

Which Businesses Respond to Surveys? Evidence from Dutch Administrative Data

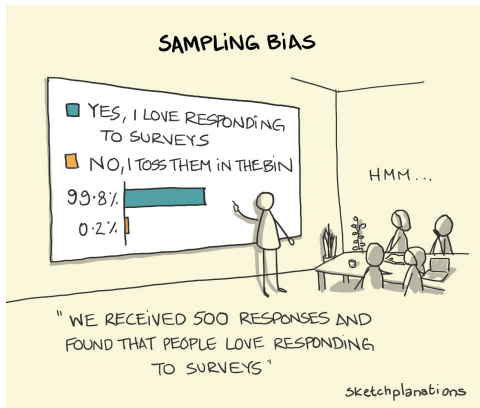
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Vrije Universiteit Amsterdam and Tinbergen Institute

November 3, 2025



Sampling Bias in Business Surveys

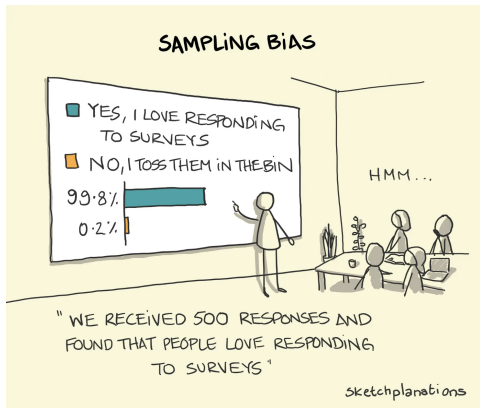


Everybody thinks that their survey is representative of their population of interest

- **Fundamental problem:** Entities differ in their propensity to answer surveys

Source: sketchplanations.com/sampling-bias

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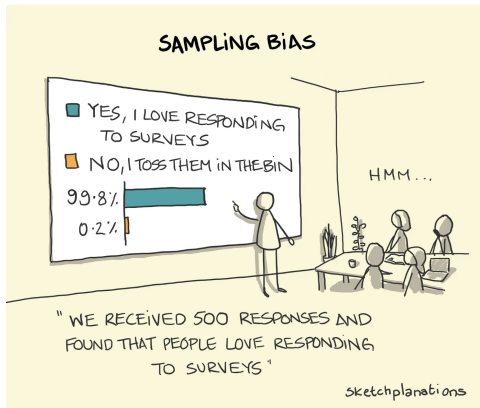
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There are well-established methods for addressing this problem in individual/household surveys

- **Idea:** Calibrate sampling/weights so samples look similar to general population data (e.g., a census)

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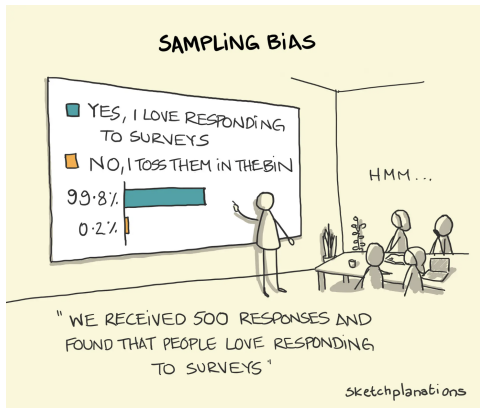
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- This is because there typically is no 'business census' containing unresponsive businesses

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Important because business surveys are often used in academia and policymaking [Literature](#)

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Highlights implementation and generalizability challenges in business surveys, as well as opportunities for improvement

LISA and the Regional Work Registers



Each year, regional work registers in the Netherlands run *werkgelegenheidsenquêtes*

- Surveys ask # male/female fulltime/parttime workers

Source: lisa.nl

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- LISA supplements the *werkgelegenheidsenquête* data with administrative records from the *Kamer van Koophandel (KVK)* and *Basisregistratie Adressen en Gebouwen (BAG)* registers

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- ▶ **End result:** Annual panel data on the universe of all establishments in the Netherlands

