

Estimating error rates in an administrative register and survey questions using a latent class model

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Abstract

Administrative register data are increasingly used worldwide to replace or supplement the census, and are thought to provide a cost-effective opportunity for longitudinal full-population data analysis in the social sciences. They are also frequently used as “validation data” to study measurement error in survey questions. In spite of quality control procedures, however, there are strong indications that administrative register data can themselves contain considerable measurement error. Moreover, typically the error process does not conform to classical measurement error models. Such errors negate the potential usefulness of administrative data, making it essential to evaluate their extent. This chapter discusses latent variable modeling as a way to estimate measurement error in administrative data by combining error-prone administrative data with an error-prone survey. To demonstrate the approach, a latent class model is applied to linked register-survey residence data from the municipality of Amsterdam.

1 Introduction

Administrative data obtained from government registers provide a wealth of potential for the social sciences (Entwisle and Elias, 2013). Collected during the normal course of public administration, for example to tax, keep track of car ownership, pay welfare benefits, or send out calls to vote in elections (Wallgren and Wallgren, 2007), registers can be used by survey researchers as direct variables of interest, or as auxiliaries in survey sampling, nonresponse adjustments, or validation studies. Such registers are often available longitudinally and for the entire population – a highly attractive combination for researchers, especially when linked to purpose-designed surveys.

While administrative registers have many redeeming qualities for survey researchers, the fact that they have been collected for administration not research can be a disadvantage. In

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particular, administrative registers may contain considerable measurement errors, including definition, reporting, timing, processing, editing, linkage, and coverage errors (Bakker, 2009; Groen, 2012). For example, Gomez and Glaser (2006) found a staggering 83.3% of Native Americans and 29.9% of Hispanics were misclassified as a different race in U.S. registers, and epidemiologists have long preferred “gold standard” autopsy data to hospital cause-of-death registers (e.g. Maudsley and Williams, 1996). Since measurement error is well-known to severely distort analyses of substantive interest (Fuller, 1987; Carroll et al., 2006), estimating the extent of such errors is essential to making administrative register data useful for social research.

Some validation studies of administrative registers exist, but often use surveys as the gold standard (e.g. Gomez and Glaser, 2006; Groen, 2012). At the same time, survey methodologists use administrative registers as a gold standard to validate surveys (e.g. Kreuter et al., 2010; West and Olson, 2010). It therefore seems likely that both sources are error-prone. But how can we estimate the extent of measurement errors in both administrative register and survey answers when neither are perfect?

This chapter demonstrates one approach to doing so: latent variable modeling. As an example it estimates the amount of classification error in survey and administrative measures of the neighborhood of residence, an important modeling and adjustment variable. From a combination of two survey measures of the neighborhood and one administrative register measure, a latent class model is built that accounts for survey mode effects as well as local dependencies between the survey measures. This allows estimation of error rates in all three measures without assuming any one of them to be perfect in advance.

Latent variable modeling has been applied to estimating measurement error in continuous administrative variables by Bakker (2012), Scholtus and Bakker (2013) and Oberski et al. (2013a) using “multitrait-multimethod” (MTMM) designs. Pavlopoulos and Vermunt (2013) used a longitudinal latent class (hidden Markov) approach to estimate misclassification in employment status registers. This previous work has not investigated, however, how misclassification may be estimated in nominal administrative and survey variables without longitudinal information. Moreover, the present application accounts for mode of data collection effects in the survey measures. Modeling these mode effects allow for the identification of both random classification errors and method effects without the need for multiple “traits” (true values). It could therefore be termed a “single-trait-multi-method” (STMM) approach.

The following section describes the data on neighborhood of residence obtained from a survey and an important Dutch official administrative register. Section 3 then details the latent class model built to estimate classification error rates in these measures. The resulting estimates are described in Section 4, after which Section 5 concludes.

