There are three kinds of lies:

lies, damned lies and statistics

– Benjamin Disraeli
Prime Minister of Great Britain (1868, 1874-1880)

When Statistics Seem to Lie

– They’re Answering a Different Question

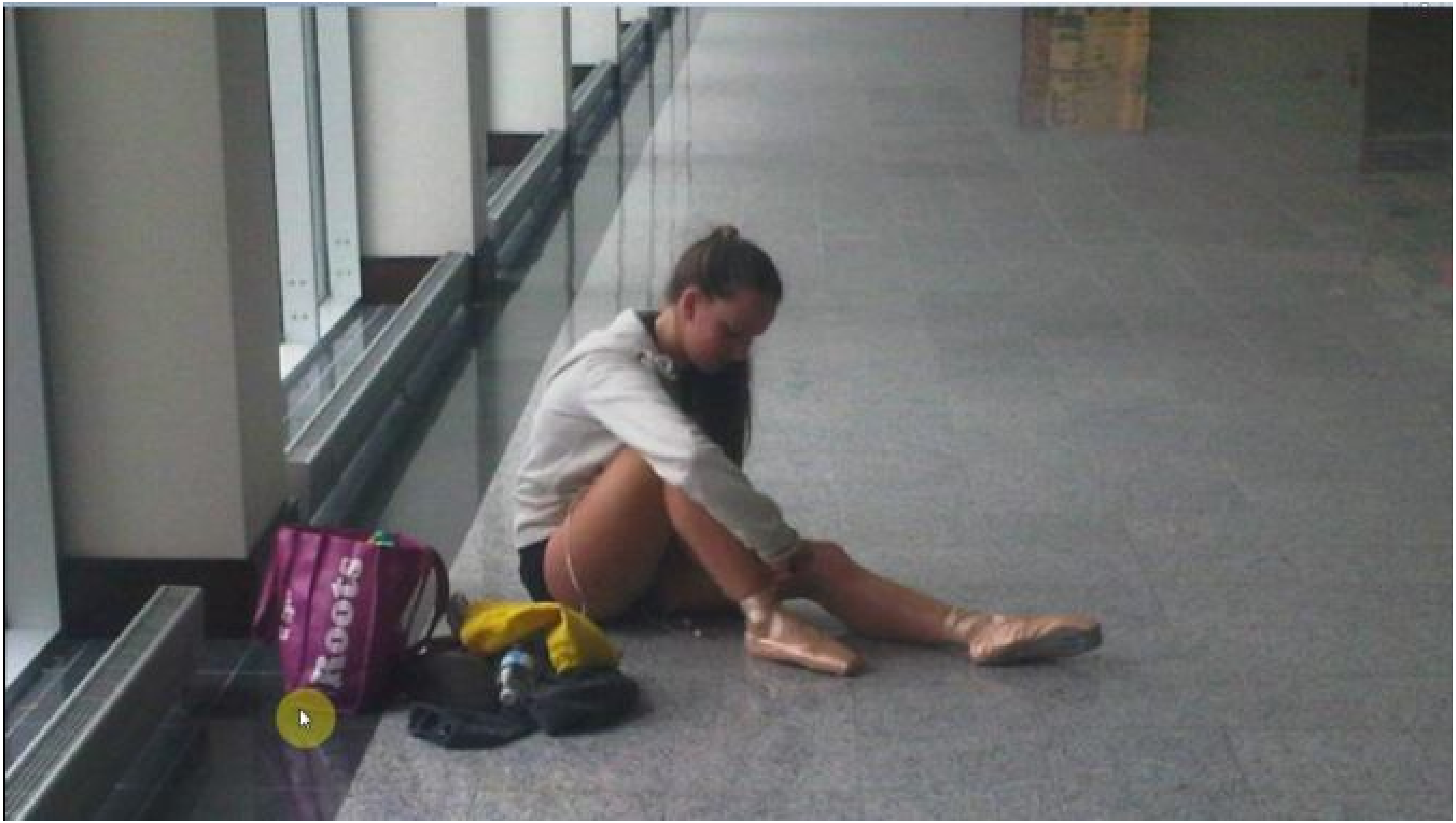
Georges Monette
York University

georges@yorku.ca


> STAR EXCLUSIVE
> STAR EX
keeps Ottawa keeps
drug reviews
under wraps
Doctors alarmed that reassessment
medications,
> STAR EXCLUSIVE


GARDASIL®
Suspension injectable en seringue préremplie
1 dose, 0,5 ml - voie IM.


KAITLYN ARMSTRONG
Whitby, Ontario


Roots


LINDA MORIN
Laval, Quebec


MORIN
ALAIN

Science shows HPV vaccine has no dark side

To attribute rare devastating occurrences to a vaccine requires evidence of causation, which the Star didn't have in its article on Gardasil.

Given the power of HPV vaccine to prevent disease and death, a long Toronto Star article that appears to suggest that the HPV vaccine causes harm is troubling and disappointing, write Juliet Guichon and Dr. Rupert Kaul.

By: Juliet Guichon Dr. Rupert Kaul Published on Wed Feb 11 2015

The HPV vaccine was created to prevent an infection that causes cancer. That is pretty exciting. After all, Terry Fox's arduous marathon a day was to raise money for a cancer cure. Did he even imagine that we would have a vaccine to prevent cancer?

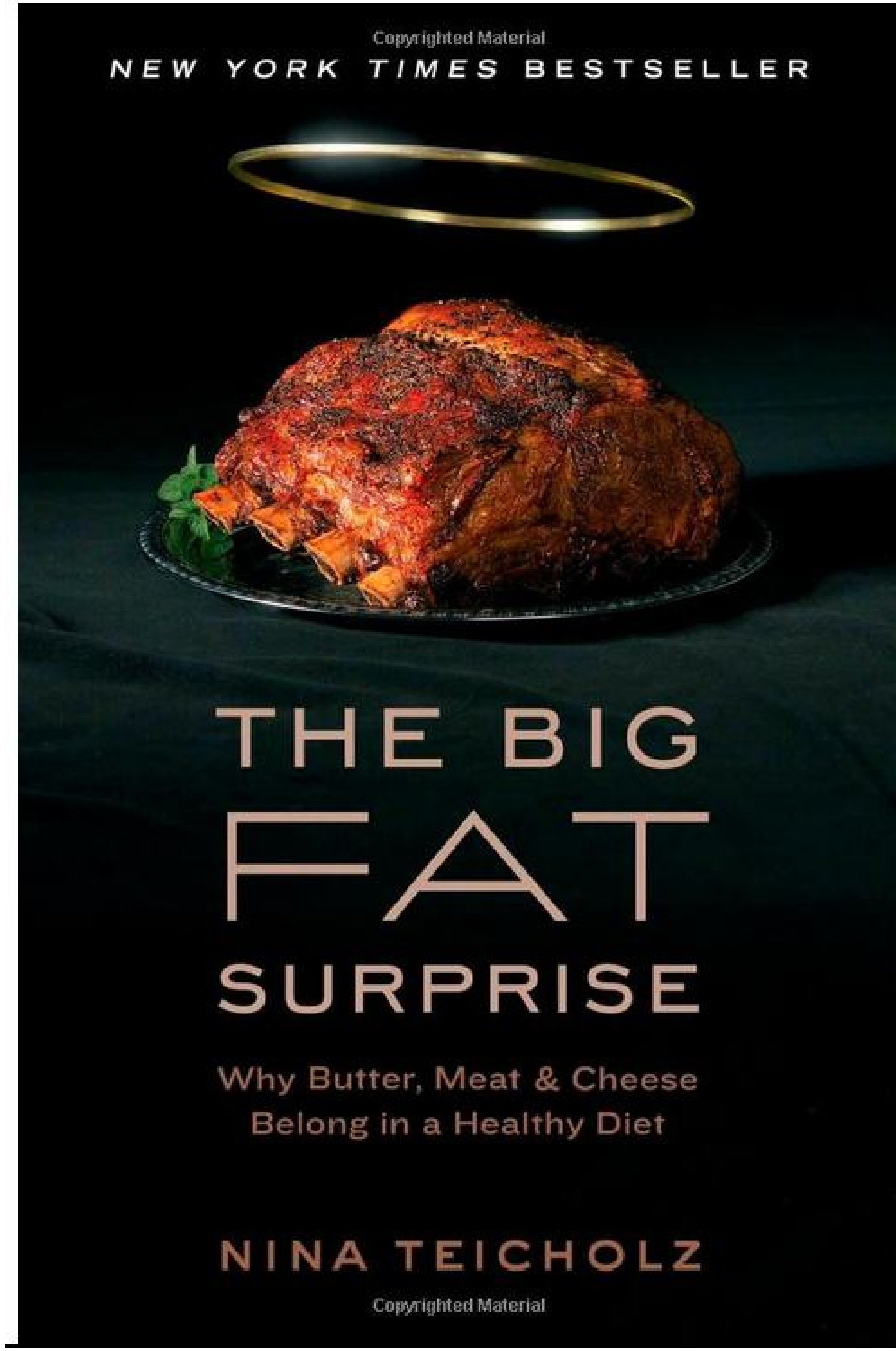
Given the power of HPV vaccine to prevent disease and death, a long Toronto Star article that appears to suggest that the HPV vaccine causes harm is troubling and disappointing. Although the article states in the fifth paragraph that "there is no conclusive evidence showing the vaccine caused a death or illness," its litany of horror stories and its innuendo give the incorrect impression that the vaccine caused the harm.

The Star story states that some people became sick and even died after being vaccinated against HPV infection. Yet, after HPV vaccination, some people might have won a major scholarship or the lottery. Does this mean the vaccine caused the award or the win? Hardly.

The fact that one event follows another does not mean that the first event caused the second — in scientific terms, correlation is not causation.

For example, the number of shark attacks and ice cream sales rise when the weather is hot. The confusion of correlation and causation here is funny because, of course, the shark attacks don't cause the ice cream sales increase. But in the case of the HPV vaccine, such confusion is not funny because HPV infection can have very serious consequences that the vaccine helps prevent.

The Star presented the stories of women who have suffered greatly. The article was engaging, dramatic and might have created fear. But study after study has shown that there is no causal link between the events the Star reported and the vaccine. About 169 million doses of the HPV vaccine have been administered worldwide. In any given large population, there will be illness and death. This is a statistical fact. To attribute rare devastating occurrences to a vaccine requires evidence of causation, of which the international scientific community and the Star article have none.



"Solid, well-reported science . . . Like a bloodhound, Teicholz tracks the process by which a hypothesis morphs into truth without the benefit of supporting data."

—*Kirkus Reviews* (starred review)

by Lara Goodrich Ezor June 5, 2014 4:55 AM

Butter Is NOT Back (And Other Truths About Saturated Fat)

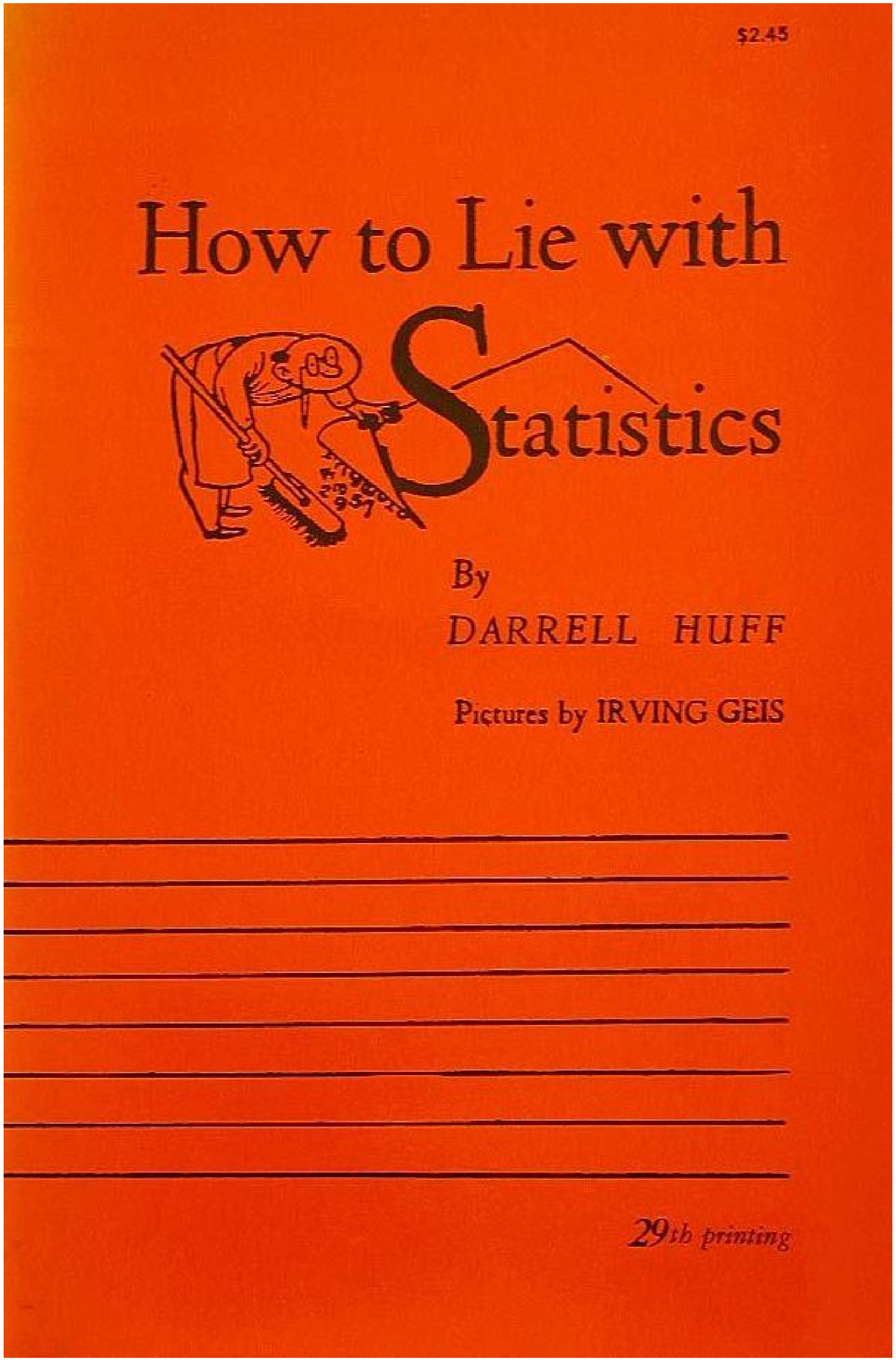
In March, *New York Times* writer and famous foodie Mark Bittman declared that "butter is back." His piece reported on the findings of a recent meta-analysis published in the *Annals of Internal Medicine* that questioned the long-standing link between saturated fat and coronary disease.

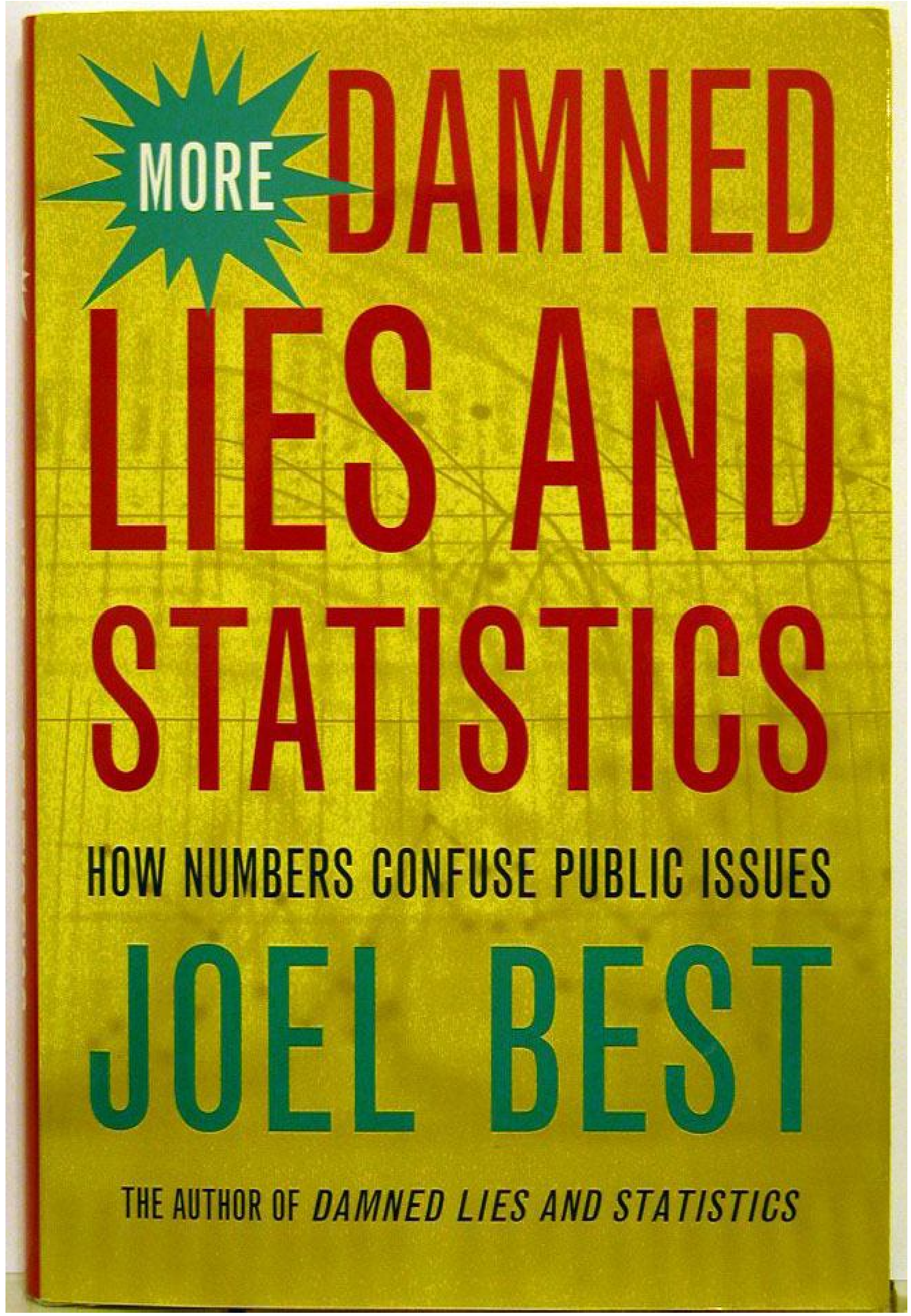
While Bittman celebrated the findings and told readers they could "go back to eating butter," nutrition and public health professionals have been quick to caution, "Not so fast!"

