

14.31x

Data Analysis for Social Scientists

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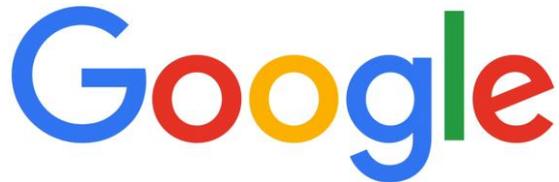
Massachusetts Institute of Technology



J-PAL

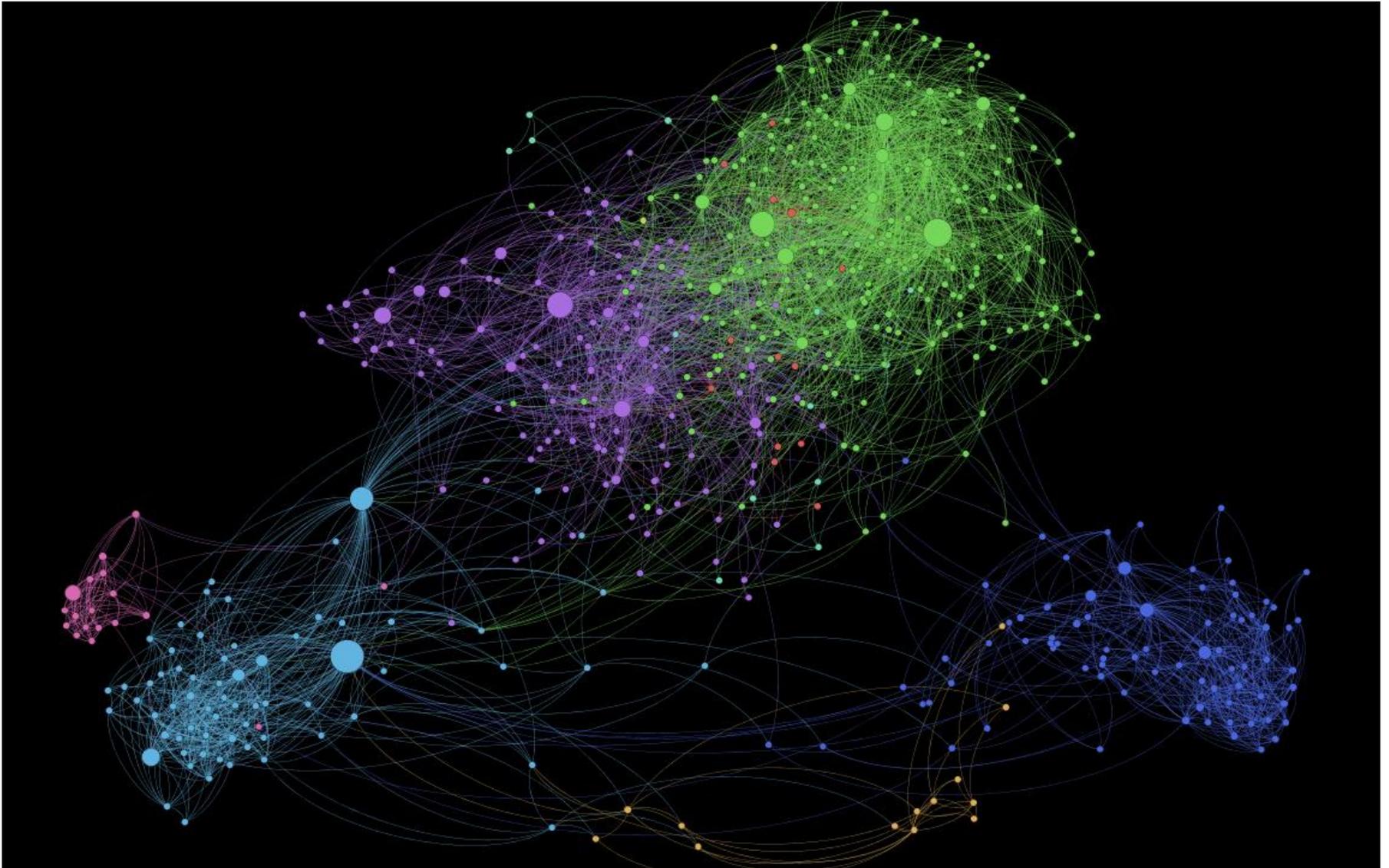
ABDUL LATIF JAMEEL POVERTY ACTION LAB

Data is Plentiful

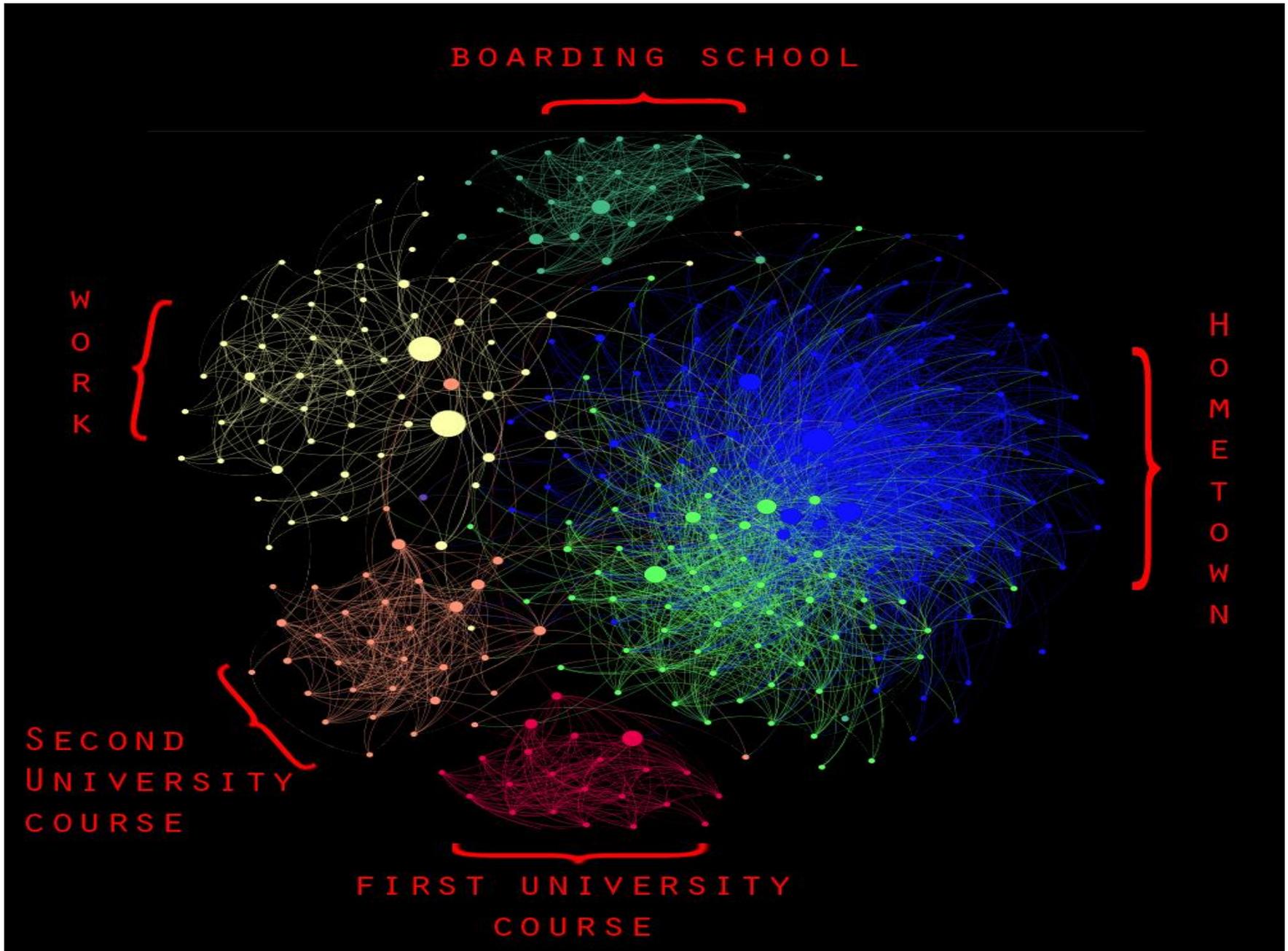


Data is Beautiful

- Example: Mapping Facebook networks of individuals from Somalia living in Eastleigh



Courtesy of Kimo Quaintance. Used with permission.