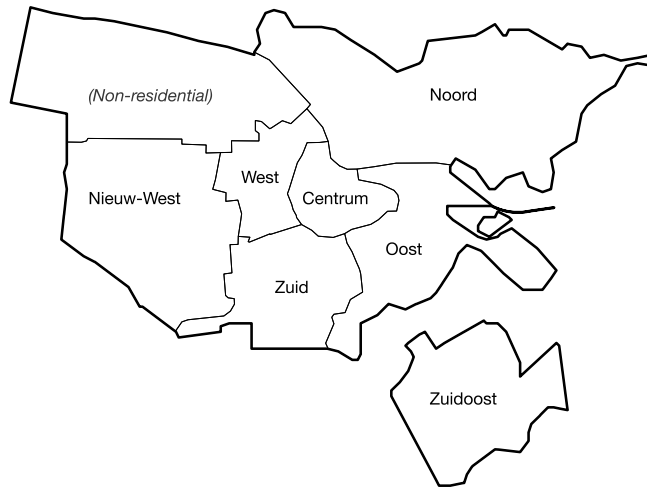


Figure 1: Neighborhoods of residence (“stadsdeel”) in Amsterdam, The Netherlands.

2 Administrative and survey measures of neighborhood

In March and April of 2013, the municipality of Amsterdam, The Netherlands, performed its biannual survey on sports participation, the “Sportmonitor”¹, among the population of approximately 711,000 residents aged 6–74. A random sample of 20,579 households was taken from the municipal register, stratified by neighborhood, ethnicity, and age group (< 18 or 18+). The data collection was a sequential mixed mode design: first, all sampled persons in the households received a personalized letter in the regular mail with the official logo of the municipality, requesting participation in an online web survey but leaving the option of returning a paper form, which a small (3%) percentage of respondents returned. A sample of nonrespondents were followed up by CATI if phone number was available or visited at their residence and interviewed using CAPI otherwise. This led to a mix of 59% web or paper-and-pencil mode, 30% CATI, and 11% CAPI. The final number of respondents was 4,266, making the response rate $4,266/20,579 = 20.7\%$ (AAPOR RR1 and RR2).

Our target variable of interest is the neighborhood of residence or “stadsdeel”, a key variable in data analysis for public policies, for various “big data” services linking neighborhood to other official statistics, and for sample survey design. Amsterdam contains eight such neighborhoods, of which one is the port, a non-residential area. These are shown in Figure 1. Figure 2 shows the two survey questions about neighborhood. The question first directly asks the respondent their neighborhood of residence, while the second asks it indirectly through the postcode. Of note is the fact that the survey asks the postcode at a high level of detail: it is common for surveys to ask only the first four digits rather than all six. This may have contributed to the higher number of missing values in this variable – 7.7% of values are missing in the second question while this is only 0.9% in the first.

While the survey gathered two separate measures of the respondent’s neighborhood, the

¹https://www.amsterdam.nl/publish/pages/422998/sportmonitor_2013_def.pdf

[Survey: <i>direct question</i>]. In which neighborhood do you live? 1. Centrum 2. Westpoort 3. West 4. Nieuw-West 5. Zuid 6. Oost 7. Noord 8. Zuidoost 9. Don't know [Survey: <i>postcode</i>]. What is your postcode? - - - - [- -]
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Figure 2: Formulation of the 2013 Sportmonitor survey questions asking neighborhood of residence. The postcode (ZIP code) is asked at the most detailed level possible.

municipality also has this information in its administrative register (“GBA”). The Dutch municipal register is one of the bases of the Dutch official statistical system, as well as a crucial source of information for various Dutch government services. It is collected at the municipal level but used at the national level as input to construct the virtual census, draw samples for official, academic, and commercial probability surveys, and to divide welfare transfers and decide local public policies. The GBA’s accuracy is therefore under heavy scrutiny, as evidenced by the 2007 official instruction by Parliament to “improve accuracy to at least 99%”². This instruction has prompted a series of audits, in which investigating officers with special powers are trained by local governments to investigate and visit addresses until the accurate values for the corresponding GBA record can be verified with certainty, a very costly effort. Based on this expensive investigation, the municipality of Amsterdam estimated the inaccuracy of the neighborhood of residence to be around 1.7%; one point of interest is whether this estimate could have been arrived at more cheaply.