Data is on *establishments*, rather than *firms*

(Non-)Response

In 2022, just over 20% of Dutch establishments responded to the regional *werkgelegenheidsenquêtes* (survey type ≤ 20)

| Code | Description | % Establishments in 2022 LISA |
|------|--|-------------------------------|
| 1 | Data directly from company, statement per branch, obtained in writing, online, or by telephone | 19.066% |
| 8 | Data directly from company, temporarily no employees | 0.011% |
| 11 | Data directly from company, statement per branch, through the intervention of a third party authorized by LISA | 0.001% |
| 20 | Data directly from company total statement, to be allocated to branches | 1.205% |
| 30 | Data from secondary source per branch (e.g., KVK [recent], annual report, website, press release) | 1.407% |
| 40 | Data from secondary source total, to be allocated to branches | 0.021% |
| 50 | Data increased from previous year, VR management module | 72.55% |
| 51 | Data increased from previous year, other method | 3.963% |
| 60 | Data imputed, VR management module | 0.182% |
| 61 | Data imputed, other method | 0.103% |
| 72 | Data estimated, guesswork | 0.029% |
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Over 72% of establishments' data in the 2022 LISA register were imputed by LISA Standard LISA Imputation

- I introduce a random forest approach which more accurately imputes missing employee headcounts Random Forest Imputation
Performance Improvements

Main Variables

Main data source is FIRMBACKBONE employment data (Gerbrands et al. 2025)

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Surveyed data (observed for responsive establishments, imputed for unresponsive):

- ▶ Employee headcounts (regional *werkgelegenheidsenquêtes* and LISA/RF imputations)
- ▶ Proportions of employees that are fulltime and female (computed from employee headcounts)

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Linked administrative data (always observed):

- ▶ Establishment surface area and facility zoning function (Kadaster BAG)
- ▶ Year founded and 2008 SBI sector code (KVK)

Descriptives

| | P0.5 | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 | Mean | SD | N |
|---|------|------|-------|-------|------|-------|-------|------|------|---------|-------|----------|----------|---------|
| Employees, 2021, LISA Imputation | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 5 | 12 | 60 | 120 | 4.853 | 49.72 | 1433393 |
| Fulltime Employees, 2021, LISA Imputation | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 4 | 10 | 51 | 103 | 4.169 | 46.157 | 1433393 |
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| Proportion Employees Fulltime, 2022, LISA Imputation | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.814 | 0.366 | 1433239 |
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| Establishment Surface Area, m^2 | 17 | 28 | 55 | 70 | 100 | 140 | 233 | 695 | 1700 | 9160.16 | 16481 | 625.924 | 4784.077 | 1433393 |
| Year Founded | 2000 | 2001 | 2007 | 2010 | 2015 | 2018 | 2020 | 2022 | 2022 | 2022 | 2023 | 2016.775 | 4.803 | 1433071 |

Unbounded continuous variables exhibit extreme skew

- For firm size measures, about as much variation between the 0.5th and 99th percentiles as there is between the 99th and 99.5th percentiles
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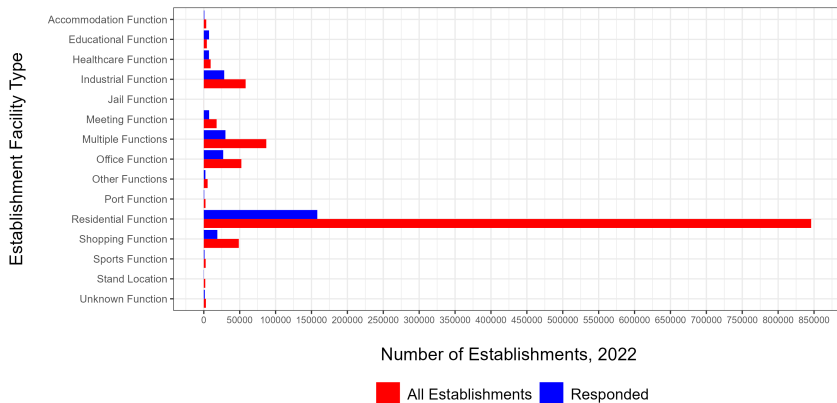
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The median establishment is a solo enterprise

- Not unique to Dutch context; similar patterns in the U.S. (Conway et al. 2018)

Facility Types



By far most common type of facility is residential, reflecting small enterprises that register at an owner's home address

[Sectors](#)[Regions](#)

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(1) is useful for understanding the generalizability of existing business surveys, whereas (2) can help plan for future business surveys

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Thanks to conditional randomization, controlling for all of these determinants in matrix X renders $\mathbb{E}[Y(1) - Y(0) \mid X = x]$ an unbiased estimator for $\mathbb{E}[Y(1) - Y(0) \mid C = c]$

