THE DEMAND FOR URBAN BUS TRANSIT IN CANADA

By Mark W. Frankena*

I. INTRODUCTION

All levels of government in Canada have become increasingly involved in promoting urban public transit, and public ownership and subsidies are now the rule. Government involvement has increased partly in order to stem the decline in ridership and related financial problems facing transit companies, and partly in response to growing public concern over urban, environmental and energy issues.

If governments and transit authorities are to make rational decisions on urban transit policy, they will need information concerning the determinants of transit ridership. The purpose of this paper is to provide empirical estimates of demand functions for urban bus services in Canada. The study uses annual city-wide data for bus systems in 28 urban areas during the years 1962 to 1974, and estimates the demand functions, using two-stage least squares.

Previous studies which have used city-wide data to estimate demand functions for public transit are summarised in Table 1. Other studies have used data on the number of transit trips between pairs of zones (Domencich *et al.* [5]) and on individual routes (Schmenner [24]) within urban areas. These demand studies attempt to explain the number of trips by transit. There are also a large number of modal choice studies which attempt to explain the choice between travel by transit and by automobile at the individual level ([4], [6], [14], [17], [19], [23], [33] and several other studies) or the percentage of trips made by transit rather than automobile between pairs of zones ([30] and other transportation planning studies) or on a city-wide basis [32].

We begin in section II by specifying two alternative demand functions. In section III we present a simultaneous equation model of a transit system which incorporates these demand functions. In sections IV through VI we discuss the estimation and data and compare our empirical results with those of other studies of the demand for transit and modal choice. In section VII we summarise our findings.

*Associate Professor of Economics at the University of Western Ontario. The author would like to thank Åke G. Blomqvist, Gordon W. Davies, Arthur J. Robson, David T. Scheffman, and Robert S. Woodward for suggestions, Kenneth Engelhart and Bernard Yeung for research assistance, and the Canadian Urban Transit Association and Statistics Canada for providing access to unpublished data. This research was financed by a grant from General Motors Corporation, which does not necessarily endorse the analysis or findings.

II. SPECIFICATION OF THE DEMAND FUNCTIONS

We hypothesise that the quantity of bus service demanded *per capita* in an urban area depends upon the money and time costs of travel by bus and by private automobile, average income and other socioeconomic characteristics of the population, and geographical characteristics of the urban area.

Variables

Quantity of bus services per capita

Because Canadian bus companies record data for number of passengers (R) but not for lengths of passenger trips, the dependent variable in the demand function specified here is number of bus rides *per capita* (R/P).[1] Population (P) is measured for the area served by the bus system.

Money and time costs of travel by bus

The money cost of travel by bus is measured by the smaller of the adult ticket and cash fares per ride (F).[2] Like all monetary variables in the study, fares are measured in real terms. Fares are adjusted to 1974 cents by using the national consumer price index, because suitable provincial and municipal CPIs are not available.[3]

We hypothesise that the coefficient on fare in the demand equation is negative. We are also interested in testing the rule-of-thumb used in the transit industry that the fare elasticity of demand is −0.33.

One of the important time costs of travel by bus is the time spent walking to a bus stop, waiting for a bus, and transferring. In principle, average walking and waiting time per trip by bus could be measured by the annual number of bus miles of service per square mile of area served (M/A). If an urban area has more bus miles of service per square mile of area, it typically has a higher density of routes and/or more frequent service.[4] Consequently, average walking and waiting time per ride are generally lower in an urban area with more bus miles per square mile of area.

Unfortunately, the available data on area appear to be highly inaccurate as measures of area served. They generally measure the areas of political jurisdictions,

[1] Because population (P) is included among the exogenous independent variables in the demand equation and because we take logarithms of both R/P and P, there would have been no differences between the empirical estimates of any of the coefficients except P if the dependent variable had been specified as total rides (R).

[2] For most of the observations in the sample, the fare did not depend on the length of the trip. In a few urban areas, primarily in the early years covered by this study, a small additional charge was made for trips beyond the city limits, but such trips were a small percentage of the total for each of these observations.

[3] The municipal CPIs computed by Statistics Canada have a different base in each urban area, and hence cannot be used to compare the cost of living in different cities. Use of the national CPI rather than the appropriate municipal CPIs introduces an error of observation into each of the monetary variables. Since M/P and P may be correlated with the error of observation, a number of coefficients could be biased.

[4] An urban area with more bus miles of service per square mile might also have service during more hours per week. Public transit systems in larger urban areas tend to offer service during more hours of the day and more days of the week [10].

TABLE 1

Studies of Demand for Bus Transit using City-Wide Data

Author (Year)	*Data*	*Model and Estimation*	*Dependent Variable*	*Independent Variables and Elasticities*[a]	
Boyd and Nelson (1973)[f]	Time series of cross-sections 17 U.S. cities Annual 1960-1970 Bus only	Single equation OLS	R/R_{-1}	F/F_{-1} F_{-1}/F_{-2} $(M/P)/(M/P)_{-1}$ $(M/P)_{-1}/(M/P)_{-2}$	−0.47* −0.06 0.76* 0.001
Carstens and Csanyi (1968)[b]	Time series of cross sections 13 Iowa cities Annual 1955-1965 Bus and cable railway combined	Single equation OLS	R/P	F M/P P $S5$	−* +* +* +†
Fairhurst and Morris (1975)[f]	Time series London, U.K. Annual 1953-1973 Bus only	Single equation OLS	R/R_{-1}	F/F_{-1} M/M_{-1} Y/Y_{-1}	−0.3* 0.5* 0.15
Garbade and Soss (1976)[c]	Time series New York City Annual 1954-1973 Bus only	Simultaneous Equation TSLS and Cochrane-Orcutt $T3$ endogenous	R/P	F $T3$ $B2$ $(R/P)_{-1}$	−0.37* +* +* +*
Gaudry (1975)[g]	Time series Montreal Monthly 1956-1971 Bus and subway combined Adults only	Single equation Cochrane-Orcutt[e]	R	F $T1$ $T2$ $X4$ $X6$ Y $W4$ $W2$ $W3$ $W5$	−0.15* −0.54* −0.27* −0.10 0.42** 0.08 – –* – +*

Huang (1973)	Time series Edmonton Annual 1961-1970 Bus only	Single equation OLS	*R*	*F*2 $F2_{-1}$ *X*7 *Y* *P*		−0.22* −0.17** 0.63** 1.11 0.36**
Litt (1975)	Cross section 39 Canadian Cities Annual 1971 Bus and subway combined	Single equation OLS	*R*/*P*	*F* *M*/*P* *M*2/*P* *X*4/*P* *Y* *S*3 *S*6 *P*/*A*		−0.15 1.03* 0.75* −0.75* −0.32 0.15* 1.16* −0.10
Nelson (1972)	Cross section 44 and 51 U.S. Cities Annual 1960 and 1968 Bus only	Simultaneous equation TSLS *F* and *M*/*P* endogenous	*R*	*F* *M*/*P* *X*4/*P* *P*/*X*8 *Y*1 *Y*2 *S*1 *S*2 *P* *A*	*1960* −0.81* 0.92* −0.11 n.i. – – – – 1.11† 0.002	*1968* −0.67* 1.35* −0.18 0.16 −† −†† −† −† 1.10† 0.021
Sohn (1975)	Time series New York City Annual 1947-1971 Bus and subway combined	Single equation OLS	*R*/*P*	*F* *X*4/*H* *X*7 *Y* *N*		−0.30* −0.65* 0.65* −0.14† 0.40

Author (Year)	*Data*	*Model and Estimation*	*Dependent Variable*	*Independent Variables and Elasticities*[a]	
Veatch (1973)	Cross section 36 U.S. Cities Annual 1970 Bus only	Simultaneous equation TSLS[d] *M* and *X*5 endogenous	*R*	*M* *X*5 *P* *A*	+* +* −* −
Wabe and Coles (1975)	Cross section 30 U.K. Cities Annual 1966 Bus only Nonwork only	Single equation OLS	*R/P*	*F*3 *M/P* *X*4/*N* *P*	−0.49* 0.76* −0.60* −0.14†

Notes: n.i.: Not included.
*, **, †, ††: See Notes to Table 2.
a: Subscript"−1" means lagged one period, "−2" means lagged two periods.
b: *F, P,* and *S*5 appear in interactive forms. Significance levels apply to the interactive terms.
c: *Y* and *N* not significant and left out.
d: OLS results very similar.
e: Grouped-equation estimates presented in Gaudry [12] are very similar to Cochrane-Orcutt estimates.
f: Time trend (implicit in constant) was negative but not significant.
g: Also trend, seasonal, and dummy variables.

