the tolled route. Many respondents may have anticipated such effects and valued these benefits in their stated willingness to pay to continue driving. But it is very likely that many respondents did not make such an association, so that the out-of-pocket WTP values reported here are biased low. In the face of time savings and reduced travel time uncertainty, Austinites are likely to be willing to pay more than predicted here.

Values of Travel Time (VOTT)

Survey respondents were asked what tolls they would be willing to pay to obtain total travel time savings of 20 minutes on their daily work (and school) commutes. Out of the 417 weighted responses, 139 did not respond to this question. The mean value of VOTT computed for the rest of the weighted sample turned out to be about $2.66 for a 20-minute savings, or $7.95 per hour. This is comparable to the $3.50 to $5.00 per hour that Calfee and Winston (1998) obtained from their stated preference (SP) experiments using a random sample of respondents from major U.S. regions. However, it is considerably lower than the estimates obtained from revealed preference studies on California's I-15 and SR-91 corridors. Yan et al. (2002) VOTT estimates for SR 91's express lanes[19] lie between $13 to $16 per hour, and Brownstone's (2002) median estimate for the I-15 corridor was roughly $30 per hour of commute time[20]. It may be that reduced travel time uncertainty, perceptions of safety, and other benefits (real or perceived) of congestion-priced lane use will generate a higher willingness to pay than survey respondents presently anticipate, given the question as it was posed.

Inferences about people's VOTT to work were drawn based on log-linear OLS models shown in Table 8. Average commute distance and number of peak-hour trips were controlled for in all models, and the results indicate that older persons, those with college degrees, and those with children were willing to pay more for travel time savings. Carpoolers were less willing to pay high tolls (65% lesser tolls per day), which may be because such people are extremely sensitive to monetary costs in the first place and are willing to sacrifice time and convenience for vehicle ownership, gasoline and other cost savings. VOTT was surprisingly independent of income (per household member), and the introduction of a squared income variable (designed to capture nonlinear dependencies) did not noticeably enhance the model. One reason for this result is that 27% of the respondents reported zero on this question; apparently, they do not feel that 20 minutes of daily travel time savings is worth paying a toll. Another reason may be the fact that students reported a substantially higher willingness to pay (146% more per day) than non-students. Since all respondents were asked to imagine themselves in a work-trip commute, the students may have been envisioning themselves as employed – and having much higher incomes than the (current) income variable that was tested.

As congestion worsens and pricing policies evolve, today's youths are likely to become many of tomorrow's tolled. It is of interest that they are relatively supportive of such policies, as evidenced by their reported willingness to pay – and their support for such policies (as described earlier).

Conclusions and Extensions

Credit-based congestion pricing (CBCP) is a wholly new policy to permit efficient road use while counteracting most, if not all, equity (and regressivity) issues. CBCP scenarios for Austin roadways were developed for a survey whose respondents were contacted via housecalls, public interception, random digit dialing, web sites, and the news media. Though initially respondents were totally unfamiliar with this new strategy, 24.9% clearly supported it after fifteen minutes of reading and answering questions related to it. This is rather substantial for such a complex policy involving road pricing and is likely to grow; experience with road-pricing policies and education on this new strategy seem key mechanisms for promotion and greater acceptance. Policy privacy was not a primary issue for Austinites; implementation, cost, and equity are bigger concerns. Regular travel experiences and individual and household characteristics are also key. For example, men perceive congestion to be less of a problem in Austin than women and demonstrated less flexibility before shifting to other modes and/or changing travel plans in response to tolls. Retired and unemployed persons view congestion in a more negative context and expressed a willingness to modify their plans more often to avoid congestion.

Public acceptance of a novel and as yet untested policy such as CBCP is likely to require substantial education of the public about the benefits of congestion pricing. As tolling gains greater application and understanding (abroad and in the U.S., through central district cordon tolls, variable pricing pilot programs, HOT lanes, and other strategies), it seems likely that CBCP can emerge as a viable, cost-effective and strongly supported strategy. This policy promises substantial benefits for network efficiency and welfare equity, addressing key issues that can undermine other proposals.