Contact Determinants and Response Probability



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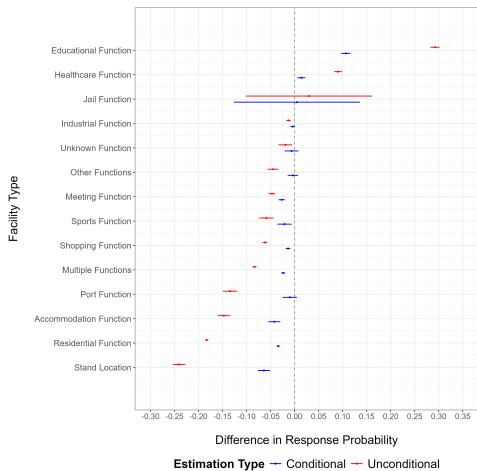
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Because these specifications control for prior year survey type, these response rate differences should only be explained by differences in contact probability

- ▶ Controlling for these determinants yields unbiased estimates of contact-conditional differences in response probability

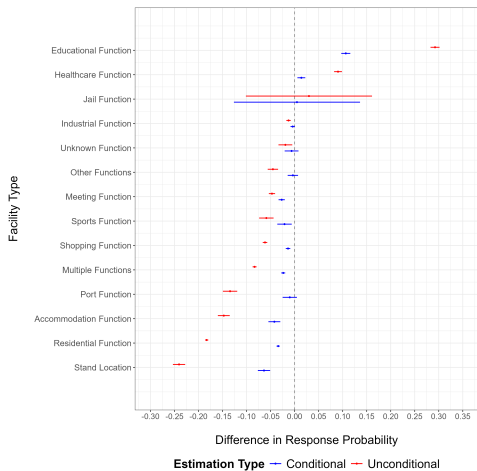
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- Educational facilities are significantly more likely to be responsive, both conditionally and unconditionally

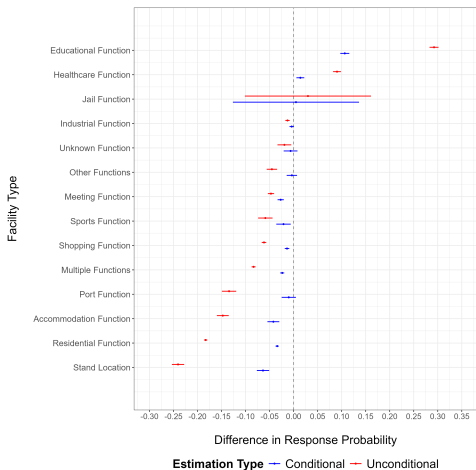
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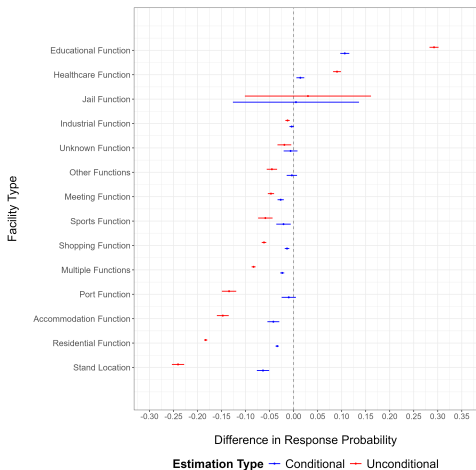
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Residential addresses are 18 p.p. less likely to respond than the average office

- ▶ Remember, residential properties are by far the most common type!

Facility Types



Compared to offices:

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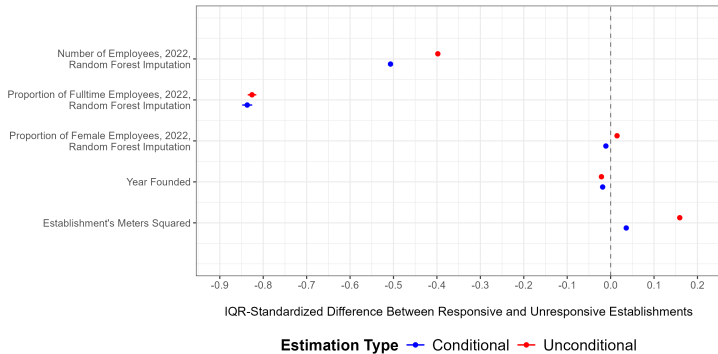
Residential addresses are 18 p.p. less likely to respond than the average office

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Controlling for contact probability collapses these estimates by over two thirds

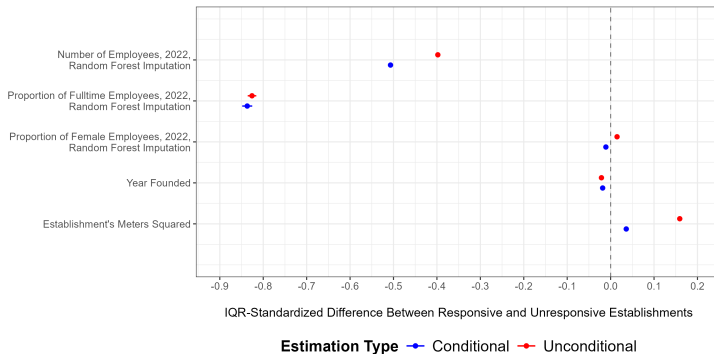
- ▶ Implies much of this representativeness gap is driven by differences in contact probability