Dr. David Katz, Director of the Yale Prevention and Research Center, responded to the piece, pointing out Bittman's lack of qualifications for interpreting scientific studies and ultimately calling the writer "a potential danger to the public health."

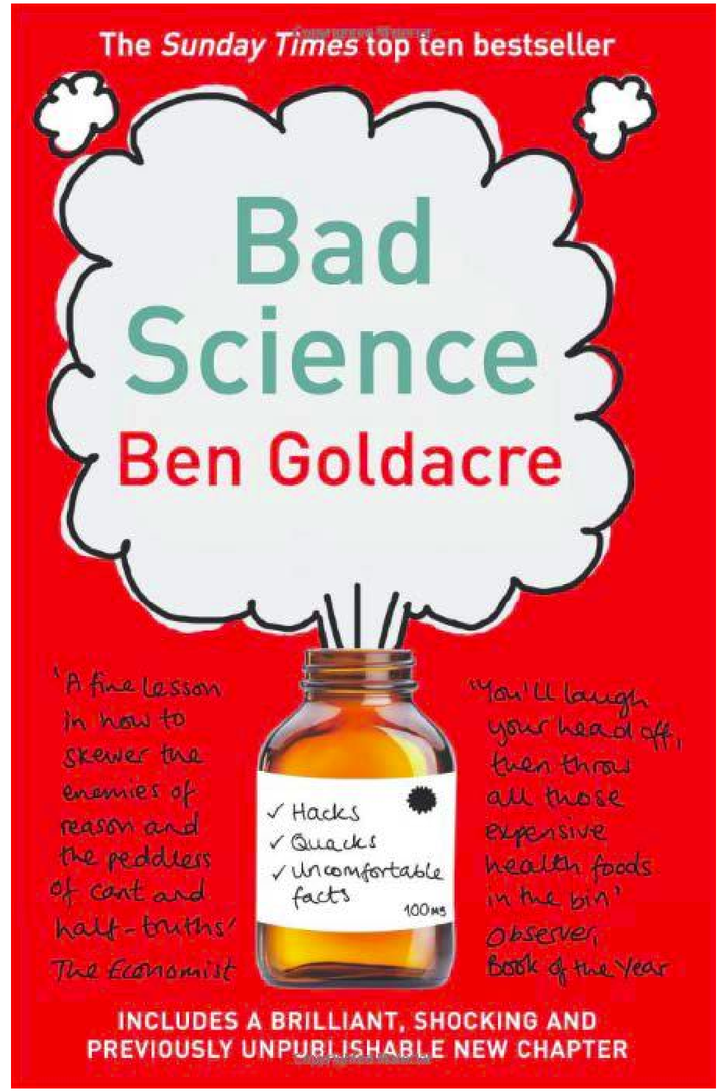
The Harvard School of Public Health put out a statement in the wake of the meta-analysis' publication calling its conclusions "seriously misleading," highlighting "many errors and omissions."

Best selling stats book of all times

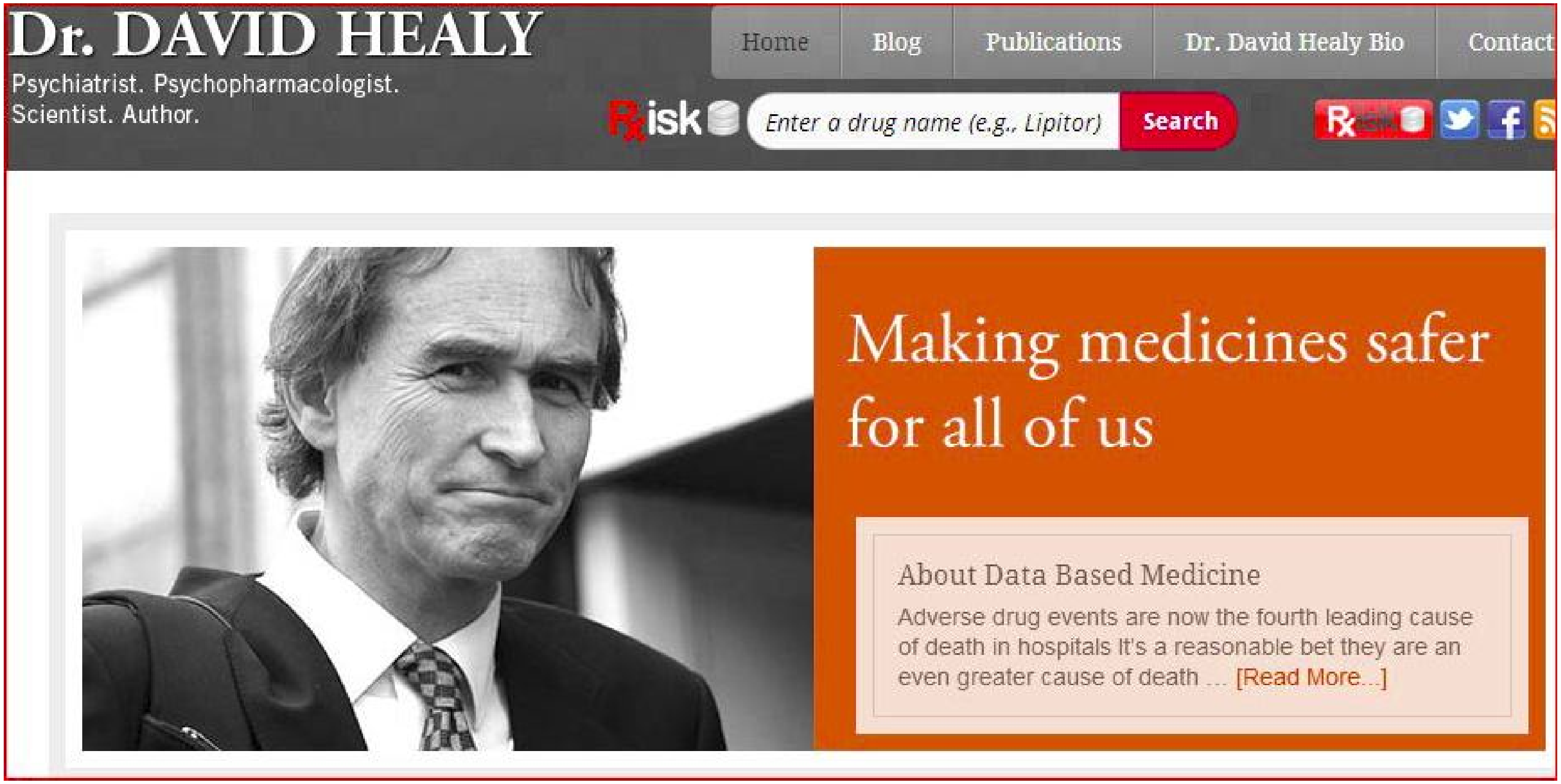


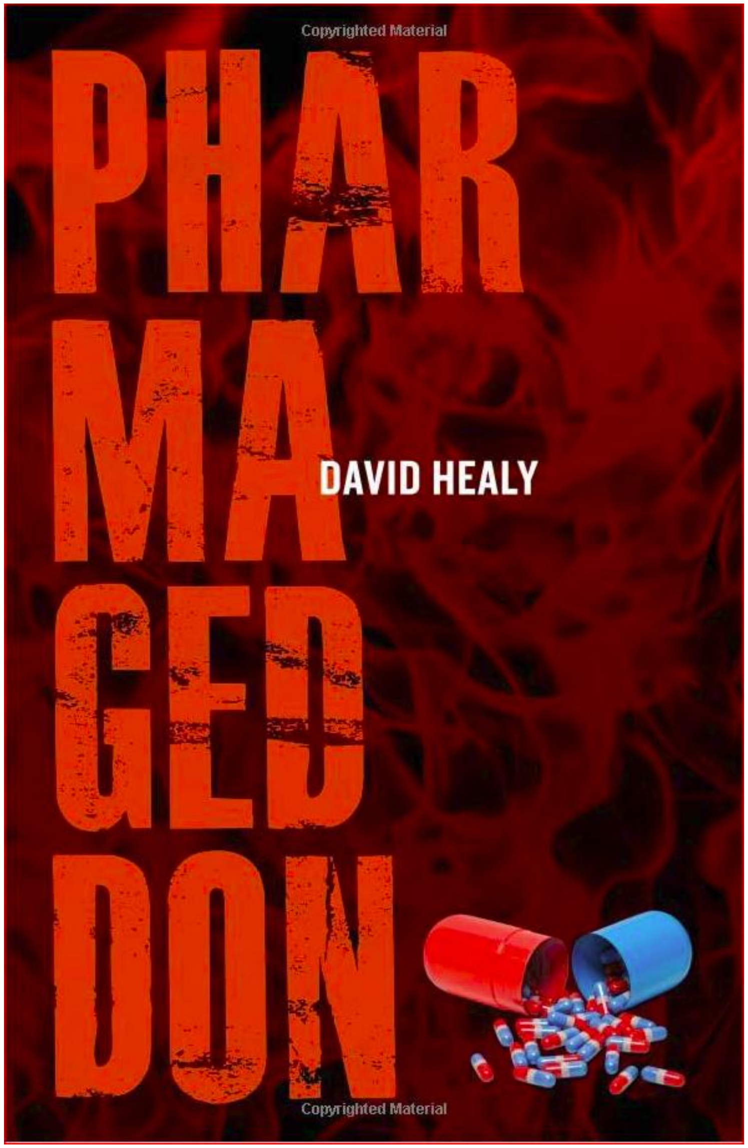

MORE
DAMNED
LIES AND
STATISTICS
HOW NUMBERS CONFUSE PUBLIC ISSUES
JOEL BEST
THE AUTHOR OF DAMNED LIES AND STATISTICS


Bad Pharma™
Ben Goldacre
Bestselling author of Bad Science
How drug companies mislead doctors and harm patients
364 pages
4th


The Sunday Times top ten bestseller
Bad Science
Ben Goldacre
'A fine lesson in how to skewer the enemies of reason and the peddlers of cant and half-truths'
The Economist
✓ Hacks
✓ Quacks
✓ Uncomfortable facts
100mg
'You'll laugh your head off, then throw all those expensive health foods in the bin'
Observer, Book of the Year
INCLUDES A BRILLIANT, SHOCKING AND PREVIOUSLY UNPUBLISHABLE NEW CHAPTER

Going further: David Healy (of CAMH fame):





David Healy takes Goldacre's argument one step further and questions whether relying Clinical Trials can give us the answers we need.

Statistical thinking will one day
be as necessary
for efficient citizenship
as the ability
to read and write.

– H. G. Wells

Misunderstand statistics?
Splitting hairs?
Does it really matter?

Misunderstand statistics?
Splitting hairs?
Does it really matter?

A few consequences?

- The global economic meltdown
- Wrongful murder convictions
- Delayed response to health effects of tobacco
- Poor health policies and treatment decisions

Meet the man whose big idea felled Wall Street

Math whiz proposed applying this statistical formula to credit risk, and financial meltdown ensued

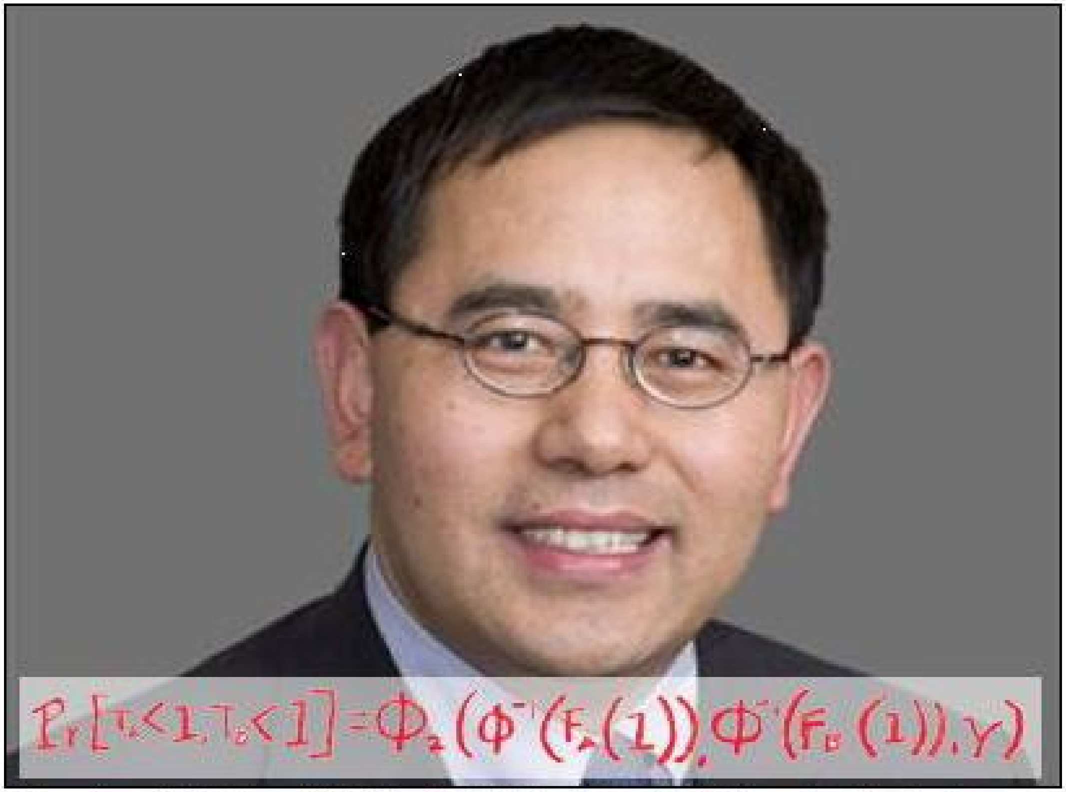
Mar 18, 2009 04:30 AM

Comments on this story (102)

CATHAL KELLY
STAFF REPORTER

Note: This article has been edited to correct a previously published version.

Former University of Waterloo statistician David X. Li didn't burn down the American economy. He just supplied the matches.



University of Waterloo statistician David Li is shown in this handout photo, along with his statistical formula for modeling the behaviour of several correlated risks at once.

As economists and market watchers cast about for people to blame for the U.S. market meltdown, Li has surfaced as a scapegoat. Recently, *Wired* magazine ran an article on Li's work subtitled, "The Formula That Killed Wall Street."

The formula in question is the so-called Gaussian copula function. On the most basic level, the formula allows statisticians to model the behaviour of several correlated risks at once.

In a scholarly paper published in 2000, Li proposed the theorem be applied to credit risks, encompassing everything from bonds to mortgages. This particular copula was not new, but the financial application Li proposed for it was.

Disastrously, it was just simple enough for untrained financial analysts to use, but too complex for them to properly understand. It appeared to allow them to definitively determine risk, effectively eliminating it. The result was an orgy of misspending that sent the U.S. banking system over a cliff.

"To say David brought down the market is like blaming Einstein for Hiroshima," says Prof. Harry Panjer, Li's mentor at the University of Waterloo. "He wasn't in charge of the financial world. He just wrote an article."

It is easy to lie with statistics.
It is hard to tell the truth without it.

– *Andrejs Dunkels*

Pot use before 18 lowers IQ by 8 points

THERESA BOYLE
HEALTH REPORTER

Persistent, dependent use of marijuana before age 18 has been shown to cause lasting harm to a person's intelligence, attention and memory, according to a study in The Proceedings of the National Academy of Sciences of the U.S.

Among a long-range study cohort of more than 1,000 New Zealanders, individuals who started using cannabis in adolescence and used it for years afterward showed an average decline in IQ of eight points when their IQs were compared at ages 13 and 38. Quitting pot did not appear to reverse the loss either, said lead re-

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Don't forget to brush your teeth

Good oral health could lower risk of dementia

NATASJA SHERIFF
REUTERS

People who keep their teeth and gums healthy with regular brushing may have a lower risk of developing dementia later in life, according to a new study.

Researchers, who followed close to 5,500 elderly people over an 18-year period, found those who reported brushing their teeth less than once a day were up to 65 per cent more likely to develop dementia than those who brushed daily.

Not just global issues.
Also everyday decisions:

Does using cellphones cause brain cancer?

Plastic bottles? Are they poisonous?

- Controversy over Bisphenol-A bottles

New drugs: are they safe?

Will taking more Vitamin D help to prevent cancer?

Most of these issues boil down to asking:

Will X cause Y?

Why can’t the experts agree?

How do I make a wise decision for myself?

Should I or Shouldn't I do X?

Does doing X cause Y?

