Assessing the Quality of Origin–Destination Matrices Derived from Activity Travel Surveys

Results from a Monte Carlo Experiment

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To support policy makers combating travel-related externalities, quality data are required for the design and management of transportation systems and policies. To this end, much money has been spent on collecting household- and person-based data. The main objective of this paper is to assess the quality of origin–destination (O-D) matrices derived from household activity travel surveys. To this purpose, a Monte Carlo experiment is set up to estimate the precision of O-D matrices given different sampling rates. The Belgian 2001 census data, containing work- and school-related travel information for all 10,296,350 residents, are used for the experiment. For different sampling rates, 2,000 random stratified samples are drawn. For each sample, three O-D matrices are composed: one at the municipality level, one at the district level, and one at the provincial level. The correspondence between the samples and the population is assessed by using the mean absolute percentage error (MAPE) and a censored version of the MAPE (MCAPE). The results show that no accurate O-D matrices can be derived directly from these surveys. Only when half of the population is queried is an acceptable O-D matrix obtained at the provincial level. Therefore, use of additional information to grasp better the behavioral realism underlying destination choices and collection of information about particular O-D pairs by means of vehicle intercept surveys are recommended. In addition, results suggest using the MCAPE next to traditional criteria to examine dissimilarities between different O-D matrices. An important avenue for further research is the investigation of the effect of sampling proportions on travel demand model outcomes.

In modern cosmopolitan society, travel is a cornerstone for human development, for both personal and commercial reasons: travel is not only regarded as one of the boosting forces behind economic growth, but is also seen as a social need providing people the opportunity for self-fulfillment and relaxation. As a result of the continuous evolution of modern society (e.g., urban sprawl, increasing female participation in labor, decline in traditional household structures), transportation challenges have accrued and have become more complex (*1*). Consequently, combating environmental (e.g., greenhouse gas emissions, noise), economic (e.g., use of nonrenewable energy sources, time lost due to congestion), and societal (e.g., health problems such as cardiovascular and respiratory diseases, traffic casualties, community severance and loss of community space) repercussions is a tremendous task (*2*).

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To support policy makers in addressing these externalities, quality data are required for the design and management of transportation systems and policies (*3*). To this end, during the last four decades, a lot of money has been spent on collecting household- and person-based data. For most metropolitan areas, the largest part of planning budgets (an estimated $7.4 million per year) was devoted to the conduct of household and person travel surveys (*4*). The data collected by these surveys are used for a wide variety of applications, including traffic forecasting, transportation planning and policy, and system monitoring (*3*).

The main objective of this paper is to assess the quality of origin–destination (O-D) matrices derived from travel surveys. O-D matrices are core components in both traditional four-step and modern activity-based travel demand models. A sample size experiment is set up to estimate the precision of the O-D matrices given different sampling rates. Thus, an assessment of the appropriateness of travel surveys for deriving O-D relations can be made. Note that different types of travel surveys exist: Cambridge Systematics (*5*) distinguished seven different commonly used types of surveys (household activity travel; vehicle intercept and external; transit on-board; commercial vehicle; workplace and establishment; hotel–visitor; and parking). Each of these survey types provides a unique perspective for input into travel demand models. In this paper, the term "travel survey" is confined to the household activity travel survey.

In a household activity travel survey, respondents are queried about their household characteristics, the personal characteristics of household members, and about recent activity travel experiences of some or all household members. For most regions, household activity travel surveys remain the best source of trip generation and distribution data, and therefore are an important building block for travel demand models. In addition to model building purposes, these surveys are also used to poll specific target populations (such as transit users and nonusers), to assess the potential demand and level of public support for major infrastructural projects, and to create a deeper understanding of travel behavior in the region (*5*). For a more elaborate discussion concerning travel surveys the reader is referred to *The Online Travel Survey Manual: A Dynamic Document for Transportation Professionals* (*3*), Cambridge Systematics' *Travel Survey Manual* (*5*), and Tourangeau et al. (*6*). Recent trends in household travel surveys are discussed by Stopher and Greaves (*7*).

The remainder of this paper is organized as follows. The next section provides an extended discussion on the setup of the sample size experiment. The relationship between sampling rates and the precision of a general statistic (i.e., the proportion of the commuting population) follow, along with the results and corresponding discussion of the statistical analysis of the main sample size experiment. Finally, some general conclusions are formulated and avenues for further research indicated.

SETUP OF SAMPLE SIZE EXPERIMENT

As mentioned in the introduction, the main goal of this paper is the assessment of the quality of O-D matrices derived from household activity travel surveys and, consequently, providing an answer to the question of how large a sample size should be to provide accurate O-D information in a region. To this end a Monte Carlo experiment is set up to estimate the precision of the O-D matrices given different sampling rates. A Monte Carlo experiment involves the use of random sampling techniques and computer simulation to obtain approximate solutions to mathematical problems. It involves repeating a simulation process, using in each simulation a particular set of values of random variables generated in accordance with their corresponding probability distribution functions (*8*). A Monte Carlo experiment is a viable approach for obtaining information about the sampling distribution of a statistic (in this study the precision of an O-D matrix) of which a theoretical sampling distribution may not be available due to the complexity. Monte Carlo simulation is generally suitable for addressing questions related to sampling distribution, especially when (*a*) the theoretical assumptions of the statistical theory are violated; (*b*) the theory about the statistic of interest is weak; or (*c*) no theory exists about the statistic of interest (*9*). The latter is the case in this study (i.e., the precision of O-D matrices given different sampling rates).

The Monte Carlo experiment reported in this paper focuses on commuting (i.e., work- and school-related) trips made in Belgium. The 2001 census data will be used for the experiment. In particular, the census queried information about the departure and arrival times and locations of work and school trips (when applicable) for all 10,296,350 residents. For different sampling rates, ranging from one (the full population) to a million, 2,000 random stratified samples were drawn (2,000 for each sampling rate). Note that this number is common in transportation-oriented simulation experiments [see, for example, Patel and Thompson (*10*) and Awasthi et al. (*11*)]. To ensure that the persons in the samples were geographically distributed, the sample was stratified by geographical area: three nested stratification levels—province, district, and municipality—were taken into account. The sample was proportionately allocated to the strata. In other words, the sample in each stratum was selected with the same probabilities of selection (*12*).

For each sample, the proportion of persons making commuting trips was calculated, and three corresponding (morning commute) O-D matrices were composed: one O-D matrix on the municipality level (589 × 589), one O-D matrix on the district level (43 × 43), and one on the provincial level (11 × 11). A side note has to be made for the latter O-D matrix: actually there are only 10 provinces in Belgium, but the Brussels metropolitan capital area (accounting for about one-tenth of the entire population) was treated as a separate province. The correspondence of the sample proportion and sample O-D matrices with the population (census) proportion and O-D matrices was then tabulated.

The correspondence between the sample and the population is assessed by using the mean absolute percentage error (MAPE) and an accommodated version of the MAPE. The MAPE is the mean of the absolute percentage error (APE) and is calculated by

$$\text{MAPE}_{ij} = \frac{\sum_i \sum_j \text{APE}_{ij}}{N} \qquad \text{APE}_{ij} = \left| \frac{A_{ij} - E_{ij}}{A_{ij}} \right| \times 100$$

where

A_{ij} = population count for the morning commute from origin *i* to destination *j*,
E_{ij} = sample count (scaled up to population level) for this morning commute, and
N = total number of O-D cells.