Continuous Characteristics



Responsive establishments have ~ 2 fewer workers and are more composed of parttime workers (~ 15 p.p.); consistent with responsive establishments being more likely to efficiently divide labor

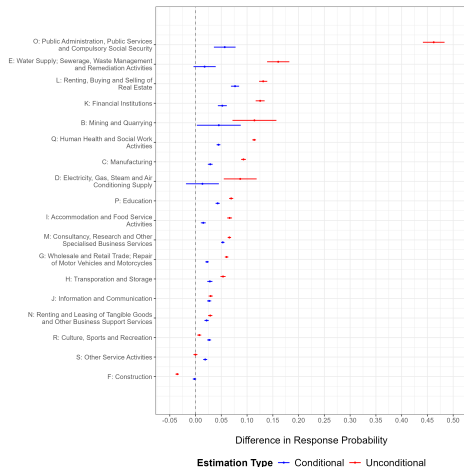
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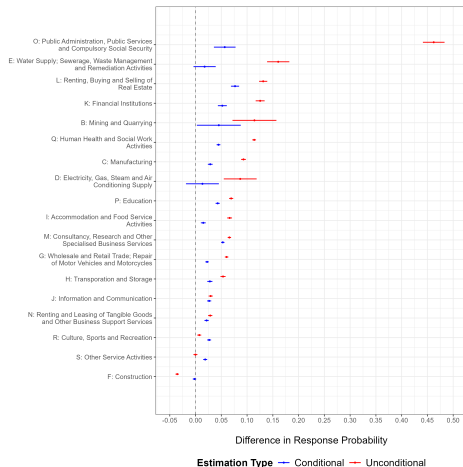
- Some measurable difference in literal establishment size, but only by $\sim 10m^2$

Sectors



Huge overrepresentation of white-collar industries in responsive establishments

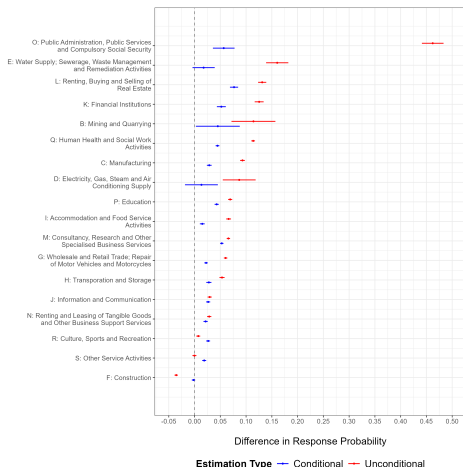
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Sectors



Huge overrepresentation of white-collar industries in responsive establishments

- Three of top four include public administration, real estate, and financial institutions

Again, controlling for contact probability attenuates estimated gaps in contact probability by up to 84%

- 11 of the 19 sectoral response rate advantages attenuate by more than half after controlling for contact probability

Conclusion

People running/analyzing business surveys need to recognize that their sample is likely unrepresentative

- ▶ Responsive establishments are likely smaller, have larger shares of parttime workers, are concentrated in white-collar industries, and are relatively unlikely to be solo enterprises

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Future directions: Survey weighting for business surveys





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Why Should We Care?

Business surveys are routinely used to survey firm expectations and financial management practices which are unobservable in administrative data (e.g., see Zimmermann 1999; Collins 2001; Hansson, Jansson, & Löf 2005; Baker & Mukherjee 2007; Clar, Duque, & Moreno 2007; Klein & Özmucur 2010; Baker, Singleton, & Veit 2011; Snijkers et al. 2013; Altig et al. 2022)

- ▶ Often used for understanding and forecasting market and economic outcomes

Many (sub)disciplines in management and finance rely heavily on business surveys

- ▶ 32-41% of empirical research publications in management information systems use survey data, of which over 41% target firms as the primary unit of analysis (Karanja, Sharma, & Salama 2020)

If the businesses who respond to these surveys are unrepresentative, then the surveys may yield misleading generalizations on firms, markets, and the economy

- ▶ But if we know *how* and *why* the surveys are unrepresentative, then we can leverage this information to correct sampling biases and improve survey design

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LISA's Standard Imputation Procedure

For each employee headcount of (1) fulltime females, (2) parttime females, (3) fulltime males, and (4) parttime males...