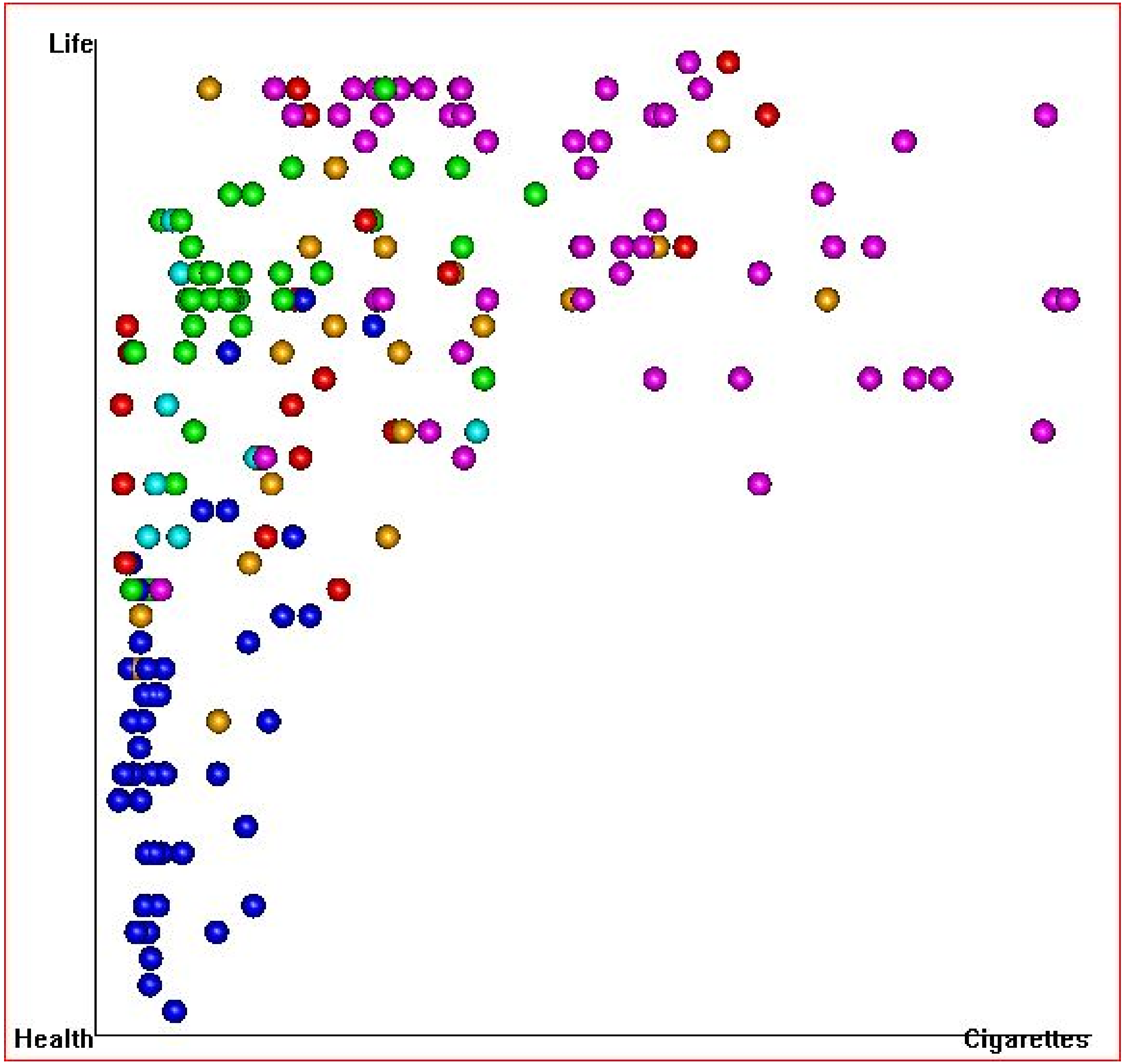
Answering an important question:

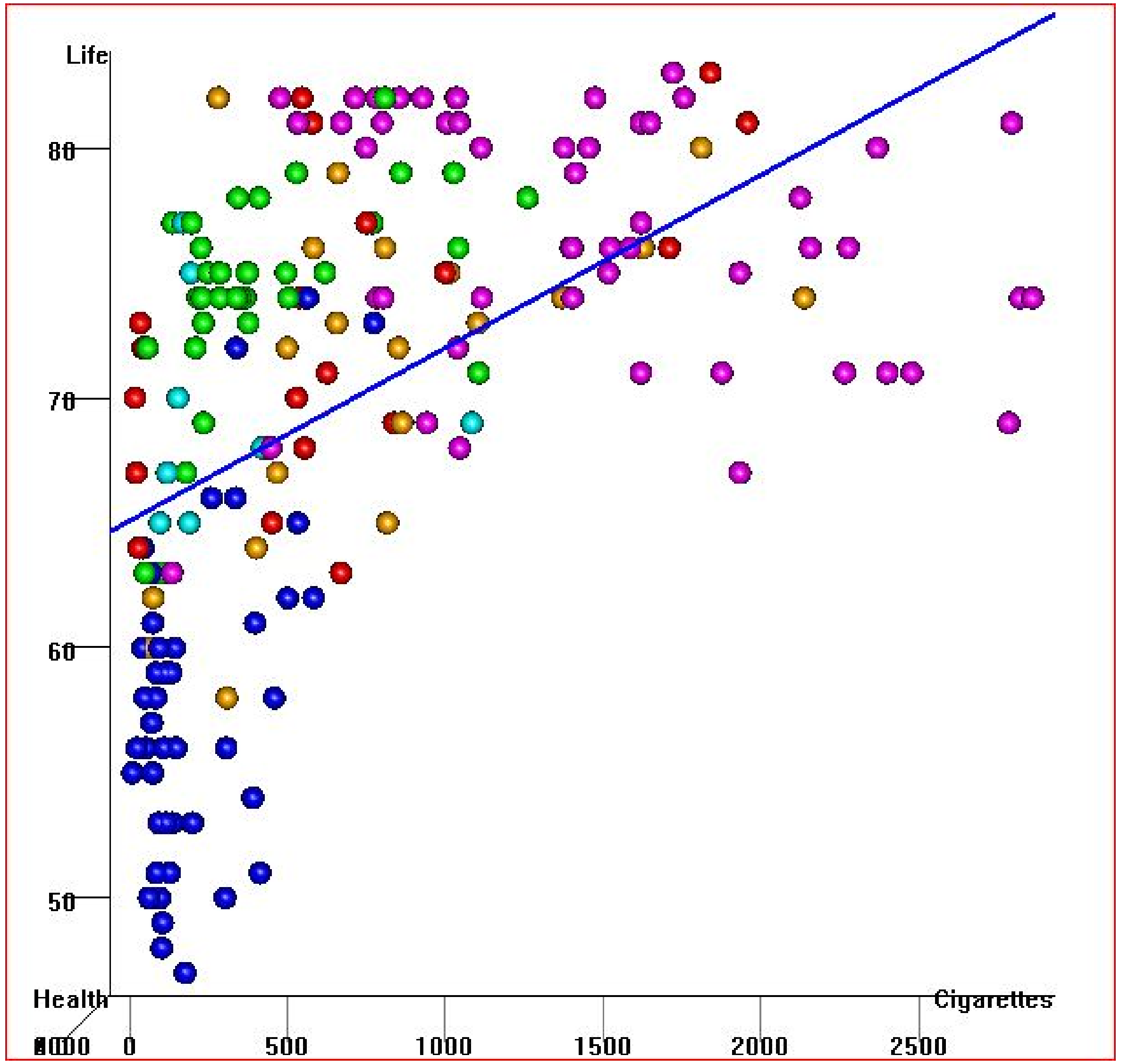
Just how harmful is smoking anyways?

Use data for an ‘evidence-based’ answer:

We can go to the web (e.g. Gapminder.org) to get data on
Smoking and on **Life Expectancy**
from most countries in the world

We’ll see just how much smoking is bad for your health by looking at the **relationship** between **Smoking** and **Life Expectancy**


Life
Health
Cigarettes



Coefficients	Estimate	Std.Error	DF	t-value	p-value
(Intercept)	65.075840	0.855974	183	76.025515	<.00001
Cigarettes	0.006915	0.000855	183	8.090493	<.00001

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What does this actually mean?

One extra **cigarette per year** adds

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```

What does this actually mean?

One extra **cigarette per year** adds

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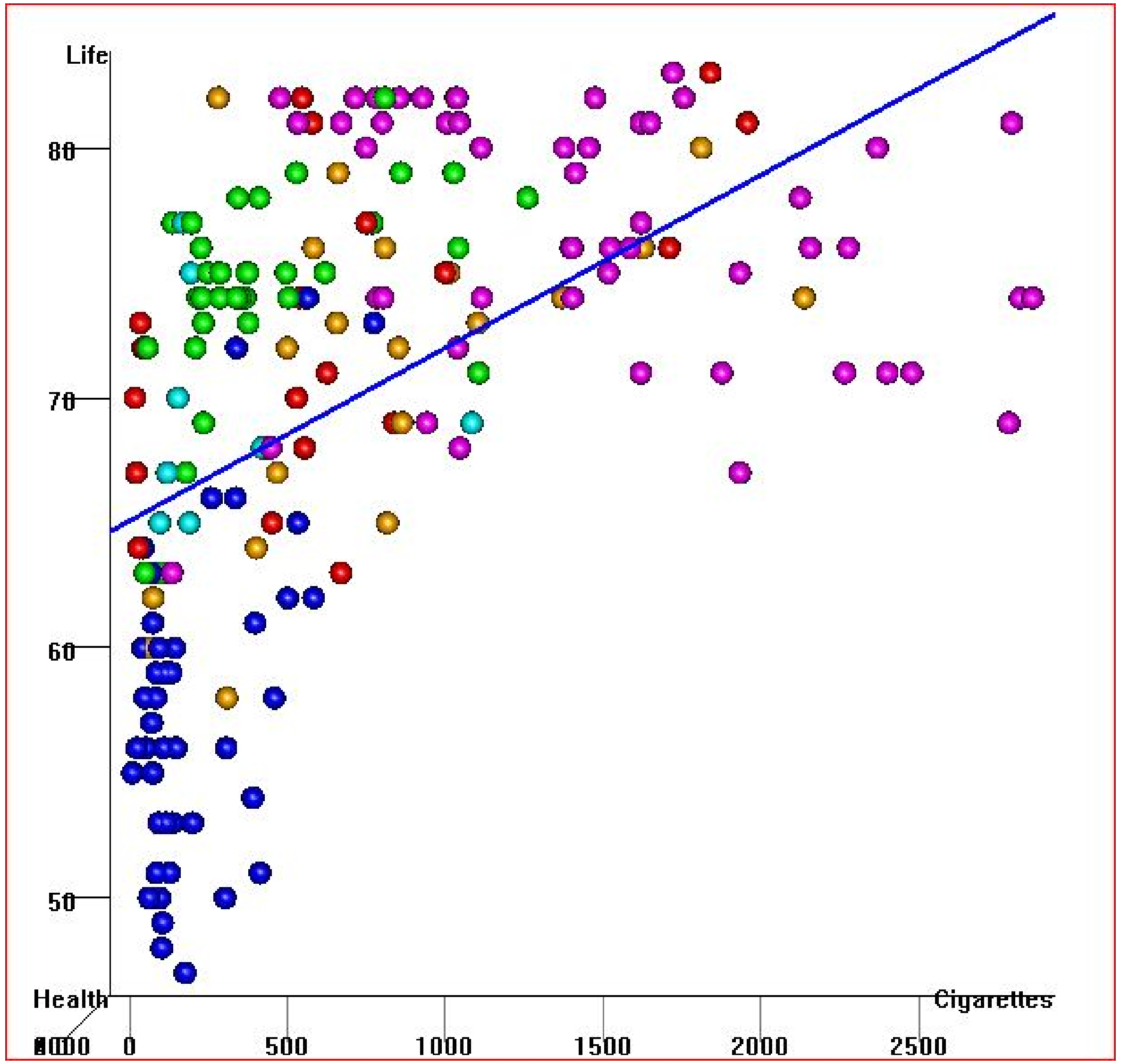
Not very impressive but in better units:

All it takes is 4 cigarettes a day

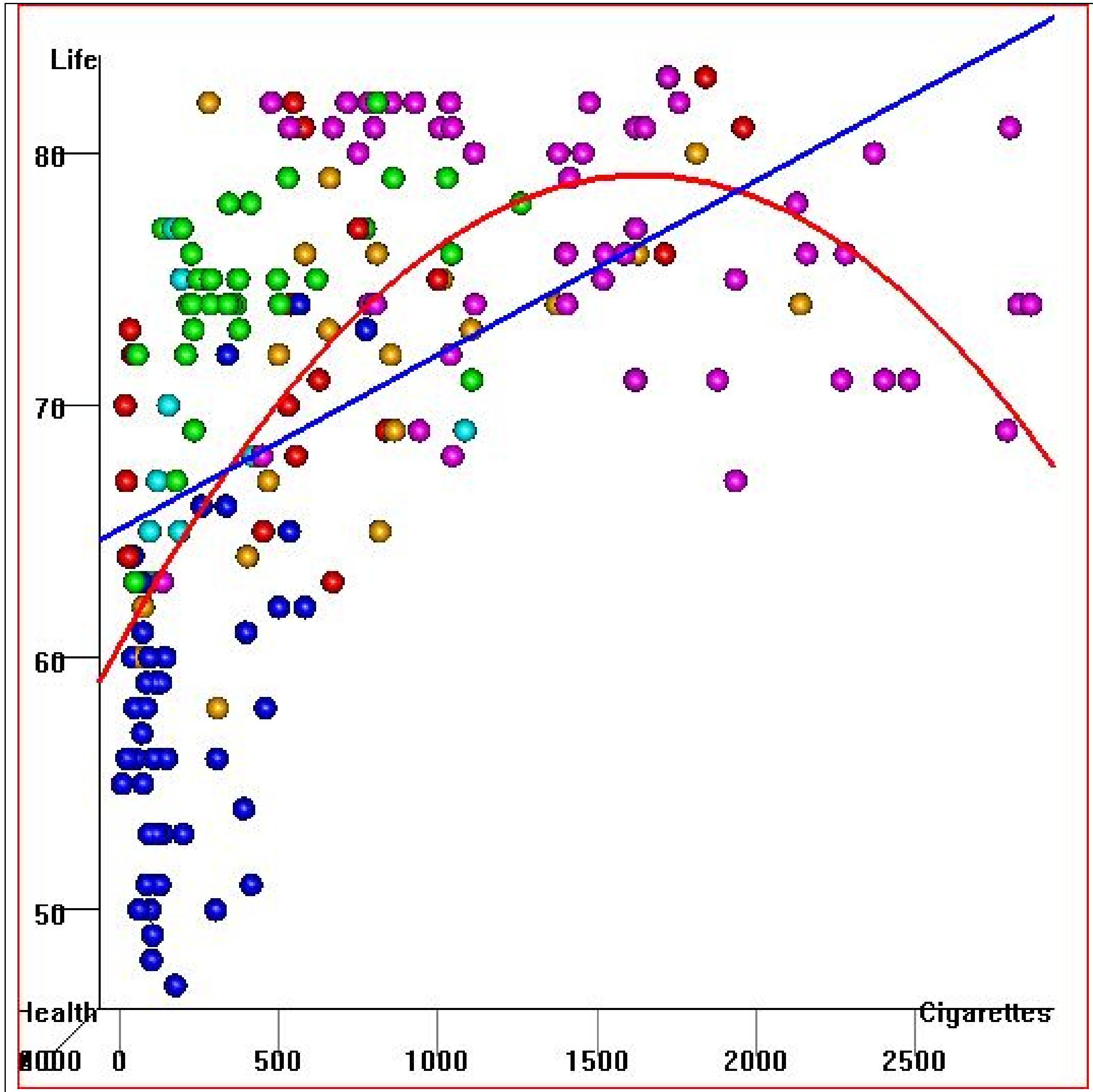
to add 10 years to your life



Life
80
70
60
50
Health
Cigarettes
0
500
1000
1500
2000
2500

A good statistician would tell you
that this is ridiculous.

There’s obvious curvature in the relationship

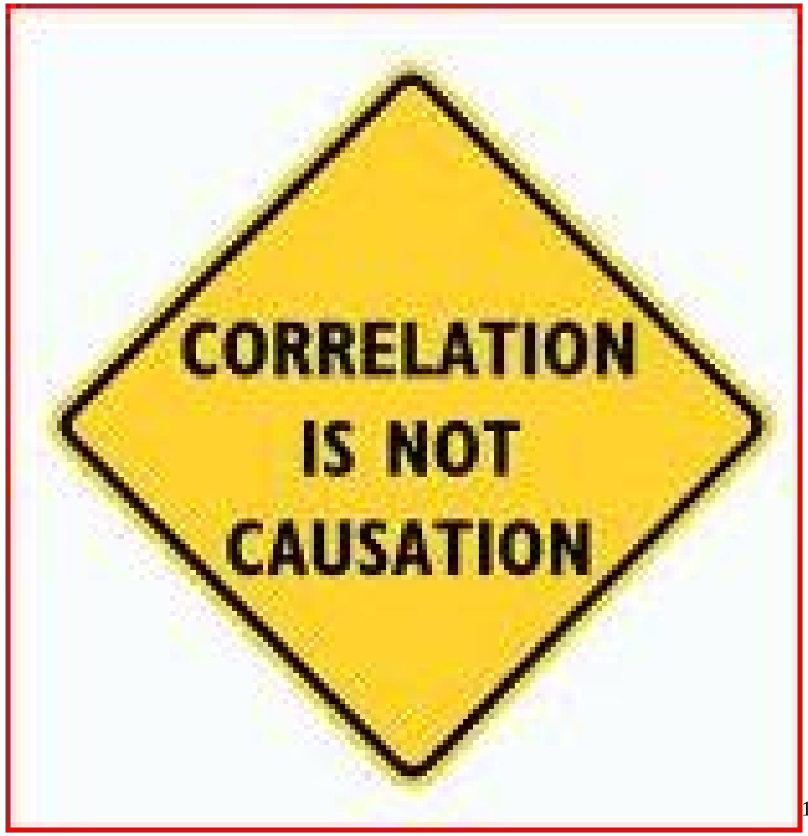


Fitting a quadratic model and maximizing the quadratic shows that

4.495 cigarettes/day

is actually optimal

What’s the problem?



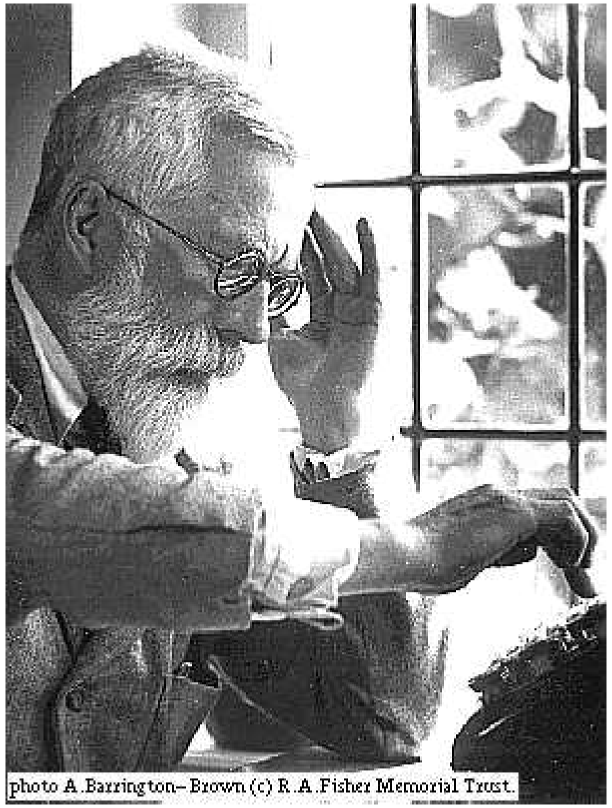
[1]

[1] Adapted from a sign by Edward Tufte

Maybe it isn’t smoking that’s responsible for higher life expectancies.

Maybe it's something else –
a **CONFOUNDING VARIABLE**
(also called a "**LURKING VARIABLE**" or "**LURKING FACTOR**")
that causes **BOTH**
higher life expectancies
and higher rates of smoking.

