Volume 3 Number 3
December 2000
ISSN 1094-8848

BUREAU OF TRANSPORTATION STATISTICS UNITED STATES DEPARTMENT OF TRANSPORTATION

JOURNAL OF TRANSPORTATION AND STATISTICS

JOURNAL OF TRANSPORTATION AND STATISTICS

DAVID BANKS Editor-in-Chief
SUSAN LAPHAM Associate Editor
CAROLE ZOK Associate Editor
DEBORAH MOORE Managing Editor
MARTHA COURTNEY Editor
MARSHA FENN Project Manager
DAVIDA BALDWIN Editorial Assistant
LORISA SMITH Editorial Assistant

JOURNAL OF TRANSPORTATION AND STATISTICS

Volume 3 Number 3
December 2000
ISSN 1094-8848

BUREAU OF TRANSPORTATION STATISTICS UNITED STATES DEPARTMENT OF TRANSPORTATION

Bureau of Transportation Statistics

Our mission is to lead in developing transportation data and information of high quality and to advance their effective use in both public and private transportation decisionmaking.

Our vision for the future: Data and information of high quality will support every significant transportation policy decision, thus advancing the quality of life and the economic well-being of all Americans.

The *Journal of Transportation and Statistics* is published by the

Bureau of Transportation Statistics
U.S. Department of Transportation
Room 3430
400 7th Street SW
Washington, DC 20590
USA
journal@bts.gov

Subscription information

To receive a complimentary subscription or a BTS Product Catalog:

mail	Product Orders Bureau of Transportation Statistics U.S. Department of Transportation Room 3430 400 7th Street SW Washington, DC 20590 USA
phone	202.366.DATA
fax	202.366.3640
internet	www.bts.gov

Cover and text design Susan JZ Hoffmeyer
Layout Gardner Smith of OmniDigital
Cover photo Image® copyright 2001 PhotoDisc, Inc.

The Secretary of Transportation has determined that the publication of this periodical is necessary in the transaction of the public business required by law of this Department.

JOURNAL OF TRANSPORTATION AND STATISTICS

Volume 3 Number 3
December 2000

Contents

Regularities in Travel Demand: An International Perspective

ANDREAS SCHAFER

Massachusetts Institute of Technology

ABSTRACT

This paper compares major mobility variables from about 30 travel surveys in more than 10 countries. The analysis of cross-sectional and longitudinal data broadly confirms earlier findings of regularities in time and money expenditure shares for passenger travel (travel budgets). Despite the rather rough stability, travel demand characteristics, influenced by the two travel budgets, show strong regularities across space and time for all countries examined.

INTRODUCTION

Although travel demand characteristics have been analyzed at all aggregation levels (individual, urban, regional, national, world-regional, and global), surprisingly little research has been dedicated to quantifying and comparing travel characteristics across national boundaries. Such cross-country comparison is important since it can reveal general trends and differences in the evolution of travel demand, possibly leading to a better understanding of underlying forces. Perhaps the most comprehensive work in this regard was performed jointly by the Organization for Economic Cooperation and Development (OECD), the Euro-

---

Andreas Schafer, Center for Technology, Policy & Industrial Development and MIT Joint Program on the Science and Policy of Global Change, Massachusetts Institute of Technology, Room E40–255, Cambridge, MA 02139. Email: aschafer@mit.edu.

pean Conference of the Ministers of Transport, and the Europe an Economic Community more than two decades ago (OECD 1977). This detailed, multiyear analysis, however, examined the integration of transportation infrastructures of Western European countries and thus inherently focused on long distance travel, defined there as a one-way trip of at least 80 kilometers. More recently, two studies compared the demand characteristics of primarily short distance travel between countries (Orfeuil and Salomon 1993; Schipper et al. 1995). Although these latter two studies offer useful analyses, both concentrated on *summarizing* travel patterns resulting from surveys and aggregate national data, such as reporting the number of trips per capita by purpose and mode, annual distance traveled, and other indicators of the transportation system; only little attempt was made to examine relationships between these mobility variables or across countries. Instead of comparing separate, aggregate indicators, the present comparison of mobility variables takes into account their interdependence. Following that more systematic approach, this study shows that travel patterns are very similar across all countries.

Central to such similarity is that fundamental travel behavior is stable across space and time. In the 1960s, Tanner (1961) first suggested that people dedicate the same generalized expenditures, the aggregate of money and monetarized time, for daily travel, on average, regardless of whether they reside in an urban or a rural area. However, the quality of Tanner's underlying travel time data was questionable since they completely excluded nonmotorized modes of transport and were derived from a combination of traffic volume data and only rough speed estimates for motorized modes. In the 1970s, Zahavi, basing his conclusion mainly on cross-sectional survey data from cities within and outside the United States, proposed that urban *travelers*, residents who make at least one motorized trip a day, spend a constant amount of time on their daily travel: about 1.1 hours per day (1981). In addition to maintaining a constant "travel time budget," urban travelers spend three to five percent of their income on travel if their associated household relies entirely on public transport. This fraction rises to 10 to 15% of income when the household owns at least 1 automobile. Working with these two fundamental constraints, Zahavi formulated an urban travel demand model simulating travel distances, modal splits, trip speeds, and other characteristics of the transportation system. Other analysts have examined the two "Zahavi budgets," generalizing them to the average *person*, rather than traveler. Among those, Goodwin (1976), basing his conclusion on 1975/1976 United Kingdom travel survey data, showed that the per person daily travel time, including walking, is stable over population density but varies with age, income, and motorization. Numerous subsequent researchers particularly examined the stability of the travel time budget for individual countries and cities. Some studies examined country averages, such as Hupkes (1982), while others differentiated according to city size, such as Katiyar and Ohta (1993). Since the travel budgets are broadly stable on aggregate levels but vary with several variables on a lower level of aggregation, there is an ongoing dispute regarding travel budgets' validity. While some researchers try to identify stability at high aggregation levels, others seek to understand variability at disaggregated levels (Kirby 1981).

The present paper reexamines the evidence of the per person travel time budget and travel money budget based on cross-sectional and longitudinal, mainly national, travel survey data from around the world and explores some budget implications on travel demand. A rough analysis of these data suggests that the travel budgets are only broadly stable on national aggregation levels; nevertheless, their implications on travel patterns are crucial. This analysis is divided into five main sections. The following section briefly describes the differences in the travel surveys employed. Thereafter the "big picture" of travel demand is presented, based on its main variables: two travel budgets and two travel components, trip rate and distance. In the subsequent section, the two travel budgets are considered in greater depth. Before the summary, the paper examines the budget implications for mode choice, land use, and human spatial interaction. The appendix presents the data used in this paper and estimates the daily distance traveled in Singapore.

COMPARABILITY OF UNDERLYING TRAVEL SURVEYS

Twenty-six national travel surveys from 11 industrialized countries, 5 city surveys from the developing world, and 3 surveys from African villages (table 1) form the basis of this analysis. All of these surveys describe travel behavior, including trip rate, trip distance, travel time, mode choice, and trip purpose. However, the data must be interpreted cautiously for a number of reasons.

Perhaps most importantly, survey methods differ across space and time. The attempt to improve the reporting of travel behavior through more sophisticated survey methods has at the same time weakened the basis for consistent comparison. While earlier surveys often relied on questionnaires that asked respondents to recall travel activities on a given day, today's more sophisticated surveys employ a travel diary in which a respondent records each place visited during the course of a day, along with the transportation mode used, time of day, and trip distance. Pretests of the 1995 U.S. travel survey showed that employing the diary method alone added 0.5 trip per capita per day, on average, to the number of daily trips per capita obtained using recall methods (PlanTrans 1997). Ideally, the travel diary is combined with a computer-assisted telephone interview (CATI) that allows real-time editing and internal consistency checks of respondents' indications.[1] Utilization of CATI in conjunction with the travel diary captures still more travel activities. For example, the Swiss 1994 survey, employing both diary and CATI, showed a 7% increase (from 82.4% in 1989 to

[1] In the 1995 Great Britain survey, a computer-assisted personal interview (CAPI) method was used.

TABLE 1 Travel Surveys Used

	Survey year	Reference
Countries		
Australia	1985/86	Adena and Montesin (1988)
Austria	1995	Herry et al. (1998)
France	1982, 1994	Madre and Maffre (1997)
Great Britain	1975/76, 1985/86, 1989/91, 1994/96	Department of Transport (1979, 1988, 1993), Department of the Environment, Transport and the Regions (1997)
Japan (urban areas)	1987, 1992	Ministry of Infrastructure (n.d.)
Netherlands	1985, 1990, 1995	Konen (1999)
Norway	1985, 1992	Vibe (1993)
Singapore	1991	Olszewski et al. (1994)
Switzerland	1984, 1989, 1994	Stab für Gesamtverkehrsfragen (1986) Dienst für Gesamtverkehrsfragen (1991) Bundesamt für Statistik (1996)
United States	1977, 1983, 1990, 1995	U.S. Department of Transportation (1983, 1986, 1991, 1994), Research Triangle Institute (1997)
West Germany	1976, 1982, 1989	Kloas et al. (1993)
Others		
Rural areas in Ghana, Tanzania, Zambia	late 1980s 1986	Riverson and Carapetis (1991) Immers et al. (1988)
Katmandu	1984	Pendakur and Guarnaschelli (1991)
4 Delhi suburbs	1981, 1982	Maunder (1982, 1983)

88.3% in 1994) in the mobile population compared with the mobile population in 1989, as ascertained by the travel diary method alone (Bundesamt für Statistik 1996). While all surveys except the 1977, 1983, and 1990 U.S. surveys employed the travel diary method, only the Dutch (all surveys), Norwegian (1992), Swiss (1994), and U.S. (1995) surveys combined the diary method with CATI (see table 2).

Another factor limiting the comparability of travel surveys is inherent bias. Although all sampling units are typically identified by multi-stage random sampling procedures ensuring an approximately balanced representation of the population, sampling errors remain. For example, households without a telephone connection obviously cannot be interviewed by the CATI technique described above. In the United States, about six percent of all households do not have a telephone connection, predominantly those in the South and those consisting of a single person (USDOC 1999). Travel patterns of these groups are underreported. Sampling-related biases can also result from the included age classes in a sample population. For example, excluding the very young population typically results in a higher average mobility. Survey length can also result in bias: a short survey, for example may not properly take into account seasonal influences on travel. Table 2 shows how most surveys' fieldwork spans at least a year in order to minimize such seasonal bias. Since all of these biases can be corrected only to some extent through appropriate weighting procedures, misrepresentations remain, and survey comparability is limited.

An increasingly important bias results from nonresponse. Societal groups difficult to engage include comparatively mobile persons (since they are harder to reach), people with visual disabilities, and male teenagers (DOT 1993). Their exclusion from surveys results in underreported travel activities. For example, the 1989 German survey underestimates travel probably because highly mobile people were not reached (Kloas, Kunert, and Kuhfeld 1993). An indirect measure of how well hard-to-reach groups are included in a survey is the response rate: the ratio of fully cooperating households to eligible households. Compared to the 1976 and 1982 German surveys, the underreported 1989 German travel survey has, in fact, the lowest response rate. However, since response rates are inherently lower for travel diary-plus-CATI surveys (due to the multiple interview steps involved), care must be taken when employing response rate as an indicator for survey bias.

Other survey inconsistencies result from different survey designs, objectives, and definitions. Some surveys examined did not focus on reporting a balanced, complete picture of mobility. For example, travel times indicated in the 1975/1976 Great Britain survey are unreliable in part because they were collected for only the seventh day of the week (DOETR 1995). Also, several surveys did not examine trip distances, such as the Japanese 1987 and 1992 surveys and the Singapore 1991 survey. In the latter case, trip distances could be estimated based on independent data (Appendix B). Other surveys provide a detailed picture only for weekdays; among those, neither the 1982 nor 1994 French survey reports walking trips on the weekend, and the 1995 Austrian travel survey does not consider weekend travel at all. These surveys could be taken into account only to a very limited extent. Likewise, other surveys that have employed different trip definitions, such as the Swedish surveys (Statistics Sweden 1987), could not be taken into account. Finally, since most of the examined surveys concentrate on the "typical daily travel," they underreport longer distance travel and thus travel time. Exceptions are the surveys from the Netherlands, Norway, and the United States.

In this initial step of a larger project, the pure survey results are compared without making adjustments for the inconsistencies described above. Instead, this paper considers inconsistencies by discussing their possible effects on the survey results. The next step of this project will be a more formal statistical analysis based on a larger number of surveys, which will then be corrected for their major inconsistencies.

BASIC TRAVEL TRENDS

As economies expand, travel increases, working hours gradually decline, and new opportunities for time use arise. While time dedicated to sleep and especially leisure activities rises with declining work time (at a 95% confidence level), time expen-

TABLE 2 Major Characteristics of All Travel Surveys Used in This Paper

	Fieldwork period	Age group	Sample size (# HH interviews)		Response rate	Degree of travel reporting: survey-to-total travel	Major survey characteristics
	month/year	years	#HH	percent population	percent	percent PKMT (all modes)	
Australia	N/A	≥ 9	18,000	0.12	N/A	76.0	Self-completion, mail questionnaire. No further information available.
Austria	10–12/96	≥ 6	12,564	0.56	73.4	N/A	Self-completion, mail questionnaire; tel. interview if missing written responses; proxy interviews; confirming zero trips; trips only collected for workdays; travel diary.
France	3/81–2/82	≥ 6	6,619	0.03	87.0	59.0	Travel diary and car diary (odometer reading after each trip); no walk trips reported on weekends; reported trip distance up to 80 km; con firming zero trips.
	5/93–4/94	≥ 6	14,213	0.06	70.9	58.3	Personal interview with one household member; car travel diary; no walk trips reported on weekends; reported trip distance up to 80 km; confirming zero trips.
Great Britain	7/75–6/76	≥ 3	9,589	0.05	65.4	83.4	Initial interview-self-completion questionnaire-second interview; travel diary.
	7/85–6/86	≥ 0	10,266	0.05	75.6	78.2	Initial interview-self-completion questionnaire-second interview; travel diary.
	1/89–12/91	≥ 0	10,752	0.05	79.8	61.2	Initial interview-self-completion questionnaire-second interview; travel diary.
	7/94–6/97	≥ 0	9,960	0.04	73.4	72.2	CAPI; travel diary; proxy interviews; confirming zero trips.
Japan	N/A	N/A	N/A	N/A	N/A	N/A	Survey limited to urban areas; trip distance only reported for automobile travel.
	N/A	N/A	N/A	N/A	N/A	N/A	Survey limited to urban areas; trip distance only reported for automobile travel.
Netherlands	1–12/85	> 12	9,287	0.17	61.1	109.6	CATI; travel diary; proxy interviews; confirming zero trips.
	1–12/90	> 12	10,139	0.17	55.2	101.9	CATI; travel diary; proxy interviews; confirming zero trips.
	1–12/95	≥ 0	68,433	1.05	53.7	95.8	CATI; travel diary; proxy interviews; confirming zero trips.
Norway	9/84–9/85	≥ 13	4,320[a]	0.10	77.1	101.8	Personal interview; travel diary; confirming zero trips.
	9/91–9/92	≥ 13	5,992[a]	0.14	67.5	103.7	CATI; travel diary; confirming zero trips.
Singapore	N/A	≥ 4	2,665	0.34	34.8	N/A	No trip distance reported; travel diary; only includes walk trips greater than 100 meters.
Switzerland	5–6/84	≥ 14	3,513	0.13	58.2[b]	69.8	Self-completion, mail questionnaire; travel diary; confirming zero trips.
	5–6/89	≥ 14	20,472	0.73	63.0[b]	87.7	Self-completion, mail questionnaire; travel diary; confirming zero trips.
	1–12/94	≥ 6	16,570	0.55	74.8	74.2	CATI; travel diary; proxy interviews; confirming zero trips.
United States	N/A	≥ 5	17,949	0.02	85.3	70.0	In-home interviews; no travel diary; no proxy interviews.
	2/83–1/84	≥ 5	6,438	0.01	93.3	74.1	In-home interviews; no travel diary; no proxy interviews.
	3/90–2/91	≥ 5	21,869	0.02	83.6	72.7	In-home interviews; no travel diary; no proxy interviews.
	5/95–6/96	≥ 5	42,015	0.04	50.8	94.7	CATI; travel diary; proxy interviews; confirming zero trips. Only travel day file considered here.

TABLE 2 Major Characteristics of All Travel Surveys Used in This Paper *(continued)*

	Fieldwork period	Age group	Sample size (# HH Interviews)		Response rate	Degree of travel reporting: survey-to-total travel	Major survey characteristics
	month/year	years	#HH	percent population	percent	percent PKMT (all modes)	
West Germany	6/75–5/77	≥ 10	19,906	0.02	71.9	106.7	Self-completion, mail questionnaire; travel diary; proxy interviews; confirming zero trips.
	1–12/82	≥ 10	15,582	0.01	65.7	110.3	Self-completion, mail questionnaire; travel diary; proxy interviews; confirming zero trips.
	2/89–1/90	≥ 10[c]	24,849	0.02	64.0	83.8	Forms distributed and collected in person; travel diary; in-home interview if required; telephone interview if missing written responses; proxy interviews; confirming zero trips.
Delhi Suburbs	N/A		705–977	1.5–2.3		N/A	Personal interviews with whole household (prime income-earning member).

[a] Persons instead of households

[b] Basis includes non-eligible households

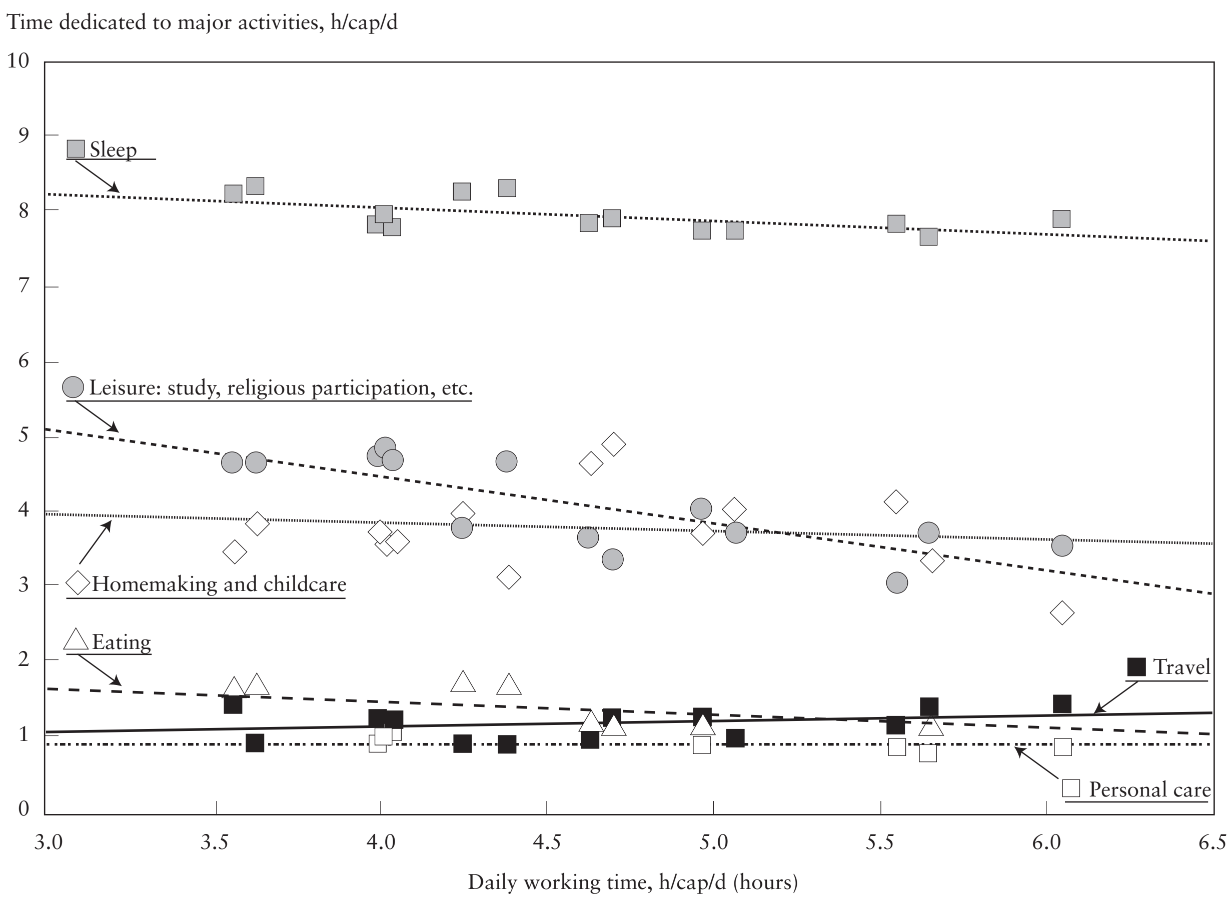
[c] Originally ≥ 6 years, however, better comparability of the 3 surveys requires neglecting the age group 6 through 9 years.

Note: For survey references, see table 1. Sources for national traffic volume: ICAO statistics for scheduled and charter air travel. All other modes from national statistics: Australia: Australian Bureau of Statistics (various years); Austria: not applicable since survey excludes travel on weekends; France: INSEE (1986, 1995); Japan: not applicable since survey includes trip length only for automobiles; Netherlands: Statistics Netherlands (1998); Norway: Statistics Norway (various years); Singapore: independent statistics not available; Switzerland: Bundesamt für Statistik (1997); Great Britain: Department of Transport (various years), United States: U.S. Department of Transportation (several years), Davis (1998); West Germany: Deutsches Institut für Wirtschaftsforschung (1987, 1996).

HH: household, PKMT: passenger-kilometers traveled. The response rate is defined as the number of complete household interviews to the number of eligible households ditures for other purposes do not undergo such a systematic change. Among the latter is time dedicated to transportation. Figure 1 reports trends in time allocation to major activities as a function of work time in 14 agglomerations for 1965/1966. The cross-sectional data suggest that travel time averaged 1.22 hours per capita per day (h/cap/d), with a standard deviation 16% of the mean value. Because it is cross-sectional *and* longitudinal, the view of four fundamental mobility variables, including travel time expenditures, shown in figure 2 is more comprehensive. Figure 2a suggests that residents in very low income, latter-1980s African villages (data points 22, 23); high income, high population-density, 1970s–1990s Europe (data points 2 to 16); and very high income, low population-density United States in 1995 (data point 21) all spent roughly one hour traveling each day, despite differences in daily distance traveled of up to one order of magnitude.

Despite the observed overall stability, travel time expenditures vary across individual country data points (mean value 1.09 h/cap/d, standard deviation 0.16 h/cap/d). Cross-sectional and, to a lesser extent, longitudinal, data for Western European countries (data points 2 to 16) suggest that travel time has increased slightly with daily distance traveled. One could argue that this increase may in part indicate behavioral change since all these country surveys were conducted with travel diaries and thus are broadly consistent (see table 2). More importantly, however, the observed increase in travel time results from differences in survey techniques (all building on the

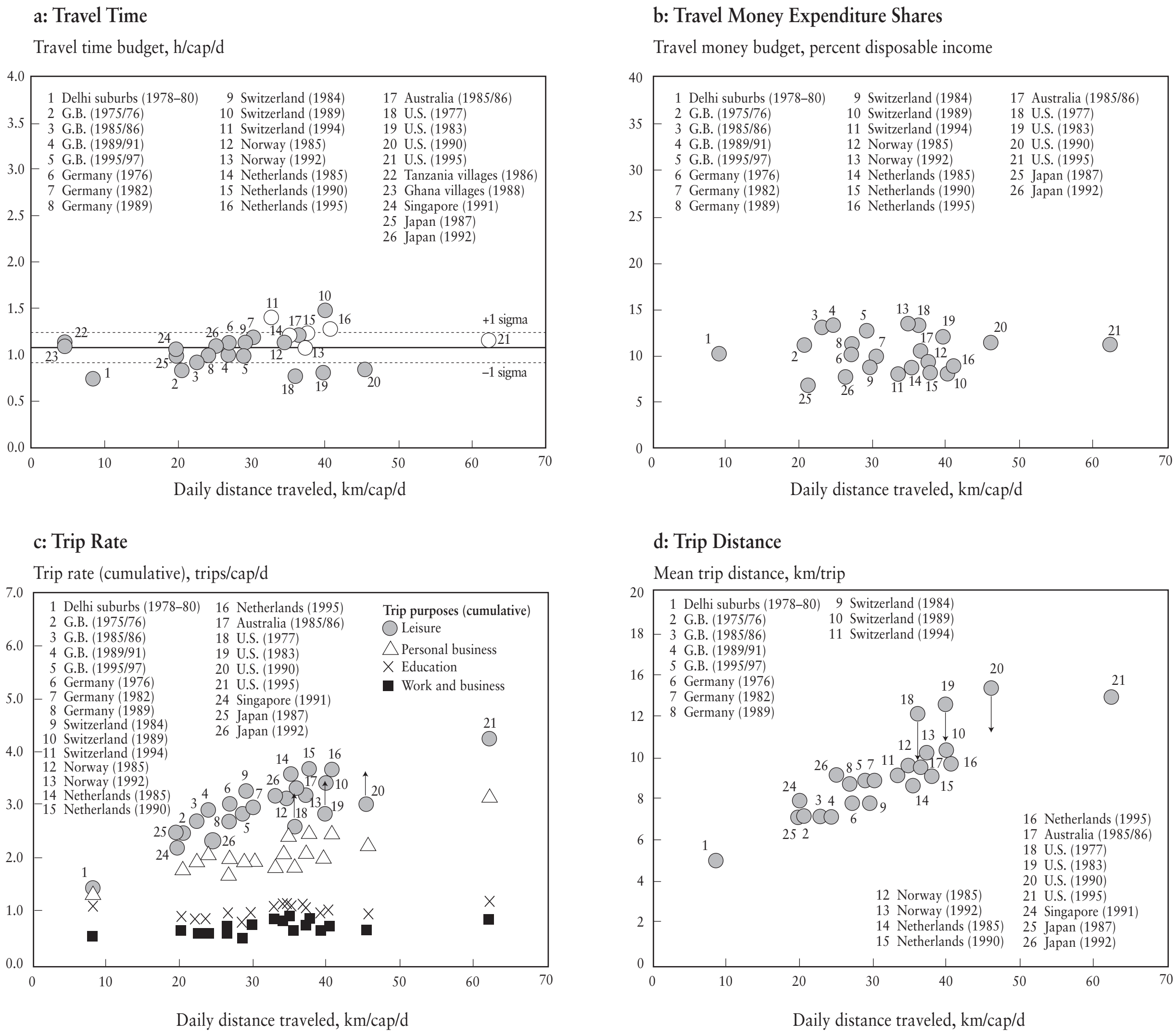
FIGURE 1 Time Expenditure for Major Activities as a Function of Work Time: 1965/1966



Notes: Data are taken from 14 different locations: Belgium, Kazanlik (Bulgaria), Olomouc (Czechoslovakia), 6 cities (France), Osnabrück (West Germany), Hoyerswerde (East Germany), Gyoer (Hungary), Lima-Callao (Peru), Torun (Poland), 44 cities (United States), Jackson (United States), Pskov (former Soviet Union), Kraguijevac (Yugoslavia), and Maribor (Yugoslavia). All data include the population between 18 and 65 years old. Changes in time dedicated to sleep and leisure are statistically significant at the 95% confidence level, as opposed to all other categories.

Source: Szalai et al. (1972)

FIGURE 2 Basic Variables of Human Mobility as Functions of Daily Distance Traveled



Empty circles in 2a = travel diary plus CATI
Dashed lines in 2a = ± 1 standard deviation

Note: The daily distances traveled in African villages were estimated by multiplying the travel time budget by a mean walking speed of four kilometers per hour. Those in Japan were derived from Japan's Statistic Bureau (1995) and multiplied by 0.86, the ratio of the survey-based automobile travel distance to that reported by official transit statistics. The data points in 2b slightly overestimate travel money expenditure shares since the survey-based daily travel distances often underestimate long distance travel (see table 2), whereas the economic statistics-based travel money budget figures account for all travel.

Sources: Table 1 for travel time and components, OECD (various years), and U.S. Department of Commerce (various years)

travel diary), included age groups, and degree of travel reporting.

Based on a rough estimate, table 3 reveals that these factors account for most of the differences in travel time expenditures between Great Britain in 1985/1986 (data point 3) and the Netherlands in 1985 (data point 14). Travel time data by age group from Great Britain 1985/1986, 1989/1991, and 1994/1996 travel surveys show that the exclusion of the age group of 0 to 11 years raises the per person travel time by nearly 6% (Williams 2000). In addition, complete travel reporting from originally 78% (see table 2) to 100% should result in an increase in per person travel time by roughly 9%. The factor 1.09 was estimated by extending the survey coverage to total passenger-kilometers (1/0.78), assuming a three-fold mean speed of long distance travel, 1+(1/0.78 – 1)/3, compared to the reported daily travel. Finally, the CATI method is reported to have increased the number of trips by seven percent in Switzerland (see above). We assume the same increase in per person travel time

TABLE 3 Daily per Person Travel Time Expeditures in Great Britain (1985/86) and the Netherlands (1985)

Per person travel time in Great Britain, 1985/86	0.92
Excluding age group of 0 to 11 years (• 1.06)	0.98
Complete travel reporting (• 1.09)	1.07
CATI method (• 1.07)	1.15
Per person travel time in the Netherlands, 1985	1.21

Note: Rough adjustments to the Great Britain survey for the age group not reported in the Netherlands survey, degree of travel reporting, and computer-assisted telephone interview (CATI) technique lead to a travel time budget similar to that of the Netherlands.

since although these "forgotten" trips plausibly occur over shorter distances, they are likely to be made by significantly slower, non-motorized modes. For comparison, Great Britain 1994/1996 National Travel Survey suggests that per person daily travel time declines by 14% from 0.98 to 0.84 h/cap/d if we exclude all walk trips below a distance of 1 mile. The resulting compounded estimate of 1.15 hours per day only differs by 5% from the 1985 per person travel time of 1.21 hours per day.

Improvements in survey methods, notably the transition from recall to the travel diary, along with the increase in travel reporting (by 35% between 1970 and 1995) have also strongly contributed to the increase in travel time in the United States (data points 18 to 21; see also table 2). Hence, if we compare only survey data points based on the most accurate method, travel diary plus CATI, with a travel coverage of close to 100% (see empty circles in figure 2a), the pattern of a cross-sectional increase in travel time with rising daily distance traveled becomes less evident, and mean travel time increases to 1.23 h/cap/d, with a standard deviation of 0.17 hours. According to table 2, the included age groups still differ between these countries. These numbers compare very well with those from time-use surveys designed to precisely capture time allocations, as displayed in figure 1, suggesting that 1.1 hours per capita per day, as often found in the literature, may underestimate average daily travel time.

From a longitudinal viewpoint that eliminates the effect of some exogenous forces on mobility patterns, such as from cross-country differences in land use, prices, and so forth, travel time expenditures follow no unique trend across countries. For example, Dutch travel diary plus CATI-based surveys suggest that travel time continuously increased from 1.21 h/cap/d in 1985 to 1.25 hours in 1990, to 1.30 hours in 1995. The 4% increase between 1990 and 1995 occurred despite an extension of the survey age group from people at least 12 years old to the entire population (see table 2). By contrast, travel time in Norway declined between 1985 and 1992, despite the transition from travel diary and personal interview to the more accurate, combined method of travel diary plus CATI.

Figure 2b reports travel money expenditure shares and deserves two explanations. First, as travel surveys typically do not investigate consumer expenditure behavior, we must use independent statistical data to analyze the relationship between money expenditure patterns and travel demand. For that purpose, we employ OECD National and Income Accounts (OECD various years) and National Accounts of the European Community (Eurostat various years). Second, the relationship between daily distance traveled and the travel money budget in figure 2b is not reflected precisely since the travel money budget measures the expenditure share for total travel including long-distance, while travel surveys typically underestimate long distance travel (see table 2). Thus, the travel money budget is slightly overestimated.

The spread of travel money expenditures is large compared to that of travel time expenditures (mean value 10.73, standard deviation 3.28, or a 31% deviation from the mean). It results from different price levels in the countries' respective economies. It also results to some extent from limited access to transportation systems. For example, due to a limited supply of parking spaces, automobile ownership in Japan is constrained. Travel money expenditure shares also depend on the underlying methods of estimation and the range of consumer groups included. Differences in these factors contribute to significantly different travel money expenditure shares, accounting for 11 to

13% of disposable income, if based on the personal consumption expenditures component of the National Income and Products Account (shown here), and for roughly 18% of disposable income if based on the consumer expenditure survey conducted by the United States Department of Labor (1997).

In contrast to the roughly horizontal development of the two travel budgets, both travel components increase uniformly with daily distance traveled. At low levels of daily distance traveled, people seem to undertake one to two trips per day, such as in Delhi suburbs in the late 1970s;[2] the associated mean trip distance is somewhat higher than five kilometers. Daily trip rate and distance (figures 2c and 2d, respectively) rise with increasing daily distance traveled to more than 4 trips and almost 15 kilometers, respectively (United States in 1995), exhibiting strong regularities. At low mobility levels, one trip in a day is dedicated to a combination of work (short term survival) and education (longer term well-being), and about half a trip on average is dedicated largely to personal business (essentially, shopping at local markets). The absolute number of trips per person in Delhi suburbs and the trips' distribution by purpose are consistent with the number found by many other surveys from developing countries not considered here since they don't report distance traveled. Examples included Jakarta (Badan Pengkajian dan Penerapan Teknologi and Forschungszentrum 1991), Sao Paulo (Metrõ 1989), and Santiago de Chile (Comisión de Planificación de Inversiones en Infraestructura de Transporte 1992). Daily distance traveled grows together with additional trips for personal business, such as for shopping, health care, religious services, and leisure, including holidays. At high income levels comparable to those of OECD countries, people make more than three trips per day, devoting approximately one trip to work or education, one to two trips for personal business, and one trip for leisure. The highest trip rate can be observed for the United States (1995), where the largest daily per person distance is traveled. Here, personal business trips account for nearly half of all trips made.

The development in trip rate by purpose is broadly stable, but here also differences exist. Variations result in part from inconsistent survey methods. Compared with work and education trips, best remembered by survey respondents and stable across all examined societies, occasional trips for personal business and leisure typically go underreported more often. Thus, the observed increase with rising daily distance traveled of these trips may at least in part result from improved survey methods. This is most evident for the 1977, 1983, and 1990 U.S. surveys, due mainly to the absence of a travel diary. Adding 0.5 trip to the per capita trip rates of the corresponding data points (18 to 20) to correct for the missing travel diary would lead to a cross-sectional trajectory in trip rate more consistent with all other surveys (see arrows in figure 2c). In all other cases, the increase in trip rate with rising daily distance traveled is essentially cross-sectional and remains approximately level within countries with rising daily distance traveled.

The evolution of trip rate is also influenced by differences in land-use: a lower population density tends to reduce trip rate and increase trip distance.[3] Comparing only those country data points based on a travel diary in combination with CATI yields land-use related differences in trip rate at a given daily travel distance. For example, it is lower in low population density Norway and higher in the high density Netherlands. Obviously, the variation in trip distance results directly from the variation in trip rate. Mean trip distance can be expressed by the ratio of daily distance traveled to trip rate and,

[2] The basic unit for measuring transportation activities is a trip, generally defined as a one-way move from an origin to a destination, motivated by a main purpose, and involving a public infrastructure. This definition is not always consistent across countries and surveys. Surveys with clearly inconsistent trip definitions were adjusted when possible and when not, were not taken into account. Another source of inconsistency is the fact that people are increasingly involved in more than one activity at a time, making phone calls during their daily commute; doing work, or enjoying leisure activities, while on an airplane; and so forth. Simultaneous activities cannot be taken into account here, as we must simplify human travel behavior in order to understand its fundamental characteristics.