Co-introduction of complementary programs, such as employer-sponsored ridesharing and transit improvements, promise even greater success, particularly for those having to make regular peak-hour commutes. Those tending to view CBCP most favorably also perceive greater trip-making flexibility and report higher incomes. Thus, for truly widespread popular support, further considerations should be given to constrained travelers within the framework of a CBCP policy.

Further research can illuminate specific cases of populations less likely to benefit from a CBCP policy. Access to competitive alternative modes (such as buses, casual carpools, and commuter rail) at both home and work, and home and school, needs to be thoughtfully appraised. Models for destination, mode, and departure time choice under CBCP need to be developed for impact simulation. Changes in land use and land values are likely to be key and should be studied using integrated transportation-land use models (see, e.g., Krishnamurthy and Kockelman's [2004] recent Austin applications). Welfare impacts to the Austin region will help in assessing impact of a CBCP application and in developing further policy recommendations for eventual implementation of this very promising policy.

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References

Arnott, R., and Small, K. (1994). "The Economics of Traffic Congestion." *American Scientist*, 82:446-455.

Arnott, R., de Palma, A. and Lindsey, R. (1990). "Departure Time and Route Choice for the Morning Commute." *Transportation Research*, 24B (3): 209-228.

Arnott, R., de Palma, A. and Lindsey, R. (1993). "A Structural Model of Peak-period Congestion: A Traffic Bottleneck with Elastic Demand." *American Economic Review* 83: 161-179.

Arnott, R., de Palma, A. and Lindsey, R. (1994). "The Welfare Effects of Congestion Tolls with Heterogeneous Commuters." *Journal of Transport Economics and Policy* 28**:**139-161.
Ben-Akiva, M., and Lerman, S. R. (1985) *Discrete Choice Analysis*. Cambridge, Massachusetts; MIT Press.

Brownstone, D., Ghosh, A., Golob, T.F., Kazimi, C. and Amelsfort, D.V. (2002). "Driver's Willingness-to-Pay to Reduce Travel Time: Evidence from the San Diego I-15 Congestion Pricing Project." *Transportation Research Part A.* 37:373-387.

CAAA (1990) *Clean Air Act Amendments of 1990.* 42 USC 7401-7671q, P.L. 101-549, 104 Stat. 2399.

Calfee, J., and Winston C. (1998) "The Value of Automobile Travel Time: Implications for Congestion Policy." *Journal of Public Economics*. 69: 83-102.

Crozet, Y. and Marlot, G. (2001) "Congestion and Road Pricing: Where is the Bug?" *9th World Conference on Transport Research*, Seoul, Korea.

Daganzo, C. (1995). "A Pareto Optimum Congestion Reduction Scheme." *Transportation Research.* 29B:139-154.

DeCorla-Souza, P. (1995) "Applying the Cashing Out Approach to Congestion Pricing." *Transportation Research Record*. No. 1450: 34-37.

Dial, R.B. (1999). "Minimal Revenue Congestion Pricing Part I: A Fast Algorithm for the Single-Origin Case." *Transportation Research.* 33B:189-202.

Evans, A.W. (1992) "Road Congestion Pricing: When is it a Good Policy?" *Journal of Transportation Economics and Policy*. 26(3): 213-244.

Gomez-Ibanez, J.A., and Small, K. A (1994) "Road Pricing for Congestion Management: A Survey of International Practice." *National Cooperative Highway Research program, Synthesis of Highway Practice 210*, TRB, National Academy Press, Washington, D.C.

Greene, W. H. (1995). *LIMDEP: User's Manual* (Version 7.0). Bellport, NY: Econometric Software.
Greene, W. H. (2000). *Econometric Analysis.* Fourth Edition. New Jersey, Prentice Hall.

Jones, P. (1998). “Urban Road Pricing: Public Acceptability and Barriers to Implementation.” In: Button K.J., Verhoef, E.T. (Eds.). *Road Pricing, Traffic Congestion and the Environment.* Edward Elgar Publishing: Cheltenham, UK.

Fimrite, P. (2002), “Traffic Tops List of Bay Area Banes, Weak Economy is Number 2 Bane, Survey Shows.” *San Francisco Chronicle.* (5, December 2002). Accessed from http://sfgate.com/cgi-bin/article.cgi?file=/c/a/2002/12/05/MN51835.DTL#sections.

