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Tackling city-regional dynamics in a survey using grid sampling

Seppo Laaksonen
Social Research, University of Helsinki

Teemu Kemppainen
Social Research, University of Helsinki

Mats Stjernberg
Geosciences and Geography, University of Helsinki

Matti Kortteinen
Social Research, University of Helsinki

Mari Vaattovaara
Geosciences and Geography, University of Helsinki

Henrik Lönnqvist
Urban Facts, City of Helsinki

The paper examines a Finnish survey that takes advantage of explicit stratification. The stratification is of special kind due to its dual nature. The first is a standard municipality-based stratification while the second takes advantage of the grid database in which the grid size is 250 metres by 250 metres. The objective of grid stratification is to obtain more statistical power for both ends of the income spectrum of neighbourhoods, which is needed for the analysis of city-regional dynamics. Hence, the grid database is used to construct two explicit strata, one consisting of such grids where the median tax income of the adults is low (i. e., "poor" grids), and the other in which the median income is high (i. e., "rich" grids). The correct handling of these stratified data requires first merging them together, followed by the creation of single sampling weights and, finally, adjustment of these weights due to a 60 per cent non-response rate, which helps to reduce the bias of the estimates. The adjustment is strengthened with good auxiliary data from both the grid data base and other administrative sources.

Keywords: conditional sampling design, grid sampling, city-regional dynamics, administrative auxiliary variables, urban studies, segregation

1 Introduction

Is socioeconomic differentiation or segregation of a city-region a problem? If so, whose problem? These are among the most classic, yet urgently contemporary, questions in urban studies. The growing differentiation of city-regions, combined with changes in socioeconomic distributions, has focused attention on these questions in the Nordic Welfare states as well (Burgers & Vranken, 2004; Musterd, Bontje, Chapain, Kovacs, & Murie, 2007; Musterd & Ostendorf, 1998).

This is where our line of surveys begins. We have developed a series of survey settings that addresses theoretically, but also structurally meaningful differentiation. Instead of focusing on the national or municipal administrative units, our latest survey targets empirically analyzed locally meaningful structures of our city-region.

Small areas are useful in sampling designing, whether they serve as clusters or strata. In both cases, these areas require reasonable statistics. In most countries, census districts or postal codes are the smallest administrative areas available. Even so, they are rather large and living conditions may vary substantially within each such area. Grid-based data provide the opportunity to carry on toward smaller areas and offers the opportunity to avoid these problems, provided the grids are small enough. In Finland, the size of the smallest grids is 250 metres by 250 metres (Statistics Finland, 2013). This minimum size is determined for reasons of confidentiality. In this paper, we use these grids, except those with less than ten adults with tax income, for which Statistics Finland does not release any data (Table 1).

We used small grids in our sampling for a specific region-related reason. Since the early 1960s, major urban areas of the region have implemented policies of social mixing; the planning and construction of new, high-rise housing areas have mixed different tenure types, resulting in a mosaic-like socio-economic mix in the spatial structure of the city (Vaattovaara, 1998). Because both, socio-economic and ethnic differences, have grown significantly since the early 1990s (Vaattovaara & Kortteinen, 2003), spatial differentiation within this fine-grained social mix has deepened (also Vaattovaara, Schulman, & Kortteinen, 2012). To come to grips with this micro-level differentiation, we created three types of grids based on the median taxable income of the adults. We carried this out in a straightforward manner so

Contact information: Seppo Laaksonen, Social Research, Box 68, 00022 Helsinki University, Finland (seppo.laaksonen@helsinki.fi)

Table 1
Statistics of grids where one or more adults living

Type of area	Number of grids	Population of 25–74 years
The first sampling frame	2245	302798
Stratum of poor grids	1058	232416
Stratum of rich grids	1187	70382
The second sampling frame	6636	396927
Municipality strata without confidentiality exclusion	5020	390142
Excluded due to confidentiality from the grid-based sample but not from the municipality sampling	1616	6785
All	8881	699725

that one group covers the grids of the highest income quintile, and the second, the lowest one, respectively. We later call these "Rich grids" and "Poor grids", and the remaining group, "Intermediate grids". The greatest differences in attitudes, opinions and so on are expected to arise between those margin grids.

Our small grids are artificial, but they are the only available way to understand the effects and significance of this policy under the conditions of differentiation. Fortunately, the use of small grids also allows for creating new, larger areas by merging, a sensible approach in the growing, detached, unmixed suburban fringes. As a result, grid-based sampling allows the flexible use of different scales in various parts of the region based on their spatial structure and on the question our analysis aims to address. (Flatley & McIntosh, 1999; Flatley, McIntosh, & Vaattovaara, 1999).