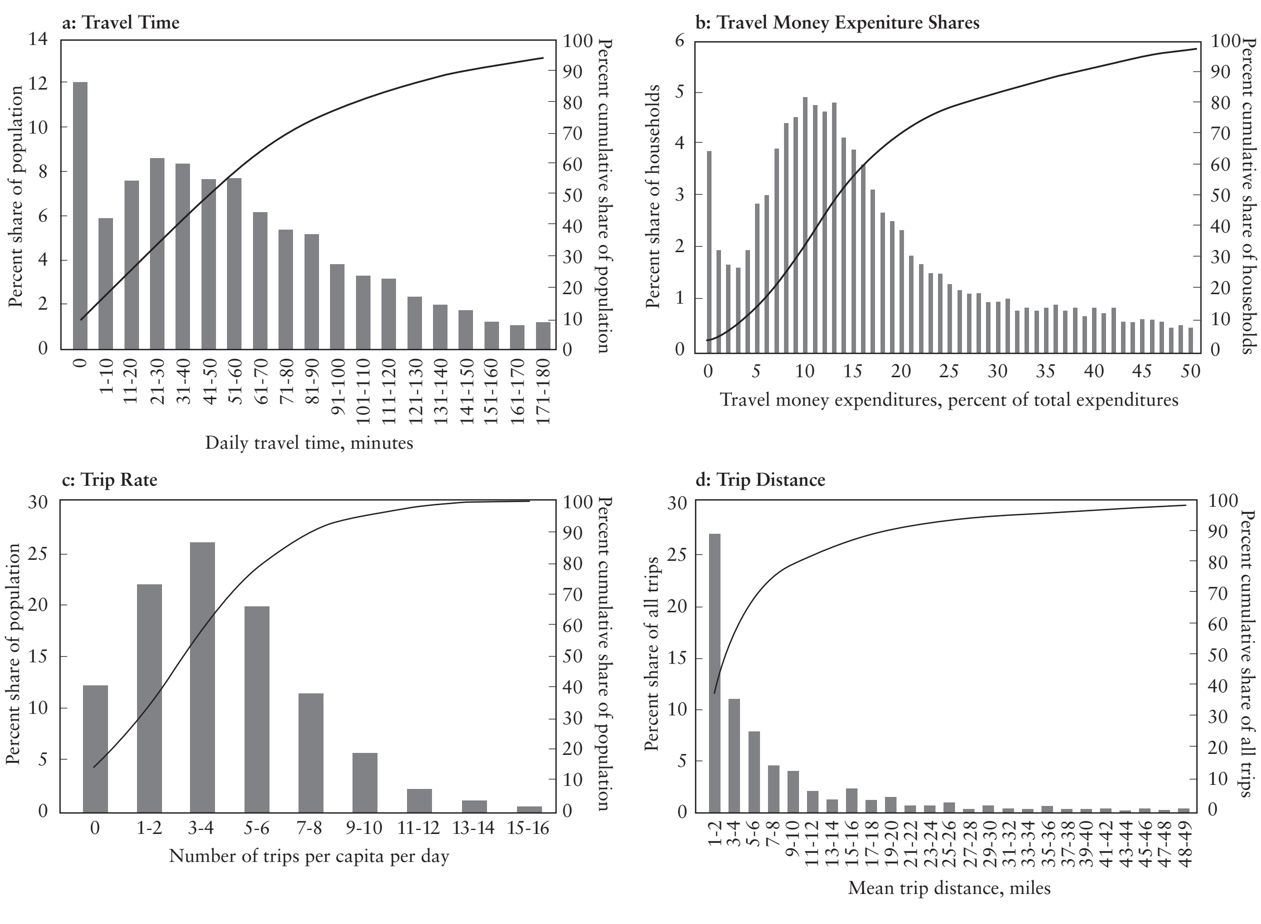
[3] Differences in trip rate also result from cultural and regional factors. For example, residents in hot areas such as Southern Europe and especially Africa are likely to have more work-related trips since many return home for lunch to escape the high heat for several hours (not shown here).

thus, from the different degrees of trip reporting within and between countries, over time. The arrows in figure 2d for the 1977, 1983, and 1990 U.S. travel surveys reflect the decline in mean trip distance resulting from correcting the trip rate.

TRAVEL BUDGETS

Analogous to figure 2, figure 3 illustrates the density and cumulative distribution functions of the four fundamental travel variables for the U.S. population in 1995. Only the travel money expenditure distribution is shown for 1989, the last year for which household consumer expenditures can be easily extracted from data tapes. The asymmetric shape of the density functions, reflecting a wide range of preferences by and constraints to individuals, causes the respective mean and median to differ strongly. For example, the average per capita travel time is 1.18 hours a day, while the typical U.S. resident travels only 50 minutes, 0.83 hours a day; approximately seven percent of the U.S. population travels longer than three hours per day. Similarly, figure 3b suggests that mean household transportation expenditures account for 19.3% of total expenditures, while the typical U.S. household dedicates only 13% of total expenditures to transportation. Still, three percent of U.S. households devote more than half of their expenditures to transportation. Finally, figures 3c and 3d show the well-known gamma functions and the corresponding cumulative distributions for trip rate and distance. Since all four travel variables in figure 3 are characterized by skewed distributions, the question of why travel time and money expenditure shares should remain constant, while trip rate and distance increase, arises. We will pursue this question in more detail in the following subsections.

FIGURE 3 Distributions of Basic Mobility Variables in the United States



Sources: Research Triangle Institute (1997) for travel time, trip rate, and trip distance; Nelson (1994) for travel money expenditures

Travel Time Budget

Since we cannot analyze the stability of the travel time distribution in figure 3 more carefully due to the lack of long-term, historical, cross-sectional raw data, we examine the available averages on a more disaggregate level. Figure 4 reports average travel time associated with different trip purposes. The overall development over daily distance traveled is illustrated in figure 4a. At first glance, travel time associated with work, including work-related business, and education seems to remain roughly constant at 0.21 and 0.09 h/cap/d, respectively, in industrialized countries, while travel time associated with personal business and leisure travel increases slightly. To better understand to what extent these trends may be influenced by changes in travel behavior and survey methods, we decompose per capita daily travel time into two factors, trips per capita per day (figure 2c) and mean travel time per trip for each trip purpose (figures 4b through 4f).

We begin with commuting, typically remembered best by survey respondents and thus least affected by inconsistent survey methods. Figure 2c shows that the number of trips associated with commuting is roughly stable over the entire range of daily travel distances. In addition, figure 4b demonstrates that the increasing mean distance to work has led to a slight cross-sectional and longitudinal rise in travel time in nearly all countries. Apparently, commuters have been unable to completely compensate for the longer commute to work with higher speed. Together, both trends suggest that mean daily commuting time per capita is slightly rising.[4] Essentially, the same relationship applies to work-related business trips (figure 4d). The slight increase, however, is not unique for all countries. In Norway, both travel time and trip rate for work and related business travel have essentially remained constant. The distinct trajectories in both figures of U.S. travel and other, mostly Western European travel, reflect differences in mean speed and, in turn, land-use.

Completely different settings with respect to mean travel speed and land-use can significantly widen the relatively close range between commuting distance and time. The two data points representing time expenditures above 0.7 hours illustrate the difficulty of keeping commuting time down in low income countries (Delhi suburbs between 1978 and 1980, data point 24) and high population density cities (Singapore in 1991, data point 25), where residents are constrained in selection of an appropriate residential location and transport mode. Due to the limited travel time budget, travel time associated with purposes less important than work, which ensure short-term survival, is therefore significantly reduced.[5]

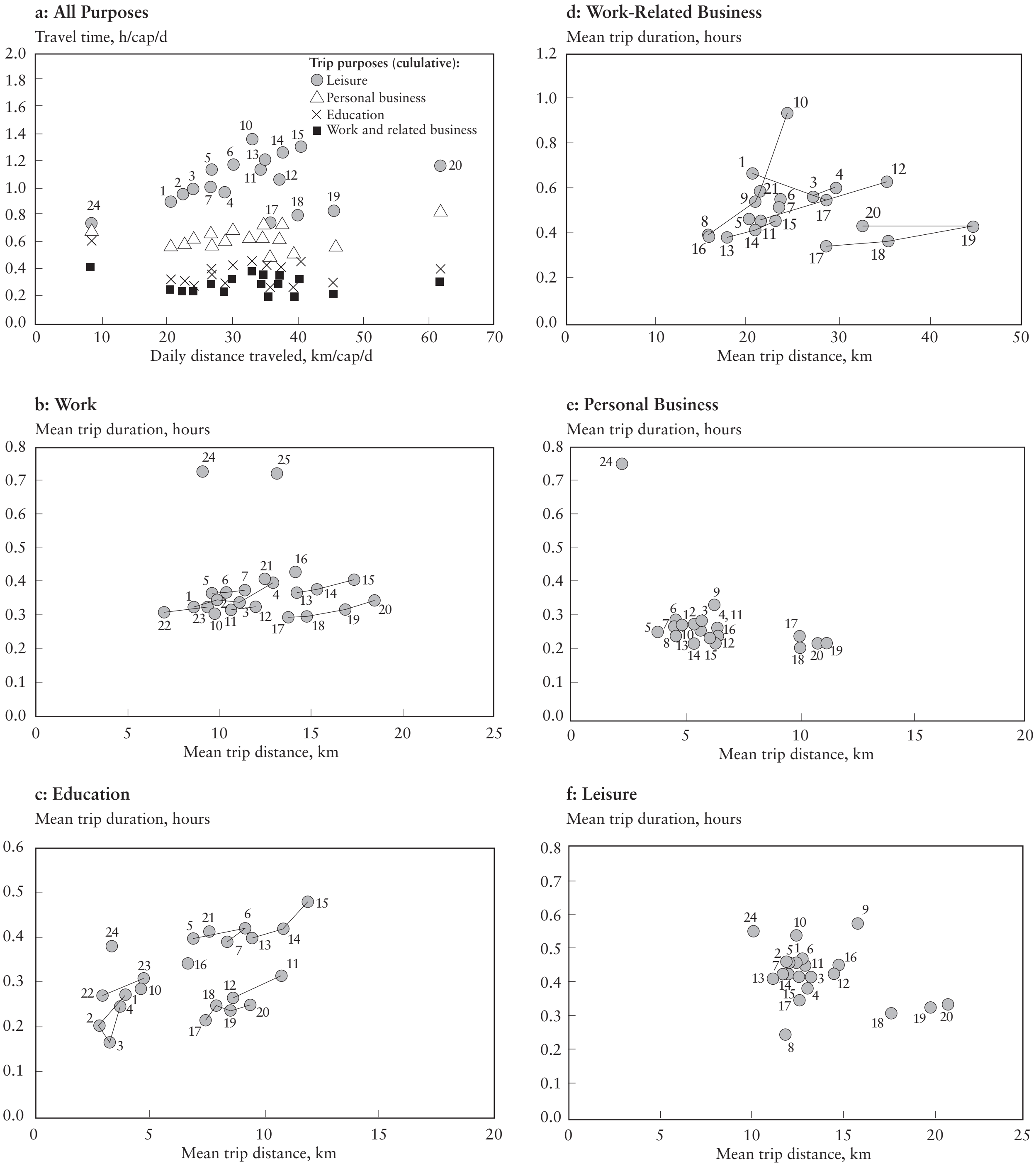
The increase in travel time over trip distance for education-related trips is stronger compared to work and work-related business trips since students are typically more constrained in their choice of transportation modes (figure 4c). The mainly cross-sectional increase in travel time results from a comparable speed, distance per trip (abscissa) divided by time per trip (ordinate), of the average mode of transport in different environments (for example, location and accessibility of schools). Land-use differences, as well as different modal constraints, are responsible for altering mean speeds, i.e., higher in the United States and Norway (low population density) and lower in Western Europe (higher population density). Combined with a roughly stable trip rate, per capita travel time for education trips has remained roughly constant within most of and across the examined countries.

Travel time expenditures for personal business and leisure trips (figures 4e and 4f) do not rise with trip distance and thus roughly follow a budget-like development, an independent and thus horizontal trajectory over mean trip distance, exempting the comparatively high travel time associated with especially personal business but also leisure trips in

[4] This increase in work-related travel time rejects conventional wisdom, which suggests that commuting time would remain generally constant over time and the increased distance would be completely absorbed by land-use changes. See, for example, Levinson and Lumar (1994) and the discussion on journey-to-work trip times in Kenworthy and Laube (1999).

[5] Similarly high average commuting times can be observed in Russian cities in the early Twentieth century (Zuzanek 1980) and for high population density Japan in 1996 (Statistics Bureau 1998). High average commuting times are also observed in Western high density cities. For example, according to the 1992–1994 United Kingdom travel survey, Londoners have spent an average 0.83 hours getting to work in central London, twice the national average (DOETR 1995).

FIGURE 4 Allocation of Travel Time



Legend

1 G.B. (1975/76)	5 Germany (1976)	9 Switzerland (1989)	13 Netherlands (1985)	17 U.S. (1977)	21 Austria (1995)
2 G.B. (1985/86)	6 Germany (1982)	10 Switzerland (1994)	14 Netherlands (1990)	18 U.S. (1983)	22 France (1982)
3 G.B. (1989/91)	7 Germany (1989)	11 Norway (1985)	15 Netherlands (1995)	19 U.S. (1990)	23 France (1994)
4 G.B. (1995/97)	8 Switzerland (1984)	12 Norway (1992)	16 Australia (1985/86)	20 U.S. (1995)	24 Delhi suburbs (1978-80)
					25 Singapore (1991)

Sources: Tables A-1 and A-2

Delhi suburbs (data point 24). In general, people seem to be willing to spend only 0.22 to 0.34 hours for personal business trips (figure 4e), on average, independent of the distance. Similarly, the trip duration of leisure trips (figure 4f) has remained constant in the United States, while trip distance has increased by almost 50%. If we exclude the three Swiss survey data points with implausibly large variation (data points 8 to 10) in the same chart, leisure trips in Western Europe show a less diffuse pattern and can be considered roughly constant. The total effect of the two factors, the mainly cross-sectional increase in trip rate and the roughly constant travel time per trip, is an essentially cross-sectional increase in travel time per capita and day associated with personal business and leisure trips. Only in the Netherlands and the United States, where trip rates have increased slightly with rising daily distance traveled, we conclude a gradual longitudinal increase in per capita travel time associated with these two trip purposes.

Overall, without any compensation mechanism, the slight longitudinal increase in travel time associated with work and related business trips, observed for nearly all countries, leads to a gradual increase in total per capita daily travel time. This increase may be amplified by a rise in travel time associated with other trip purposes; however, since such a rise was mainly observed across countries, it can also reflect exogenous factors rather than revealing a longer term longitudinal trend. A compensation mechanism leading to lower trip rates with rising travel time per trip can only be observed in extreme cases, such as between the industrialized world and the developing countries or very high population density areas. In these settings, people are forced to perform drastically less since they spend significantly more time on trips. Since none of the trends in rising travel time described above is uniform across all countries, these trends are likely to be much smaller on a higher, world-regional and global aggregation level. Thus, it occurs that the per person travel time budget can most appropriately be considered as roughly constant on such high aggregation levels.

Travel Money Budget

After housing and food, transportation expenses typically represent the third major household expenditure item, accounting for 3 to 5% for zero-car households and stabilizing at 10 to 15% of disposable income for households with at least one automobile, as suggested by Zahavi (1981). Figure 5 confirms these shares in total consumer expenditures for six countries, France, Italy, the Netherlands, the United Kingdom, the United States, and West Germany. While food expenditure shares, including restaurant visits, have strongly declined during the past decades, those associated with housing and especially with transportation have shown much less variation.[6] In most countries, travel money expenditure shares have remained especially stable above motorization rates of 0.30 cars per capita or about 0.85 cars per household since beyond this threshold nearly all households own and operate an automobile on average (see gray arrows in figure 5). Only in West Germany have transportation expenditure shares continued to rise. Perhaps most interesting, travel money expenditure shares have remained stable even during the two oil shocks in 1973/1974 and in 1978/1979. Data from the United States suggest that travelers have adjusted by buying more fuel-efficient cars and temporarily reducing automobile travel (see Schafer and Victor 2000).

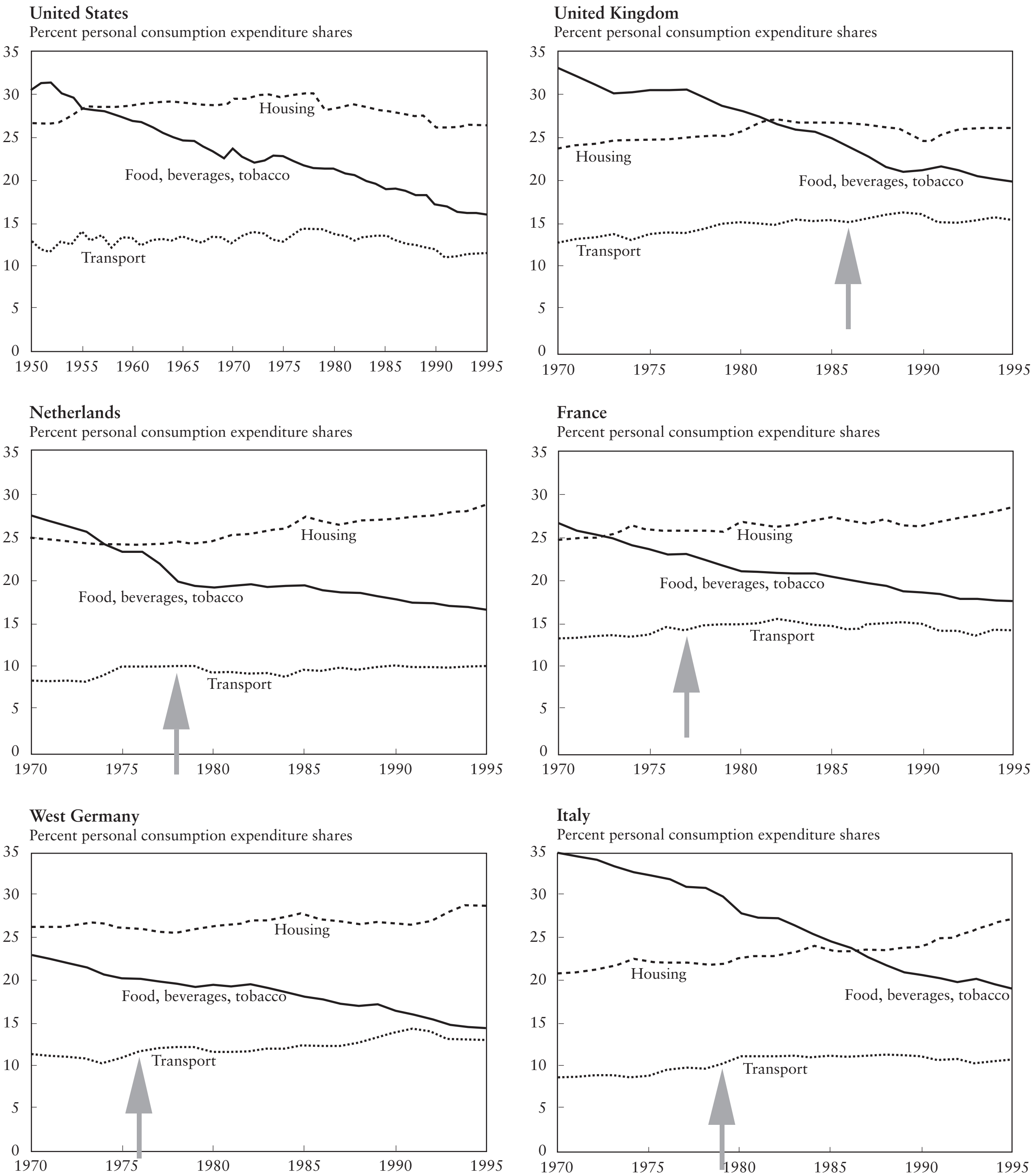
As with the travel time expenditures, the slightly different development of the travel money expenditure shares (approximately constant above 0.30 cars per capita in the United States, the United Kingdom, the Netherlands, France, and Italy while continuously rising in West Germany above that threshold) implies that higher confidence of a stable travel money budget exists at a higher aggregation level than the country data shown here.

Travel Budget Substitutability

A tight stability of both travel time and money expenditures implies that both travel budgets are independent and thus not substitutable on aggregate levels. However, even after correcting for the survey

[6] On a net basis, the declining food expenditure shares were compensated by services, ranging from medical expenses to recreation and education.

FIGURE 5 Personal Consumption Expenditures as a Fraction of Total Personal Consumption Expenditures



Note: Arrows indicate a motorization rate of 0.30 cars per capita (about 0.85 cars per household), at which nearly all households own and operate an automobile on average.

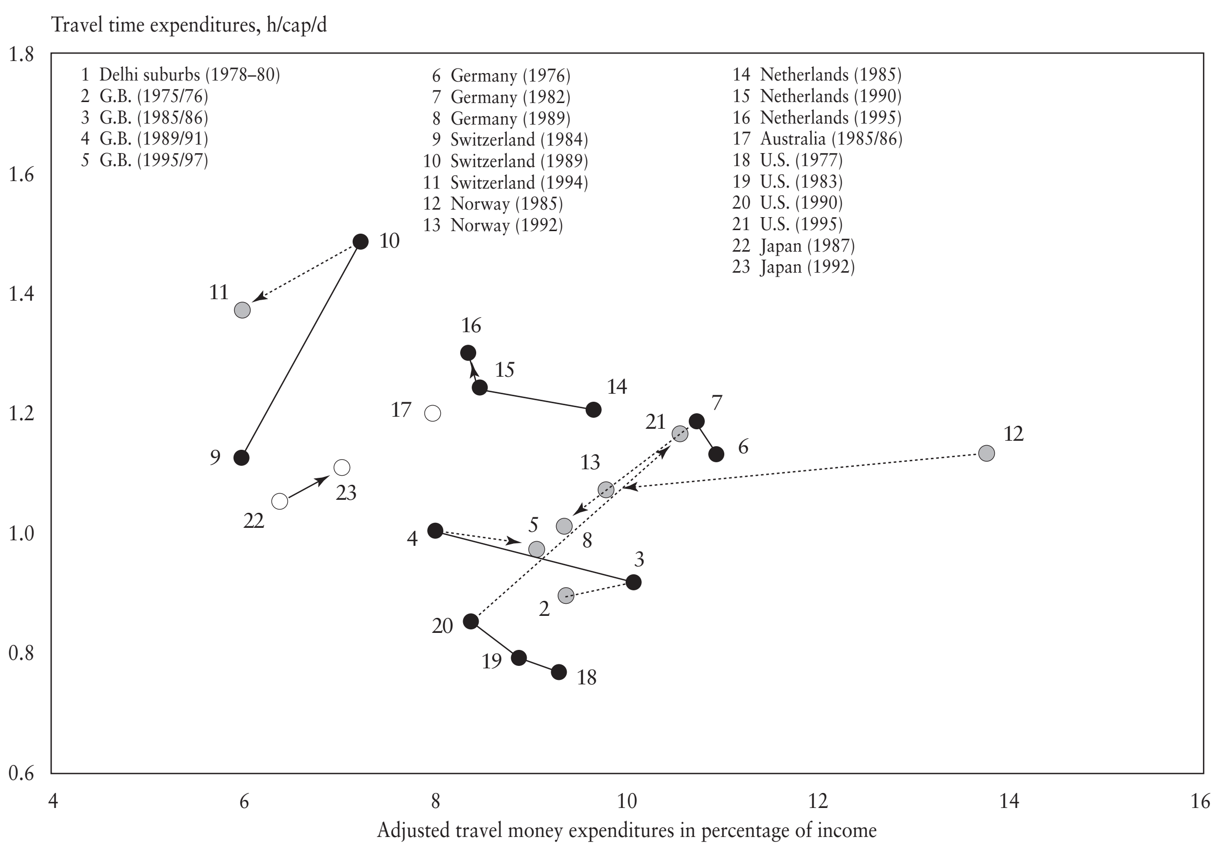
Sources: U.S. Department of Commerce (various years) and Eurostat (various years) inconsistencies, some variations of both budgets in figures 2a and 2b remain, raising the question of whether they are systematic, and thus reflecting the substitution occurring on a national level, or just "noise" due to survey methods' inconsistencies.

Answering this question requires travel time and money expenditure data be measured consistently. This, however, is not the case. While travel money expenditures are derived from independent national economic accounts that cover total travel, including long-distance (air) travel, travel time expenditures are based on the travel surveys listed in table 1, which, in most cases, only capture typical daily travel. We roughly adjust the travel money budget by simply multiplying it by the ratio of travel survey-reported daily travel distance to independent transport statistics daily travel distance from table 2.[7] In addition, travel time expenditures are underestimated in some surveys, since, for example, short trips, typically made on foot and requiring a comparatively long time per distance, are underreported (see the three early U.S. surveys, represented by data points 18 to 20). Although we cannot directly correct for this second source of inconsistency, we can largely eliminate it by focussing only on such series of surveys that were conducted using similar methods.

Figure 6 reports a simple test of budget substitutability. Most of the country data points, based on surveys with consistent methods and without any obvious bias (black circles), suggest that budget substitution has in fact occurred. Among those are the 1976 and 1982 Germany surveys (the 1989 survey underreported travel behavior of the highly mobile population), the 1985/1986 and 1989/1991

[7] This adjustment is based on the assumption that costs per passenger-kilometer are equal for long and short distance travel. However, in 1995 costs for air travel were 8 cents per passenger-kilometer (pkm) in the United States, while automobile and public transport costs were about 20 and 17 cents per pkm, respectively (APTA 1998; Davis 1998; USDOC 1998). Therefore, this correction may slightly overestimate the "adjusted travel money expenditures."

FIGURE 6 Substitution of Travel Time and Money Expenditures



Note: Surveys with consistent methods and without obvious bias are represented with black data points. White dots indicate unknown survey methods or when only one survey was available.

Sources: Table 1 for travel time budgets; OECD (various years) and U.S. Department of Commerce (various years) for money expeditures.

Great Britain surveys, the three surveys from the Netherlands, and the three early U.S. surveys. In contrast, the Swiss 1984 and 1989 surveys do not follow such a trend. Neither do the two Norwegian surveys, where the shift from travel diary to travel diary plus CATI has even resulted in a decline in travel time.

In summary, figure 6 suggests that substitution between travel budgets occurs on a national level; however, exceptions exist. This confirms the conclusion that both budgets can most appropriately be considered as roughly constant on higher than national aggregation levels.

INTERPRETATIONS OF TRAVEL BUDGET STABILITY

Transportation analysts have formulated different hypotheses to explain the roughly stable travel budgets. For the most thorough and critical discussion, see Goodwin (1981). Kirby (1981) classifies these hypotheses into three fundamental ways of interpreting travel budgets.

One interpretation regards the budgets as purely empirical laws of travel behavior for groups of individuals. Marchetti (1994), for example, considers the travel time budget as an instinct-driven, anthropogenic invariant. He suggests that people are "cave animals" who control their exposure time to risk, their time traveling in the unprotected environment, to about one hour per capita per day.

A different way to consider the travel budgets is to treat them as byproducts of allocations of time and money. The time constraints of primary activities naturally limits travel. Figure 1, for example, shows that people spend approximately 8 hours per day sleeping, almost 4 hours on homemaking and childcare, and 8 to 9 hours on the aggregate of work and leisure. With the addition of about two hours for eating and personal care, only somewhat more than one hour per day is left for travel. (Such a direct limitation does not exist for the travel components.) The money consumed by primary activities also limits travel, and a similar analysis can be made on the basis of travel money expenditures (see figure 5).

Another interpretation considers the budgets as input for decisionmaking, such as how to maximize utility. Hupkes (1982), for example, suggests decomposing the utility of travel time into a derived utility and an intrinsic utility. The derived utility, a measure of the need for travel to pursue a primary activity, increases with travel time, saturates, and subsequently declines as less time becomes available to pursue additional activities. The intrinsic utility, the satisfaction of travel as an end in itself, follows the same pattern, albeit at a much lower utility level. The total utility of travel time is then the sum of the derived and the intrinsic utility. Hupkes acknowledges that the resulting total utility curves not only differ by person but also change over a person's lifetime.

None of these hypotheses alone provides a sufficiently rigorous explanation, despite the observed rough stability of the travel budgets. In fact, some of them can be ruled out as independent hypotheses. For example, if the travel time budget were exclusively a fundamental human constant, its distribution over a population should be normal with a small spread. However, that is clearly not the case, as shown in figure 3a. Also, the travel time budget is certainly not a pure residual since time allocations to work differ greatly across nations. In figure 1, work time varies from 3.6 to 5.7 h/cap/d; nevertheless, the change in travel time is statistically insignificant across all data points. While each of the above interpretations fails to explain the stability of the travel budgets individually, it appears that they do, to some extent, complement one another. Travel time and money expenditures are byproducts of spatially separated primary activities and simultaneously represent enabling factors for or constraints to performing additional activities, depending on their utility.

It should also be noted that neither budget is unique. For example, the stability of personal care time expenditures in figure 1 is reflected by a mean of 0.92 h/cap/d, with a standard deviation of 18% of the mean value. Thus, analogous to the "travel time budget," a "personal care time budget" can be defined. Similarly, the money expenditure shares to housing in figure 5 are relatively stable, except perhaps in Italy. This phenomenon may also allow for the definition of a "housing money budget," accounting for 20 to 30% of total household expenditures.

TRAVEL BUDGET IMPLICATIONS FOR MOBILITY

Despite their rough stability, the two travel budgets have important implications on travel patterns. We begin with mode choice and then turn our attention to land-use changes. An examination of the daily range of human interaction closes the section.

Mode Choice

The travel money budget represents the fraction of disposable income devoted to travel. Thus, a fixed travel money budget establishes a direct relationship between disposable income and daily distance traveled, provided average user costs of transport remain constant (see Schafer and Victor 2000).[8] While the constant travel money budget leads to rising travel demand, the roughly constant travel time budget requires travel at a higher speed and thus shifts toward faster modes. In the subsequent subsections, we explore the modal shifts in short distance and long distance travel.

Short Distance Travel

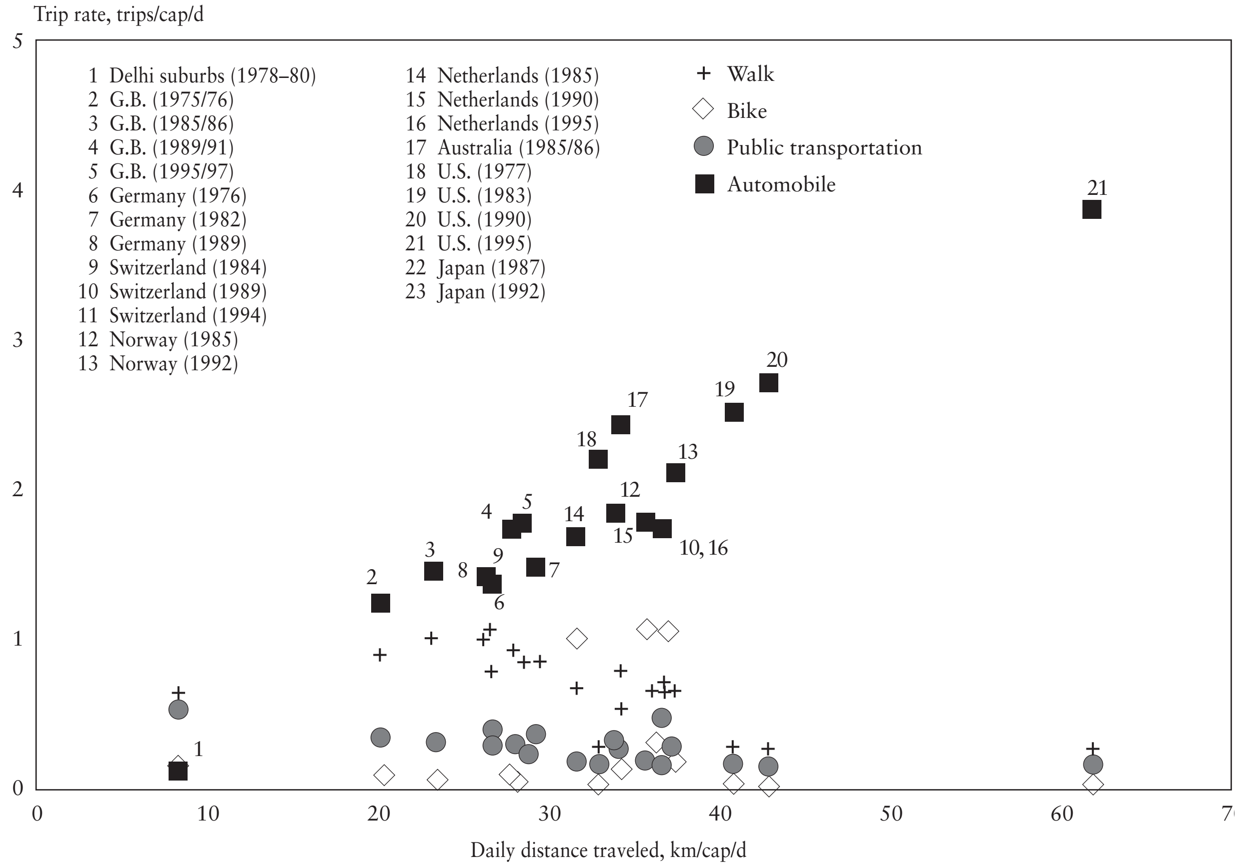
To stay within the travel time budget, traveling longer distances requires a higher mean speed. As the automobile offers the highest mean door-to-door speed of all modes in short distance transport, it therefore provides a continuously increasing number of trips as the daily distance traveled increases. At the same time, the use of low speed public transport and nonmotorized means has to decline. Figure 7 reports the trends of the continuous, nearly linear growth in automobile trips and the declining trip rate of nonmotorized and public transport modes above a daily distance traveled of 25 kilometers. The following points are noteworthy.

In contrast to the broadly consistent automobile trajectory in figure 7, the trips by nonmotorized and public modes of transport are underestimated in the 1977, 1983, and 1990 U.S. surveys, as can be seen by comparing their data points' locations with corresponding data points of other countries at similar daily distances traveled. For example, at a daily travel distance of about 34 kilometers, Americans only walk 0.25 trips per day, according to the 1977 U.S. survey (data point 18), whereas Australians (data point 17) perform more than twice as many walking trips. The same applies to trips by public transport modes. This suggests that the lower trip rate of mainly personal business trips of the 1977, 1983, and 1990 U.S. surveys in figure 2c largely results from the underreported trips by nonmotorized and public transport modes. The latter roughly add 0.5 trips per capita, reflecting the average difference in trip rate between the diary method and the recall methods in pretests of the 1995 U.S. travel survey.

Although the number of trips by mode broadly follows the same trend, quantitative differences again exist. The most significant difference can be observed at a daily distance traveled of roughly 37 kilometers, when the number of trips by automobile ranges from 1.8 (the Netherlands in 1990) to 2.5 (Australia in 1986). This difference results mainly from different levels of travel reporting in these countries. While the reported daily travel distance in the 1990 Netherlands survey is very close to those indicated by independent statistics, the Australian survey underestimated daily distance traveled by 24% (see table 2). Thus, in a consistent comparison, the Australian trip rates should be closer to the automobile trajectory. In other words, data point 17 should be slightly higher, taking into account long distance automobile trips, and at a 32% (1/(1–0.24)) higher daily distance traveled. A second, albeit weaker, factor contributing to the differences in automobile trip rate between the countries is difference in land-use settings, culture, and transport policies. Australia has a high automobile trip rate and is a country with extremely low urban population densities while the Netherlands has a low automobile trip rate and is densely populated. Additionally, the Netherlands has a range of transportation systems management measures and the bicycle pro-

[8] Estimating average user costs from the ratio of transportation expenditures, disposable income times travel money budget, and daily travel distance, including long distance (air) travel, suggests that they have remained roughly constant over the survey years and are 10 cents (1995 U.S.$)/passenger-kilometer (c/pkm) in the United States, 11 to 12 c/pkm in the Netherlands, 11 to 14 c/pkm in Great Britain, 15 to 16 c/pkm in Switzerland, 15 to 17 c/pkm in Norway, 19 to 20 c/pkm in Germany, and 23 to 24 c/pkm in Japan (OECD various years; Eurostat various years; and references listed in table 2).

FIGURE 7 Number of Trips by Mode versus Daily Distance Traveled from Table 1



Note: Above a daily distance traveled of 25 kilometers, the automobile provides all additional trips and increasingly substitutes for trips originally taken with other, slower modes. See tables 1 and A-2.

vides an average of one trip per person per day.[9] Note, however, that bicycles do not only substitute for very short distance automobile trips but also for trips made by public transport or on foot (see the comparatively lower share of these trips in figure 7). A quantification of this substitution, however, requires harmonized travel surveys. This example illustrates that differences in land-use and transportation policy can alter the number of automobile trips within a limited range but are unable to change the fundamental relationships of the transportation system expressed by the two travel budgets.

Figure 7 also shows that aggregate, independent cross-country comparisons of trip rates by mode may give a distorted view of travel patterns. U.S. residents make nearly four automobile trips per person a day, compared to only two to three trips that Western European residents make, mainly because U.S. residents travel a much longer distance per day. Thus, an increase in daily distance traveled in Western Europe will also lead to a higher level of automobile trips and a corresponding decline in trips covered by public and nonmotorized modes. However, despite the consistent trajectory for automobile trip rates over the entire range of daily distance traveled, it is unlikely that the Japanese and Europeans will ever match the high U.S. level of automobile usage. Since automobiles operate at lower mean speeds in more densely populated Europe and, especially, Japan (see table A-2), travelers need to shift to high speed transport modes at a lower automobile trip level in order to increase their daily distance traveled if they do not accept higher travel times.