Hau, T. D. (1992), “Economic Fundamentals of Road Pricing: A Diagrammatic Analysis.” *World Bank Policy Research Working Paper Series*. WPS No. 1070, December, The World Bank, Washington, D.C., pp. 1-96.

Knickerbocker, Brad. (2000). “Forget Crime - But Please Fix the Traffic.” *Christian Science Monitor*. (February 16)

Knight, F. (1924). “Some Fallacies in the Interpretation of Social Costs.” *Quarterly Journal of Economics*. 38(4): 582-606.

Krishnamurthy, S. and K. Kockelman. (2004) Uncertainty Propagation in Integrated Transportation-Land Use Models: An Application to Austin, Texas. Forthcoming in *Transportation Research Record*.

LRNA (2001). “Light Rail Now! Austin.” (27, February 2003). Accessed from http://www.lightrailnow.org/lrn_austin/news.html.

Mishra, R S., and Sinha S.K. (2001).“On Doubly and Singly Truncated Negative Binomial Distributions with and without Weighting.” Presented at *International Conference on Statistics, Combinatorics and Related Areas and the Eighth International Conference of Forum for Interdisciplinary Mathematics*. Wollongong, Australia.

Nakamura, K. and Kockelman, K. (2002). “Congestion Pricing & Roadspace Rationing: An Application to the San Francisco Bay Bridge Corridor.” *Transportation Research A.* 36(5): 403-417.

Oberholzer-Gee, F. and Weck-Hannemann, H. (2002). “Pricing Road Use: Politico-economic and Fairness Considerations.” *Transportation Research D.* 7(5): 357-371.

Parry, I.W.H. and Bento, A. (1999). “Revenue Recycling and the Welfare Effects of Road Pricing.” *Working Papers - Public Sector Management. Decentralization, participatory planning.* World Bank.

Penchina, C. M. (2001). “Minimal-Revenue Congestion Pricing: Some More Good-News and Bad-News.” Submitted to *Transportation Research B.*

Pigou, A.C. (1920). *Wealth and Welfare.* Macmillan, London.

Poole, R.W., and Orski, C.K. (2003). *HOT Networks: A New Plan for Congestion Relief and Better Transit.* Reason Public Policy Institute.

Research and Technology Transporter (2001). “November/December 2001 Transporter” (27, Feb 2003). Accessed from http://www.tfhrc.gov/trnsptr/novdec01/novdec01.htm.

Rietveld, P. and Verhoef E.T. (1998). "Social feasibilities of policies to reduce externalities in transport." Road Pricing, Traffic Congestion and Environment. (Ed) Button K.J. and Verhoef E.T., Cheltenham, UK.

Sahr, R. (2002) "Inflation Conversion Factors for Dollars 1665 to Estimated 2012." *Consumer Price Index (CPI) Conversion factors.* (11, February 2003). Accessed from http://oregonstate.edu/Dept/pol_sci/fac/sahr/sahr.htm

Scheibal, S. (2002). "New Planning Group Kicks-off Effort with Survey on What Area Residents Want." *Austin American Statesman*. (August 26).

Schrank, D. and Lomax T. (2002). *The Urban Mobility Report*. Texas Transportation Institute, College Station, TX.

Smith L. (2002). "Advance Payments: Congestion Pricing." (18, December 2002). Accessed from http://www.path.berkeley.edu/~leap/TTM/Demand_Manage/pricing.html.

Small K. (1983). "The incidence of Congestion Tolls on Urban Highways." *Journal of Urban Economics.* Vol 13, pp. 90-111.

Sullivan, E., with Bakely, K., Daly, J., Gilpin, J., Mastako, K., Small, K., and Yan, J. (2000) *Continuation Study to Evaluate the Impacts of the SR 91 Value-Priced Express Lanes: Final Report*. Department of Civil and Environmental Engineering, California Polytechnic State University at San Luis Obispo. (13, December 2002) Accessed from http://ceenve.ceng.calpoly.edu/sullivan/SR91/

Texas Freeway (2002). "Austin Tollways." (25, March 2003). Accessed from http://www.texasfreeway.com/austin/new_freeway/austin_tollways.shtml

Varian, H. R. (1999). *Intermediate Microeconomics: A Modern Approach*. 5th ed., W. W. Norton College Books.