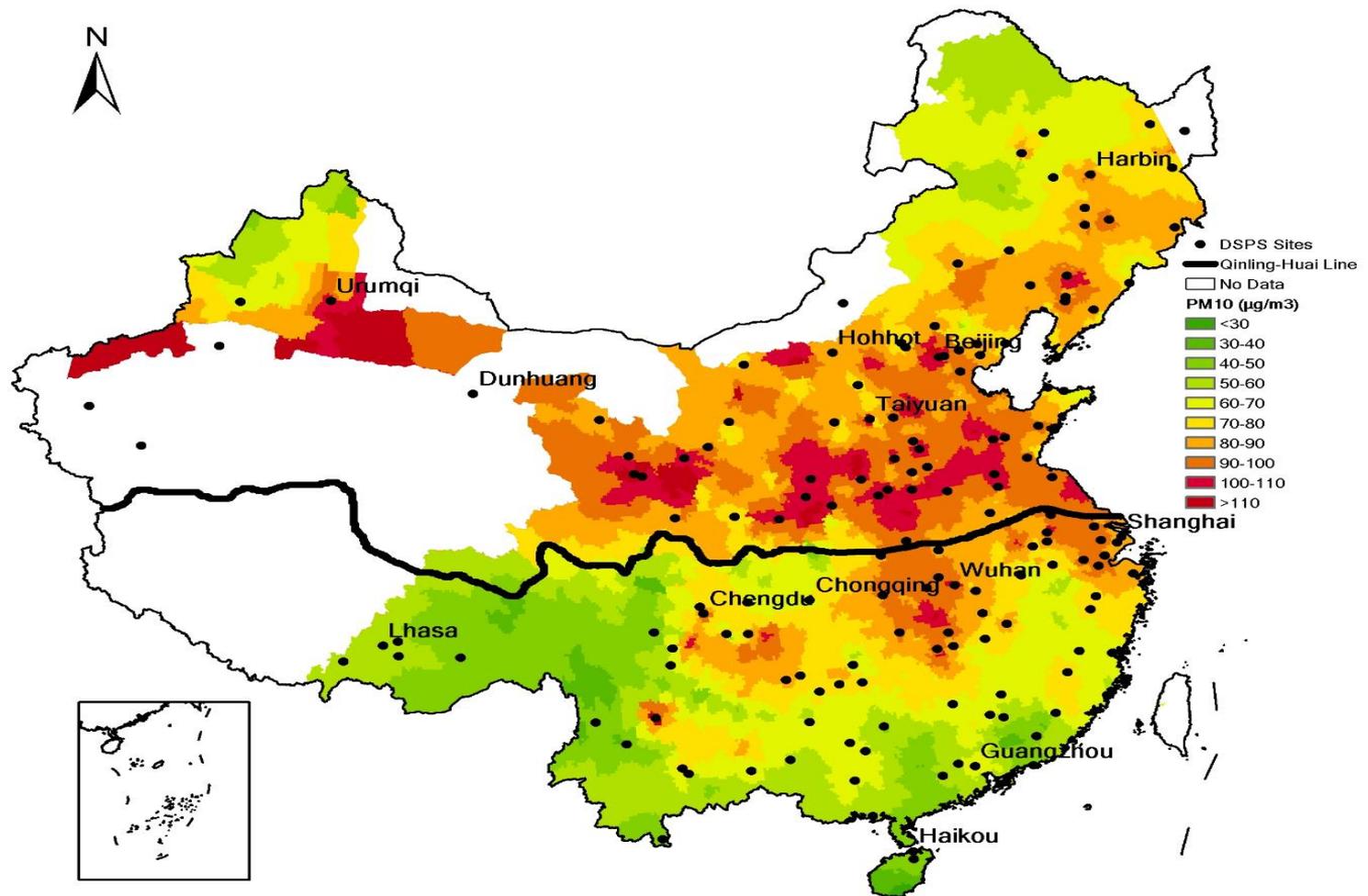
Courtesy of Kimo Quaintance. Used with permission.

Data is Insightful

- Example: Pollution in China

Figure 1

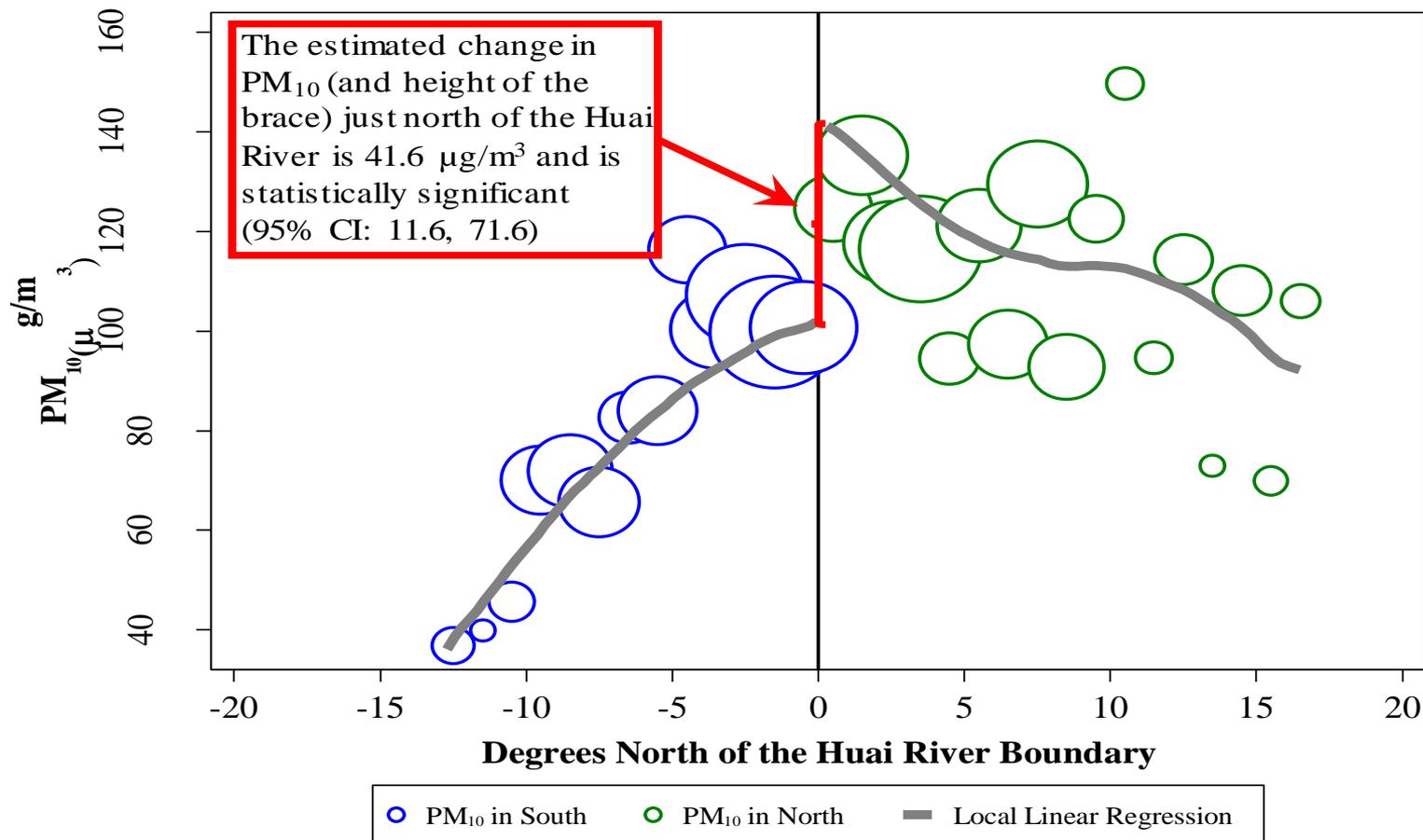
Pollution in China and the Huai River/Qinling Mountain Range