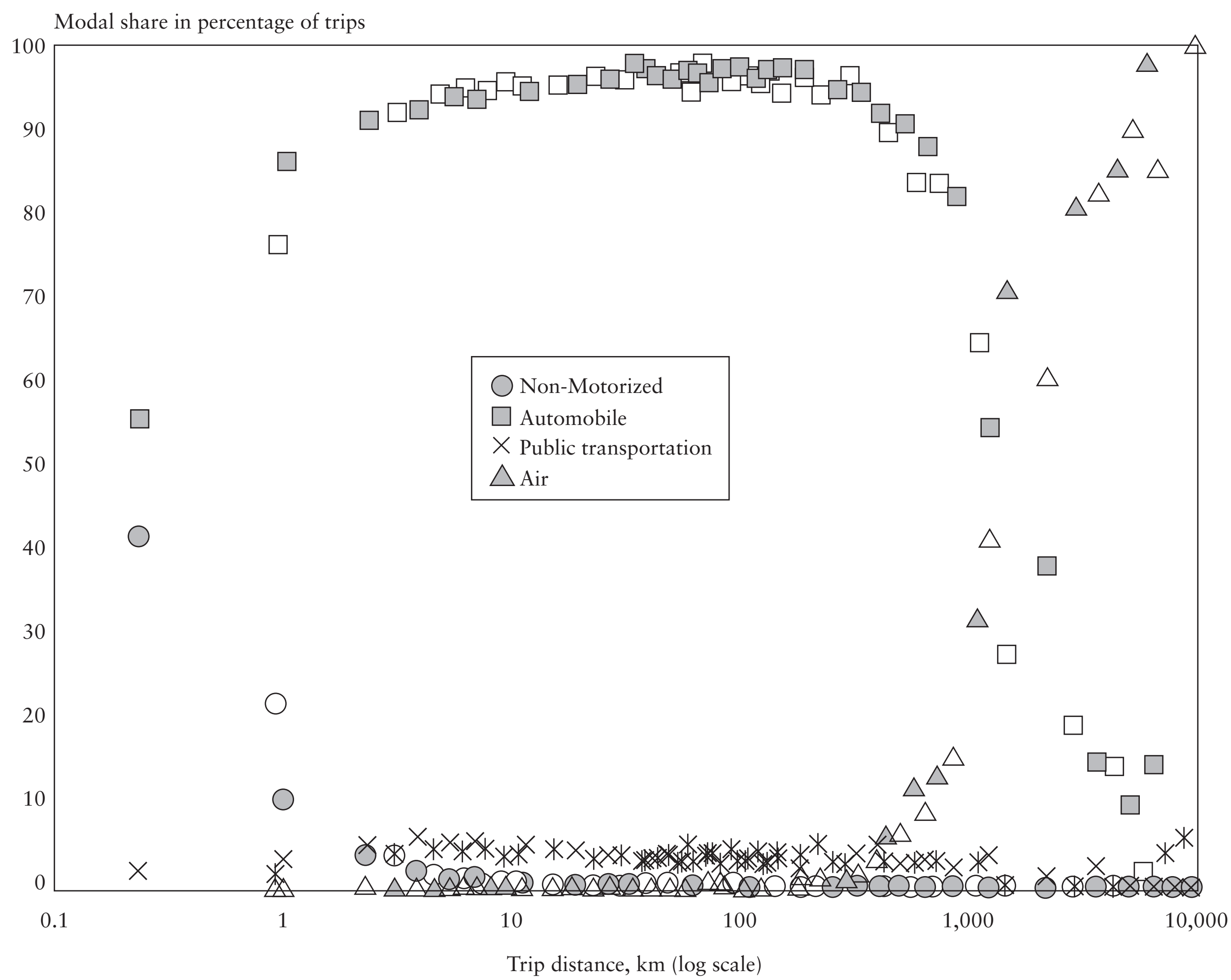
[9] Bicycle usage is high due to a number of extremely favorable conditions, such as active government policy supporting bicycle use; the country's geography, high population density and the associated constrained supply of parking spaces, plain surface area, and numerous small cities; and a relatively dry climate (Welleman et al. 1995).

Long Distance Travel

A continuous increase in daily distance traveled ultimately requires automobile usage over the entire range of trip distances when this mode offers a speed advantage over other travel modes. The dominant role of the automobile in passenger travel over a wide range of trip distances is shown in figure 8 for the United States in 1990 and 1995. The automobile already replaces walking for distances below 1 kilometer and dominates transportation supply over 3 orders of magnitude, that is, to trip distances of about 1,000 kilometers. This corresponds to one day trip by automobile (10 hours at 100 kilometers per hour (km/h). Longer distance trips are predominantly provided by higher speed aircraft. Other modes, such as bicycles and public short distance transport (mainly urban buses, commuter rail, and subways), operate in niche markets, such as in densely populated areas and for transport of children and the elderly, for example. Their maximum share is well below 10% of all trips. The share of these niche market modes can be significantly higher at short travel distances in other, Western European countries. In the Netherlands, for example, bicycles account for almost half of all trips at a distance of two kilometers.

Figure 8 roughly depicts the long term "equilibrium state" of short distance travel, as the potential for further increases in the transport system's mean speed seems nearly exhausted. Greater potential for

FIGURE 8 Modal Split (Trips) in the United States for Short and Long Distance Travel



Gray data points = 1990
White data points = 1995

Note: Trips consist of day trips and period trips (longer than one day).

Sources: U.S. Department of Transportation (1991) and Research Triangle Institute (1997) increased mean speed and thus daily distance traveled exists in long distance travel, for which aircraft can replace automobiles at distances below 1,000 kilometers. According to the 1995 Nationwide Personal Transportation Survey (Research Triangle Institute 1997), mean aircraft speed typically exceeds that of automobiles already at a distance of 400 kilometers.[10] While aircraft account for only 5% of all trips of that distance today, a continuous increase in daily distance traveled will require substitution of automobile travel by air travel at distances between 400 and 1,000 kilometers in the future, or about 15% of the 1995 total passenger traffic volume. In addition, high speed ground transportation and rapidly accessible short haul jet aircraft offer further potential for increasing mean speed at distances between 100 and 400 kilometers for intercity travel, corresponding to another 15% of the total passenger traffic volume in 1995. This trend is consistent with the projected increase in air travel at the expense of automobile travel, first in the industrialized countries and later worldwide (Schafer and Victor 2000).

Land-Use Changes

In the past, the gradual increase in mean travel speed has led to increasing trip distances in general and to significant changes in land use in particular. Using the trip distance between home and work as an aggregate indicator for land-use changes, figure 9 reports the associated increasing population spread versus daily travel distance. The upper extreme of the substantial vertical variation in mean distance to work mainly results from constrained choices of residence and transport mode (Delhi suburbs, data point 1 and Singapore, data point 24), whereas the lower extreme represents different commuting behavior of Swiss residents (data point 11).[11] While the growth relationship between daily travel distance and mean distance to work suggests that people do not chose their residence by minimizing their commuting distance, they, however, seem to experience an upper commuting boundary. Without the special cases of Delhi suburbs and Singapore, the data points for Great Britain (2 to 5) and the United States (especially 18, 20, and 21) represent the maximum average distance people are willing to commute at a given daily travel distance. This boundary seems to level off with rising daily travel distance; otherwise, commuting time would rise more sharply as observed in figure 4b. Only the introduction of a faster travel mode could provide a further significant increase in commuting distance.

The same figure may also help explain why land-use policies aiming at reducing (automobile) traffic are limited on an average, national scale. While figure 7 suggests that automobile trips can be limited by reducing daily distance traveled, figure 9 shows that the mean distance to work has increased in all countries, including the Netherlands, which has one of the highest population densities and best-practiced transportation systems management measures in the world. Perhaps most striking, the mean trip distance to work is almost 15 kilometers, higher than all other European countries examined here, including low population density Norway.

Daily Range of Human Interaction

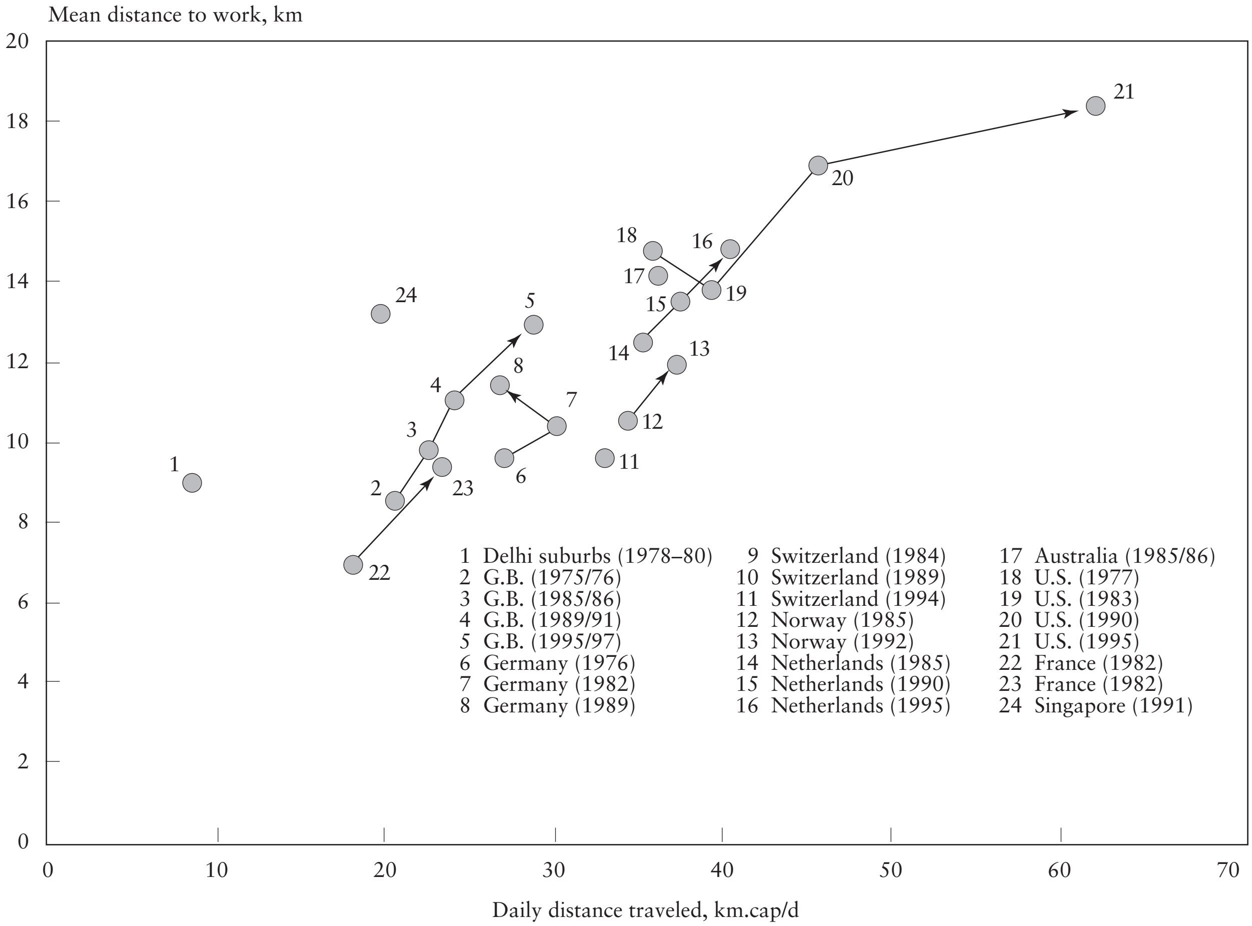
A constant travel money budget translates rising income into rising traffic volume, especially trip distance. On an aggregate level, the relationship is determined by the mean speed of the dominant mode of transport and by the travel time budget. Figure 10 summarizes the resulting daily range of human interaction in terms of the cumulative share of trips versus travel distance. In low income rural Zambia in 1986, 90% of all trips associated with fundamental daily needs, such as fetching water or reaching work in the field, require less than 3 kilometers of travel, allowing one home-based, non-motorized return trip within the daily travel time budget of 1.2 hours. Trip distances to collect firewood are somewhat longer and are longest for trips to rural health care centers and school. In

---

[10] This threshold can be also derived from a mean aircraft speed of 500 km/h and a return trip time of 3 hours from city center to airport and a mean automobile speed of 100 km/h in long distance travel.

[11] Swiss residents travel comparatively short distances to work since a considerable fraction, 40% of commuters, make two additional trips to return home for lunch (Bundesamt für Statistik 1996).

FIGURE 9 Mean Trip Distance to Work



Source: Table B-1

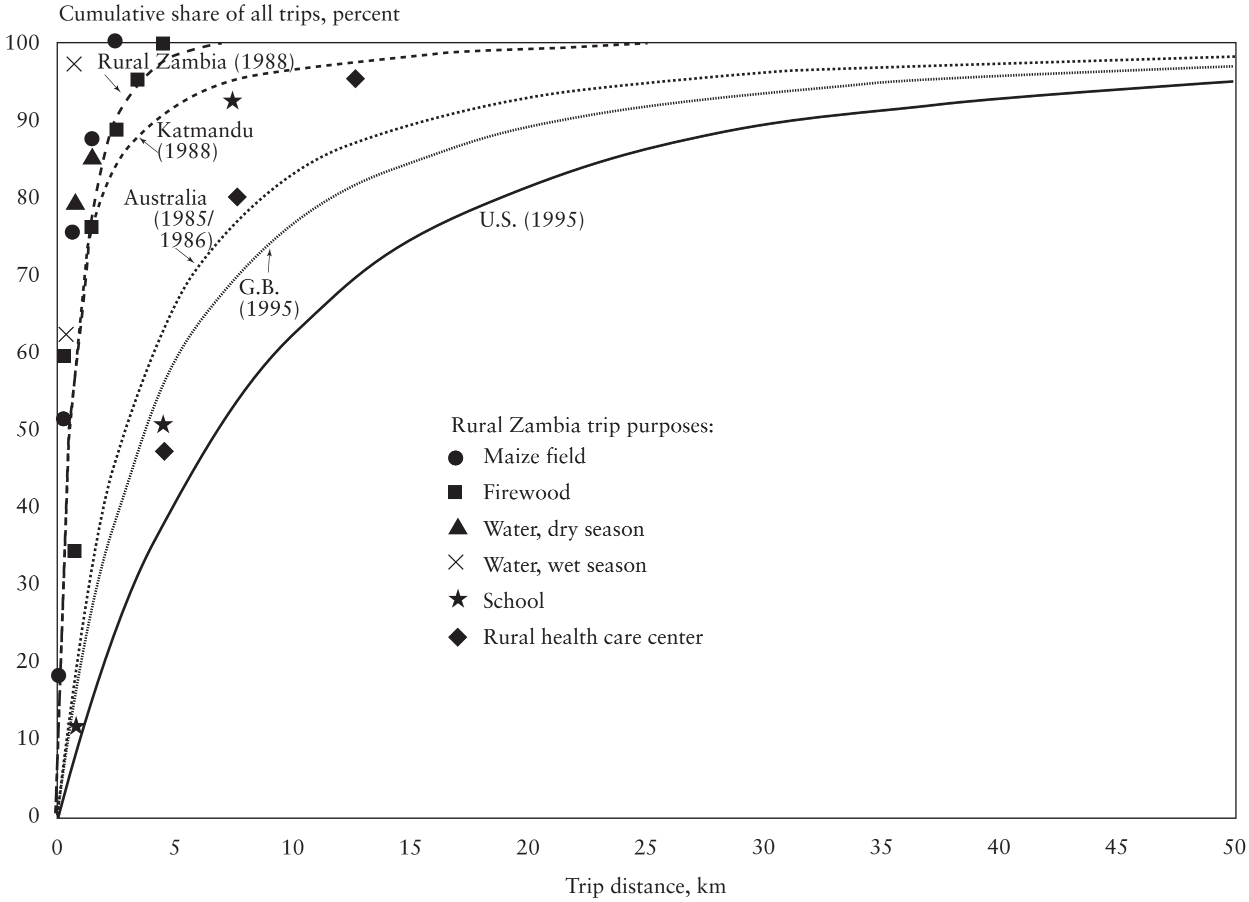
response to exogenously imposed requirements to travel long distances to school, people don't adjust: pupils reportedly do not to attend classes on a regular basis (Immers et al. 1988). Altogether, 95% of all trips are less than 5 kilometers, the mean distance a person can travel on foot within 1.2 hours.

Higher income results in longer travel distances since people can purchase faster transportation, thus enabling longer distances be covered within a given time. In the 200,000-inhabitant capital of Nepal, Katmandu, 95% of all trips evolved well below a distance of 10 kilometers in 1988. The almost two-fold mean travel speed as compared with rural Zambia results from the 25% trip share of buses and other forms of commercial public transport in Katmandu. With rising incomes and a fixed travel money budget, people increase their mean speed and daily travel distance by allocating more money to travel. In the high income, automobile-dominated United States, 95% of all trips are made within a distance of 50 kilometers, the distance that can be covered by automobile within the travel time budget. With even greater income and a continuous supply of high speed transport, 95% of all trips will be longer distance. Ultimately, in a transportation world dominated by high speed modes, the trip boundary may rise to 500 kilometers, corresponding to the distance aircraft and high speed ground transportation systems, such as magnetic levitation trains, can cover within a travel time of slightly more than one hour.

CONCLUSIONS

Aggregate travel behavior is determined largely by two budgets: the share of monetary expenditure and the amount of time that individuals allocate to transportation. However, neither budget is unique or completely stable. We have shown that time and

FIGURE 10 Cumulative Distribution of per Capita Trip Rate for All Modes by Trip Distance and Purpose



Note: The fitted curves are of the type $y = k\left[1/(-c)^b - 1/(x-c)^b\right]$
Source: See table 1.

money budgets dedicated to activities other than travel exist with at least the same statistical stability and that both travel budgets are variable, cross-sectionally and longitudinally. While probably most of these budgets' variation can be attributed to inconsistent survey methods, part of the variation may also be due to behavioral change. Given the fact that the two budgets vary differently across countries, it may be most suitable to consider them as approximately constant on only very high (world-regional, global) aggregation levels.

Both travel budgets are of very rough nature only. However, since they apply to virtually all people, independent of income, space, and time, strong regularities in aggregate travel patterns are observed when we compare cross-sectional and longitudinal data of all travel surveys, including those from the developing world. The travel money budget along with country-specific characteristics of the transportation system (land-use, prices, etc.) translates disposable income into daily distance traveled. All other patterns can be largely explained by the travel time budget. Using this approach, travel patterns of countries with very different characteristics at first glance evolve on nearly uniform trajectories. Thus, despite their only rough stability, the travel budgets offer a simple, elegant framework on the basis of which average travel behavior characteristics can be approximated on aggregate levels. Whether both budgets will remain roughly stable on highly aggregate levels over the long term depends on several factors, ranging from how society adjusts to new information and telecommunications technology to the effect of societal transformations with respect to changing age profiles and altered values. So far, however, such changes have not induced large alterations in either travel budget.

ACKNOWLEDGMENTS

The author is grateful to Moshe Ben-Akiva for helpful discussions and suggestions; to Kay Axhausen, David Greene, and three anonymous referees for providing constructive comments; to Noboru Harata for furnishing and discussing Japanese travel surveys; to Rico Konen for supplying Dutch travel survey data; to Darren Williams for disaggregated Great Britain travel time budget data; to Jimmy Armoogum for providing details from the 1982 French National Transportation Survey methods; and to Deborah Moore for her skillful editing of the manuscript and enormous patience with last-minute changes.

REFERENCES

Adena, M.A. and H.J. Montesin. 1988. *Day-to-Day Travel in Australia 1985-86*. Department of Transport and Communicatsions, Federal Office of Road Safety. Canberra, Australia.

Ang, B.W. 1993. An Energy and Environmental Sound Urban Transport System: The Case of Singapore. *International Journal of Vehicle Design* 14, no. 5/6:431–44.

Australian Bureau of Statistics. Various years. *Year Book Australia*. Canberra, Australia.

Badan Pengkajian dan Penerapan Teknologi and Forschungszentrum. 1991. Air Quality Model for the Traffic Sector, Data, Modeling and Results. *Environmental Impacts of Energy Strategies for Indonesia*. March.

Bundesamt für Statistik. 1996. *Verkehrsverhalten in der Schweiz. 1994*. Dienst für Gesamtverkehrsfragen. Bern, Switzerland.

_____. 1997. *Statistisches Jahrbuch der Schweiz 1998*. Verlag Neue Zürcher Zeitung. Zürich, Switzerland.

Comisión de Planificación de Inversiones en Infraestructura de Transporte. 1992. *Encuesta Origen Destino de Viajes del Gran Santiago*. Santiago, Chile.

Davis, S.C. 1998. *Transportation Energy Data Book: Edition 18*. ORNL-6491, Oak Ridge, TN: Oak Ridge National Laboratory.

Department of the Environment, Transport and the Regions (DOETR). 1995. Transport Statistics Report, National Travel Survey 1992/94. London: The Stationary Office.

_____. 1997. Transport Statistics Report, National Travel Survey 1994/96. London: The Stationary Office.

Department of Transport (DOT). 1979. *National Travel Survey: 1975/6 Report*. London: HMSO.

_____. 1988. *National Travel Survey: 1985/86 Report–Part 1: An Analysis of Personal Travel*. London: HMSO.

_____. 1993. *National Travel Survey 1989/91*. London: HMSO.

_____. Various years. Transport Statistics Great Britain. London: HMSO.

Deutsches Institut für Wirtschaftsforschung. 1987, 1996. *Verkehr in Zahlen*. Bundesminister für Verkehr. Bonn, Germany.

Dienst für Gesamtverkehrsfragen. 1991. *Verkehrsverhalten in der Schweiz 1989*. GFV-Bericht 6/91. Bern, Switzerland.

Eurostat. Various years. National Accounts—Detailed Tables by Branch, Luxembourg.

Fwa, T.F., B.W. Ang, and T.T. Gn. 1993. Study of Car Travel Characteristics in Singapore. *Transportation Research Record* 1412:1–9.

Goodwin, P.B. 1976. Travel Choice and Time Budgets, Transportation Models, Summer Annual Meeting. University of Warwick, England.

_____. 1981. The Usefulness of Travel Budgets. *Transportation Research A* 15:97–106.

Herry, M., G. Sammer, M. Schuster, M. Russ, and G. Röschl. 1998. *Mobilitätserhebung österreichischer Haushalte*. Forschungsarbeiten aus dem Verkehrswesen, Bundesministerium für Wissenschaft und Verkehr. Wien, Germany.

Hupkes, G. 1982. The Law of Constant Travel Time and Trip Rates. *Futures,* February, 3846.

Immers, B.H., E.J. Malipard, and M.J.H. Oldenhof. 1988. Transport in Rural Areas of Developing Countries: Empirical Findings from Western Province, Zambia. *Transportation Research Record* 1167:51–8.

Institut National de la Statistique et des Études Économiques (INSEE). 1986. Les Comptes des Transports en 1985. Paris, France.

_____. 1995. Les Comptes des Transports en 1994. Paris, France.

Katiyar, R. and K. Ohta. 1993. The Concept of "Daily Travel Time" and Its Applicability to Travel Demand Analysis. *Journal of the Faculty of Engineering, The University of Tokyo* (B) 42, no 2:109–21.

Kenworthy, J.R. and F.B. Laube. 1999. Patterns of Automobile Dependence in Cities: An International Overview of Key Physical and Economic Dimensions with Some Implications for Urban Policy. *Transportation Research A* 33, no.7/8:691–723.

Kirby, H.R. 1981. Foreword to Conference Proceedings. T*ransportation Research A* 15:1–6.

Kloas, J., U. Kunert, and H. Kuhfeld. 1993. *Vergleichende Auswertungen von Haushalts-befragungen zum Personennahverkehr (KONTIV 1976, 1982, 1989)*. Gutachten im Auftrage des Bundesministers für Verkehr, Deutsches Institut für Wirtschaftsforschung, Berlin, Germany.

Konen, R. 1999. Central Bureau of Statistics. CBS Heerlen, Sector HVV. Personal communication. March.

Levison, D.M. and A. Kumar. 1994. The Rational Locator: Why Travel Times Have Remained Stable. *Journal of the American Planning Association* 60, no. 3:319–32.

Madre, J.L. and J. Maffre. 1997. *La Mobilité régulière et la mobilité locale en 1982 and 1994*. INSEE Résultats No. 532–533.

Marchetti, C. 1994. Anthropological Invariants in Travel Behavior. *Technological Forecasting and Social Change* 47, 75–88.

Maunder, D.A.C. 1982. Household and Travel Characteristics in Two Middle Income Residential Colonies of Delhi, India. 1981. Supplementary Report 755, Overseas Unit. Crowthorne, Berkshire: Transport and Road Research Laboratory.

_____. 1983. Household and Travel Characteristics in two Suburban Areas of Delhi, India. 1982. Supplementary Report 767, Overseas Unit. Crowthorne, Berkshire: Transport and Road Research Laboratory.

Metrõ. 1989. *Pesquisa OD/87–Síntese das Informações*. São Paulo, Brazil.

Ministry of Infrastructure. n.d. *Trends in Person Trips in Urban Areas*. Results of the Second Nationwide Urban Transportation Survey [1987, 1992], Office of Urban Transportation. Tokyo, Japan.

Nelson, J.A. 1994. Consumer Expenditure Surveys, 1980-1989: Interview Surveys for Household-Level Analysis [Computer file]. Ann Arbor: Inter-university Consortium for Political and Social Research.

Olszewski, P., Y.-D. Wong, J.W. Polak, and P.M. Jones. 1994. Analysis of Travel Behavior in Singapore. Center for Transportation Studies Report 94-02. Singapore: Nanyang Technological University.

Orfeuil, J.P. and I. Salomon. 1993. Travel Patterns of the Europeans in Everyday Life. *A Billion Trips a Day, Tradition and Transition in European Travel Patterns*. Dordrecht: Kluwer Academic Publishers.

Organization for Economic Cooperation and Development (OECD). 1977. *The Future of European Passenger Transport*. Paris, France.

_____. Various years. *National Accounts*. Detailed Tables, volume 2, Paris, France.

Pendakur, V.S. and M. Guarnaschelli. 1991. Motorized and Non-Motorized Transport in Katmandu, Nepal: Where Do the Pedestrians Fit? *Transportation Research Record* 1294.

PlanTrans. 1997. Draft report on NPTS Pretest Methods, cited in P.S. Hu and J.R. Young. 1999. Summary of Travel Trends 1995 Nationwide Personal Transportation Survey, draft. Oak Ridge, TN: Oak Ridge National Laboratory.

Research Triangle Institute. 1997. User's Guide for the Public Use Data Tape, 1995 Nationwide Personal Transportation Survey, Federal Highway Administration, U.S. Department of Transportation, Publication No. FHWA-PL-98-002. Available at: http://www-cta.ornl.gov/npts/1995/Doc/index.shtml.

Riverson, J.D.N. and S. Carapetis. 1991. Intermediate Means of Transport in Sub-Saharan Africa—Its Potential for Improving Rural Travel and Transport. World Bank Technical Paper Number 161, Technical Department Series. Washington: The World Bank.

Schafer, A. and D. Victor. 2000. The Future Mobility of the World Population. *Transportation Research A* 34, no. 3:171–205.

Schipper, L., M.J. Figueroa, and R. Gorham. 1995. People on the Move: A Comparison of Travel Patterns in OECD Countries. The Institute of Urban and Regional Development, University of California, Berkely.

Stab für Gesamtverkehrsfragen. 1986. *Verkehrsverhalten in der Schweiz 1984,* GVF-Bericht 2/86. Bern, Switzerland.

Statistics Bureau. 1995. Japan Statistical Yearbook. Management and Coordination Agency, Government of Japan. Tokyo, Japan.

_____. 1998. Japan Statistical Yearbook. Management and Coordination Agency, Government of Japan. Tokyo, Japan.

Statistics Netherlands. 1998. Statistical Yearbook 1998 of the Netherlands. Voorberg/Herleen.

Statistics Norway. Various years. Statistical Yearbook of Norway, Statistisk Sentralbyrå, Oslo-Kongsvinger.

Statistics Sweden. 1987. Resvaneundersökningen 1984/85. Statistika Meddelanden T 11 SM 8701. Örebro, Sweden.

Szalai, A., P.E. Converse, P. Feldheim, E.K.Scheuch, and P.J. Stone. 1972. *The Use of Time: Daily Activities of Urban and Suburban Populations in 12 Countries*. The Hague: Mouton.

Tanaboriboon, Y., S.S. Hwa, and C.H. Chor. 1986. Pedestrian Characteristics in Singapore. *Journal of Transportation Engineering* 114, 6.

Tanner, J.C. 1961. Factors Affecting the Amount of Travel. Road Research Technical Paper no. 51. London: HMSO.

Tjahjati, B., S. Soegijoko, and S.I. Horthy. 1991. Role of Non-Motorized Transport Modes in Indonesian Cities. *Transportation Research Record* 1294, 16–25.

U.S. Department of Commerce (USDOC), Census Bureau. 1999. *Statistical Abstract of the United States*. Washington, DC.

U.S. Department of Labor (USDOL), Bureau of Labor Statistics (BLS). 1997. *Consumer Expenditure Survey.* Washington, DC.

U.S. Department of Transportation (USDOT), Federal Highway Administration (FHWA). 1983. *1977 Nationwide Personal Transportation Survey: Person Trips Characteristics*. Report 11. Washington, DC.

_____. 1986. *Personal Travel in the United States, volume 2, 1983–1984 Nationwide Personal Transportation Study.* Washington, DC.

_____. 1991. *Nationwide Personal Transportation Survey 1990,* Public User Diskettes. Washington, DC.

_____. 1994. *Nationwide Personal Transportation Survey 1990,* Databook, vol I and II. Washington, DC.

_____. Various years. *Highway Statistics.* Washington, DC.

Vibe, N. 1993. *Våre deglige Reiser–Endringer I nordmenns reisevaner fra 1985 til 1992,* Transportokonomisk Institutt, Rapport 171/1993, Oslo, Norway.

Welleman, A.G., J.L Cees, and D.M. Ligtermoet. 1995. Bicycles in Cities. *China's Urban Transport Development Strategy, Proceedings of a Symposium in Beijing,* November 8–10. World Bank Discussion Paper No. 352, East Asia and Pacific Region Series.

Williams, D. 2000. Department of the Environment, Transport and the Regions. Data of Travel Time by Age Group. Personal communication. November.

Zahavi, Y. 1981. *The UMOT-Urban Interactions,* DOT-RSPA-DPB 10/7, U.S. Department of Transportation, Washington, DC.

Zuzanek, J. 1980. *Work and Leisure in the Soviet Union.* New York: Praeger.

APPENDIX

Mobility Indicators by Trip Purpose and by Major Mode of Transport for Seven Industrialized Countries

Tables A-1 and A-2 report averages for per capita trip rate, mean trip distance, and mean trip duration, as well as the resulting daily per person traffic volume and time, by trip purpose and transportation mode, from travel surveys in seven industrialized countries and four Delhi suburbs. Note that the two tables' totals for one and the same survey may differ slightly, due to their differing treatments of not-ascertained and non-responses. Also, due to rounding, numbers may not add up to totals displayed.

Since travel surveys are often based on different methods, the reader must be cautious when comparing indicators not only across countries but also across different years for the same country. This is especially true for comparisons of the 1990 and 1995 trip rates in the United States. The reported numbers give only a rough picture of people's mobility (see section on the comparability of the underlying travel surveys).

Estimate of Average Daily Travel Distances in Singapore

Because the Singapore survey did not report travel distances, these had to be estimated based on the travel time distribution and estimated mean speeds by mode. Table B-1 reports all data used for the estimation, including the estimates in detail. Also, the trip distance to work of 13.2 kilometers (figure 4b) was approximated based on a travel time of 43.2 minutes per trip and the mean speed as given in table B-1.

TABLE A-1 Indicators of Daily Mobility by Trip Purpose for Seven OECD Countries

	1975–1977					1982–1986					1989–1992					1994–1996				
	TR T/ cap	TD km/ T	TV km/ cap	TL h/ T	TT h/ cap	TR T/ cap	TD km/ T	TV km/ cap	TL h/ T	TT h/ cap	TR T/ cap	TD km/ T	TV km/ cap	TL h/ T	TT h/ cap	TR T/ cap	TD km/ T	TV km/ cap	TL h/ T	TT h/ cap
Australia																				
Work & education						0.69	12.4	8.5	0.41	0.28										
work						0.51	14.1	7.2	0.43	0.22										
business						0.02	15.1	0.3	0.39	0.01										
education						0.16	6.6	1.1	0.35	0.06										
Personal business						0.80	6.5	5.2	0.25	0.20										
Leisure						0.57	14.8	8.5	0.45	0.25										
Home						1.31	10.6	14.0	0.35	0.47										
All travel						3.37	10.7	36.2	0.36	1.21										
Great Britain																				
Work & education	0.99	8.2	8.1	0.34	0.34	0.88	9.3	8.2	0.32	0.28	0.93	10.6	9.9	0.32	0.30	0.86	11.5	9.9	0.37	0.32
work	0.56	8.5	4.8	0.33	0.19	0.51	9.8	5.0	0.35	0.18	0.53	11.1	5.9	0.34	0.18	0.44	12.9	5.6	0.40	0.17
business	0.10	20.3	2.1	0.67	0.07	0.08	28.4	2.3	0.63	0.05	0.11	27.5	3.0	0.55	0.06	0.10	29.6	3.1	0.61	0.06
education	0.32	3.9	1.2	0.27	0.08	0.29	2.8	0.8	0.21	0.06	0.29	3.2	0.9	0.17	0.05	0.32	3.7	1.2	0.25	0.08
Personal business	0.86	4.8	4.2	0.28	0.24	1.02	5.5	5.6	0.28	0.29	1.21	5.7	6.9	0.29	0.35	1.13	6.4	7.2	0.27	0.30
Leisure	0.69	12.6	8.7	0.47	0.32	0.77	11.9	9.2	0.46	0.35	0.85	13.3	11.3	0.42	0.36	0.90	13.1	11.8	0.40	0.36
All travel	2.54	8.3	21.0	0.36	0.90	2.67	8.6	23.0	0.34	0.92	2.99	9.4	28.1	0.34	1.01	2.90	10.0	28.9	0.34	0.98
Netherlands																				
Work & education						1.16	13.3	15.4	0.37	0.43	1.07	14.5	15.5	0.39	0.41	1.06	15.8	16.7	0.46	0.46
work						0.58	12.2	7.1	0.36	0.21	0.63	13.3	8.5	0.36	0.23	0.52	14.8	7.7	0.39	0.20
business						0.36	17.3	6.3	0.39	0.14	0.25	20.4	5.1	0.42	0.11	0.24	22.8	5.4	0.47	0.11
education						0.21	9.4	2.0	0.40	0.08	0.18	10.7	2.0	0.42	0.08	0.30	11.9	3.6	0.48	0.14
Personal business						1.35	5.4	7.3	0.23	0.31	1.47	5.4	7.9	0.22	0.32	1.48	6.2	9.2	0.24	0.35
Leisure						1.13	11.1	12.5	0.42	0.47	1.21	11.9	14.3	0.43	0.52	1.17	12.6	14.7	0.42	0.49
All travel						3.64	9.7	35.2	0.33	1.21	3.75	10.1	37.7	0.33	1.25	3.71	10.9	40.6	0.35	1.30
Norway																				
Work & education						1.19	12.2	14.5	0.34	0.40	1.16	13.0	15.1	0.34	0.39					
work						0.67	10.6	7.1	0.32	0.21	0.67	11.9	8.0	0.33	0.22					
business						0.18	21.1	3.8	0.46	0.08	0.11	34.9	3.8	0.64	0.07					
education						0.34	10.7	3.6	0.32	0.11	0.38	8.6	3.3	0.27	0.10					
Personal business						0.93	6.4	6.0	0.27	0.25	1.03	6.4	6.6	0.23	0.23					
Leisure						1.07	12.9	13.9	0.46	0.49	1.06	14.6	15.5	0.43	0.46					
All travel						3.19	10.8	34.4	0.36	1.14	3.25	11.4	37.2	0.33	1.08					

TABLE A-1 Indicators of Daily Mobility by Trip Purpose for Seven OECD Countries (*continued*)

	1975–1977					1982–1986					1989–1992					1994–1996				
	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap
Switzerland																				
Work & education						1.33	8.9	13.7	0.31	0.47	1.52	8.1	16.0	0.40	0.60	1.16	10.6	12.3	0.40	0.46
work						N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.73	9.6	7.0	0.31	0.23
business						0.12	15.2	1.8	0.40	0.13	0.30	20.5	6.1	0.56	0.17	0.17	24.1	4.1	0.94	0.08
education						N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.26	4.6	1.2	0.29	0.16
Personal business						0.79	4.6	3.6	0.26	0.20	0.78	6.3	4.9	0.34	0.26	0.75	5.7	4.3	0.26	0.19
Leisure						1.00	11.9	11.9	0.33	0.38	1.14	15.8	18.0	0.58	0.66	1.34	12.4	16.6	0.54	0.72
All travel						3.35	8.8	29.2	0.30	1.04	3.45	11.5	39.8	0.45	1.54	3.25	10.2	33.2	0.42	1.38
United States																				
Work & education	1.03	13.6	13.9	0.29	0.29	1.02	13.2	13.5	0.29	0.30	1.01	15.1	15.3	0.30	0.31	1.25	16.9	21.1	0.33	0.41
work	0.57	14.7	8.4	0.31	0.18	0.60	13.7	8.3	0.30	0.18	0.62	16.8	10.4	0.33	0.20	0.76	18.4	14.0	0.35	0.27
business	0.11	28.3	3.0	0.35	0.04	0.07	35.1	2.4	0.38	0.03	0.04	44.4	1.9	0.44	0.02	0.11	32.3	3.6	0.44	0.05
education	0.35	7.4	2.6	0.22	0.08	0.35	7.9	2.7	0.25	0.09	0.35	8.5	3.0	0.24	0.09	0.38	9.4	3.6	0.25	0.10
Personal business	0.91	10.1	9.2	0.24	0.22	1.05	10.1	10.6	0.23	0.24	1.30	11.0	14.4	0.22	0.29	1.97	11.0	21.7	0.22	0.44
Leisure	0.71	12.6	12.6	0.35	0.25	0.82	19.8	16.2	0.31	0.26	0.76	20.8	15.9	0.34	0.26	1.08	17.8	19.2	0.31	0.33
All travel	2.65	13.5	35.8	0.30	0.80	2.89	14.0	40.3	0.28	0.80	3.08	14.8	45.6	0.28	0.86	4.30	14.4	61.9	0.27	1.18
West Germany																				
Work & education	1.07	10.4	11.1	0.39	0.42	1.06	12.1	12.8	0.41	0.43	0.93	12.2	11.3	0.40	0.37					
work	0.68	9.6	6.5	0.37	0.25	0.64	10.4	6.7	0.37	0.24	0.63	11.4	7.2	0.38	0.24					
business	0.15	20.0	3.0	0.47	0.07	0.17	22.9	3.9	0.54	0.09	0.11	22.9	2.5	0.52	0.06					
education	0.24	6.9	1.7	0.40	0.10	0.25	9.2	2.3	0.42	0.10	0.19	8.3	1.6	0.39	0.07					
Personal business	1.01	3.8	3.8	0.26	0.27	0.95	4.7	4.5	0.29	0.28	0.82	4.7	3.9	0.27	0.22					
Leisure	1.01	12.0	12.1	0.46	0.46	1.01	12.8	12.9	0.47	0.48	0.98	11.7	11.5	0.43	0.42					
All travel	3.09	8.7	26.9	0.37	1.14	3.02	10.0	30.2	0.39	1.19	2.73	9.8	26.8	0.37	1.02					
4 Delhi suburbs																				
Work & education						1.17	6.2	7.2	0.55	0.65										
work						0.58	9.0	5.2	0.73	0.42										
business						N/A	N/A	N/A	N/A	N/A										
education						0.59	3.3	2.0	0.38	0.23										
Personal business						0.25	2.2	0.6	0.24	0.06										
Leisure						0.07	10.1	0.7	0.56	0.04										
All travel						1.49	5.7	8.5	0.50	0.65										