Despite its widespread use, the MAPE has several disadvantages. Armstrong and Collopy (*13*) for instance, argued that the MAPE is bounded on the low side by an error of 100% (O-D counts are all positive integers), but there is no bound on the high side. In response to this comment, Makridakis (*14*) proposed a modified MAPE (MDAPE), which is often referred to as SAPE (smoothed absolute percentage error) or SMAPE (symmetric mean absolute percentage error). This modified MAPE (MDMAPE) is given by

$$\text{MDMAPE}_{ij} = \frac{\sum_i \sum_j \text{MDAPE}_{ij}}{N}$$

where

$$\text{MDAPE}_{ij} = \left| \frac{A_{ij} - E_{ij}}{\frac{\left(A_{ij} + E_{ij}\right)}{2}} \right| \times 100$$

Although this modification accommodates the above described problem, it treats large positive and negative errors very differently (*15*). Therefore, in this paper, a new modification of the MAPE is proposed, named the mean censored absolute percentage error (MCAPE). This new statistic takes into account the above described comments by limiting the positive values to a maximum of 100. Mathematically, the MCAPE is given by the following formula:

$$\text{MCAPE}_{ij} = \frac{\sum_i \sum_j \text{CAPE}_{ij}}{N}$$

where

$$\text{CAPE}_{ij} = \min\left\{100, \left| \frac{A_{ij} - E_{ij}}{A_{ij}} \right| \times 100 \right\}$$

When A_{ij} in the above formulas would be equal to zero, the different criteria would be undefined. This has been remedied by equalizing the APE_{ij}, MDAPE_{ij}, and CAPE_{ij} to zero in these occasions. After all, when the true population count equals zero (no person in the full population corresponds to the considered O-D pair) the up-scaled sample count also equals zero, and thus the true zero is correctly estimated.

The correspondence between the sample proportion (p) of persons making commuting trips and population proportion (π) is calculated by simply calculating the APE:

$$\text{APE} = \left| \frac{\pi - p}{\pi} \right| \times 100$$

No accommodation of this APE was required, as the population proportion (π) was equal to 62.59%, and consequentially the APE could not exceed 100.

To recapitulate, for each sampling rate, 2,000 MAPE and MCAPE values are calculated for the O-D matrix on the municipality level, for the O-D matrix on the district level, and for the O-D matrix on the provincial level. In addition 2,000 APE values are computed for the commuting proportion. For each of these sets of 2,000 values, the 2.5th, 5th, 95th, and 97.5th percentiles were calculated. The *k*th percentile is that value *x*, such that the probability that an observation drawn at random from the population is smaller than *x*, equals *k* percent (*16*). The 2.5th and 97.5th percentiles are used to construct the 95th percentile interval, which will be illustrated graphically as lower and upper bounds for the median. The 5th and 95th percentiles will be displayed in the corresponding tables because one is most often only interested in the one-sided alternative. In addition, the median (the 50th percentile) and the arithmetic mean are also computed.

To guarantee that the Monte Carlo experiment is estimating the precision of the O-D matrices in function of different sample rates, rather than in function of other (unobserved) effects, one could take a look at the different sources of errors and biases in surveys. Groves (*17*) distinguished different sources of inaccuracy in surveys, of which an overview is given in Figure 1. Because in this experiment the true population values are known, and samples are drawn under ideal circumstances (no response bias, no selection bias, no observation errors, no nonresponse, and perfect coverage), the resulting variations in the experiment are only a consequence of the sampling variance (indicated with a gray box, framed with a thick black line in Figure 1). Thus, as intended, the relationship between different sample sizes and the precision and accuracy (sample variance) of the quantities under study are investigated.

RESULTS

Proportion of Commuting Population

Before elaboration on the quality of O-D matrices, an assessment of the appropriateness of travel surveys for deriving traditional indices—such as the mean number of trips made or the mean number of activities performed by individuals or households, or the proportion of the population making work- and school-related trips—is made. For traditional indices such as the mean number of trips made–activities performed by individuals or households, classical sample size calculations can be used to determine optimal sample sizes. Cools et al. (*18*), for instance, calculated the required number of households for a household activity survey using the following formula:

$$n \geq \frac{z^2 p(1-p)}{\mathrm{md}^2}$$

where

n = sample size,
p = sample (survey) proportion,
md = maximal deviation, and
z = z-value of desired confidence interval.

For the "safest" case (i.e., $p = 0.5$), a maximal deviation of 2% and a confidence level of 95% would require a minimum of at least 2,401 households. This example illustrates that for aggregate indices, such as the proportion of the commuting population, a clear theory exists and Monte Carlo simulation is not per se required. Notwithstanding, an investigation of the relationship between sampling rates and precision (sample variance) is still valuable, and especially contributes to the literature when the focus is turned to the different percentiles that are examined.

Results from the Monte Carlo experiment for the proportion of commuters in the population are graphically displayed in Figure 2 and numerically represented in Table 1. Figure 2 shows a clear relationship between the APE and the sampling proportion. As expected, the additional improvement in precision decreases as the sampling rate increases: for instance the increase in precision (decrease in APE) from a sampling rate of one-millionth (Base-10 logarithm of the sampling proportion = –6) to one-hundred-thousandth (Base-10 logarithm = –5) is considerably larger than the increase in precision from a sampling rate of 1,000 to 100. This is especially so for the upper bound of the 95% percentile interval (97.5th percentile).

The results also show that when the full population is sampled, an absolute precision is obtained (absence of all variation). By definition this result should be obtained. When an average deviation of 5% is considered acceptable, a sample rate between one-hundred- and two-hundred-thousandths is required (5% lies between the mean values 4.293 and 6.083). On the other hand, from the median value one could conclude that in 50% of the cases the maximal deviation (APE) is smaller than 5.192%. A more cautious approach entails the use of the 95th percentiles. If the APE were allowed to exceed 2 in only 5% of the cases, then a sampling rate of about 5 ten-thousandths would be required, which roughly corresponds to sampling 5,000 persons.

Precision of O-D Matrices

In this part of the result section, an assessment of the appropriateness of household activity travel surveys for deriving O-D matrices is made. Recall that a Monte Carlo simulation is particularly suitable for addressing the questions concerning the distribution of the precision of these O-D matrices, as no real theoretical background of this distribution exists. First, attention will be paid to O-D matrices at the municipality level. Afterward, the focus is on O-D matrices at district and provincial levels.

O-D Matrices at Municipality Level

Before expanding on the results of the Monte Carlo experiment, it is important to mention that the true O-D matrix (O-D matrix composed from the full population) is a very large and sparse matrix: of the 346,921 O-D pairs (589 × 589), 77.8% are zero-cells. As zero-cells in the full population are by definition correctly predicted by taking a sample from this population, the actual overall precision is significantly boosted by the sparseness of the true O-D matrix. Therefore, the decision was made to present the results based on the 76,882 non-zero-cells. To derive the values that include the zero-cells, one only needs to divide the MAPE and MCAPE values by 4.512 [= all cells/(all cells—zero-cells)].