Verhoef, E. T. (2002) "Second-best Congestion Pricing in General Static Transportation Networks with Elastic Demands." *Regional Science and Urban Economics.* 32(3): 281-310.

Verhoef E., Nijkamp P., Rietveld P. (1996) "Tradable Permits: Their Potential in the Regulation of Road Transport Externalities." Working Paper, Tinbergen Institute.

Viegas J. M. (2001). "Making Urban Road Pricing Acceptable and Effective: Searching for Quality and Equity in Urban Mobility." Transport Policy. 8(4): 289-294.

Vickrey, W. (1963). "Pricing in Urban and Suburban Transport." *American Economic Review*, 52 (2): 452–465.

Vickrey, W. (1969). "Congestion Theory and Transport Investment." *American Economic Review*, 59 (2): 251–260.

VPPP (2002) "Value Pricing Pilot Program - FHWA Office of Transportation Policy Studies." (27 Feb., 2003). Accessed from http://www.fhwa.dot.gov/policy/13-hmpg.htm.

Walters, A.A. (1961). "The Theory and Measurement of Private and Social Cost of Highway Congestion." *Econometrica*. 29(4): 676-697.

Yan, J. Small, K. and Sullivan, E. (2002) "Choice Models of Route, Occupancy, and Time-of-Day with Value Priced Tolls." *Transportation Research Record*. No. 1812: 69-77.

Endnotes

[1] Supply-side solutions to congestion are often subject to the Pigou-Knight-Downs paradox as well as Braess's paradox, which unleash additional demand upon expanding road capacity and increase travel time upon adding a link in congested networks. (Arnott and Small, 1994)
[2] They explored no-toll, optimum-constant-toll, optimum-step-toll and optimal-time-varying-toll regimes for routes with capacity both exogenous and optimally chosen.
[3] In 1996, the United States Congress created the FHWA's Value-Pricing Pilot Program via the Transportation Equity Act for the 21st Century (TEA-21). Under TEA-21, the Secretary of Transportation can enter into cooperative agreements with up to fifteen State or local governments, or other public authorities, in order to establish, maintain and monitor local value pricing pilot programs. TEA-21 provides that any value-pricing project may involve the use of tolls on the Interstate system as an exception to provisions contained in 23 U.S.C. 129 and 301. TEA-21 also allows single-occupant vehicles to occupy High Occupancy Vehicle (HOV) lanes under such a pricing program (as an exception to 23 U.S.C. 102). (VPPP, 2002)
[4] Women between ages 30 and 50 formed the main user group, and driving comfort and the perception of greater safety were the principal supplemental benefits cited by travelers who choose to use the toll lanes even when expected value of their time savings was clearly less than the tolls paid. (Sullivan et al. (2000)
[5] HOT lanes are HOV lanes or carpool lanes that non-carpool drivers may use by paying a toll.
[6] Under regular conditions, tolls vary from $0.50 to $4; in exceptional circumstances, they may rise to $8. If the toll changes during a motorist's use of the lanes, the system algorithms charge the user the lowest toll he/she may have seen on the message signs. (Smith, 2002)
[7] Those with higher VOTTs often have higher incomes. Arnott et al. (1994) recognized different schedule delay costs and VOTTs, but assumed a single *relative* cost of late-to-early arrival and a single preferred arrival time, for all travelers. In the special cases where either (1) individuals had different costs of late arrival but the same preferred arrival times and VOTTs, or (2) commuters had different preferred arrival times but the same schedule delay costs and VOTTs, they found the optimal toll to be welfare neutral and a rebate policy to be welfare enhancing for all commuter groups.
[8] Penchina (2003) demonstrated that if the demand is not highly price elastic, Dial's (1999) minimal revenue (MR) pricing has some important advantages over marginal cost (MC) pricing like lower tolls, fewer tolled links, and more stable tolls under time-varying demands translating to lower transaction costs, less "user confusion", and more "perceived equitability".
[9] Verhoef et al. (1996) considered a simple network with several origin-destination pairs and with alternate routes, one of which was not tolled. They showed that a second-best toll on the tolled route could be *negative*, in order to discourage usage of the non-tolled route.
[10] According to the Research and Technology Transporter (2001), FAIR lanes involve demarcating congested freeway lanes into Fast lanes and Regular lanes (e.g., by using plastic pylons and striping). The Fast lanes would allow "para-transit" and limousine-type services, and would be electronically tolled, with tolls set in real time to limit traffic to the free-flowing maximum. Electronic message boards located in advance of the Fast lane entry points would advise motorists of the toll rate changes. In the Regular lanes, constricted flow would continue; however, drivers with electronic toll tags would be compensated with credits. Credits could be used as toll payments on days when drivers choose to use the Fast lanes or as payment for transit and para-transit services, which would be subsidized using toll revenues. The credits would compensate motorists for giving up their right to free use of the lanes converted to Fast lanes.
[11] In November 2001, Travis County voters approved a $66 million bond issue to pay for S.H. 130 right-of-way costs, and $32 million for S.H. 45 right-of-way costs. In November 2000, neighboring Williamson County's voters passed a $350 million bond issue with about $150 million designated for tollway right-of-way acquisition and utility relocation. (Texas Freeway 2002)
[12] For the random digit telephone numbers, the first 5 of 7 digits were pulled in a systematic fashion from the telephone directory. The final 2 digits were randomly generated. In effect, random number dialing of residential telephone numbers was achieved.
[13] Sahr's (2002) adjustment factor of 14.94% was used to inflate 1997 dollar amounts to 2002 dollar amounts. The data from five ATS survey income groups (less than $10,000, $10,000 to $20,000, $20,000 to $35,000, $35,000 to $50,000, and over $50,000, in 1997 dollars) was regrouped (using linear interpolation) into the four CBCP survey income groups.
[14] Note that "income" is per household member in these models, in order to recognize that household size has a major impact on household wealth or individually perceived purchasing power.
[15] Austin's Capital Metro light rail proposal was defeated on November 7, 2000, by just over 2000 votes, an extremely thin margin. Moreover, 50.6% of voters within the City of Austin voted in favor of the proposal. Support for light rail was often strongest along the proposed routes, in precincts within a half-mile of the initial-system routes. (LRNA 2001)