Grid-level data are becoming more widely available in Europe. The other Nordic countries and some other European countries (i. e. The Netherlands, Slovenia and Spain) have for years produced respective data sets. Furthermore, Eurostat have undertaken initiatives to develop a European-wide population grid data set (see the Geostat Website[1]). Although grid data are not really applied for sampling purposes, some plans fortunately exist. Portugal (Santos & Schoenmakers, 2013), for example, has developed a sampling infrastructure with 1×1 km grids, stating that this approach incorporates a degree of freedom in the sampling process upon application of the infrastructure. Although their grids are larger than ours, they are smaller than, for example, postal codes.

Because these small grids are available in many countries with varying urban policies and structures, the mode of sampling we propose could, if applied internationally, provide empirical grounds for evaluating the effects of very different traditions of urban policies on the micro level. Another equally important benefit of contextual data, such as grid data, is to be able to tackle the alarmingly high non-response, which is a challenge that becomes even more pressing in the future, as response rates continue to decrease. A thorough analysis of non-response helps to obtain more accurate results, which is evidently important regarding policy implications.

The municipality data were expected to be sufficiently accurate, while we had to be able to compare those three grid groups (rich, poor and intermediate). Thus, the sampling design is two-fold: one part of the design is based on the strata of the two margin grid groups, and the second, on traditional municipality strata. This enables us to compare these two designs thoroughly. Because we wish to analyze all the data in the same framework at the same time, and because we are using a single data set, we must create only the single rather than several sampling weights, which would complicate the analysis.

This paper focuses on presenting the methodology for our two sampling designs and for constructing the sampling weights for the single data set of the respondents, along with some basic results. In the next section, we present our target population and the frame population, respectively. One special part of the frame is thus the grid database; we present its principles in Section 2. Section 3 explains the other features of the sampling design. The response rate of the survey was lower than expected, so without sophisticated weighting adjustments, non-response bias could pose the problem. Section 4 describes the methodology for adjustments. The same section also highlights the importance of the auxiliary variables in the adjustments. The final two sections present some sample results with and without adjustments, as well as summarize our findings and conclusions.

2 The target population, the frame data and the starting points of the sampling design

The target population of the survey comprises people from 25 to 74 years of age living in southern Finland whose mother tongue is either Finnish or Swedish, the official languages of the country. Those with other languages as their mother tongue were excluded, as the topic of the survey is likely of little interest to most of them. The questions of the survey enquire about issues, such as attitudes and opinions that are easier to answer if the respondent has been living for a long time the local area. It is important to note that Finnish- or Swedish-speaking residents with little interest in their living area may also be uninterested in participating in the survey. Section 4 illustrates these features through our auxiliary variables.

The survey takes advantage of explicit stratification so that sample units are drawn randomly within strata. Stratification

[1] http://epp.eurostat.ec.europa.eu/portal/page/portal/gisco_Geographical_information_maps/geostat_project

is unusual, due to the two types of strata and the two sampling frames respectively. These correspond to a dual-frame sampling design in which units within the target population are selected via independent probability samples drawn from each of two frames (Buskirk, 2008). These two frames of our study, the first for the grid sampling and the second for the municipality sampling, comprise the target population and also overlap (see Table 1 for statistics of grids and population). Our first stratification thus is of a special kind, covers only the selected parts of the region and stems from the need to cover both ends of the income scale more extensively than can conventional stratification alone. The second strata are constructed on the basis of municipalities and cover the study region exhaustively. This second stratification is thus ordinary and need not be explained in detail. We will therefore focus next on explaining the first grid-based stratification.

Statistics Finland maintains the grid database and downloads its population and tax data from registers to each grid. The data are quite up-to-date: the latest update for population data is two months old, but the tax data are more than one year old. Such register grid-based information has been served first to create the two explicit strata: one consisting of grids containing the median tax income of adults belonging to the highest quintile, whereas the second explicit stratum consists of grids with the median income from the lowest quintile. We call the previous grids “rich grids” and the latter grids “poor grids,” respectively; the remaining “intermediate” grids are excluded from the first stratification, but appear randomly in the municipality data.

Figure 1 illustrates these grids in one part of the covered region. We clearly see that the different types of grids are spread around, although some concentration is also present; it is clear, however, that the municipal boundaries are not important. Thus, the use of such grid-based stratification is beneficial. The figure also shows completely empty grids as well as confidential ones that could not be used for our sample (cf. Section 1).

Table 1 provides some statistics on all populated grids. The number of confidential grids is rather large, but the number of people living there is small so that we lose few potential respondents. Of course, our target population does not include the grids of rare people. Interestingly, the grids of rich people are far less populated than the grids of poor people, which is important to remember when interpreting the results later. On the other hand, the use of traditional stratification would make it obvious that obtaining enough people of rich grids in particular would be difficult. Fortunately, our large enough sample allocation for both types of grids guaranteed in advance that this would not be a problem.

Note that this grid-based sample does not include the intermediate income quintile grids. Fortunately, the people living in the intermediate grids have a non-zero inclusion probability in the second sample, which is part of a traditional stratified random sampling with explicit administrative strata (municipalities, merged municipalities or submunicipalities). It is important to recognize that the survey from both explicit strata can include the target population of residents in both rich and poor grids, respectively. Thus, the second sampling design is conditional on the first sampling design.