Combining the survey with the administrative register, we have four observed variables: the direct survey question with the postcode-derived measure shown in Figure 2, the administrative register, and the survey mode. The table of cross-classifications of these variables was provided by the research service of the municipality of Amsterdam. It should be noted here that we did not obtain any postcode values, but only the derived neighborhood. Since each of the residential neighborhoods is estimated to be inhabited by at least 84,000 people, privacy is not a concern for this cross-tabulation. Such concerns did prevent a larger level of detail from being made available, so that it was not possible to include further covariates in the analysis.

Table 1 cross-tabulates the two survey measures (columns) with the administrative register. The Table shows that the correspondence among these measures is rather large, as may be expected with this variable. However, it is far from perfect. For example, in the direct question 51 respondents (13%) who live in Nieuw-West according to the register claim to live in the more affluent West neighborhood. The postcode-derived measure indicates this

²Dutch Parliament, Motion 31 200 VII-34.

	Survey: direct							Survey: postcode						
	A	E	F	K	M	N	T	A	E	F	K	M	N	T
<i>Register</i>														
A	432	5	1	0	3	0	0	412	1	0	0	0	1	0
E	1	356	11	1	2	0	1	0	351	0	2	2	0	1
F	0	51	341	1	0	2	0	0	0	372	0	0	2	0
K	8	5	3	1669	2	1	8	0	2	1	1536	0	0	1
M	2	5	0	1	402	2	0	0	2	1	0	386	1	0
N	0	0	1	1	1	441	0	0	0	1	1	0	422	0
T	0	0	0	0	0	3	355	0	0	0	0	0	0	340

Table 1: Cross-tabulation of the observed survey measures with the administrative measure. A: Centrum, E: West, F: Nieuw-West, K: Zuid, M: Oost, N: Noord, T: Zuidoost.

as well, so that the most likely explanation here is measurement error in the direct question. However, there are also 3 respondents ($\sim 1\%$) in this group who live in entirely different non-adjointing neighborhoods according to both survey measures; such cases may indicate that the administrative register, too, contains some classification error. Alternatively, this may be a case of consistent mistake-making on the part of the respondent—it is impossible to tell purely from these cross-tables. It is this difficulty of drawing conclusions by inspecting Table 1 that impels us to use a different tool: latent class models.

3 A latent class model for neighborhood of residence

From the three observed measures and the survey mode indicator, our goal is to estimate the classification error in each of the measures. Since none of the three measures are perfect, a latent variable model is used in which the unobserved (“latent”) true neighborhood is measured with error by the three indicators. Such models in which the latent variable is categorical are known as “latent class models” in the literature (e.g. Hagenaars and McCutcheon, 2002) and have been applied to the estimation of classification error in survey data by Lazarsfeld (1950), McCutcheon (1987) and, more recently, Biemer (2011) and Oberski (2013).

The standard latent class model assumes one single latent class variable, S , say, conditionally upon which the observed indicators y_1 , y_2 , and y_3 are independent. For example, in our seven-neighborhood case, a seven-class model might be formulated:

$$P(y_1, y_2, y_3) = \sum_{s=1}^7 P(y_1|S)P(y_2|S)P(y_3|S)P(S). \quad (1)$$

Responding “Don’t know” or not providing a postcode can simply be modeled as separate categories of the observed variables. However, this standard model implies that the two survey measures are independent of each other given the latent class, $P(y_2, y_3|S) = P(y_2|S)P(y_3|S)$. This “local independence” assumption will be violated when respondents who do not answer the direct survey question also do not (wish to) provide their postcode;