T = trip; TR = mean trip rate; TD = mean trip distance; TV = mean daily per capita traffic volume; TL = mean trip length; TT = mean daily per capita travel time

For data source and exact survey years, see table 1

TABLE A-2 Indicators of Daily Mobility by Major Mode for Seven OECD Countries

	1975–1977						1982–1986						1989–1992						1994–1996					
	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h
Australia																								
Walk							0.55	1.0	0.6	0.25	0.13	4.2												
Bike							0.13	2.5	0.3	0.25	0.03	9.9												
Public transport							0.27	11.7	3.1	0.49	0.13	23.8												
Automobiles							2.41	12.4	30.0	0.35	0.84	35.8												
All travel							3.38	10.1	34.3	0.34	1.14	30.0												
Great Britain																								
Walk	0.89	1.0	0.9	0.26	0.23	3.8	0.96	1.0	0.9	0.24	0.23	4.0	0.90	1.0	0.9	0.25	0.23	3.8	0.83	1.0	0.8	0.24	0.20	4.0
Bike	0.08	2.7	0.2	0.23	0.02	11.7	0.07	2.7	0.2	0.24	0.02	11.4	0.06	3.1	0.2	0.24	0.01	12.8	0.05	3.5	0.2	0.29	0.01	12.0
Public transport	0.35	10.5	3.6	0.56	0.19	18.6	0.30	12.0	3.6	0.59	0.18	20.4	0.28	13.8	3.9	0.62	0.18	22.4	0.25	13.8	3.5	0.61	0.16	22.6
Automobiles	1.22	12.8	15.6	0.37	0.45	34.5	1.45	12.8	18.6	0.34	0.49	37.9	1.73	13.4	23.1	0.34	0.59	39.3	1.75	13.8	24.1	0.34	0.60	40.0
All travel	2.53	8.0	20.3	0.35	0.89	22.7	2.78	8.4	23.3	0.33	0.92	25.5	2.97	9.5	28.1	0.34	1.01	27.9	2.88	9.9	28.6	0.34	0.98	29.3
Netherlands																								
Walk							0.71	1.2	0.8	0.28	0.20	4.3	0.65	1.2	0.7	0.27	0.17	4.3	0.69	1.3	0.9	0.27	0.18	4.7
Bike							0.99	3.2	3.1	0.25	0.25	12.5	1.07	3.1	3.3	0.26	0.27	12.2	1.04	3.2	3.3	0.25	0.26	12.6
Public transport							0.17	23.0	3.9	0.83	0.14	27.7	0.18	27.4	4.9	0.89	0.16	30.8	0.17	29.5	4.9	0.90	0.15	32.6
Automobiles							1.68	14.2	23.8	0.34	0.56	42.2	1.76	15.2	26.8	0.34	0.60	44.5	1.72	16.1	27.7	0.36	0.61	45.2
All travel							3.55	8.9	31.7	0.33	1.15	27.5	3.66	9.8	35.8	0.33	1.21	29.6	3.62	10.2	36.8	0.33	1.21	30.4
Norway																								
Walk							0.79	1.4	1.1	0.29	0.23	4.8	0.66	1.4	0.9	0.25	0.16	5.7						
Bike							0.20	2.1	0.4	0.21	0.04	10.1	0.20	2.6	0.5	0.21	0.04	12.7						
Public transport							0.31	32.4	10.0	0.85	0.26	38.0	0.26	27.0	7.0	0.83	0.21	32.7						
Automobiles							1.84	12.2	22.5	0.32	0.59	38.1	2.09	13.9	29.0	0.31	0.66	44.2						
All travel							3.14	10.8	34.1	0.36	1.13	30.2	3.21	11.7	37.5	0.3	1.07	34.9						
Switzerland																								
Walk							0.98	0.8	1.0	0.23	0.28	3.6	0.75	1.6	1.2	0.34	0.26	4.5						
Bike							0.35	2.0	0.8	0.18	0.08	11.0	0.33	2.9	1.0	0.30	0.10	9.6						
Public transport							0.38	12.3	5.5	0.53	0.24	23.2	0.46	17.1	7.9	0.80	0.37	21.4						
Automobiles							1.42	11.3	19.2	0.29	0.50	38.7	1.72	15.1	25.9	0.42	0.72	36.2						
All travel							1.71	13.0	26.6	0.29	0.59	45.1	3.41	10.8	36.9	0.44	1.49	24.8						

TABLE A-2 Indicators of Daily Mobility by Major Mode for Seven OECD Countries (*continued*)

	1975–1977						1982–1986						1989–1992						1994–1996					
	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h	TR T/cap	TD km/T	TV km/cap	TL h/T	TT h/cap	V km/h
United States																								
Walk	0.25	0.4	0.1	0.16	0.04	2.7	0.26	0.6	0.1	0.17	0.04	3.5	0.22	1.0	0.2	0.17	0.04	6.2	0.24	0.8	0.2	0.17	0.04	4.7
Bike	0.02	5.8	0.1	0.22	0.00	26.5	0.02	3.3	0.1	0.26	0.01	13.0	0.02	3.2	0.1	0.22	0.00	14.5	0.04	2.1	0.1	0.19	0.01	11.4
Public transport	0.16	12.4	2.0	0.49	0.08	25.4	0.16	13.9	2.2	0.51	0.08	28.5	0.15	15.4	2.3	0.47	0.07	32.7	0.16	28.4	4.6	0.68	0.11	41.7
Automobiles	2.19	13.8	30.2	0.29	0.64	47.1	2.49	15.5	38.5	0.29	0.69	56.0	2.68	15.1	40.5	0.27	0.72	56.1	3.85	14.8	57.1	0.28	1.06	53.9
All travel	2.65	12.5	33.1	0.29	0.78	42.6	2.93	14.0	40.9	0.29	0.81	50.4	3.07	14.0	43.1	0.27	0.83	51.7	4.30	14.4	62.0	0.28	1.22	50.9
West Germany																								
Walk	1.05	1.1	1.2	0.30	0.31	3.8	0.84	1.2	1.0	0.32	0.27	3.7	0.77	1.5	1.1	0.30	0.23	4.9						
Bike	0.28	2.1	0.6	0.25	0.07	8.1	0.34	2.6	0.9	0.28	0.10	9.3	0.33	3.0	1.0	0.28	0.09	10.5						
Public transport	0.37	15.1	5.6	0.69	0.26	21.9	0.37	17.3	6.5	0.73	0.28	23.5	0.27	17.3	4.6	0.63	0.17	27.6						
Automobiles	1.39	14.0	19.5	0.36	0.51	38.3	1.47	14.3	21.0	0.37	0.55	38.4	1.37	14.6	20.0	0.38	0.53	38.0						
All travel	3.09	8.7	26.9	0.37	1.15	23.4	3.02	9.7	29.4	0.39	1.19	24.7	2.75	9.8	26.8	0.37	1.02	26.2						
4 Delhi suburbs																								
Walk							0.67	N/A	N/A	N/A	N/A	N/A												
Bike							0.15	N/A	N/A	N/A	N/A	N/A												
Public transport							0.53	N/A	N/A	N/A	N/A	N/A												
Automobiles							0.11	N/A	N/A	N/A	N/A	N/A												
All travel							1.45	5.7	8.5	0.50	0.65	13.1												

T = trip; TR = mean trip rate; TD = mean trip distance; TV = mean daily per capita traffic volume; TL = mean trip length; TT = mean daily per capita travel time; V = mean trip speed

For data source and exact survey years, see table 1.

TABLE B-1 Estimate of Average Daily Travel Distances in Singapore

Mode	Travel time min/cap/d	Mean speed km/h	Distance traveled km/cap/d	Reference/comments
Walk	8.9	4.4	0.65	Tanaboriboon (1986)
Bike	0.2	6.0	0.02	Relates to Indonesian cities (Tjahjati et al. 1991)
Motor Bike	1.6	32.3	0.86	Assumed to equal automobile speed
Automobile	11.5	32.3	6.19	Fwa et al. (1993)
Bus	34.5	17.0	9.78	Mean over different services and times, Ang (1993)
MRT	6.8	17.0	1.93	Assumed to equal bus speed
Others	1.2	17.0	0.34	Assumed to equal bus speed
Total	**64.7**	**18.3**	**19.77**	Resulting from above data

Sources: Travel times by mode are derived from Singapore survey (Olszewski et al. 1994, tables 7.7, 8.1, and 10.2). All mean speeds are taken from the indicated references or are estimates

New and Existing Roadway Inventory Data Acquisition Methods

AEMAL J. KHATTAK

University of Nebraska—Lincoln

JOSEPH E. HUMMER

North Carolina State University

HASSAN A. KARIMI

University of Pittsburgh

ABSTRACT

A number of agencies collect roadway inventory data using the traditional manual method. Representing an advancement in roadway inventory data collection, mobile mapping systems use state-of-the-art imaging, georeference, and software technologies to collect data and are emerging as an alternative to the manual method. To gain an in-depth understanding of which method is more accurate and economical for an inventory job, this study compares the two data collection methods. Four experiments examine descriptive inventory data collected by the two methods, considering data accuracy in different roadway environments, type of inventory element, and data collection time. Because there are mobile mapping systems with different technological characteristics, the four experiments utilize four different mobile mapping systems to cover the spectrum of various systems available for data collection.

Statistical analysis shows that the accuracy of descriptive inventory data depends on the method of collection and that the manual method provides slightly more accurate data. Furthermore, the roadway environment and the type of inventory element measured affect data accuracy. Compared

Aemal J. Khattak, University of Nebraska—Lincoln, W348 Nebraska Hall, Lincoln, NE 68588–0531. Email: akhattak@unl.edu.

with the manual method, the mobile mapping systems required less time during field operations but more time during office processing. This research suggests that transportation agencies interested in adopting mobile mapping systems for data collection might not see significant improvements in descriptive inventory data accuracy. However, the use of mobile mapping systems for inventory data collection provides other benefits.

INTRODUCTION

Transportation agencies across the United States maintain and regularly update vast inventories of a variety of roadway elements. Information from these inventories serves as the basis for many transportation-related policy decisions. A roadway inventory may include elements such as lane width, traffic sign width, traffic sign height, and sign condition. For inventory purposes, an element must have two types of data: georeference and descriptive. The georeference data provide location of the element in space: latitude, longitude, and altitude. Descriptive data define the element: length, width, height, and condition. The accuracy of both georeference and descriptive data significantly determines the usefulness of an inventory element. Both georeference and descriptive data accuracy, is critical in a number of applications such as crash analysis, short term and long term transportation planning, maintenance operations, and lawsuits against a roadway agency.

Inventory Data Collection

The process of roadway inventory data collection requires a means for transportation, a means for measuring and recording georeference data, and a means for measuring and recording descriptive data. Roadway agencies in the United States have traditionally employed the manual method, typically involving data collectors, a vehicle (usually a van or a truck), a distance measuring instrument (DMI), and paper and pencil to collect inventory data. In this method, the collector locates an inventory element in the field and obtains its georeference data using a linear referencing method, such as a milepoint, a reference post, or an engineering station. The collector also records descriptive data, usually personal estimates, pertinent to the inventory element. This method of inventory data collection is the most common among state departments of transportation (DOTs) in the United States (Karimi et al. 2000).

Representing a significant advancement in the roadway inventory data collection practice, the mobile mapping system (MMS) requires data collectors and a vehicle (usually a van or sport utility vehicle) equipped with such technologies as a Global Positioning System (GPS) receiver, a DMI, an inertial navigation system (INS), and digital cameras. After integration of data collected by the different sensors, collectors can obtain descriptive inventory data by making digital measurements on inventory elements captured in the camera images with the use of photogrammetric software packages. Digital measurements refer to geometric measurements in the three spatial dimensions (x, y, and z) on roadway elements captured in the images (see Agouris et al. 1997 for details). Wang (2000) provides information on the design of MMSs for pavement distress data collection. Obtaining inventory data with an MMS offers the possibility of reduced time spent in the field, reduced exposure to hazardous traffic conditions, and possible elimination of subsequent field visits.

Many roadway agencies using the manual method of data collection are considering adopting an MMS. Previous research has shown that the georeference accuracy of inventory elements collected by different MMSs is sufficiently high for roadway inventory purposes (Coetsee et al. 1994, Center for Mapping 1994, Vaidya et al. 1994, Whited and Kadolph 1995, Shaw and Guthrie 1997, Schwarz and El-Sheimy 1997, Novak and Nimz 1997). However, the literature lacks information on the accuracy of descriptive data collected by MMSs. This makes the MMS adoption decision difficult for agencies contemplating a change in their data collection practice.

This paper presents the results of four experiments comparing the accuracy of descriptive inventory data collected by the MMS method with data collected by the manual method. Because several systems with varying capabilities qualify as MMSs, the authors chose four different systems to cover the spectrum of available MMSs. Each experiment used one of the chosen MMS's and compared data it collected with manually collected data. The conclusion uses these results to consider accuracy and other merits of data collection by the two methods.

LITERATURE REVIEW

Accuracy of Manually Acquired Descriptive Data

Several researchers have investigated human capability to visually estimate object dimensions and distances. Gibson (1950) presented the idea that the human brain represents space using the ground surface as a reference frame. A major aspect of Gibson's "ground theory" is that when the ground surface between the observer and the target object is disrupted, the visual system cannot establish a reliable reference frame and consequently fails to judge correctly object dimensions and distance to the target. Subsequently, Barlow (1961) and Sedgwick (1983) proposed that the human brain might use a quasi two-dimensional coordinate system with respect to the ground surface to judge distances rather than a three-dimensional spatial coordinate system.

Sinai et al. (1998) tested Gibson's theory by placing a target on the far side of a 0.50-meter deep by 1.30-meter wide gap in the ground surface. The task of the observers in the experiment was to judge the distance from the point of observation to the target. The average estimated distance of 4.24 meters overestimated the actual distance of 3.66 meters by 0.68 meters. As a control, the examiners tested other observers over the same distance of 3.66 meters on a continuous surface. They found that the estimated distance for the continuous surface condition was 3.54 meters, much closer to the actual distance. Changes in the observer's placement, the gap depth, and the gap width produced similar results.

These researchers further tested the influence of surface texture discontinuity on distance judgment (Sinai et al. 1998). They found that, on average, observers underestimated the actual distance of 7.62 meters as 6.50 meters if the surface between the observer and the target was part concrete and part grass. Estimates by the observers were close to the actual distance when the surface was either only concrete or only grass. Overall, their results indicated that distance judgment was affected by the presence of discontinuities either in the form of gaps in the surface (resulting in overestimation) or discontinuities in surface texture (resulting in underestimation). They concluded that their results supported Gibson's proposal that the human brain uses ground surface as a frame of reference for judging distances.

Accuracy of Descriptive Data Acquired by MMS

In a comparative study of data obtained by an MMS and ground truth observations, Lee et al. (1991) concluded that the data obtained by an MMS was of "reasonable" accuracy. The conclusion was not based on any statistical analysis, nor was a definition of "reasonable" accuracy provided. Mastandrea et al. (1995) reported an accuracy of 5 to 10 centimeters for various inventory elements collected by an MMS. They did not report on the evaluation methodology or data elements used in the evaluation or provide analysis details. El-Sheimy (1996) compared the accuracy of descriptive data obtained with an MMS to ground truth observations. His findings indicated that errors in digital measurements increased with increasing distance between the object and the camera. However, El-Sheimy does not provide information on the identity and size of the measured inventory elements or on the number of observations made on the elements.

In a test of crack identification and classification, Roadware Corporation (1994) compared the accuracy of its photogrammetric software package for crack identification with the long term pavement performance (LTPP) procedure and found them comparable. However, there was no similarity in crack classification (block, fatigue, transverse, longitudinal wheelpath, and edge) in the two methods. In another test, Roadware Corporation (1996) shows that its photogrammetric software package was able to automatically classify collected data on pavement cracks into the LTPP categories. However, there was no indication if the classification was correct.

In summary, the literature indicates that accuracy of the manual method depends on the surface composition and continuity between the point of observation and the target object. Literature on the accuracy of descriptive data obtained by MMSs is insufficient to judge whether MMSs provide accuracy comparable to the manual method.

EXPERIMENT DESIGN

Because data collected by MMSs with different design and photgrammetric software characteristics all qualify as data collected by the MMS method, the authors used four different systems to cover the spectrum of MMS data collection methods. The four experiments, each utilizing one of the chosen MMSs and the manual method, took place at different locations.

A comparison of data collected by a collection method with ground truth values determined the accuracy of that method. The ground truth value represented the "true" dimension of an inventory element and required the measurement of an inventory element in the field as accurately as possible. For example, careful measurement of the width of a traffic sign in the field with a tape measure resulted in the ground truth observation for the width of that traffic sign. We termed the statistic representing the accuracy of measurement by a particular method as the percent measurement error (PME) and defined it for the manual method as

$$PME_{Manual} = \left[\frac{X_{Manual} - X_{GroundTruth}}{X_{GroundTruth}}\right]100 \qquad (1)$$

where:

X_{Manual} equals observation on an inventory element by the manual method, and

$X_{GroundTruth}$ equals ground truth observation for that inventory element.

The authors calculated the PME values for the MMSs (PME_{MMS}) by substituting the observation on an inventory element made by the particular MMS (X_{MMS}) used in the experiment for X_{Manual} in equation (1). The positive or negative sign of the PME indicates if a particular data collection method overestimates (positive sign) or underestimates (negative sign) the true dimension of the inventory element.

Each experiment was conducted in three different roadway environments: urban streets, two-lane rural, and interstate highway, the three environments in which most transportation agencies collect their inventory data. Termed experiments 1, 2, 3, and 4, each experiment includes data collected on equipment cost, field data collection time, and time spent in the office during data processing and computer inputting.

The main factors under investigation in each experiment were (1) the method of data collection, (2) the roadway environment, and (3) the inventory element type. The method of data collection had two levels: the particular MMS used in the experiment and the manual method. The roadway environment factor had three levels: urban streets, two-lane rural highway, and rural interstate highway. For the third main factor, type of inventory element, the authors chose lane width, traffic sign width, and lateral placement of traffic signs from lane edge, with all three representing the x-dimension; barrier height and traffic sign height, both representing the y-dimension; streetlight spacing and driveway width, both representing the z-dimension; and road sideslope, representing a combination of x- and y-dimensions. Several of these elements represent the same dimension. The authors included this redundancy because some inventory elements may not be present on a roadway test section and because different elements are at different distances from the MMS cameras. These elements are measurable by both collection methods under investigation and constitute typical elements in a road inventory.

In each experiment, the dependent variable was PME and was quantitative, and the three main factors were categorical. The authors used analysis of variance (ANOVA) with fixed factor levels to explore the significance of the factors involved in the four experiments. The F-test is appropriate for testing the significance of the factors and the factor interactions (Neter et al. 1990, Devore 1991). The authors chose the customary significance level of $\alpha = 0.05$ for the tests.

Avoidance of Possible Biases

Most transportation agencies install standardized regulatory and warning signs. Bias in favor of the manual method may creep into observations if the data collector is familiar with the standard dimensions of those signs. To avoid such bias in the data, this study limited the observations to guide signs only. Guide signs have non-standardized dimensions, ensuring unbiased data. With the manual method, bias can also appear in the data if two or more people collect them; therefore, only one person was designated to collect data by the manual method in all four experiments. That person also completed a pilot data collection effort to reduce any learning effects that could bias the data. The study controlled for other possibly biasing factors to the extent possible: collection of data on similar terrain (flat or rolling), under similar weather conditions (clear weather), and under similar natural light (adequate sunlight). Most roadway agencies typically collect their inventory data under these conditions. Because the study did not include data collection in mountainous terrain or low light conditions in the four experiments, these results cannot be applied to those situations.

MOBILE MAPPING SYSTEMS USED IN THE STUDY

Table 1 summarizes the hardware used in each of the four MMSs in this study. MMS1, for experiment 1, required two digital, full frame, progressive scan charged-couple device (CCD) cameras mounted on a van. These cameras captured 60 degrees of panoramic images of the targeted environment. One camera had black and white film because it provides better identification of certain objects. The system compressed the images into a Joint Photographic Experts Group (JPEG) format and stored data on removable computer hard drives. Environmental enclosures housed the cameras, keeping the sensitive components free of dust. The enclosures also maintained optimal operating temperature and humidity levels for the cameras. The photogrammetric software package for data extraction was PC-based, and the identification of an object or a point of interest captured in image pairs provided the basis for the extraction of descriptive data.

MMS2, for experiment 2, required up to eight digital cameras housed in pressurized, temperature-controlled cases and mounted inside two towers attached to the vehicle. The PC-based photogrammetric software package allowed extraction of descriptive data from digital images by identifying conjugate points in image pairs.

MMS3, for experiment 3, employed a single, full-frame digital camera to capture digital imagery. Computer hard drives or CDs stored images in JPEG format (a 650 megabyte CD could store up to 110 miles of images). The photogrammetric Macintosh-based software package allowed extraction of descriptive data using a single image. The software package lacked the capability to make measurements in the z-dimension. This limited data to lane width, sign width, sign height, sign support height, and lateral placement of traffic signs.

MMS4, for experiment 4, was equipped with a single progressive scan digital camera that captured roadway imagery. Data extraction from the imagery involved the use of a calibrated grid with 0.5 by 0.5 meter gridlines overlaid on each captured digital image. Comparing inventory elements with the superimposed grid and judging their dimensions permitted data extraction. Because the

TABLE 1 Summary of Hardware Used in the MMSs

Collection method	GPS receiver	Digital camera (pixel resolution)	INS	DMI
MMS1	Trimble 7400	Pulnix (768×484)*	Litton*	Daytron*
MMS2	Ashtech Z-12	COHO 4980 RS-170 (640×480)	Honeywell Laser Ref III	Vehicle ABS
MMS3	Novatel*	Sony XC-007 (640×480)	INS with 3 gyros and 2 accelerometers	Vehicle ABS
MMS4	Leica MX 9212	Sony DXC 9000 (559×494)	Litton Laser Gyro	Hengstler R158-T/1800

* Exact make or model is proprietary information.
INS = inertial navigation system
DMI = distance measuring instrument

grid was calibrated on a flat surface at ground level, only measurements across and along the roadway (x- and z-dimensions) could be collected. This limited the data to lane width, driveway width, streetlight spacing, and traffic sign lateral placement.

DATA COLLECTION

Field data collection during each of the four experiments involved driving a particular MMS on a selected roadway section, collecting the data by the manual method and, lastly, collecting the ground truth data. Due to the absence of any prior information on sample sizes, as many observations as possible were collected. In-office processing of the MMS data involved application of differential corrections to the GPS data, merging data from the various sensors, and transferring them to the photogrammetric software package. Digital measurement capabilities of the software packages yielded descriptive data on selected inventory elements. For the manual method, in-office processing involved keying the data from the paper forms into a computer spreadsheet.

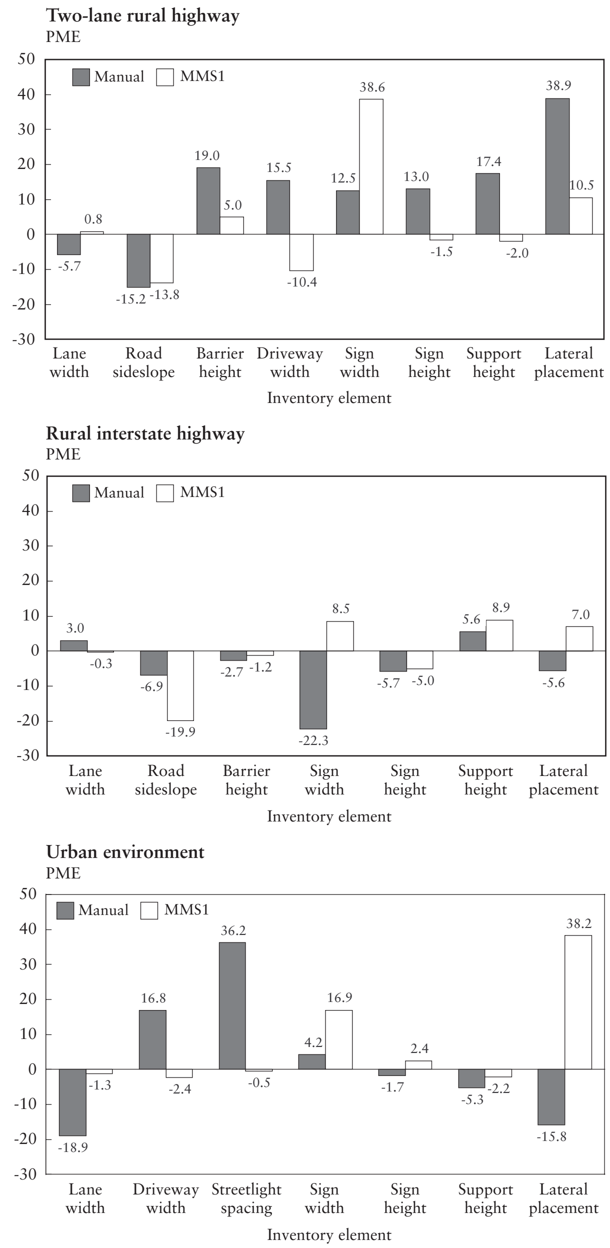
During experiment 1, MMS1 was driven on 8 miles of a two-lane rural highway, 31 miles of a rural interstate highway, and 7 miles of urban streets to collect data in the three environments. The MMS used in experiment 2 was driven on 17 miles of a two-lane rural highway, 25 miles of a rural interstate highway, and 8 miles of urban streets. MMS3 was driven on 13 miles of a two-lane rural highway, 16 miles of a rural interstate highway, and 13 miles of urban streets for collection of data by the MMS method. MMS4 was driven on 21 miles of a two-lane rural highway, 17 miles of a rural interstate highway and 5 miles of urban streets.

DATA ANALYSIS

Experiment 1

The descriptive inventory data collected by MMS1 and the manual method were compared with ground truth observations for accuracy assessment. Figure 1 graphically presents a summary of the mean PME values for the two methods. At the roadway environment level, MMS1 appears to be more accurate in the two-lane rural and the rural interstate environments. The manual method

FIGURE 1 Summary of PME Values, Experiment 1



appears to be more accurate in the urban environment. At the inventory element level, both methods significantly underestimated sideslope perhaps because it involves two dimensions, x and y. The manual method resulted in significant error in the measurement of driveway width and streetlight spacing, both involving the z-dimension. Inventory data pertaining to traffic signs were generally overestimated by both methods. MMS1 resulted in considerably high PME values for measurement of sign width and sign lateral placement.

Analysis of variance (ANOVA) was carried out on the collected data. ANOVA required that road

TABLE 2 Accuracy Differences at Different Experimental Levels

		Inventory Element										
Experiment	**Environment**	Lane width	Sign width	Sign lateral placement	Drive-way width	Street light spacing	Barrier height	Sign height	Sign support height	Side slope	**For all elements**	**Overall**
Experiment 1	Two-lane rural	V_{MMS1}	*	*	V_{MMS1}	–	*	*	V_{MMS1}	*	V_{MMS1}	
	Rural interstate	V_{MMS1}	V_{MMSI}	M	–	–	*	*	*	*	V_{MMS1}*	M*
	Urban	V_{MMS1}	M	M	V_{MMS1}	V_{MMS1}	–	*	*		M*	
Experiment 2	Two-lane rural	*	*	*	*	–	*	*	*	*	V_{MMS2}*	
	Rural interstate	*	*	*	–	–	*	*	*	*	V_{MMS2}*	M*
	Urban	*	*	*	*	*	–	*	*	–	M*	
Experiment 3	Two-lane rural	*	*	*	–	–	–	*	*	–	M	
	Rural interstate	*	*	*	–	–	–	*	*	–	V_{MMS3}*	M*
	Urban	*	*	*	–	–	–	*	*		M*	
Experiment 4	Two-lane rural	V_{MMS4}	–	M	M	–	–	–	–	–	M*	
	Rural interstate	*†	–	M	–	–	–	–	–	–	M*	M*
	Urban	V_{MMS4}	–	M	V_{MMS4}	V_{MMS4}	–	–	–	–	M*	

Table legend
– = Not tested
* = Not statistically different at the 95% confidence level
M = Data collected by the manual method are statistically more accurate at the 95% confidence level
V_{MMS1}, V_{MMS2}, V_{MMS3}, V_{MMS4} = Data collected by the particular method are statistically more accurate at the 95% confidence level
† = Shoulder width measured in place of lane width

sideslope, barrier height, driveway width, and streetlight spacing be excluded from the analysis because these factors are not common across all levels. The *F*-value for the model was statistically significant at the 95% confidence level, indicating model viability. The 3 main factors were statistically significant at the 95% level in the ANOVA.[1] However, a conclusion regarding significant differences in the means could not be reached due to the significance of interaction effects. All interactions among the main factors were statistically significant. The significance of the three-way interaction among method of data collection, roadway environment, and inventory element type indicated that it is necessary to look at the combinations of individual levels of each of the three main effects for differences in the means. The individual comparisons, excluded from the ANOVA (road sideslope, barrier height, driveway width, and streetlight spacing), included the levels of the inventory element type factor.

Paired *t*-tests between the manual and the MMS1 PME values for the inventory elements in the two-lane environment indicated that the MMS1 method of data collection provided data that were more accurate for lane width, sign support height, and driveway width (see table 2). The differences in the measurement of other inventory elements were not statistically significant. Paired *t*-tests among PME values in the rural interstate environment indicated that in comparison with the manual method of data collection, the MMS1 method provided data that were more accurate for lane width and sign width while the manual method provided data that were more accurate for lateral placement of traffic signs. Paired *t*-tests among PME values in the urban environment showed that the MMS1 method outperformed the manual method in the measurement of lane width, streetlight spacing, and driveway width, while the manual method performed better for sign width and sign support height.

Findings from Experiment 1

Analysis of data collected in experiment 1 indicated no clear-cut trend in terms of overestimation or underestimation by either of the two methods. ANOVA confirmed that 1) there is a difference in the accuracy of descriptive data collected by the MMS1 and the manual method, 2) the accuracy of descrip-

[1] Detailed ANOVA model diagnostics are reported in Khattak (1999).

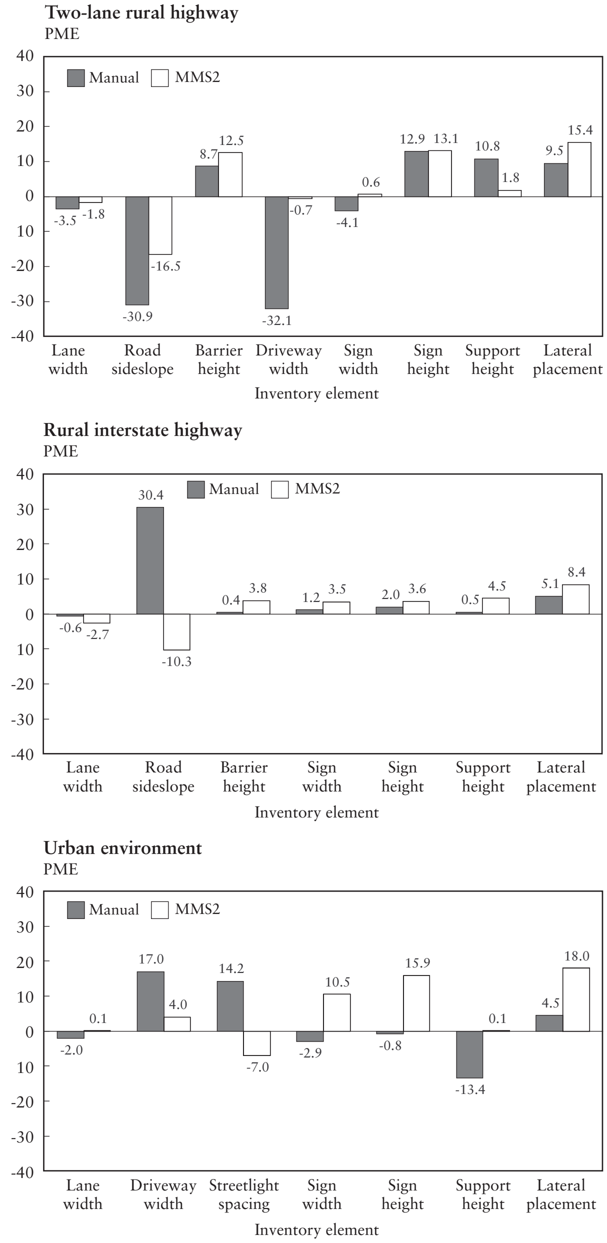
tive data varies across different roadway environments, and 3) the accuracy of descriptive data varies across different inventory elements. However, ANOVA also indicated that the accuracy of data collection by the two methods depends on the roadway environment and type of inventory element.

There are three possible reasons why the MMS1 method performed better in the two-lane rural and the rural interstate environments while the manual method performed better in the urban environment. First, inventory elements are typically located farther from the vehicle on two-lane and interstate roadways than on urban roadways. Although the accuracy of measurements by both the MMS1 and the manual method decreases with increasing distance from the point of observation, this rate of decrease may be higher in the case of the manual method. The manual method was superior to the MMS1 method at close range (in the urban environment), but due to the higher accuracy deterioration rate, it underperformed in the two-lane and interstate environments. Second, the reduced accuracy of data collected by the manual method in the rural environments may be due to gaps and surface discontinuities between the observer and the target object as Sinai et al. (1998) describe. Gaps such as drainage ditches and surface discontinuities such as guardrails exist more often on two-lane rural and rural interstate highways than on urban streets. Third, the underperformance of the MMS1 method in the urban environment may be due to possible loss of the GPS signal, more likely in an urban environment where large buildings may interfere with the satellite signal. In the case of GPS signal loss, the system accuracy degrades over the next few minutes until the signal is recovered by the GPS receiver. This accuracy degradation is then reflected in the descriptive data obtained by the photogrammetric software package. However, a check of the raw data did not reveal loss of the GPS signal during data collection in the urban environment. Therefore, the first reason, higher rate of accuracy deterioration in the manual method, is more likely to have contributed to this accuracy pattern.

Experiment 2

Figure 2 is a graphical representation of the mean PME values for data collected during experiment 2.

FIGURE 2 Summary of PME Values, Experiment 2



At the inventory element level, the manual method underestimated inventory elements in the two-lane rural environment, while the MMS2 method overestimated them. In the other two environments, both methods overestimated nearly all inventory elements. At the inventory element level, both methods resulted in substantial errors in the measurement of sideslope, again perhaps due to the involvement of *x*- and *y*-dimensions in sideslope measurement. The manual method resulted in significant error in the measurement of streetlight spacing, while the MMS2 method resulted in sizeable error in the measurement of lateral placement of traffic signs.

The authors analyzed the data using ANOVA after excluding road sideslope, barrier height, driveway width, and streetlight spacing because these elements were not common across all factors. The *F*-value for the overall model was statistically significant at the 95% confidence level (details reported in Khattak 1999). The type of inventory element proved statistically significant, indicating that the accuracy of measurement depends on the type of inventory element collected. The method of data collection was also statistically significant, but the roadway environment factor was not. Due to the significance of the interaction between the method of collection and the environment (the only significant interaction), nothing could be conclusively said about the effect of the collection method alone on PME.

Data collected by the MMS2 method in the two-lane rural and the rural interstate environments were more accurate whereas data collected by the manual method in the urban environment were more accurate (see table 2). However, none of the differences between the MMS2 and manual methods were statistically significant for individual elements.

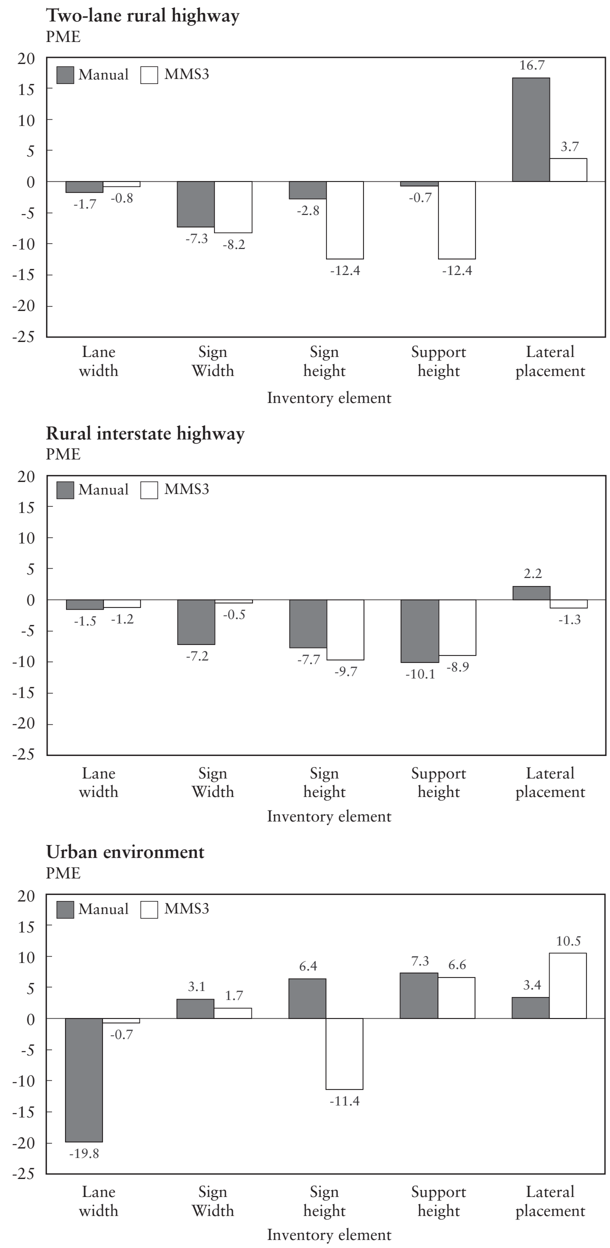
Findings from Experiment 2

Data collected in experiment 2 indicated overestimation by the MMS2 method in all three roadway environments. ANOVA also indicated that the accuracy of inventory data depended on the type of data element measured. The significance of the interaction between the other two main effects showed that the accuracy of inventory data depended on the method of data collection in different roadway environments. Data collected by the MMS2 method in the two-lane rural and the rural interstate environments were more accurate compared with the data collected by the manual method. However, data collected by the manual method in the urban environment were more accurate than that collected by the MMS2 method. This pattern was similar to the accuracy pattern in experiment 1, probably for the same reasons.