Inspection of Table 2 immediately reveals that no accurate O-D matrices are obtained at the municipality level, even if zero-cells are taken into account: a survey that would query half of the population still would have an average APE of 11.99% when zero-cells are included and correspondingly of 54.11% when only the actual predictions (non-zero-cells) are taken into account. This clearly indicates that the direct derivation of O-D matrices from household activity travel surveys should be avoided. Notwithstanding, O-D matrices derived from household activity travel surveys are very

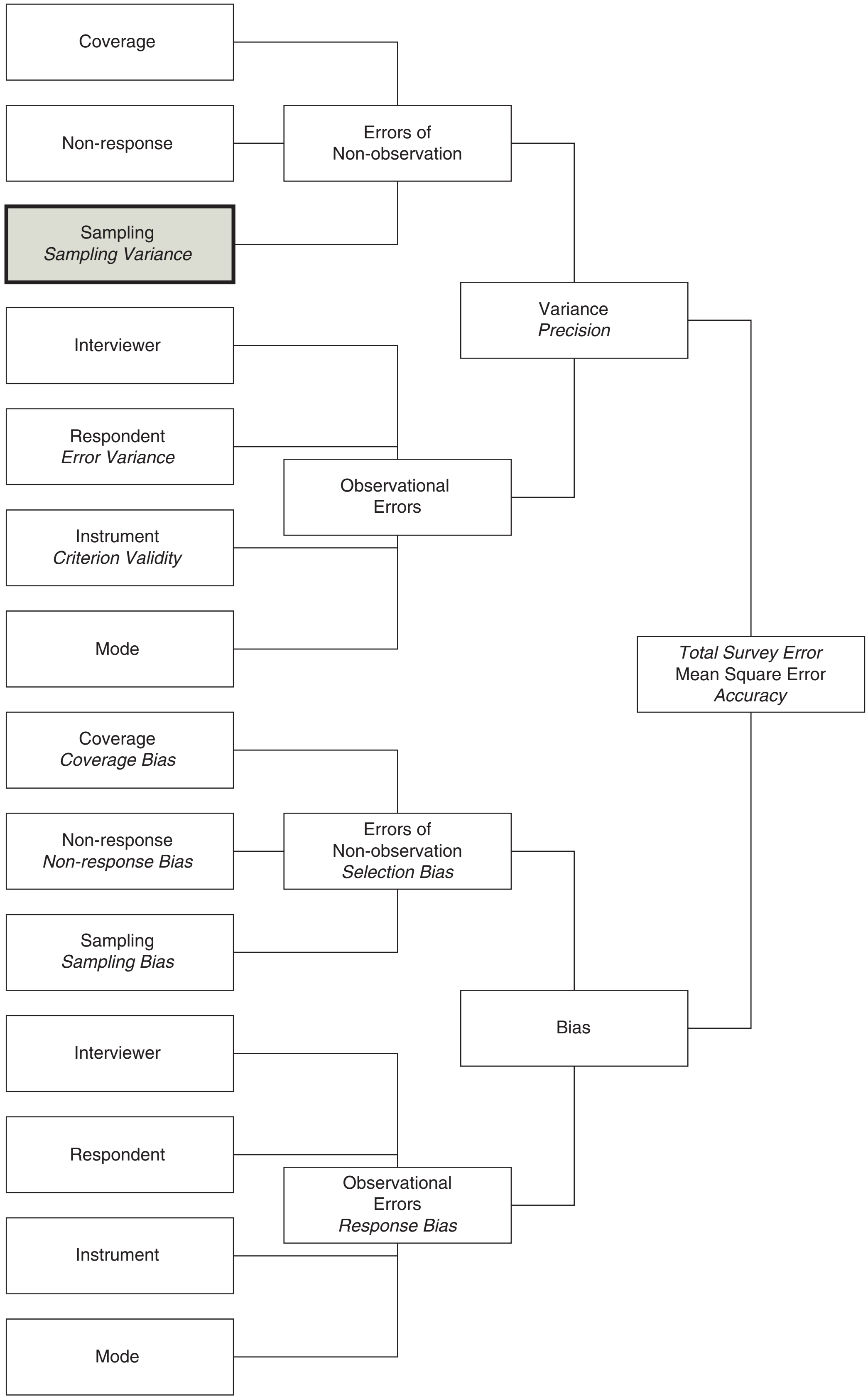

FIGURE 1 Potential sources of total survey error.

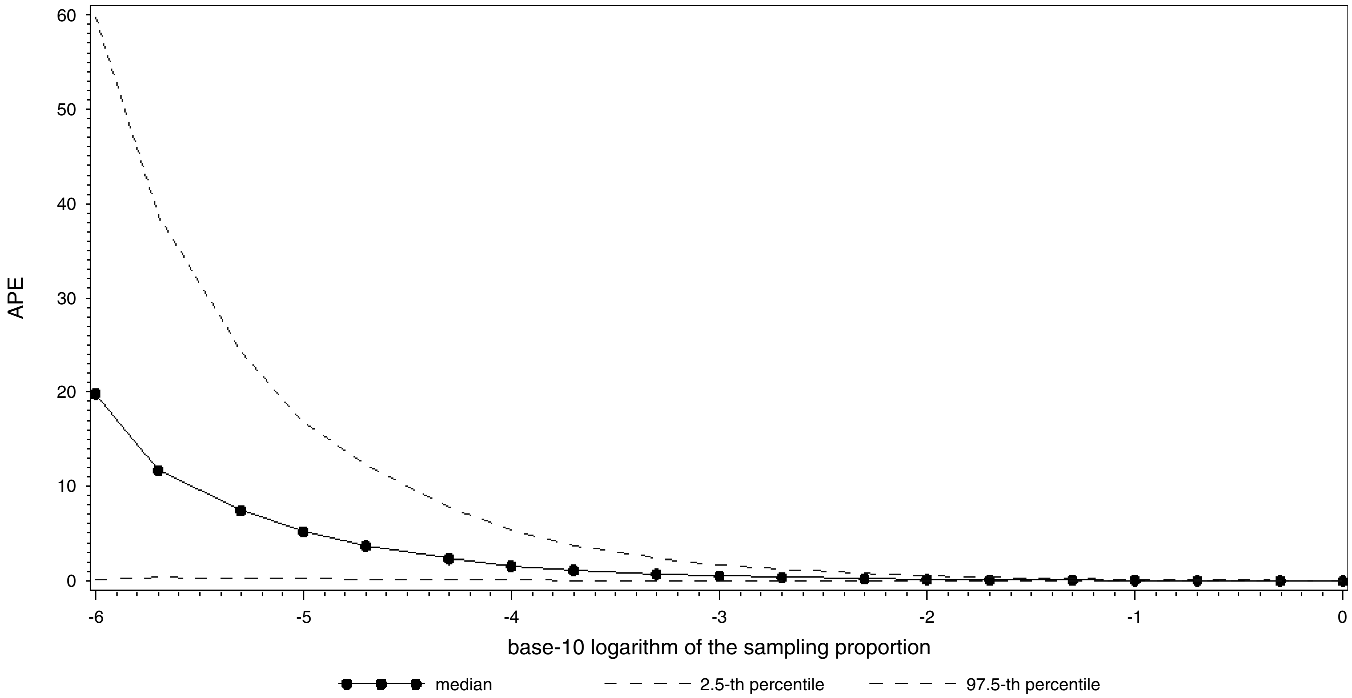

FIGURE 2 Relationship between APE and sampling rate for commuting proportion.