Glossary of Names of Variables in Table 1

Name	*Description*
A	Area
*B*2	Fraction of New York City population residing in the outer borough of Queens County
F	Real fare
*F*2	Nominal fare
*F*3	Fare per passenger mile
H	Number of households
M	Vehicle miles
*M*2	Subway route miles
N	Employment
P	Population
R	Rides
*S*1	Percentage of population under 15 or 18
*S*2	Percentage of population 65 or over
*S*3	Percentage of population born outside Canada
*S*5	Ratio of nonworkers to workers in population
*S*6	Labour force participation rate
*T*1	Transit waiting time
*T*2	Transit in-vehicle travel time
*T*3	Transit frequency
*W*2	Rainfall
*W*3	Snowfall
*W*4	Absolute value of difference between actual and "desired" temperature
*W*5	Cumulative snowfall
*X*4	Number of automobiles
*X*5	Number of households without an automobile
*X*6	Automobile in-vehicle travel time
*X*7	Cost of owning and operating an automobile
*X*8	Highway capacity
Y	Real income
*Y*1	Percentage of population with annual income under $3,000
*Y*2	Percentage of population with annual income over $10,000

which often include large undeveloped sections of the city. Consequently, in this study we use reported data on population served as a proxy for area served. The justification for this is that we expect the developed area of the city which is served by the bus system to be more closely related to population than to total area. We hypothesise that the coefficient of bus miles *per capita* (M/P) is positive.

It should be noted that use of population as a proxy for area introduces two problems, because population is not proportional to area.[5] First, if population is proportional to a power of area, $P=\gamma A^{1/\delta}$ where $\delta \neq 1$,[6] then use of P (rather than P^{δ}) as a proxy for A in the bus service variable involves a misspecification. Second, if the relationship between population and area is stochastic, use of P (or P^{δ}) as a proxy for A also introduces an error of observation problem. Consequently, one expects that the estimated coefficients of the bus miles variable and any variables correlated with area served will be biased. For example, for a given population served, if a city with a smaller area served systematically has a larger level of bus miles of service, which is what the model outlined in section III would predict, then use of P as a proxy for A will lead to an upward bias in the estimated coefficient of the bus miles variable.[7]

Data on speed of buses could not be obtained. However, average speed may vary between urban areas of different sizes because of differences in traffic congestion and occasional use of express buses. Consequently, as a crude proxy for speed, we include the population of the area served (P) as an independent variable. However, for reasons which are discussed in the following sections, population may also serve as a proxy for a number of other determinants of the demand for bus services *per capita*. Furthermore, as we have indicated above, use of P as a proxy for A in the bus miles variable will probably bias the coefficient on P. As a result, we have no hypothesis concerning the sign of the coefficient on population, and we cannot use that coefficient to test specific hypotheses about the effect of the speed of buses.

Money and time costs of travel by automobile

Four costs of travel by automobile are included in the demand equation on the ground that they measure the price of the principal substitute for bus travel: two indexes of the costs of owning an automobile, the price of gasoline, and an index of the speed of travel by automobile and the cost of parking an automobile.

[5] Although several of the other studies of the demand for transit which are summarised in Table 1 have measured service by bus miles *per capita*, they have not considered the implications of this misspecification in interpreting their empirical results.

[6] There is casual evidence from Australia [22] that if a city's boundary is defined as occurring where population density falls to 500 people per square mile, this relation holds with $\delta = 0.7$.

[7] As an example of the latter bias, suppose that two cities have the same population but that city I has half the area, twice the bus miles of service, and twice the total bus ridership found in city II, while all other things are equal. In this case, rides *per capita* and bus miles *per capita* would be twice as high in city I as in city II, while bus miles per square mile of area would be four times higher in city I than in city II. One would estimate that the arc elasticity of demand for rides *per capita* with respect to bus miles *per square mile* was 0.56, and that the arc elasticity of demand for rides *per capita* with respect to bus miles *per capita* was unity. In this case, the unbiased estimate of the elasticity of demand with respect to bus miles of service (holding area and population constant) would be 0.56, not unity.

The two indexes of the costs of owning an automobile measure real depreciation and real net interest costs. First, we use an index of the real purchase price of an automobile (X_1) constructed from Statistics Canada and Canadian Red Book data. Second, we use an index of the interest cost of funds used to hold an automobile net of the capital gains on a non-depreciating automobile (X_2). The latter index is constructed as the prime lending rate of commercial banks minus the percentage increase in the nominal purchase price of an automobile. We assume that depreciation is proportional to X_1 while the net interest cost of holding an automobile is proportional to the product $X_2 X_1$.

We use the real price of gasoline (X_3) to measure one of the costs of operating an automobile.[8] As a crude proxy for the speed of automobiles and for the real cost of parking an automobile, we use the population of the area served by the bus company (P).

We hypothesise that the coefficients of all these costs of owning and using an automobile are positive. However, for reasons which are discussed in other sections, we have no hypothesis concerning the sign of the population variable.

We also considered an alternative specification of the demand function for bus rides *per capita* in which the stock of private automobiles *per capita* was included as an explanatory variable. In this case, the two indexes of the costs of owning an automobile were omitted from the demand function for bus rides, but an additional equation explaining automobile ownership *per capita* was specified. This alternative approach is not pursued in this paper because our empirical work found no support for the hypothesis that the demand for bus rides depends on the stock of automobiles.

Although this finding is surprising, Nelson [20] obtained a similar result in a study based on U.S. data. By contrast, a majority of the studies of the demand for transit and modal choice which have included an automobile ownership variable have found that automobile ownership has a significant negative effect on transit usage [6], [16], [25], [32]. Our findings may be due to the inappropriateness of using Statistics Canada annual automobile registration data, which pertain to urban areas and in some cases counties, as measures of automobile ownership in areas served by bus companies. In this case, since income is an important determinant of automobile ownership, and since automobile ownership *per capita* may be correlated with population, omission of the correct automobile ownership variable could significantly influence the income-elasticity of demand for transit and the coefficient of the population variable in the present study.

Income and other socioeconomic variables

We hypothesise that the demand for bus rides *per capita* depends on average real income. Other studies of urban travel behaviour generally indicate that on average people with higher incomes (a) take more intraurban trips [21] but (b) own more automobiles, put a higher value on time savings, and therefore are less likely to take a given trip by bus, since travel by bus is almost invariably less expensive but slower than travel by automobile [8]. The net effect of average income on bus rides *per*

[8] Maintenance costs are not included because of lack of satisfactory data.

capita depends on whether the effect of income on total number of trips by all modes outweighs the effect of income on choice of mode. Thus we have no hypothesis concerning the sign of the coefficient of income. Income is measured as average real weekly wage and salary income per employed worker (Y).