R. A. Fisher's brilliant solution (~1920):



Randomized Experiment

using **Random Assignment** to treatments (levels of the X variable)

To avoid the possibility that some factor other than smoking is responsible for the difference in health:

Toss a coin to choose who gets to smoke and who doesn't

Observe for many years and then compare smokers and non-smokers

If there's a difference between the two groups either smoking that's responsible **OR** it's due to something else ***BY CHANCE – which we can measure***

If we compare a group of **smokers** with a group of **non-smokers** the two groups **could be different** in all sorts of ways other than the mere fact that one group smokes and the other doesn't. And these other differences could be responsible for differences in health.

Fisher's idea:

- Make sure the two groups are similar ***except for chance.***

- How? Take one group of willing subjects and ***RANDOMLY ASSIGN*** [3] subject to the two ‘treatments’: one randomly selected group smokes for 20 years and the other does not.

---

[3] There are many ways of doing this but the idea is that a RANDOM mechanism, e.g coin flip or random number generator, must be used somewhere.

Should we only use experimental data to determine whether X causes Y?

Problems with experimental data:

- too costly
- too risky
- too long
- subjects who are willing and available may not be typical of target population
- observational data already on hand so let's use it
- won't give an answer until it's too late
- experimental situation not realistic
- we can only tell whether **assignment to treatment groups** makes a difference. What if subjects don't comply?

For example: clinical trials are used to assess the **effectivenes** of drugs but not useful to discover possible rare side-effects. These need to be monitored with observational data when the drug is being used.

"Second best" method for causal inference:

Use observational data with care

How?

Use *observational data* and try to control for the possible effects of a confounding factor(s) by measuring it and

1) Analyzing each *stratum* with similar values for the confounding factor(s). This is called *stratification*.

OR

2) Building a statistical model in that includes the confounding factor(s) and using *multiple regression*.

OR

3) Use new advanced methods: propensity score matching, discontinuity models, etc.

This are no perfect solutions and they all require judgment to assess studies based on these methods:
Problems:

1) The confounding factor may be known but may be measured with error so that it is not fully controlled.

2) Some important confounding factors might not be known.

Note that these are NOT problems for randomized experiments.

Understanding the problem:

<table>
<tr><td colspan="2" rowspan="2">The fundamental
2 x 2 table of statistics</td><td colspan="2"></td></tr>
<tr><td></td><td></td></tr>
<tr><td rowspan="2">Questions</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
</table>

Understanding the problem:

The fundamental 2 x 2 table of statistics			
Questions	**Causal** what would happen if …?		
	Predictive passive guessing		

Understanding the problem:

The fundamental 2 x 2 table of statistics		**Data**	
		Experimental random assignment to treatments (X)	**Observational** X is not controlled
Questions	**Causal** what would happen if …?		
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Understanding the problem:

The fundamental 2 x 2 table of statistics

		Data	
		Experimental random assignment to treatments (X)	**Observational** X is not controlled
Questions	**Causal** what would happen if …?	**Ideal** where Fisher wants to be	
	Predictive passive guessing		**Ideal** for prediction under the same conditions as those observed

Understanding the problem:

The fundamental
2 x 2 table of statistics

		Data	
		Experimental random assignment to treatments (X)	**Observational** X is not controlled
Questions	**Causal** what would happen if …?	**Ideal** where Fisher wants to be	**Where most of the difficult questions are**
	Predictive passive guessing	Hardly ever	**Ideal** for prediction under the same conditions as those observed

Hints of causal effects based on correlations (observational data) are everywhere:

How should we react to them?

(how would we like our students to react to them)

How can we do better than Fisher?

Should we even try?

Recent example in the news:

People who use sunscreen lotion have a higher risk of skin cancer than people who don’t

Should I stop using SSL?

How can we make wise decisions when faced with this kind of information?

The solution to the problem involves
asking questions
more than finding answers!

What question do we want to ask?
Is the question causal or predictive?

What kind of data do we have?
How were people assigned randomly
to use more or less SSL?

If the answer is yes, then we go on to ask more questions: Were the subjects like me? Did they comply with the random assignment?

If the answer is ‘not randomly’ then we need to think of possible confounding factors.

Understanding these issues is important for simple everyday questions.

But also for very large questions

Conjectures::

1. Most scientific and social controversies subsist on conflicting interpretations of evidence

2. Most conflicting interpretations of evidence are rooted in difficulties inferring causality from observational data

Caution:

Taking a hard line "**correlation is not causation**" may be as problematic as seeing causation in every correlation.

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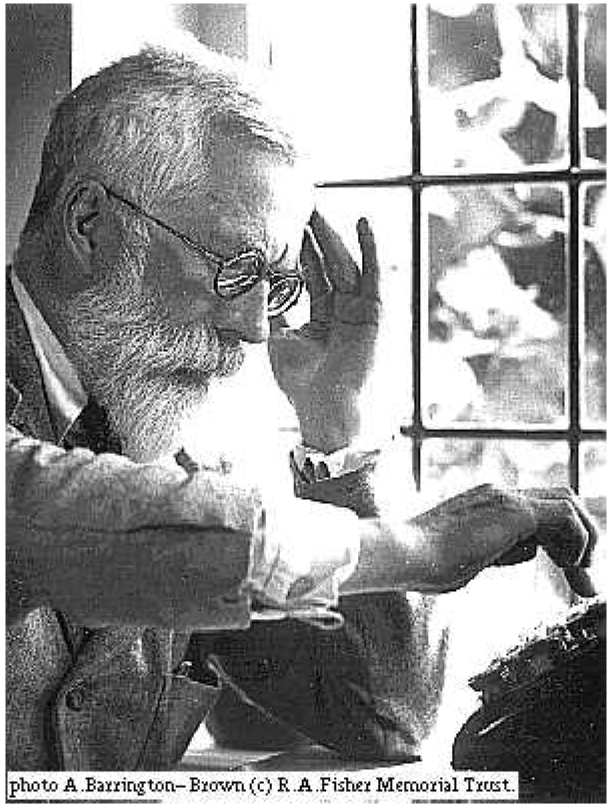
Taking a hard line “**correlation is not causation**”
may be as problematic as seeing causation in every correlation.

For many important issues, we only have observational data.

This is a major challenge for modern Statistics and for the interpretation of scientific evidence.

We need to find a balance between extreme skepticism and extreme gullibility.

R. A. Fisher's brilliant solution (~1920):



Randomized Experiment

To avoid the possibility that some factor other than smoking is responsible for the difference in health:

Toss a coin to choose who gets to smoke and who doesn't

Observe for many years and then compare smokers and non-smokers

If there's a difference between the two groups either smoking that's responsible **OR** it's due to something else ***BY CHANCE – which we can measure***

What can it mean when a variable X (Smoking) is correlated (associated) with another variable Y (Life Expectancy) in a sample of data

If we compare a group of **smokers** with a group of **non-smokers** the two groups **could be different** in all sorts of ways other than the mere fact that one group smokes and the other doesn't. And these other differences could be responsible for differences in health.

Fisher's idea:

- Make sure the two groups are similar ***except for chance.***
- Take one group of willing subjects and ***RANDOMLY***[1] split them into two groups: one group smokes for 20 years and the other does not.
- At the end of 20 years, if one group is healthier than the other it's due to having been allocated to the smoking or to the non-smoking group **or** it could be due to other differences in the two

---

[1] There are many ways of doing this but the idea is that a RANDOM mechanism, e.g coin flip or random number generator, must be used somewhere.

groups BUT only BY CHANCE – which statisticians can calculate.

Data obtained through an experiment with random allocation to *conditions* (also referred to as *treatments*, *treatment and control*, *groups*, *experimental factor*) is called

Experimental Data

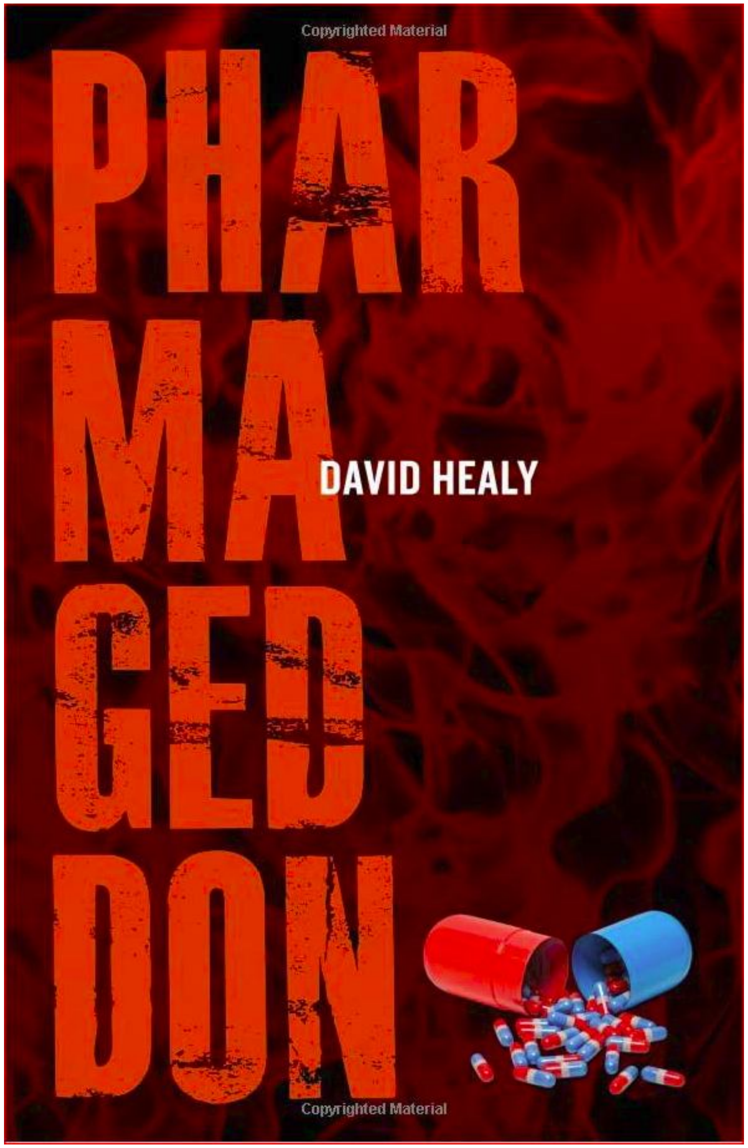
In pharmaceutical studies, the process of testing drugs with randomized experiments is called ***clinical trials***.

On relationships between X and Y:

The fundamental 2 x 2 table of statistics

Data

Questions	**Experimental** Levels of X decided by tossing a coin	**Observational** Levels of X observed as they occur without intervention
Causal Should I or Shouldn't I do X?	**Gold standard:** Fisher insists on this for causal inference	The main challenge of statistics and research
Predictive Will I or Won't I be Y?	Problematic but rarely an issue	**OK**



David Healy takes Goldacre's argument one step further and questions whether relying Clinical Trials can give us the answers we need.

Health Canada should have power to require greater monitoring of medication, report says

JOANNA SMITH
OTTAWA BUREAU

OTTAWA—Health Canada should be able to require better monitoring of prescription drugs after they hit the market and get better at warning Canadians when something might be wrong, says a recently released Senate committee report.

"The monitoring of a drug's performance, once it enters the population, is an enormously important opportunity to collect information to benefit the health of Canadians and that is not being done," Conservative Sen. Kelvin Ogilvie said Wednesday.

Ogilvie chairs the Senate committee on social affairs, science and technology, which last week published the result of its study on the safety and effectiveness

Meta analysis: Combining information from many studies

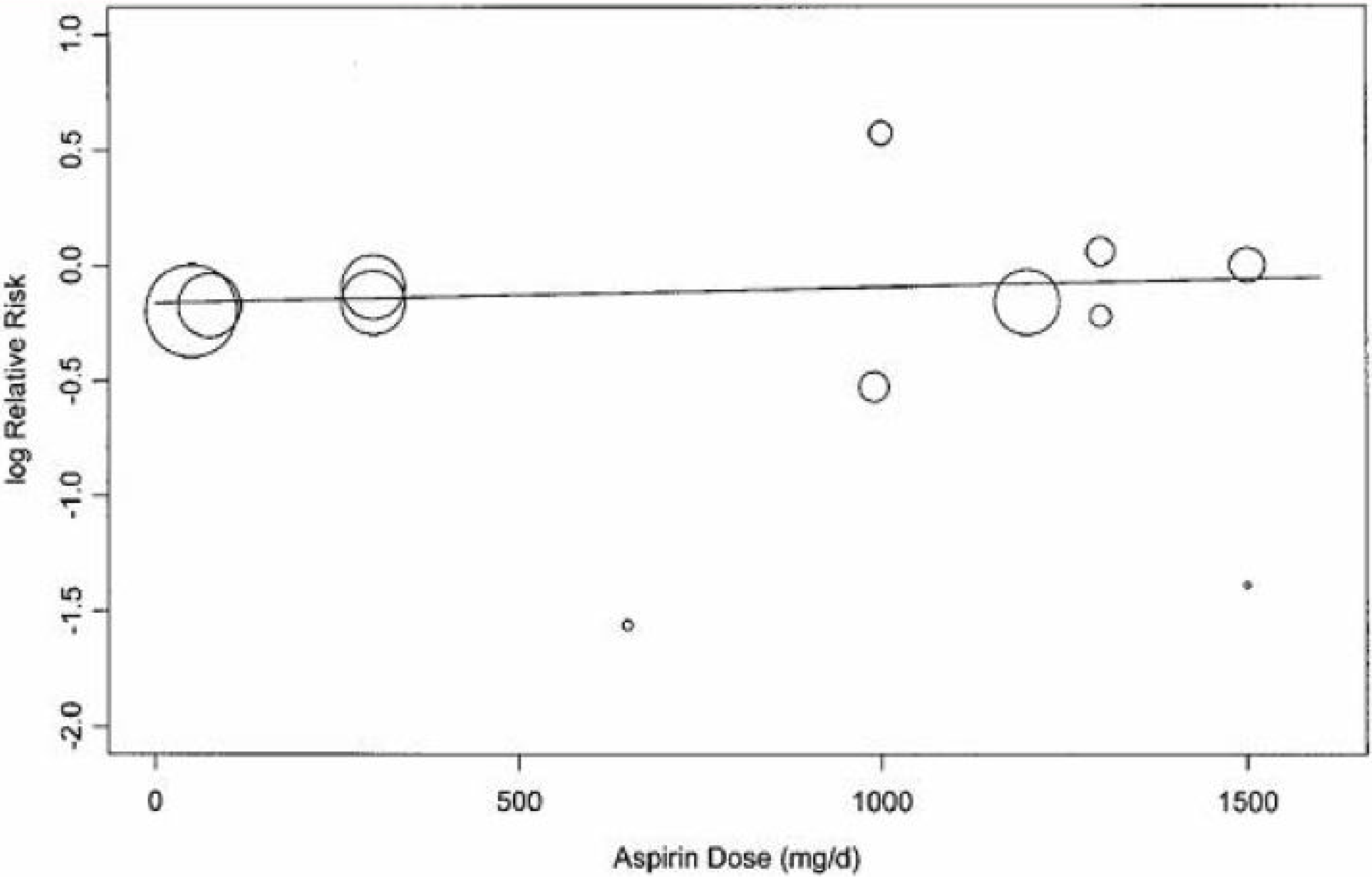


Figure 1. Log relative risk of stroke in 13 trials of aspirin versus placebo [6], according to aspirin dose, together with a summary random effects meta-regression. The area of each circle is inversely proportional to the variance of the log relative risk estimate.

Meet the man whose big idea felled Wall Street

Math whiz proposed applying this statistical formula to credit risk, and financial meltdown ensued

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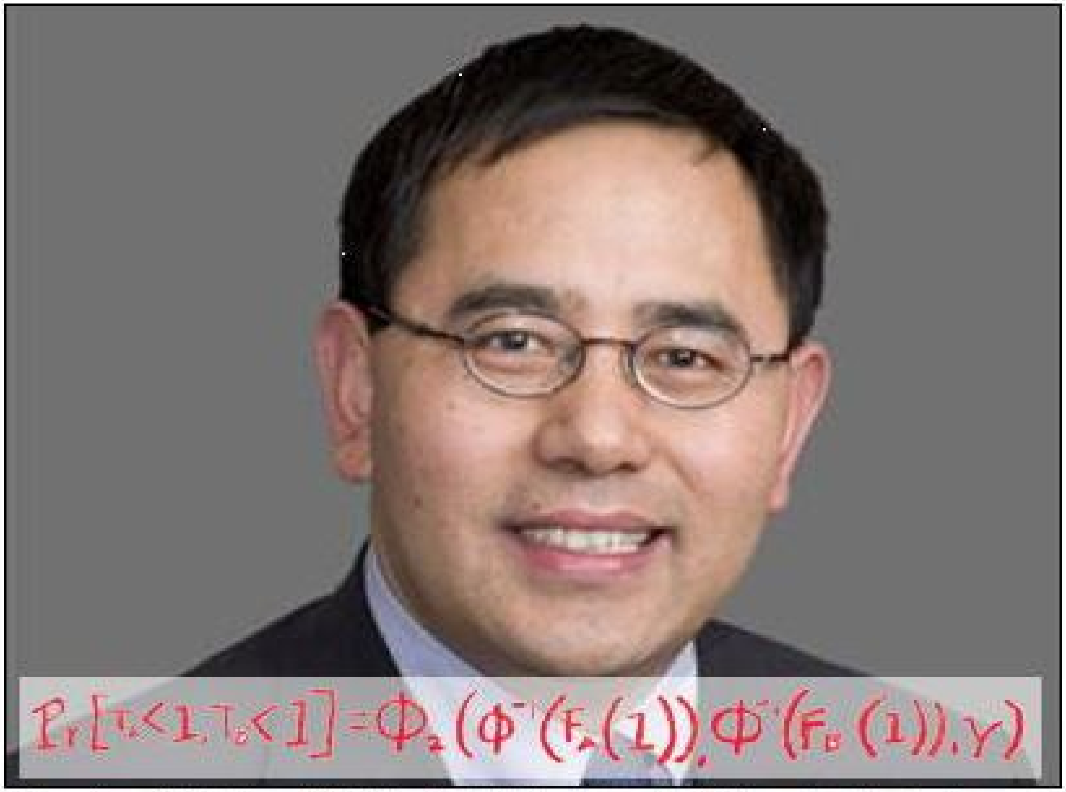

University of Waterloo statistician David Li is shown in this handout photo, along with his statistical formula for modeling the behaviour of several correlated risks at once.