Notes : The cities shown are the locations of the Disease Surveillance Points. Cities north of the solid line were covered by the home heating policy. The figure coloring is generated by interpolating PM₁₀ levels at the 12 nearest pollution monitoring stations to create a high resolution grid of pollution throughout China (.1 degree latitude cell width). Areas are left in white which are not within acceptable range of a station.

Figure 2

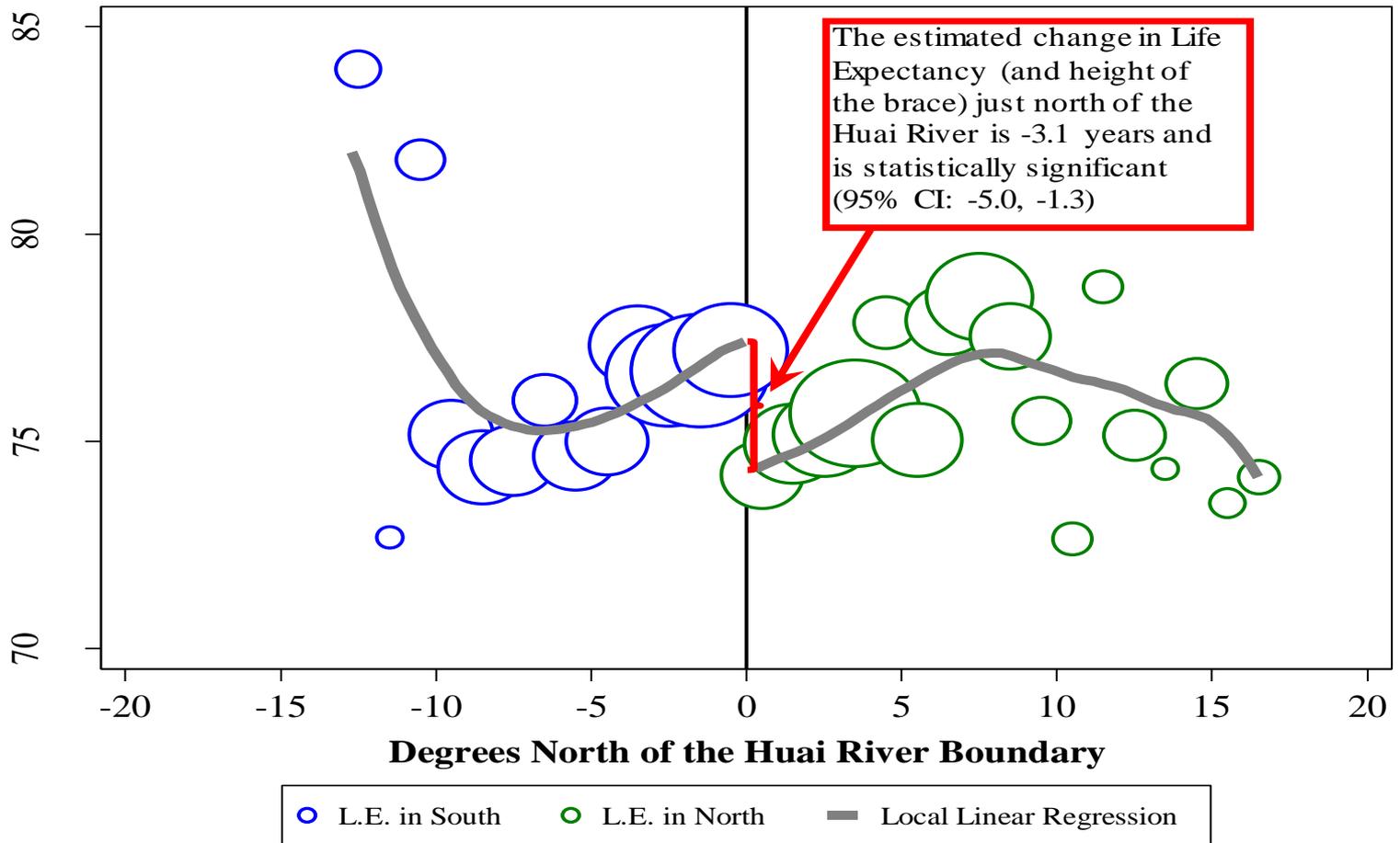
Particulate Matter Levels (PM₁₀) South and North of the Huai River Boundary



Surveillance Point locations within a 1 degree latitude range, weighted by the population at each location. The size of the circle is in proportion to the total population at DSP locations within the 1 degree latitude range. The plotted line reports a local linear regression plot estimated separately on each side of the Huai River.

Figure 3

Life Expectancy South and North of the Huai River Boundary



Notes : Each observation (circle) is generated by averaging life expectancy across the Disease Surveillance Point locations within a 1 degree latitude range, weighted by the population at each location. The size of the circle is in proportion to the total population at DSP locations within the 1 degree latitude range. The plotted line reports a local linear regression plot estimated separately on each side of the Huai River.

Data is Powerful

- Example: Changing regulation in India

Figure 2: Audit and Backcheck Readings for Suspended Particulate Matter (SPM, mg/Nm³), Midline