We hypothesise that a number of other socioeconomic characteristics of the population influence the demand for bus services. We include percentage of the population under 15 years old (S_1) and percentage of the population 65 years old and over (S_2). One expects that members of these age groups will (a) take fewer intraurban trips but (b) be more likely to take a given trip by bus, at least in the case of the young. Consequently, we have no *a priori* hypotheses about the signs of the coefficients of these variables.

We also include percentage of the population born outside Canada (S_3). This variable is included because other studies have sometimes found that variables such as percentage of immigrants in the population [16] and non-white race [6], [24] have a significant positive effect on use of public transit.

Finally, we include the female labour force participation rate (S_4). Females account for 60 to 77 percent of bus passengers in a sample of eight Canadian urban areas for which data are available [10], and Warner [33] found that, other things being equal, females are more likely to travel by public transit than are males. It is hypothesised that the coefficient of S_4 is positive.

All four of these socioeconomic variables are measured from census data for 1971 rather than data for the years of the actual observations, and hence they are time-invariant.

Geographical Variables

We hypothesise that the demand for bus trips *per capita* depends on the spatial structure, climate, and size of the urban area. Probably the most important feature of urban spatial structure is the percentage of employment which is located in the central business district and therefore relatively accessible by bus. The female labour force participation rate may act as one proxy for location of employment, because urban areas with large female proportions of workers may have relatively large, centrally located office sectors. This is one reason for anticipating a positive coefficient on the female participation rate. We also include the percentage of dwelling units constructed before 1920 (B) as a measure of the age of the urban area. Employment may be more centralised in older urban areas, and consequently we hypothesise that the coefficient on B will be positive.

We hypothesise that the demand for bus trips depends on the severity of the winter and on precipitation.[9] We include the number of days per year with temperature below freezing (W_1), inches of rain per year (W_2), and inches of snow per year (W_3). We have no hypotheses concerning the signs of these weather variables. In bad weather, some people might stay home or travel by car rather than travel by bus. However, some might travel by bus rather than by car, while still others might travel by bus rather than walk or ride bicycles. All weather variables are measured by long-term averages, and are time-invariant.

[9] An alternative hypothesis, which we did not test, would be that the demand for bus trips depends on the deviation of weather conditions from their long-term averages.

There are at least five reasons why the size of the urban area may affect the number of bus trips demanded *per capita*. Three reasons have been discussed already. First, the real cost of parking may be higher in larger urban areas. Second, the average speed of buses and automobiles may depend upon the size of the urban area. Third, automobile ownership *per capita* may be lower in larger cities. Fourth, the average trip may be longer in larger urban areas. Bus fares are charged per ride regardless of length, while automobile operating costs are proportional to distance. Consequently, for a given fare level and gas price, the relative money cost of travel by bus may be lower in larger urban areas. Finally, if the average trip is longer in larger urban areas, fewer trips by all modes may be taken.

As a measure of size, we use the population served by the bus system (P). We have no hypothesis concerning the net effect of population on demand for bus rides *per capita*.

Form of the Demand Function

The dependent variable and, with one exception, all independent variables in the demand function are transformed into natural logarithmic form. Thus, we impose the assumption of constant elasticity of demand with respect to these independent variables. The one exception is the fare, which is used without transformation in order to make the fare-elasticity of demand depend on the level of fare, more or less in the way it would along a straight-line demand curve.[10]

Thus, we hypothesise:

$$(1) \quad \ln\left(\frac{R}{P}\right) = \alpha_0 + \alpha_1 F + \alpha_2 \ln\left(\frac{M}{P}\right) + \sum_{i=1}^{3} \alpha_{1+2} \ln X_i + \alpha_6 \ln Y + \sum_{i=1}^{4} \alpha_{i+6} \ln S_i + \alpha_{11} \ln B + \sum_{i=1}^{3} \alpha_{i+11} \ln W_i + \alpha_{15} \ln P + \epsilon_1$$

$$\alpha_1 < 0; \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_9, \alpha_{10}, \alpha_{11} > 0; \alpha_6, \alpha_7, \alpha_8, \alpha_{12}, \alpha_{13}, \alpha_{14}, \alpha_{15} \gtreqless 0.$$

Because we are using pooled cross-section and time-series data, we also wish to consider a covariance model to test the hypothesis that the intercept in the demand equation takes on different values in different cities. The hypothesis of different intercepts is plausible because of our failure to include in the demand equation variables providing adequate measures of a number of those determinants of the demand for transit which are likely to vary between cities, such as automobile ownership, speeds of cars and buses, area served, and location of travel destinations. Our interest in this hypothesis arises principally because omission of such variables could bias the estimates of the coefficients of the included variables.

The hypothesis of different intercepts can be tested by estimating an alternative to (1) which includes dummy variables for the different cities. However, these

[10] I owe this feature of the specification to Nelson [20] and Fairhurst and Morris [7]. We do not wish to assume a constant elasticity of demand with respect to fare as well as with respect to miles of bus service, because, according to the condition in equation (3) below, the absolute values of these elasticities should be equal in equilibrium for a bus firm which maximises rides. However, if one uses the logarithm of the fare as an independent variable, the fare elasticity at the sample mean and the other coefficients are virtually unaffected in our empirical estimation.

dummy variables would be perfectly collinear with the time-invariant variables in the demand equation, S_1, S_2, S_3, S_4, B, W_1, W_2, and W_3. Consequently, the covariance model can be estimated only if these other variables are dropped. Thus, as an alternative to (1) we hypothesise:

$$(1') \qquad \ln\left(\frac{R}{P}\right) = \alpha_0 + \sum_{j=2}^{28} \rho_j N_j + \alpha_1 F + \alpha_2 \ln\left(\frac{M}{P}\right) + \sum_{i=1}^{3} \alpha_{i+2} \ln X_i + \alpha_6 \ln Y + \alpha_{15} \ln P + \epsilon_1'$$

where hypothesised signs of α_i are the same as for model (1); N_j are dummy variables for cities which take the values 1 and 0; and $\rho_j \gtreqless 0$.

The fare-elasticity of demand E_F is given by $\alpha_1 F$ in both (1) and (1'), and we wish to test the rule-of-thumb that $E_F = -0.33$ at the sample mean.

III. SIMULTANEOUS EQUATION MODEL OF A TRANSIT SYSTEM

Consideration of the process by which the number of bus trips *per capita* is determined quickly convinces one that at least two variables on the right-hand side of the demand equation—fare and bus miles *per capita*—are determined simultaneously with bus trips *per capita*. Assume that bus companies set the fare and bus miles variables to maximise ridership, subject to a constraint on the cost-revenue ratio. When ridership *per capita* is unusually high because of an unmeasured attribute of the transport system, population or city (that is, when there is a large positive error in the demand equation), then the bus system will have an unusually high revenue and will respond by reducing the fare and/or increasing the bus miles of service; that is F and M/P will be correlated with the error in the demand equation. Use of ordinary least squares (*OLS*) to estimate the demand equation would attribute the higher ridership to the lower F and/or higher M/P in such cases, and hence lead to inconsistent estimates of the fare and service elasticities of demand. In particular, one would expect the *OLS* estimates to be biased away from zero. In order to avoid this simultaneous equations bias, we use two-stage least squares (TSLS) to estimate the demand equations. TSLS purges F and M/P of the correlation with the error in the demand equation and hence yields consistent estimates of their parameters.