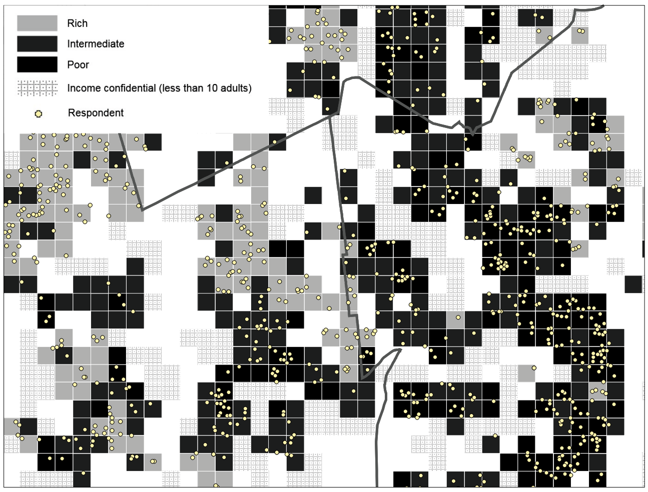

Figure 1. Grids in a selected border region of three municipalities, and the respondents of the survey. White grids are without inhabitants. The minimum income of rich grids is 73.2 k €, the maximum of poor grids is 32.1 k €

The design is conditional such that if a person has been selected for the first (grid) sample, he or she and his or her entire dwelling is excluded from the second sample selection. This overlap leads to a special strategy for creating inclusion probabilities and, consequently, the sampling weights for the entire data set, since we aim to create the correct single weights for each sampled person (and later for each respondent). This is especially possible for the second (municipality) sample, since we know their frame population from the register.

The next section explores any detailed sampling issues and presents the formulae for the non-traditional design weights. The data collection mode in our survey is mixed, since a potential respondent had the opportunity to reply via either the web or an ordinary paper questionnaire. The overall response rate was rather low, about 36 per cent. Use of the web mode was somewhat unpopular, possibly because the external fieldwork sub-contractor provided insufficient incentive to use this mode. The web was more popular in rich grids (17.3% replied via the web), and less popular in the intermediate grids (15.5%). Section 4 presents additional results from the fieldwork outcome and focuses on the non-response analysis. We were able to provide useful auxiliary data from registers for this purpose. As a consequence of the non-response analysis, we created the adjusted weights used in the subject-matter analysis. This procedure also appears in Section 4.

3 Details of the sampling design and design weights

The survey covers the 16 municipalities of southern Finland (see Table 2). The grid survey was not conducted in two municipalities (Lahti and Lohja), but because the grid data were incorporated into these municipalities later, we know whether a gross sample person lives in a rich or poor grid in all municipalities. The remaining people live in intermediate grids. These income groups are determined by the tax statistics of the 14 municipalities.

The sampling design is based on explicit stratification so that within each stratum a random selection was used. This is easy for the first sample, which uses two grid-based strata, but is more complex for the second sample, since it should exclude the sample units from the first sample. Below we explain this conditionality problem in detail, but first, we present how the first sample has been designed.

Section 2 presented the procedure for determining the two strata from all grids. The grid database on tax income is the most recent possible, from 2010, though the sample and the survey fieldwork were conducted in 2012.

The first sample is thus drawn randomly from the two strata. The people can be selected from all municipalities (except Lahti and Lohja), although some municipalities seem to be quite empty of both grid strata. Another criterion for selecting a person is that only one person can be selected from any dwelling unit, which in most cases corresponds to a household, but can also be much larger.

The second sample, respectively, has been drawn from each municipality stratum (Table 2), also at random, but such that a dwelling unit already selected for the first sample is no longer available for the second sampling frame, a condition that is difficult to implement. Consequently, we must calculate the inclusion probabilities for the entire sample with certain assumptions. One is that we explicitly know the population of the target population by municipality strata (for all 699725 inhabitants; Table 2). We also know the population of both grid strata (Table 1). One initial problem was that we did not know the populations of the poor and rich grids by municipality. Fortunately, we obtained this information later from another register. This information now served to create post-strata for the first sample in order to distinguish these grid sample units from those of the second sample (municipality). Since the initial sample for both strata was selected at random, such post-stratification is allowed to add strata within both initial strata.

Our strategy for calculating the inclusion probabilities and the design weights, respectively, is as follows. Let π_k be the inclusion probability of target person k. Moreover, h refers to the municipality stratum used for the two municipalities (Lahti and Lohja). The inclusion probability for these municipalities is simply

$$\pi_k = \frac{n_h}{N_h} \quad , \tag{1}$$

with N being the size of the target population.