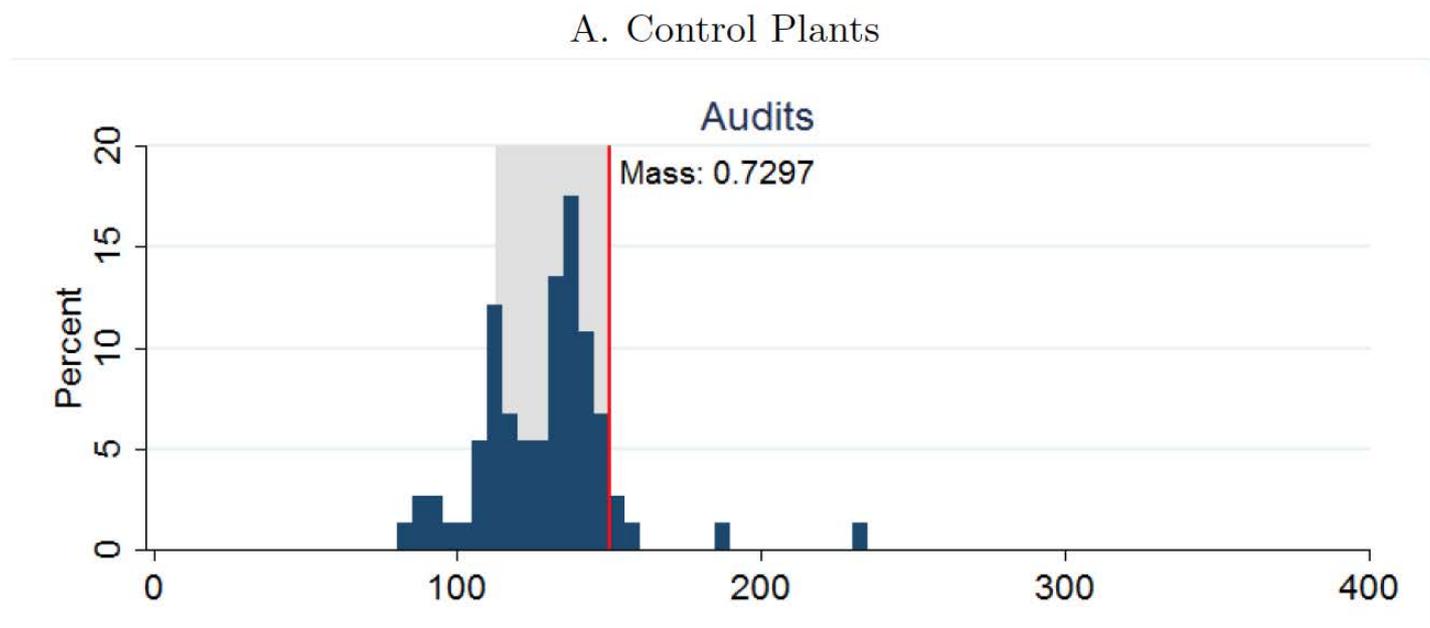


Figure 2: Audit and Backcheck Readings for Suspended Particulate Matter (SPM, mg/Nm³), Midline

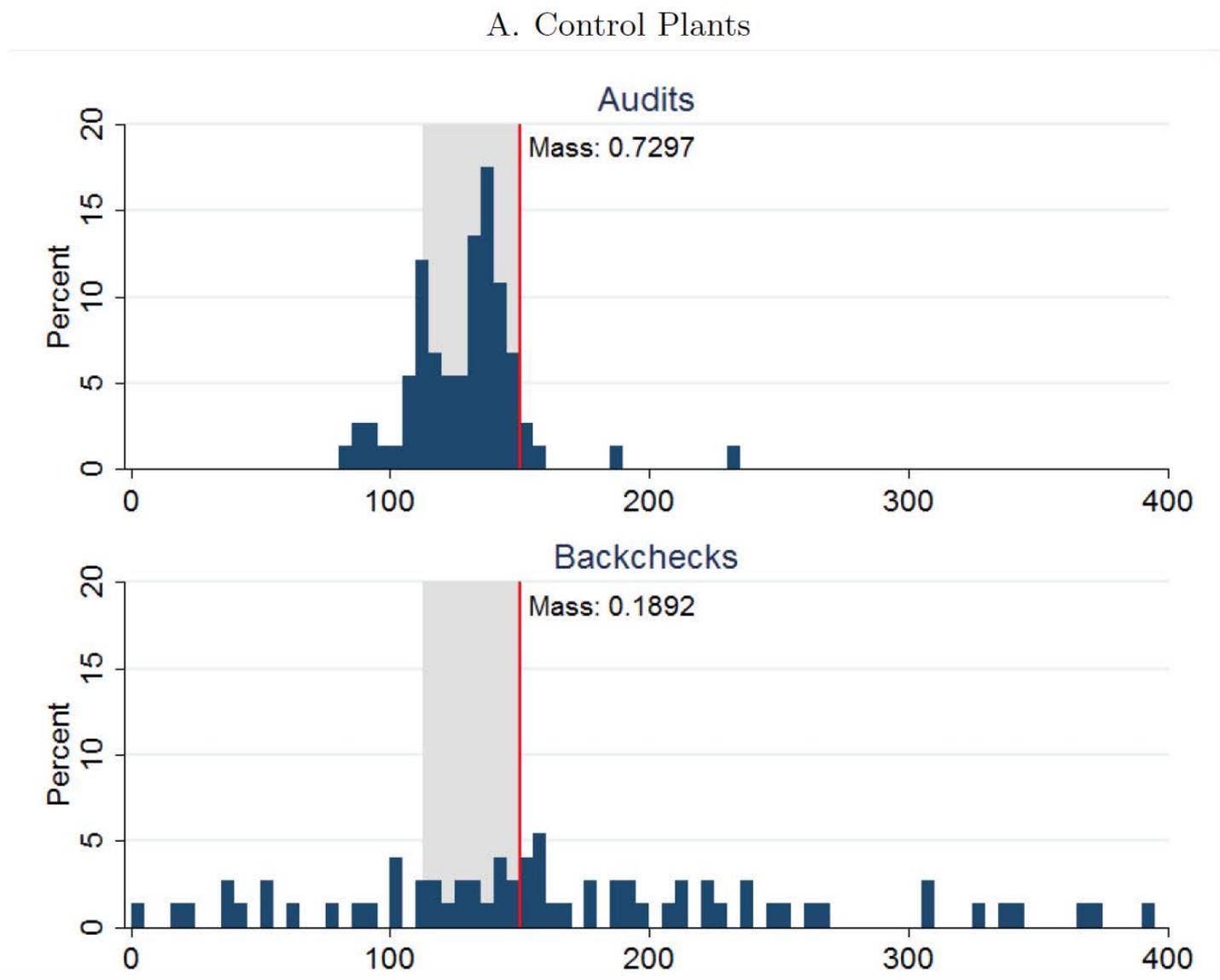
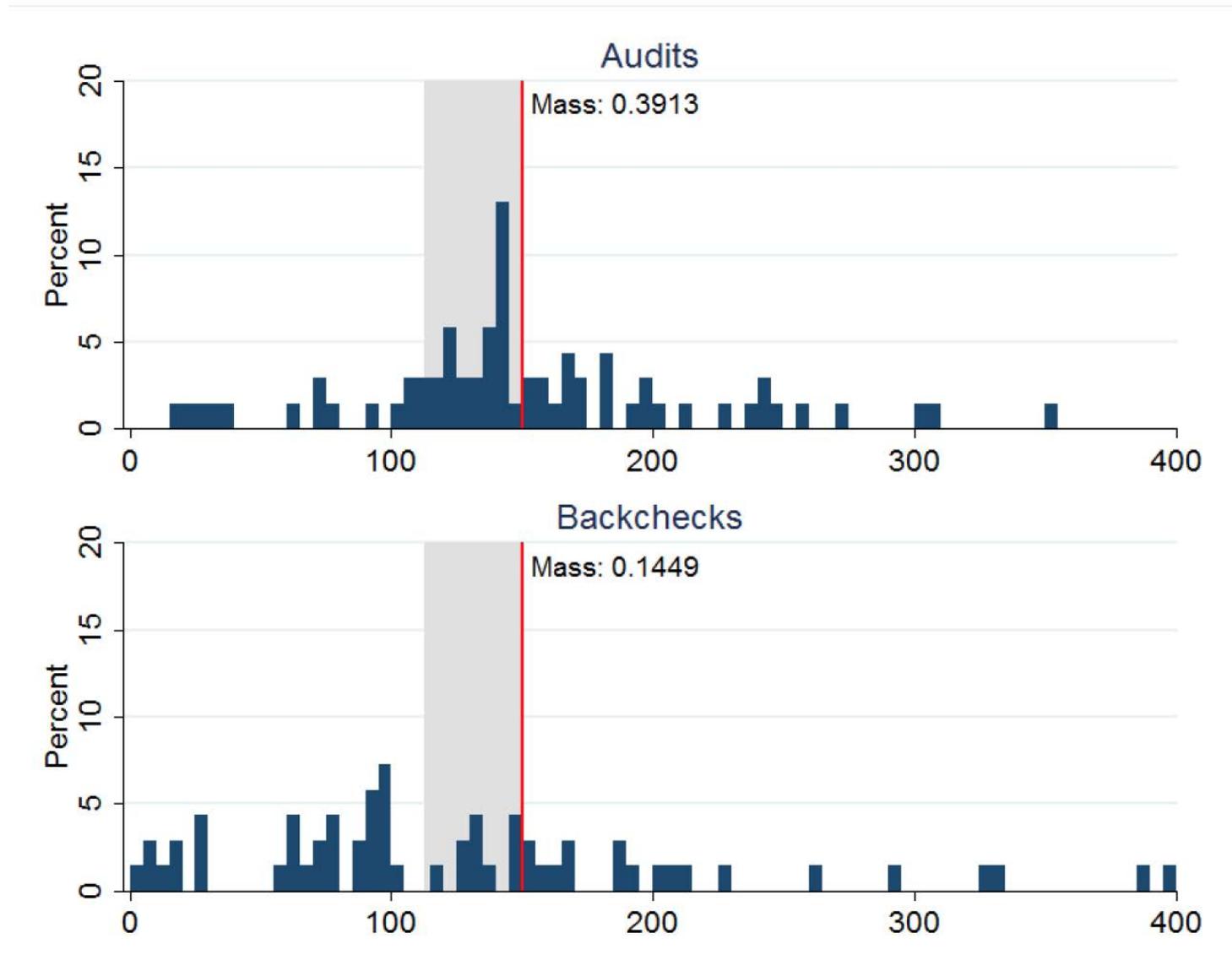


