

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

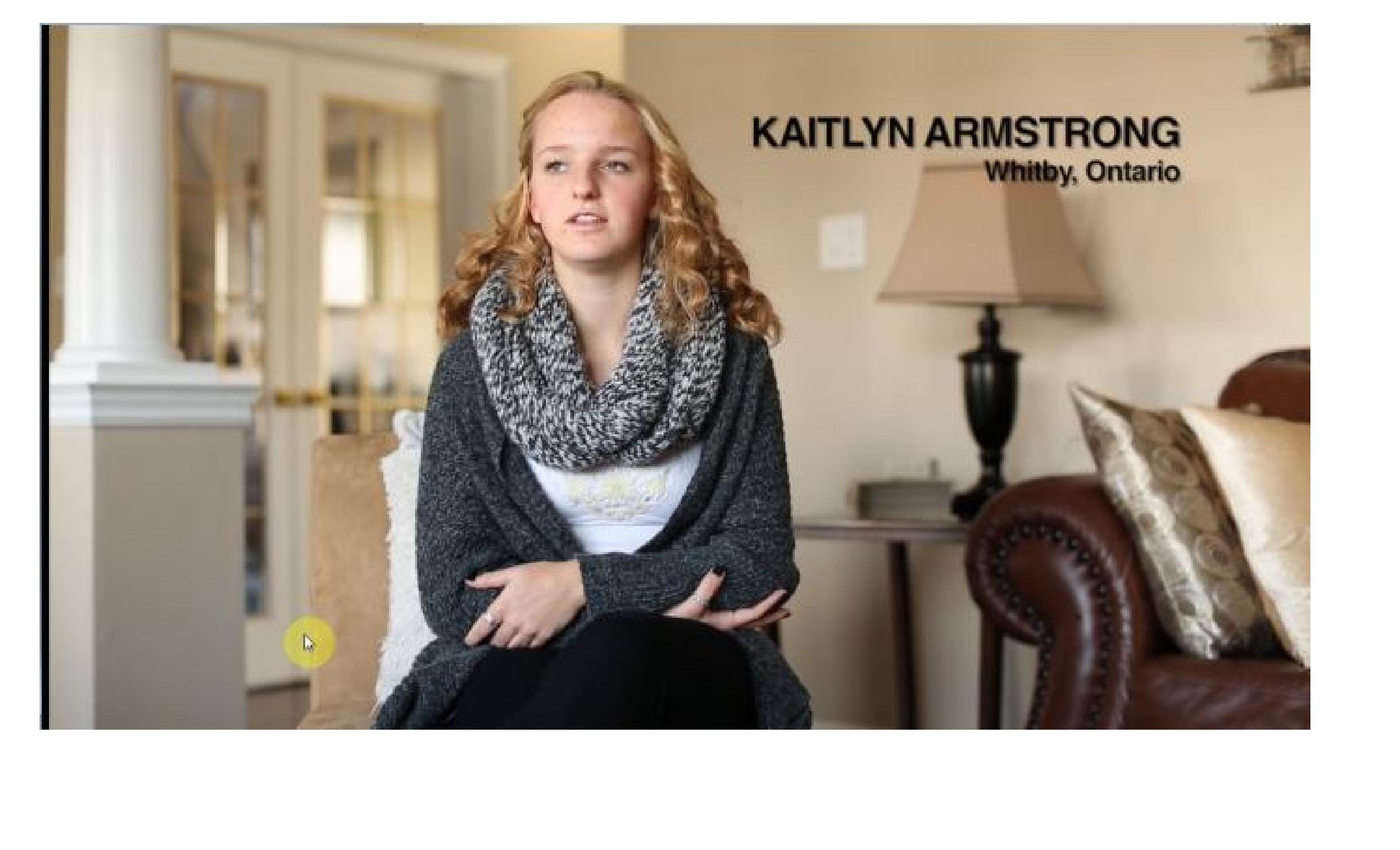
Canada keeps Ottawa keeps Ottawa reviews drug reviews under wraps