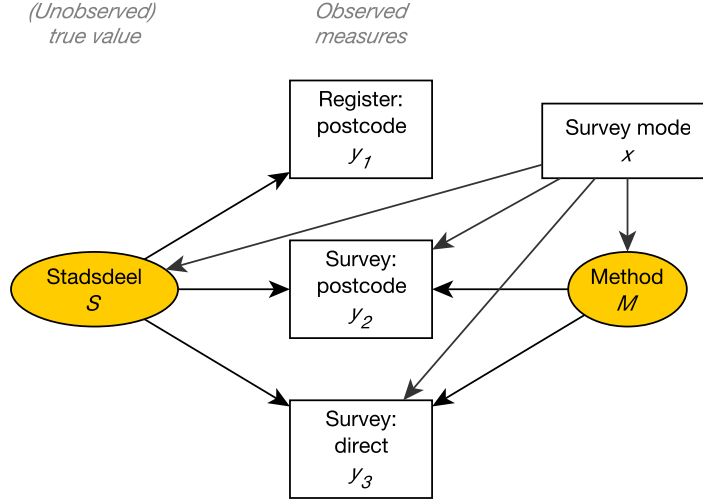


Figure 3: Latent class measurement model for the three measurements of neighborhood of residence. Latent variables are shown in shaded ovals, while observed variables are shown as rectangles.

or when the classification error differs over survey mode. For a more general discussion of possible reasons for local dependence, see Biemer (2011, Sec 5.2).

In order to account for possible local dependence between the survey measures, we allow for a “method factor”: a latent variable that represents an individual tendency to answer in a certain way, independent of the true neighborhood of residence. Note that this means the “method factor”, instead of being a systematic bias, is a stochastic effect shared by the two survey questions. For example, this unobserved variable may represent a person’s tendency to keep their neighborhood secret from the researcher. To investigate the effect of survey mode, we also include the survey mode chosen as a covariate in the model. Since mode is not randomized, it may correlate with the true neighborhood of residence. There is no reason to suppose, however, that survey mode affects the measurement of the administrative register, an assumption that allows the identification of the method factor. The resulting model is shown in Figure 3.

From Figure 3, the likelihood of the observed measures y_1 , y_2 , and y_3 given the fixed “survey mode” covariate x is

$$P(y_1, y_2, y_3|x) = \sum_{s=1}^7 \sum_{m=1}^2 P(y_1|S)P(y_2|S, M, x)P(y_3|S, M, x)P(S|x)P(M|x), \quad (2)$$

where we have chosen two categories for the latent method factor. That is, the likelihood is that of a latent class model with two separate latent class variables, one representing the true neighborhood of residence S and the other the respondent’s answer tendency in the survey M . Given the latent S , the observed register y_1 is assumed independent of (y_2, y_3, x) , while y_2 and y_3 are only mutually independent given S , M , and x . The latent “trait” S and “method” M are assumed independent given the survey mode.

The conditional probabilities on the right-hand side of Equation 2 are parameterized using a logistic regression model. For instance, for the survey postcode question, the conditional probability is modeled as a logit with main and second-order interaction effects from its categorical regressors,

$$P(y_2 = k | S = s, M = m, x) = \frac{\exp(\tau_k + \lambda_{ks} + \lambda_{km} + \gamma_{kx})}{\sum_{k'} \exp(\tau_{k'} + \lambda_{k's} + \lambda_{k'm} + \gamma_{k'x})}, \quad (3)$$

where, as in multinomial logistic regression, the reference category parameters are set to zero for identification purposes, $\tau_1 = \lambda_{1\cdot} = \gamma_{1x} = 0$. It is, in principle, also possible to incorporate higher-order interactions. For instance, the logistic “loading” λ_{ks} , which is directly related to the measurement quality, could be allowed to vary over survey mode by replacing the parameter λ_{ks} by λ_{ksx} , a possibility that can be tested using the data. Even without such an interaction, however, the classification probability in Equation 3 will differ over survey mode simply due to the nonlinear nature of the logistic regression.