Figure 2: Audit and Backcheck Readings for Suspended Particulate Matter (SPM, mg/Nm³), Midline

B. Treatment Plants



Lessons

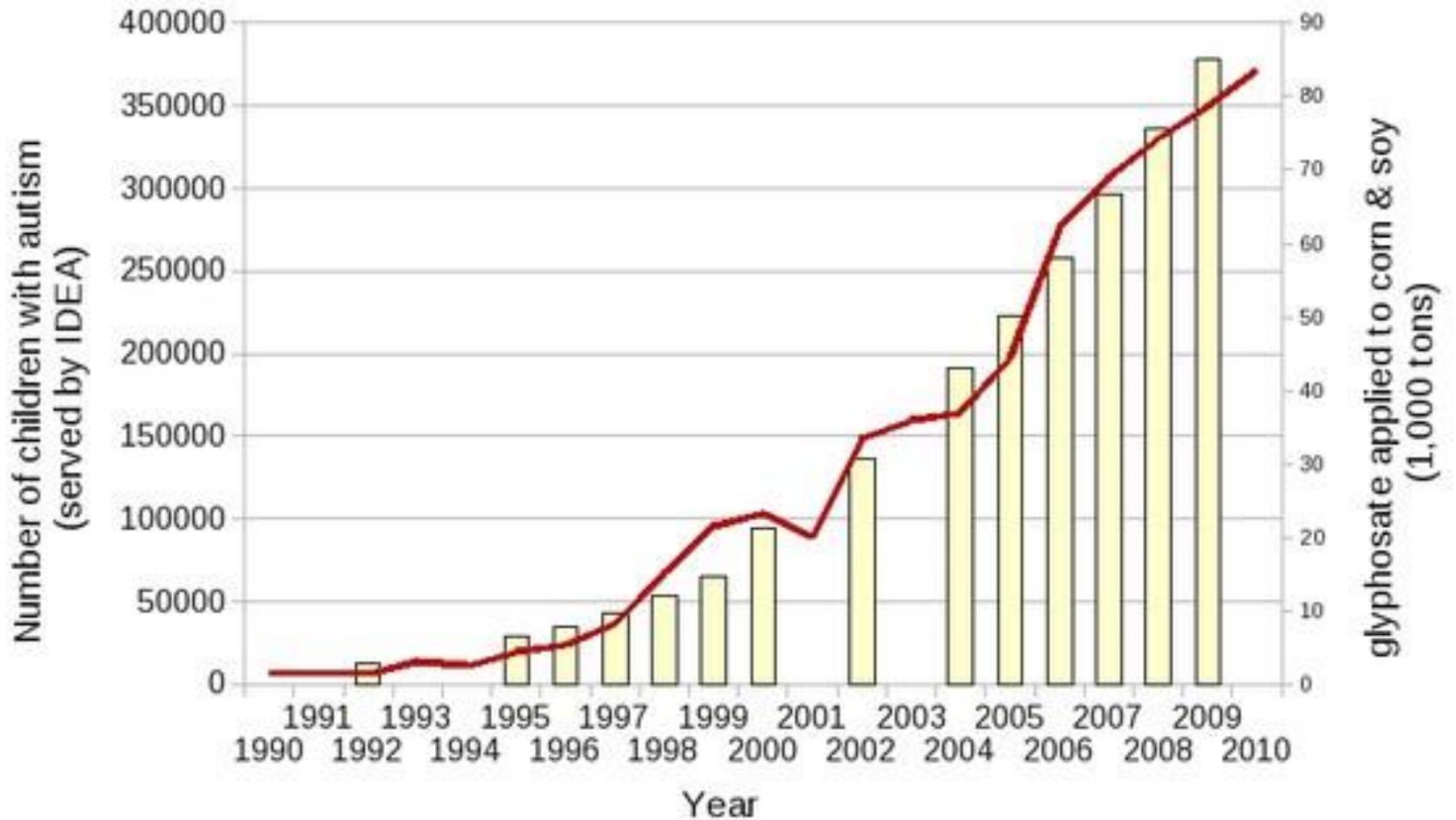
- Conflict of interest leads auditor to cheat on the data they report to the government
- An experiment that changes the reporting structure to eliminate the conflict of interest largely solves the problem.
- This demonstration leads the government of Gujarat to change their policy!
- To date 207 million people have been touched by programs that J-PAL has shown to be effective based on RCT