Assessments of 151 medications, will stay secret

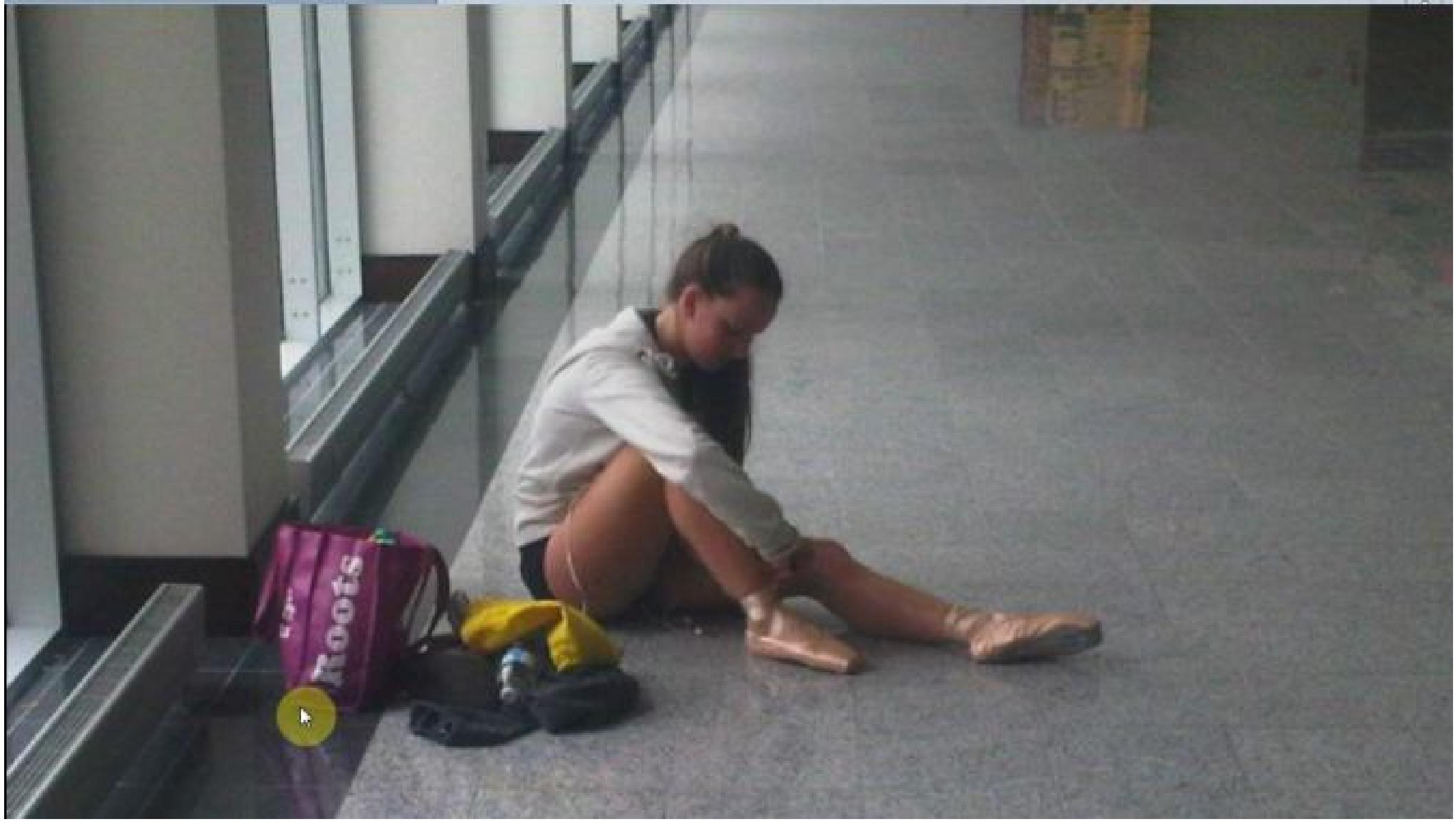
Doctors alarmed that reassessment of medications may

> **STAR EXCLUSIVE**





KAITLYN ARMSTRONG
Whitby, Ontario





LINDA MORIN
Laval, Quebec



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.



Tweet



1,327



g+1
23



reddit this!



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.