Maximum-likelihood estimation of the model can proceed by directly maximizing the likelihood in Equation 2, or by expectation-maximization (EM), starting the E-step by choosing starting values for the model parameter estimates $\hat{\vartheta}_{t-1}$, and calculating, for each observation, the posterior joint probability of the 7×2 latent variable values given the observation,

$$\hat{P}(S, M | x, y_1, y_2, y_3) = \frac{\hat{P}(y_1, y_2, y_3 | x, S, M) \hat{P}(S | x) \hat{P}(M | x)}{\sum_{s=1}^7 \sum_{m=1}^2 \hat{P}(y_1, y_2, y_3 | x, S, M) \hat{P}(S | x) \hat{P}(M | x)}, \quad (4)$$

where $\hat{P}(\cdot) := \hat{P}(\cdot | \hat{\vartheta}_{t-1})$. In the maximization step, new parameter estimates are then obtained by standard estimation techniques for linear regression, by iterative proportional fitting, or by pseudo-ML, using the posteriors as weights,

$$\hat{\vartheta}_t = \arg \max_{\vartheta} \sum_{i=1}^n \sum_{s=1}^7 \sum_{m=1}^2 \hat{P}(S, M | x, y_1, y_2, y_3) \ln P(y_1, y_2, y_3 | x, S, M, \vartheta). \quad (5)$$

The E-step in Equation 4 and M-step in Equation 5 are then iterated until convergence. In practice it is usually not necessary to create custom computer programs to obtain the estimates, since the model formulated above can be readily estimated in standard software for latent class analysis such as Mplus (Muthén and Muthén, 2012), ℓ EM (Vermunt, 1997), or Latent GOLD (Vermunt and Magidson, 2013). The present analysis uses Latent GOLD 5.0.

Freely estimating the class sizes will often lead to class size estimates that differ from the official proportions of citizens living in each neighborhood, π_s , say. If this is not desired, a possible solution is to fix the class sizes to these known official proportions. However, this entails the complication that the meaning of the classes in terms of the observed indicators must also be restricted in the estimation procedure, to ensure, for instance, that a class chosen to represent the Zuid neighborhood has the correct fixed proportion. Moreover, due to the presence of covariates this restriction needs to be made in terms of the marginal $\sum_x \hat{P}(S | x)$. In short, while possible, imposing such restrictions can be challenging in practice. A simpler solution is to poststratify the posterior in Equation 4: when calculating misclassification rates,

instead of a mean of posteriors within a particular category of an observed measure we then take the weighted mean, where the weights are chosen to be the poststratification weights,

$$w_s = \pi_s / \tilde{P}(S = s).$$

From Equation 4 it can be verified that this poststratification corresponds to one cycle of the EM algorithm, in which the M-step is performed separately for each variable.

4 Results

4.1 Model fit

The previous section made certain choices for the specification of the model. A first step in analysis is to see whether these choices were necessary to fit the data, or whether a simpler model could have been fit. Conversely, some of the choices may have been too restrictive and it is of interest to see whether these restrictions fit the data. Table 2 investigates this by comparing different specifications using as fit measures the BIC, AIC, AIC3 and CAIC. All of these information criteria seek a balance between model-data fit and model complexity, but do so in slightly different ways, leading to different preferred models shown in bold face in the Table (lower values are better). The total “bivariate residual” (Vermunt and Magidson, 2013; Oberski et al., 2013b) is also given, in the last column (BVR): a sum of chi-squares measuring the distance between observed and expected frequencies in the bivariate cross-tables.

The rows in Table 2 correspond to models that result from combining the choices of survey mode effect with the number of latent method classes. The first model fitted (row 1) was the seven-class local independence model in Equation 1. None of the fit measures prefer this model, clearly indicating residual dependence. Model 1 as well as models 2–4 had one method class, which simply means there was no method factor (as can be verified from Equation 2). Models 8–10, on the other hand, were fit to investigate whether the previous Section’s choice of two method classes should be extended to three classes. Comparing these three groups it is clear that all fit measures prefer a model with two method classes. Moreover, the total BVR is most reduced when going from no method factor at all to a method factor with two classes. There is indeed a dependence between the two survey measures that is adequately accounted for by allowing for two method factor classes.