Data can be Deceitful

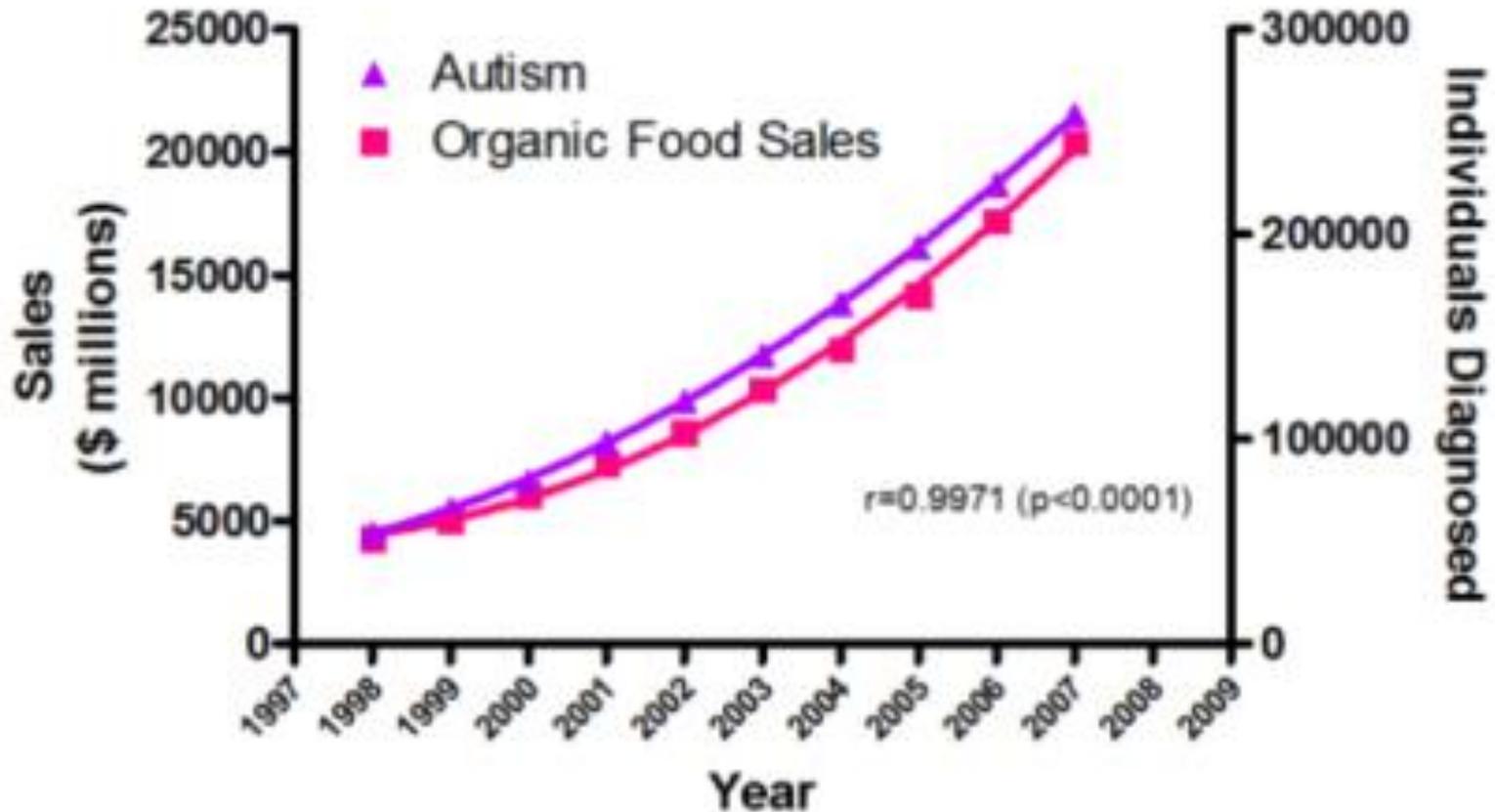
- Example: Correlations with autism

Number of children (6-21yrs) with autism served by IDEA
 plotted against glyphosate use on corn & soy

■ # w/ autism
— Glyphosate applied to Corn & Soy



The real cause of increasing autism prevalence?



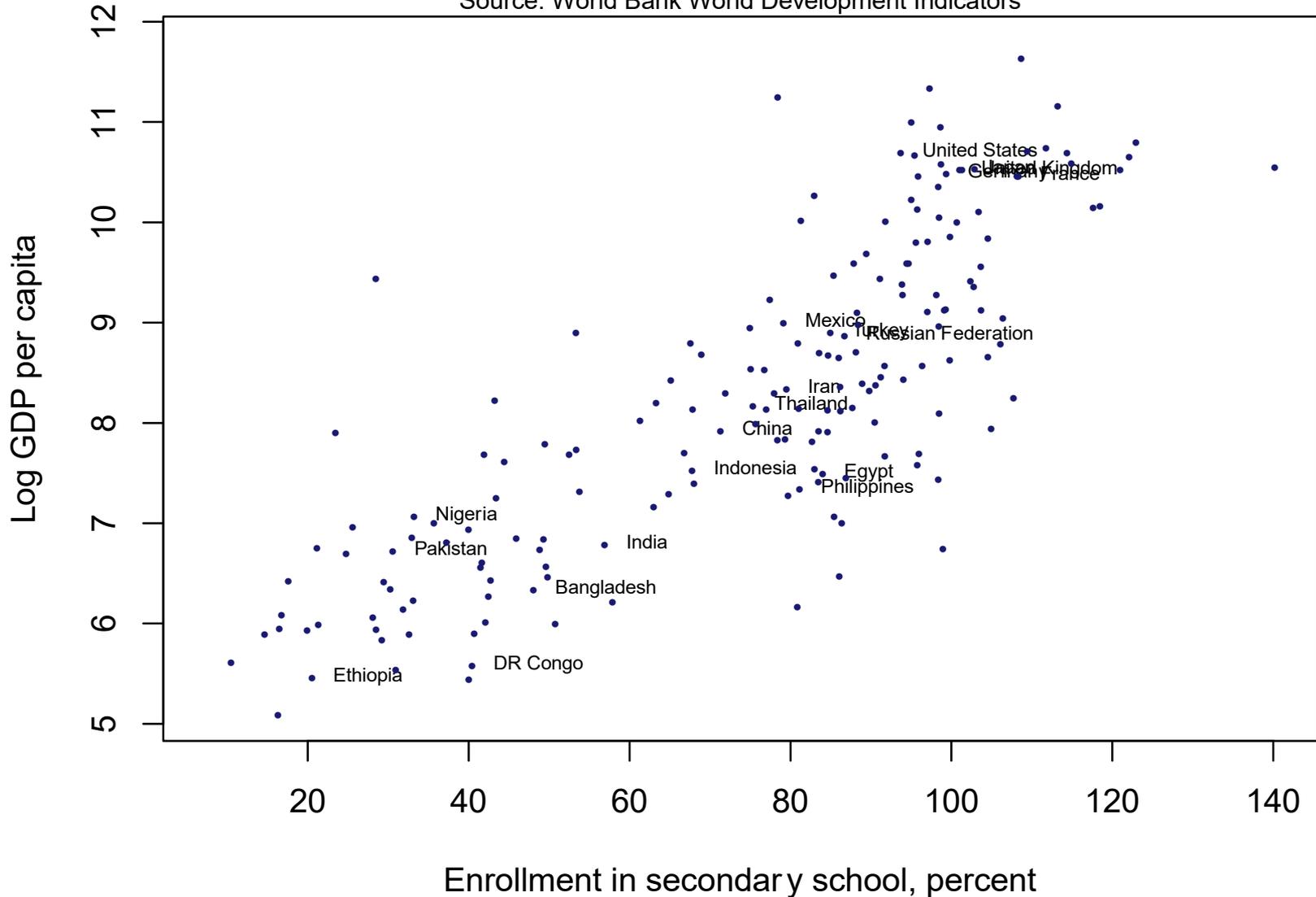
Sources: Organic Trade Association, 2011 Organic Industry Survey; U.S. Department of Education, Office of Special Education Programs, Data Analysis System (DANS), OMB# 1820-0043: "Children with Disabilities Receiving Special Education Under Part B of the Individuals with Disabilities Education Act"

Data can be Deceitful

- That one is trivial but... how about some less obvious ones?