[16] These respondents explicitly noted that they would oppose any form of CP application in Austin.

[17] Log-linear models ensure positive predictions of the response variable, willingness to pay (WTP). To convert the regression results to dollar values, one must use the exponential function. In notation form, $E(\ln(WTP))=\beta x$, so $E(WTP)\approx\exp(\beta x)$. While weights were available for 417 survey respondents, 124 of these did not respond to the "limiting toll" scenario question. 20 of these non-respondents refused on the grounds that they did not approve of the policy (a point that they clearly noted in "comments" sections of the survey). Others may have found the scenario too complex to respond confidently.

[18] If valid explanatory variables are removed simply because of statistical significance issues, remaining correlated variables will proxy for the removed, latent variables, producing biased parameter estimates. (See, e.g., Greene 2000, for discussion of such issues.)

[19] Yan et al's (2002) estimates of VOTT come from 3 models: a multinomial logit model for route choice; a nested logit models for mode, transponder and route choice; and a nested logit model of time of day, transponder and route choice. The VOTT estimates were $16, $15 and $ 13.32 per hour, respectively.

[20] Brownstone et al (2002) expect their estimates to be biased high due to a perception that toll facilities provide safer driving conditions.

Table 1a. Demographics of Survey Respondents: Before and After Weighting

Age	% in Weighted Sample	% in Initial Sample	**Years lived in Austin**	% in Weighted Sample	% in Initial Sample	**Education**	% in Weighted Sample	% in Initial Sample	**Employment status**	% in Weighted Sample	% in Initial Sample
16 to 19 years	1.1	0.7	Less than a year	4.5	3.6	Some high school	0.2	0.2	Full-time employee	74.6	79.6
20 to 24 years	19.2	12.7	1 and 2 years	7.3	7.7	Vocational training certificate	17.6	12.7	Part-time employee	8	5.8
25 to 34 years	28.1	33.1	3 to 5 years	20.9	21.6	High school diploma/GED certificate	4.8	4.6	Full-time student	10	7.2
35 to 44 years	16.4	22.1	More than 5 years	66.7	66.4	Under-graduate. degree	44.1	46.8	Part-time student	1.5	1.2
45 to 59 years	28.4	25.9	Missing	0.7	0.7	Graduate degree or higher	33.2	35.7	Unemployed, (non-student & not retired)	1.5	2.2
Over 60 years	6.8	5.5							Retired	4.1	3.6
									Volunteer	0.4	0.5
Total %	100	100	Total	100	100	Total	100	100	Total	100	100