Experiment 3

Because there is no measurement capability in the *z*-dimension, the photogrammetric software package used in experiment 3 only provided data on

FIGURE 3 Summary of PME Values, Experiment 3



lane width, sign width, sign height, sign support height, and lateral placement of traffic signs. PME values for the collected data are graphically shown in figure 3. At the roadway environment level, the manual method appears to provide more accurate data in the urban environment. At the inventory element level, the two methods present mixed results regarding underestimation or overestimation. The MMS3 method resulted in relatively more accurate measurements for lane width, sign width, and lateral placement, all in the *x*-dimension, as opposed to sign height and sign support height, in the *y*-dimension. This may be due to GPS characteristics since the altitude component (i.e., the *y*-dimension) in the GPS is the weakest (El-Sheimy et al. 1995).

Experiment 3 data did not present the empty cell problem, and the ANOVA results indicated a statistically significant model at the 95% confidence level (detailed model-specific statistics are reported in Khattak 1999). The method of data collection and the environment factors were not statistically significant. The inventory element type factor was statistically significant, indicating that the type of inventory element affected the descriptive data accuracy. None of the two- or three-way interactions among the main factors were statistically significant.

Findings from Experiment 3

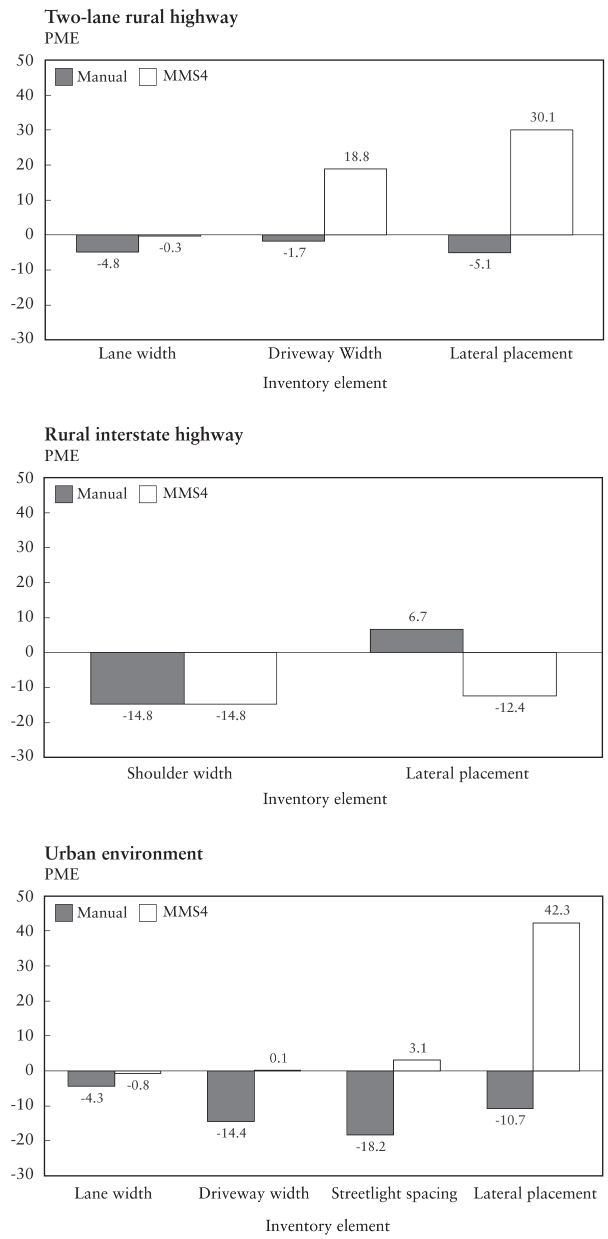
Experiment 3 provided no consistent pattern regarding the accuracy of the MMS3 and manual methods. However, it appears that the relatively inconsistent GPS altitude data resulted in greater inaccuracy in the measurement of inventory elements in the *y*-dimension as compared with the *x*-dimension.

Experiment 4

Data collection was limited to lane width, driveway width, streetlight spacing, and lateral placement of traffic signs in experiment 4 because superimposing a grid, calibrated at the ground level in front of the vehicle, restricted measurements to the *x*- and *z*-dimensions. In addition, the width of the shoulder substituted for lane width measurements due to unsafe conditions on the interstate highway. Figure 4 presents a graphical summary of mean PME values. There was no consistent pattern regarding underestimation or overestimation of measurements at the roadway environment and inventory element levels by the two methods. However, the accuracy of the MMS4 method at the inventory element level tended to decrease with increasing distance between the camera and the inventory element.

Because they were not available across all environments, data on driveway width and streetlight spacing from the ANOVA were dropped. The *F*-value for the overall model was statistically significant at the 95% level (model details reported in Khattak 1999). ANOVA results showed that the three main effects under investigation were all statistically significant. However, the significance of the interaction terms made reaching a conclusion regarding their effect on data accuracy difficult.

FIGURE 4 Summary of PME Values, Experiment 4



Both two-way interactions involving the inventory method factor and the three-way interaction among the three main effects were all statistically significant. This indicated the need for a separate examination of the mean PME values for each inventory element in each roadway environment and across each data collection method. A comparison of mean values of PME for the MMS4 and manual methods for the two-lane rural environment (table 2) indicated that lane width was more accurately measured by the MMS4 method, whereas lateral placement of signs and driveway width were more accurately measured by the manual method. All differences were statistically significant.

A comparison of mean values of PME for the MMS4 and the manual methods for the rural interstate environment indicated that the lateral placement of signs was measured more accurately by the manual method, and the difference between the two methods for this inventory element was statistically significant. Lane width was also measured with higher accuracy by the manual method, but the difference between the manual and MMS4 methods was not statistically significant.

A comparison of data collected in the urban environment indicated that the MMS4 method outperformed the manual method in measuring lane width, driveway width, and streetlight spacing. The manual method produced more accurate results for the lateral placement of traffic signs. All differences were statistically significant.

Findings from Experiment 4

Analysis of the data collected in experiment 4 indicated a mixed pattern regarding underestimation or overestimation of inventory elements. For lateral and longitudinal measurements in urban environment, the MMS4 method performed better than the manual method. The manual method produced better results in the two-lane rural and the rural interstate environments. The analysis confirmed that there is a difference in the accuracy of the data collected by the MMS4 and the manual methods and that the accuracy of descriptive data varies across different roadway environments. Furthermore, the experiment showed that the descriptive data accuracy varied across different types of inventory elements.

Overall, the manual method appeared more accurate than the MMS4 method. This may be because the MMS4 method requires the data collector to use a 0.50 by 0.50 meter grid overlay on the computer monitor. As such, the MMS4 method is not as automated as the other three MMSs investigated and likely more prone to human error.

DATA COLLECTION TIME AND COST

Table 3 summarizes information on data collection time (including data storage and presentation) and equipment costs for the collection methods under investigation. Overall, data collection by the manual method was more time-consuming in the field in all three roadway environments because the

TABLE 3 Summary of Time and Cost of Data Collection by Different Methods

	Manual method			MMS1–4		
Item	**Two-lane rural**	**Rural interstate**	**Urban**	**Two-lane rural**	**Rural interstate**	**Urban**
Mean collection time for 100 inventory elements in the field, including equipment setup and driving the roadway (person-minutes)	38	40	36	7 8 8 6	9 7 8 7	9 10 9 8
Mean in-office processing time for 100 inventory elements (person-minutes)	–	–	–	5*	5*	5*
Mean inventory data extraction time for 100 inventory elements, inputting to computer, and creation of inventory database including transfer to GIS (person-minutes)	45	45	45	76 82 72 84	80 77 76 82	78 80 77 75
Sum of mean collection, processing, and extraction times	**83**	**85**	**81**	**87**	**92**	**92**
One-time purchase of equipment (hardware, software, and peripherals, in dollars	30,000 †			250,000 and above ‡		

– = Not applicable
* = Approximately the same time for all four methods using vehicle systems
† = Manual method cost includes purchase of vehicle and a computer workstation
‡ = The cost of the methods employing vehicle systems depend on the number and type of sensors installed onboard and varies significantly

observer had to make frequent stops during data collection to achieve any reasonable degree of accuracy for the elements of interest. Note that for safe operations, the MMSs required two operators: a vehicle driver and a technician who monitored the various data collection sensors, while manual collection required just one person. The four MMSs required data processing time in the office, consisting of downloading the data from the vehicle, Differential Global Positioning System (DGPS) processing, and aggregation of the data from the different collection sensors (DGPS, INS, DMI, digital cameras, and so forth. This time was not required for the manual method.

Inventory data extraction and the creation of a database in the case of the manual method included coding the data from paper forms into a computer spreadsheet and then transferring the data to a geographic information system (GIS). In the cases of MMS1, MMS2, and MMS3, inventory data extraction and database creation involved making digital measurements with photogrammetric software packages and then transferring the data to a GIS. Overall, these methods were more time-consuming as compared with the manual method because the data collector carefully executed multiple point-and-clicks with the computer mouse on inventory elements captured in the digital images. Because the MMS4 method did not involve the use of any photogrammetric software package, obtaining data from the digital images was less time- consuming than for MMS1, MMS2, and MMS3.

Table 3 provides general information on one-time purchasing costs of equipment for inventory data collection and processing. The cost of the manual method is based on the purchase of a vehicle and a computer workstation. There is significant variation in the cost of a MMS because it depends on the type and number of sensors installed. Training costs and costs due to software incompatibility are not considered because of the wide variation in these factors. Overall, the one-time cost for the vehicle systems employing digital image capture technologies is significantly higher than the one-time equipment cost of the manual method.

CONCLUSIONS

Data collected during the four experiments on the selected inventory elements indicated a mixed pattern regarding overestimation or underestimation. Based on the experimental findings, we conclude the following:

- The accuracy of roadway descriptive inventory data depends on the method of collection. Even though for some inventory elements under certain roadway environments data collection by MMSs results in higher accuracy of descriptive data, the manual method overall provides data that are somewhat more accurate.
- The accuracy of descriptive inventory data depends on the roadway environment. Specifically, whether an inventory element is in a two-lane rural, rural interstate, or urban environment affects the accuracy of descriptive data.
- The type of roadway inventory element affects the descriptive data accuracy. As expected, elements closer to the observer or cameras were estimated more accurately.
- Data collection by MMSs is speedier in the field as compared with the manual method. However, data processing and extraction of descriptive data from digital images with photogrammetric software packages takes more time in the office as compared with the manual method.
- The total time consumed by the manual method was less than the time required by MMS methods on the sample of elements tested in this research.

The conclusions are valid only for the inventory elements, the three roadway environments, and the particular MMSs used in this study. Further, the inventory elements were chosen based on their ability to be measured by both the manual and the MMS methods. It is possible that certain inventory elements can only be measured by one of the two methods, in which case that method would have a clear advantage over the other.

The MMS method offers several advantages over the manual method, including avoidance of sending out large crews for field data collection and the opportunity to keep agency personnel off the dangerous highway environments,[2] the resulting temporal and spatially stamped digital imagery that can be used by several units within an agency, avoidance of subsequent field trips, and the ability to make measurements on inventory elements that would otherwise require closure of a lane (e.g., bridge clearance) or significant traffic control measures. Results from this study indicate that MMSs may not result in significantly improved descriptive inventory data accuracy, at least for the elements considered in this study, or substantial benefits from limited use of MMS. Transportation agencies looking to improve inventory data collection practices, however, may choose to consider nonaccuracy-related benefits that accrue from the use of MMSs.

ACKNOWLDGMENTS

The research presented in this paper was conducted as part of NCHRP Project 15-15 "Roadway Inventory Data Collection and Presentation." The authors wish to thank the NCHRP staff, state DOTs, roadway data collection companies, and numerous other persons for their support during the research.

REFERENCE LIST

Agouris, P., A. Stefanidis, and K. Beard. 1997. Digital Photogrammetric Techniques for Transportation Data Acquisition and Management. *Transportation Research Record* 1599:111–7.

Barlow, H. 1961. Possible Principles Underlying the Transformations of Sensory Messages. *Sensory Communication*. Cambridge: MIT Press.

Center for Mapping. 1994. Project report, Clark County Mapping Project. Columbus: Ohio State University.

Coetsee, J., A. Brown, and J. Bossler. 1994. GIS Data Collection Using GPS Van Supported by a GPS/Inertial Mapping System, in *Proceedings of ION GPS-94*, Salt Lake City, UT, 20–23 September. Alexandria, VA: The Institute of Navigation.

Devore, J. 1991. *Probability and Statistics for Engineering and Science*. Pacific Grove, CA: Brooks/Cole Publishing Company.

[2] Field data collectors are highly vulnerable because of the nature of their job and the amount of mileage involved in inventory processes.

El-Sheimy, N. 1996. A Mobile Multi-Sensor System for GIS Application in Urban Centers, in *ISPRS Conference Proceedings,* Vienna, Austria, 9–19 July. Vienna: International Society for Photogrammetry and Remote Sensing.

El-Sheimy, N., K. Schwarz, M. Wei, and M. Lavigne. 1995. VISAT: A Mobile City Survey System of High Accuracy, in *Proceedings of ION GPS-95*, Palm Springs, CA, 12–15 September. Alexandria, VA: The Institute of Navigation.

Gibson, J. 1950. *The Perception of the Visual World*. Cambridge: The Riverside Press.

Karimi, H.A., J.E. Hummer, and A.J. Khattak. 2000. Collection and Presentation of Roadway Inventory Data. National Cooperative Highway Research Program report 437, National Research Council, Washington, DC.

Khattak, A.J. 1999. Evaluation of descriptive roadway inventory data collection methods: A test protocol. Ph.D. diss., North Carolina State University.

Lee, H., M.A. Weissman, and J.P. Powell. 1991. Measuring Highway Inventory Features Using Stereoscopic Imaging System, in *Applications of Advance Technologies in Transportation Engineering,* Minneapolis, MN, 18–21 August.

Mastandrea, A., B. Swindall, and G. Klassen. 1995. Development and Implementation of an Automated Facility Inventory System. *Transportation Research Record* 1500: 127–33.

Neter, J., W. Wasserman, and M. Kutner. 1990. *Applied Linear Statistical Models*. Boston: IRWIN.

Novak, K. and J. Nimz. 1997. Transportation Infrastructure Management: Seneca County Creates a Complete Inventory of its Transportation Infrastructure. Paper presented at the GIS for Transportation Symposium. Greensboro, NC. March.

Roadware Corporation. 1994. Test Results, North Carolina Department of Transportation. Sponsored by the U.S. Federal Highway Administration.

____. 1996. Test Results, Kansas Department of Transportation.

Schwarz, K. and N. El-Sheimy. 1997. Kinematic Multi-Sensor Systems for Close Range Digital Imaging, in *Proceedings of ISPRS Commission V, Working Group III*.

Sedgwick, H. 1983. *Environment-Centered Representation of Spatial Layout: Available Visual Information from Texture and Perspective*. New York, NY: Academic Press.

Shaw, L.E. and M.F. Guthrie. 1997. Eaton County, Michigan, Global Positioning Systems Pilot Study. Paper presented at the GIS for Transportation Symposium. Greensboro, NC.

Sinai, M., T. Ooi, and Z. He. 1998. Terrain Influences the Accurate Judgment of Distance. *Nature* 395:497–500.

Vaidya, A., D. Baraniak, and K. Novak. 1994. CONRAIL's GIS Incorporates Kinematic GPS and Stereo Digital Imaging, in *AM/FM International Conference Proceedings,* Aurora, CO.

Wang, C.P. 2000. Designs and Implementation of Automated Systems for Pavement Surface Distress Survey. *Journal of Infrastructure Systems*. March: 24–32.

Whited, J. and S. Kadolph. 1995. Automated Collection of Sign Inventory Information by Integrating Global Positioning System (GPS) with Videologging Data Collection Activities. Office of Planning Services, Iowa Department of Transportation.

Behavioral Distinctions: The Use of Light-Duty Trucks and Passenger Cars

KARA MARIA KOCKELMAN

YONG ZHAO

University of Texas at Austin

ABSTRACT

In the United States, pickup trucks, sport utility vehicles (SUVs), and minivans are classified as light-duty trucks (LDTs), resulting in a variety of regulatory protections. Production and purchase trends suggest that Americans have shifted toward a significantly higher use of such vehicles for personal travel. Using the 1995 Nationwide Personal Transportation Survey (NPTS) data set, this research explores the subtle differences in ownership and use patterns between LDTs and passenger cars. Based on a variety of model specifications and response variables, the results suggest that the average LDT is used over longer distances with more people aboard and is purchased by wealthier households in less dense neighborhoods. Pickups tend to be driven by males, be owned by smaller households, and carry fewer people. There is no indication that SUVs or minivans serve additional work purposes for American households; however, their occupancies and total annual mileages are higher than those of passenger cars. Additionally, SUVs are relatively popular for weekend travel.

Kara Maria Kockelman, University of Texas at Austin, 6.90 E. Cockrell Jr. Hall, Austin, TX 78712–1076. Email: kkockelm@mail.utexas.edu.

INTRODUCTION

Before purchasing a vehicle today, many American households consider pickups, minivans, sport utility vehicles (SUVs), and passenger cars. These first three vehicle types are classified as light-duty trucks (LDTs) and currently capture 51% of new U.S. passenger vehicle sales,[1] a share much larger than the 9.8% they had in 1972 (64 *Federal Register* 82). Due to differences in federal regulation of passenger cars and LDTs, this shift in ownership and use is marked by reductions in fleetwide fuel economy, relative increases in pollutant emissions, and changes in crash frequency and severity. Ideally, regulatory differences across vehicle manufacturers and vehicle types should counterbalance differences in consumption externalities, both positive and negative. If regulations favor goods that do not provide external benefits, markets are likely to be inefficient (see, for example, Varian 1992). To illuminate the differences in household use of various vehicle types, this paper analyzes the 1995 Nationwide Personal Transportation Survey (NPTS) data (USDOT FHWA 1995).

When the Corporate Average Fuel Economy legislation was introduced in the early 1970s (Public Law 94–163), the argument for distinct classification was that light-duty[2] pickups and cargo vans were almost exclusively used as work vehicles for hauling cargo rather than for personal travel. At that time, economic censuses suggested that about 50% of U.S. trucks under 10,000 pounds of gross vehicle weight were used primarily for personal transportation; this figure is 75% today (USDOC 1985 and 1999). Also at that time, manufacturers specializing in light trucks and vans argued that, due to differences in body and engine types, they would not be able to meet the standards set for passenger cars requiring an average fuel economy of 27.5 miles per gallon (mpg) in 1985 and beyond. These arguments prevailed, and LDTs were subjected to a significantly lower standard, 20.7 mpg.[3] For reasons also largely related to body and engine differences, LDTs enjoy higher emissions caps[4] and do not endure luxury goods or gas guzzler taxes. Pickups also enjoy substantial import tax protection.

On the basis of structural similarities, particularly in early models, minivans and sport utility vehicles (SUVs) also were classified as LDTs, rather than as passenger cars, in the legislation. As these vehicles become more prevalent for personal travel, policymakers may question whether these vehicles also deserve regulatory protections. Analysis of household purchase and use patterns can suggest whether certain differences exist. By employing the 1995 National Personal Travel Survey data, this research estimates a variety of models that illuminate these behaviors and identify any behavioral distinctions. In identifying such distinctions, this research aims to educate policymakers and others on American travel habits across vehicle types so that related policies can be tailored most appropriately.

DATA SET, MODELS USED, AND RESULTS

The data come from the 1995 Nationwide Personal Transportation Survey (NPTS), which offers travel-behavior information for a broad cross-section of roughly 42,000 American house-

[1] The source of these 1999 data is the Polk Company (without Hummer, Winnebago, and Workhorse truck makes). While these data are the most recent available, they are unpublished, and Polk restricts their use.

[2] The Code of Federal Regulations (CFR) defines a light-duty truck to be any motor vehicle having a gross vehicle weight rating (curb weight plus payload) of no more than 8,500 pounds, "1) Designed primarily for purposes of transportation of property or is a derivation of such a vehicle or 2) Designed primarily for transportation of persons and has a capacity of more than 12 persons or 3) Available with special features enabling off-street or off-highway operation and use." (40 CFR 86.082-2.) The "special features" enabling off-road use are four-wheel drive and at least four of the following five clearance characteristics: an approach angle of not less than 28 degrees, a breakover angle of not less than 14 degrees; a departure angle of not less than 20 degrees, a running clearance of not less than 8 inches, and front and rear axle clearances of not less than 7 inches each. (40 CFR 86.084-2.)

[3] The LDT fuel-economy standard is set by Department of Transportation rule-making; it is not incorporated into formal statute, as in the case of passenger-car fuel economy.

[4] The EPA's Tier II plans for 2009 call for averaging emissions across a manufacturer's entire fleet of vehicles. Under this plan, LDTs are likely to continue emitting more than cars, on average, but low-emitting vehicles will have to be sold to meet the average, forcing individual manufacturers to balance emissions impacts of their LDT fleets against emissions benefits of their car sales. Ideally, manufacturers should be able to trade credits with one another, but the rule-making does not allow this.

holds, with members of at least five years of age recording all trips on a single day. The specific NPTS data incorporated here as explanatory and response variables are shown in table 1. Unfortunately, due to non-reporting of variables like annual income and VMT, many records are not complete. However, comparisons of variable distributions before and after record removal suggests that there are no sig-

TABLE 1 Definitions of Variables Used

		Mean*	SD*
Dependent variables:			
Annual VMT	Annual vehicle-miles traveled in vehicle, as estimated by household respondent.	11,040	8,230
Number of person-trips	Number of person-trips in the vehicle on the survey day	7.11	6.20
Number of recreational person-trips	Number of person-trips in the vehicle on the survey day for trips of recreational purpose (including social, shopping, and eating-out purposes)	2.20	3.06
Trip occupancy: all purposes	Number of vehicle occupants during trip	1.84	1.10
Trip occupancy: recreational purposes	Number of vehicle occupants during recreational trip (including social, shopping, and eating-out purposes)	1.71	0.99
Vehicle type choses for trip	Type of vehicle chosen by driver for trip (all purposes included)	NA	NA
Newest vehicle owned	Type of newest-vehicle owned (identified by latest model year); includes passenger car, SUV, pickup, & minivan	NA	NA
Explanatory variables:			
Population density	Population density of census tract (persons per square mile)	3,858	5,306
Income per household member	Annual household income (1995 US$) divided by household size (where income is taken to be middle of class range)	$19,075	$13,561
Vehicle age	1996 minus model year of vehicle	6.02	4.96
Household members per vehicle owned	Household size divided by vehicles owned by household	1.48	0.80
LDT indicator	Equals one for SUVs, pickups & minivans (zero otherwise)	0.26	0.44
SUV indicator	Equals one for SUVs (zero otherwise)	0.08	0.27
Pickup indicator	Equals one for pickups (zero otherwise)	0.11	0.31
Minivan indicator	Equals one for minivans (zero otherwise)	0.08	0.27
Vehicle price/income	Average purchase price of new vehicle (based on 1997 sales data) divided by annual household income)	0.74	0.14
Household size	Number of household members	2.83	1.31
Number of vehicles already owned	Number of vehicles already owned by household, of that vehicle type	0.92	0.87
Number of cars already owned	Number of passenger cars already owned by household	0.56	0.69
Weekend day	Equals one for Saturday and Sunday trips (zero otherwise)	0.22	0.42
Vehicle occupancy	Number of vehicle occupants (for model of vehicle-type choice)	1.58	0.99
Trip length	Self-reported trip travel time (minutes)	14.21	13.0

Note: Means and standard deviations (SDs) vary slightly in some cases, according to sample used/model applied.

nificant distinctions in the full and culled samples. Thus, the analysis of the various models presented use only complete record. These models estimate vehicle-miles traveled (VMT) per vehicle, number of person-trips per vehicle, vehicle occupancy, vehicle choice for trip making, and vehicle ownership. Several statistical specifications are necessary to model the different response variables most appropriately. Numeric results follow the description of all model specifications.

Models of Vehicle-Miles Traveled

With household estimates of annual VMT for each vehicle owned, two weighted least squares (WLS) models of VMT were developed. One model groups all LDTs together in a single class, while the second permits distinct VMT effects for each of the LDT vehicle types. With everything else constant, additional household members add driving distance to individual vehicles; therefore, the variance associated with VMT is expected to rise with household size. Thus, the weights used in these models are the inverse of household size. Finally, the decision to use only complete vehicle records required the removal of 42% of the records due to the lack of VMT information.

The results are shown in table 2, which suggests that all parameter estimates differ from zero in a highly statistically significant way, evidenced by negligible p-values. As expected, newer vehicles

TABLE 2 Weighted Least Squares Models of VMT

Dependent variable: annual VMT

Variable	Beta	SE	*t*-stat	P-value
Constant	9,979	174.7	57.12	0.000
Population density	–0.151	0.009	–16.21	0.000
Income per household member	4.010E-02	0.003	12.72	0.000
Vehicle age	– 408.0	8.753	– 46.62	0.000
HH members per vehicle owned	1,883	84.55	22.27	0.000
LDT indicator	1,162	1,11.0	10.47	0.000

Adjusted R^2: 0.123
Number of observations: 26,398 vehicles
Weighted by: 1/household size
Model form: VMT = $\beta'\chi + \varepsilon$, where $\varepsilon \sim N(0, \sigma^2 \times \text{household size})$

Dependent variable: annual VMT

Variable	Beta	SE	*t*-stat	P-value
Constant	10,043	175.0	57.40	0.000
Population density	–0.153	0.009	–16.30	0.000
Income per household member	4.00E-02	0.003	12.60	0.000
Vehicle age	– 405.4	8.76	– 46.20	0.000
HH members per vehicle owned	1,821	85.2	21.40	0.000
SUV indicator	1,027	189	5.44	0.000
Pickup indicator	721.7	152	4.74	0.000
Minivan indicator	2,150	202	10.60	0.000

Adjusted R^2: 0.125
Number of observations: 26,398 vehicles
Weighted by: 1/household size
Model form: VMT = $\beta'\chi + \varepsilon$, where $\varepsilon \sim N(0, \sigma^2 \times \text{household size})$

driven by wealthier households residing in less population-dense neighborhoods appear to be driven longer distances. Also, as the number of household members per vehicle owned increases, a vehicle's annual mileage increases. What is surprising is that after controlling for all these factors, LDTs are found to be driven substantially more than passenger cars, particularly minivans and SUVs. All else unchanged, the additional mileage driven in an SUV, pickup, and minivan is estimated to represent 9.3%, 6.5%, and 20% of a passenger car's VMT, respectively. Such figures suggest that these vehicles are more popular or more useful to households or both. Their larger carrying capacity (eight passengers in many minivans and towing options for virtually all pickups) and off-road capability, in the case of many SUVs and pickups, make these vehicles more versatile. Such qualities are a large part of the reason these vehicles generally cost significantly more than passenger cars. In 1997, the average SUV, pickup, and minivan cost about 58%, 39%, and 21% more than the average passenger car sold.[5] Applying the numeric results from table 2, we find that a doubling of population density, from its mean value of 3,858 people per square mile (6 people per acre or 4.9 people per hectare) to 7,716 would provoke, on average, a per-vehicle VMT drop of 590 miles. This suggests a very significant density shift, but its effect is much lesser than the extra VMT associated with SUVs (1,027 miles) and minivans (2,150). Of course, one's vehicle choice is, to some extent, a function of environmental qualities such as density since, for example, it may be harder to park a larger vehicle in a denser environment, and people seeking denser living environments may prefer to drive less. Density may be proxying for some effects of unobserved personal preferences. Thus, if LDT sales decline or densities increase, VMT is not guaranteed to fall. But, a comparison of mileages across distinct densities and vehicle types illustrates a rather remarkable magnitude of difference. This is also apparent in the effects of the income variable: if we double mean incomes per household member, the effect on VMT is a rather negligible 76 miles per year per vehicle. It seems clear that LDTs are driven substantially further, on average, even after controlling for their age.

Models of Person-Trips per Vehicle

Due to its non-negative integer nature, the number of person-trips per vehicle in the data set was estimated using negative binomial regression models.[6] This variable's mean was specified as an exponential function so that the expected number of trips is equal to $\exp(\boldsymbol{\beta}'X)$. Unlike a Poisson distribution, which implies that the variance equal the mean, a negative binomial specification permits over-dispersion in observed values. Its variance equals its mean times the quantity one plus a non-negative over-dispersion parameter. Log-likelihood results are shown for the assumption of a Poisson model, alongside the results for the negative binomial specification.

The results of person-trip-per-vehicle models raise the question of whether one vehicle type is used more than another and whether this differs by trip type. Since SUVs are heavily marketed for their off-road abilities and cargo space for long trips, one may expect to find evidence of this in the nature of their use. For example, they may be used more often, particularly for trips of a recreational nature. In contrast, pickups have been portrayed as providing non-recreational, heavy work uses, and they generally safely seat no more than three occupants.[7] Therefore, one may expect pickups to make fewer recreational trips.

Originally, three person-trip models were estimated: one counts trips of all purpose types, another counts only those trips of a recreational nature, and a third counts those trips with a work purpose. Almost all parameters are estimated to differ significantly from zero in a statistical sense. The empirical results of the third, work-purpose model are not provided because their overall predictive value is almost zero (pseudo-R^2s < 0.01). Their low predictive value is probably due to the fact that most work trips are made solo since two U.S. workers rarely share the same workplace location.

---

[5] These numbers come from *Ward's Automotive Yearbook* (1997) prices and Automotive News (1998) sales data. They are based on sales-weighted values.

[6] See Cameron and Trivedi's 1986 discussion of such models.

[7] However, this is changing via new four-door "car-plus-truck" models.

TABLE 3 Negative Binomial Regressions for Number of Person-Trips: All Purposes and Recreational Purposes

Dependent variable: number of person-trips for all purposes

Variable	Beta	SE	*t*-stat	P-value
Constant	1.672	0.012	138.00	0.000
HH members per vehicle owned	0.255	0.004	59.20	0.000
Income per household member	–3.16E-06	2.77E-07	–11.40	0.000
Population density	–4.42E-06	6.10E-07	–7.25	0.000
Vehicle age	–0.014	0.001	–20.80	0.000
Weekend day indicator	0.100	0.007	13.50	0.000
SUV indicator	0.045	0.012	3.85	0.000
Pickup indicator	–0.164	0.011	–14.90	0.000
Minivan indicator	0.302	0.011	28.50	0.000
Over-dispersion parameter	0.351	0.004	97.10	0.000

Log-likelihood Function	Negative binomial regression	Poisson regression
Constant only	–121,113.3	–160,951.3
Convergence	–117,983.1	–148,642.7
Pseudo-R^2	0.026	0.076

Number of observations: 41,538 vehicles
Model form: Number of person-trips ~ negative binomial with expected value exp(($\beta' X$)) and non-negative over-dispersion parameter

Dependent variable: number of person-trips for recreational purposes

Variable	Beta	SE	t-stat	P-value
Constant	0.485	0.021	22.80	0.000
HH members per vehicle owned	0.204	0.008	25.90	0.000
Income per household member	–3.14E-06	4.73E-07	–6.60	0.000
Population density	–6.12E-06	1.09E-06	–5.60	0.000
Vehicle age	–0.018	0.001	–15.60	0.000
Weekend day indicator	0.590	0.014	41.40	0.000
SUV indicator	0.005	0.021	0.20	0.814
Pickup indicator	–0.292	0.019	–15.20	0.000
Minivan indicator	0.308	0.020	15.70	0.000
Over-dispersion parameter	1.009	0.011	93.40	0.000

Log-likelihood function	Negative binomial regression	Poisson regression
Constant only	–82,460.37	–10,6536.4
Convergence	–80,612.10	–99,753.51
Pseudo-R^2	0.022	0.064

Number of observations: 41,538 vehicles
Model form: Number of person-trips ~ negative binomial with expected value exp ($\beta' X$) and non-negative over-dispersion parameter

Table 3 provides the estimates resulting from application of the all-purposes and recreational-purposes person-trip models. These data are based on a single day's trips, introducing much random variation. This variation is evident in a low goodness-of-fit, as measured by pseudo-R^2. While a Poisson stochastic specification superficially suggests better fit, the negative binomial specifications are statistically superior (the addition of a single parameter, the over-dispersion coefficient, increases the log-likelihood significantly).

Table 3 shows that newer vehicles belonging to households in lower density environments with higher incomes and more household members per vehicle owned carry more person-trips per day. However, these models' mean values are characterized by exponential functions, and halving density from its average value reduces person-trips by just one percent. Doubling incomes (per household member) from their current mean produces only a six percent change. Of all trip types, 10% more person-trips are estimated to occur on weekends (versus weekdays); this difference becomes a significant 80% when trips are of a recreational nature.

The general distinctions among different vehicle types in table 3 are not surprising: minivans make the most person-trips per day, followed by SUVs, passenger cars, and finally pickups. SUVs are estimated to make, on average, 4.6% more person-trips per day than passenger cars, while pickups average 15% fewer, and minivans average an impressive 35% more. For recreational purposes, the figures are less than 1% more for SUVs, a remarkable 25% fewer for pickups, and 36% more for minivans. Person-trip models bundling all LDTs into a single category show the average differences translate to six percent more person-trips across all trip purposes carried by LDTs and only one percent more for recreational purposes.[8]

In summary, these results suggest that SUV and "average" LDT person-trip counts are very close to those of passenger cars. However, minivans are estimated to make significantly more person-trips and pickups, significantly fewer. It is surprising that SUVs are not making more recreational person-trips, on average, than passenger cars. The 58% higher purchase price and performance distinctions of the average new SUV, relative to the average new car, are not reflected in this form of use.

[8] In the interest of space, these models are not shown.

Models of Vehicle Occupancy

Ordered probit models were used to study vehicle occupancy during trip-making.[9] Relative to the negative binomial specifications used above (for estimation of person-trip counts), an ordered probit specification can provide some important flexibility by removing implications of cardinality. For example, it can distinguish two-person vehicle occupancy from two times single-person occupancy. Additional occupants are frequently non-driving children or others whose reasons for travel may be distinct from those of the vehicle's driver. For this reason, we hypothesize the existence of latent variables whose thresholds, which essentially are cut-off points for integer occupancy values, differ only ordinally. This set up contrasts with underlying, cardinal rates fundamental to Poisson and negative binomial specifications.

Tables 4a and 4b provide the results of the trip-occupancy estimations for trips of all types and for only those trips with a recreational purpose. Without cardinality, the magnitudes of ordered probit parameters are not as easily interpreted as those of the WLS and negative binomial models; however, it is clear that trips made by lower income households for shopping, eating out, or other, recreational purposes tend to exhibit higher occupancies. The same is true of weekend trips made by households having more members per vehicle. In general, minivans draw the largest occupancies, followed by SUVs, cars, and, lastly, pickups.

In the all-trip-purposes model of occupancies (Table 4a), the minivan, eating out, and weekend indicator variables have coefficients high enough to almost raise expected occupancy by one, while few of the other variables exert comparable effects. For example, occupancy appears to be negligibly influenced by income levels and population density: the parameter estimates suggest it would take more than a $47,000 reduction in the average income per household member or almost 90 more persons per acre (36 more per hectare) to find people occupying passenger cars to the degree they occupy minivans.

[9] See Greene's (1993) discussion of this model specification.

TABLE 4a Ordered Probit Model for Trip Occupancy: All Trip Purposes

Dependent variable: trip occupancy (all purposes)

Variable	Beta	SE	*t*-stat	P-value
Constant	–0.565	0.007	–79.90	0.000
HH members per vehicle owned	0.340	0.002	153.00	0.000
Income per household member	–1.06E-05	2.05E-07	–51.50	0.000
Population density	–8.79E-06	4.27E-07	–20.60	0.000
Weekend day indicator	0.474	0.005	91.20	0.000
SUV indicator	0.174	0.008	20.90	0.000
Pickup indicator	–0.229	0.008	–30.40	0.000
Minivan indicator	0.500	0.006	78.80	0.000
Shopping indicator	0.021	0.006	3.21	0.001
Eat out indicator	0.544	0.011	49.20	0.000
μ_o	0.000	na	na	na
μ_1	0.875	0.003	302.00	0.000
μ_2	1.431	0.004	365.00	0.000
μ_3	2.039	0.006	368.00	0.000

Note: Trip occupancy is grouped into 1, 2, 3, 4, and 5+ person levels.

