

A "big data" gaze at why electronic transactions and web-scraped data are no panacea Jens Mehrhoff, Eurostat 15th Meeting of the Ottawa Group Eltville am Rhein, 10 – 12 May 2017

Structure of the presentation

- 1. The supposed population of transactions
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"Is an 80% non-random sample 'better' than a 5% random sample in measurable terms? 90%? 95%? 99%?" (Wu, 2012)



1. The supposed population of transactions

- A (non-random) **sample of quotes** from abstracts for this meeting:
 - "Scanner data have big advantages over survey data because such data contain transaction prices of **all items sold**..."
 - "...bilateral methods ... do not capture the **full population dynamics** expressed by scanner data..."
 - "A further solution would be the use of transaction data (scanner data) to capture **all ... prices** on the market."
 - "It is the first time that the evolution of ... prices has been traced down using a dataset that covers the **population of transactions**..."



1. The supposed population of transactions

Transactions not recorded electronically	Electronic transactions data not available to NSIs
	Available transactions data deleted by cleansing
	Unmatched data not used in index calculation
	Actual information exploited from "big data" sample



- Let us consider a case where we have an **administrative record** covering f_a percent of the population, and a **simple random sample (SRS)** from the **same population** which only covers f_s percent, where $f_s \ll f_a$.
- How large should f_a/f_s be before an estimator from the administrative record dominates the corresponding one from the SRS, say in terms of MSE?

Source: Meng, X.L. (2016), "Statistical paradises and paradoxes in big data," *RSS Annual Conference*.



• Our key interest here is to **compare the MSEs of two estimators** of the finite-sample population mean \bar{X}_N , namely,

$$\bar{x}_a = \frac{1}{n_a} \sum_{i=1}^{N} x_i R_i \text{ and } \bar{x}_s = \frac{1}{n_s} \sum_{i=1}^{N} x_i I_i$$

where we let $R_i = 1$ ($I_i = 1$) whenever x_i is recorded (sampled) and zero otherwise, i = 1, ..., N.

• The administrative record has no probabilistic mechanism imposed by the data collector.



• Expressing the **exact error**, where $f_a = n_a/N$:

$$\bar{x}_{a} - \bar{X}_{N} = \frac{\mathbf{E}[xR]}{\mathbf{E}[R]} - \mathbf{E}[x] = \frac{\mathbf{Cov}[x, R]}{\mathbf{E}[R]}$$
$$= \underbrace{\rho_{x,R}}_{\text{Data}} \cdot \underbrace{\sigma_{x}}_{\text{Problem}} \cdot \underbrace{\sqrt{\frac{1 - f_{a}}{f_{a}}}}_{\text{Data}}.$$

• Given that \bar{x}_s is **unbiased**, its MSE is the same as its variance.



• The **MSE** of \bar{x}_a is more complicated, mostly because R_i depends on x_i :

$$MSE[\bar{x}_a] = E[\rho_{x,R}^2] \cdot \sigma_x^2 \cdot \left(\frac{1 - f_a}{f_a}\right).$$

For biased estimators resulting from a large self-selected sample, the MSE is dominated (and bounded below) by the squared bias term, which is controlled by the relative sample size f_a.



• To guarantee $MSE[\bar{x}_a] \le Var[\bar{x}_s]$, we must require (ignoring the finite population correction $1 - f_s$)

$$f_a \ge \frac{n_s \rho_{x,R}^2}{1 + n_s \rho_{x,R}^2}, \text{ or equivalently}$$
$$n_s \le \left(\frac{f_a}{1 - f_a}\right) \frac{1}{\rho_{x,R}^2} = \left(\frac{n_a}{N - n_a}\right) \rho_{x,R}^{-2}$$

• A key message here is that, as far as statistical inference goes, what makes a "big data" set big is typically not its absolute size, but its relative size to its population.



- Therefore, the question which data set one should trust more is unanswerable without knowing N.
- But the general message is the same: when dealing with self-reported data sets, do not be fooled by their apparent large sizes.
- This reconfirms the power of probabilistic sampling and reminds us of the danger in blindly trusting that "big data" must give us better answers.
- Lesson learned: What matters most is the quality, not the quantity.