Since the grid-based sampling was drawn first, and simple random sampling took place within the two strata, we can calculate without difficulty the inclusion probabilities for these two strata similarly to Equation (1). These are thus the groups concerned $k \in \{\text{poor}\}$ or $k \in \{\text{rich}\}$. Such inclusion probabilities can be used for the separate grid-based sample, but doing so it is not satisfactory, since we wish to obtain only one single data set. Consequently, we first merged both data sets according to postal zip codes. At this stage, we have the correct inclusion probabilities only for the two municipalities Lahti and Lohja.

Thus, if

$$k \notin \{(\text{poor}, h) \cup (\text{rich}, h)\} \quad ,$$

then the inclusion probability of k is the inclusion probability under the second (municipality-based) sampling. Calculating the correct probabilities for these units leads to three explicit strata by 14 municipalities, that is, the grids of rich people, the grids of poor people and the area of all types of people independently of whether their grids are rich, poor or intermediate (“all, h” in Table 2).

To calculate these 3×14 inclusion probabilities, both gross sample sizes n_{hd} and the population figures N_{hd} are needed where d refer to the further partitions of the initial municipality strata. Our solution to this partition is post-stratification. This method is conditional to the sampling design that was stratified simple random sampling. We thus create three post-strata for each municipality yielding 42 such strata altogether.

The subscripts “rich, hd” and “poor, hd” refer to the grid-based post-strata within municipality stratum h; consequently, the subscript “all, hd” refers to the post-stratum that may include all types of grids. These figures appear in Table 2. The number of all strata is $3 \times 14 + 2 = 44$. Here the number 2 concerns the municipalities Lahti and Lohja.

Moreover, we also need the correct target population size for each post-stratum. As noted above, we could calculate these figures from the separate population register data. Symbolising these figures as $N_{\text{rich},hd}$ and $N_{\text{poor},hd}$, it follows that

$$N_{\text{all},hd} = N_h - (N_{\text{poor},hd} + N_{\text{rich},hd}) \tag{2}$$

We can now straightforwardly calculate the inclusion probabilities for each post-stratum.

Formula (3) is for the rich grids in each municipality h, as in the other two post-strata poor and all.

$$\pi_k = \frac{n_{\text{rich},hd}}{N_{\text{rich},hd}} \tag{3}$$

Table 2
Distribution of the gross sample to strata (n). The group "Others" in the above scheme is equal to municipality gross sample size. For the symbols, see also the text. Even though a grid can cross the boundary of municipalities, it is unambiguously assigned to one municipality in the grid data base (c. f. Figure 1)

	Poor grids poor, h	Rich grids rich, h	Municipality all, h	Total	25-74 year Population N_h
Helsinki, most urbanised southern area	110	46	1000	1156	27465
Helsinki, most urbanised northern area	1142	8	1000	2150	40206
Helsinki, suburb	2501	1324	2500	6325	147098
Espoo and Kauniainen	546	3127	2000	5673	131840
Hyvinkää	248	64	600	912	24944
Järvenpää	115	38	600	753	21717
Kerava	124	48	600	772	18874
Kirkkonummi	89	173	600	862	20065
Lahti	0	0	1000	1000	57059
Lohja	0	0	600	600	22613
Mäntsälä and Pornainen	49	22	600	671	13850
Nurmijärvi	85	120	600	805	21924
Sipoo	48	134	600	782	10269
Tuusula	118	201	600	919	20948
Vantaa	746	574	1500	2820	104930
Vihti	81	121	600	802	15923
All	6000	6000	15000	27000	699725

We can now calculate the sampling design weights as the inverses of the inclusion probabilities. The gross sample figures of Table 3 provide some statistics about these weights.

4 Weights for the respondents

Our mixed-mode survey was inexpensive, but obtaining high response rates without personal contacts is difficult. This was expected, so our allocation for gross sample sizes was rather high. The overall response rate is fairly low, but we are satisfied with the numbers of the respondents. Although the response rates varied, we were able to further control for them with auxiliary variables. Figure 2 illustrates these differences by areas, though not all details are easily recognised. However, it is clear that people in metropolitan Helsinki (the southern part of the figure) participated relatively well, possibly for the following two reasons: (i) participation by web was an option, and people in this area are more familiar with web; (ii) the survey motivated more urban people than rural people to participate.

The gross sample weights described in Section 3 must be converted for the respondents. This was first done assuming that the response mechanism is ignorable within each stratum or post-stratum. It follows that replacing gross samples sizes, n, with the respective number of the respondents, r, yield the sampling weights. These weights for the respondents are called the "initial weights" and are symbolised as w_k. We do not present these formulas here, but some figures

Figure 2. Local Response Rates. Rates were calculated for the neighbourhood (300 nearest neighbours) of each gross sample unit (n = 27000). Darker shades indicate lower response rates. There is a small amount of random noise in the coordinates due to information security

Table 3
Some statistics for the gross/net sample design weights, and for adjusted weights

Statistics	Grid part Gross	Grid part Net	Municipality part Gross	Municipality part Net	Adjusted for for all
Observations	12000	4387	15000	5222	9609
Population	302798	302798	396927	396927	699725
Mean	25.8	70.6	27.1	77.8	74.6
Minimum	8.3	18.2	13.1	39.0	11.0
Maximum	45.6	164.2	57.1	167.8	834.3
CV (%)	54.6	61.4	36.4	39.9	68.9

for the weights appear in Table 3.