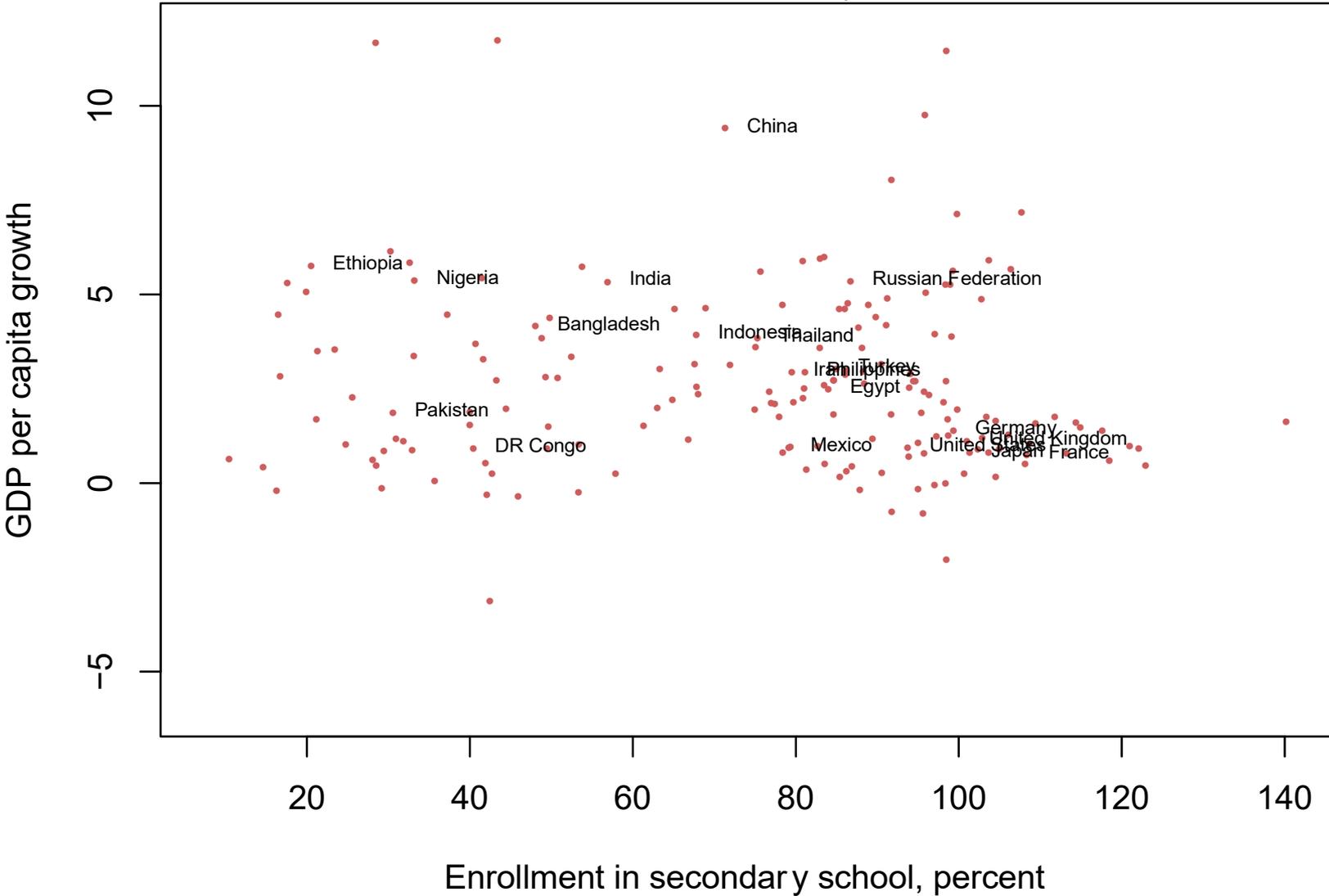
Log GDP per capita and education, (2000–2012 average)

Source: World Bank World Development Indicators



GDP per capita growth and education, (2000–2012 average)

Source: World Bank World Development Indicators



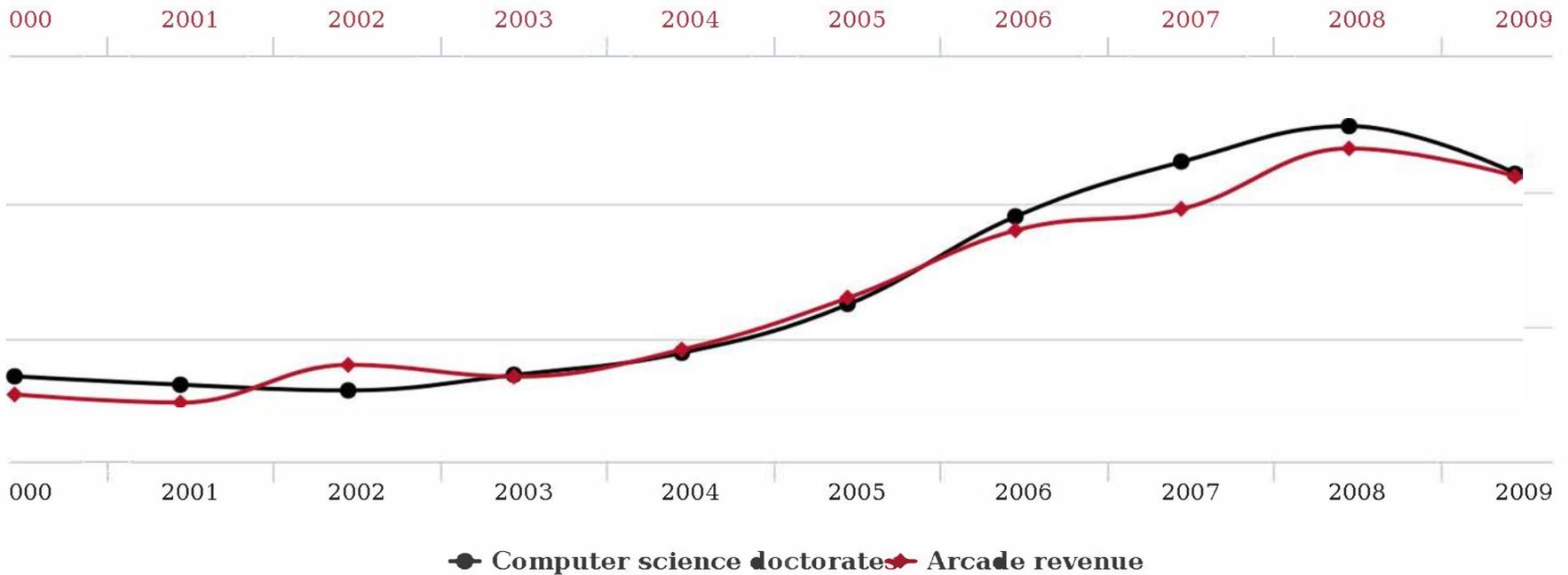
Causation versus Correlation

- Correlation is not causality
- A causal *story* is not causality either...
- Even more sophisticated data use may still not be causality.