Among the models that had two method classes, models 5–7 differ on how the survey mode effect was specified. Model 5 only related the survey mode to the true neighborhood S , but not directly to the survey measures (in Figure 3, no direct arrows from x to y_2 or y_3). Model 7 is the model shown in Figure 3, allowing both direct and indirect effects. It is preferred by AIC. While Model 5 is preferred by the BIC and CAIC, the total BVR is still relatively large; the bootstrapped p -value for this measure of misfit is $p = 0.010$, indicating that this model may be too parsimonious. Since the misfit relative to model 7 can only result from the omission of the two direct arrows, the source of the misfit can be discovered by inspecting the individual BVR’s for these cross-tables (between x and each of y_2 and

	Mode	Method classes	# par.	L^2	BIC	AIC	AIC3	CAIC	Total BVR
1.	No effect	1	153	1198	-10101	-1514	-2870	-11457	15.9
2.	Only indirect	1	165	505	-10694	-2183	-3527	-12038	15.9
3.	(In)direct, y_3	1	181	443	-10624	-2213	-3541	-11952	13.5
4.	(In)direct, (y_2, y_3)	1	195	162	-10788	-2466	-3780	-12102	0.99
5.	Only indirect	2	183	205	-10844	-2447	-3773	-12170	3.08
6.	(In)direct, y_3	2	199	133	-10783	-2487	-3797	-12093	0.39
7.	(In)direct, (y_2, y_3)	2	213	105	-10695	-2487	-3783	-11991	0.21
8.	Only indirect	3	201	151	-10749	-2465	-3773	-12057	0.71
9.	(In)direct, y_3	3	217	100	-10666	-2484	-3776	-11958	0.38
10.	(In)direct, (y_2, y_3)	3	231	83	-10566	-2473	-3751	-11844	0.15

Table 2: Model fit measures for different specifications of the latent class model. The best fit according to each measure has been indicated in **bold face**.

y_3). These BVR’s show that most of the misfit was caused by the direct question, y_3 . A model only allowing a direct effect on y_3 , model 6, was therefore also fitted to the data as a compromise between Models 5 and 7. This model is preferred by AIC3. The total BVR after freeing only this one direct effect rather than both has a bootstrapped p -value of 0.120. Model 6 therefore appears to fit well in both relative and absolute terms, and provides a reasonable balance between complexity and fit. This model was therefore selected.

4.2 Error rate estimates

From the final model we calculate the estimated overall (mis)classification rates $\hat{P}(y|S)$ by marginalizing over the mode and method. These (mis)classification rates are shown for the three measures of neighborhood of residence in Table 3. Given each “true neighborhood” (columns), the conditional probability of observing a particular category of the three measures (rows) is shown. For example, when answering the direct question, respondents who belong to the latent class labeled “Nieuw-West” (truly live in Nieuw-West) have an estimated probability of 0.1287 of answering mistakenly that they live in West.

Overall, as one might expect, Table 3 shows the administrative register is estimated to be of the highest measurement quality overall. This can be seen by comparing the diagonal estimated correct classification probabilities between the three measures. The average misclassification, weighted by class size was 0.5% for the administrative register, 7% for the postcode-derived survey measure, and 4.8% for the direct survey question. However, these misclassification rates include the “missing” category as “misclassification”. If missingness were to be ignored, the misclassification rates for the postcode-derived and direct survey measure would be 0.15% and 3.8%, respectively. That is, ignoring the missing data, the postcode-derived measure is estimated to contain less measurement error than the administrative register. However, missingness in the postcode-derived survey measure does appear to be larger for the Zuid neighborhood (deviance 18.5 on 6 df , $p = 0.005$), so that it may not be ignorable for certain purposes.