We find that the weights vary more in the grid part due to fairly detailed post-stratification. Naturally, the weights are increasing for the respondents due to non-response, but it is not necessarily a concern for the relative weights. This is due to large differences in the sampling fractions, since we wished to get enough respondents from rural municipalities as well. Correspondingly, their gross sample weights are fairly small, but because their response rates are relatively low, their initial weights are relatively high. This is a peculiarity of this survey, and its implications can also be found in the final results.

We can analyze many things with a cross sample, since we were able to download from the registers a rather rich auxiliary data pattern. However, because our survey analysis can only be completed on the respondents, we must analyze the non-response and, consequently, to create the adjusted weights. Our strategy for the weighting adjustments is as follows (Laaksonen, 2007; Laaksonen & Heiskanen, 2014):

1. We take initial weights w_k and divide them by the estimated response probabilities (called also response propensities) of each respondent obtained from the logit model and symbolised by p_k.

2. Before moving forward, it is good to ensure that probabilities p_k are realistic, that is, they are not, for instance, too small. Naturally, all probabilities are less than one.

3. Since the sum of weights w_k does not match the known population statistics by strata h or by post-strata "rich, hd", "poor, hd" or "all, hd", they should be calibrated so that the sums are equal to the sums of the initial weights in each stratum or post-stratum. This is possible by multiplying the weights w_k by the ratio

$$q_h = \frac{\sum_h w_k}{\sum_h \frac{w_k}{p_k}}$$

in which h may refer to post-strata also.

4. It is also important to verify these weights against basic statistics, such as those presented in Table 3. If the weights are implausible, the model should be revised.

Step 1 also includes the non-response analysis. Here we applied the logit regression in an attempt to apply about fifty auxiliary variables from the individual, building and grid levels. One drawback was that we could not obtain individual-level education information.

We constructed the response propensity model using the auxiliary variables that we supposed to be related to the phenomenon of non-response. What is noteworthy in our model is the incorporation of grid-level variables into the model building process. To our knowledge, this is the first use of grid-level information to adjust weights for non-response. Balancing the goal of prediction with a modest degree of parsimony, we eventually settled on a model that includes the following variables (Table 4):

- interactively coded variable of age (categorical) and gender
- income (categorical)
- the proportion of residents with a higher university degree in the grid (categorical)
- rough area variable based on the first three digits of the postal code
- mother tongue
- employment status
- current and previous living area
- change in two most recent home sizes
- type of grid (this was also available for the municipality part when adjusting, but not in sampling)
- dwelling size.

Our data provide an opportunity to try a number of areal categorisations, but we chose a categorization based on three-digit postal codes in order to capture some of the effect of the unobserved, spatially correlated variables; we merged very small categories with their neighbours.

Age and gender were coded interactively in order to allow for the interaction of these basic demographic variables. The categorisation of the income and education variables was based on the tree algorithm of SPSS ("IBM SPSS Decision Trees 20," n.d.). We performed a simple classification individually for both continuous variables with respect to the response indicator. The class boundaries obtained served to categorise the variables.

For reasons of confidentiality, information on the educational level of the grid was unavailable for certain grids. For

Table 4
Outcomes from the response propensity modeling by logistic regression. The detailed area variable not included

Category	Estimate	Standard error	p-value
Type of grid (ref.: Rich)			
Intermediate	0.0362	0.0099	<.0001
Poor	0.0578	0.0109	<.0001
Gender *x* Age group (ref.: Female 65-74))			
Male 25-34	−1.768	0.0136	<.0001
Male 35-44	−1.6270	0.0139	<.0001
Male 45-54	−1.4304	0.0129	<.0001
Male 55-64	−0.8467	0.0121	<.0001
Male 65-74	−0.3299	0.0664	<.0001
Female 25-34	−0.9540	0.0127	<.0001
Female 35-44	−1.0827	0.0133	<.0001
Female 45-54	−0.8301	0.0122	<.0001
Female 55-64	−0.3384	0.0112	<.0001
Mother tongue (ref.: Swedish)			
Finnish	−0.002	0.0117	0.8639
Income group (ref.: Highest)			
Lowest	−0.9835	0.0106	<.0001
Second lowest	−0.6248	0.0102	<.0001
Third lowest	−0.3733	0.0099	<.0001
Third highest	−0.4978	0.0096	<.0001
Second highest	−0.2588	0.0072	<.0001
Employment (ref.: employed)			
Unemployed	−0.0748	0.0134	<.0001
Education of grid (ref.:Lowest)			
Second lowest	0.1154	0.0009	<.0001
Second highest	0.1886	0.0080	<.0001
Highest	0.2896	0.0120	<.0001
Number of people in the dwelling (ref.: 6+)			
1	0.2929	0.0234	<.0001
2	0.5262	0.0221	<.0001
3	0.3701	0.0226	<.0001
4	0.3619	0.0226	<.0001
5	0.2648	0.0250	<.0001
Moved to the current house (ref.: after 2006)			
Before 1995	0.0201	0.0066	0.0022
Between 1995-2006	−0.0793	0.0078	<.0001
Size of current house (ref.: Substantially larger)			
Substantially smaller -0.0733	0.0064	<.0001	
About as big as earlier	−0.0342	0.0073	<.0001
Current and previous living area (ref.: Moved within the seam zip code area)			
Moved to southern Finland	0.0365	0.0125	0.0036
Moved a longer distance	0.0506	0.00658	<.0001