valuable: even a simple gravity model with the inverse squared distance as deterrence function, taking into account the productions and attractions derived from the surveys, already results in a clear improvement of the O-D matrices. This is certainly a plea for travel demand models that incorporate the behavioral underpinnings of destination choices (activity location choices) given a certain origin, like, for instance, models that make use of space–time prisms [e.g., Pendyala et al. (*19*)], and models that combine data from different sources, such as data integration tools [e.g., Nakamya et al. (*20*)]. In addition, O-D matrices derived from travel surveys form a good basis for O-D matrices derived from traffic counts: as multiple O-D matrices can be derived from the same set of traffic counts, O-D matrices derived from travel surveys provide a good basis for constraining the matrices derived from traffic counts (*21*). A thorough look at Table 2 also reveals that when half the population is sampled, the values for the MAPE and MCAPE are the same. This can be explained by the fact that when half of the population is used, none of the 2,000 samples has a MAPE higher than 1.

When the general tendency of the precision of the O-D matrices derived from travel surveys is discussed, Figures 3 and 4 provide a clear insight into the relationship between the precision and the sampling rate. From Figure 3 one can clearly see that the median MAPE first increases when samples are becoming larger and then starts to decrease. The increase in median MAPE for the smallest sampling rates can be accounted for by the fact that on average more cells are seriously overestimated, whereas the maximum underestimations are bounded by 100%. This effect is filtered out by using the MCAPE, as can be seen from Figure 4; a clear decreasing relationship is visible here. Next to the difference in relationships between the MAPE and MCAPE, one could also observe a clear difference between the percentile interval for the MAPE and the percentile interval for the MCAPE. By condensing the APE to a maximum of 1 (i.e., the CAPE), almost all variability around the median value is filtered out: the 2.5th and 97.5th percentiles almost coincide with the median values in case of the MCAPE.

When this decreasing pattern of the MCAPE (Figure 4) is compared with the one of the proportions (Figure 2), a clear contrast in the tendency can be seen: while the pattern for proportion is a convex decreasing function, for the O-D matrices this is a concave

TABLE 1 APE Statistics for Commuting Proportion Given Different Sampling Rates

Sampling Rate (SR)	$\log_{10}$ SR	Mean	P5	Median	P95
0.000001	−6.00	20.270	1.670	19.826	46.744
0.000002	−5.70	13.915	1.096	11.684	34.377
0.000005	−5.30	8.642	0.659	7.412	21.509
0.000010	−5.00	6.083	0.474	5.192	14.849
0.000020	−4.70	4.293	0.343	3.671	10.618
0.000050	−4.30	2.741	0.213	2.317	6.793
0.000100	−4.00	1.879	0.137	1.574	4.586
0.000200	−3.70	1.330	0.097	1.140	3.219
0.000500	−3.30	0.853	0.072	0.723	2.097
0.001000	−3.00	0.602	0.052	0.508	1.485
0.002000	−2.70	0.430	0.040	0.362	1.054
0.005000	−2.30	0.269	0.022	0.227	0.659
0.010000	−2.00	0.190	0.015	0.160	0.462
0.020000	−1.70	0.129	0.010	0.109	0.313
0.050000	−1.30	0.080	0.007	0.067	0.197
0.100000	−1.00	0.053	0.004	0.045	0.132
0.200000	−0.70	0.034	0.003	0.029	0.082
0.500000	−0.30	0.016	0.001	0.013	0.038
1.000000	0.00	0.000	0.000	0.000	0.000

NOTE: P = percentile; e.g., P5 stands for 5th percentile.

TABLE 2 MAPE and MCAPE for O-D Matrices Derived at Municipality Level

Sampling Rate (SR)	$\log_{10}$ SR	MAPE				MCAPE			
		Mean	P5	Median	P95	Mean	P5	Median	P95
0.000001	−6.00	205.996	100.902	115.559	753.493	100.000	100.000	100.000	100.000
0.000002	−5.70	200.992	102.528	129.575	754.266	100.000	100.000	100.000	100.000
0.000005	−5.30	199.861	109.279	155.540	431.119	99.999	99.998	99.999	100.000
0.000010	−5.00	199.089	116.768	175.588	352.896	99.997	99.995	99.997	99.999
0.000020	−4.70	198.647	127.682	187.707	304.125	99.994	99.992	99.994	99.996
0.000050	−4.30	198.338	148.261	194.723	259.440	99.977	99.972	99.977	99.981
0.000100	−4.00	199.452	160.661	198.325	243.313	99.927	99.919	99.927	99.936
0.000200	−3.70	197.459	170.778	196.746	226.279	99.784	99.769	99.784	99.798
0.000500	−3.30	195.930	178.611	195.344	215.156	99.414	99.391	99.414	99.437
0.001000	−3.00	193.624	181.284	193.511	206.508	98.999	98.973	98.999	99.026
0.002000	−2.70	190.182	181.664	189.982	199.411	98.393	98.360	98.392	98.427
0.005000	−2.30	183.425	177.916	183.465	188.907	97.033	96.990	97.033	97.077
0.010000	−2.00	175.654	171.907	175.659	179.551	95.352	95.298	95.353	95.407
0.020000	−1.70	164.993	162.373	165.044	167.739	92.797	92.730	92.798	92.865
0.050000	−1.30	145.263	143.745	145.271	146.836	87.514	87.424	87.515	87.598
0.100000	−1.00	124.970	124.078	124.960	125.866	81.369	81.273	81.369	81.469
0.200000	−0.70	99.172	98.724	99.169	99.631	72.293	72.193	72.294	72.392
0.500000	−0.30	54.108	54.089	54.108	54.128	54.108	54.089	54.108	54.128
1.000000	0.00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