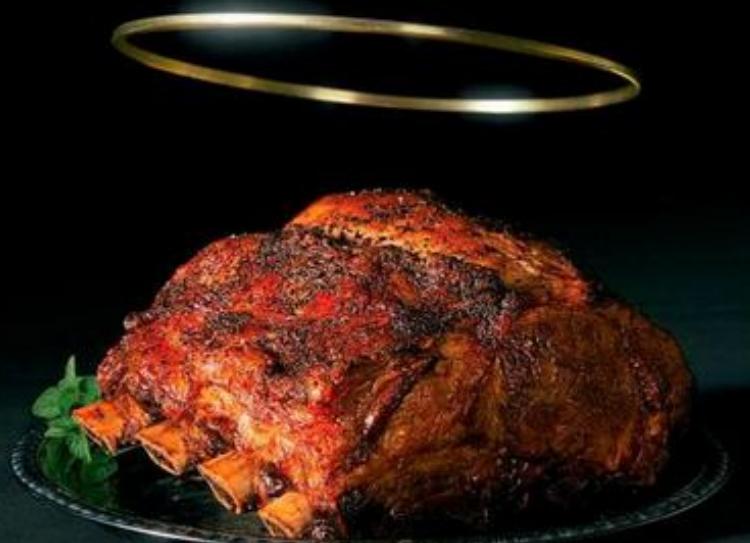
The fact that one event follows another does not mean that the first event caused the second — in scientific terms, correlation is not causation.

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.

Copyrighted Material

NEW YORK TIMES BESTSELLER



THE BIG FAT SURPRISE

Why Butter, Meat & Cheese
Belong in a Healthy Diet

NINA TEICHOLZ

Copyrighted Material

“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)



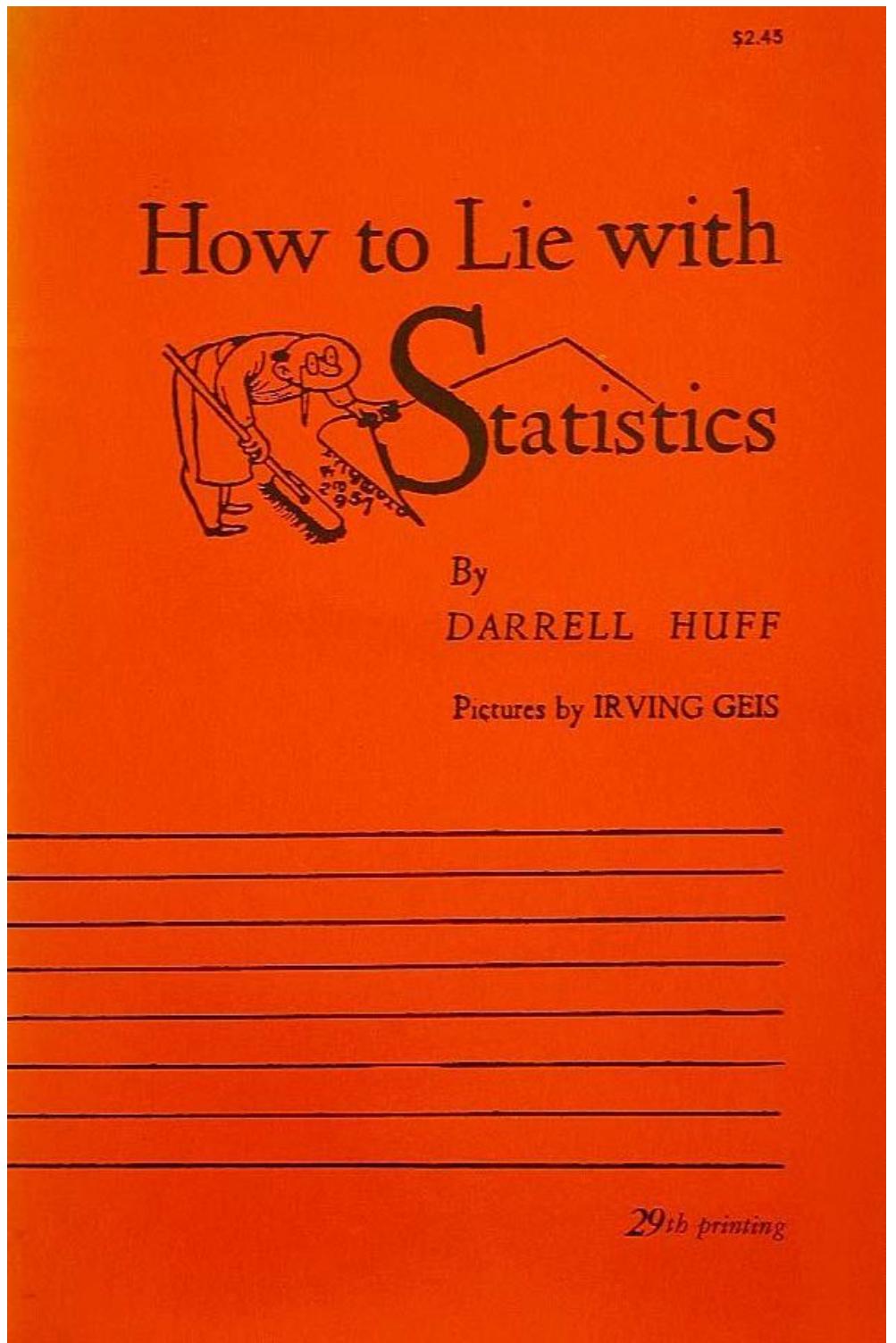
In March, *New York Times* writer and famous foodie Mark Bittman declared that “[butter is back](#).” His piece reported on the findings of a recent meta-analysis published in the *Annals of Internal Medicine* that questioned the long-standing link between saturated fat and coronary disease.