these grids, we imputed the average educational level at a postal-code level (three digits). The confidentiality issue precluded the use of this solution for six postal code areas. As a work-around, we imputed the value of the nearest neighbouring postal code area with a valid value.

The results of the response propensity model appear in Table 4. Women were, as usual, more likely to respond than men. Response propensity increases in both genders with age. There is a clear gradient with individual income such that those with higher incomes are more likely to respond. When accounting for the other variables, the proportion of residents with a higher university degree in the grid predicts response propensity, even though its predictive power is fairly weak.

It should be noted that we tested more variables before settling on this model. As an example, individual-level variables on employment status had no predictive power once we included income in the model. Grid-level unemployment had virtually no predictive power when the model included the above-mentioned education variable. Because we did not obtain the individual-level education variable, we should offer no strong conclusions about possible effects of neighbourhood education level on survey response. Inclusion of the corresponding individual variable would likely have rendered negligible the predictive power of the grid-level education variable. The predictive power of the individual income variable might also decrease with the inclusion of individual education.

Because they are uninteresting to outsiders, the areal results do not appear in Table 4. One result, however, is worth mentioning. The persons sampled within the capital city, Helsinki (especially its suburban areas), replied more often than did those in other municipalities (see also Fig. 2). This is not usual in Finnish surveys, possibly because the survey is more interesting for people living in semi-highly populated areas.

Estimates for this type of grid seem surprising, since the worst respondents were in the rich grids, possibly due to two other variables in the model: the income and education level of a grid, respectively. This difference in response rate is evident from a model without these auxiliary variables. In this case, people in rich grids reply the best, whereas those in poor grids reply the worst.

We found no significant difference according to mother tongue, but the dwelling size was significant. As often single people were often less interested in participating, but those living in large dwellings were even less so, possibly because such large dwellings are in most cases student houses, elderly homes and other non-conventional households.

It is difficult to interpret the results of the last three variables of Table 4. It is surprising that people continuing to live in the same postal area were quite unwilling to participate. In contrast, if a new home is substantially larger than

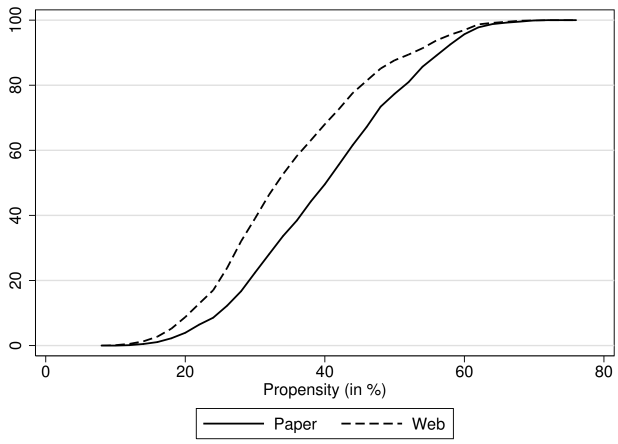

Figure 3. Example of the cumulative response propensities for the respondents via web (dashed line) and via paper (solid line), respectively

the previous one, the person living there was more motivated to participate in this survey.

We cannot straightforwardly compare the response activity by our two survey modes (paper and web), but our model provides the opportunity to calculate the distribution of response propensities by both types of respondents; the result (see Figure 3) shows lower propensities for web responses than for paper responses, respectively. This is due to the model with many auxiliary variables. We interpret the result so that the web option motivates different types of people to participate. Respectively, without a web option the response rate would be even lower.

Figure 3 also shows the highest and lowest propensities, though the variation is negligible and unproblematic when adjusting for the sampling weights. Naturally, however, their variation increases; the coefficient of variation is now 68.9 percent, which is somewhat higher than that of the initial weights for the grid-based respondents (61.4%; Table 3). Of course, the adjustment does not change the mean or the sum of the weights.

5 An example of the survey results

In this article, we do not in this study focus on subject-matter issues, but present some key results in Table 5. They show substantial differences between rich, poor and intermediate small areas measured as 250×250 metres grids. People in rich grids seem more satisfied in their living areas, a result that could not be found in the administrative regions.