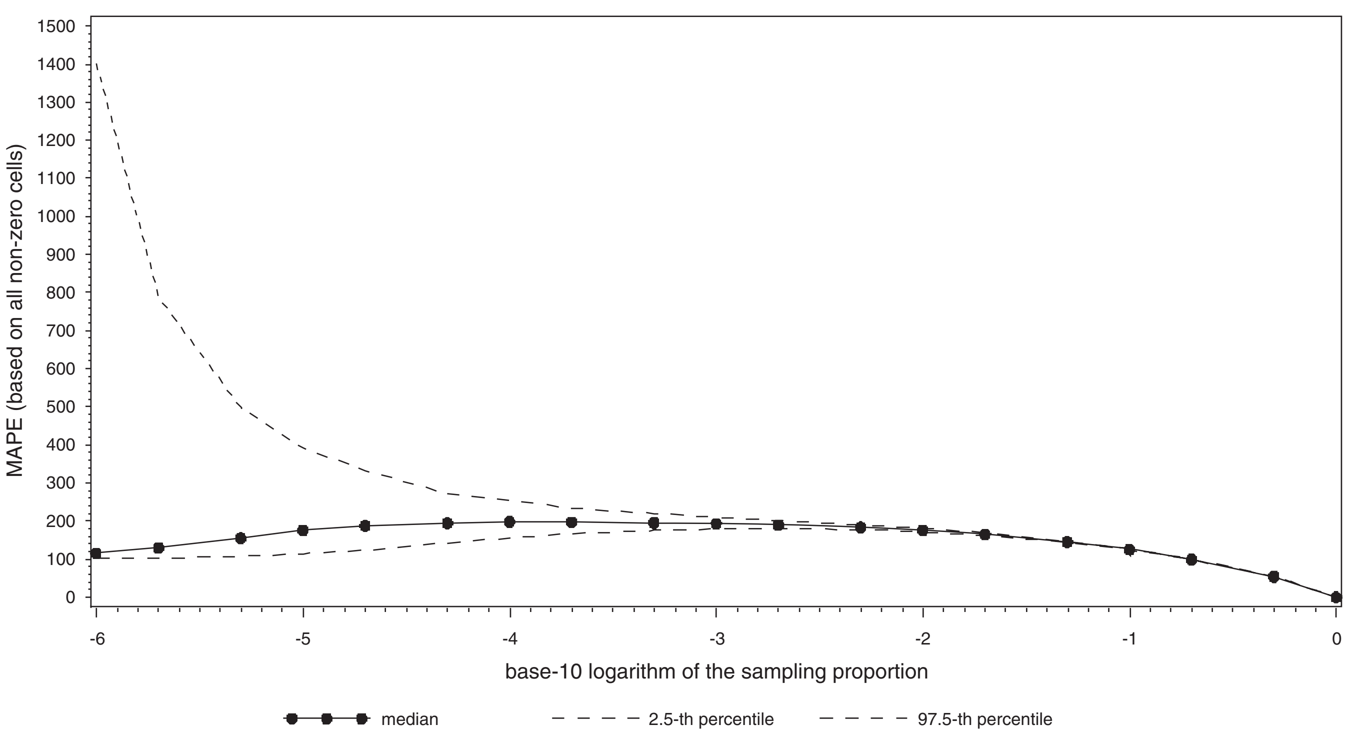

FIGURE 3 Relationship at municipality level between MAPE and Base-10 logarithm of sampling rate.

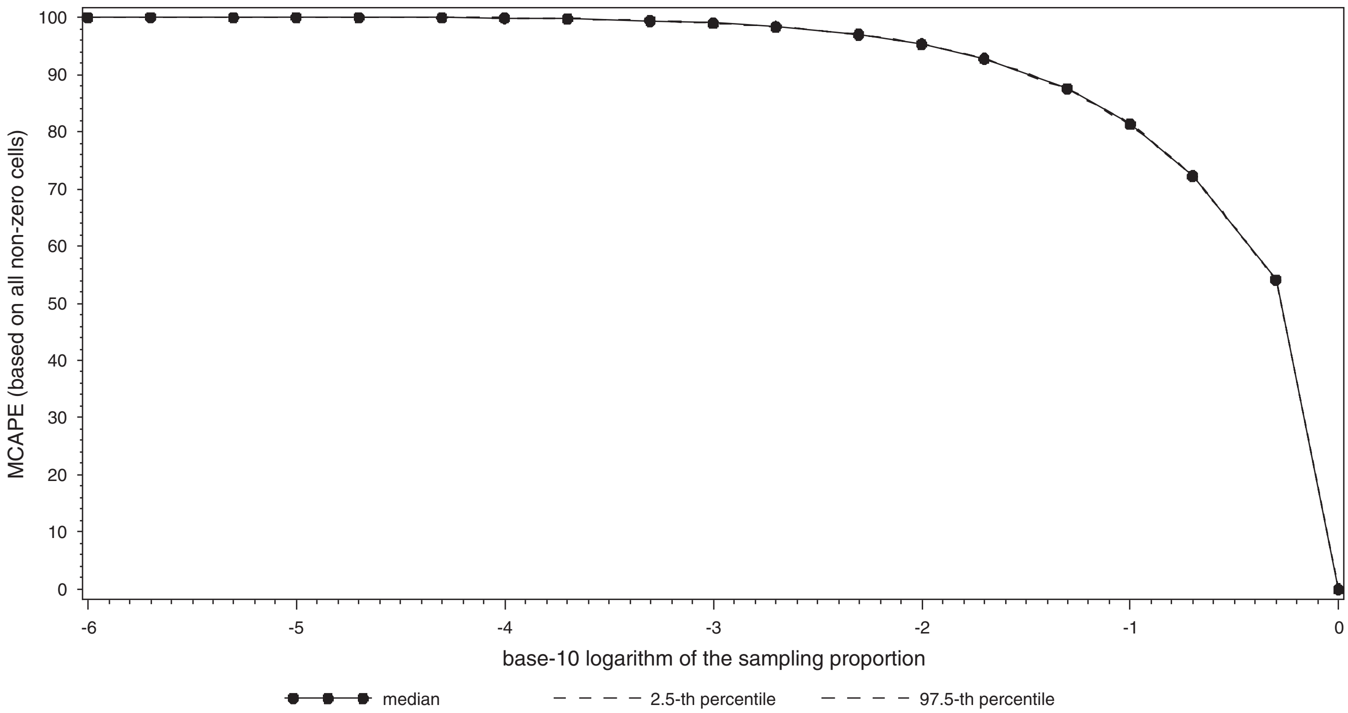

FIGURE 4 Relationship at municipality level between MCAPE and Base-10 logarithm of sampling rate.

decreasing function. This difference in pattern, as well as the difference in precision, can be explained by the fact that proportions are aggregate indices, and that surveys are extremely suitable for capturing these aggregate figures, while in O-D matrices all individual information is used.

O-D Matrices at District Level

Similar to the true O-D matrix at the municipality level, the true O-D matrix at the district level (43×43) comprises a nonnegligible amount of zero-cells. Nonetheless, the number of non-zero-cells is considerably smaller: 10.4% of the 1,849 O-D pairs are zero-cells. Recall that zero-cells in the full population are by definition correctly predicted by taking a sample from this population. Therefore, similar to the previous paragraph, the results are based on the 1,657 non-zero-cells. The values that include the zero-cells can be calculated by dividing the MAPE and MCAPE values by 1.116.

A thorough look at Table 3 shows that also at the district level no accurate O-D matrices can be derived. Even if zero-cells are included in the calculations, surveying half of the population would result in an average APE of 22.25% (24.832 divided by 1.116). When compared with the results of O-D matrices derived at the municipality level, the results including the zero-cells are worse at the district level (an average MAPE of 22.25% versus one of 11.99%). This is because at the municipality level a much larger share (77.8% versus 10.4%) of zero-cells is automatically correctly predicted. In contrast, when the results of only the non-zero-cells are compared, the precision of the O-D matrices derived at the district level is higher than the precision of the O-D matrices derived at the municipality level. This confirms that predictions on a more aggregate level are more precise.