Log-likelihood function	
Constant only	–324471.0
Convergence	–298694.3
Pseudo-R^2	0.079

Number of observations: 263,031 trips
Model form: Pr(Occupancy = 1) = Pr($\mu^* \leq \mu_o$), Pr(Occupancy = 2) = Pr($\mu_o \leq \mu^* \leq$ m1), Pr(Occupancy = 3) = Pr($\mu 1 \leq \mu^* \leq \mu_2$), Pr(Occupancy = 4) = Pr($\mu_2 \leq \mu^* \leq \mu_3$), and Pr(Occupancy ≥ 5) = Pr($\mu_3 \leq \mu^*$), where $\mu^* = \beta' X + \varepsilon$, and ε ~ Normal(0, 1)

In the recreational-trip-purposes model of occupancies (Table 4b), the minivan indicator variable has a coefficient estimate that almost raises expected occupancy by one. Weekend day and members-per-vehicle variables also exert strong effects. In contrast, recreational-trip occupancy appears to be only very slightly influenced by income levels and population density: the parameter estimates suggest it would require more than a $53,000 reduction in average income per household member to find people occupying passenger cars to the degree they occupy minivans.

Note that the parameter sign on the variable of population density changes between the two trip-occupancy models. Neighborhood density is associated with reduced occupancies in general (that is, across all trip types) but with higher occupancies for recreational trips. In practical terms, density's effect on recreational-trip occupancy is estimated to be effectively zero. It appears that density does not affect that decision.

In general, these occupancy results across vehicle types are consistent with expectations and the person-trips-per-vehicle results. Minivans carry significantly more occupants per trip than do passenger cars, while pickups carry fewer. In regard to the other variables, density and income do not exert very strong effects, but day of the week, trip purpose, and number of household members per vehicle owned do.

TABLE 4b Ordered Probit Model for Trip Occupancy: All Recreational Purposes

Dependent variable: trip occupancy (all recreational purposes)

Variable	Beta	SE	*t*-stat	P-value
Constant	0.043	0.020	2.136	0.033
HH members per vehicle owned	0.349	0.006	57.435	0.000
Income per household member	–9.77E-06	5.55E-07	–17.622	0.000
Population density	1.95E-07	8.11E-08	2.404	0.016
Weekend day indicator	0.341	0.014	24.810	0.000
SUV indicator	0.316	0.027	11.925	0.000
Pickup indicator	–0.196	0.025	–7.802	0.000
Minivan indicator	0.524	0.019	27.929	0.000
μ_o	0.000	na	na	na
μ_1	1.055	0.009	113.721	0.000
μ_2	1.612	0.011	146.304	0.000
μ_3	2.247	0.014	160.105	0.000

Note: Trip occupancy is grouped into 1, 2, 3, 4, and 5+ person levels.

Log-likelihood function	
Constant only	–38686.52
Convergence	–35948.44
Pseudo-R^2	0.071

Number of observations:26,190 trips
Model form: Pr(Occupancy = 1) = Pr($\mu^* \leq \mu_o$), Pr(Occupancy = 2) = Pr($\mu_o \leq \mu^* \leq$ m1), Pr(Occupancy = 3) = Pr($\mu 1 \leq \mu^* \leq \mu_2$), Pr(Occupancy = 4) = Pr($\mu_2 \leq \mu^* \leq \mu_3$), and Pr(Occupancy ≥ 5) = Pr($\mu_3 \leq \mu^*$), where $\mu^* = \beta' X + \varepsilon$, and $\varepsilon \sim$ Normal(0, 1)

Model of Mode Choice

Another model of vehicle use emphasizes a driver's vehicle choice. When multiple vehicle types are available, the driver's probabilities of electing each type can be examined. Here the choices are clearly discrete so a multinomial logit (MNL) specification provides estimation.[10] To avoid issues of correlation in unobserved components of similar vehicle types, only trip records by drivers residing in households with no more than one vehicle of each type are examined.[11] Since all explanatory variables, except that of vehicle age, are constant across driver trip records, they are interacted with indicator variables of vehicle type. In addition, a reference alternative is necessary for parameter identifiability. Therefore, all parameter estimates are relative to choice of a passenger car, whose parameter estimates effectively are forced to equal zero here. As a consequence, three parameters are estimated for all but the vehicle age variable; these correspond to the three noncar vehicle types.

Table 5 shows the results of this model's estimation, and they suggest that in general cars are more likely to be chosen, or assigned, depending on household vehicle use constraints. Driver age plays a role for SUV use, with drivers in their late 40s most likely to be using an SUV when other alternatives exist. The role of driver age is not

[10] See, for example, Greene's (1993) discussion of this model.
[11] A nested-logit specification would avoid the record removal used here. In such a framework, all passenger cars available to a household form one nest of choices: all minivans form a different nest, and so on. Our interest lies in distinctions across vehicle types, rather than among vehicles of a single type (that is, within a nest), so the removal of households with more than one vehicle of any type was adopted, simplifying the estimation.

TABLE 5 Multinomial Logit Model for Vehicle Type Chosen for Trip by Driver

Dependent variable: vehicle type choice

Variable		Beta	SE	*t*-stat	P-value
Constant	SUV	–2.464	0.244	-10.108	0.000
	Pickup	–2.322	0.145	–16.046	0.000
	Minivan	–2.687	0.183	–14.653	0.000
Vehicle age		–0.056	0.002	–31.158	0.000
Age of traveler	SUV	0.077	0.012	6.550	0.000
	Pickup	0.047	0.006	7.239	0.000
	Minivan	0.112	0.008	13.575	0.000
Age^2 of traveler	SUV	–8.34E–04	1.36E–04	–6.119	0.000
	Pickup	–5.71E–04	7.04E–05	–8.111	0.000
	Minivan	–1.09E–03	9.09E–05	–11.977	0.000
Male driver	SUV	0.550	0.048	11.401	0.000
	Pickup	3.172	0.035	91.060	0.000
	Minivan	–0.411	0.035	–11.806	0.000
Employed driver	SUV	0.119	0.071	1.685	0.092
	Pickup	0.089	0.046	1.927	0.054
	Minivan	–0.330	0.048	–6.824	0.000
Work trip	SUV	0.058	0.063	0.919	0.358
	Pickup	0.359	0.042	8.549	0.000
	Minivan	–0.034	0.048	–0.713	0.476
Recreational trip	SUV	0.056	0.059	0.947	0.344
	Pickup	–0.170	0.037	–4.579	0.000
	Minivan	–0.032	0.041	–0.773	0.440
Population density	SUV	8.37E–06	5.34E–06	1.567	0.117
	Pickup	–1.54E–06	4.15E–06	–0.370	0.711
	Minivan	1.66E–06	3.75E–06	0.443	0.658
Income per person	SUV	6.21E–07	1.67E–06	0.371	0.710
	Pickup	–6.29E–06	1.40E–06	–4.509	0.000
	Minivan	4.76E–06	1.64E–06	2.896	0.004
Weekend indictor	SUV	0.169	0.053	3.199	0.001
	Pickup	–0.046	0.033	–1.387	0.166
	Minivan	–0.042	0.037	–1.138	0.255
Vehicle occupancy	SUV	0.229	0.029	7.970	0.000
	Pickup	–0.449	0.020	–22.796	0.000
	Minivan	0.385	0.017	22.138	0.000
Trip length (min.)	SUV	–0.40E–03	0.17E–02	0.228	0.820
	Pickup	–1.00E–03	0.11E–02	–0.882	0.378
	Minivan	–0.51E–02	0.13E–02	–3.866	0.001

Log-likelihood function	
Constant only	–36009.5
Convergence	–27703.3
Pseudo–R^2	0.231

Number of observations: 50,865 vehicle trips

Model form: Pr(vehicle chosen) = $\Pr(u_i \geq u_j\ \forall \geq j) = \Pr(\boldsymbol{\beta}'_i\, \boldsymbol{x}_i + \varepsilon_i \geq \boldsymbol{\beta}'_j\, \boldsymbol{x}_i + \varepsilon_j \forall\, i > j)$

$$= \frac{\exp(\boldsymbol{\beta}'_i\, \boldsymbol{x}_i)}{\sum_j \exp(\boldsymbol{\beta}'_j\, \boldsymbol{x}_j)}, \text{ where } \varepsilon_i \sim \text{iid Gumbel}$$

practically significant, however, for minivan or pickup choice/assignment. Males are far more likely to use pickups and somewhat more likely to use SUVs, while women have a tendency to drive minivans. Employed persons have a slight tendency to favor pickups and SUVs but a stronger tendency to avoid minivans. If the trip's purpose is work-related, pickups are more likely, and if the purpose is recreational in nature, the converse is true. In contrast, trip purpose effects for minivans and SUVs are not statistically significant. Population density does not show statistical significance for any of the these vehicle choices relative to passenger cars.

On weekend days, the model results suggest that an SUV is a more likely choice and a pickup somewhat less likely. Its effect, however, is not quite significant, in neither a statistical nor a practical sense. Vehicle trips made with more occupants lead to a higher probablity of SUV and minivan choice but lower likelihood of pickup. This result echoes the results of the occupancy models. Perhaps unexpectedly, trip length, as measured in time units reported by drivers, does not have an impact on SUV and pickup choices but negatively affects the likelihood of minivan choice.

Models of Vehicle Ownership

The final pair of models estimated center on vehicle ownership. Similar to the above analysis of vehicle types chosen for specific trips, a multinomial logit model was used first. This specification predicts the type of "newest vehicle owned," as measured by model year, in a household's fleet. In addition, a set of simultaneous Poisson regression equations, for the various numbers of different vehicle types owned, was estimated. The simultaneity in this second form of ownership model results from restricting the parameter of vehicle price-over-income variable to be the same for all of the exponential equations.[12] Tables 6 and 7 show the results of these models.

As is evident in the negative constant terms for various LDT vehicle types in both these tables, passenger cars are relatively favored, on average. However, current total sales figures indicate that LDTs as a class are catching up and starting to surpass passenger car sales. Moreover, some LDTs are held longer by households than are passenger cars, suggesting that household vehicle holdings may differ substantially in the coming years.[13] As results reported above suggest, LDTs are driven significantly more miles each year and minivans serve substantially more person-trips than passenger cars. Therefore, LDTs contribute significantly more toward congestion, pollution, and crashes than ownership information alone suggests.

Results of tables 6 and 7 results also suggest that as household sizes increase, SUVs and minivans are more popular choices than passenger cars, while pickups are becoming a slightly less likely choice. Furthermore, as incomes per household member increase, SUVs become more common, and pickups become less common. Minivan ownership response to higher incomes is not as significant, statistically or practically.

Table 6 suggests that when a household owns multiple cars, the addition of minivans and pickups is favored, but an SUV's addition is not affected in a statistically significant way. Ownership of a relatively new minivan becomes less likely as a household's overall fleet size increases. Finally, results of both tables 6 and 7 indicate that LDTs are more popular in lower density environments. This result may be reflective of longer travel distances in such locations and fewer parking issues for these larger vehicles.[14]

---

[12] A series of independent Poissons or simultaneous-in-unknown-parameters Poissons (as specified here), conditioned on the sum, is equivalent to a multinomial distribution for the combinations of vehicles owned. The price-over-income variable was restricted to a single coefficient because the prices were constant for each vehicle type here (using 1997 average sales prices). Thus, this variable would have simply reflected the inverse of income had its parameters been allowed to vary. A multiariate negative binomial also was attempted to allow heterogeneity across the vehicle ownership levels (see Kockelman [2000b] for an example application of this specification); however, this model's maximum-likelihood estimation would not converge due to the dispersion parameter's tendency for near-zero values. Finally, a series of independent, non-simultaneous Poissons was run, without the price-over-income variable, and the pseudo-R^2 of this model was 4.93%.

[13] For example, the average household pickup age in the 1995 NPTS data set was 8.22 years, versus 6.83 for passenger cars. The average age of minivans and SUVs in the sample was just 4.72 and 5.16 years, which may be due to the fact that these body types have not been available in the market for nearly as long as pickups and passenger cars.

[14] The average van and pickup sold in 1997 were 8.2 and 16.2% longer and 9.2 and 12.2% wider, respectively, than the average car.

TABLE 6 Multinomial Logit Model for Newest Vehicle Owned

Dependent variable: newest vehicle owned

Variable		Beta	SE	*t*-stat	P-value
Constant	SUV	–3.137	0.096	–32.6	0.000
	Pickup	–1.258	0.067	–18.9	0.000
	Minivan	–3.515	0.093	–38.0	0.000
Vehicle price/household income		–0.660	0.074	–9.0	0.000
Household size	SUV	0.242	0.020	11.9	0.000
	Pickup	–0.058	0.016	–3.5	0.000
	Minivan	0.542	0.018	30.6	0.000
Population density	SUV	–2.81E-05	4.19E-06	–6.7	0.000
	Pickup	–6.91E-05	4.21E-06	–16.4	0.000
	Minivan	–3.93E-05	4.25E-06	–9.3	0.000
Income per household member	SUV	1.78E-05	1.58E-06	11.2	0.000
	Pickup	–1.55E-05	1.58E-06	–9.8	0.000
	Minivan	1.15E-06	2.08E-06	0.6	0.580
Number of vehicles already owned	SUV	0.206	0.04	5.9	0.000
	Pickup	0.193	0.03	6.9	0.000
	Minivan	–0.046	0.04	–1.3	0.209
Number of cars already owned	SUV	0.016	0.04	0.4	0.696
	Pickup	0.362	0.03	10.8	0.000
	Minivan	0.135	0.04	3.2	0.001

Log-likelihood function	
Constant only	–28,725.37
Convergence	–27,080.58
Pseudo-R^2	0.057

Number of observations: 30,949 households

Model form: $\Pr(\textit{vehicle chosen}) = \Pr(u_i \geq u_j)\ \forall\, i \neq j = (\boldsymbol{\beta}'_i\, x_i + \varepsilon_i \geq \boldsymbol{\beta}'_j\, x_i + \varepsilon_j \forall\, i \neq j)$

$$= \frac{\exp(\boldsymbol{\beta}'_i\, x_i)}{\sum_j \exp(\boldsymbol{\beta}'_j\, x_j)}, \text{ where } \varepsilon_i \sim \text{iid Gumbel}$$

These ownership models are based on a single, 1995 cross-section of data. In reality, preferences, products, and markets change over time. With a panel data set, temporal ownership patterns could be analyzed, illuminating consumer trends and providing more insights to policymakers. However, the 1995 NPTS data are useful in that they validate many commonly held perceptions about present consumption of light-duty trucks versus passenger cars. For example, larger household sizes favor minivans the most, SUVs next, and pickups least. Higher income households favor SUVs but not pickups, and lower population densities favor pickups the most and passenger cars the least.

CONCLUSIONS

The U.S. government has taken an active regulatory stance in the area of emissions, as well as the safety, fuel economy, and size of different vehicle types. In many ways, cars and light-duty trucks, including minivans, SUVs, and pickups, are regulated very differently even though households may use them for very similar purposes. This paper presented an investigation of the 1995 Nationwide Personal Transportation Survey data set for evidence of household use differences across light-duty trucks and passenger cars in the United States.

Total vehicle-miles traveled, daily person-trips served, vehicle occupancies, drivers' vehicle type choices, and household ownership choices were analyzed to illuminate any significant differences in

TABLE 7 Simultaneous Poissons Model for Vehicle Fleet Ownership

Dependent variable: total vehicles owned and distribution among cars, SUVs, pickups, and vans

Variable	Beta	SE	*t*-stat	P-value
Vehicle price/income	–0.2213	0.0075	–29.40	0.000
Car:				
Constant	0.148	0.021	7.03	0.000
Household size	0.0699	0.0043	16.30	0.000
Population density	–0.1519	0.0081	–18.70	0.000
Income per HH member	0.02	0.0042	4.77	0.000
SUV:				
Constant	–2.8437	0.0553	–51.40	0.000
Household size	0.273	0.0118	23.10	0.000
Population density	–0.4526	0.0311	–14.60	0.000
Income per HH member	0.1899	0.0095	20.00	0.000
Pickup:				
Constant	–0.6725	0.0383	–17.60	0.000
Household size	0.0715	0.008	8.92	0.000
Population density	–0.9598	0.0281	–34.20	0.000
Income per HH member	–0.1102	0.0093	–11.80	0.000
Minivan:				
Constant	–3.1526	0.058	–54.30	0.000
Household size	0.4446	0.0103	43.00	0.000
Population density	–0.3993	0.0303	–13.20	0.000
Income per HH member	0.0262	0.0141	1.86	0.031
Log-likelihood function				
Constant only	–89026.8			
Convergence	–84399.8			
Pseudo-R^2	0.0520			

Number of observations: 32,596 households
Model form: Number of vehicles of type i owned ~ Poisson (λ_i) with $\lambda_i = \exp(\beta_i' X_i) + \beta_{\text{price/income}} \times \text{Price/Income}$

vehicle use. Weighted least squares (for VMT), negative binomials (for person-trips), ordered probit (for occupancy), multinomial logits (for vehicles chosen by drivers [for trip-making] and for newest vehicle owned), and an MNL conditioned on a Poisson (for fleet combinations) were the stochastic specifications employed.

While the NPTS questionnaires do not target special uses of LDTs by households specifically, analysis of these data offers insights and does suggest use differences. In general, it appears that households drive LDTs significantly more miles (up to 25% more, on average). Minivans are found to carry more occupants on any given trip and serve 35% more person-trips over the course of a day than passenger cars, while pickups are associated with significantly fewer occupants per trip and 15% fewer person-trips. SUVs, on the other hand, are used for the same number of person-trips as passenger cars, and their occupancies are quite similar, except in the case of vehicle trips made for recreational purposes.

Light-duty-truck ownership decisions are strongly associated with household size, incomes, population density, and vehicles already owned. For example, SUVs are more likely to be found in higher income, larger households in low-density environments with multiple vehicles. In terms of within fleet vehicle choice for trip making, several driver and trip characteristics are relevant. For example, males are far more likely to drive a pickup, and employed persons are unlikely to drive the household minivan. Pickups are more common for work-related trips, and SUVs are a more likely choice for weekend trips.

Taken together, the various models' results suggest that, when available, LDTs are used more regularly than cars for trips of a personal nature. However, the NPTS data offer no strong indications that minivans and SUVs are used as "work" vehicles, the original basis for separate classification of LDTs from passenger cars. Pickups are more popular among households than they were 20 years ago when American life was less urban, so it is not clear that pickups are performing unusual services either.

Even if LDTs perform special services for their owners, such as towing boats, hauling home furniture, or carrying many occupants, these benefits largely accrue only to their owners. In fact, such vehicles impose many negative externalities (Kockelman 2000a, Kockelman and Shabih 2000). Thus, it may be argued that their owners should be paying for these impacts rather than enjoying more lenient regulation.

ACKNOWLEDGMENTS

The authors wish to acknowledge the University of Texas at Austin Department of Civil Engineering and the Luce Foundation for their support of this research effort.

REFERENCES

40 CFR 86.082–2 (1 July 2000 Revised).

64 *Federal Register* 82 (29 April 1999).

Automotive News. 1998. *Automotive News—1998 Market Data Book*. Detroit, MI: Crain Communications Inc.

Cameron, A. and P. Trivedi. 1986. Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests. *Journal of Applied Econometrics* 1:29–54.

Greene, W.H. 1993. *Econometric Analysis*. New York: Macmillan.

Kockelman, K. 2000a. To LDT or Not to LDT: An Assessment of the Principal Impacts of Light-Duty Trucks. *Transportation Research Record*. Forthcoming.

Kockelman, K. 2000b. A Model for Time- and Budget-Constrained Activity Demand Analysis. *Transportation Research B*. Forthcoming.

Kockelman, K. and R. Shabih. 2000. Effect of Vehicle Type on the Capacity of Signalized Intersections: The Case of Light-Duty Trucks. *Journal of Transportation Engineering*. 126, no. 6:506–12.

Public Law 94-163. 22 December 1975.

U.S. Department of Commerce (USDOC), Census Bureau. 1985. *1982 Census of Transportation: Truck Inventory and Use Survey*. Report #TC82-T-52. Washington, DC.

_____.1999. *1997 Census of Transportation: Vehicle Inventory and Use Survey*. Report #EC97TV-US. Washington, DC.

U.S. Department of Transportation (USDOT), Federal Highway Administration (FHWA). 1995. Nationwide Personal Transportation Survey data. Washington, DC.

Varian, H.R. 1992. *Microeconomic Analysis*. New York: Norton.

Ward's Automotive Yearbook 1997. 1997. Southfield, MI: Ward's Communications.

Efficiency Measures and Output Specification: The Case of European Railways

PEDRO CANTOS
JOSÉ M. PASTOR
LORENZO SERRANO
Universidad de Valencia

ABSTRACT

This study analyzes the sensitivity of the efficiency indicators of a sample of European railway companies to different alternatives in output specification. The results vary according to the specification selected. However, investigating the causes of these differences reveals that the efficiency indicators obtained with different specifications can be brought substantially closer, particularly when the efficiency indicators obtained by considering freight and passenger train-kilometers as output variables are corrected to account for the impact of the load factor.

INTRODUCTION

The literature on productivity and efficiency frequently reports different rankings in terms of both productivity and efficiency indicators, depending on the output variables used in the construction of the model.[1] In the case of railways, there are very few studies, besides that by Oum and Yu (1994), in which this phenomenon has been tested since most

[1] Berg et al. (1992) and Grifell et al. (1993) analyze the levels of efficiency for a sample of banks and show the sensitivity of the results obtained to the specification adopted for the output.

Pedro Cantos, Departamento de Análisis Económico, Universidad de Valencia, Edificio Departamental Oriental, Campus del Tarongers, s/n 46022 Valencia, Spain. Email: Pedro.Cantos@uv.es.

estimates use a single specification for output. Recently, Oum et al. (1999) published a complete review of productivity and efficiency estimates in rail transport in which it is clear that the results of these estimates are very sensitive to output specification.

Other papers have estimated technical efficiency levels for European railways on the basis of a deterministic production function (Perelman and Pestieau 1988) or a stochastic one (Gathon and Pestieau 1995). Cantos et al. (1999) obtained efficiency indicators using a non-parametric approach, and Cowie and Riddington (1996) used alternative methodologies. According to the latter, accurate measurement of efficiency is not possible although research is able to indicate good and bad performers. In most of the studies quoted, such as in Cantos et al. (1999), some companies are generally very efficient, as in the case of Sweden's SJ, Holland's NS, or Switzerland's CFF. However, others are very inefficient, such as the Greek CH, the Danish DSB, and the Irish CIE.

A notable feature of the railway industry is its multi-product character: there are various types of passenger railway output (long distance, urban, high speed, etc.) and freight output (general, intermodal, parcels, etc.). However, due to the shortage of data, most studies restrict the output vector to two aggregate dimensions, passenger and freight. The measurements most commonly used are the number of passenger-kilometers and ton-kilometers (see Caves et al. 1980, 1982, and 1985; McGeehan 1993; and Cantos et al. 1999). These demand-related measurements for output enable an assessment of the level of user consumption and the value they place on the service. As indicated by Oum and Yu (1994), this specification is recommended when there is little government control, such as when the restrictions imposed on the level of service (frequency) or prices are of little importance. In that case, the indices of passenger-kilometers and ton-kilometers adequately reflect the efficient productive behavior of the various production units.

On the other hand, if there is a high degree of government control over decisions about pricing or frequency, the above specification will not adequately reflect the greater or lesser efficiency of the companies since output will be influenced by these regulatory measures. In this case, supply-related or intermediate measurements for output which place the emphasis on the degree of capacity or service level supplied by the companies are more suitable. For this reason, Nash (1985), Deprins and Simar (1989), Preston (1996), and Cantos and Maudos (2000) use the number of freight and passenger train-kilometers as output. These types of measurements isolate the effect of governmental control measures. Nevertheless, the use of this second type of measurement may lead to paradoxical results, such as situations in which companies with very low indices of load factor but with high levels of train-kilometers run are even more efficient than companies with high indices of load factor and low levels of train-kilometers run.

The problem with grouping companies from different countries is that the degree of governmental intervention and control is very different, complicating choice of measurement type. Oum and Yu (1994) estimate efficiency indicators on the basis of a Data Employment Analysis (DEA) model, using two different sets of measurements, passenger-kilometers and ton-kilometers on the one hand and passenger train-kilometers and freight train-kilometers on the other. Their results confirm that levels and rankings of efficiency differ, depending on which measurement is used. Thus, some companies such as the Spanish RENFE or the Norwegian NSB are clearly inefficient when measured by passenger-kilometers and ton-kilometers; however, with the other type of measurement, both companies notably improve their efficiency indicators. Therefore, the choice of output specification used continues to be a problem in studies of the estimation of efficiency and productivity.

Our study aims to analyze the differences in the efficiency indicators for the railway sector when different variables are specified as output. For this purpose, we use a non-parametric DEA model to calculate the efficiency indicators of a sample of European railway companies using the two types of output mentioned above. We then regress the difference between the efficiency indicators obtained on the indices of load factor of the supplied trains and show that when one of the efficiency indicators is corrected for the effect of these variables, the efficiency indicators of the two types of output become similar.

Our results, then, demonstrate that the differences in efficiency indicators can be explained by the differences in the output specification used, suggesting that efficiency indicators are compatible once differences in output specification are considered. When passenger and freight train-kilometers are specified as output, the efficiency is analyzed only as a function of the level of capacity or service supplied in terms of the volume of kilometers traveled. Meanwhile, when the number of passenger-kilometers and ton-kilometers is used, efficiency is evaluated as a function of the degree of use of the capacity or service supplied. Our study shows that the levels and rankings of efficiency obtained on the basis of different output specifications can be approximated by analyzing the differences between the output variables used.

METHODOLOGY, DATA, AND RESULTS

Methodology

In this study, we use the non-parametric technique, Data Envelopment Analysis (DEA), to estimate the technical efficiency of railway companies. DEA has two advantages over other techniques. First, it does not require specification of any functional form for production, avoiding the bias produced by an incorrect functional form. Second, DEA is better than parametric techniques at assessing the productive efficiency of railway companies since it can handle the multi-product nature of some companies.[2]

We calculate efficiency indicators with DEA by constructing a frontier through mathematical programming. A comparison of the companies relative to this production frontier gives us the measurements of individual effectiveness. Unlike parametric techniques, this technique does not estimate a previously specified functional form but instead calculates a convex frontier that "envelops" the observations. In this sense, the data themselves "dictate" the profile of the frontier. This technique's flexibility (it makes few assumptions) and applicability have led to its use in a large number of studies in recent years.[3]

To illustrate this technique,[4] let us suppose that the N companies forming the sample ($i = 1, \ldots, N$) use a vector of input $x_i = (x_{i1}, \ldots, x_{in})^T \in R^n +$ to produce a vector of output $y_i = (y_{i1}, \ldots, y_{im})^T \in R^m +$. The measurement of the efficiency of company j (θ_j) is obtained by comparing this company's performance with a linear combination of the N companies of the sample:

$$
\begin{aligned}
&\mathrm{Max}_{\theta,\lambda}\ \theta_j \\
&\text{such that: } Y\lambda \geq \theta_j\, y_j, \\
&X\lambda \leq x_j, \qquad (1) \\
&\lambda \geq 0
\end{aligned}
$$

where x_j and y_j are vectors of dimensions ($nX1$) and ($mx1$), respectively; λ is a vector of dimension ($nx1$), while X and Y are matrices of dimensions (nxN) and (mxN), respectively.

From the resolution of this problem for each of the N companies of the sample, we obtain N weightings (λ) and N optimum solutions (θ^*). Each optimum solution θ^* is the parameter of efficiency of each company that, by construction, satisfies $\theta^* \geq 1$. Companies with $\theta > 1$ are considered inefficient, while those with $\theta = 1$ catalogued as efficient are those that stand at the frontier. The inherent virtues of the DEA technique have encouraged studies comparing this methodology with alternative techniques, with varying results.[5]

[2] In this respect, some authors, such as Cowie and Riddington (1996), analyze the productive efficiency of railway companies by using parametric techniques as well as DEA. However, since parametric techniques only allow specification of a production function with a single output, these authors chose the number of passenger train-kilometers as the output, without considering that the companies also carry freight. The consideration of a single output causes a bias in the efficiency measurements obtained, undervaluing the efficiency of those companies that specialize in freight.

[3] Seiford and Thrall (1990) counted more than 400 articles on the application of DEA between 1978 and 1990. More recently, Førsund and Seiford (1999) count the empirical applications of this technique in the thousands.

[4] See details in Charnes, Cooper, and Rhodes (1978).

[5] See Banker, Conrad, and Strauss (1986); Gong and Sickless (1992); Ferrier and Lovell (1990); Bjurek, Hjalmarsson, and Førsund (1990); Pastor (1996); Cowie and Riddington (1996); etc. However, the precision of the estimation of efficiency with DEA can only be assessed on the basis of simulated data where the efficiency is known in advance. In this respect, Banker et al. (1988) compare the results of a translogarithmic function, using simulated data for a known underlying technology, concluding that

From an intuitive viewpoint, to analyze the efficiency of the productive scheme of company j (y_j,x_j) the problem constructs a feasible scheme as a linear combination of the schemes of the N companies of the samples that produce $\theta_j y_j$, using a lower or equal amount of input. Therefore, (θ_j-1) indicates the maximum radial expansion to which the vector of the output of company j can be subjected without needing to increase the level of input. When $\theta_j = 1$, no linear combination of companies producing more with less input can be found, so the company is catalogued as efficient. In the other cases, $\theta_j > 1$, and so a feasible alternative scheme which obtains a higher amount of output using the same input does exist.

Data

A panel of 17 European companies over the period of 1970 to 1995 was selected. The information was taken mostly from the reports published by the Union International des Chemins de Fer and was completed with the data published in the companies' statistical memoranda. Table 1 provides a set of the main characteristics of the railways used. Two sets of output were selected: 1) the number of passenger-kilometers (PKT) and ton-kilometers (TOKT) and 2) the passenger train-kilometers (PTK) and freight train-kilometers (FTK). For both, we estimate the efficiency indicators of the European companies using a non-parametric frontier approach (DEA). The variables used as input were 1) number of workers, 2) consumption of energy and materials,[6] 3) number of locomotives, 4) number of passenger carriages, 5) number of freight cars, and 6) number of track-kilometers.[7]

It should be noted that there are other factors that can affect the level of efficiency. The different indices of the quality of service or of infrastructure may bias the results if they are not taken into account. Another important factor is the degree of circuitousness. For example, if the infrastructure is expanded to allow for less circuitous routes, the number of passenger-kilometers or ton-kilometers will decrease even though the outcome is unchanged. The lack of relevant information on this type of variable makes it impossible to consider them in our study.

Results

The individual average inefficiency indicators for the period are shown in table 2.[8] INEF refers to the results obtained using the number of passenger-kilometers and ton-kilometers as output, and INEG refers to results obtained using passenger train-kilometers and freight train-kilometers. Each type of measurement refers to different aspects of the efficiency in the use of input, as noted in the previous section. The average correlation indices measured by the Pearson coefficient and the Spearman ranking coefficient between INEF and INEG are respectively 0.62 and 0.76, each with a standard error of 0.16.

Alternatively, a parametric test was made of the similarity of the two measurements, using ordinary least squares (OLS) to regress the inefficiency indicators obtained in INEF against the indicators obtained in INEG. The value of the parameter estimated was 0.937, with a standard error of 0.008. In this case, the null hypothesis that the parameter is equal to one can be rejected; in other words, it can be rejected that both measurements of efficiency are statistically equal (student's t is 7.80).

the predominance of DEA over parametric methods with regard to lesser deviation from the true values is due to DEA's greater flexibility of approach to the true functional form. Banker et al. (1988) also verify that the accuracy of the DEA results is greater when the size of the sample is increased, suggesting that DEA estimators show the property of consistency, subsequently shown theoretically by Banker (1993). In this same sense, Gong and Sickles (1992) conclude that the disadvantages of DEA relative to other methods depend on the choice of functional form. If the chosen specification coincides with the underlying one, parametric methods work better. On the other hand, the advantages of DEA are more evident when errors of specification exist.

[6] This variable was converted into U.S. currency using the Purchasing Power Parity Index obtained from the Organisation for Economic Cooperation and Development (OECD) reports (2000) and deflated to constant 1975 value.

[7] A more detailed discussion of the data used in this study can be found in Cantos et al. (1999).

[8] We will follow Farrell's (1957) definition of the technical efficiency of a company: it is not possible to produce more output with less input. In the results of table 2, a company is technically efficient in this way when the index has a value of 1, whereas if the index is higher than 1, the company would be able to increase output without needing to increase input.

TABLE 1 Average Values for Variables: 1970 to 1995

Company	**Country**	**PKT** (mill.)	**TOKT** (mill.)	**LT** (km)	**PTK** (thous.)	**FTK** (thous.)	**PT**	**TT**
BR[a]	UK	30,917	18,200	17,387	345,279	78,297	90.14	239.24
CFF	Switzerland	9,586	7,067	2,960	75,880	27,847	127.17	253.64
CFL	Luxemburg	234	658	272	3,335	1,520	74.53	435.71
CH	Greece	1,687	695	2,494	13,787	2,998	123.82	238.13
CIE	Ireland	1,007	590	2010	8,413	4,231	117.91	140.05
CP	Portugal	4,940	1,272	3,434	27,477	6,639	178.64	183.36
DB[b]	Germany	41,977	60,638	28,094	40,049	198,841	100.62	305.12
DSB	Denmark	4,081	1,793	2,227	40,919	7,982	99.89	227.25
FS	Italy	40,679	18,912	16,257	227,877	60,584	177.46	309.88
NS	Holland	9,928	3,114	2,851	98,918	13,156	98.40	238.07
NSB	Norway	2,097	2,694	4,180	23,235	10,217	90.30	263.94
ÖBB	Austria	7,536	11,203	5,781	66,622	36,501	114.56	304.63
RENFE	Spain	15,361	11,441	13,083	101,791	44,353	155.33	255.86
SJ	Sweden	5,741	16,595	11,110	59,839	40,042	95.52	414.47
SNCB	Belgium	6,940	8,235	3,975	68,786	21,667	102.05	379.89
SNCF	France	54,967	60,519	34,716	290,831	189,179	188.75	320.02
VR	Finland	3,027	7,617	5,941	24,651	17,816	122.65	426.18

[a] Does not include information for period 1970–1973
[b] Does not include information for 1995
PKT: number of total passenger-kilometers
TOKT: number of total ton-kilometers
LT: length of track
PTK: number of passenger train-kilometers
FTK: number of freight train-kilometers
PT: index of passengers per train
TT: index of tons per train

TABLE 2 Inefficiency Levels

	INEF		INEG		INEGC
CIE	1.703	**CH**	1.528	**CIE**	1.512
CH	1.475	**FS**	1.520	**CH**	1.476
BR	1.352	**SNCB**	1.449	**DSB**	1.375
DSB	1.269	**CIE**	1.428	**SNCB**	1.344
NSB	1.183	**DSB**	1.349	**BR**	1.339
SNCB	1.107	**CP**	1.296	**FS**	1.268
RENFE	1.045	**BR**	1.295	**CP**	1.188
FS	1.029	**RENFE**	1.109	**NSB**	1.109
DB	1.027	**NSB**	1.087	**CFL**	1.045
CP	1.022	**VR**	1.079	**NS**	1.013
ÖBB	1.020	**ÖBB**	1.062	**DB**	0.995
SNCF	1.014	**CFL**	1.054	**RENFE**	0.994
CFL	1.004	**SNCF**	1.037	**ÖBB**	0.992
VR	1.000	**DB**	1.031	**CFF**	0.941
SJ	1.000	**CFF**	1.000	**VR**	0.937
CFF	1.000	**NS**	1.000	**SJ**	0.928
NS	1.000	**SJ**	1.000	**SNCF**	0.851

INEF: inefficiency index when passenger-kilometers and ton-kilometers are used as output measurements

INEG: inefficency index when passenger train-kilometers and freight train-kilometers are used as output measurements

INEGC: corrected inefficiency measures when passenger train-kilometers and freight train-kilometers are used as output measurements

We would expect the different degrees of utilization of trains to explain a large part of the differences. In particular, companies with high indices of load factor are much more efficient when passenger-kilometers and ton-kilometers are used as measures of output. See the values for variables representing the number of passengers per train (PT) and freight tons per train (TT) in table 1 for VR, SNCB, or FS. On the other hand, companies with low indices of load factor, such as NSB, are more efficient when output is expressed as train-kilometers.

In any event, due to the multi-product nature of railway companies and the wide range of input used, there is no simple transformation between the two output measurements or between the measurements of efficiency obtained in each case. This can only occur when there is a single output and a single input. In this case, if we know that the company offers only passenger services, we can use two measurements of output, passenger-kilometers (PKT) or passenger train-kilometers (PTK). If we only have one input (I), a measurement of productivity can be constructed from the ratio of PKT/I or PTK/I. Therefore, a simple transformation exists between the two measurements using the ratio PKT/PTK. However, this is not the case for the railway industry.

We define DINEF as the difference between the logs of INEG and INEF and regress it by OLS on the logs of the number of passengers per train (LPT) and the freight-tons per train (LTT). Thus, DINEF = log (INEG/INEF). The regression results, including time effects (DUMMY_t), follow[9]:

$$\mathrm{DINEF}_{it} = \mathrm{DUMMY}_t + 0.2493\ \mathrm{LPT}_{it} + 0.175\ \mathrm{LTT}_{it}$$
$$R^2 = .2984;\ N{=}442,^{10} \tag{2}$$

where the LPT coefficient has a t-statistic of 10.60 and the LTT coefficient has a t-statistic of 8.19. Other reasons for the difference between these two measurements of efficiency may exist, such as the different passenger and freight traffic. In the case of passenger traffic, the companies that focus their production on urban services will carry a larger number of passenger-kilometers out of the same number of kilometers supplied than the companies focusing on long distance services. In this example, the lack of this type of information prevents a better fit of the regression given in equation (2).