Table 5 also illustrates differences between estimates and their standard errors without using any weights and with sophisticatedly adjusted weights, respectively; the latter ones showed less biased. Interestingly, the standard errors of these latter estimates are smaller, likely due to the fact that the re-

Table 5
Weighted and un-weighted averages on people's opinion on their living area by the type of a grid. Indicators are scaled so that 0 = lowest, 100= highest

	No weights		Adjusted weights	
	Mean	Std. Err.	Mean	Std. Err.
General assessment of living area				
Rich	83.7	0.64	83.2	0.44
Intermediate	79.3	0.53	74.5	0.48
Poor	65.1	0.82	61.7	0.55
All	74.6	0.19	72.2	0.24
Quality of environment				
Rich	79.8	0.49	79.6	0.32
Intermediate	75.2	0.36	74.4	0.37
Poor	65.6	0.55	65.2	0.38
All	73.6	0.17	71.0	0.22
Unsafety				
Rich	1.8	0.26	2.0	0.34
Intermediate	5.1	0.37	5.3	0.44
Poor	12.7	0.58	13.0	0.67
All	6.8	0.26	8.3	0.35
Quality of services				
Rich	69.4	0.61	68.8	0.43
Intermediate	73.8	0.43	69.0	0.37
Poor	75.8	0.57	73.1	0.38
All	70.6	0.20	70.8	0.24
Amount of problems				
Rich	34.9	0.92	34.9	0.58
Intermediate	49.7	0.71	44.3	0.61
Poor	70.6	0.90	66.9	0.58
All	48.8	0.33	53.2	0.38
Subjective poverty				
Rich	26.4	0.38	27.6	0.43
Intermediate	34.8	0.36	37.1	0.44
Poor	40.3	0.40	42.5	0.50
All	34.3	0.23	38.2	0.30

sponse rates in rural areas are lower, though their sampling fractions are higher.

Both the un-weighted and adjusted estimates are fairly similar for rich people grids, but not for other grids. Thus, when comparing different grid groups, un-weighted results could lead to incorrect conclusions. Table 5 also shows the estimates of the entire target population (all) both with and without adjusted weights. Except for quality of services, all other estimated indicators differ significantly. However, these differences are significant for poor and intermediate groups, but not for rich groups.

We thus find that the use of small grids provides an opportunity to analyze neighbourhoods in much more detail than ordinary analysis with administrative areas do. But how well could such analysis be conducted without grid-based sampling? We cannot answer this question completely, but we can illustrate it with the two alternative approaches that use our data from the respondents.

Our gross sample in the grid-sample municipalities is 12 000 for the grid sampling and 15 000 for the municipality sampling. These samplings differ little, but the grid-based estimates might be a bit more accurate if the sampling sizes were more equal. We were therefore able to draw a fairly large sample from rich grids and also a relatively large sample from poor grids, thereby making the point estimates — and the accuracy estimates in particular — more precise. The intermediate grids can easily be covered well even with traditional approaches, but these approaches are of little interest to us.

To illustrate the quality of the estimates, we calculated the average estimates of all six indicators of Table 5 based on both municipality data and grid-based data. The point estimates differ relatively little, so we do not present them in detail: the standard errors, on the other hand, are more interesting. The average standard error of their six indicators is 0.65 for municipality data and 0.47 for grid-based data, respectively; in other words, the reduction with grids is 28 percent. For rich grids, the corresponding figures are 0.86 and 0.34. The reduction in the standard errors is thus even greater, 60 percent. This reduction especially reveals the importance of our sample for analysing rich grids.

6 Summary and Conclusion

This paper represents one methodological outcome of the project that aims to elucidate the city-regional dynamics of the Helsinki metropolitan area. Previous studies have used similar questions, but their ability to tackle micro spatial variation has remained weak as the administrative unit has usually been postal code if any. Administrative areas distinguish poorly between people's neighbourhoods, which can significantly influence their living conditions, attitudes and opinions. We noticed that areas smaller than municipalities or postal code zones are necessary to carry out a deeper analysis.

This study found that the use of small grid cells is possible not only in the analysis, but also in designing the survey. This led to sampling that exploited grids so as to identify two special types: grids with rich people, and those with poor people. On the other hand, the second sample was designed ordinarily. Although this dual partition did not facilitate we nevertheless did manage to create the sampling weights that enabled us to analyze everything with a one single data set.

The survey mode of the study was mixed so that everyone could reply via either web or paper. A majority chose the paper questionnaire, although we anticipated more web responders. Nevertheless, the overall response rate was low (36 percent). The selectiveness of the respondents was rather clear, but less alarming than expected based on a rich pattern of auxiliary variables used in the non-response analysis. Our logit regression served to adjust for the initial weights in order to reduce the bias in the results.

Many countries have developed grid-based data, and the EU statistical office Eurostat has focused their attention on this approach. Geostat was launched at the beginning of 2010 in co-operation with the European Forum for GeoStatistics (EFGS) to promote grid-based statistics and, more generally, to work towards integrating statistical and geospatial information into a common information infrastructure for the EU.

