Big Data and Small Surveys: Which one should we trust more?

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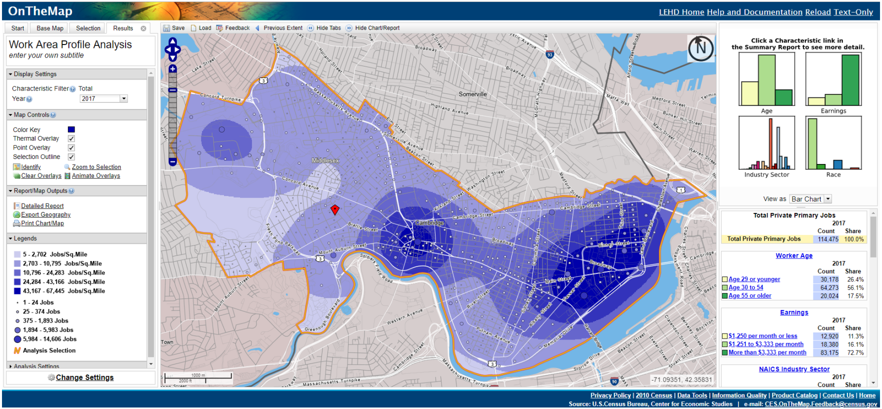
- Thanks to many students and colleagues for augmenting my intelligence, and to on-line sources for enhancing my presentation.

OnTheMap Project of US Census Bureau



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  - *Unemployment Insurance record was never intended for statistical inference purposes.*

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- **But is an 80% non-random sample "better" than a 5% random sample in measurable terms? 90%? 95%? 99%?** (Jeremy Wu 2012)
- "**Which one should we trust more: a 1% survey with 60% response rate or a non-probabilistic dataset covering 80% of the population?**" (Keiding and Louis, 2016, *Journal of Royal Statistical Society, Series B*)

Surveys: Infer a Population of N by a Sample of $n << N$

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- First implementation in 1940 US Census led by Morris Hansen

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- **But what happens when we fail to stir (well)?**

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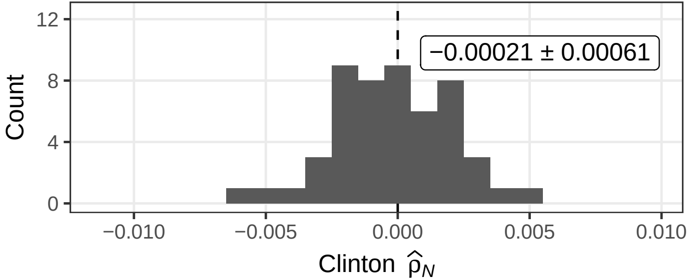
Three and only three ways to control the estimation error:

$$\underbrace{\bar{X}_n - \bar{X}_N}_{\textbf{Estimation Error}} = \underbrace{\mathrm{Corr}(R, X)}_{\textbf{Data Quality}} \times \underbrace{\sqrt{\frac{N-n}{n}}}_{\textbf{Data Quantity}} \times \underbrace{\mathrm{St.Dev}(X)}_{\textbf{Problem Difficulty}} .$$

Assessing $\hat{\rho}_N = \mathrm{Corr}(R, X)$ via Cooperative Congressional Election Study (50 states + Washington DC)



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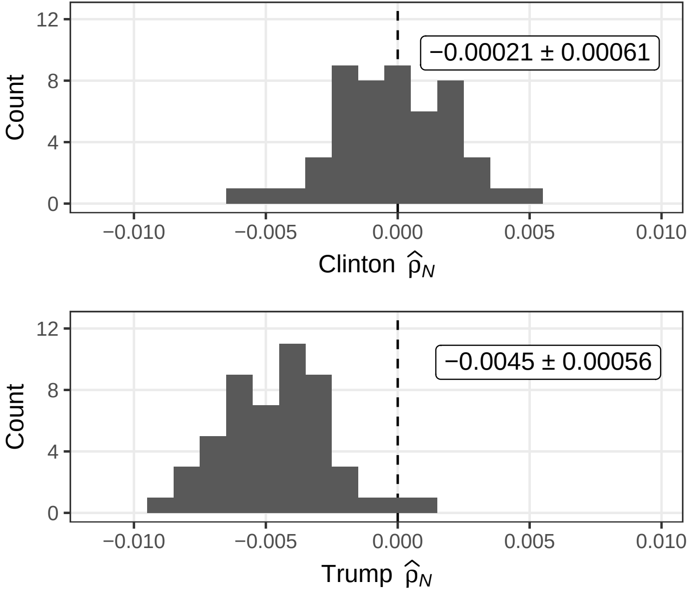