Former University of Waterloo statistician David X. Li didn't burn down the American economy. He just supplied the matches.

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The formula in question is the so-called Gaussian copula function. On the most basic level, the formula allows statisticians to model the behaviour of several correlated risks at once.

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"To say David brought down the market is like blaming Einstein for Hiroshima," says Prof. Harry Panjer, Li's mentor at the University of Waterloo. "He wasn't in charge of the financial world. He just wrote an article."

Note: There are other important issues for experiments to work well: blinding of subject, blinding of assessor, double blind, use of placebo.

The *ideal* experiment is often called a:

Randomized Controlled Double Blind Experiment

Correlation is not necessarily causation unless you are analyzing an experiment

Sir Ronald A. Fisher laid the foundations of Experimental Design ca 1925 to 1940

Fisher insisted that only an experiment can determine whether X causes Y.

He went so far as to defend tobacco companies in the 50s because there was no experimental evidence that tobacco was harmful, only "observational data".

With observational data, X is not controlled by the experimenter. It is just observed as it happens to have been determined naturally. For example, by personal choice to smoke or not smoke.

Should we only use experimental data to determine whether X causes Y?

Problems with experimental data:

- too costly
- too risky
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Why does choosing treatments at random work?

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Taking a hard line "**correlation is not causation**" may be as problematic as seeing causation in every correlation.

Caution:

Taking a hard line "**correlation is not causation**" may be as problematic as seeing causation in every correlation.

For many important issues, we only have observational data.

This is a major challenge for modern Statistics and for the interpretation of scientific evidence

EXAMPLES

Public policy:
Fighting crime:
Does capital punishment work.

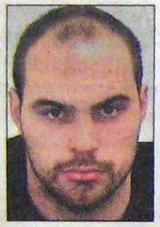
8 inside Syria
WORLD — AA1

World Tour? Our pick is . . .
LIVING — L1

CRUSHED
Phillies on verge of winning Series
SPORTS — S1

Shock, sadness spread over senseless shooting

'Extremely dangerous' man, right, sought in murder of innocent bystander Bailey Zaveda outside Duke of York tavern


Kyle Weese

CAROLA VYHNAK
AND HENRY STANCU
STAFF REPORTERS

An "extremely dangerous" Toronto resident is the subject of a Canada-wide police manhunt following the weekend shooting death of a young woman innocently taking a smoke break outside a Queen St. E. tavern.

Toronto police say they'll do whatever it takes to track down Kyle Weese, 25, described by Det. Sgt. Gary Giroux of the homicide squad yesterday as an "extremely violent man with an extremely violent history."

Weese is "extremely" well-known to both detectives and uniform officers in 55 Division, Giroux said yesterday as he announced the arrest warrant.

Bailey Zaveda, 23, died of gunshot

JUSTICE REFORM

Reports virtually ignored, critics say

Despite hype, experts' recommendations produce few changes

TRACEY TYLER
LEGAL AFFAIRS REPORTER

Just last week, at virtually the time a 15-year-old was cha with murdering Brampton te er Rajiv Dharamdial, govern printing presses were gearing publish a major new report o venting youth crime.

Commissioned last year b mier Dalton McGuinty aft year-old Jordan Manners w dead in a Toronto school, the examines the "root caus youth criminal behaviour. It sents months of work b McMurtry, Ontario's former justice, and former Liberal ca minister Alvin Curling.

"I'm sure the premier . . . is to take the report seriou McMurtry said in an interv "But there will certainly be people in government who m be quite happy to see it buried."

While McMurtry doesn't do the sincerity of McGuinty or cabinet in wanting to do someth about youth crime, a lowering of pectations might be prudent.

In recent years, the province

U.S. c
hit ta
insid

8 killed as milita 'takes matters into own hands' insurgents' line

ALBERT AJI
ASSOCIATED PRESS

DAMASCUS—U.S. mil ters yesterday attack side Syria close to Iraq, killing eight p the Syrian governm as "serious aggress

A U.S. military of by special forces eign fighter net through Syria i where the Am unable to shut was out of the

"We are tak own hands," Associated anonymity.

A Syrian carried by News Ager attacked th the town o metres ins

"You try to move on but you can't. It brings everything back," she said. "(Violence) is happening more and the justice system is at fault for protecting young offenders."

New York Times November 18, 2007	(see below)

Does Death Penalty Save Lives? A New Debate

Joe Raedle/Getty Image

The Supreme Court is considering how to assess the constitutionality of lethal injections. Above, the Texas death chamber.

By ADAM LIPTAK
Published: November 18, 2007

E-MAIL
PRINT
SINGLE PAGE
REPRINTS
SAVE

For the first time in a generation, the question of whether the death penalty deters murders has captured the attention of scholars in law and economics, setting off an

USES AND ABUSES OF EMPIRICAL EVIDENCE IN THE DEATH PENALTY DEBATE

John J. Donohue* and Justin Wolfers**

Figure 1. Homicides and Execution in the United States

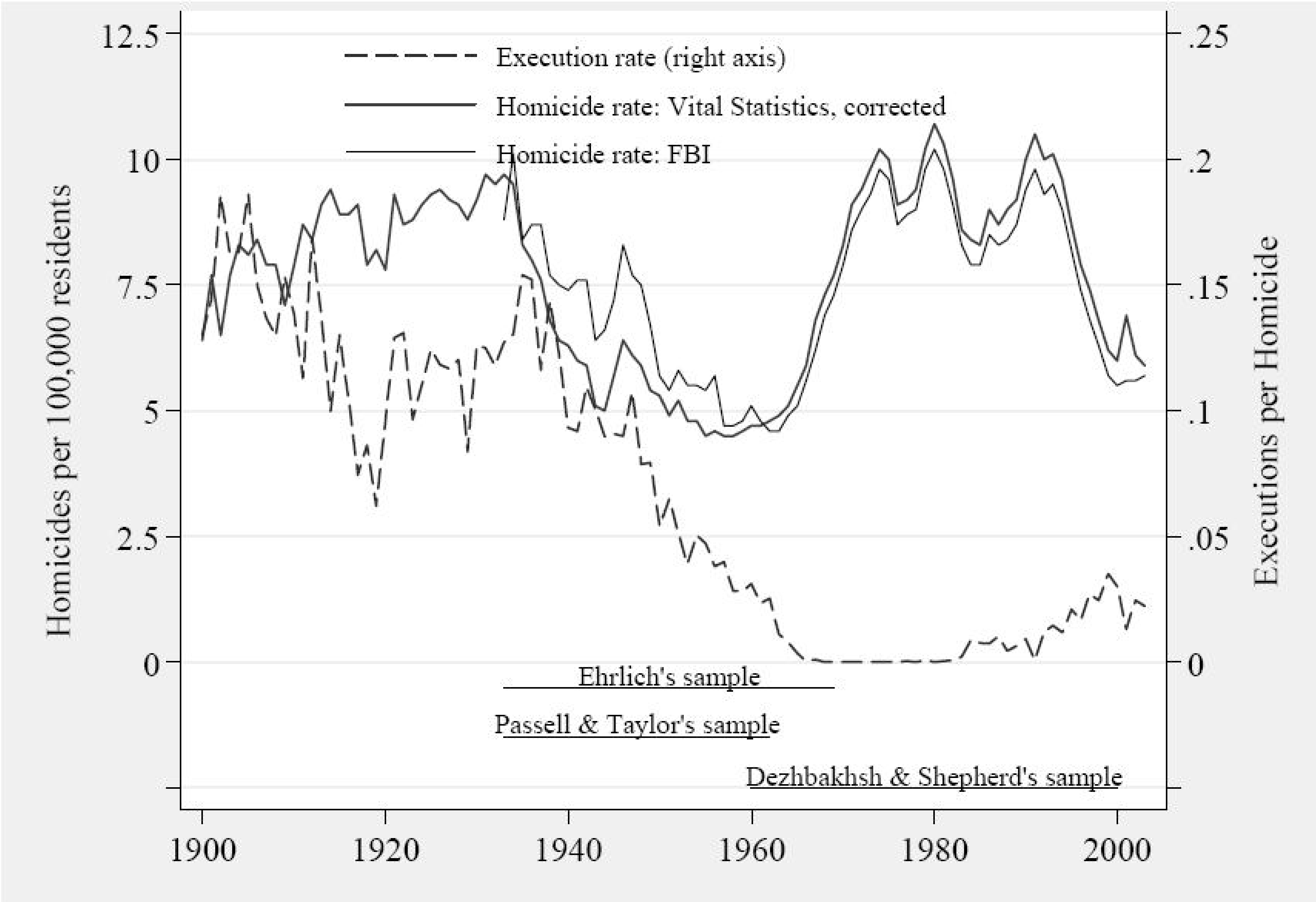
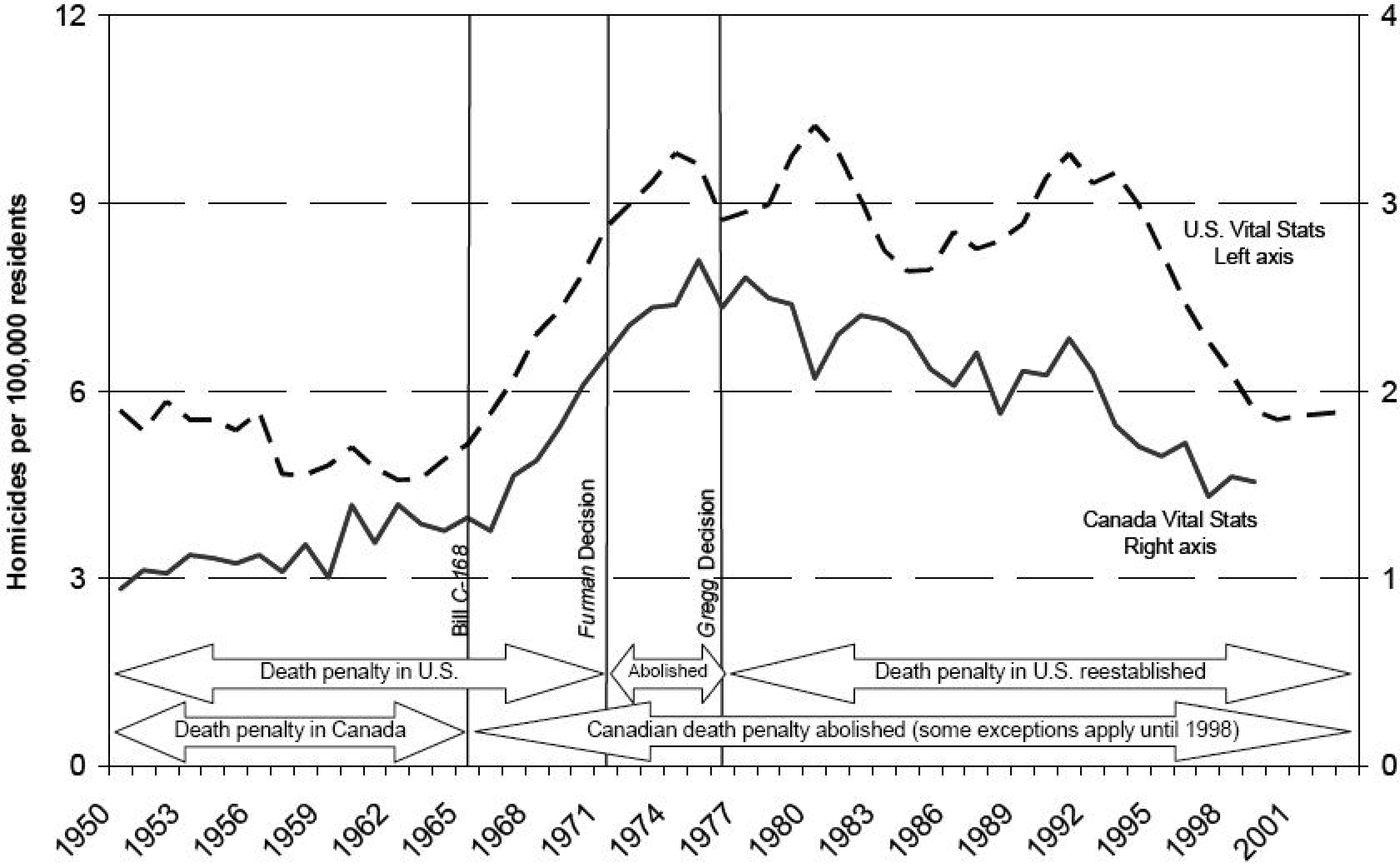
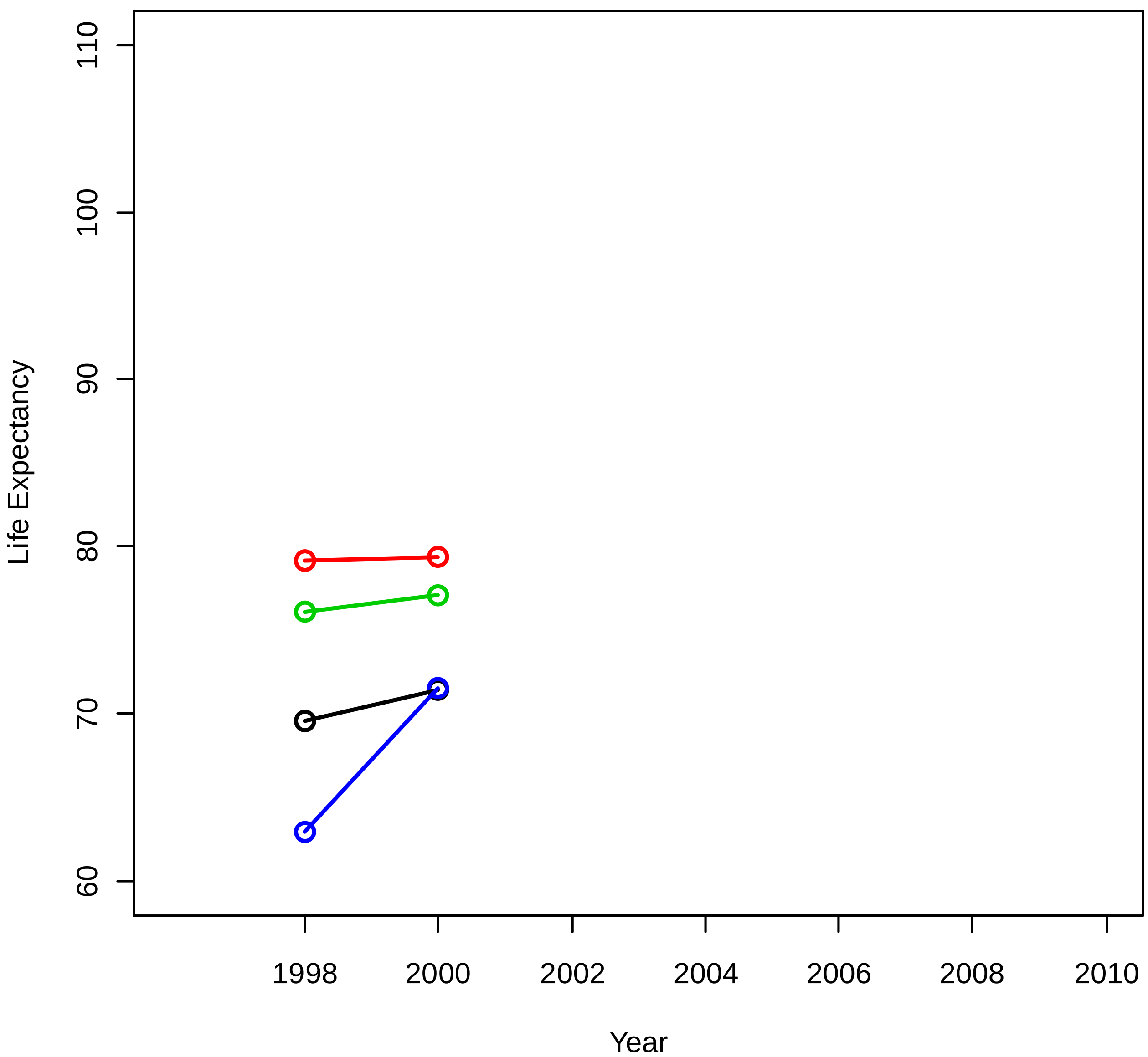


Figure 2. Homicide Rates and the Death Penalty in the United States and Canada



Another common way of thinking that can mislead:


Life Expectancy
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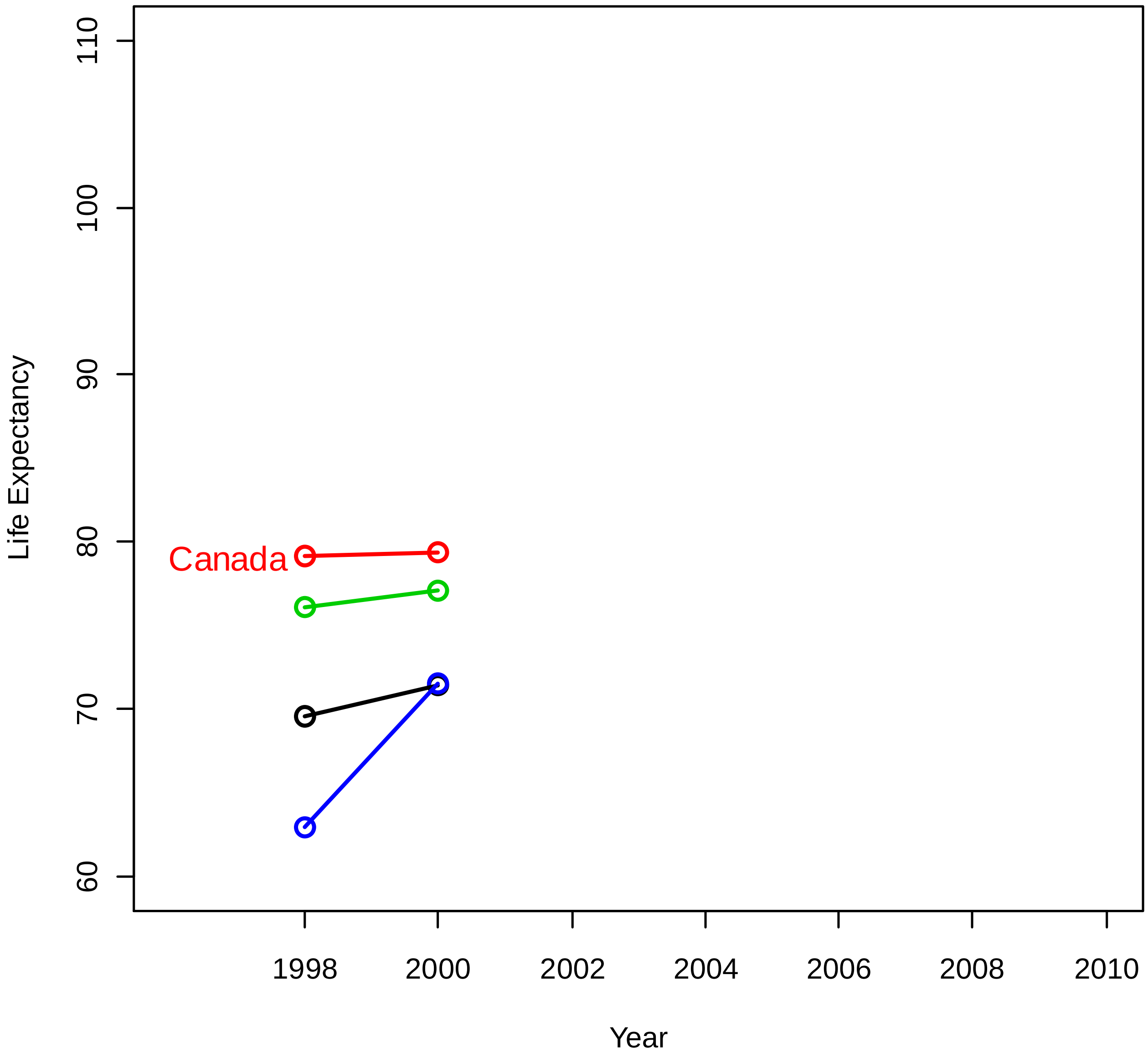