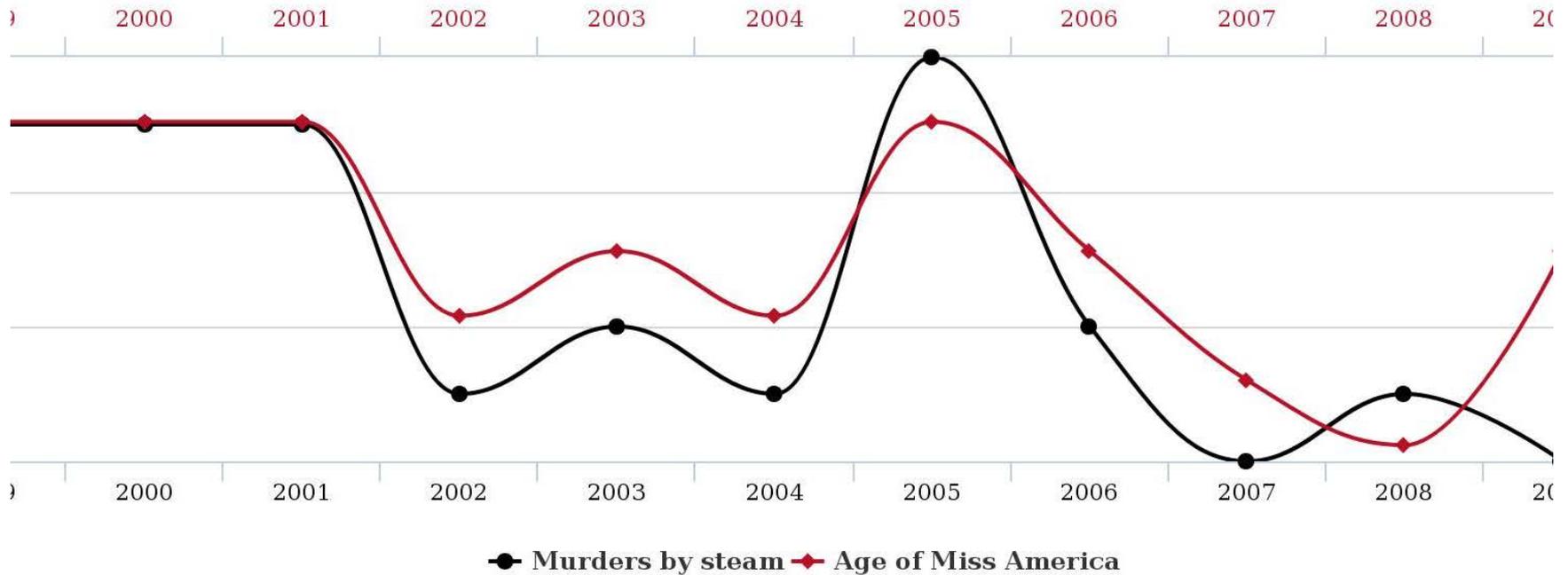
Causation versus Correlation

- Data by the chokefull
 - There is so much data available that it is possible to infer from the data very powerful predictive patterns:
 - What do people who live in Boston, search for capoeira classes video and websites for children before going on the spurious statistics web site to download a couple of graphs, and buy PlanToys doll house may want to buy next?
 - Are people with a specific gene more likely to be patient?
 - But you want to be careful of patterns you observe in the data... they are not always meaningful.

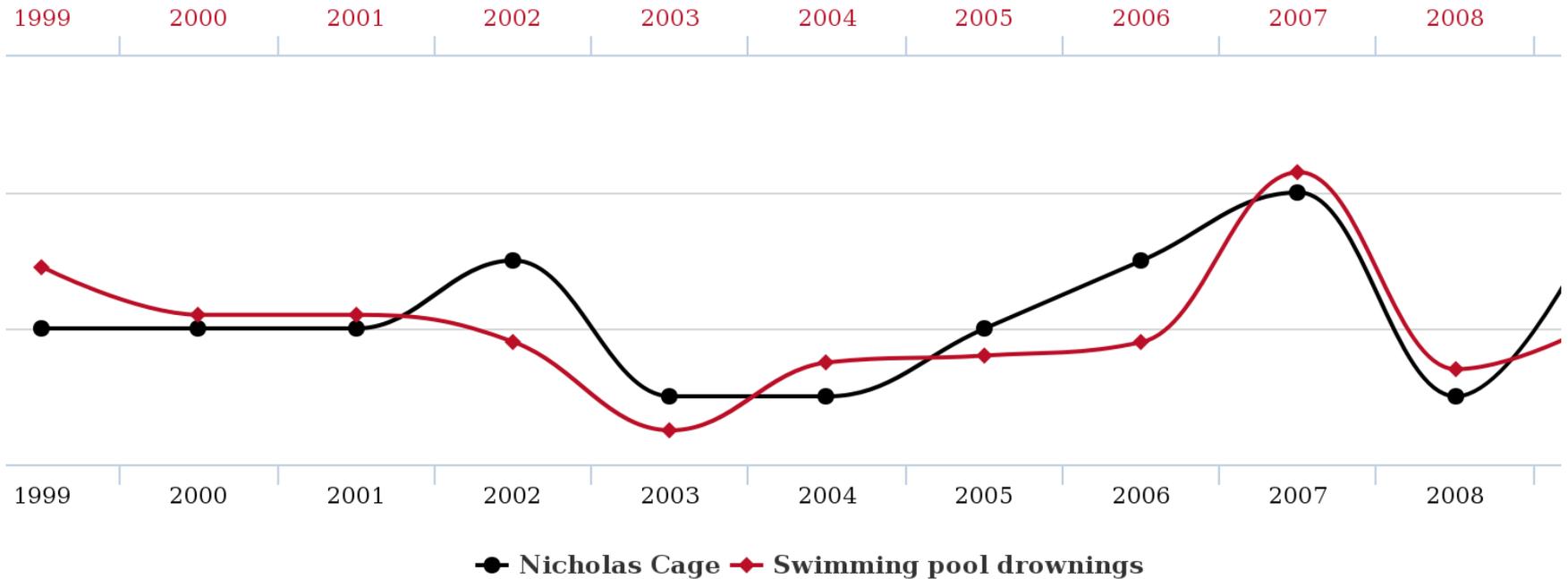
Total revenue generated by arcades correlates with Computer science doctorates awarded in the US



Age of Miss America correlates with Murders by steam, hot vapours and hot objects



Number of people who drowned by falling into a pool correlates with Films Nicolas Cage appeared in



What we need to learn

- How do we model the processes that might have generated our data?
 - Probability
- How do we summarize and describe data, and try to uncover what process may have generated it?
 - Statistics
- How do we uncover pattern between variables?
 - Exploratory data analysis
 - Econometrics
 - Machine Learning

What we need to learn

- How do we think of causality?
 - A causal framework
 - RCTs, AB/testing, etc.
 - Regressions
- How do we do all this in practice?
 - R
 - Experiment design
 - Where to get data?
- How do we present our results in a compelling (and truthful!) way?
 - Beautiful graphs: GIS, networks, etc.
 - Insightful tables
 - Enlightening text!

5. **Course Outline:** The number of lectures devoted to each topic is approximate and subject to change.

Introduction and Motivation	1 lecture
Probability	8 lectures
Definitions	
Random variables	
Distributions of RVs	
Functions of RVs	
Expectation, variance	
Basic estimation and inference	3 lectures
Definitions	
Estimators	
CLT	
Confidence intervals	
Hypothesis testing	
Randomized controlled trials	2 lectures
Nonparametric estimation	1 lecture
Causality	1 lecture
Regression analysis	4 lectures
Design of experiment	2 lectures
Machine learning	2 lectures
Assorted topics, such as visual display	1 lecture

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Spend a chunk of time on probability---this provides necessary foundation for all of the data analysis we will do later on

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To give you some idea
of topics---will not stick
to this order or
allocation

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Throughout semester, we will be mixing in instruction on R, information about data sources, empirical techniques, such as web-scraping, online surveys, etc.

Sources

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