We can see that both variables are highly significant and positive. Therefore, estimates of efficiency that use indices of train-kilometers penalize the companies with high indices of load factor. Estimates that use indices of passenger-kilometers and ton-kilometers favor companies with high indices of load factor. A higher degree of load factor involves a higher level of inefficiency when only train-kilometers are used as a measurement of output. We can obtain a corrected measurement of INEG (INEGC) by taking into account the effect of the degree of load factor:

$$\mathrm{INEGC}_{it} = \exp(\log \mathrm{INEG}_{it} - \widehat{\mathrm{DINEF}}_{it}),$$
$$\text{where } \widehat{\mathrm{DINEF}}_{it} = \widehat{\mathrm{DUMMY}}_t + 0.2493\ \mathrm{LPT}_{it} + 0.175\ \mathrm{LTT}_{it}. \tag{3}$$

With this, we aim to correct such a bias. The individual average levels of this corrected measurement of inefficiency are shown in table 2. The correlation between INEGC and INEF rises to 0.82, a value clearly higher than the 0.62 obtained for the original inefficiencies. In the case of Spearman's correlation coefficient, the growth is more modest, passing from an initial 0.76 to 0.84, with a standard error of 0.13. As for the alternative test of the two measurements of efficiency, if INEF is now regressed against INEGC, the parameter estimated for INEGC is 0.989, with a standard error of 0.006. In this case, the null hypothesis that these measurements are equal cannot be rejected (student's t is 1.63). The results indicate that once we take into account the different focus of each type of output measurements, the inefficiencies we obtain are largely consistent. The results show a similar view of the performance of European companies over the period and that in an analysis of efficiency it is not only important to know a company's position in the ranking but also its relative level of efficiency.

[9] Note that the regression does not include a constant since all the time effects were included in the estimation. Alternative specifications were also tried for the variables of the regression (semi-logarithmic transformation, estimation of levels, etc.). The results were very similar to those of equation (2), so the logarithmic specification was chosen due to the advantages of its ease of interpretation and the reduction of problems of heteroscedasticity.

[10] The F-test for the joint significance for LPT and LTT is $F_{2,416} = 55.49$. However, the F-test for the significance for LPT, LTT, and the time effects is $F_{27,442} = 6.52$. In both cases, the null hypothesis of nonsignificance is clearly rejected.

CONCLUSIONS

This paper verifies the sensitivity of the efficiency indicators to the output specification in the rail sector. Additionally, it shows that the results obtained with two different specifications for railway output can be harmonized. In particular, when the efficiency indicators obtained with one of the specifications, number of passengers and freight train- kilometers, are corrected to take the degree of utilization of the trains into account, the efficiency indicators obtained with this new specification are very similar to those obtained when the number of passengers and ton-kilometers are used as output measures. This study shows, therefore, that the analysis of the differences between the alternatives for the specification of measurements of output helps to explain the differences between the indicators of efficiency that such measurements can generate. Thus, this analysis serves as an additional means of testing the consistency of the efficiency results obtained.

ACKNOWLEDGMENTS

The authors are grateful for the comments and suggestions made by the anonymous referees of the *Journal of Transportation and Statistics* and for the financial support of the DCICYT SEC98-0895.

REFERENCES

Banker, R.D. 1993. Maximum Likelihood, Consistency and Data Envelopment Analysis: A Statistical Foundation. *Management Science* 39, no. 10:1265–73.

Banker, R.D., A. Charnes, W.W. Cooper, and A. Maindirata. 1988. A Comparison of Alternative Approaches to the Measurement of Productive Efficiency. *Applications of Modern Production Theory: Efficiency and Productivity*. Boston, MA: Kluwer Academic Publishers.

Banker, R.D., R. Conrad, and R. Strauss. 1986. A Comparative Application of Data Envelopment Analysis and Translog Methods: An Illustrative Study of Hospital Production. *Management Science* 32, no. 1:30–44.

Berg, S., F.R. Førsund, and E.S. Jansen. 1992. Technical Efficiency of Norwegian Banks: The Non-Parametric Approach to Efficiency Measurement. *The Journal of Productivity Analysis* 2, 127–42.

Bjureck, H., L. Hjalmarsson, and F.R. Førsund. 1990. Deterministic Parametric and Non-Parametric Estimation of Efficiency in Service Production, A Comparison. *Journal of Econometrics* 46, 213–27.

Cantos, P. and J. Maudos. 2000. Efficiency, Technical Change and Productivity in the European Rail Sector: A Stochastic Frontier Approach. *International Journal of Transport Economics* 27, no. 1:55–75.

Cantos, P., J.M. Pastor, and L. Serrano. 1999. Productivity, Efficiency and Technical Change in the European Railways: A Non-Parametric Approach. *Transportation* 26, no. 4:337–57.

Caves, D.W., L.R. Christensen, and J.A. Swanson. 1980. Productivity Growth, Scale Economies and Capacity Utilization in U.S. Railroads, 1955–1974. *American Economic Review* 71, December: 994–1002.

Caves, D.W., L.R. Christensen, M.W. Tretheway, and R.J. Windle. 1985. Network Effects and Measurement of Returns to Scale and Density in U.S. Railroads. *Analytical Studies in Transport Economics*. Cambridge, MA: Cambridge University Press.

Caves, D.W., L.R. Christensen, and W.E. Diewert. 1982. The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. *Econometrica* 50, 1393–414.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research* 2, 429–44.

Cowie, J. and G. Riddington. 1996. Measuring the Efficiency of European Railways. *Applied Economics* 28, 1027–35.

Deprins, D. and L. Simar. 1989. Estimating Technical Inefficiencies with Correction for Environmental Conditions with an Application to Railway Companies. *Annals of Public and Co-operative Economics*, 81–101.

Ferrier, G. and C.A.K. Lovell. 1990. Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence. *Journal of Econometrics* 46, 229–45.

Førsund, F. and L.M. Seiford. 1999. The Evolution of DEA Economics and Operations Research Perspectives. Paper presented at the Sixth European Workshop on Efficiency and Productivity Analysis, Copenhagen, Denmark, October.

Gathon, H.J. and P. Pestieau. 1995. Decomposing Efficiency into its Managerial and its Regulatory Components: The Case of European Railways. *European Journal of Operational Research* 12, 500–7.

Gong, B.H. and R.C. Sickles. 1992. Finite Sample Evidence on the Performance of Stochastic Frontiers and Data Envelopment Analysis Using Panel Data. *Journal of Econometrics* 51, 259–84.

Grifell, E., D. Prior, and V. Salas. 1993. Efficiency Scores Are Sensitive to Variable Specification: An Application to Banking. Working Paper. Universitat Autónoma de Barcelona, Bellaterra.

McGeehan, H. 1993. Railway Costs and Productivity Growth. *Journal of Transport Economics and Policy* 27, no. 1:19–32.

Nash, C.A. 1985. European Rail Comparisons—What Can We Learn? *International Railway Economics: Studies in Management and Efficiency*. Aldershot, England: Ashgate Publishing Company.

Organisation for Economic Cooperation and Development (OECD). 2000. Purchasing Power Parity Index. Available at www.oecd.org/statistics.

Oum, T.H. and C. Yu. 1994. Economic Efficiency of Railways and Implications for Public Policy. *Journal of Transport Economics and Policy* 28, no. 2:121–38.

Oum, T.H., W.G. Waters II, and C. Yu. 1999. A Survey of Productivity and Efficiency Measurement in Rail Transport. *Journal of Transport Economics and Policy* 33, no. 1:9–42.

Pastor, J.M. 1996. Diferentes metodologías para el análisis de la eficiencia de los bancos y cajas de ahorros españoles. *Fundación Fondo para la Investigación Económica y Social* (FIES). Documento de trabajo 123.

Perelman, S. and P. Pestieau. 1988. Technical Performance in Public Enterprises: A Comparative Study of Railways and Postal Services. *European Economic Review* 32, 432–41.

Preston, J. 1996. Economics of British Rail Privatisation: An Assessment. *Transport Reviews* 16, no. 1:1–21.

Seiford, L.M. and R.M. Thrall. 1990. Recent Developments in DEA, The Mathematical Programming Approach to Frontier Analysis. *Journal of Econometrics* 46, 7–38.

Vehicle Speed Considerations in Traffic Management: Development of a New Speed Monitoring Program

DARREN L. JORGENSON

Ernst and Young

MATTHEW G. KARLAFTIS

National Technical University of Athens

KUMARES C. SINHA

Purdue University

ABSTRACT

Since the passage of the National Maximum Speed Limit (NMSL) of 55 miles per hour (mph) in 1974 through its repeal in 1995, the federal government has mandated speed monitoring programs. The speed monitoring program was primarily intended to provide reliable data for inclusion in states' annual certification for Federal Aid Highway Projects. The repeal of the NMSL in 1995 not only authorized states to set their own speed limits but also allowed them to develop their own speed monitoring programs. This paper develops a seven-step framework for a speed monitoring program tailored to meet the needs of individual agencies using speed monitoring data at the state level. The proposed speed monitoring plan distributes speed monitoring stations to highway classes according to three primary criteria: spatial distribution, crash distribution, and daily vehicle-miles traveled (DVMT) distribution. The proposed plan is also compared with the existing speed monitoring program.

INTRODUCTION

The objective behind the design of any engineered public facility is to satisfy the demand for service in the safest and most efficient manner. As such, speed

Matthew G. Karlaftis, National Technical University of Athens, Iroon Polytechniou 5, 157 73 Athens, Greece. Email: mgk@central.ntua.gr.

is one of the traveler's foremost concerns when selecting alternate routes or transportation modes. Directly related to its speed, convenience and economy largely determine the value of a transportation facility in carrying people and goods.

At the same time, speed relates to travel safety. The National Crash Severity Study (NCSS), an investigation of approximately 10,000 crashes from 1977 to 1979, revealed that the possibility of fatality increases dramatically as the change in velocity during the collision increases (Flora 1982). This study showed that a driver crashing with a change in velocity of 50 miles per hour (mph) is twice as likely to be killed as one crashing with a change in velocity of 40 mph.

Vehicle speed contributes to crash probability, and an exceptionally important factor is the *variability* in speed on the same segment of highway. Speed variance, a measure of the relative distribution of travel speeds on a roadway, relates to crash frequency in that a greater variance in speed between vehicles correlates with a greater frequency of crashes, especially crashes involving two or more vehicles (Garber 1991). A wider variability in speed increases the frequency of motorists passing one another, thereby increasing opportunities for multi-vehicle crashes. Because vehicles traveling the same speed in the same direction do not overtake one another, as long as the same speed is maintained, they cannot collide. There have been several notable and exhaustive literature reviews in the area of speeding and crash probabilities, covering both the U.S. and abroad, worth consulting. See Transportation Research Board (TRB) (1998).

An important determinant of traffic safety is effective speed enforcement. While enforcement techniques have changed over the years, the principal reasons for controlling vehicle speeds, protection of life and property against the hazards of highway travel and efficient use of street and highway systems, have not. Speed monitoring data allow agencies to set up enforcement strategies, which will reduce speeds and, consequently, increase safety. Vaa (1997) conducted a field experiment in which a 35-kilometer stretch of road was subjected to an increase in police enforcement. Speed was measured in 60 and 80 kilometer per hour (km/h) speed limit zones before, during, and after enforcement withdrawal and compared with another stretch of road. Average speeds were reduced in both speed limit zones for all times of day. For some time intervals, the average speed and the percentage of speeding drivers were reduced for several weeks after the period of enforcement, demonstrating a time-halo effect[1] of eight weeks.

The present study discusses the necessary steps in developing a speed monitoring program and uses data from the state of Indiana to adjust the program to the needs of the state. Several factors warrant the present study. First, the existing speed monitoring program is designed to meet federal requirements and does not necessarily address the particular needs of state agencies. Second, speed monitoring stations are distributed to highway classes based solely on daily vehicle-miles traveled (DVMT), while states may find it appropriate to use additional criteria for monitoring station distribution. Finally, the existing program does not account for geographic gaps between stations where no monitoring occurs. The remainder of this paper is organized as follows: the second section discusses the existing, federally mandated, speed monitoring program and the current speed monitoring practices in various states. The third section identifies the speed monitoring needs for the state of Indiana and provides an overall strategic framework for the proposed speed monitoring plan. The fourth section presents the proposed speed monitoring program along with a comparison of the existing program, and the last section offers some concluding remarks and recommendations.

BACKGROUND

In 1973, Congress established a National Maximum Speed Limit (NMSL) of 55 mph, initially as a temporary energy conservation measure. In 1974, Congress made the national maximum speed limit permanent. The Federal Aid Amendments of 1974 made annual state enforcement certification a prerequisite for approval of federal aid highway projects. Summary data from state speed monitoring programs were a part of

[1]The time-halo effect is the length of time during which the effect of enforcement is still present after police activity has been withdrawn.

these annual certifications. The "Procedural Guide for Speed Monitoring," issued September 1975, provided the first federal guidelines for speed monitoring (USDOT FHWA 1975). The original speed monitoring procedures were designed to collect data and produce statistics for each of five highway types in a state on level, tangent highway sections under "free-flow" conditions. The methods for calculating statewide statistics, however, varied among the states, making the value of state-to-state comparisons questionable.

Slowly declining compliance with the 55-mph speed limit and increasing accident and fatality rates prompted the U.S. Department of Transportation (USDOT) to recommend, and Congress to approve, significant changes in the speed limit legislation in 1978 (USDOT FHWA 1978). The Highway Safety Act of 1978 provided for both withholding of federal aid highway funds and awarding incentive grants based on annually submitted speed compliance data. An estimate of the percentage of motor vehicles exceeding 55 mph became the major reporting requirement. Further changes to the speed monitoring program included that "free-flow" would no longer be the only condition monitored. Speed statistics must be representative of all travel; thus, all vehicles passing a monitoring station during the observation period had to be measured. Furthermore, speeds could be monitored on other than level, tangent sections of highway.

In 1980, further changes were made when the "Speed Monitoring Program Procedural Manual" (SMPPM) (USDOT FHWA 1980) was issued. Some of the most important points include the following: 1) sampling sessions were to be 24 hours long in order to account for varying daily traffic conditions affecting speeds; 2) highways were stratified into 6 categories based on Federal Highway Administration (FHWA) classifications instead of the 5 categories based on geometry as they were previously defined; 3) sampling sessions were allocated among highway categories based on the statewide DVMT, subject to the 55-mph speed limit in each highway category; 4) within a category, locations were picked using simple random sampling with probabilities proportional to mileage, commonly known as probability sampling; and 5) the target sampling accuracy of the annual statewide value of percentage of DVMT over 55 mph was 2.0% at a 95% confidence level. The number of sampling locations was established as the greater of the numbers needed to meet the target sampling accuracy and the DVMT subject to the 55-mph limit divided by two million.

On April 2, 1987, the Federal Aid Highway Act of 1987 gave "the states the authority to increase, without the loss of Federal Aid-funds, the maximum speed limit to no more than 65 mph…on Interstate Systems located outside an urbanized area of 50,000 (population) or more." Also, "Any state choosing to increase the speed limit from 55 mph…will have to adjust the speed sampling and analysis plan in effect for the fiscal year in which the limit is raised." A memorandum the FHWA distributed advised states choosing to increase the speed limit on eligible sections of rural interstate highways that DVMT represented by mileage in areas where the speed limit had been raised above 55 mph would not figure into the calculation of 55-mph-speed-limit compliance statistics for fiscal year (FY) 1987. In essence, DVMT factors would be adjusted to exclude all rural interstate locations where the maximum speed limit had been reposted to 65 mph. Even though a process of redistribution of DVMT weighting factors would exclude the requirement of monitoring and reporting statistics for rural interstate highways, the same number of locations would continue to be distributed among the (remaining) functional groupings in the same proportion as before.

In December of 1991, the Intermodal Surface Transportation Efficiency Act (ISTEA) was signed into law. FHWA and the National Highway Traffic Safety Administration (NHTSA) subsequently published modifications governing the National Maximum Speed Limit (NMSL). The revised procedures established speed-limit compliance requirements on both 55-mph and 65-mph roads. This statute assigned greater weight for speed limit violations in proportion to the degree motor vehicles exceed the speed limit. Additionally, the ISTEA compliance formula was tied more closely to the relative risk of fatality and to a measure of crash severity. On November 28, 1995, new federal legislation repealed the National Maximum Speed Limits, ending two decades of mandates. Effective December 8, 1995, states were again authorized to set their own speed limits and speed monitoring policies.

Jorgenson (1998) conducted a survey of the current speed monitoring practices from May of 1997 through July of 1998 in all 50 states. Since the repeal of the NMSL, 30 states have elected to change their speed monitoring programs. Of those 30 states, 8 states currently have more monitoring stations than previously mandated by the FHWA. Of the 22 states that reduced the number of monitoring stations, 11 dropped the speed monitoring program altogether (table 1).

IDENTIFICATION OF SPEED MONITORING NEEDS

After the repeal of the NMSL, the most important question for the state of Indiana became if the speed monitoring program should be continued. A simple questionnaire was distributed to parties interested in speed monitoring: the Indiana State Police, the Indiana Department of Transportation (INDOT) Planning Division, INDOT Roadway Management Division, FHWA safety engineers, and others. As table 2 shows, the respondents almost unanimously supported a speed management program. The respondents considered it important to continue speed monitoring following the repeal of the NMSL in order to devise suitable enforcement measures, ensure safety on the state road network, provide speed information to various public and private agencies, and have reliable data readily available for design, operational, and research needs.

Once the need for and desire to participate in a new speed monitoring program was established, the second question became the criteria by which monitoring sites were to be distributed among highway classes. After discussions with the participants in the preliminary study, three considerations for site allocation were chosen: 1) spatial distribution, 2) relative DVMT distribution, and 3) relative crash distribution. The crash distribution criterion was further broken down into four types of crashes: all crashes, all fatal crashes, speed-related crashes, and fatal speed-related crashes. The six highway classes chosen were rural interstates, urban interstates, rural U.S. roads, urban U.S. roads, rural state roads, and urban state roads. Sites have historically been distributed by functional highway class. In the proposed plan, two factors influenced the decision to consider a different highway classification scheme. First, all supporting data used in the present study, such as vehicle-miles traveled and crash data, were available for the new classification scheme. This consistency allows any agency using speed data to easily investigate causal

TABLE 1 State Survey of Speed Monitoring Programs

Number of stations	Number of responses	Percentage
Increase	8	16.0
Decrease	11	22.5
No change	19	39.0
Discontinued	11	22.5
Vehicle classification		**Percentage**
Yes	13	34
No	25	66
Monitoring direction		**Percentage**
One direction	19	50
Both directions	19	50
Sessions per year		**Percentage**
Daily	4	10
Monthly	1	3
Quarterly	20	53
Semi-annually	3	8
Annually	4	10
As needed	6	16
Session duration		**Percentage**
24 hours	33	87
48 hours	2	5
72 hours	1	3
Continuous	2	5

TABLE 2 Continuation of Speed Monitoring

Continue monitoring?	Number of responses	Percentage
Yes	30	97
No	1	3
Use data?	**Number of responses**	**Percentage**
Yes	29	94
No	2	6

relationships. Second, there was evidence of a statistically significant difference in the mean speed of these highway classes (Jorgenson 1998).

We used a Delphi study to ensure that the allocation of speed monitoring stations be consistent with the requirements of those using the resulting data by ranking and rating the site distribution criteria. The Delphi process allows a group with varying opinions to come to a consensus. In the present study, the objective was to rank and rate speed-monitoring station distribution criteria. The Delphi process replaces direct confrontation and debate with a carefully planned, orderly program of sequential discussions, carried out through an iterative survey (Dalkey et al. 1969). Typically, a presentation of observed, expert concurrence in a given application area where none existed previously results (Sackman 1974). In this portion of the survey, participants were first asked to allocate 100 points among the three distribution criteria. The higher the number, the more important that criterion was deemed. For the next step, participants allocated 100 points among the four crash categories. Again, the higher the number, the more important that crash type was deemed.

Table 3 provides the results of the Delphi process. Following the first round, DVMT was the highest rated distribution criterion with 36 points. Crash distribution was second with 33 points, and spatial distribution was third with an allocation of 31 points. The crash results showed speed-related crashes to be the most important crash distribution criterion with an average 29.3 points. Fatal speed crashes followed with an average of 28.6 points. All crashes came in third with an average of 24.7 points, and all fatal crashes was fourth with an average of 20.0 points. In the second round, the order of importance for both the distribution criteria and crash types changed. As table 2 shows, DVMT continued to be the most important distribution criterion with an average 34.8 points. This was closely followed by spatial distribution, up from third place in the first round with an average value of 34.2. Crash distribution was last with a mean value of 31.0. While this result may seem counterintuitive to some in that crash distribution would be deemed the least important, it demonstrates the power of the Delphi approach: criteria importance is based on collective results rather than on single opinions.

The order of importance for crash types also changed. Speed-related crashes remained in first place with an average 28.8 points. All crashes moved up from third to second with an average 27.9. Fatal speed crashes dropped from second to third place with an average of 24.3. Finally, all fatal crashes remained fourth with an average of 19.0. Because the Delphi process deliberately manipulates responses toward minimum dispersion of opinion in the name of consensus (Martino 1972), there is no advantage to continuing beyond two rounds (Dalkey 1970). Therefore, the survey stopped at that point. Having identified both the desire and need for a speed monitoring program and the criteria to develop it, we then developed the basic procedure to define the number, location, and monitoring time of the new program.

TABLE 3 Delphi Process for Speed Monitoring Program Results

Distribution criteria	Round 1 Mean	Round 1 Standard Deviation	Round 1 Rank	Round 2 Mean	Round 2 Standard Deviation	Round 2 Rank
Spatial	31.0	13.8	3	34.2	11.3	2
Crash	33.0	10.9	2	31.0	9.4	3
DVMT	36.0	9.4	1	34.8	6.7	1
Crash type						
All	24.7	18.3	3	27.9	16.9	2
All fatal	20.0	9.6	4	19.0	8.2	4
Speed	29.3	9.8	1	28.8	7.4	1
Fatal speed	28.6	8.9	2	24.3	10.3	3

DESIGN OF THE SPEED MONITORING PLAN

In order to maintain, as much as possible, compatibility with the data collected under the FHWA program, the new program's design, follows the statistical requirement of a 2.0 mph maximum error of estimate, with 95% confidence, as used in the federal program (USDOT 1992). This requirement determined the following seven core components of the proposed program: 1) the number of monitoring sessions per year, 2) duration of monitoring period for individual sampling sessions, 3) monitoring speed by direction of travel, 4) monitoring speed by vehicle length, 5) the minimum number of statewide sampling locations, 6) monitoring station site distribution, and 7) selection of monitoring locations. Finally, the proposed program has speed monitoring stations allocated by highway class based on the distribution criteria discussed in the previous section. We also discuss here a procedure to help determine locations of monitoring sites utilizing existing speed monitoring, weigh-in-motion (WIM), and automated traffic recording (ATR) stations.

Number of Monitoring Sessions per Year

The federally developed monitoring program collects speed data every quarter (USDOT 1992). However, while it is well documented that traffic volume varies by time of year (McShane and Roess 1990), the variation in mean speed by time of year may not be significant. The present study examines the need for quarterly speed monitoring. The existence of a significant difference in mean speed by quarters and of a significant difference between each quarterly speed distribution could determine the necessity of quarterly speed monitoring.

A three-stage, nested factorial design (Montgomery 1997) serves as the statistical model used to analyze the number of monitoring sessions per year. A nested, factorial design was chosen because levels of one factor are similar but not identical for different levels of another factor. This means, for example, that highway class one in district one of year one is similar to, but not identical to, highway class one in district one of year two. Therefore, highway class is nested under district one in year one. This analysis used the historical 1983 through 1997 speed monitoring data collected in Indiana. The database covered 15 years, 4 annual quarters, 6 districts, and 6 highway classes. The total of 320 stations represented different monitoring locations used over the 15-year period. Appendix one shows the model for the three-staged, nested factorial design used in this experiment representing the main effects and their associated interactions. The model was estimated with SAS (1998) in order to test for significant main and interaction effects. The Student-Newman-Keuls (SNK) multiple range test was used on all main effect means (Everitt 1992). The SNK method compares all pairs of treatment means in an effort to discern which means differ.

The experiments of interest in this analysis were variation by quarter, variation by quarter by class, variation by quarter by district, and variation by quarter by district by class. Table 4 shows the significance probabilities associated with each main effect and interaction this analysis used. From this table we can determine the significance of the relevant main effects and their interactions. The probability associated with the main effect of quarter, denoted by γ_m (0.9054), indicates that no significant difference in mean speed existed between quarters. Mean speeds stratified by quarter, pre-

TABLE 4 Probability Table for the Three-Staged, Nested Factorial Mixed Effects Model

Source	Effect	Pr > *F*
α_i	YEAR	0.0001
β_j	DIST	0.0001
χ_k	CLASS	0.0001
$\alpha\beta_{ij}$	YEAR*DIST	0.9986
$\alpha\chi_{ik}$	YEAR*CLASS	0.9911
$\beta\chi_{jk}$	DIST*CLASS	0.0001
$\alpha\beta\chi_{ijk}$	YEAR*DIST*CLASS	0.9636
$\delta_{(ijk)l}$	STA(YEAR DIST CLASS)	—
γ_m	QRT	0.9054
$\alpha\gamma_{im}$	YEAR*QRT	0.5219
$\beta\gamma_{jm}$	QRT*DIST	0.5505
$\chi\gamma_{km}$	QRT*CLASS	0.8790
$\alpha\beta\gamma_{ijm}$	YEAR*QRT*DIST	0.0024
$\alpha\chi\gamma_{ikm}$	YEAR*QRT*CLASS	0.0001
$\beta\chi\gamma_{jkm}$	QRT*DIST*CLASS	0.6947
$\alpha\beta\chi\gamma_{ijkm}$	YEAR*DIST*CLASS*QRT	0.001778
$\delta\gamma_{(ijk)lm}$	STA(YEAR DIST CLASS)*QRT	—

Note: Please see Appendix for the statistical model used.

TABLE 5 Student-Newman-Keuls Test for Quarter

SNK grouping*	Mean	Quarter
A	58.9	4
A	58.9	3
A	58.8	2
A	58.8	1

*Means with the same SNK groupings are not significantly different

sented in table 5, demonstrate that the mean speed only varied from 58.8 mph in quarter 1 to 58.9 mph in quarter 4, further showing that mean speed was not significantly different by quarter. The probability associated with the quarter by class interaction effect, denoted by $\chi\gamma_{km}$ (0.8790), indicates that mean speed is not significantly different by quarter and highway class. The probability associated with the quarter by district interaction effect, deno ted by $\beta\gamma_{jm}$ (0.5505), indicates that mean speed is not significantly different by quarter and district. The probability associated with the quarter by district by class interaction effect, denoted by $\alpha\beta\chi\gamma_{ijkm}$ (0.6947), indicates that mean speed is not significantly different by quarter within each highway class and district. Nevertheless, it should be noted that there is preliminary evidence that although the mean speed was found not to be different by quarter, the speed *distributions* may be. This hypothesis was tested using Fisher's c^2-test (Jorgenson 1998). Consequently, it may be desirable to continue to monitor speed every quarter.

Duration of Monitoring Period for Individual Sampling Sessions

Under the original FHWA program, a 24-hour monitoring period was selected for the following reasons. First, it accounted for the varying traffic conditions affecting speeds within a day. Second, the within-cluster (daily) variation would not allow for a reduction in the number of locations required even if much longer periods were used. The 24-hour monitoring period minimized cost in terms of the combination of sampling locations required and the need for equipment. For the proposed program, the Indiana State Police wanted to test whether day of week was a significant factor in determining mean speed. If so, it would be necessary to monitor speeds for a longer period, thus the need for this analysis. With a two-stage, nested factorial mixed effects model with data from 27 WIM stations distributed throughout the state, it was concluded that, at the 95% level of significance, the effect of day on mean speed was not a significant factor in explaining the variation in mean speeds in Indiana; thus, the future program should continue to monitor speeds 24 hours a day.

Monitoring Speed by Direction of Travel

The survey of state-wide speed monitoring practices revealed that half of the states that continue to monitor speeds do so in both directions of travel. Consequently, INDOT wanted to see if it was necessary for Indiana to measure speed by direction. Also, the Indiana State Police felt speed by direction could be important for enforcement purposes. A two-stage, nested factorial mixed effects model determined at the 99% level of significance that mean speeds were different by direction of travel. Based on this finding, speed should be monitored for each travel direction, particularly for divided highways.

Monitoring Speed by Vehicle Length

Since trucks are much heavier and have slower acceleration and deceleration rates than passenger vehicles, there is an increased potential for severity in cases of crashes between trucks and smaller vehicles. Higher speeds add to the severity of these crashes. At the same time, speed variance increases when trucks travel at a different speed than other vehicles. In Indiana, the speed limit for trucks on rural interstates is 60 mph, while for passenger vehicles it is 65 mph. Representatives from Indiana State Police, INDOT, and the Department of Revenue requested that an analysis determine if a difference existed in mean vehicle speed based on vehicle length, not only on rural interstates but also on other roads. A two-stage, nested factorial mixed effects model was estimated with station nested under highway class. Station is nested under highway class because different levels of station are similar but not identical for different levels of highway class. As the federal program suggested, speed by vehicle class was not monitored. A special data collection effort was made during the four quarters of 1997 to record speed data separately for trucks at randomly selected existing monitoring stations.

Three vehicle classes were considered. Class 1 consisted of passenger cars 20 feet long or less; class 2, medium sized trucks between 21 and 40 feet long; and class 3, large trucks 40 feet long or greater.

Of interest in this experiment was whether vehicle class and the interaction between highway class and vehicle class were significant. Results show that highway class, vehicle length, and the interaction between highway class and vehicle length were all significant with probability (Pr > *F*) values of 0.0001. Because Indiana currently employs differential speed limits on rural interstates, the interaction between highway class and vehicle class could be significant. It was found that mean speeds for the three vehicle classes considered were significantly different from each other. Passenger cars had a mean speed of 60.2 mph; single unit trucks and buses had a mean speed of 58.2 mph, and combination trucks had a mean speed of 59.4 mph. The results are somewhat surprising because one would expect single unit trucks to travel at a higher speed than combination trucks.

Number of Statewide Monitoring Stations

Two concepts were used to determine the number of statewide monitoring stations: reliability of statistical estimates and coverage of population sampled (Miller et al. 1990). In the FHWA program, the standard statistical requirements for determining sample size depend on the statewide standard deviation of the percentage of vehicles exceeding the posted speed limit rather than on mileage or vehicle-miles traveled (USDOT 1992). Since this figure would be similar in most states, the resulting sample sizes would be nearly the same, with the exceptions of very small states. This meant that, statistically, the sizes of the speed populations of different states had very little influence on the sample sizes required for estimation. Having nearly equal samples for the different states did not provide data representative of the widely varying travel characteristics found among the states. The concept of "coverage of population sampled" instead provided balance to the work load among the states and a margin of increased accuracy for the larger states with larger mileages and DVMT.

The FHWA program determined the minimum sample size needed for a state under each of the two concepts and then selected the larger of the two numbers as the statewide minimum sample size. In this manner, the reliability requirement can always be met, and the sample size can be sensitive to the varying amounts of travel in the states. The present study adopted the FHWA approach in determining the total number of stations in the proposed program. To determine the number of locations required for the desired precision, a preliminary estimate of the standard deviation was estimated. The present study used the default value for this parameter, set by the FHWA at 7.0%, to determine the number of stations required. The formula to calculate the number of monitoring stations follows.

$$n_o = \left[\frac{z_{.95} \times S(P_{st})}{d} \right]^2 \qquad (1)$$

where

n_o = sample size,

$z_{.95}$ = value of the normal distribution based on a one-sided 95% confidence interval,

$S(P_{st})$ = standard deviation of the percentage of vehicles exceeding the posted speed limit,

d = precision level required (2.0 mph).

For Indiana, the number of sampling segments required by the reliability of statistical estimates criterion was 38.

The coverage concept was designed to allocate locations based on the amount of travel, DVMT, subject to the posted speed limit in the state. This concept served various purposes: 1) to provide a balanced sample size; 2) to compensate for the additional variation possibly present due to larger volume or larger mileage; and 3) to account for the potential variation in speed enforcement activities of different police departments, districts, or jurisdictions within a state. With DVMT data from the 1997 Highway and Pavement Management System (HPMS) (USDOT 1995) database, the number of monitoring stations required for Indiana under the coverage concept is 26 (Jorgenson 1998). Therefore, the greater of the reliability criterion and the coverage criterion require 38 stations in the proposed program.

Monitoring Station Site Distribution

Concept

With the statewide number of necessary speed monitoring stations determined, the next step was to distribute them by highway class. As mentioned in the previous section, the three distribution criteria adopted in the present study are spatial distribution, DVMT distribution, and crash distribution. The crash distribution criterion was further broken into four crash types: all crashes, all fatal crashes, speed related crashes, and fatal speed related crashes. The expected site distributions were first computed for each criterion and crash type. The individual distributions were then combined into a composite distribution based on the individual criterion's importance.

Spatial Distribution

The procedure used to distribute the speed monitoring stations by highway class according to the spatial criterion considered the six INDOT districts as separate geographical areas. The HPMS database served to calculate the number of lane-miles in each highway class for each district, giving the percentage of lane-miles by highway class by district. This percentage was then multiplied by the total number of stations, yielding the number of stations by highway class by district. The number of sites in each highway class was then summed over the district, giving the expected number of stations in each highway class for the state, as shown in table 6.

DVMT Distribution

To determine site distribution based on the DVMT criterion, the HPMS database was used to compute DVMT for each highway class. The DVMT for each highway class was then divided by the total DVMT subject to the 55-mph or greater speed limit, giving the percentage of DVMT for each highway class. That percentage was then multiplied by the total number of stations, giving the expected number of stations by highway class for the DVMT criterion. These calculations are shown in table 7.

Crash Distribution

To allocate stations according to crash criteria, an average crash distribution was computed for each of the four crash types. The 1991–1995 crash data from the Indiana State Police Crash Information System Crash Master Files is a database containing records on all reported crashes in Indiana. Table 8 shows the average crash distributions for all crashes; this process was repeated for all crash types. Once the average crash distribution for each crash type and for each highway class was computed, the percentage value was multiplied by the total number of stations, giving the expected number of stations by highway class for each crash criterion. This procedure was repeated for each of the four crash types, and the results for all crashes are shown in table 9.

Composite Site Distribution

After obtaining six separate site distributions schemes, we then combined them into a composite distribution. The importance ratings provided by the Delphi study played a role at this stage. A weighted average site distribution scheme was devised by multiplying the associated weights with the respective site distributions and summing them

TABLE 6 Statewide Site Distribution by Lane-Miles

Highway class		Lane-miles Percentage	Lane-miles Total	Number of stations
Interstates	Rural	39.75	3,444	15
	Urban	17.41	1,508	7
U.S. roads	Rural	19.81	1,716	8
	Urban	3.19	277	1
State roads	Rural	17.58	1,523	6
	Urban	2.26	196	1
TOTAL		100.00	8,665	38

TABLE 7 Statewide Site Distribution by DVMT

Highway class		DVMT Percentage	DVMT Total miles	Number of stations
Interstates	Rural	40.74	20,469,678	15
	Urban	38.41	19,298,759	15
U.S. roads	Rural	10.59	5,320,672	4
	Urban	2.57	1,291,299	1
State roads	Rural	5.78	2,906,413	2
	Urban	1.90	956,518	1
TOTAL		100.00	50,243,340	38

TABLE 8 Average Distribution of All Crashes

Highway class		Percentage 1991	1992	1993	1994	1995	Average
Interstates	Rural	12.53	11.70	11.65	12.04	11.90	11.97
	Urban	6.06	5.75	6.40	6.21	6.25	6.13
U.S. roads	Rural	19.46	19.55	18.51	18.99	17.55	18.81
	Urban	13.57	14.10	14.30	14.98	15.67	14.52
State roads	Rural	34.41	34.61	33.73	32.72	32.56	33.61
	Urban	13.97	14.29	15.41	15.06	16.07	14.96
TOTAL		100.00	100.00	100.00	100.00	100.00	100.00

TABLE 9 Site Distribution Based on All Crashes

Highway class		Percentage	Total	Number of stations
Interstates	Rural	11.97	6,695	5
	Urban	6.13	3,437	2
U.S. roads	Rural	18.81	10,506	7
	Urban	14.52	8,146	6
State roads	Rural	33.61	18,800	13
	Urban	14.96	8,396	6
TOTAL		100.00	55,980	38

over each highway class. The goal was to have a composite site distribution that statistically satisfied each site distribution criterion: the proportion of sites in each highway class for each distribution criterion should be equal to the proportion of sites in each highway class for the composite distribution. Because it would be almost impossible to find a composite site distribution that statistically satisfied all three distribution criteria, the present study attempted to satisfy the two most important site distribution criteria, DVMT and spatial distribution.

In order to obtain a composite site distribution, monitoring stations were allocated to highway classes, making the composite distribution statistically close to both the DVMT and spatial distribution. The proposed site distribution has 13 stations in rural interstates, 10 in urban interstates, 7 in rural U.S. roads, 2 in urban U.S. roads, 4 in rural state roads, and 2 in urban state roads.

Selection of Monitoring Station Location

The proposed program makes maximum use of the existing speed monitoring, WIM, and ATR stations without affecting the statistical reliability of the proposed monitoring plan. The three options considered for this purpose vary by the level of use of existing stations: minor, moderate, and major change.

The first option, minor change, uses existing stations if they are in the same district and highway class of the proposed station. In this option, existing stations receive priority in the site selection process. If a certain highway class in an existing station is not available, a new site is randomly selected. Cost savings is the benefit of this method because very few new stations need to be installed. The main drawback is the reduction in randomness of the site selection process. To select the monitoring location for minor change, an iterative procedure helps allocate sites to highway classes within districts according to a range of plus or minus one of the recommended number of sites, based on the number of sites available. The recommended number of stations was computed by taking the percentage of lane-miles in a given highway class for a given district and multiplying that number by the total number of stations in that highway class. This procedure ensures that sites are distributed evenly throughout the state and minimizes the difference between the actual and recommended stations per district and highway class.