The simultaneous equation model which we use is similar to one introduced by Nelson [20] and estimated by him on U.S. data. We suppose that the bus firm in a particular urban area is a monopolist which sets the fare per trip and the number of bus miles of service to maximise the number of bus trips taken.[11] The bus firm

[11] This objective is plausible for publicly owned firms, but probably not for privately owned ones. Of the 223 observations in the sample, 20 are for privately owned firms. For reasons which are explained below in connection with equation (6), when the demand equation is estimated we include among the instruments a dummy variable which measures whether the firm is public or private. This variable may pick up not only the effects of differing access to subsidies but also the effects of different objective functions. Another way to formulate the model would be to let the bus company choose bus hours (rather than miles) of service and let bus speed, and hence bus miles of service, be determined by congestion. This modification might be important if we were concerned primarily with the supply side of the model, but it would not have much effect on our technique of estimating the demand equations from the available data.

takes as exogenously given the population and area served[12]; therefore in effect it chooses the fare per trip and the number of bus miles of service per square mile of area (M/A) to maximise the number of bus trips taken *per capita*. The firm operates under a constraint on its cost-revenue ratio imposed by government regulatory and subsidy policies. The cost per bus mile of service is a constant.[13]

Thus, the firm chooses F and M/A to maximise the number of bus trips demanded *per capita*:

(1″) $R/P = f(F, M/A)$

subject to the constraint:

(2) $CM/FR = K$

where

R = passenger rides by bus;
P = population of area served;
F = fare in cents per ride;
M = bus miles of service;
A = area served in square miles;
C = cost in cents per bus mile of service;
K = cost-revenue ratio.

A necessary condition for this maximum is:

(3) $1 > E_{M/A} = -E_F > 0$

where $E_{M/A}$ and E_F are the elasticities of demand with respect to bus miles of service per square mile of area and with respect to the fare.

Suppose that the demand function is:

$$(1''') \quad ln \frac{R}{P} = \alpha_0 + \alpha_1 F + \alpha'_2 ln \left(\frac{M}{A}\right)$$

Solving the constrained maximisation problem for F and M/A, taking logarithms, and adding stochastic error terms, one derives the following equations describing the behaviour of the bus firm:

$$(4) \quad ln\, F = ln(-\alpha'_2/\alpha_1) + \varepsilon_2$$

$$(5) \quad ln(M/A) = ln(-\alpha'_2/\alpha_1) + ln\, K - ln\, C + ln(R/P) + ln\, P - ln\, A + \varepsilon_3$$

From constraint (2), one can determine that $\varepsilon_2 = \varepsilon_3$ in equations (4) and (5).

For reasons which we have discussed in section II, we use M/P rather than M/A in the empirical estimation. Solving equation (5) for $ln\,(M/P)$, one obtains:

$$(5') \quad ln\left(\frac{M}{P}\right) = ln(-\alpha'_2/\alpha_1) + ln\, K - ln\, C + ln\left(\frac{R}{P}\right) + \varepsilon_3$$

Further, we hypothesise that the cost-revenue ratio of the bus firm can be explained by its ownership and control and by government subsidy policies. In particular, we assume that the cost-revenue ratio depends on the following five variables:[14]

[12] A case could be made for treating the population and area served as endogenous, since a bus firm may not serve the entire urban area in which it operates.

[13] The assumption that the cost per bus mile is constant is consistent with empirical cost studies by Lee and Steedman [15] and Nelson [20].

[14] A case could be made for treating D_2, D_3, and D_4 as endogenous.

(i) D_1: If the firm which operates the bus company also supplies electric power, it can (and typically does) subsidise its bus operations from profits earned on its electricity operations. $D_1 = 1$ if the bus firm also supplies electricity and 0 otherwise.

(ii) D_2: If the firm is publicly owned, we hypothesise that it will receive larger government subsidies. $D_2 = 1$ if the bus firm is publicly owned and 0 if it is privately owned.

(iii) D_3: If the bus system is not only publicly owned but operated as a municipal department under the direct control of the city council, we hypothesise that it will receive more government subsidies than if it is operated by a commission which is at least nominally independent of the city council. $D_3 = 1$ if the bus system is operated as a municipal department and 0 if it is operated by an independent commission.

(iv) D_4: If the provincial government subsidises the bus company, it will operate with a higher cost-revenue ratio. $D_4 = 1$ if the province gave a subsidy to the bus firm and 0 if it did not.

(v) T: Over time, government subsidies have increased. T is a trend variable which takes a value of 101 in 1962, 102 in 1963, etc.

Thus, we hypothesise that:[15]

(6)
$$\ln K = \beta_0 + \sum_{i=1}^{4} \beta_i D_i + \beta_5 \ln T + \epsilon_4$$

and

$$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 > 0.$$

The full simultaneous equation model consists of the three equations (1) (or alternatively (1′)), (5′), and (6), describing the behaviour of transit riders, operators, and regulatory agencies respectively, plus the constraint given by (2). Equation (4) is redundant, since it is implied by (5′) and (2). The error term in each equation is assumed to be normally distributed with zero mean and constant variance and to be independent both cross-sectionally and in time.

IV. BACKGROUND TO ESTIMATION

In estimating the demand equation, we treat R/P, F, M/P, and K as endogenous. Because we have no data on K or C, we are forced to ignore constraint (2) and proceed as if the model consisted of the four equations (1) (or alternatively (1′)), (4), (5′), and (6).

Specification (1)

We have no data on the cost per bus mile, C, but we have data on three components of cost. Therefore we use these three elements of cost rather than *ln C* as in-

[15] An alternative specification for equation (7) would drop the constant term and include a separate dummy variable for each of the twelve categories of firms implied by D_1, D_2, D_3, and D_4. This specification was not used because several of the resulting categories would include only one firm.

struments in the two-stage least squares estimation of the demand equation. The three elements of cost for which we have data are the log of the wage rate of bus drivers per hour ($ln\ C_1$), the log of the price of diesel fuel per gallon to the bus firm (excluding the fuel tax in cases where the bus firm is exempt) ($ln\ C_2$), and a dummary variable (C_3) which takes a value of one if the bus firm pays municipal property tax and a value of zero if it is exempt.[16]

In addition to the exogenous variables in equations (1), (5′), and (6), we use the log of the area served by the bus company ($ln\ A$) as an instrument in the two-stage least squares estimation of the demand equation. Thus, the full list of instruments used in estimating specification (1) is: $ln\ X_1$, $ln\ X_2$, $ln\ X_3$, $ln\ Y$, $ln\ S_1$, $ln\ S_2$, $ln\ S_3$, $ln\ S_4$, $ln\ B$, $ln\ W_1$, $ln\ W_2$, $ln\ W_3$, lnP, $ln\ C_1$, $ln\ C_2$, C_3, D_1, D_2, D_3, D_4, $ln\ T$, $ln\ A$, and a constant.

Specification (1′)

A number of the instruments used in estimating specification (1) are time-invariant for each city, and hence collinear with the set of city dummies used for specification (1′). These time-invariant instruments were dropped, so the full list of instruments used in estimating specification (1′) is: $ln\ X_1$, $ln\ X_2$, $ln\ X_3$, $ln\ Y$, $ln\ P$, $ln\ C_1$, $ln\ C_2$, D_4, $ln\ T$, $ln\ A$, $N_j (j = 2,\ldots,28)$, and a constant.