Table 1b. Description of All Variables (Weighted Results)

Variable Type	Variable name	Description	N	Minimum	Maximum	Mean	SD
Dependent variables	CONGLEVEL	Perception of congestion (0 - not a problem, 1 - minor problem, 2 - problem, 3 – major problem)	409	0	3	2.344	0.765
	FREQMOD	Frequency of modifying trips to avoid congestion (0 - never, 1 - sometimes, 2 -often, 3 - always)	410	0	3	1.644	0.91
	NDAYS	Number of days per month one would change trip mode and/or time to save credits	346	0	20	3.575	5.054
	ALTMODTOLL	Minimum toll ($) for exploring alternate modes/times facing insufficient CBCP credits	347	0	20	4.959	5.661
	CARTOBUSTOLL	Toll price ($) causing commute trip mode shift from SOV car to bus, assuming 15 additional minutes each way	316	0	20	4.897	5.426
	WILLTOPAY	Willingness to pay ($) per day for 20 min. travel time saving from a CBCP policy	296	0	20	2.656	3.987
	LOGMINTOLL	Natural logarithm of minimum toll for change in trips	324	-1.386	2.996	1.181	0.998
	LOGCARTOBUS	Natural logarithm of toll for shifting from SOV to bus	290	-1.897	2.996	1.208	1.002
	LOGWTP	Natural logarithm of willingness to pay for 20 minutes travel time savings per day	267	-2.303	2.996	0.574	0.933
Respondent demographics	YRSINAUSTIN	Years living in Austin	414	0.5	8	6.343	2.505
	AGE	Age (in years)	417	17.5	69.5	38.696	14.074
	AGESQ	Age squared (years squared)	417	306.25	4830.25	1694.993	1209.370
	MALE	Indicator for gender (male =1, female =0)	417	0	1	0.504	0.501
	HHSIZE	Household size (number of persons)	417	1	7	2.223	1.083
	LICDRIV	Number of licensed drivers in the household	417	0	7	1.860	0.827
	NUMCHILD	Number of children in the household	417	0	4	0.363	0.702
	INCOMEPP	Annual household income ($) per person	417	1000	200000	30266.460	23078.470
	INCSQ	Square of annual household income	417	1.00E+06	4.00E+10	1.45E+09	2.88E+09
	VEHOWN	Number of household vehicles per driver	417	0	3	0.837	0.321
	EMPLYDF	Indicator variable for employed full time	417	0	1	0.825	0.380
	EMPLYD	Indicator variable for employed (full or part time)	417	0	1	0.746	0.436
	RETUNEMP	Indicator variable for retired or unemployed	417	0	1	0.056	0.23
	STUDENT	Indicator variable for student (full or part time)	417	0	1	0.100	0.301
	GRADUATE	Indicator variable for college graduates (1 - graduate, 0 - non-graduate)	417	0	1	0.774	0.419
	MASTERDEG	Indicator variable for masters degree holders (1 - yes, 0 - masters)	417	0	1	0.333	0.472

	CARPOOL	Indicator variable for person who carpools (1 - yes, 0 - no)	373	0	1	0.291	0.455
	WKFLEX	Indicator variable for person with highly flexible work or school hours (1 - yes, 0 - no)	417	0	1	0.124	0.329
Travel information	NPEAK	Number of Peak-hour trips per week (7.30 to 9.30 a.m. & 4.30 to 6.30 p.m.)	417	0	50	8.030	4.525
	DISTWORK	One-way travel distance (to work or school) (miles)	369	0	200	13.771	23.283
	TIMEPK	Travel time during peak hours (min)	377	0	120	26.968	18.282
	TIMEOFFPK	Travel time without congestion (min)	377	0	100	14.400	10.405
	TIMELOSSPM	Travel time lost per mile in peak hours (min)	361	0	11.5	1.284	1.098

Note: Data that was obtained categorically (e.g., income and age classes) has been modified to approximate continuous values for Table 1's values andfor use in the regression models. Wherever applicable, class midpoints were used as approximations. An average value of 8 years was assumed for people who lived in Austin for more than 5 years. An average income of $200,000 was assumed for those whose income exceeded $170.000. There were no respondents older than 80 years of age, so the penultimate bracket's mid-point (69.5 years) was thus the highest coded age.