The second option, moderate change, also utilizes existing stations but in a different manner. The stations are first randomly selected. Then, existing stations are chosen if they match the characteristics of the randomly selected stations (DVMT, number of lanes, location, preferably the same continuous highway, and so forth). This method has a moderate cost and degree of randomness.

The third option, major change, relies totally on random selection of sites. The benefit of this alternative is that sample segments are completely random. The drawback is the high cost associated with installing new stations. Moderate and minor change have the same number of stations in each district and highway class; the difference between the two methods is in how the highway segments for monitoring stations are selected. To allocate the monitoring locations for moderate and major change, a procedure similar to the iterative one used in minor change was followed, except that there was no constraint requiring the use of available stations. For moderate change, the randomly selected stations were substituted for existing stations, when feasible. For major change, no such substitution took place. For this reason, the actual locations of individual monitoring stations are different under moderate and major changes, even if the distribution of stations remains the same.

Based on the minor change option, 38 existing stations would be used in the monitoring program. With the moderate change option, 22 existing and 16 new stations would be used. Based on the major change option, of the 38 randomly selected segments, 37 would be new stations and only 1 would be an existing station. It was a coincidence that this existing station was randomly selected. Because the primary objective of the study was to utilize as many existing speed monitoring stations as possible, the present study uses the minor change option of 38 existing speed monitoring stations.

Comparison of Proposed with Existing Site Layout

A comparison of the proposed site layout with the existing site layout indicated if the proposed site layout would be an improvement over the existing program. The underlying assumption in the present study's sample size calculation was that the relative precision of the estimates would not exceed 2.0 mph. The relative precision can be calculated using the sample size and standard deviation of the percentage of vehicles exceeding the posted speed limit. The calculation of relative precision for the existing program used data from existing sites. For the proposed program, the standard deviation of the percentage of vehicles exceeding the posted speed limit had to be estimated using historical data.

Table 10 shows the proposed and existing site layouts with the expected number of stations for each of the site distribution criteria. The probability-values (p) under the expected values indicate the probability that the given site distribution will be similar to the distribution occurring from the listed site distribution criteria. A low p-value ($< .05$) indicates significant evidence of dissimilarity between the distributions. From this table, we can see that the proposed distribution is similar to the distribution yielded by the DVMT and spatial criteria. This means that the proposed distribution is not significantly different from those distributions based on the DVMT and spatial criteria. The existing distribution, however, is only similar to the distribution yielded by the crash criterion. In other words, the proposed station distribution satisfies two of the three distribution criteria, while the existing site distribution only satisfies one distributional criterion.

TABLE 10 Comparisons of Site Distributions for Existing and Proposed Programs

	Actual stations		Expected number of stations based on		
Highway class	Proposed	Existing	DVMT	SITE	CRASH
Rural interstates	13	8	15	15	6
Urban interstates	10	7	14	6	4
Rural U.S. roads	7	15	5	8	7
Urban U.S. roads	2	3	1	2	3
Rural state roads	4	12	2	6	15
Urban state roads	2	1	1	1	3
Proposed program	p-value		0.052	0.2620	0.001
Existing program	p-value		0.001	0.001	0.114

CONCLUSIONS

The present research reviews the federal speed monitoring program from its inception in 1956 through the repeal of the NMSL in 1996. A survey of relevant agencies in Indiana indicates that Indiana should continue to monitor speeds under a formal program. Also, the present study analyzes the core components of the FHWA program and presents a new methodology to allocate speed monitoring stations based on three criteria: spatial distribution, DVMT distribution, and crash distribution. The present study evaluates three different approaches to select sampling locations throughout the state. Finally, the proposed station distribution is compared with the existing station distribution.

We have shown the need to continue a formal monitoring speed program at the state level. The present study uses statistical models to demonstrate that mean speed does not vary by quarter but that daily speed distributions do. As such, Indiana may wish to monitor speeds every quarter. The results indicate that day of week is not significant, while direction of travel is. The state of Indiana should monitor speeds for a 24-hour period in both directions of travel. Also, a statistical model was developed and shows that speed varies by vehicle class, suggesting that Indiana should monitor speeds based on vehicle class. Finally, Indiana should utilize a site layout which incorporates 38 existing speed monitoring, WIM, and ATR stations.

REFERENCES

Dalkey, N.C. 1970. Use of Self Ratings to Improve Group Estimates. *Journal of Technological Forecasting and Social Change* 1, no. 3.

Dalkey, N.C., B.B. Brown, and S. Cochran. 1969. *The Delphi Method.* Santa Monica, CA: Rand.

Everitt, B. 1992. *The Analysis of Contingency Tables.* New York, NY: Chapman and Hall.

Flora, J.O. 1982. Alternative Measures of Restraint System Effectiveness: Interaction with Crash Severity Factors. SAE Technical Paper 820798, Society of Automotive Engineers, Warrandale, PA.

Garber, N.G. 1991. *Impacts of Differential Speed Limits on Highway Speeds and Accidents.* Washington, DC: AAA Foundation for Traffic Safety.

Jorgenson, D.L. 1998. The Development of a Speed Monitoring Program for Indiana, Master's Thesis, School of Civil Engineering, Purdue University, West Lafayette, IN.

Martino, J.P. 1972. *Technological Forecasting for Decision Making,* Elsevier Science.

McShane, W.R. and R.P. Roess. 1990. *Traffic Engineering.* Englewood Cliffs, NJ: Prentice-Hall.

Miller, I., J.E. Freund, and R.A. Johnson. 1990. *Probability and Statistics for Engineers.* Englewood Cliffs, NJ: Prentice–Hall.

Montgomery, D.C. 1997. *Design and Analysis of Experiments.* New York, NY: J.W. Wiley.

Sackman, H. 1974. *Delphi Critique: Expert Opinion, Forecasting, and Group Process.* Lexington, MA: Lexington Books.

SAS Institute Inc. 1988. *SAS/STAT User's Guide.* Cary, NC: SAS Institute Inc.

Transportation Research Board (TRB). 1998. Managing Speed. Special Report 254. Washington, DC: National Academy Press.

U.S. Department of Transportation (USDOT), Federal Highway Administration (FHWA). 1975. Procedural Guide for Speed Monitoring. Office of Highway Planning, Washington, DC.

_____. 1978. Interim Speed Monitoring Procedures. Office of Highway Planning, Washington, DC.

_____. 1980. Speed Monitoring Program Procedural Manual. Office of Highway Planning, Washington, DC.

_____. 1992. Speed Monitoring Program Procedural Manual. Office of Highway Planning, Washington, DC.

_____. 1995. Highway Performance Monitoring System Field Manual. Office of Highway Planning. Washington, DC.

Vaa, T. 1997. Increased Police Enforcement: Effects on Speed. *Accident Analysis and Prevention* 29, no. 3:373–85.

APPENDIX

The statistical model for the three-stage, nested factorial design used in the number of monitoring stations per year experiment follows (similar two-stage models were developed for the other experiments as well):

$$y_{ijklm} = \mu + \alpha_i + \beta_j + \chi_k + \alpha\beta_{ij} + \alpha\chi_{ik} + \beta\chi_{jk} + \alpha\beta\chi_{ijk} + \delta_{(ijk)l} + \gamma_m + \alpha\gamma_{im} + \beta\gamma_{jm} + \alpha\beta\gamma_{ijm} + \alpha\chi\gamma_{ikm} + \beta\chi\gamma_{jkm} + \alpha\beta\chi\gamma_{ijkm} + \delta\gamma_{(ijk)lm} \qquad (2)$$

where

μ is the overall sample mean, α_i is the effect of the i^{th} year, β_j is the effect of the j^{th} district, χ_k is the effect of the k^{th} highway class, $\alpha\beta_{ij}$ is the interaction between the i^{th} year and j^{th} district, $\alpha\chi_{ik}$ is the interaction between the i^{th} year and k^{th} highway class, $\beta\chi_{jk}$ is the interaction between the j^{th} district and k^{th} highway, $\alpha\beta\chi_{ijk}$ is the interaction between the i^{th} year j^{th} district and k^{th} highway class, $\delta_{(ijk)l}$ is the effect of the l^{th} station within the k^{th} highway class within the j^{th} district within the i^{th} year, γ_m is the effect of the m^{th} quarter, $\alpha\gamma_{im}$ is the effect of the interaction between the i^{th} year and m^{th} quarter, $\beta\gamma_{jm}$ is the effect of the interaction between the j^{th} district and m^{th} quarter, $\chi\gamma_{km}$ is the effect of the interaction between the k^{th} highway class and m^{th} quarter, $\alpha\beta\gamma_{ijm}$ is the effect of the interaction between the i^{th} year the k^{th} highway class and the m^{th} quarter, $\alpha\chi\gamma_{ikm}$ is the effect of the interaction between the i^{th} year the k^{th} highway class and the m^{th} quarter, $\beta\chi\gamma_{jkm}$ is the effect of the interaction between the j^{th} district the k^{th} highway class and the m^{th} quarter, $\alpha\beta\chi\gamma_{ijkm}$ is the effect of the interaction between the i^{th} year the j^{th} district the k^{th} highway class and the m^{th} quarter, and $\delta\gamma_{(ijk)lm}$ is the effect of the interaction between the l^{th} station within the k^{th} highway class within the j^{th} district within the i^{th} year and the m^{th} quarter.

Valuing Long-Haul and Metropolitan Freight Travel Time and Reliability

MARCUS WIGAN

Oxford Systematics

NIGEL ROCKLIFFE

Economic Outcomes

THOROLF THORESEN

DIMITRIS TSOLAKIS

ARRB Transport Research

ABSTRACT

Most evaluations and economic assessments of transport proposals and policies in Australia omit a valuation of the time spent in transit for individual items or loads of freight. Knowing about delays, and indeed the practical value of reliability, is useful to shippers and receivers, but this information does not necessarily appear directly in vehicle operating costs and person travel times. As a result, benefits generated by improvements from road investment and traffic management may be understated, and expenditure decisions may be biased towards passenger movements. The present paper applies contextual stated preference (CSP) methods and the associated multinomial logit models to estimate the value of such factors from an Australian survey of freight shippers using road freight transport in 1998. The estimated value of \$1.40 per hour per pallet for metropolitan multidrop freight services, potentially a substantial value not currently tracked consistently or utilized in transport evaluation procedures in Australia, illustrates the significance of these results.

Marcus Wigan, Oxford Systematics, Monash University, GPO Box 126, Heidelberg, Victoria, Australia. Email: mwigan@vaxc.cc.monash.edu.au.

INTRODUCTION

Faster, more reliable freight movements make up a substantial portion of the benefits generated by road and transport investments. However, the techniques for assessing and valuing the different components of this economic benefit have been rather limited in Australia.

Freight-travel time savings are quite different from vehicle operating cost and person-travel time savings. Freight travel time is a larger and more inclusive concept than are the inventory capital costs associated with freight holding and the transit time of the vehicle and driver. The Road User Cost Steering Group within Austroads identified this evaluation gap, resulting in the undertaking of this study by FDF Management and Oxford Systematics in conjunction with ARRB Transport Research as an Austroads NSRP Project. Freight transit times are critically important to freight shippers and, as a result, have a large impact on the potential benefits from transport investments. This concept is independent of mode and relies only on the perceptions and economic drivers of the shippers and receivers. It is appropriate, therefore, to tap these perceptions directly. These perceptions do not require the valuations of time for each mode be the same in cases where mixed or alternative modes are significant since the mode (or mode mix) choices are not explicitly modeled in the present stage of this work and mode selection is usually affected by the overall speed differences between the available modes for any particular shipment.

The survey technique of contextual stated preference (CSP) achieves this "tapping" through the construction of a series of freight service alternatives patterned after current real world freight services as defined by associated costs, delays, freight damage, and reliability factors. The alternatives can readily be translated into a questionnaire for administration to freight shippers. The questionnaire aims to force respondents to choose between bundles of variations from real world base values. This allows for the assessment of underlying utility tradeoffs without the results being dominated by travel time factors alone. In CSP surveys, an underlying conjoint design ensures that no alternative is clearly superior or inferior to all the others.

The shift toward the use of fewer and larger vehicles to move a given amount of freight has caused one of the systematic biases in current methods of road evaluation. This change may result in the association of the movement of increased tonnage with a reduction in benefits since currently the assessment of these benefits is based on vehicle operating costs factors alone. Declining benefits associated with the greater productivity of larger vehicles is an ironic outcome, and it reflects a reduction in the overall pool of road user costs that can be affected by road improvements. This observation highlights the urgent need to identify the values that can redress this basic bias.

The CSP approach for estimating freight-travel time values has been successfully used in Europe, and the method shows promise for Australia. The model on which the present work is based most closely resembles that of the Hague Consulting Group (de Jong et al. 1992; de Jong et al. 1995; de Jong 1996). These studies measured freight rates, reliability, damage, level of service, and delays using a CSP approach by examining the effects of variations on the actual observed mean values of these attributes. A number of other European studies have used stated preference methods to determine freight rate, time, damage, and reliability tradeoffs. These include an adaptive SP technique (Fowkes et al. 1989; Fowkes et al. 1991) using a laptop computer to dynamically adapt the SP design as the interview proceeds, choices between own-account and third-party carriers (Fridstrom & Madslien 1995), and freight choices made in low density rural areas in Sweden (Westin 1994).

For the present study, the choice of variables was carefully developed. The segmentation of the markets for freight does not coincide well with the types of information required to monitor freight systems (Wigan 1979), and the choice of market segments and experimental variables drew on both the current investigations and previous work. Relevant early work is summarized by Grey (1982) and by the findings of the French analyses of the large scale 1998 INRETS freight shipper survey usually referred to as the SITRAM (Information System for Freight Transport) database of the French Ministry of Transport (Bredeloupe et al.

1989). Reliability, damage (or the likelihood of damage), and the form of packing used for loading, such as pallets, have been reported to be appropriate variables (Jiang, Johnson & Calzada 1995). The choice of market segments also emerged from the consultations and analyses at the first stage of the project.

FREIGHT SHIPPER SURVEY

The central issue for data collection in this project was the need to ensure that judgments and values of Australian shippers were effectively tapped and that interactions between interviewers and respondents were as effective and credible as possible. Both the full team at the field design phases and FDF management in the data collection stages took special care to ensure that the approach to shippers, the expert freight background for the interviewers, and the feedback to the respondent all complied with this goal. This later proved critical to the very high response rates and the quality of the model estimates obtained.

The survey CSP instrument was administered in the form of a printed survey, and no adaptive PC-based techniques were used. The median values of the variables were modified by 20% in either direction in the CSP design. The shippers felt these values and variations fell within a realistic range. Each shipper completed three different CSP experiments, one for each of three different market segments. This process proved time consuming but effective once all parties fully understood it. The high level of understanding within the team led to modifications to survey procedures. Normally, we would expect a significant level of non-response from a survey of this type, however, these administrative modifications increased the number of expected returns by approximately 40% over initial expectations.

The preliminary skirmish used to screen possible respondents and to obtain mean values for real world freight costs and the associated probabilities of delay and damage obtained a response rate of 25% only. Professional freight transport operators with long-standing and extensive experience of operations in Australia further assessed the values. These values were further refined at the pilot testing stage when the full survey form and process were field tested and subsequently modified for the final survey work. Interviewers expert in the freight industry administered the final survey, and the response and completion rates were very high: 43 people completed 129 responses, indicating that all of the different CSP experiments, each in a different market segment, were completed by all parties. There were no replications of the CSP experiment on the same individual within the same market segment. It is essential to note that the survey was directed at freight shippers, not vehicle operators.

"Damage" was defined as the portion of the designated delivery that was not accepted because it had been damaged in transit. "Reliability" was defined as the portion of the designated delivery that was late. These definitions were understood by interviewers and respondents, all industry experts. Both parameters raise the interesting research question of the degree to which other freight populations would apply the same interpretations. This additional work has not yet been undertaken. Flexibility and other attribute possibilities were not rated as highly. The respondents accepted the chosen attribute set as realistic.

There were other benefits in using expert freight operators as interviewers. They shared the culture of those interviewed and actively ensured a consistent interpretation of the terms "reliability" and "damage." The more common adaptive CSP approach involving personal computers was not used, and the fixed attribute sets in the personally administered designs adopted may also have been a factor in obtaining such high response rates.

A possible minor weakness of this project was the need to use an opportunity ("snowball") sample that emerged from building on the industry contacts of the team, combined with forward referrals from initial respondents. An important requirement of the method used was that all respondents be at a senior, expert, and decision-making level. Although the respondents were not randomly sampled from a specified population, they were all real and operational freight shipping managers who frequently made freight service decisions for their organizations. Consequently, the output of this project is based on a sample of respondents regularly making genuine operational decisions and can therefore potentially be used to represent this specific group and provide a basis for further work.

STUDY DESIGN

Base case values for freight rate, travel time, damage and reliability were determined from the industry survey, and variations of 20% above and below these values were specified in order to develop contrasting freight service alternatives. This process was repeated for the three distinct freight market segments. The basic experimental technique involved a two-stage fractional factorial design (Hensher 1997) to create a series of sets of alternative values of freight rate, travel time, damage, and reliability drawn from these values. The general approach is to determine utilities for each of these four factors from the forced choices made from sets of alternatives presented to the respondents (Hensher 1994). A survey using the full range of alternatives for three attributes, for example, would be too much to administer using a straightforward design. Therefore, a fractional design was adopted (Hahn & Shapiro 1966), providing an economical and concise survey instrument, at the cost of the assumption that interaction effects could be ignored. Prior to survey activities, all components were drawn into a consistent experimental design (Thoresen 1997), developed initially for nonurban freight movements but later generalized to include urban freight movements.

The freight market segmentation structure adopted also emerged as a key analytic issue (de Jong et al. 1995). The Hague Consulting group examined a range of dimensions: unfinished and finished goods, high and low value density, and high and low time sensitivity. A smaller number of segments was used in the study outlined in this paper.

The present study considered an additional criterion, length of haul. Replicating the Dutch study would require the surveying of eight industry sectors: one for each of the four Dutch sectors, each split further by long and short haul. Since resources were limited, this was impractical. Instead the study focused on haul length and type, resulting in the choice of the following three freight market segments:

- **Intercapital FTL (full truck load)** describes a common consignment in Australia: a fully laden articulated truck taking pallets typically on an overnight run between Melbourne and Sydney or Adelaide. Normally, these runs are from plant to plant or from plant to warehouse. On arrival, the goods go directly into stock, hence time-sensitivity is not expected to be as high as, for example, multidrops.
- **Metropolitan FTL** describes another common consignment: a fully laden articulated truck transporting loaded pallets within Melbourne. Like intercapital FTL, these runs are normally from plant to plant or plant to warehouse and are for stock. Unlike intercapital FTL, they typically occur during the day.
- **Metropolitan multidrop** is also a very common urban freight movement involving a rigid truck or light commercial vehicle with many deliveries. The consignment may consist of pallets of parcels. Normally, these runs are from plant to wholesaler, retailer, or service outlets. The goods are often required immediately, hence time-sensitivity is expected to be high.

Each respondent was offered a set of CSP alternatives in each of the three market segments. All respondents completed all three, creating 129 responses from 43 respondents.

Variation in approach and outcome between the Dutch and the present survey may reflect the differences in road transport patterns in the two locations. In Australia, for geographical reasons, there tends to be a polar split in haul length, with intercapital hauls of up to 1,000 kilometers or more, metropolitan hauls of less than 100 kilometers, and little in between. In Europe, haul lengths tend to vary continuously over a narrow range of distances.

SURVEY SEGMENTATION

Respondents for the CSP survey were drawn from the following industries: automotive parts, food and beverages, certain building materials, and packaging. Although superficially different, all respondents indicated similar freight rates per pallet and had similar transport requirements regarding reliability and damage. For these reasons, the team chose to not further segment by industry in the first instance. However, the industry of each respondent is recorded in the data set, making it possible to segment by industry in future analyses.

RESULTS

A full analysis of survey data was carried out using NLOGIT, a component of the Limdep 7 software package (Greene 1997) for several different specified multinomial logit models. None of these had a nested structure. The results were broadly comparable for each segment. The findings reported here are for the most straightforward model, which used a linear specification for all attributes. The results of the preliminary and skirmish surveys gave mean values of the attributes as shown in table 1.

Table 2 summarizes the coefficients estimated for the different attributes for the three different markets considered. The pseudo R^2 values are all above 0.5, and the coefficients estimated are all statistically significant and in the expected directions.

The standard errors for the time coefficient are substantial but not large enough to compromise statistical significance. Other coefficients have smaller relative standard errors. Table 3 shows the values in a more direct and useful form. In this table, unit values for freight travel, service reliability, and damage have been constructed from the information contained in table 2. As indicated in table 2, the estimated coefficients for travel time for intercapital FTL and multidrop were significant at the five percent level, while all other coefficients were significant at the one percent level.

INTERPRETING THE RESULTS

The values obtained here are short run values: they reflect the perceived utilities of the shippers today. Even in this context, it would be desirable to analyze a sample of real shipments to assess the relevance of CSP results and to identify hidden assumptions. One such assumption worth further investigation is the perception of respondents that they already had freight rate control, thereby leading to a greater emphasis on the other aspects of the freight service.

These results are presented irrespective of whether they will subsequently be confirmed or qualified by follow up investigations. They should also be seen as underestimates of longer term values since structural change within the industry continues and incorporates the efficiencies obtained from transport infrastructure and operational improvements (Wynter 1995).

It should be noted that the segmentation of the freight industry is quite different from that for pas-

TABLE 1 Mean Values of the Attributes

Mean values	Intercapital (FTL)	Metropolitan (FTL)	Metropolitan Multidrop Loads
Freight Rate (pallet)	35.087	9.0440	12.032
Time (hours)	15.033	4.0045	6.0026
Reliability	0.0502	0.0501	0.0498
Damage	0.0030	0.0031	0.0031

TABLE 2 Summary Results for Linear Attribute Models

Segment	Freight rate/pallet	Time	Reliability	Damage	Pseudo R^2
Intercapital (FTL)					
Coefficient	–0.100[a]	–0.066[b]	–25.6[a]	–497[a]	0.51
Standard error	0.014	0.031	2.9	48	
Metropolitan (FTL)					
Coefficient	–0.298[a]	–0.401[a]	–37.1[a]	–545[a]	0.56
Standard error	0.054	0.110	3.4	52	
Metropolitan multidrop deliveries					
Coefficient	–0.177[a]	–0.244[b]	–34.9[a]	–479[a]	0.52
Standard error	0.049	0.102	3.2	49	

[a] $p < 0.001$
[b] $p < 0.05$

TABLE 3 Freight Travel Time: Implicit Unit Values (in 1998 $ AUD)

Segment	Freight travel time	Reliability	Damage
Intercapital (FTL)	$0.66 pallet/hour	$2.56 per 1% reduction	$49.70 per 1% reduction
Urban (FTL)	$1.30 pallet/hour	$1.25 per 1% reduction	$18.29 per 1% reduction
Metropolitan multidrop deliveries	$1.40 pallet/hour	$1.97 per 1% reduction	$27.06 per 1% reduction

senger transport. The three segments selected here, however, show a heartening degree of broad agreement. In terms of results, it may be necessary to extend the coverage of the current study and improve precision in order to apply these values in economic evaluation processes. However, initial results indicate that this is both practicable, reasonable, and worthwhile.

It is critical to note that the values estimated are in many cases likely to be applicable across all modes due to the structure of Australian population center. To that extent, some of the long-standing concerns of inherent modal biases in freight evaluation may be directly addressed using this approach on a larger and more varied sample of shippers. However, this does not substitute for mode-specific analyses in cases where alternative modes are significant and decisions need to be made on a mode by mode basis.

Further study should examine many more market segments, with special attention to cross-modal measurements and a broader range of transport service attributes. The process will also clarify the requirements for expanded variables and formulations in the utility modeling to allow for specific situations and the determination of critical interactions for Australian circumstances.

CONCLUSIONS

Key results include the estimated value of long-haul freight transport travel time per pallet per hour on intercity routes at $0.7, while for metropolitan (intracity) routes it is estimated at $1.3. These estimates indicate that metropolitan freight travel time is more highly valued than that of intercity freight movements. The value of multidrop freight travel time per delivery per hour on strictly metropolitan routes is estimated at $1.4, similar to the metropolitan FTL estimate of $1.3.

The pseudo R^2 values are reasonable (~0.5), but improved models or variable specifications may be required in conjunction with larger scale or refined data collection methods to obtain more broadly applicable results. The detailed findings of this project need further corroboration but nevertheless provide a useful basis for developing a fuller set of freight travel time values.

A critical finding is that expert understanding of the freight industry and great care in survey design, data collection, and follow up are essential. For survey tasks, interviewers must either be practitioners themselves or very familiar with the industry. The data quality was vastly improved by this approach. While the models estimated provide an initial set of values for experimental use, the broader application of these methods across the freight operations in Australia is now a clear priority.

These values provide a first basis for bringing in previously unmeasured benefits in the movements of freight in Australia. This process also offers considerable benefits by estimating appropriate freight travel time values that redress the imbalance between passenger and freight valuations in economic assessment of transport proposals.

Significantly larger samples will be required to obtain more precise values for freight travel time. However, the results of this initial study are not only encouraging but also provide a first step for estimating the extent of previous biases in the freight evaluation components of a range of transport evaluation studies in Australia.

REFERENCES

Bredeloupe, E., P. Hanappe, E. Gouvernal, M. Guilbault, J.P. Hubert, and M. Mezaghani. 1989. Practique de transport des industries et des commerces de gros: resultats de l'analyse de 5,000 chaines de transports. Rapport inrets 99.

de Jong, G.C. 1996. Freight and Coach Value of Time Studies, in *Easthampstead Park Seminar on the Value of Time, Easthampstead*. London: PTRC.

de Jong, G.C., M. Gommers, H. Inwood, and J. Klooster. 1992. Time Valuation in Freight Transport: Method and Results, in *PTRC European Transport Highways and Planning 20th Annual Summer Meeting*. London: PTRC.

de Jong, G.C., Y. van de Vyvre, and H. Inwood. 1995. The Value of Time for Freight Transport, in *World Conference on Transport Research*, Sydney, NSW.

Fowkes, A.S., C.A. Nash, and G. Tweddle. 1989. *Valuing the Attributes of Freight Transport Quality: Results of the Stated Preference Survey.* Leeds, England: Institute for Transport Studies.

_____. 1991. Investigating the Market for Intermodal Freight Technologies. *Transportation Research* 25A:161–72.

Fridstrom, L. and A. Madslien. 1995. A Stated Preference Analysis of Wholesalers' Freight Choice. TOII Report 1995/09, Transport Economics Institute, Oslo, Norway.

Greene, W.H. 1997. *Limdep version 7 Users Manual*. Bellport, NY: Econometric Software.

Grey, R. 1982. Behavioral Approaches to Freight Transport Modal Choice. *Transport Reviews* 2, no. 2:161–81.

Hahn, G.J. and S.S. Shapiro. 1966. *A Catalog and Computer Program for the Design and Analysis of Orthogonal Symmetric and Asymmetric Fractional Factorial Experiments*. Schenectady, NY: General Electric Research and Development Center.

Hensher, D.A. 1994. Stated Preference Analysis of Travel Choices: The State of Practice. *Transportation* 21:107–33.

_____. 1997. Personal communication.

Jiang, F., P. Johnson, and C. Calzada. 1995. Freight Demand Characteristics and Mode Choice: An Analysis of the Results of Modeling with Disaggregate Revealed Preference Data. *Journal of Transportation and Statistics* 2, no. 2:149–59.

Thoresen, T. 1997. Estimation of Non-Urban Freight Travel Time Values: Methodological Review and Experimental Design. ARRB Report WD 97/061.

Westin, K. 1994. *Valuation of Goods Transportation Characteristics: A Study of a Sparsely Populated Area*. Umea, Sweden: Umea University.

Wigan, M.R. 1979. Indicators for Urban Commodity Movements. *Behavioural Travel Modelling*. London, England: Croom Helm.

Wynter, L.M. 1995. The Value of Time of Freight Transport in France: Estimation of Continuously Distributed Values from a Stated Preference Survey. *International Journal of Transport Economics* 22:151–65.

Guidelines for Manuscript Submission ▾ Instructions to Authors

After retaining a copy for your files, submit two double-spaced copies of your manuscript to:

Deborah Moore, Managing Editor
Journal of Transportation and Statistics
Bureau of Transportation Statistics
US Department of Transportation
Room 3430
400 7th Street SW
Washington DC 20590

As the manuscripts are subject to peer review, submission of a paper indicates the author's intention to publish in the *Journal of Transportation and Statistics*. Simultaneous submission of a manuscript to other journals is unacceptable. Previously published manuscripts, whether in an exact or approximate form, cannot be accepted. Check with the editor if in doubt.

All manuscripts must be prepared in an electronic format and double-spaced with a 1″ margin on all sides. Double-space all material, including quotations, the abstract, and any notes. All figures and tables should appear at the end of the paper, and each should be on a separate page. Include the figure name and filename on the bottom of the page.

Articles prepared in LaTeX software will be accepted.

Cover page. This page should include the title of the manuscript, the author's name, mailing and email addresses, and telephone number. The following page should contain a one-paragraph abstract of the manuscript of about 100 words. The abstract should include the title of the manuscript, briefly describe the contents of the paper, and explain the research method and results. The abstract should not contain any abbreviations or acronyms.

Graphic elements. Make sure that figures and tables are called out in the text. The title of your article, along with the figure or table number, should be written on the bottom of the page. Figures and tables should appear at the end of the paper, and each should be on a separate page. Figures need to be on high-quality paper, no more than 8½″ x 11″ in size, in black ink. Complicated graphics are to be avoided, and print should be large enough to allow for considerable reduction.

References. The reference style follows the *Chicago Manual of Style*. In the text, include the author, year, and page number. For example: Road dust also accounted for over 30 percent of emissions of very fine particles—those measuring 2.5 microns or smaller. (Barnard 1996, 17). Complete references must appear at the end of your manuscript. Include enough information in your reference so that the reader can find the document or contact its author. References should be alphabetized by authors' last names. When an author has more than one publication, place the oldest one first. Include the place of publication and publisher for books, and volume, month, or issue, and pages for journals. Examples of various types of references follow:

Gordon, R. 1990. *The Measurement of Durable Goods Prices*. Chicago, IL: University of Chicago Press.
in the text: (Gordon 1990)

Kargon, R.H., ed. 1974. *Maturing of American Science*. Washington, DC: American Association for the Advancement of Science.
in the text: (Kargon 1974)

Michaelis, L., D. Bleviss, J.-P. Orfeuil, and R. Pischinger. 1996. *Mitigation Options in the Transportation Sector. Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analysis, Contribution of Working Group II to the Second Assessment Report of the Intergovernmental Panel on Climate Change*. Edited by R.T. Watson, M.C. Zinyowera, and R.H. Moss. Cambridge, England: Cambridge University Press.
in the text: (Michaelis et al. 1996)

National Academy of Sciences (NAS), Committee on National Statistics. 1985. *Sharing Research Data*. Washington, DC: National Academy Press.
in the text: (NAS 1985)

Yates, C. 1992. Eurocontrol Comes of Age. *Jane's Airport Review* 4:3.
in the text: (Yates 1992)

Papers selected for publication in the journal. An electronic copy of the manuscript must be submitted on a 3½″ diskette, along with two paper copies of the article. Make sure the hard copy corresponds to the electronic copy. Label the diskette with your name, the date, and the title of your paper. Please specify what software was used, including the release number (e.g., Word for Windows). Send a list of filenames. Please keep a copy of the electronic file. Send separate files for each table, figure, and the text. Do not imbed tables and figures in the text files. Indicate the approximate placement of each figure and table in the text.

Once the page proofs of your manuscript are returned to you, you will be required to return them to the Managing Editor within 48 hours. If the proofs are not returned, we will assume the article is correct as is.

REVIEWERS September 1, 1999 – December 1, 2000

A	
William Ainslie	U.S. Environmental Protection Agency, Atlanta, GA
Bill Anderson	Boston University, Boston, MA
Vincent Arena	University of Pittsburgh, Pittsburgh, PA
Jimmy Armoogum	INRETS, Dest, France
Kalidas Ashok	Marketing and Planning Systems, Waltham, MA
Jesse Ausubel	Rockefeller University, New York, NY
B	
David Banks	Bureau of Transportation Statistics, USDOT, Washington, DC
Akli Berri	INRETS, Dest, France
Evelyn Blumenberg	UCLA, Los Angeles, CA
Ranjan Bose	Tate Energy Research Institute (TERI), New Dehli, India
Noble Bowie	National Highway Traffic Safety Administration, USDOT, Washington, DC
Michael Bronzini	George Mason University, Fairfax, VA
Kenneth Button	George Mason University, Fairfax, VA
C	
Steven Cadle	General Motors, Warren, MI
Kenneth Campbell	University of Michigan, Ann Arbor, MI
Promod Chandhok	Bureau of Transportation Statistics, USDOT, Washington, DC
Ted Chira-Chavala	University of California, Berkeley, CA
Tim Coburn	Abilene Christian University, Abilene, TX
Harry Cohen	Independent Consultant
Benjamin Coifman	Ohio State University, Columbus, OH
D	
Virginia Dale	Oak Ridge National Laboratory, Oak Ridge, TN
Stacy Davis	Oak Ridge National Laboratory, Oak Ridge, TN
Gerald de Jong	Hague Consulting Group, Netherlands
Andre de Palma	Université de Cergy, Pontoise, France
Robert Dunphy	Urban Land Institute, Washington, DC
E	
William Ebersold	Maritime Administration, USDOT, Washington, DC
F	
Gary Feuerberg	Bureau of Transportation Statistics, USDOT, Washington, DC
Robert Fletcher	California Air Resources Board, Sacramento, CA
David Forkenbrock	University of Iowa, Iowa City, IA
Barbara Fraumeni	Bureau of Economic Analysis, USDOC, Washington, DC
Lewis Fulton	International Energy Agency, Paris, France
G	
John Gardenier	National Center for Health Statistics, Hyattsville, MD
William Gelston	Federal Railroad Administration, USDOT, Washington, DC
David Gillen	Wilfrid Laurier University, Waterloo, Ontario, Canada
David Gold	Texas A&M University, College Station, TX
José Gomez-Ibanez	Harvard University, Cambridge, MA
Richard F. Gunst	Southern Methodist University, Dallas, TX
H	
Mark Hallenbeck	Washington State Transportation Center, Seattle, WA
Charlie Han	MacroSys Research and Technology, Washington, DC
Richard Hanley	Connecticut Department of Transportation, Rocky Hill, CT
Mark Hansen	University of California, Berkeley, CA
Glen Harrison	National Transportation Research Center, Knoxville, TN
John Hitz	Volpe National Transportation Systems Center, USDOT, Cambridge, MA
Patricia Hu	Oak Ridge National Laboratory, Oak Ridge, TN
I	
Marc Ivaldi	Institut d'Economic Industrielle, Toulouse, France
J	

Bruce Janson	University of Colorado, Denver, CO
K	
Mark Kaiser	Iowa State University, Ames, IA
Kenneth Kelly	National Renewable Energy Laboratory, Golden, CO
John Kinatader	Battelle Memorial Institute, Columbus, CO
L	
Charles Lave	University of California, Irvine, CA
Mark Levenson	U.S. Consumer Product Safety Commission, Bethesda, MD
Timothy Lomax	Texas A&M University, College Station, TX
M	
Jean-Loup Madre	INRETS, Dest, France
Fred Mannering	University of Washington, Seattle, WA
James March	Federal Highway Administration, USDOT, Washington, DC
Pat McCarthy	Ivan Allen College, Atlanta, GA
Michael Meyer	Georgia Institute of Technology, Atlanta, GA
Leon Moses	Northwestern University, Evanston, IL
Elaine Murakami	Federal Highway Administration, USDOT, Washington, DC
O	
Thomas Obremski	University of Denver, Denver, CO
Paul Ong	University of California, Los Angeles, CA
J. Keith Ord	Georgetown University, Washington, DC
P	
Ram Pendyala	University of South Florida, Tampa, FL
Bhagwant Persaud	Ryerson University, Ontario, Canada
Don H. Pickrell	Volpe National Transportation Systems Center, USDOT, Cambridge, MA
Alan Pollack	ENVIRON International Corporation, Novato, CA
Q	
Emile Quinet	Ecole Nationale des Ponts et Chaussées, Paris, France
R	
Ron Ragazzi	Colorado Department of Public Health & Environment, Aurora, CO
S	
Marti Salk	Oak Ridge National Laboratory, Oak Ridge, TN
Danilo Santini	Argonne National Laboratory, Argonne, IL
Christopher Saricks	Argonne National Laboratory, Argonne, IL
Rick Schmoyer	Oak Ridge National Laboratory, Oak Ridge, TN
Kensuke Shirakawa	Battelle Memorial Institute, Columbus, OH
Frank Southworth	Oak Ridge National Laboratory, Oak Ridge, TN
Clifford Spiegelman	Texas A&M University, College Station, TX
D. Melendrez Stapleton	University of Wisconsin, La Crosse, WI
Don Stedman	University of Denver, Denver, CO
T	
Shawn Turner	Texas A&M University, College Station, TX
Clifford Tyree	U.S. Environmental Protection Agency, Ann Arbor, MI
W	
Martin Wachs	University of California, Berkeley, CA
David Weeks	
Tommy Wright	U.S. Census Bureau, USDOC, Suitland, MD
Karl Wunderlich	Mitretek Systems, Washington, DC
Z	
Eric Ziegel	Amoco Research Center, Naperville, TN

INDEX (Vols. 1–3)

A

B

C

D

E

F

S

Y

Z

JOURNAL OF TRANSPORTATION AND STATISTICS

Volume 3 Number 3
December 2000
ISSN 1094-8848

CONTENTS