A visual representation of the relationship between the precision of the O-D matrices derived at the district level and the sampling rate is provided in Figures 5 and 6. Inspection of Figure 5 reveals a pattern very similar to the one observed in Figure 3: the MAPE first increases when samples are becoming larger, and then starts to decrease. Recall that the increase in median MAPE for the smallest sampling rates can be accounted for by the fact that more cells are seriously overestimated on average, while the maximum underestimations are bounded by 100%. By analogy with the results at the municipality level, this effect is filtered out by using the MCAPE, as could be noticed from Figure 6. Moreover, the relationship between the MCAPE and sampling proportion is a concave decreasing function, similar to the relationship between the MCAPE and sampling rate at the municipality level.

O-D Matrices at Provincial Level

In contrast to the true O-D matrices at the municipality and district levels, the true O-D matrix at the provincial level (11×11) only comprises non-zero-cells. Examination of Table 4 reveals that at the provincial level, hardly any accurate O-D matrices can be derived. Nonetheless, in contrast to the results at the municipality and district levels, for the largest sample sizes acceptable results are obtained: sampling half of the population would result in an average APE of 3.4%, and surveying one-fifth of the population results in an average APE of 7.4%. Results from Table 4 also confirm that predictions related with a more aggregate level are more precise. Notwithstanding, results at the provincial level confirm the finding unraveled at the lower levels (municipality and district)—that the direct derivation of O-D matrices from household activity travel surveys should be avoided.

The visualization of the relationship between the precision of the O-D matrices derived at the provincial level and the sampling proportion is shown in Figures 7 and 8. Analogous to the relationships between the sample rate and the precision of the O-D matrices at the municipality and district levels, the MAPE first increases when

TABLE 3 MAPE and MCAPE for O-D Matrices Derived at District Level

Sampling Rate (SR)	$\log_{10}$ SR	MAPE Mean	MAPE P5	MAPE Median	MAPE P95	MCAPE Mean	MCAPE P5	MCAPE Median	MCAPE P95
0.000001	–6.00	171.196	100.978	110.178	299.050	99.996	99.987	99.993	100.000
0.000002	–5.70	206.097	101.875	113.822	385.419	99.937	99.869	99.937	100.000
0.000005	–5.30	197.675	104.054	121.673	442.676	99.716	99.589	99.717	99.841
0.000010	–5.00	200.483	105.752	127.559	481.848	99.352	99.174	99.351	99.535
0.000020	–4.70	191.212	108.363	136.036	417.340	98.750	98.524	98.749	98.970
0.000050	–4.30	186.436	111.940	145.249	383.240	97.578	97.331	97.572	97.860
0.000100	–4.00	187.614	114.861	152.048	359.850	96.444	96.145	96.449	96.738
0.000200	–3.70	177.715	118.461	156.391	307.348	94.788	94.416	94.791	95.131
0.000500	–3.30	172.565	122.683	160.022	274.422	92.023	91.596	92.027	92.443
0.001000	–3.00	164.271	124.944	157.032	230.024	89.557	89.113	89.557	90.004
0.002000	–2.70	154.307	123.783	150.441	196.883	86.232	85.711	86.228	86.753
0.005000	–2.30	138.952	118.396	137.611	164.985	81.028	80.476	81.014	81.605
0.010000	–2.00	124.538	110.153	123.828	141.608	75.874	75.224	75.874	76.529
0.020000	–1.70	109.048	99.198	108.610	120.450	69.540	68.823	69.548	70.242
0.050000	–1.30	85.890	80.198	85.743	92.146	59.623	58.825	59.617	60.407
0.100000	–1.00	67.276	63.761	67.238	70.863	50.649	49.818	50.645	51.482
0.200000	–0.70	48.653	46.789	48.640	50.602	40.040	39.253	40.042	40.890
0.500000	–0.30	24.832	24.110	24.826	25.529	24.832	24.110	24.826	25.529
1.000000	0.00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

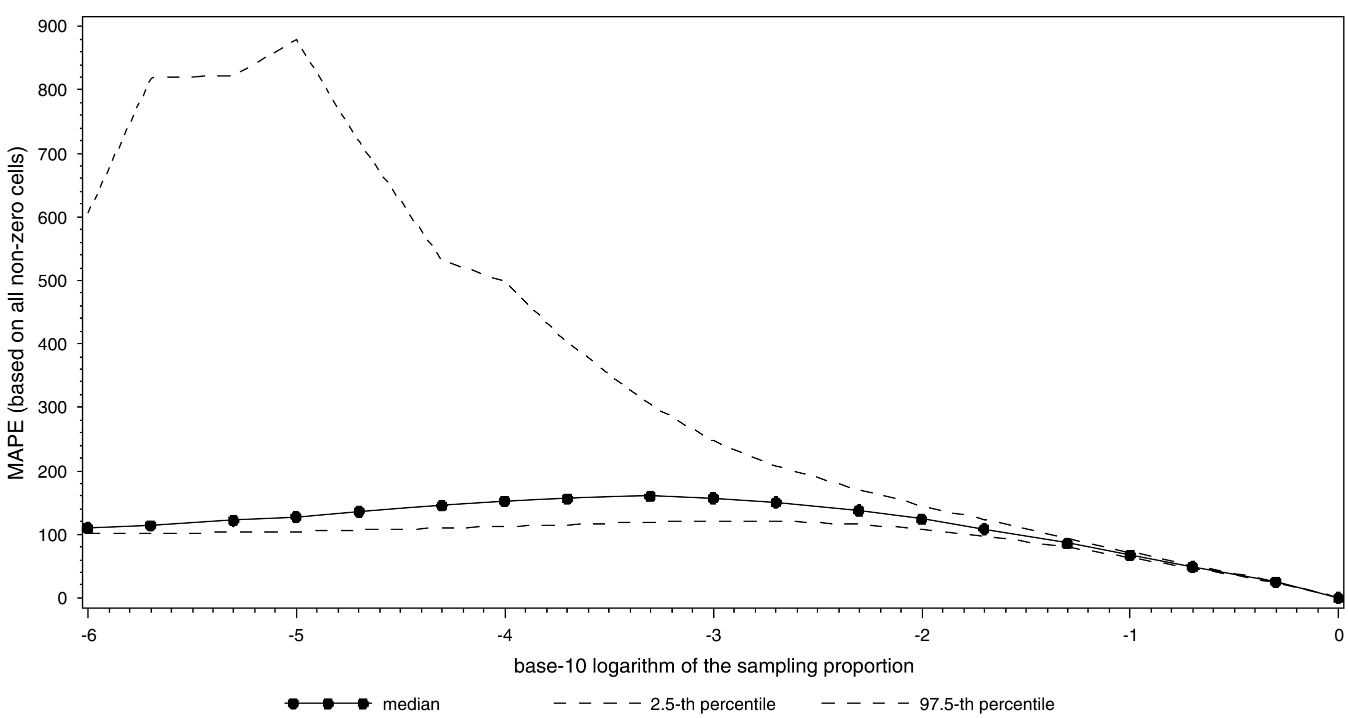

FIGURE 5 Relationship at district level between MAPE and Base-10 logarithm of sampling rate.