The demand equations are identified because the number of zero restrictions exceeds the number of endogenous variables less one. In order to use data on ridership to estimate the demand functions, we assume that there was no excess demand for bus services: that is, buses were not too full to admit all people wishing to ride.

V. DATA

The demand equations are estimated using 223 observations from 28 urban areas during the years 1962 to 1974.[17] These represent all the observations for the specified time period which meet the following criteria: (a) the urban transit system was a member of the Canadian Urban Transit Association; (b) the system operated only conventional motor and trolley buses, not streetcars, subways, or dial-a-ride buses; (c) the urban area had a school bus system which was operated separately from the public bus system; (d) the system did not sell passes to adult passengers; (e) the system was not on strike; (f) complete data for all variables for the particular urban area and year are available; and (g) at least two annual observations are available for the system.

[16] A case could be made for treating $\log C_1$, $\log C_2$, and C_3 as endogenous.

[17] Except as noted here, all data were obtained from the Canadian Urban Transit Association. The following data were obtained from Statistics Canada publications: consumer price indexes for all items and automobile purchase from Catalogue 62-002, Tables 8 and 9; average weekly earnings from Catalogue 72-002, Table 17; climatic data from *Canada Year Book* (1960, 33-77); motor vehicle fuel tax rates from *Canada Year Book*; urban spatial structure and socioeconomic variables other than population served and average weekly earnings from *1971 Census of Canada*. In addition, unpublished data on the price of gasoline for urban areas were obtained from Statistics Canada. Regional automobile price differentials were obtained from Canadian Red Book (monthly).

In interpreting the empirical results, the reader may find it helpful to know some of the properties of the pooled cross-section and time-series data that are used. The first thing to note is that the data set is "unbalanced"; that is the number of observations for each city is not uniform and ranges from two to thirteen.

The second and most striking feature of the data is that, for the dependent variable and most of the independent variables, there is considerably more cross-sectional variation than time-series variation. The time series are relatively short, while the range of city sizes covered is wide, with population served ranging from just under 25,000 in Orillia to over 900,000 in Vancouver. Moreover, a number of the independent variables and instruments used in specification (1) are time-invariant, while only two ($ln\ X_2$ and $ln\ T$) are invariant across cities. When the dependent variable in the demand equations, $ln\ R/P$, is regressed on a complete set of city dummy variables, the R^2 is 0.94. When it is regressed on a complete set of year dummy variables, the R^2 is only 0.16.

VI. EMPIRICAL RESULTS

The two-stage least squares and ordinary least squares estimates of the two specifications of the demand equation are presented in Table 2. In each case, we present the estimated fare elasticity of demand (E_F) at the mean of F. Along with the TSLS estimates of the demand equation we present the R^2 for the first-stage estimates of the reduced form equations for F and $ln\ M/P$. For specification (1′) we do not present the estimates of the constant or city dummies, since they are not of general interest.

TABLE 2

Estimates of Equations (1) *and* (1′)

		Equation (1)		*Equation* (1′)	
	Independent Variable	*TSLS*	*OLS*	*TSLS*	*OLS*
	Constant	−6.48††	−5.94†	n.i.	n.i.
		(1.81)	(−2.08)		
	27 city dummy variables	—	—	n.i.	n.i.
F	Adult bus fare	−0.015**	−0.013*	−0.0037	−0.0077*
		(−1.32)	(−3.15)	(−0.51)	(−3.60)
$ln\frac{M}{P}$	Log of bus miles *per capita*	1.12*	0.89*	0.61*	0.70*
		(13.75)	(19.43)	(3.73)	(12.07)
$ln\ X_1$	Log of automobile purchase price	−0.15	−0.10	0.0046	0.0002
		(−1.84)	(−1.31)	(0.10)	(.01)
$ln\ X_2$	Log of net interest rate on funds used to hold an automobile	−0.018	−0.021	0.0062	0.0090
		(−0.78)	(−0.95)	(0.46)	(0.92)
$ln\ X_3$	Log of gas price	0.89*	1.03*	0.37**	0.43*
		(2.91)	(3.77)	(1.64)	(2.72)
$ln\ Y$	Log of wage and salary income per worker	−0.63†	−0.69†	−0.16	−0.042
		(−2.37)	(−4.08)	(−0.71)	(−0.41)

Independent Variable		Equation (1) TSLS	Equation (1) OLS	Equation (1′) TSLS	Equation (1′) OLS
$ln\ S_1$	Log of percentage of population under 15	1.30†	1.01†	—	—
		(3.51)	(3.01)		
$ln\ S_2$	Log of percentage of population 65 and over	0.083	0.13	—	—
		(0.41)	(0.76)		
$ln\ S_3$	Log of percentage of population born outside Canada	0.15*	0.16*	—	—
		(3.38)	(4.74)		
$ln\ S_4$	Log of female labour force participation rate	0.51*	0.52*	—	—
		(1.97)	(2.34)		
$ln\ B$	Log of percentage of dwelling units constructed before 1920	0.068**	0.066**	—	—
		(1.30)	(1.40)		
$ln\ W_1$	Log of number of days below freezing	0.021	0.041	—	—
		(0.26)	(0.60)		
$ln\ W_2$	Log of rainfall	0.16†	0.11†	—	—
		(2.20)	(2.02)		
$ln\ W_3$	Log of snowfall	−0.029	−0.041	—	—
		(−0.33)	(−0.54)		
$ln\ P$	Log of population	0.11††	0.17†	−0.31†	−0.33†
		(1.78)	(5.65)	(−4.21)	(−6.17)
	Other Statistics				
	R^2	0.861	0.879	0.966	0.980
	$F(d.f.)$	86(15,207)	100(15,207)	158(34,188)	275(34,188)
	$D.W.$	0.65	0.52	1.08	1.23
	E_F at mean of F	−0.38	−0.32	−0.09	−0.19
	R^2 for stage 1 reduced form for F	0.657	—	0.782	—
	R^2 for stage 1 reduced form for $ln\ M/P$	0.797	—	0.965	—

NOTES TO TABLE 2

t-statistics are in parentheses.

*: significantly different from zero at 5 per cent level, one-tailed test.
†: significantly different from zero at 5 per cent level, two-tailed test.
**: significantly different from zero at 10 per cent level, one-tailed test.
††: significantly different from zero at 10 per cent level, two-tailed test.
n.i.: of no general interest.

A one-tailed test is applied if there is a hypothesis about the sign of the coefficient, a two-tailed test is applied if there is not. The non-significance of $ln\ X_1$ in specification (1) is due to the implausible sign rather than the absolute size of the t-statistic.

Before we consider the estimates of the individual parameters, several general features of the estimates should be noted.[18] First, since most studies of the demand for urban transit based on city-wide data have used OLS (see Table 1), it is of some interest to compare our TSLS and OLS estimates. We had expected the TSLS estimates of the fare and bus miles coefficients to be lower in absolute value than

[18] It should also be noted in passing that omission of any combination of the included variables which had signs conflicting with our hypotheses, or which were insignificant, leads to no significant or interesting change in the estimated parameters of the remaining variables.

the OLS estimates, because of the simultaneous equations bias present in the OLS estimates. The estimates of specification (1′) are consistent with this expectation, but the estimates of specification (1) are not.

Second, with the principal exception of *ln P*, virtually all the estimated coefficients are lower in absolute value for specification (1′) than for specification (1). One interpretation of this result stems from the fact that both specifications of the demand equation assume that ridership has adjusted completely to the fare, service, and other variables, while in reality the adjustment could take several time periods, because automobile ownership and locational decisions are made infrequently. Since cross-sectional variation dominates in specification (1), the estimated elasticities might be expected to be near their long-run values. By contrast, in specification (1′) the cross-sectional variation is attributed to the city dummies, and hence the estimated elasticities of ridership with respect to other variables might be expected to be near their short-run values.

