Big Data: Perspectives for Economics and Applied Econometrics

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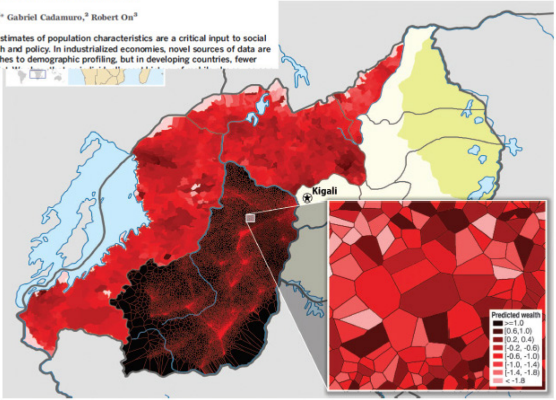
Poverty in Rwanda (predict)

ECONOMICS

Predicting poverty and wealth from mobile phone metadata

Joshua Blumenstock,[1*] Gabriel Cadamuro,[2] Robert On[3]

Accurate and timely estimates of population characteristics are a critical input to social and economic research and policy. In industrialized economies, novel sources of data are enabling new approaches to demographic profiling, but in developing countries, fewer



Prices in Argentina (measurement)

Contents lists available at SciVerse ScienceDirect
Journal of Monetary Economics
journal homepage: www.elsevier.com/locate/jme

Online and official price indexes: Measuring Argentina's inflation

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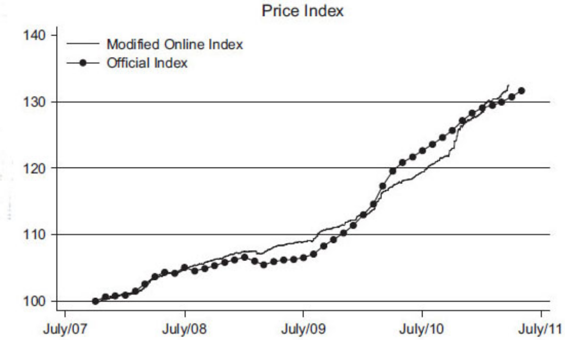

Sales tax in the US (causal effect)

Sales Taxes and Internet Commerce

Liran Einav

Dan Knoepfle

Jonathan Levin

Neel Sundaresan

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Big data vs. standard statistics

Standard statistics

- How to get the most out of few data?
- Solution: structured data (survey sampling)
- Approach: complex sampling to approximate random sampling (slow and expensive).

Big Data

- Lots of data (Volume)
- Lots of unstructured data (Variety)
- Lots of unstructured, immediate data (Velocity)
- Cheap

Econometrics

$$Y = f(X) + u$$

- Interest in $f(.)$ (marginal effects).
- Model? Theory, well designed experiment.
- Mostly causal effects.
- Probabilistic (standard errors, test)
- Good? Unbiased/consistent/valid inference.

Machine/Statistical Learning

$$Y = f(X) + u$$

- Interest in Y: predict, classify, measure.
- Model? No model. We learn it.
- Point estimate (no inference).
- Good? Predictive performance. Out of sample.

Example: LASSO

$$L(\beta) = \sum (y_i - x_i\beta)^2 + \lambda\, \beta^2$$

- $\lambda = 0$ back to OLS.
- $\lambda \neq 0$ biased but....
- ... can always outperform OLS in prediction.
- Bias is capital sin in econometrics (not in ML).
- ML Idea: bias can reduce variance dramatically.

This is ridge regression. LASSO replaces β^2 with $|\beta|$.

Model assessment

- Econometric etiquette: ex-ante. Good theory, clean identification (consistency). Robust inference.
- Machine learning: ex-post, iterative. Cross validation.
- Cross validation: keep data out to 'test' the accuracy of the model. Switch roles. 'Learn' model to maximize predictive accuracy through cross validation.
- Machine learning builds rather than estimates a model, guided by out of sample predictive/measurement ability.

Policy evaluation requires causal and predictive analysis

Kleinberg, Ludwig, Mullainathan and Obermeyer (2015):

- Hip replacement surgery: effectiveness of surgery (causal) and life expectancy (predictive).
- Crime: release policies depend on effectiveness of mechanism (Shargrodsky and Di Tella, 2013) and predicted probability of commiting a crime.
- Unemployment: training depends on effectiveness of program (causal) and expected unemployment (prediction)

Warnings

- Dependencies (do we really get big data?)
- Choice based sampling (i.e., informal markets)
- Non observed counterfactuals (can we really get *all* data?).
- Correlation fallacy.
- Transparency / privacy.
- Black box (deep learning, forests, etc.)
- Social/political consensus.

Opportunities

- Big data is not just lots but more data (small or big).
- Can identify non-linearities and heterogeneities. Bypass the 'curse of dimensionality'
- Fast (crucial for policy). Goggle Flu Trends. Price scrapping.
- Easy and inexpensive experimentation. Crucial for causal uses.
- Supplements standard official statistics (not replace).
- Coverage (Rwanda). Rural vs. urban.

Links


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