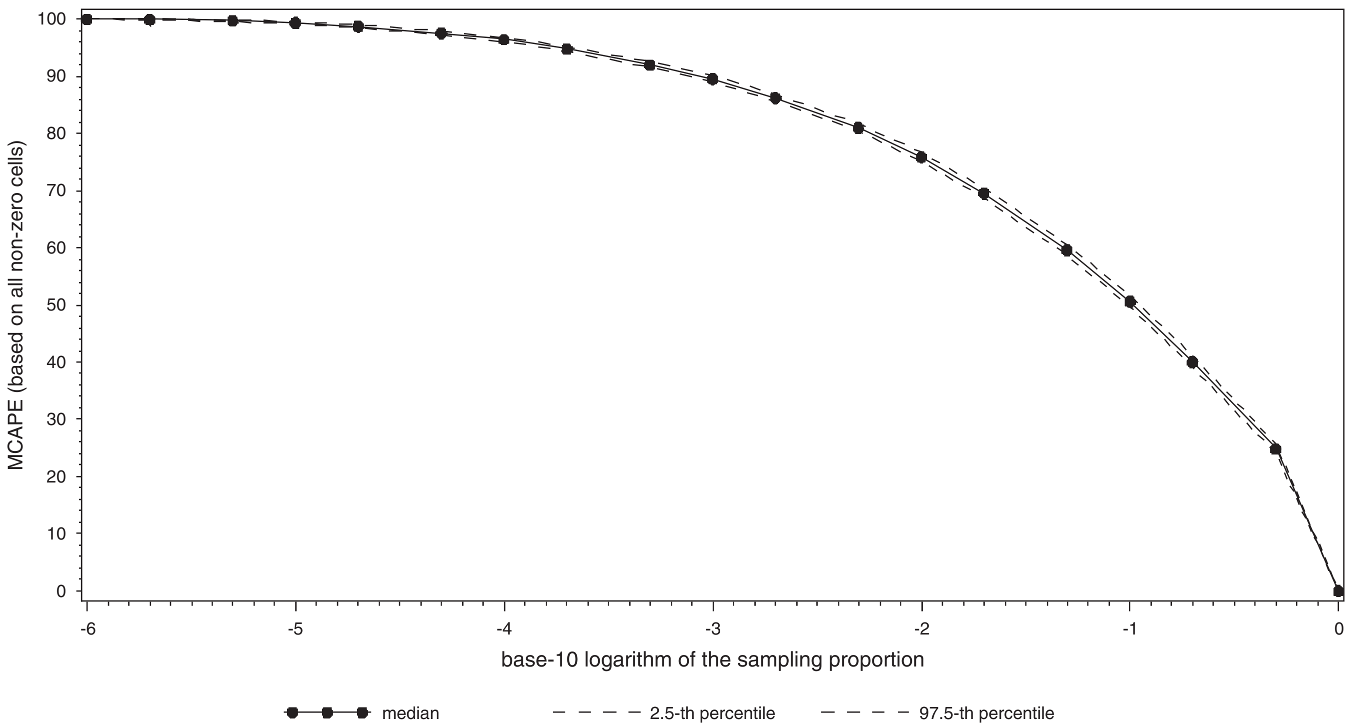

FIGURE 6 Relationship at district level between MCAPE and Base-10 logarithm of sampling rate.

TABLE 4 MAPE and MCAPE for O-D Matrices Derived at Provincial Level

Sampling Rate (SR)	$\log_{10}$ SR	MAPE				MCAPE			
		Mean	P5	Median	P95	Mean	P5	Median	P95
0.000001	−6.00	176.769	99.263	107.557	394.608	99.063	98.121	99.098	100.000
0.000002	−5.70	203.155	97.373	116.674	433.429	97.457	96.026	97.482	98.892
0.000005	−5.30	181.113	96.627	126.086	350.822	95.265	93.815	95.268	96.704
0.000010	−5.00	168.445	98.339	127.604	348.163	93.433	92.038	93.444	94.797
0.000020	−4.70	168.536	99.464	128.362	360.363	91.485	90.201	91.460	92.835
0.000050	−4.30	151.833	95.531	121.858	311.175	86.839	84.890	86.849	88.801
0.000100	−4.00	139.293	89.910	117.180	260.735	81.456	78.907	81.492	83.867
0.000200	−3.70	122.260	83.171	109.350	199.592	75.496	72.706	75.491	78.216
0.000500	−3.30	102.579	73.950	95.857	153.082	66.131	63.291	66.100	68.976
0.001000	−3.00	86.550	65.717	82.586	121.220	58.695	55.863	58.703	61.425
0.002000	−2.70	70.179	55.819	67.913	91.566	50.581	47.480	50.567	53.506
0.005000	−2.30	50.419	42.091	49.683	61.219	40.069	37.270	40.045	42.948
0.010000	−2.00	37.062	31.187	36.759	44.062	31.583	28.460	31.522	34.604
0.020000	−1.70	26.160	22.031	25.987	30.902	23.833	20.970	23.816	26.754
0.050000	−1.30	16.138	13.530	16.044	19.084	15.566	13.331	15.566	17.840
0.100000	−1.00	11.165	9.297	11.150	13.148	11.018	9.271	11.021	12.841
0.200000	−0.70	7.417	6.252	7.374	8.784	7.404	6.243	7.370	8.721
0.500000	−0.30	3.449	2.903	3.440	4.050	3.449	2.903	3.440	4.050
1.000000	0.00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