Third, specification (1′) gives a significantly better fit than specification (1). This indicates that specification (1) fails to include significant determinants of the demand for transit which vary among cities, and suggests that at least for short-run elasticities specification (1′) may be more appropriate. This finding casts some doubt on how one should interpret estimates based on a single cross section of annual city-wide data, such as [16], [20], [31] and [32].

Fourth, the Durbin-Watson statistics (adjusted for gaps in the data) reveal significantly positive first-order autocorrelation of the residuals. Consequently, the estimated standard errors of the coefficients are biased downward, and the t-statistics in Table 2 overstate the significance of the coefficients. It should be noted that the time patterns of the residuals vary substantially among cities: that is, the autocorrelation is not due primarily to omission of a time variable common to all cities.

Fare

The TSLS estimates of the coefficient of fare are negative, as expected; but in (1) the estimate is significantly different from zero only at the 10 percent level and in (1′) it is not significant. The coefficients imply point estimates of the fare elasticity of demand of −0.38 and −0.09 respectively for (1) and (1′) at the mean of the fare variable. The first is very close to the rule-of-thumb (−0.33) used in the industry and the second is not significantly different at the 10 percent level. Both are consistent with the prediction in equation (3) that $0 > E_F > -1$. This finding suggests that the typical bus system could reduce its deficit by increasing its fare.

Estimates of the fare elasticity in other studies of the demand for transit (see Table 1 for examples) range from −0.15 in Litt [16] and for adults only in Gaudry [11][19] to beyond −1.0 in Schmenner [24], and estimates larger in absolute value than −0.50 are unusual.[20]

One implication of our estimates is that in general the fare elasticity of demand

[19] In a subsequent study, Gaudry [12] reports fare elasticities of −0.16 for adults and −0.44 for schoolchildren.

[20] In comparing the results of different studies, it is important to keep in mind that estimates based on aggregate data are subject to bias when the geographical area over which the aggregation is made is not homogeneous [18].

for bus transit probably is not as high as was suggested in the pioneering study by Nelson [20]. Using a model similar to the one employed in the present study for specification (1) and the same estimating technique, Nelson estimated the fare elasticity as −0.81 and −0.67 for two cross-sectional samples. Nelson's higher fare elasticities might result from the different characteristics of his samples. One possible explanation for the difference between the fare elasticities estimated by him and by us (as well as the difference between the fare elasticities for his two samples) is that 93 and 65 percent respectively of his observations were for private firms, compared with only 9 percent of the observations in the present study. If firms with different ownership characteristics behave differently and private firms set higher fares, the estimates of the fare elasticity could depend on the ownership characteristics in the sample. This is because in equations (1) and (1′) the fare elasticity at the sample mean is proportional to the mean fare.

Bus Service

The TSLS estimates of the coefficient of bus miles of service *per capita* are positive, as expected, and significantly different from zero at the 5 percent level. The TSLS estimates of the elasticity of demand with respect to bus miles of service *per capita* are 1.12 and 0.61 for (1) and (1′) respectively. The first of these estimates appears implausibly large as a general description of the behaviour of bus transit demand. Also, contrary to the condition for ridership maximisation (3), the estimates indicate that the elasticities of demand with respect to fares and bus miles of service are not equal in absolute value. The estimates suggest that the typical bus company could increase ridership by raising fares and using the additional revenue to increase service. It should be recalled, however, that the bus miles elasticities are derived for the variable M/P rather than M/A, and, for reasons discussed in section II, it appears likely that this causes an upward bias in these estimates.[21]

Estimates of the elasticity of demand for transit trips with respect to vehicle miles of service *per capita* in other studies range from +0.76 in Boyd and Nelson [1] and for nonwork trips in Wabe and Coles [32] to +1.35 for one of the two samples in Nelson [20]. Fairhurst and Morris [7] estimate the elasticity of ridership with respect to bus miles of service to be +0.5.

The issue of an upward bias in the service elasticity is obviously important for policy purposes. One check on this can be made by examining the results of other studies which specify the bus service variable in terms of walking, waiting, and transferring time, headway, or frequency rather than bus miles. First, however, we must consider the expected relationship among these elasticities. Suppose that bus companies establish their routes and frequencies so as to maximise ridership, given the level of bus miles of service and the hours of operation. Suppose also that a one percent increase in bus miles of service permits a V percent increase in density of routes plus a $1-V$ percent increase in frequency of buses, where $0 \leq V \leq 1$. Suppose

[21] In principle, we could use equation (3) to derive an estimate of $E_{M/A}$ or α_2' in equation (1‴). However, we have not enough confidence in our specification of the behaviour of bus firms to do this. For example, bus firms may operate with both fares and bus miles of service below the levels which would maximise ridership as a result of constraints on fares imposed by municipal and provincial governments. If they do so, one would expect $E_{M/A} > -E_F$.

finally that a one percent increase in density leads to a one percent reduction in walking time, and that a one percent increase in frequency leads to a one percent reduction in headway time and a one percent reduction in waiting time. In this case, for marginal changes in service one would expect that the absolute values of the elasticities of demand with respect to bus miles of service, frequency, headway time, walking time, and waiting time would all be equal in absolute value. This equality results from identities connecting some of these measures of service and from the equilibrium conditions for ridership maximisation. It follows that one would expect the absolute value of the elasticity of demand with respect to bus miles to be half that of the elasticity with respect to the sum of walking and waiting time, or somewhat less than half the elasticity with respect to the total time spent walking, waiting, and transferring.

Turning now to studies which use these alternative measures of service, Gaudry [11] estimated the elasticity of demand with respect to transit waiting time to be −0.54, using city-wide data. Domencich *et al.* [5] estimated the elasticity of demand with respect to time spent walking (or using other access modes), waiting, and transferring to be −0.71 for work trips and less (in absolute value) than −0.59 for shopping trips, using interzonal aggregate data. Schmenner [24] estimated the elasticity of demand with respect to the headway time between buses to be −0.71 to −1.39 for various samples and specifications, using route data.

There are also a number of modal choice studies based on individual trip data which estimate the elasticity of transit choice with respect to walking and waiting time. These elasticities are different in important ways from the elasticities in most of the studies of the demand for transit. First, the modal choice studies are generally limited to subsamples such as work trips by individuals who belong to families which own an automobile. Second, these studies investigate the effect of the independent variables on the choice of mode for a trip that would be taken anyway, and do not consider their effect on the number of trips. Consequently, the studies of elasticities in demand and modal choice are not directly comparable.

McFadden [17] estimated elasticities of transit choice with respect to walking, waiting, and transfer time to be −0.43 for work trips by people with access to both cars and buses. Quarmby [23] estimated the elasticity of transit choice with respect to frequency to be +0.14 for work trips by car owners.

Apart from Schmenner's bizarre estimates, the magnitudes of the elasticities for other specifications of bus service are consistent with the view that specification of the bus service variable as M/P leads to an upward bias in the estimate of the elasticity of demand with respect to vehicle miles of service, and that specification of the demand equation as (1) rather than (1′) in the present study introduces a further severe upward bias.

Automobile Costs

Our estimates provide no empirical support for the hypothesis that an increase in the cost of owning an automobile leads to an increase in the demand for bus services.[22] This is also true of lagged values of the costs of owning an automobile, in regressions which are not presented in Table 2.