The effective sample size of a "Big Data" in terms of SRS size



- Imagine that we are given a **SRS** with $n_s = 400$:
 - If $\rho_{x,R} = 0.05$ and our intended **population is the USA**, then $N \approx 320,000,000$, and hence we will need $f_a = 50\%$ or $n_a \approx 160,000,000$ to place more trust in \bar{x}_a than in \bar{x}_s .
 - If $\rho_{x,R} = 0.1$, we will need $f_a = 80\%$ or $n_a \approx 256,000,000$ to dominate $n_s = 400$.
 - If $\rho_{x,R} = 0.5$, we will need over 99% of the population to beat a SRS with $n_s = 400$.



 What price would be most representative of the sales of the same product sold at a number of different prices for a month? The answer is the unit value (CPI Manual, 2004):

$$UV^{t} = \frac{\sum_{i=1}^{N} p_{i}^{t} q_{i}^{t}}{\sum_{i=1}^{N} q_{i}^{t}} = \frac{\mathrm{E}[p^{t} q^{t}]}{\mathrm{E}[q^{t}]}.$$

- Estimators
 - Electronic transactions data: $\widehat{UV}^t = \frac{\sum_{i=1}^N p_i^t q_i^t R_i}{\sum_{i=1}^N q_i^t R_i} = \frac{\mathbb{E}[p^t q^t R]}{\mathbb{E}[q^t R]}.$

• Web-scraped data:
$$\widehat{UV}^t = \frac{\sum_{i=1}^N p_i^t R_i}{\sum_{i=1}^N R_i} = \frac{E[p^t R]}{E[R]}$$



• Error of web-scraped data



• The **second term would not disappear** even when full population coverage could be achieved.



• Since, caused by product substitution, $E[n^t a^t]$

$$\frac{\mathrm{E}[p^t q^t]}{\mathrm{E}[q^t]} - \mathrm{E}[p^t] = \frac{\mathrm{Cov}[p^t, q^t]}{\mathrm{E}[q^t]} < 0,$$

there are just two relevant cases to distinguish:

- 1. Mainly the **upper end of the market** is covered, i.e. $Cov[p^t, R] > 0$, and hence the **total error is necessarily positive** (albeit *a posteriori* to an unknown degree).
- 2. Mainly **discounters and the like** are covered, i.e. $Cov[p^t, R] < 0$, so that it is **no longer possible to guess at what the likely sign of the total error is**.



Error of electronic transactions data



• The error of electronic transactions data is **more complicated**.



Sign of the total error	$\frac{\operatorname{Cov}[q^t, R]}{\operatorname{E}[q^t R]/UV^t} > 0$	$\frac{\operatorname{Cov}[q^t, R]}{\operatorname{E}[q^t R]/UV^t} < 0$
$\frac{\operatorname{Cov}[p^t q^t, R]}{\operatorname{E}[q^t R]} > 0$	Indefinite	Positive
$\frac{\operatorname{Cov}[p^t q^t, R]}{\operatorname{E}[q^t R]} < 0$	Negative	Indefinite



4. Panacea's potion?: changes rather than levels

 The MSE can be written as the sum of the variance of the estimator and the squared bias of the estimator:

$$MSE[(\widehat{UV}^{t} - \widehat{UV}^{t-1})] = Var[(\widehat{UV}^{t} - \widehat{UV}^{t-1})] + Bias^{2}[(\widehat{UV}^{t} - \widehat{UV}^{t-1})] = MSE[\widehat{UV}^{t}] + MSE[\widehat{UV}^{t-1}] - 2 \operatorname{Cov}[\widehat{UV}^{t}, \widehat{UV}^{t-1}] - 2 \operatorname{Bias}[\widehat{UV}^{t}] \operatorname{Bias}[\widehat{UV}^{t-1}]$$

If \$\heta V^t\$ and \$\heta V^{t-1}\$ are positively correlated and their bias is in the same direction, the total MSE of the change will be lower than the sum of the MSEs.



5. Are we impaled upon the horns of a dilemma?



Source: Wikipedia.

- Electronic transactions and web-scraped data can be very precise – but at the same time may have limited accuracy.
- The paradox: the "bigger" the data, the surer we will miss our target!



5. Are we impaled upon the horns of a dilemma?



Source: Wikipedia.

- Price data from traditional surveys will not be collected perfectly in reality because of non-probabilistic selection errors as well.
- The combination of survey data with "big data" is the ticket to the future. (Groves, 2016, IARIW General Conference)



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