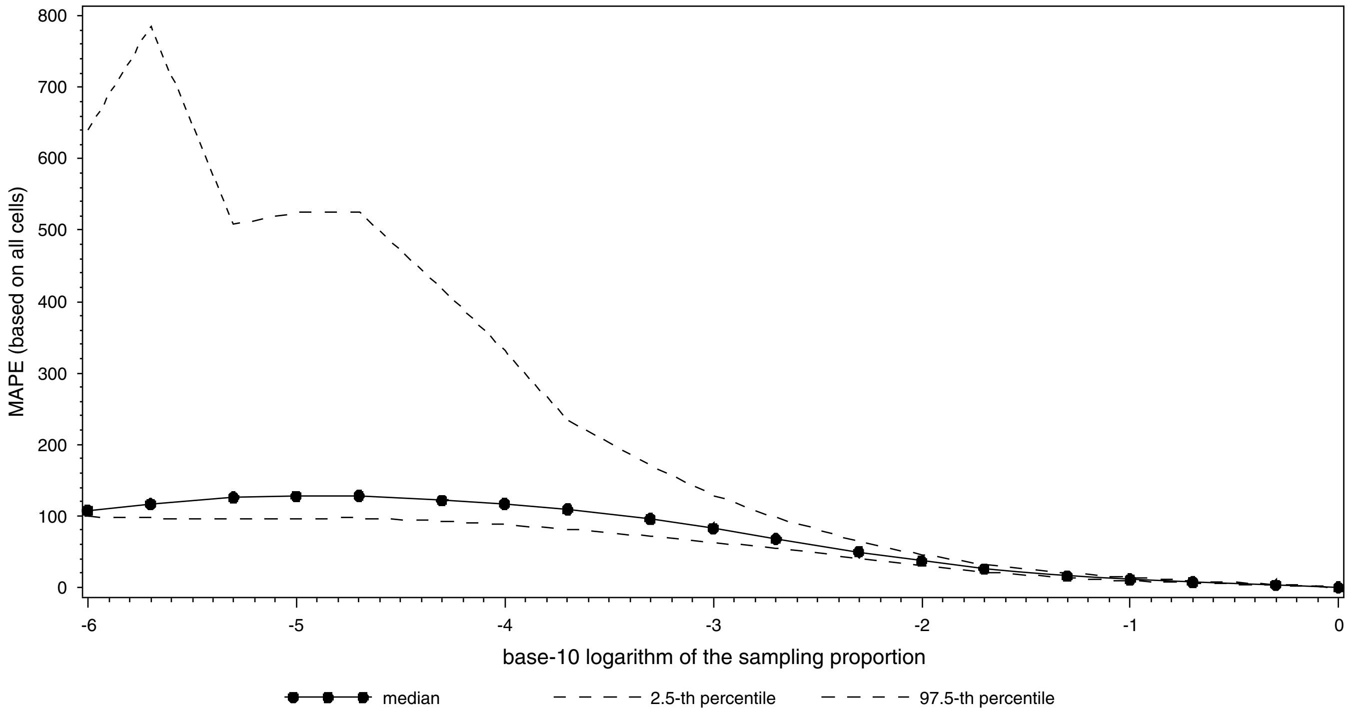

FIGURE 7 Relationship at provincial level between MAPE and Base-10 logarithm of sampling rate.

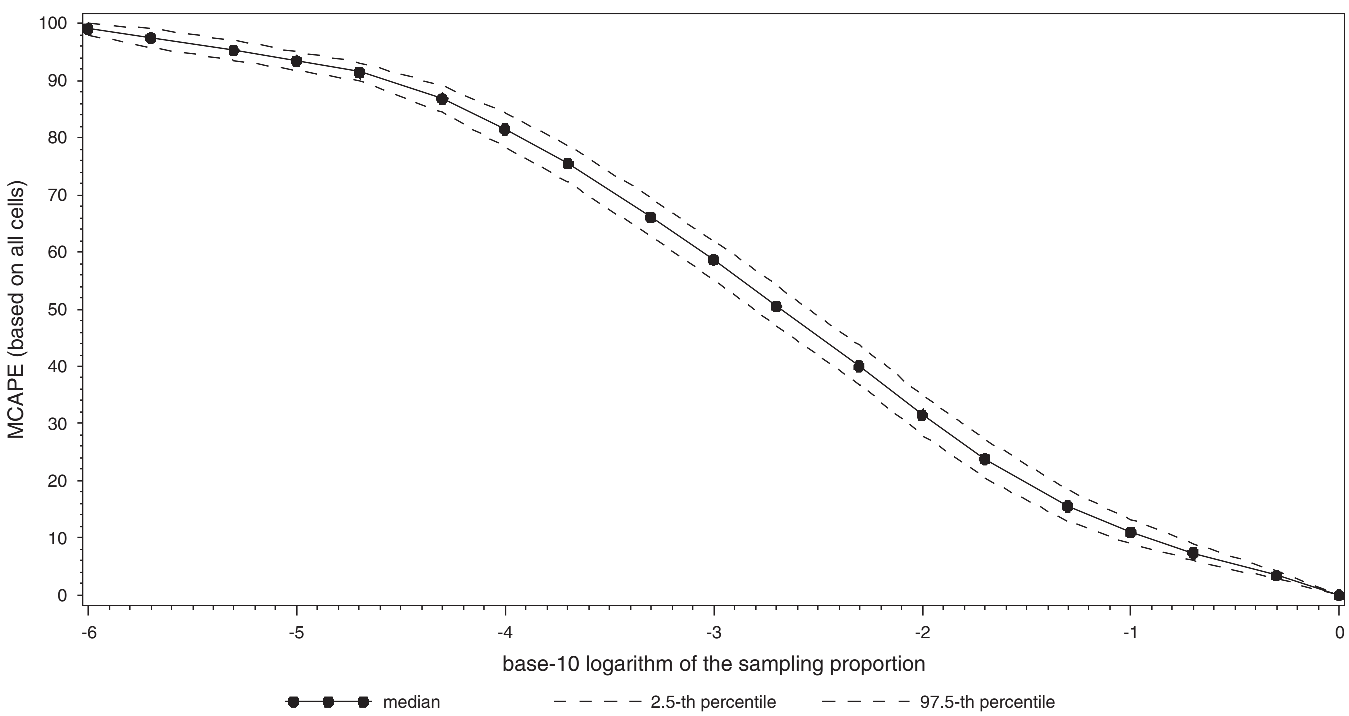

FIGURE 8 Relationship at provincial level between MCAPE and Base-10 logarithm of sampling rate.

samples are becoming larger and then starts to decrease (Figure 7). Again, the use of the MCAPE filters out this effect. In contrast to the results at the municipality and district levels, the relationship between the precision and the MCAPE reveals an *s*-shaped decreasing function: for the smallest sampling rates the relationship is concavely decreasing, similar to the O-D matrices at the municipality and district levels; but for the larger sampling rates the relationship is a convex decreasing function. Moreover, the 95th percentile interval is much wider than for the O-D matrices at less aggregated levels. The most important reasons for this are the degree of sparseness and size of the matrix: for the less aggregate levels (municipality and district levels), a lot of the variability of the precision is taken away by the large amounts of (zero-)cells.

CONCLUSIONS

In this paper, an assessment of the quality of O-D matrices derived from household activity travel surveys was made. The results showed that no accurate O-D matrices can be directly derived from these surveys. Only when half of the population is queried is an acceptable O-D matrix obtained at the provincial level. Therefore, use of additional information to better grasp the behavioral realism underlying destination choices is recommended. This is certainly a plea for travel demand models that incorporate the behavioral underpinnings of destination choices (activity location choices) given a certain origin. Moreover, matrix calibration techniques could seriously improve the quality of the matrices derived from these household activity travel surveys. In addition, collection of information about particular O-D pairs by means of vehicle intercept surveys rather than household activity travel surveys is recommended, as vehicle intercept surveys are tailored for collecting specific O-D data. Note that the results presented in this paper do not negate the value of travel surveys as was shown in the example of deriving the commuting population, but indicate that sophistication is needed in the manner in which the data are employed.

A second important finding in this paper is that traditional methods to assess the comparability of two O-D matrices could be enhanced: the MCAPE index that was proposed has clear advantages over the traditional indices, the most important being that the MCAPE filters out the noise created by the asymmetry of the traditional criteria. Therefore, when dissimilarities between different O-D matrices are investigated, use of the MCAPE index next to traditional criteria is highly recommended.

An important avenue for further research is the investigation of the relationship between the variability in the outcomes of travel demand models and underlying survey data. Triangulation of both travel demand modeling and small area estimation models could prove to be a pathway for success. An empirical investigation of the effect of sampling proportions in household activity travel surveys on final model outcomes would further illuminate the quest for optimal sample sizes. A thorough examination of the minimum required sampling rate of a household travel survey such that trip distribution models (e.g., a gravity model) could help fill in the full trip table certainly is an important step in further analyses. Model complexity and computability will certainly be key challenges in this pursuit.

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