Canada
Life Expectancy
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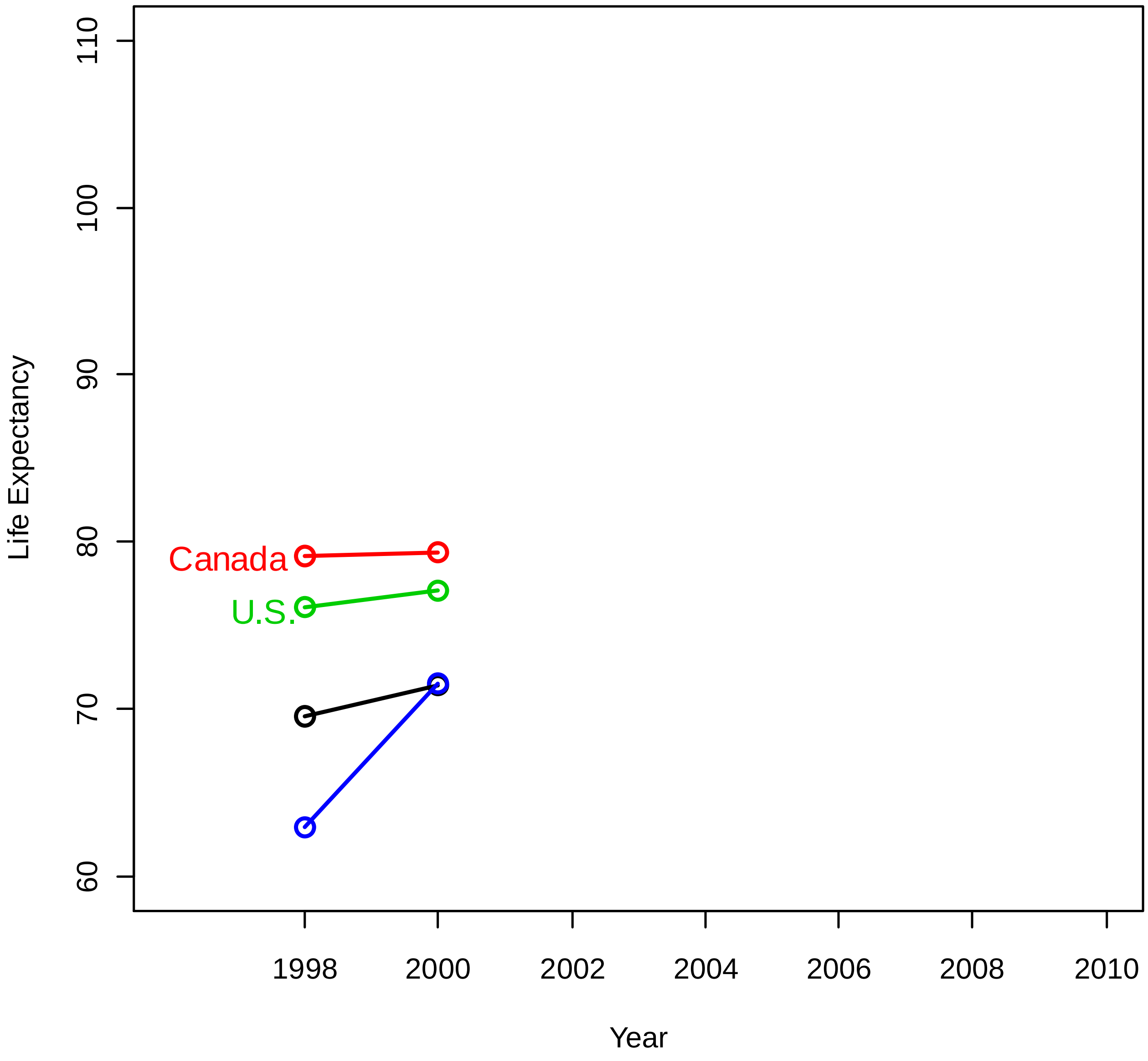

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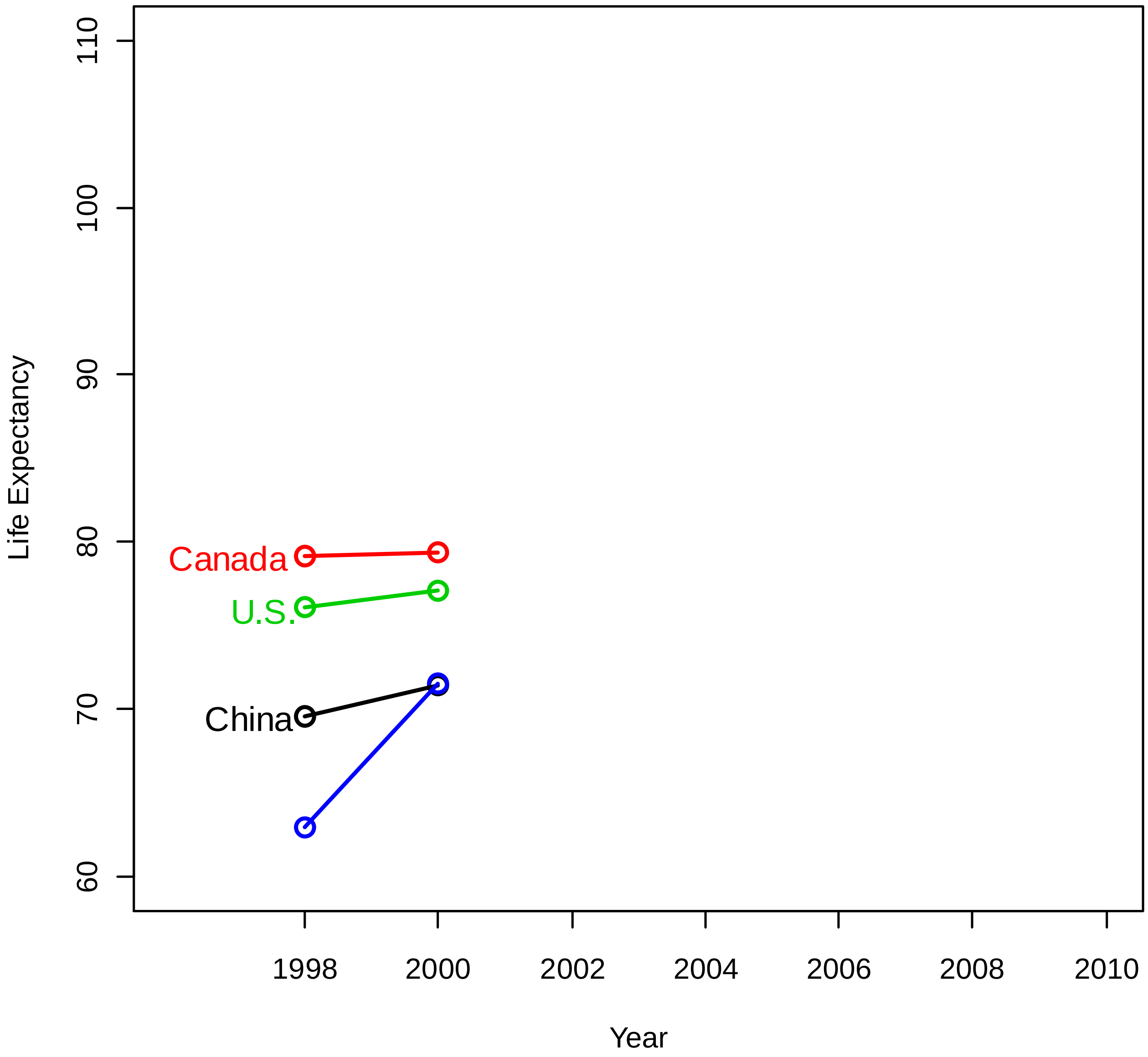
Life Expectancy
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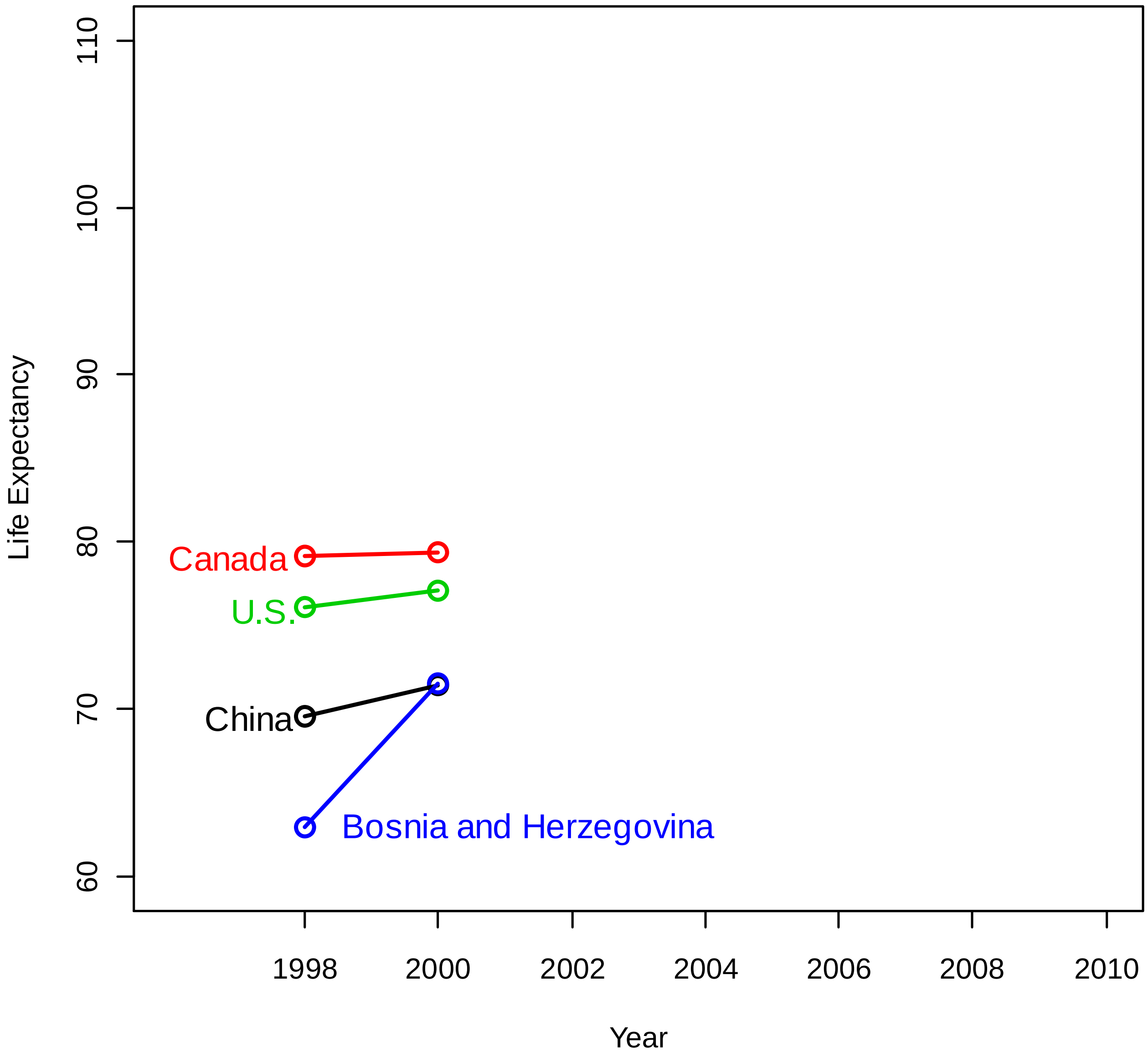
Year



Life Expectancy
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Bosnia and Herzegovina
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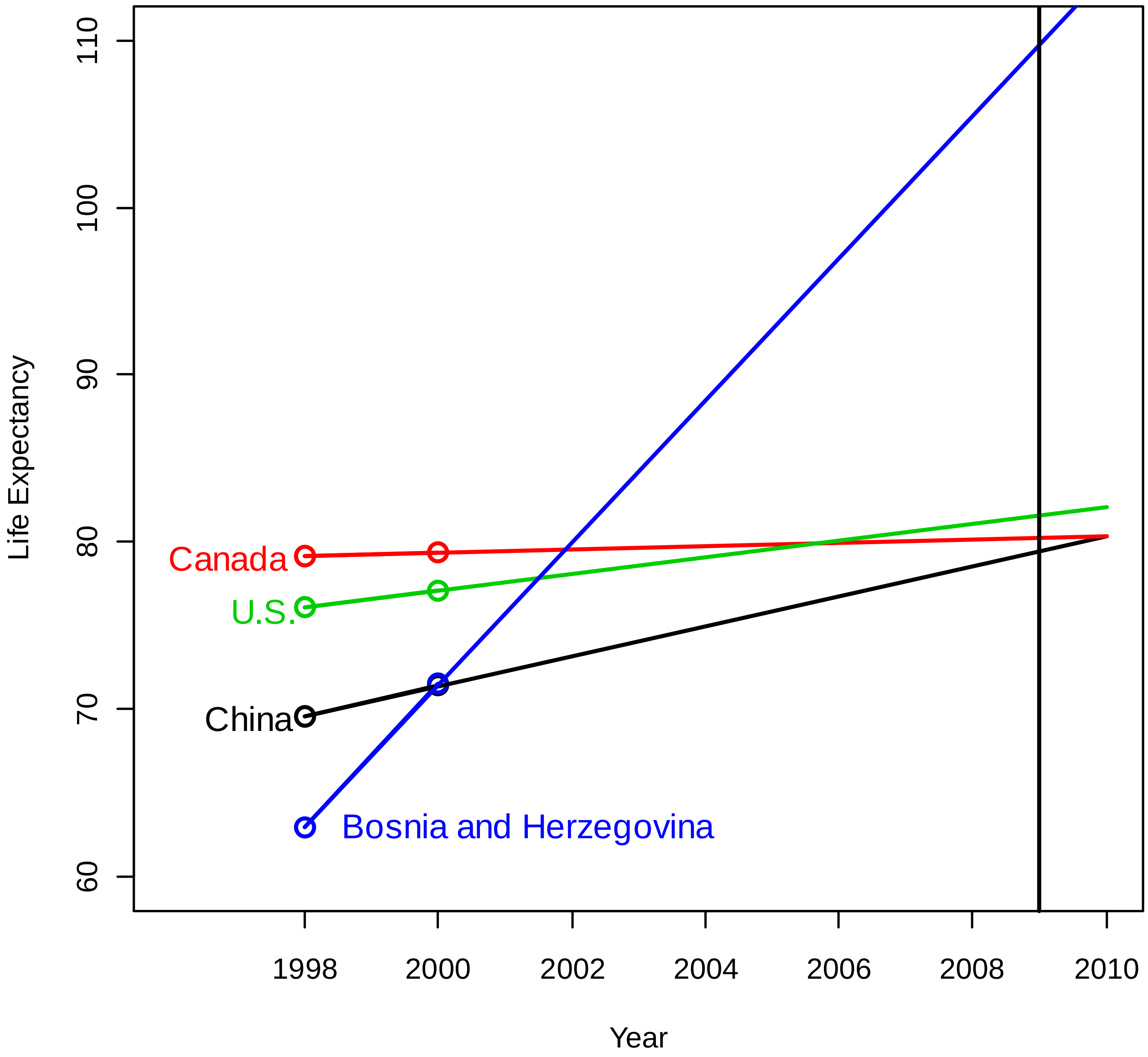
Life Expectancy
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Canada
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China
Bosnia and Herzegovina
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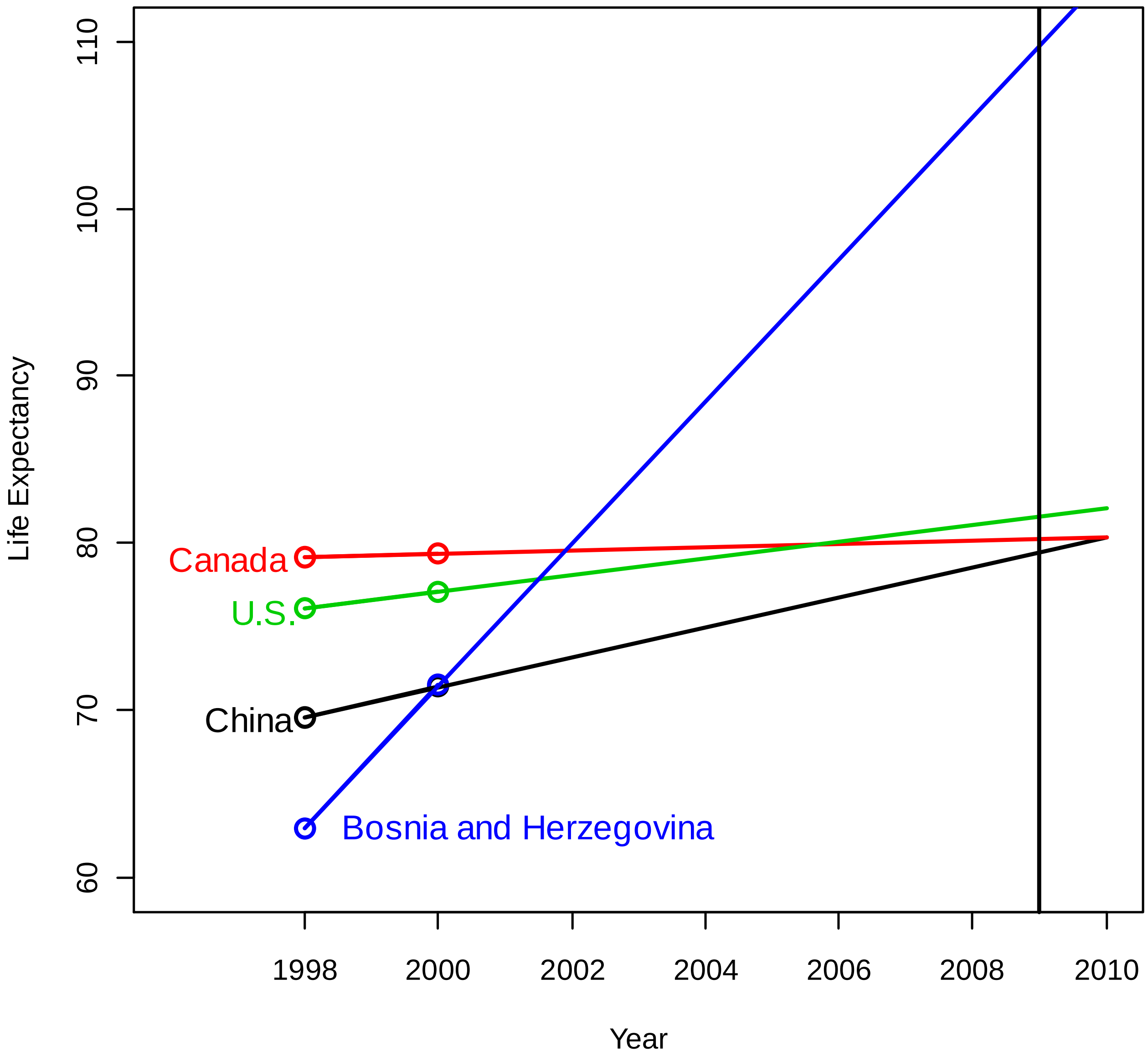
2002
2004
2006
2008
2010
Year