Population census data are available for all EU countries by 1-km grids. The grid database in Finland is not unique, and respective opportunities are available in many countries, including other Nordic countries, The Netherlands, Slovenia and Spain. Thus, grid-based sampling is also becoming possible, and the experiences of our pioneer study can be used and developed further. This kind of sampling can be used in other ways, including constructing small-area primary sampling units. It gives opportunity for new two-stage cluster sampling strategies.

Our analysis provides grounds for two conclusions. Firstly, context or area-level auxiliary information offers indispensable tools for designing targeted social surveys. It also contributes to the analysis and adjustment of non-response, especially when individual-level auxiliary information is limited, which is often the case. This kind of approach to non-response analysis is likely to extend the period of validity of random sample-based social survey research in which the non-response rate rises virtually year by year. The key advantage is to obtain estimates that are less biased and on a small-scale level. In other words, if the sampling weights are constructed as we present in this study, one can work reasonably well with both small areas and low response rates.

Secondly, a sampling technique such as this one, with sophisticated weights to adjust for the high non-response rate, allows for accurate analysis of the contextual or neighbourhood-level variance needed to cope with the results of differentiation in a fine-grained social mix prevalent in the urban centre of the Helsinki region. In conditions of small-scale social mixing, the use of multiple spatial units is especially interesting: on this basis, we can come to grips with different social settings constructed through the policy of mixing (a small group of poor in the middle of a larger, well-off neighbourhood, or vice versa). By distinguishing situations such as these in the analysis of possible neighbourhood effects, future empirical studies can, hopefully, shed light on the effects of these policies. If we can catch the intracity dynamics of the attitudes and well-being of the residents in different types of neighbourhoods within the context of a Nordic welfare state, we can hopefully contribute not only to the theorising of the mechanisms of segregation and their possible effects, but also to the globally interesting universalistic assumptions of welfare and housing policies.

References

Burgers, J. & Vranken, J. (2004). *How to make a successful urban development programme. Experiences from nine European countries*. Antwerpen/Apeldoorn: Garant.

Buskirk, T. (2008). Dual-frame sampling. Sage Research Methods. Retrieved from http://knowledge.sagepub.com/view/survey/n148.xml

Flatley, J. & McIntosh, S. (1999). *Social inequality, spatial segregation and the BETWIXT cities: the European context*. Between Integration and Exclusion: a Comparative Study in Local Dynamics of Precarity and Resistance to Exclusion in Urban Contexts. Social inequality and spatial segregation in seven European cities. Stage A Report. Co-financed by the European Commission DG XII, TSER programme.

Flatley, J., McIntosh, S., & Vaattovaara, M. (1999). *Segregation and the seven cities. The analysis of common indicators and maps: concluding review*. Between Integration and Exclusion: a Comparative Study in Local Dynamics of Precarity and Resistance to Exclusion in Urban Contexts. Social inequality and spatial segregation in seven European cities. Stage A Report. Cofinanced by the European Commission DG XII, TSER programme.

IBM SPSS Decision Trees 20. (n.d.). Retrieved from ftp://public.dhe.ibm.com/software/analytics/spss/documentation/statistics/20.0/en/client/Manuals/IBM_SPSS_Decision_Trees.pdf

Laaksonen, S. (2007). Weighting for two-phase surveyed data. *Survey Methodology*, *33*(2), 121–130.

Laaksonen, S. & Heiskanen, M. (2014). Comparison of three modes for a crime victimization survey. *Journal of Survey Statistics and Methodology*, *2*(4), 459–483.

Musterd, S., Bontje, M., Chapain, C., Kovacs, Z., & Murie, A. (2007). *Accommodating creative knowledge. A literature review from a European perspective*. ACRE report 1. Amsterdam: AMIDst.

Musterd, S. & Ostendorf, W. (1998). *Urban segregation and the welfare state. Inequality and exclusion in western cities*. London: Routledge.

Santos, A. & Schoenmakers, B.-J. (2013). *Using the European grid "ETRS89/LAEA_PT_1K" as the foundation for the new Portuguese sampling infrastructure*. European Forum for Geostatistics, Sofia Conference, 23-25 October.

Statistics Finland. (2013). Grid database. Retrieved from http://www.stat.fi/tup/ruututietokanta/index_en.html

Vaattovaara, M. (1998). *Pääkaupunkiseudun sosiaalinen erilaistuminen (recidential differentiation within the metropolitan area of Helsinki)*. Helsinki: Helsinki Urban Facts.

Vaattovaara, M. & Kortteinen, M. (2003). Beyond polarisation versus professionalisation? A case study of the development of the Helsinki region, Finland. *Urban Studies*, *40*(11), 2127–2145.

Vaattovaara, M., Schulman, H., & Kortteinen, M. (2012). A nordic welfare model at a turning point? Social housing and segregation in Finland. In J. Driant & N. Houard (Eds.), *Social housing across Europe*. Paris: La documentation Francaise.