- ▶ Within each combination of SBI code groups (A-B, C-F, G-I, H-N, O-P, Q, and S-U) and firm size classes (2-4, 5-49, and 50+)...
 1. Find the average growth rate of the relevant employee headcount between year t and $t - 1$ for responsive establishments
 2. For nonresponsive establishments with the same combination of SBI code group and firm size class, obtain the relevant employee headcount for year t by multiplying that headcount from year $t - 1$ by the relevant growth rate and rounding

The described procedure in the LISA handbook also provides for the possibility of further stratification by COROP region and some exceptions

- ▶ I ignore these because the LISA register doesn't note when these deviations have been applied

TLDR: Employee headcounts for unresponsive establishments are imputed using sector-size growth trends of responsive establishments [Back](#)

A Novel Random Forest Imputation Strategy

For each of the four employee headcounts...

1. On a randomly-selected half of the responsive establishments, fit a random forest regression model to predict the relevant employee headcount
 - ▶ `ranger` package in R (Wright & Ziegler 2017), using SBI codes, COROP regions, and the previous year's four employee headcounts and survey type as features
2. Predict the relevant headcount of unresponsive establishments using the random forest model estimated in (1) and round

Primary cost is computational power; you realistically need 64GB of RAM to run everything

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Performance Differences Between Imputation Algorithms

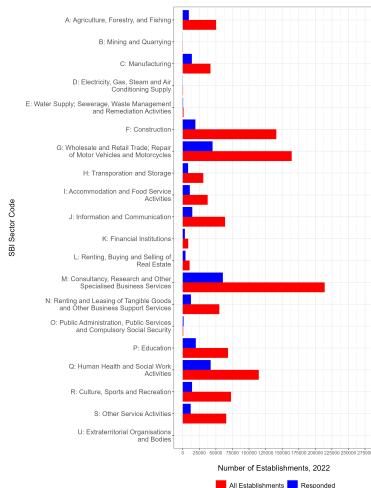
| | Same Variable, LISA Imputation | Same Variable, 2021 LISA | Same Variable, Random Forest Imputation |
|-----------------------------|-----------------------------------|-----------------------------|--|
| # Employees | 0.575 (0.046) | 1.003 (0.042) | 1.211 (0.102) |
| Relative MSPE | 1 | 0.133 | 0.37 |
| Relative MAD | 1 | 0.376 | 0.444 |
| % Employees Female | 0.815 (0.002) | 0.826 (0.002) | 0.996 (0.002) |
| Relative MSPE | 1 | 0.979 | 0.871 |
| Relative MAD | 1 | 0.973 | 1.171 |
| % Employees Fulltime | 0.455 (0.007) | 0.429 (0.006) | 0.831 (0.006) |
| Relative MSPE | 1 | 1.098 | 0.526 |
| Relative MAD | 1 | 1.04 | 0.825 |

In hold-out test data, the LISA imputation method significantly underestimates all firm composition measures of interest to my study

- Performs poorly even compared to a simple carryover imputation

Compared to LISA imputation, my random forest imputation achieves global out-of-sample improvements on both slope and fit [Back](#)

SBI Sectors

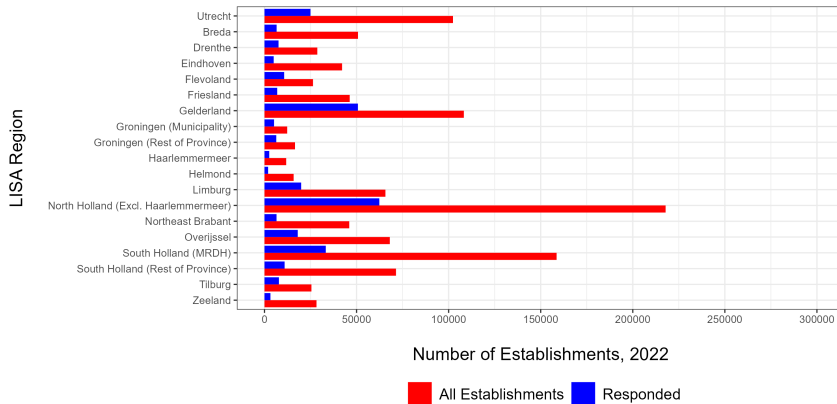


For sparsity, I focus on one-digit SBI sectors (KVK classification)

- Most common sectors are consulting, retail, and construction
- Due to high response rates, the healthcare sector is also well-represented in responsive establishments

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LISA Regions



LISA regions are represented in the data roughly according to local population

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