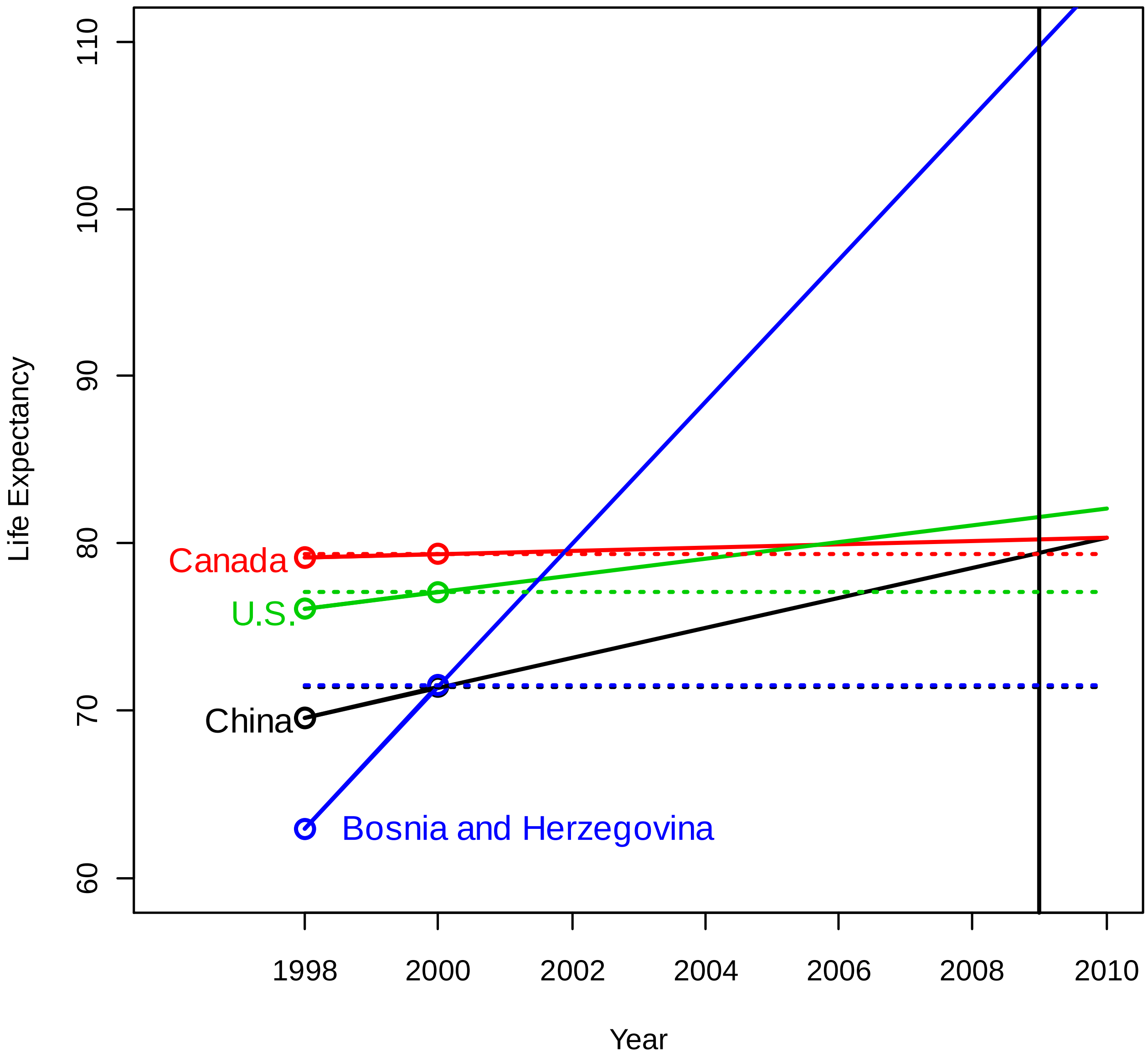
So:

To have a very long life,

move to Bosnia-Herzegovina



Sometimes the best prediction comes from projecting the trend.



Sometimes the best prediction comes from projecting the trend.

Sometimes you should use the la[st]
value.

Usually: something in between.

Do statistics lie?

OR is it misuse of statistics that lies?

Statistics ≠ calculations

Statistics = calculations + statistical reasoning

If you take away reasoning, you’re not doing statistics

Statistics is about how NOT TO LIE with data

What do you need to know about Statistics?

How can we help students develop the judgment to assess the information they see every day?

What do you need to know about Statistics?

How can we help students develop the judgment to assess the information they see every day?

What Educated Citizens Should Know About Statistics and Probability

Jessica UTTS

American Statistician, 2003

2. SEVEN IMPORTANT TOPICS

There are of course many important topics that need to be discussed in an elementary statistics course. For this article, I have selected seven topics that I have found to be commonly misunderstood by citizens, including the journalists who present statistical studies to the public. In fact researchers themselves, who present their results in journals and at the scientific meetings from which the journalists cull their stories, misunderstand many of these topics. If all students of introductory statistics understood them, there would be much less confusion and misinterpretation related to statistics and probability and findings based on them. In fact the public is often cynical about statistical studies, because these misunderstandings lead to the appearance of a stream of studies with conflicting results. This is particularly

1. When it can be concluded that a relationship is one of cause and effect, and when it cannot, including the difference between randomized experiments and observational studies.

2. The difference between statistical significance and practical importance, especially when using large sample sizes.

3. The difference between finding "no effect" or "no difference" and finding no statistically significant effect or difference, especially when using small sample sizes.

4. Common sources of bias in surveys and experiments, such as poor wording of questions, volunteer response, and socially desirable answers.

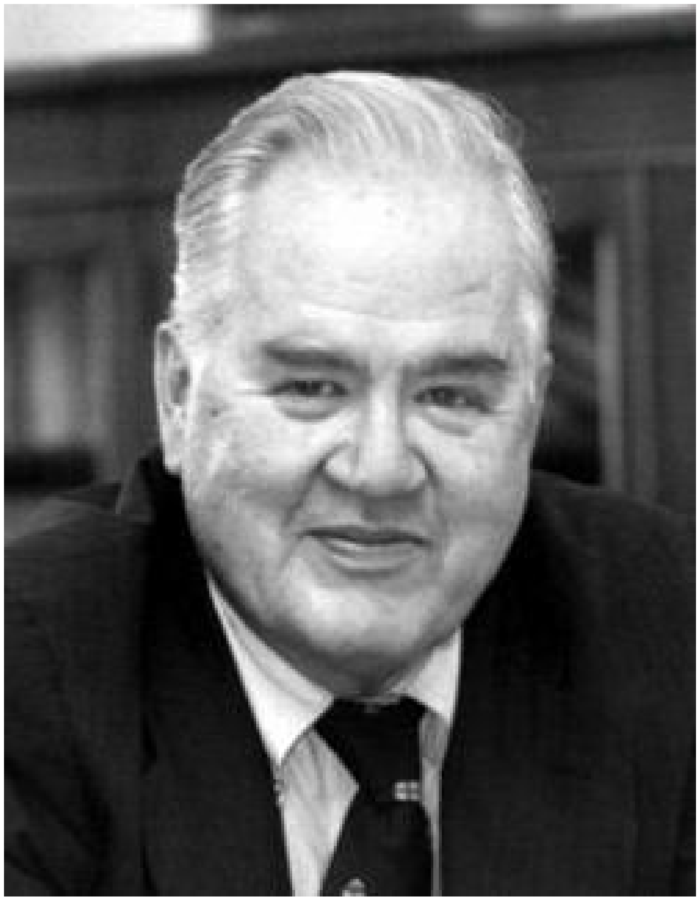
5. The idea that coincidences and seemingly very improbable events are not uncommon because there are so many possibilities.

6. "Confusion of the inverse" in which a conditional probability in one direction is confused with the conditional probability in the other direction.

7. Understanding that variability is natural, and that "normal" is not the same as "average."

Why I like being a statistician:

Why I like being a statistician:



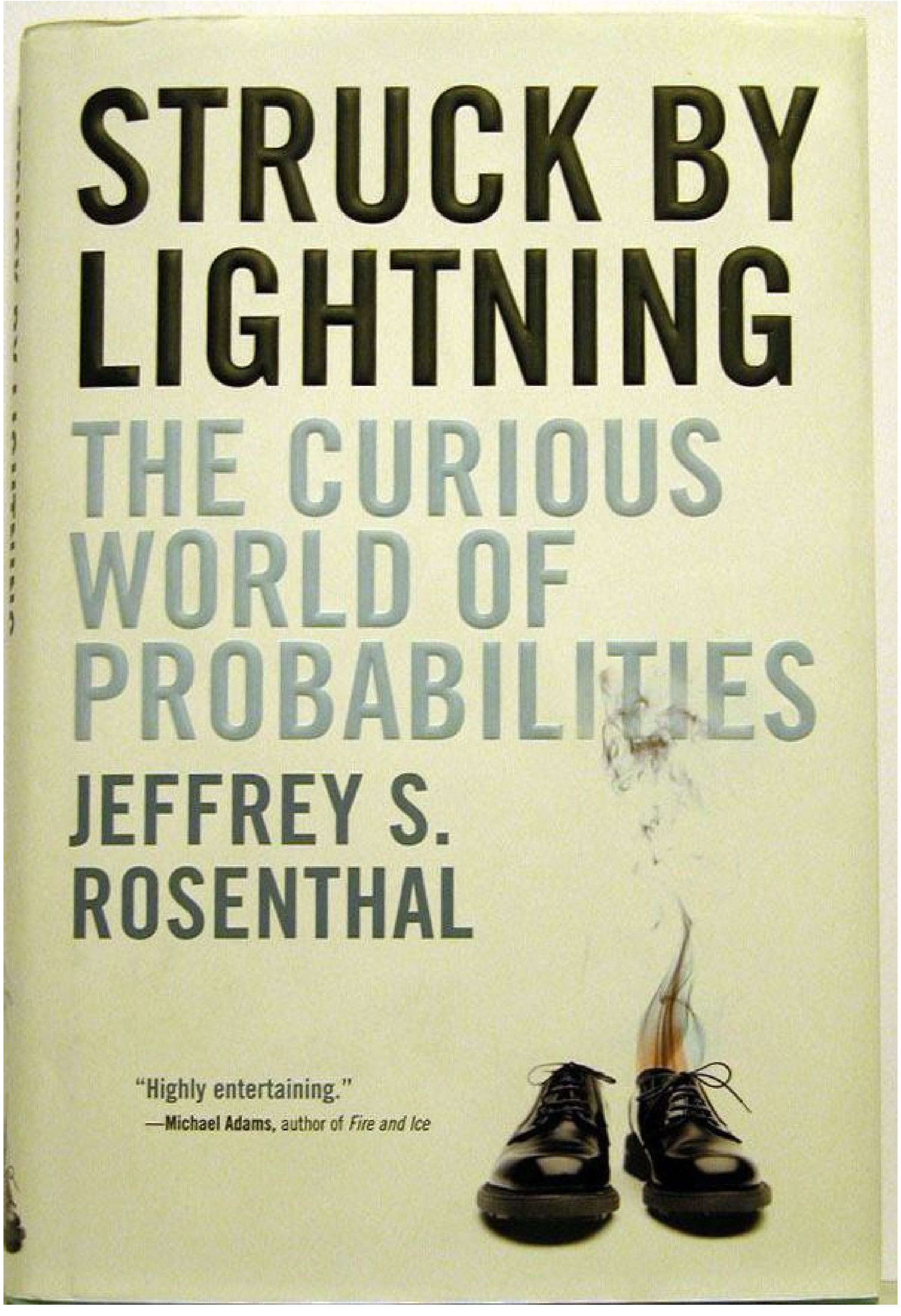
John W. Tukey:

“The best thing about being a statistician is that you get to play in everyone's backyard.”

Some practical advice from a statistician

– A few things I've learned recently

Gambling is good


STRUCK BY LIGHTNING
THE CURIOUS WORLD OF PROBABILITIES
JEFFREY S. ROSENTHAL
"Highly entertaining."
—Michael Adams, author of *Fire and Ice*

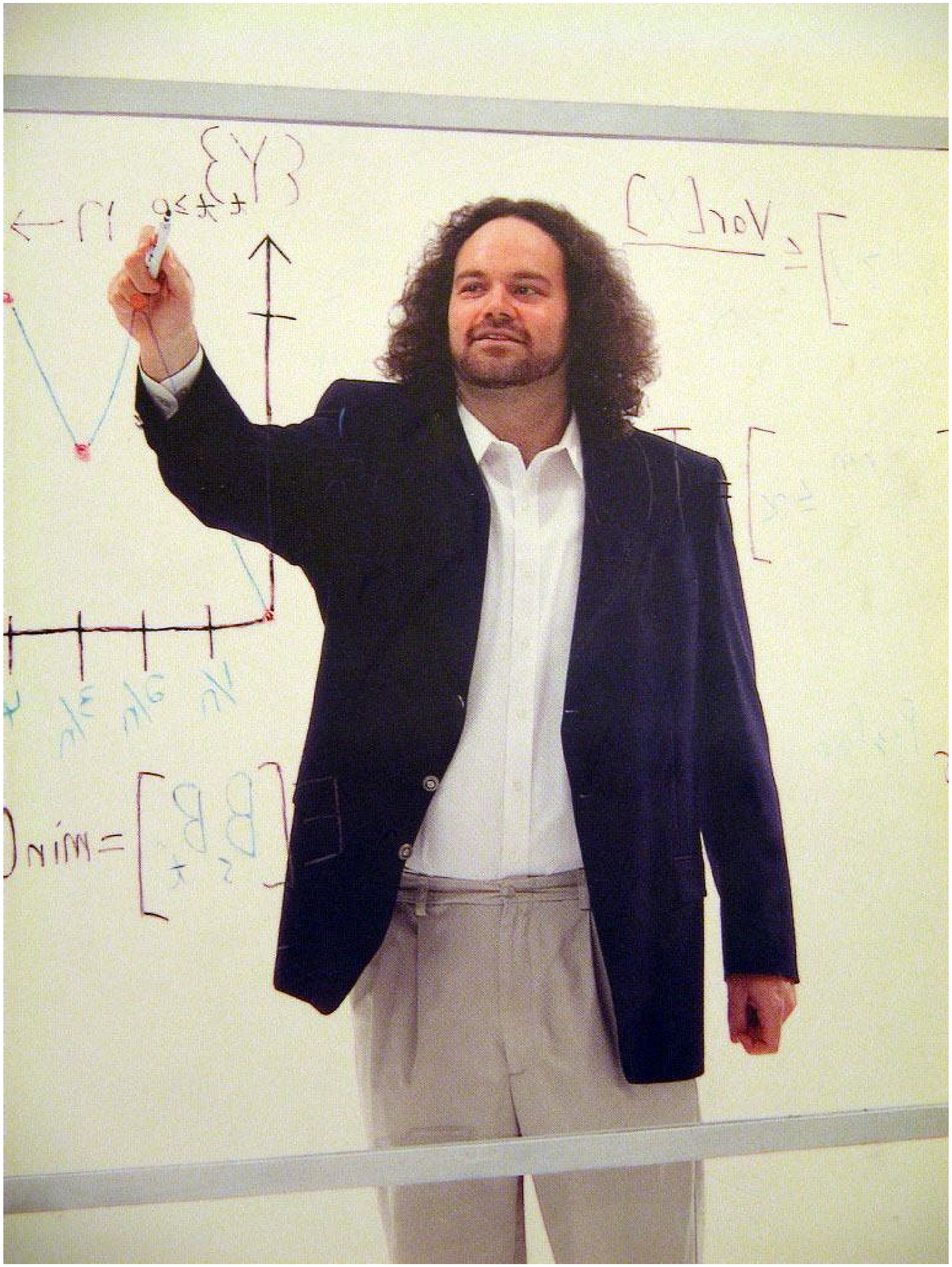


Table 3.5 Average Loss When Betting $10 at Various Casino Games

Game	Average Loss
Roulette	$0.526
Keno*	$2.51
Slot Machines	$0.50 to $1.20
Craps	$0.141
Don't Pass Line	$0.137

*Specifically, the version of keno described above; others may vary.