Table 2. Ordered Probit (OP) Model Results for Perception of Congestion in Austin

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	1.3777	0.000	1.3774	0.000
YRSINAUSTIN	0.1140	0.000	0.1137	0.000
AGE	0.0016	0.710		
MALE	-0.0891	0.345		
DISTWORK	0.0124	0.011	0.0124	0.002
TIMELOSSPM	0.1609	0.001	0.1702	0.000
NPEAK	0.0008	0.942		
INCOMEPP	-4.333E-06	0.195	-3.509E-06	0.215
NUMCHILD	-0.0899	0.363		
VEHOWN	0.0351	0.873		
EMPLYD	-0.2010	0.161	-0.2078	0.111
STUDENT	-0.4051	0.029	-0.3835	0.021
GRADUATE	0.2034	0.042	0.1827	0.049
MASTER	-0.2113	0.080	-0.2027	0.038
μ_o	0	NA	0	NA
μ_1	1.0507	0.000	1.0532	0.000
μ_2	2.1685	0.000	2.1688	0.000
N_{obs}	365		365	
Log likelihood	-357.64		-366.84	
Log Lik: Constants only	-385.17		-385.17	
LRI	0.0715		0.0692	

Note: An ordered probit model's latent mean is the sum of the regression coefficient estimates interacted with explanatory variable values. Addition of a standard normal random error term defines final classification, where the μ's identify thresholds for class limits.

Table 3. OP Model Results for Frequency of Travel Modification to Avoid Congestion

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	1.8116	0.000	1.8676	0.000
AGE	0.0113	0.000	0.0128	0.000
MALE	0.1293	0.107	0.1099	0.137
DISTWORK	2.887E-03	0.506		
NPEAK	-0.0298	0.002	-0.0313	0.001
TIMELOSSPM	0.1264	0.003	0.1166	0.006
NUMCHILD	-0.1974	0.014	-0.2056	0.010
INCOMEPP	6.373E-07	0.808		
VEHOWN	-0.4130	0.004	-0.4461	0.000
EMPLYD	-0.4069	0.001	-0.4333	0.000
STUDENT	-0.6059	0.003	-0.6056	0.002
GRADUATE	-8.684E-02	0.350		
MASTER	1.290E-01	0.253		
μ_o	0	NA	0	NA
μ_1	1.374	0.000	1.370	0.000
μ_2	2.290	0.000	2.282	0.000
N_{obs}	363		363	
Log likelihood	-442.35		-443.05	
Log Lik: Constants only	-462.66		-462.66	
LRI	0.0434		0.0424	

Table 4. Binary Logit Model for Support of Pricing Policies

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	2.7784	0.051	1.1027	0.098
YRSINAUSTIN	0.1037	0.066	0.1094	0.051
AGE	-0.0172	0.135	-0.0151	0.178
MALE	-0.2446	0.346		
NPEAK	-0.0267	0.417		
INCOMEPP	9.947E-06	0.113	8.270E-06	0.173
NUMCHILD	0.0336	0.890		
EMPLYD	-1.7194	0.126	-0.6084	0.160
STUDENT	-1.2780	0.283		
GRADUATE	-0.3935	0.265		
MASTER	0.7122	0.025	0.6233	0.030
VEHOWN	-1.0847	0.086	-1.1680	0.018
DISTWORK	-0.0186	0.128	-0.0174	0.131
TIMELOSSPM	0.0524	0.665		
WKFLEX	-0.9395	0.022	-0.9004	0.017
INFLXPRC	-0.0223	0.942		
N_{obs}	368		368	
Log likelihood	-183.6173		-185.9109	
Log Lik: Constants only	-200.4898		-200.4898	
LRI	0.0842		0.0727	