	Latent class (“true neighborhood”)						
	Centrum	West	Nw-West	Zuid	Oost	Noord	Zdoost
Class size	0.1063	0.0902	0.0972	0.4100	0.0990	0.1096	0.0876
Official stats.	0.1061	0.1738	0.1775	0.1720	0.1555	0.1108	0.1036
Register: postcode							
Centrum	1.0000	0.0000	0.0000	0.0000	0.0000	0.0022	0.0000
West	0.0000	0.9947	0.0000	0.0000	0.0050	0.0000	0.0028
Nieuw-West	0.0000	0.0000	0.9921	0.0000	0.0000	0.0044	0.0000
Zuid	0.0000	0.0000	0.0029	0.9994	0.0000	0.0000	0.0058
Oost	0.0000	0.0053	0.0025	0.0000	0.9950	0.0022	0.0000
Noord	0.0000	0.0000	0.0025	0.0006	0.0000	0.9912	0.0000
Zuidoost	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9914
Survey: postcode							
Missing	0.0656	0.0531	0.0722	0.0972	0.0584	0.0658	0.0634
Centrum	0.9321	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
West	0.0023	0.9416	0.0000	0.0012	0.0000	0.0000	0.0000
Nieuw-West	0.0000	0.0000	0.9278	0.0000	0.0000	0.0000	0.0000
Zuid	0.0000	0.0053	0.0000	0.9016	0.0000	0.0000	0.0000
Oost	0.0000	0.0000	0.0000	0.0000	0.9416	0.0000	0.0000
Noord	0.0000	0.0000	0.0000	0.0000	0.0000	0.9342	0.0000
Zuidoost	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9366
Survey: direct question							
DK	0.0023	0.0051	0.0198	0.0065	0.0050	0.0241	0.0110
Centrum	0.9774	0.0027	0.0000	0.0047	0.0049	0.0000	0.0000
West	0.0113	0.9600	0.1287	0.0029	0.0049	0.0000	0.0000
Nieuw-West	0.0023	0.0295	0.8490	0.0011	0.0000	0.0000	0.0000
Zuid	0.0000	0.0027	0.0025	0.9796	0.0024	0.0000	0.0000
Oost	0.0068	0.0000	0.0000	0.0012	0.9804	0.0022	0.0000
Noord	0.0000	0.0000	0.0000	0.0006	0.0024	0.9737	0.0082
Zuidoost	0.0000	0.0000	0.0000	0.0035	0.0000	0.0000	0.9808

Table 3: Classification rates for the three observed measures (Model 6). Shown are the estimated conditional probabilities of observing each category given the latent class. The (**bold-face**) diagonal in each table indicates the estimated proportion of correct classifications. Note that missings are considered incorrect classifications here.

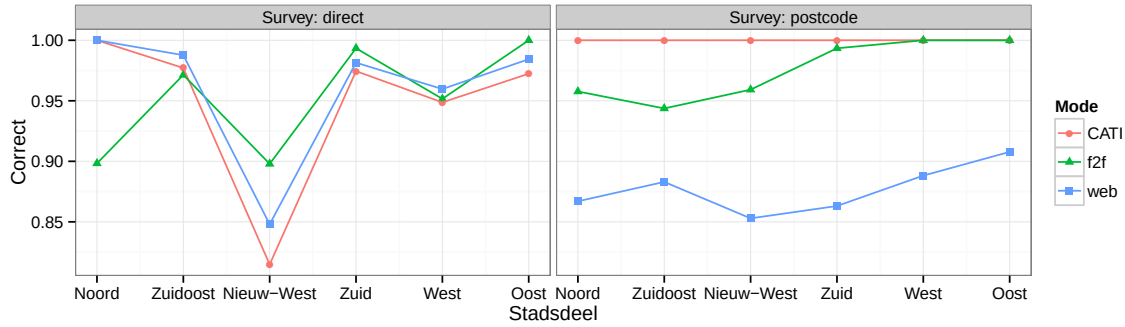


Figure 4: Estimated correct classification probabilities (excluding missing) by survey mode for the two survey measures.

Figure 3 shows how the quality of the two survey measures differs over the three survey modes. Plotted is probability of observing the correct category for each of the two survey measures, among respondents who answered in one of three survey modes. For the direct question, Figure 3 demonstrates some differences between the modes; in particular, with the exception of one neighborhood, correct classifications are somewhat more prevalent in the face-to-face mode (triangles) than in the other two modes. The largest quality differences between the modes are observed in the postcode-derived measure, however. When interviewed over telephone using CATI (dots in the Figure), the measurement quality of the postcode-derived survey measure is estimated to be perfect. The reason for this is that over the phone, respondents were read their administrative register value for the postcode and asked whether this was correct or not; if not, the value was corrected in the register. This procedure was only officially followed over the telephone. However, an interviewer visiting a respondent's home in a different neighborhood than indicated by their postcode may also have provided some correction to the survey values, leading to a high quality using face-to-face data collection (triangles). The web mode (squares) was estimated to yield the lowest quality here, with correct classification rates between 0.85 and 0.90. It should be noted at this point that the differences in measurement quality over survey modes need not be fully due to the mode of data collection only, since the choice of mode was not randomized, but determined by response status.