Table 3.5 Average Loss When Betting $10 at Various Casino Games

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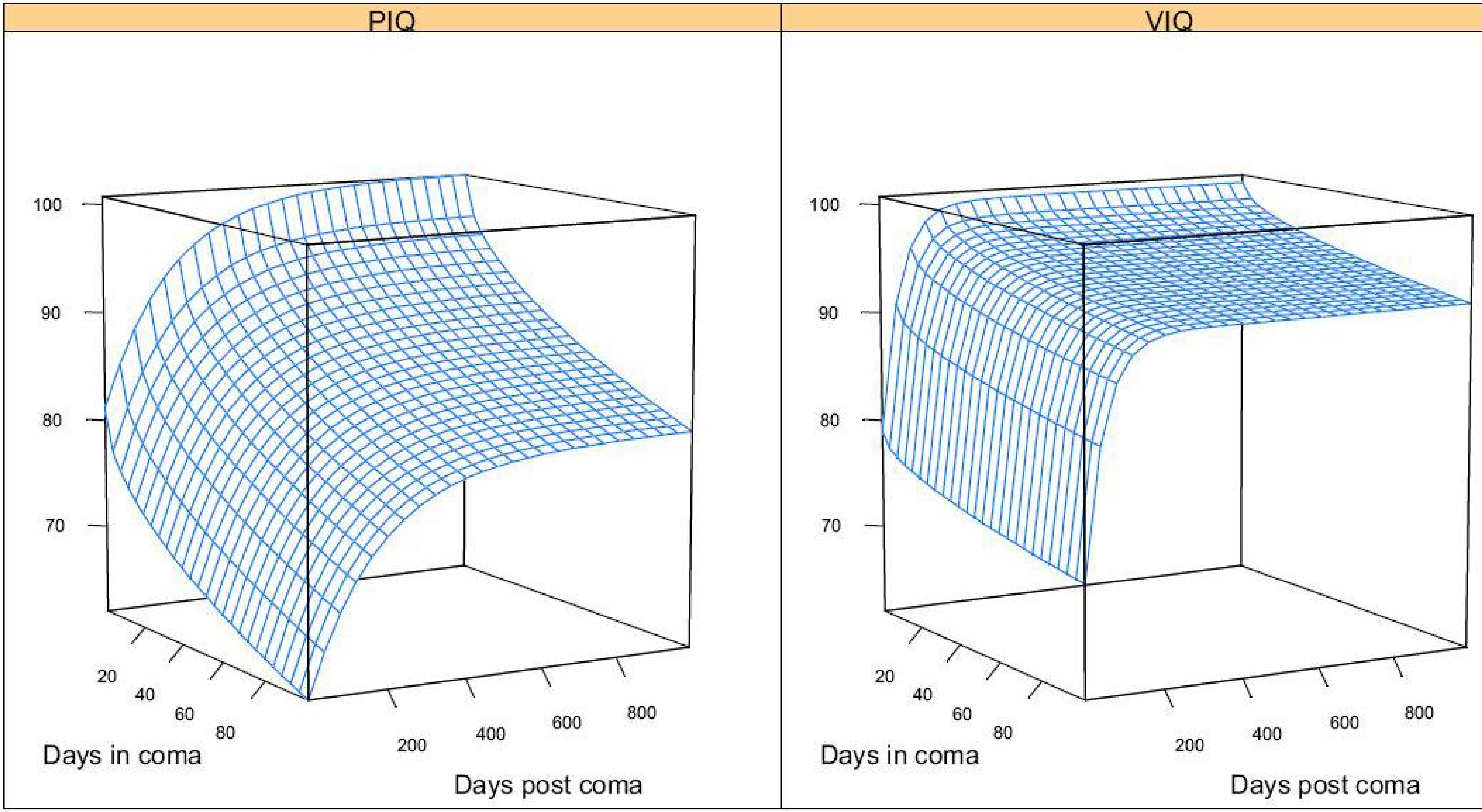
Keno*	$2.51
Slot Machines	$0.50 to $1.20
Craps	$0.141
Don't Pass Line	$0.137

*Specifically, the version of keno described above; others may vary.

Gambling is good
if you own the casino

If you are a mathematician
don’t drive a motorcycle.

If you are a mathematician
don’t drive a motorcycle.
But if you’re an english major
it might not be as bad.


PIQ
VIQ
100
90
80
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40
60
80
Days in coma
200
400
600
800
Days post coma

Don’t use a cell phone while you drive

Observational data with a very clever analysis:

Is Using a Car Phone Like Driving Drunk?

Donald A. Redelmeier and Robert J. Tibshirani enues of $25 million for the Microsoft Corporation) (Value Line Investment Survey 1997; Cellular Telecommunication Industry Association 1996).

We decided to go forward, and our first inclination was to conduct a case-control study. To do so, we planned to survey drivers who had car telephones and drivers who did not and compare the number of collisions each person experienced during a one-year interval. A brief look at the literature, however, revealed that such a study had already been completed in 1978 evaluating an early generation of mobile telephone

(Smith 1978). This survey of 498 individuals found that the overall frequency

of traffic collisions was marginally lower among mobile telephone subscribers than among members of the general public (11% vs. 12%). The difficulty in interpreting these data was the possibility of biases in favor of mobile telephone owners. In particular, prior to the 1990s most mobile telephone owners were young, intelligent urban professionals who would otherwise be expected to have very low collision rates and very safe driving patterns.

Redelmeier and Tibshirani found a clever solution to this problem:

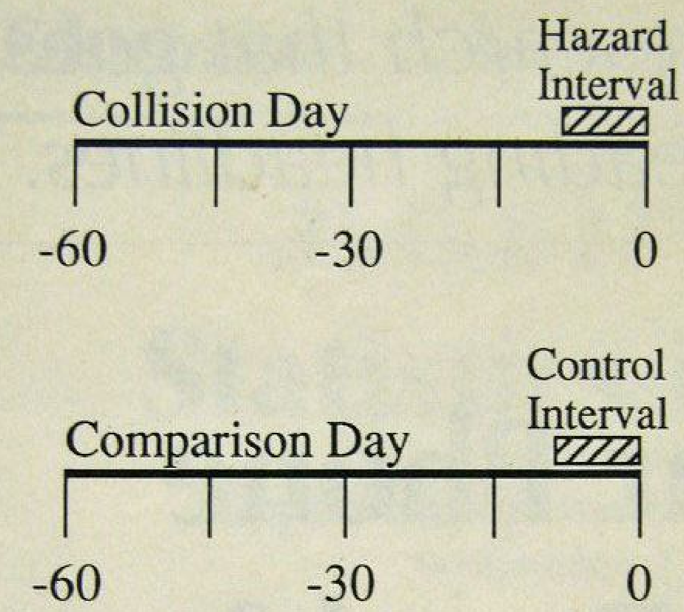

Figure 1. Essential features of the case-crossover design. Each individual is evaluated on two intervals, one in which the event occurs (hazard interval) and one in which the event does not occur (control interval). Potential exposures are then measured during each interval. Similar to a case-control design, possible associations are tested by comparing the exposures in the hazard interval to the exposures in the control interval.

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We next considered biases arising from not knowing the precise moment of every collision. We reasoned that individuals might use their cellular telephone immediately after a collision to make an emergency call. It would be a

The data showed that drivers were more likely to have made a cellular telephone call during the 10-minute interval immediately before the collision than during a similar interval on the day before the collision…

blunder to mislabel these calls made

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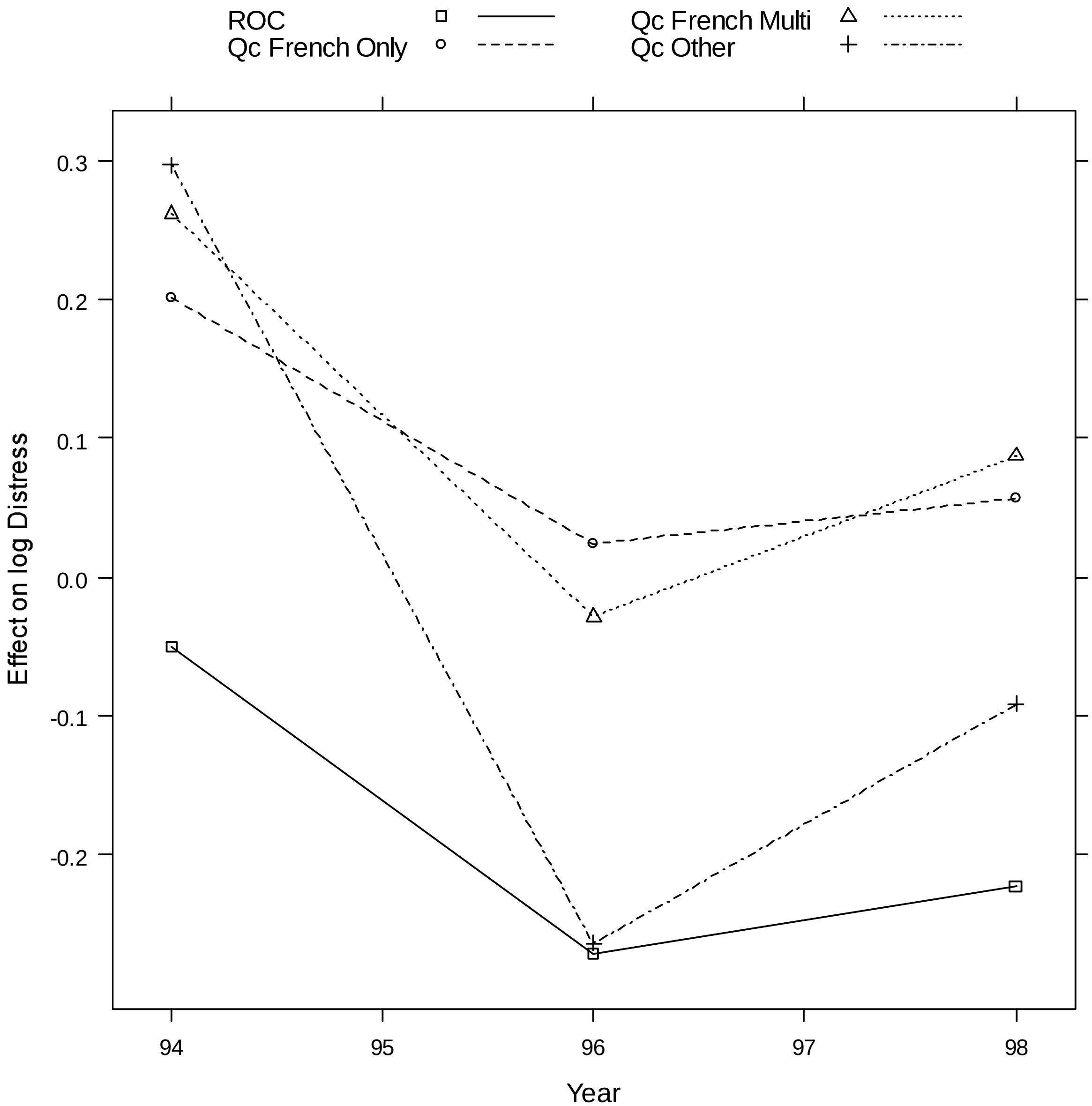
Phoning vs drinking:

Driving with a blood alcohol level at the legal limit is associated with a relative risk of 4 (Simpson 1985), which is about the same as what we found for using a cellular telephone. Driving with a blood alcohol level 50% above the legal limit, however, is associated with a factor of 10 (Simpson 1985). And greater degrees of intoxication must surely be associated with even higher relative risks.

Politics may be
good for your health


ROC
Qc French Only
Qc French Multi
Qc Other
Effect on log Distress
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0.1
0.0
-0.1
-0.2
94
95
96
97
98
Year

Politics may also be bad for your health
depending on where you live, what languages you speak
and on the outcome of the next referendum

Best and Worst Jobs Overall

The listings below shows the 10 best and worst jobs overall, according to *The 2002 Jobs Rated Almanac*, by Les Krantz (St. Martin's Griffin, 2002)

Low Stress, Autonomy, High Demand Boost Job Ratings, Author Says

"Biologist" is rated the nation's single best job in terms of low stress, high compensation, lots of autonomy, and tremendous hiring demand. Lumberjack was rated the worst job, according to The 2002 Jobs Rated Almanac by Les Krantz.

Biologist displaces financial planner, which was ranked as the nation's best-rated job in 2001, but still makes a strong showing in the No. 3 spot this year. Actuaries, who work autonomously and with little stress helping insurance providers and others determine risk, rose to No. 2. Computer systems analysts and accountants round out the top five.

Although the Monty Python comedy

BEST JOBS
Biologist Actuary Financial planner Computer-systems analyst Accountant Software engineer Meteorologist Paralegal assistant Statistician Astronomer

THE WALL STREET JOURNAL. | CAREERS

CAREERS | JANUARY 26, 2009, 11:20 A.M. ET

Doing the Math to Find the Good Jobs

Mathematicians Land Top Spot in New Ranking of Best and Worst Occupations in the U.S.

By SARAH E. NEEDLEMAN

Nineteen years ago, Jennifer Courter set out on a career path that has since provided her with a steady stream of lucrative, low-stress jobs. Now, her occupation -- mathematician -- has landed at the top spot on a new study ranking the best and worst jobs in the U.S.

Scott Brundage

"It's a lot more than just some boring subject that everybody has to take in school," says Ms. Courter, a research mathematician at mental images Inc., a maker of 3D-visualization software in San Francisco. "It's the science of problem-solving."

The study, released Tuesday from CareerCast.com, a new job site, evaluates 200 professions to determine the best and worst according to five criteria inherent to every job: environment, income, employment outlook, physical demands and stress. (CareerCast.com is published by Adicio Inc., in which Wall Street Journal owner News Corp. holds a minority stake.)

The findings were compiled by Les Krantz, author of "Jobs Rated Almanac," and are based on data from the U.S. Bureau of Labor Statistics and the Census Bureau, as well as studies from trade associations and Mr. Krantz's own expertise.

According to the study, mathematicians fared best in part because they typically work in favorable conditions -- indoors and in places free of toxic fumes or noise -- unlike those toward the bottom of the list like sewage-plant operator, painter and bricklayer. They also aren't expected to do any heavy lifting, crawling or crouching -- attributes associated with occupations such as firefighter, auto mechanic and plumber.

The study also considers pay, which was determined by measuring each job's median income and growth potential. Mathematicians' annual income was pegged at $94,160, but Ms. Courter, 38, says her salary exceeds that amount.

The Best and Worst Jobs

Of 200 Jobs studied, these came out on top -- and at the bottom:

The Best	The Worst
1. Mathematician	200. Lumberjack
2. Actuary	199. Dairy Farmer
3. Statistician	198. Taxi Driver
4. Biologist	197. Seaman
5. Software Engineer	196. EMT
6. Computer Systems Analyst	195. Roofer
7. Historian	194. Garbage Collector
8. Sociologist	193. Welder
9. Industrial Designer	192. Roustabout
10. Accountant	191. Ironworker
11. Economist	190. Construction Worker
12. Philosopher	189. Mail Carrier
13. Physicist	188. Sheet Metal Worker
14. Parole Officer	187. Auto Mechanic
15. Meteorologist	186. Butcher
16. Medical Laboratory Technician	185. Nuclear Decontamination Tech
17. Paralegal Assistant	184. Nurse (LN)
18. Computer Programmer	183. Painter
19. Motion Picture Editor	182. Child Care Worker
20. Astronomer	181. Firefighter

More on the Methodology

- For methodology info and detailed job descriptions, go to http://careercast.com/jobs/content/JobsRated_Methodology
- See the complete list of job rankings
- **Read about** the last study of the best and worst jobs.

Her job entails working as part of a virtual team that designs mathematically based computer programs, some of which have been used to make films such as "The Matrix" and "Speed Racer." She telecommutes from her home and rarely works overtime or feels stressed out. "Problem-solving involves a lot of thinking," says Ms. Courter. "I find that calming."

Other jobs at the top of the study's list include actuary, statistician, biologist, software engineer and computer-systems analyst, historian and sociologist.

What Statisticians do:

- Health and Medicine
- Finance, Banking, Insurance
- Business and Industry
- Education
- Government

Health and Medicine

- Biostatistics
- Clinical Trials
- Drug Monitoring
- Epidemiology
- Genetics
- Pharmaceutical research
- Public Health

Business and Industry

- Actuaries for Insurance and Pensions
- Agriculture
- Banking: e.g. methods to assess risk
- Chemistry
- Computer Science
- Economics
- Finance
- Manufacturing
- Market Research
- Quality Improvement and Reliability

Government:

- Statistics Canada
- Environment
- Forestry
- Government Regulation
- Law
- National Defense
- Population Research
- Risk Assessment

Notes:

R. A. Fisher and Tobacco:

R. A. Fisher and the Role of a Statistical Consultant

J. H. Bennett

Journal of the Royal Statistical Society. Series A (Statistics in Society), Vol. 154, No. 3 (1991), pp. 443-445
doi:10.2307/2983153

Extracts from R. A. Fisher's letters referring to the responsibilities of statistical consultants are considered along with his view of his own role as a scientific consultant to the Tobacco Manufacturers' Standing Committee in the late 1950s. Contrary to a recent suggestion that Fisher may have been `misrepresenting data on lung cancer while acting as an adviser to the tobacco industry', his letters show that he was very deeply concerned about the possible misrepresentation to consumers of an alleged statistical result. Further, Fisher believed that it is `only by giving students the opportunity of making fine distinctions in the logic of the subject that they can learn to recognize the difference between honest and dishonest work in statistical practice'.

American Journal of Epidemiology Vol. 133, No. 5: 416-425

When Genius Errs: R. A. Fisher and the Lung Cancer Controversy

Paul D. Stolley

Clinical Epidemiology Unit, University Pennsylvania School of Medicine 220-L Nursing Education Building, Philaiaphia, PA 19104-6095

R. A. Fisher's work on lung cancer and smoking is critically reviewed. The controversy is placed in the context of his career and personality. Although Fisher made invaluable contributions to the field of statistics, his analysis of the causal association between lung cancer and smoking was flawed by an unwillingness to examine the entire body of data

available and prematurely drawn conclusions. His views may also have been influenced by personal and professional conflicts, by his work as a consultant to the tobacco industry, and by the fact that he was himself a smoker.

Text