Table 5. Binary Logit Model for Support of Infrastructure Improvement Policies

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	34.6186	1.000	7.6056	0.000
YRSINAUSTIN	-0.2593	0.034	-0.2572	0.027
AGE	-0.0146	0.370	-0.0193	0.168
MALE	0.8681	0.037	0.7911	0.038
NPEAK	-0.0648	0.203	-0.0678	0.124
INCOMEPP	-1.537E-05	0.054	-1.451E-05	0.047
NUMCHILD	-0.8167	0.014	-0.8872	0.002
EMPLYD	-28.4297	1.000		
STUDENT	-28.4941	1.000		
GRADUATE	0.5616	0.329		
MASTER	-0.7619	0.117	-0.7583	0.059
VEHOWN	-1.8825	0.045	-1.7448	0.017
DISTWORK	0.0281	0.187		
TIMELOSSPM	0.2030	0.394		
WFLEX	-0.7301	0.166	-1.1560	0.016
INFLXWORK&TIME	0.7570	0.194		
N_{obs}	368		414	
Log likelihood	-92.0006		-104.9394	
Log Lik: Constants only	-111.9425		-124.3194	
LRI	0.1781		0.1559	

Table 6. Truncated Negative Binomial Model Results for Number of Days an SOV Driver would Modify Trip Making so as to Save CBCP Credits

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	3.8712	0.000	3.6084	0.000
AGE	-0.0206	0.007	-0.0191	0.012
INCOMEPP	-7.455E-06	0.104	-8.727E-06	0.039
NUMCHILD	-0.4575	0.002	-0.4276	0.003
EMPLYD	-0.4760	0.250		
STUDENT	-0.5493	0.307		
VEHOWN	-1.4330	0.002	-1.4028	0.001
DISTWORK	-0.0429	0.006	-0.0405	0.018
TIMEPK	-0.0252	0.040	-0.0246	0.040
TIMEOFFPK	0.0778	0.001	0.0714	0.003
NPEAK	0.0195	0.464		
Alpha	2.1757	0.000	2.2261	0.000
N_{obs}	344		344	
Log likelihood	-744.25		-746.17	
Log Lik: Constants only	-1353.11		-1353.11	
LRI	0.45		0.4485	

Note: Alpha is a measure of over-dispersion in the model and has to be greater than 1 for a negative binomial model.

Table 7. OLS Model Results for Willingness to Pay to Avoid Mode Shift from SOV to Bus

VARIABLE NAME	Y =log(Toll) Coefficients	P-value	Y = Log(toll) Coefficients	P-value
CONSTANT	0.7228	0.086	0.3901	0.125
AGE	0.0112	0.034	0.0087	0.046
MALE	0.1535	0.210	0.1621	0.165
INCOMEPP	2.133E-06	0.464		
EMPLYDF	0.2807	0.166	0.2677	0.042
STUDENT	-0.1128	0.685		
GRADUATE	-0.2049	0.229		
VEHOWN	-0.3869	0.102		
WKFLEX	0.3201	0.093	0.317	0.073
DISTWORK	0.0035	0.592		
TIMELOSSPM	-0.0049	0.933		
NPEAK	0.0215	0.176	0.0227	0.129
N_{obs}	257		289	
Adjusted R^2	0.048		0.033	

Y = Natural log of maximum toll willing to pay to avoid bus use (assuming 15 additional minutes of commute time each way)

Table 8. OLS Model Results for Value of 20 minutes Travel Time Savings

VARIABLE NAME	Initial Estimates	P-value	Final Estimates	P-value
CONSTANT	0.5793	0.210	0.4243	0.289
AGE	0.0073	0.190	0.0067	0.210
MALE	-0.1045	0.409		
INCOMEPP	-1.367E-06	0.626		
NUMCHILD	0.1894	0.104	0.1856	0.101
EMPLYD	-0.0824	0.673		
STUDENT	0.7355	0.008	0.9018	0.000
GRADUATE	0.4451	0.005	0.4435	0.004
NPEAK	-0.4343	0.174	-0.4750	0.125
CARPOOL	-0.3985	0.006	-0.4201	0.003
DISTWORK	-0.0086	0.089	-0.0073	0.136
NPEAK	-0.0007	0.966		
TIMELOSSPM	-0.0297	0.614		
Number of observations	211		215	
Adjusted R^2	0.1116		0.1360	

Y = Natural log of value of 20-minute travel time savings during commute round-trip