[22] The hypothesis concerning the real interest cost of holding an automobile is tested using α_4. The hypothesis concerning depreciation is tested using $(\alpha_3 - \alpha_4)$.

The coefficients of the real price of gasoline are positive as expected, and significantly different from zero at the 5 or 10 percent level. The TSLS point estimates of the elasticity of demand for bus trips with respect to the price of gasoline are 0.89 and 0.37 for (1) and (1′) respectively. Lagged values of the price of gas are not significant in regressions which are not presented in Table 2.

In the average city in the sample, roughly 10 percent of all trips by either bus or car are taken by bus [8]. Consequently, elasticities of demand for bus trips with respect to the price of gasoline of 0.89 and 0.37 would imply that a 10 percent increase in the price of gasoline would divert over to buses about one percent and 0.4 percent respectively of the people travelling by automobile.

However, the elasticities of 0.89 and 0.37 are implausibly large in absolute value, compared with the fare elasticities of −0.38 and −0.09 respectively. First, one would expect that a \$0.01 change in the fare per ride (F) would affect the number of bus rides demanded (R) by more than a \$0.01 change in the gasoline cost (G) for an automobile trip of the length of the average bus ride:

$$\left|\frac{\partial R}{\partial F}\right| > \left|\frac{\partial R}{\partial G}\right|$$

This follows unambiguously if we ignore income effects, assume that some members of the population choose between travel by bus and travel on foot or non-travel activities, and recall that cars often have two or more occupants to share the cost of gasoline. Second, assuming that the average bus trip is under 5 miles long (as it certainly is in our sample) and that the cost of gasoline is \$0.05 per mile, the gasoline cost would be less than the bus fare (\$0.25) for the average trip: $F > G$. Consequently, one would expect:

$$\left|\frac{\partial R}{\partial F}\right| \cdot \frac{F}{R} > \left|\frac{\partial R}{\partial G}\right| \cdot \frac{G}{R}$$

That is, the absolute value of the elasticity of demand for bus rides with respect to the cost of gasoline would be less than the absolute value of the fare elasticity.

Since the cost of gasoline would probably be one-third or less of total automobile operating and parking costs for the average trip, gas price elasticities of 0.89 and 0.37 would imply elasticities of demand for transit with respect to automobile operating and parking costs of around 2.7 and 1.1 respectively. By contrast, Sohn [25] estimated the elasticity with respect to the costs of owning and operating an automobile to be 0.65, using city-wide data. Domencich *et al.* [5] found that the elasticity with respect to automobile travel cost is not significantly different from zero. However, the figure 1.1 is not far from some other estimates. Warner [33] and McFadden [17] both estimated the elasticity of transit choice with respect to automobile travel cost to be 0.97 for work trips by people who have automobiles, and McGillivray [19] estimated this elasticity to be 1.16.

Income

The TSLS coefficient of average weekly wage and salary income is negative for both (1) and (1′). It is significantly different from zero at the 5 percent level for (1) but not for (1′). The TSLS point estimates of the elasticity of demand with respect

to wage and salary income are −0.63 and −0.16 for (1) and (1′) respectively. This indicates that bus transit is not a superior good.[23]

It should be recalled at this point that, for reasons discussed above, we have not included automobile ownership as an independent variable in the demand equation. Consequently, our result should be interpreted as an estimate of the "total" elasticity of demand for transit with respect to income. A number of other studies either include an automobile ownership variable or restrict the observations to individuals who have automobiles. In such cases, the estimates should be interpreted as "partial" elasticities of demand with respect to income. It is possible for the partial elasticity to be positive or zero while the total elasticity is negative; therefore the sign of the partial elasticity does not necessarily indicate whether transit is an inferior good.

There is no consensus in the literature regarding the effect of income on either demand for transit or transit mode choice, regardless of whether automobile ownership is controlled. Litt [16] and Sohn [25] estimated the income elasticity to be −0.32 (not significant) and −0.14 respectively in specifications which included significant negative automobile ownership elasticities. Gaudry [11], on the other hand, estimated the income elasticity to be 0.08 and the automobile ownership elasticity to be −0.10, but neither is significantly different from zero. Fairhurst and Morris [7] estimated the income elasticity of demand for bus trips to be 0.15 (not significant) in a specification which included a negative time trend but no automobile ownership variable. Huang [13] estimated the income elasticity to be 1.11 (not significant) in a specification which did not include an automobile ownership variable; he dropped the automobile ownership variable because it was not significant. Domencich *et al.* [5] estimated that for work trips the elasticities of demand for transit with respect to income and automobile ownership were 1.14 and over 0.61 respectively, while for shopping trips the income elasticity was −0.05 in a specification which did not include an automobile ownership variable. Nelson [20] presents results which suggest that the income elasticity was positive at low income levels and negative at high income levels, while the automobile ownership elasticity (−0.18) was not significantly different from zero. Although his results depend on the specifications for other variables, Schmenner [24] generally found positive income elasticities in a specification which did not include automobile ownership.

Among the modal choice studies, Domencich and McFadden [6] found no effect of income on mode choice in a specification which included a significant automobile ownership variable, but they consider their results inconclusive because about half the observations on family income represent estimates made by interviewers. Warner [33] estimated the income elasticity of transit choice to be −0.17 for work trips and −0.59 for nonwork trips in a specification which controlled for automobile ownership. In addition, studies by Lave [14], de Donnea [4] and McFadden [17] have supported the hypothesis that the value of travel time is propor-

[23] Strictly speaking, superior goods are usually defined with respect to exogenous changes in the consumer's budget which do not change relative prices. By contrast, if hours of work are variable, a change in wage and salary income involves a change in the relative prices of leisure, time-consuming activities such as bus travel, and other consumption goods.

tional to the after-tax wage rate. Since transit travel is almost invariably slower but cheaper than automobile travel, this implies that the wage-income elasticity of transit mode choice is negative.

This review of the evidence suggests to the present author that at higher income levels a lower percentage of trips is taken by transit, at least if one allows for the effect of income on automobile ownership. It also appears likely that the "total" income elasticity of demand for transit is not very far from zero.

Socioeconomic Variables

Among the socioeconomic variables, which are included only in specification (1), the coefficients of percentage of population under 15, percentage of population born outside Canada, and female labour force participation rate are positive and significantly different from zero at the 5 percent level. The coefficient of percentage of population 65 and over is not significantly different from zero.

There is no consensus among other studies concerning the effect of these or other socioeconomic variables on the demand for transit or modal choice. In contrast to our results, Nelson [20] found that the percentages of population 18 and under and 65 and over had negative coefficients, which were significant in one of his two samples but not in the other. Litt [16] found that percentage of population born outside Canada and labour force participation rate had significant positive coefficients. Schmenner [24] did not get consistent results for an age variable for different samples and specifications. Neither age nor sex variable was found to have a significant effect on modal choice in McFadden [17] or Domencich and McFadden [6], but de Donnea [4] found that people under 25 and over 55 had a higher probability of choosing transit, and Warner [33] found that females had a higher probability of choosing transit. Lave [14] found that older people have a higher probability of choosing transit, but that sex does not affect modal choice.

Spatial Structure

The coefficients of the two variables which were expected to serve as proxies for the spatial structure of employment are positive, as hypothesised. As we have already reported, the coefficient of female labour force participation rate is significantly different from zero at the 5 percent level. The coefficient of percentage of dwelling units constructed before 1920 is significantly different from zero at the 10 percent level. These results provide indirect evidence that the demand for bus rides is greater if a larger percentage of employment is located in the central business district. It should be recalled, however, that these variables are included only in specification (1).