The effect of the method classes is shown in Table 4. Membership of class 2 appears to be most strongly related to proving a missing value on both survey measures. Thus, the method factor here predominantly represents a tendency to refuse to report one's neighborhood in a survey. While this tendency is strong within class 1 with a probability of 0.858 of omitting the postcode, only about 9% of respondents are estimated to belong to this class.

5 Discussion and conclusion

This chapter demonstrated how measurement error rates can be estimated in survey and administrative measures of a categorical variable without the need for a golden standard. Using

Method class	Class size	Mis.	Centrum	West	Nw-West	Zuid	Oost	Noord	Zdoost
<i>Survey: postcode</i>									
Class 1	0.090	0.858	0.036	0.022	0.000	0.038	0.033	0.005	0.008
Class 2	0.910	0.000	0.105	0.092	0.099	0.403	0.099	0.112	0.090
<i>Survey: direct</i>									
Class 1	0.090	0.031	0.120	0.097	0.062	0.445	0.091	0.085	0.069
Class 2	0.910	0.007	0.105	0.102	0.088	0.398	0.099	0.110	0.089

Table 4: Estimated conditional probabilities within method classes.

linked survey-register data from the municipality of Amsterdam on the neighborhood of residence, a multiple latent variable model estimated error rates, both in the administrative register and in the survey for different data collection modes. The register was indeed estimated to be of excellent quality with an average 0.5% error rate. In this case, therefore, often-made assumptions about this administrative register’s quality do not appear to be far from the truth.

The average error rate estimated here (0.5%) was lower than that estimated from expensive audits performed by the local government, which had put the estimated average error rate at about 1.7%. On the one hand, thus, latent variable modeling may have somewhat overestimated the quality of the administrative register. On the other hand, the costs of full-scale audits compared with latent variable modeling are gigantic, meaning that a small inaccuracy still leaves latent variable modeling an attractive alternative. More studies comparing the results of such audits with those using the latent variable approach are needed, however. Particularly relevant in the Dutch context is that one estimate is below the officially mandated 1% limit and the other above it.

The two survey measures, one direct and the other derived from a question asking the respondents’ postcode, clearly showed a lower quality. When asked over the web, for instance, postcode-derived neighborhood of residence was estimated to have an error rate of between 10% and 15%. Such an error rate may be acceptably small for certain applications, while for others it may lead to rather large distortions in the final analyses of interest. For example, when the neighborhood of residence is used to link survey answers to background variables on the neighborhood level, measurement error in these linked background variables will result.

Some limitations of the present study remain. First, the administrative register in question is of course collected all over the Netherlands, not just in one municipality. This chapter’s results can therefore not be generalized to the GBA register as a whole. Second, the survey mode was not randomized so that it is difficult to attribute quality differences over survey modes to either mode or selection effects. Third, the assumption that measurement error in the administrative register is conditionally independent of the survey answers may be problematic in some cases – especially when there are strong personal incentives to provide incorrect values consistent with the register, for example when renting illegally. This possibly explains the higher estimate of quality obtained here. Fourth and finally, because only one register

measure was available it was not possible here to incorporate a method factor for the register as well as the survey measures.

In summary, latent variable modeling of linked survey-register data can be viewed as an attractive method of investigating the assumption that administrative registers are perfect. Moreover, it is the only way of estimating measurement error in “objective” survey questions without requiring a gold standard. Since objective variables such as the neighborhood of residence play a central part in many analyses, this approach appears to be a fruitful way of preventing distortions in such analyses.

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