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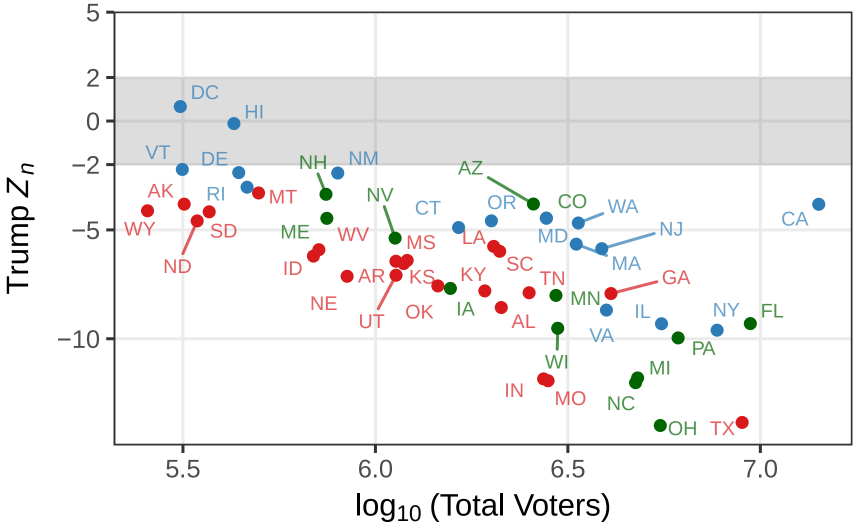
- **Butterfly Effect** due to Law of Large Populations (LLP)

$$\textbf{Relative Error} = \sqrt{\mathbf{N-1}}\,\hat{\rho}_{\mathbf{N}}$$

LLP: The more voters, the higher the bias in our prediction



The Big Data Paradox:

If we do not pay attention to data quality, then

The bigger the data,

the surer we fool ourselves.

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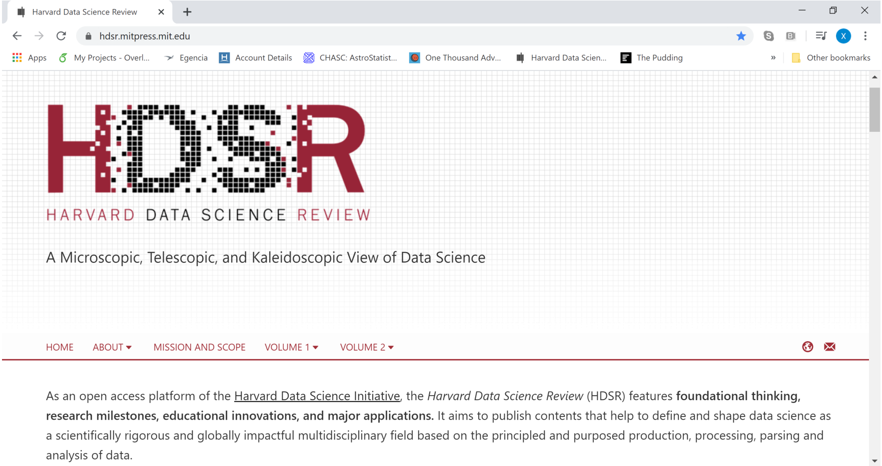

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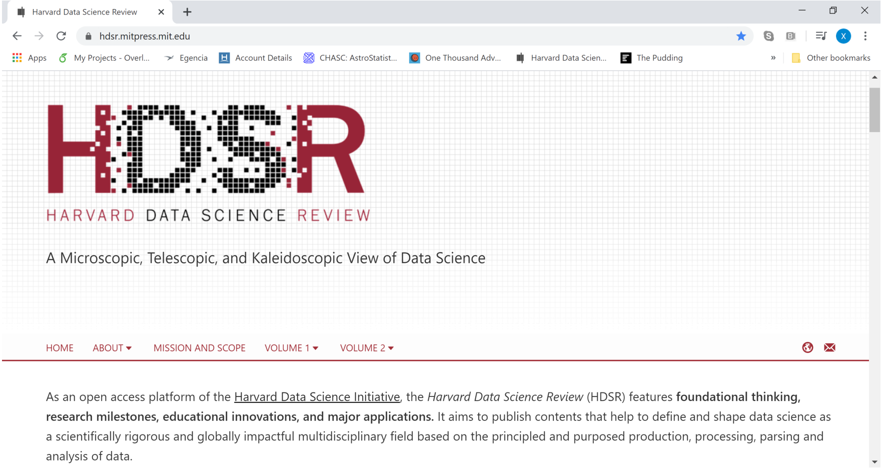

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Everything Data Science and Data Science for Everyone

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