Weather

Among the weather variables, which are included only in specification (1), the coefficient of average rainfall is positive and significantly different from zero at the 5 percent level. However, neither average number of days below freezing nor average snowfall appears to have a significant effect on demand for bus transit.

Among other studies, Fairhurst and Morris [7] and Gaudry [11] found that rainfall had a significant negative effect on demand, while Domencich and McFadden

[6] found that rainfall did not significantly affect modal choice. Fairhurst and Morris found that higher temperature increased demand for transit, while Gaudry and Domencich and McFadden found that temperature variables were not significant. Using monthly data, Gaudry also found that current snowfall was not significant but that cumulative snowfall for the season had a significant positive effect on the demand for transit.

Population

The TSLS coefficients of the population variables are positive and negative respectively for (1) and (1′). In view of the very general nature of the population proxy, one cannot conclude very much from the coefficient of this variable.

VII. CONCLUSION

In summary, the empirical results are consistent with our hypotheses concerning the determinants of the demand for bus services, except that there is no evidence that the costs of owning an automobile affect this demand.

On balance, specification (1′), which includes city dummies, appears preferable to specification (1). Specification (1′) gives a better fit and, with the possible exception of the fare elasticity, considerably more plausible parameter estimates. Looking at specification (1′), we have suggested that there may be an upward bias in the elasticity of demand with respect to bus miles of service, and the elasticity of demand with respect to the price of gasoline is higher relative to the fare-elasticity than we would expect. The income elasticity is not significantly different from zero.

Finally, assuming that specification (1′) is appropriate, it is important to note that, as expected, the TSLS estimates of the elasticities of demand with respect to fare and bus miles of service are lower in absolute value than the OLS estimates. This suggests that the OLS estimates are affected by simultaneous equations bias and that TSLS is a preferable estimation technique.

These findings lead one to speculate that many of the existing studies of the demand for transit based on city-wide data contain at least one problem of specification or estimation which may lead to significant biases in the fare and service elasticities of demand: for example there appear to be significant problems involved in using a single cross-sectional sample, in measuring service by bus miles *per capita*, and in using ordinary least squares. In addition, of course, all studies based on aggregate data are subject to bias when the geographical area over which the aggregation is made is not homogeneous.

REFERENCES

[1] Boyd, J. H., and G. R. Nelson: *Demand for Urban Bus Transit: Two Studies of Fare and Service Elasticities.* Paper P-983, Institute for Defense Analyses, Arlington, Virginia, 1975.

[2] Canadian Red Book (monthly): *Official Used Car Valuations.* Toronto.

[3] Carstens, R. L., and L. H. Csanyi: "A Model for Estimating Transit Usage in Cities in Iowa." *Highway Research Record* 213, pp. 42-49, 1968.

[4] de Donnea, F. X.: *The Determinants of Transport Mode Choice in Dutch Cities.* Rotterdam University Press, Rotterdam, 1971.

[5] Domencich, T. A., G. Kraft, and J.-P. Valette: "Estimation of Urban Passenger Travel Behavior: An Economic Demand Model." *Highway Research Record* 238, pp. 64-78, 1968.

[6] Domencich, T. A., and D. McFadden: *Urban Travel Demand.* North-Holland, Amsterdam, 1975.
[7] Fairhurst, M. H., and D. J. Morris: *Variations in the Demand for Bus and Rail Travel up to 1974.* London Transport Executive, 1975.
[8] Frankena, M.: *Urban Transportation Economics and Canadian Policy.* Butterworths, Toronto, 1979.
[9] Garbade, K. D., and N. M. Soss: "Fare Policies for Mass Transit Deficit Control: Analysis by Optimization." *Transportation Research* 10, pp. 237-247, 1976.
[10] Garner, D.: "Transit Planning and Characteristics of Ontario Transit Operations." In J. H. Shortreed, ed.: *Urban Bus Transit: A Planning Guide.* Department of Civil Engineering, University of Waterloo, Waterloo, Ontario, pp. 1-38, 1974.
[11] Gaudry, M.: "An Aggregate Time-Series Analysis of Urban Transit Demand: The Montreal Case." *Transportation Research* 9, pp. 249-58, 1975.
[12] Gaudry, M.: "Seemingly Unrelated Urban Travel Demands." *Transportation Research,* 12, pp. 195-211, 1978.
[13] Huang, T.-J.: *An Econometric Analysis of the Determinants of Demand for Local Transit in Edmonton, 1961-1970.* Department of Finance, City of Edmonton, 1973.
[14] Lave, C. A.: "A Behavioral Approach to Modal Split Forecasting." *Transportation Research* 3, pp. 463-480, 1969.
[15] Lee, N., and I. Steedman: "Economies of Scale in Bus Transport." *Journal of Transport Economics and Policy* 4, pp. 15-28, January 1970.
[16] Litt, R. M.: *A Cross-Sectional Study of the Demand for Urban Transit in Canada.* Department of Economics, University of Western Ontario, London, Ontario, 1975.
[17] McFadden, D.: "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3, pp. 303-328, 1974.
[18] McFadden, D., and F. Reid: "Aggregate Travel Demand Forecasting from Disaggregated Behavioral Models." *Transportation Research Record* 534, 1975.
[19] McGillivray, R. G.: "Demand and Choice Models of Modal Split." *Journal of Transport Economics and Policy* 4, pp. 192-207, May 1970.
[20] Nelson, G. R.: *An Econometric Model of Urban Bus Transit Operations.* Paper P-863, Institute for Defense Analyses, Arlington, Virginia, 1972.
[21] Oi, W. Y., and P. W. Shuldiner: *An Analysis of Urban Travel Demands.* Northwestern University Press, Evanston, 1962.
[22] Pearce, C., P. Simpson, and W. Venables: "Urban Density Models." In G. F. Newell, ed.: *Traffic Flow and Transportation.* American Elsevier, New York, pp. 439-453, 1972.
[23] Quarmby, D. A.: "Choice of Travel Mode for the Journey to Work." *Journal of Transport Economics and Policy* 1, pp. 273-314, September 1967.
[24] Schmenner, R. W.: "The Demand for Urban Bus Transit." *Journal of Transport Economics and Policy* 10, pp. 68-86, January 1976.
[25] Sohn, C. M.: *The Demand for Mass Transportation in New York City.* Ph.D. thesis, Department of Economics, State University of New York, Albany, 1975.
[26] Statistics Canada (annual): *Canada Year Book.* Information Canada, Ottawa.
[27] Statistics Canada (monthly): *Employment, Earnings and Hours.* Catalogue 72-002, Information Canada, Ottawa.
[28] Statistics Canada: *1971 Census of Canada.* Catalogue 92-715, 92-720, 92-727, 93-702, 93-731, 93-737, 94-703, 95-701 through 95-759, Information Canada, Ottawa, 1973-75.
[29] Statistics Canada (monthly): *Prices and Price Indexes.* Catalogue 62-002, Information Canada, Ottawa.
[30] Traffic Research Corporation: *Modal Split Analysis.* Metropolitan Toronto and Region Transportation Study, Toronto, 1965.
[31] Veatch, J. F.: *Cost and Demand for Urban Bus Transit.* Ph.D. thesis, Department of Economics, University of Illinois, Urbana-Champaign, 1973.
[32] Wabe, J. S., and O. B. Coles: "The Peak and Off-Peak Demand for Bus Transport: A Cross-Sectional Analysis of British Municipal Operators." *Applied Economics* 7, pp. 25-30, 1975.
[33] Warner, S. L.: *Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice.* Northwestern University Press, Evanston, 1962.