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



"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):

Dr. DAVID HEALY

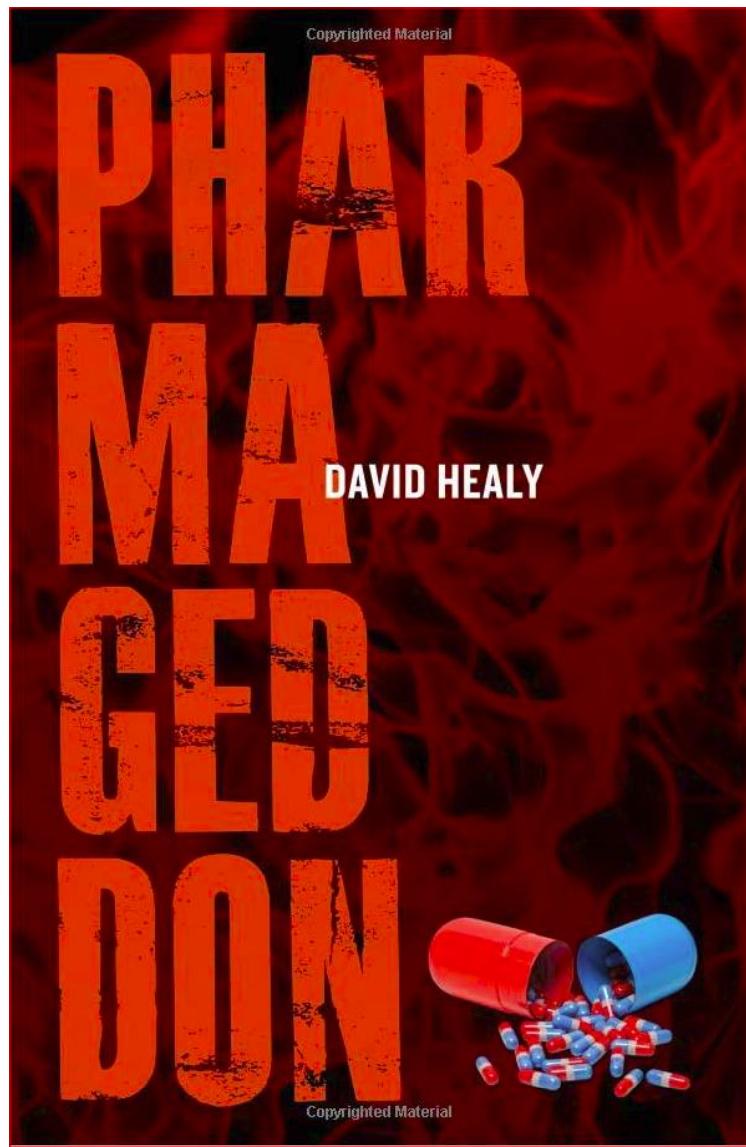
Psychiatrist. Psychopharmacologist.
Scientist. Author.

Risk  Enter a drug name (e.g., Lipitor) [Search](#)



Making medicines safer
for all of us

About Data Based Medicine
Adverse drug events are now the fourth leading cause
of death in hospitals It's a reasonable bet they are an
even greater cause of death ... [\[Read More...\]](#)



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-

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-

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?

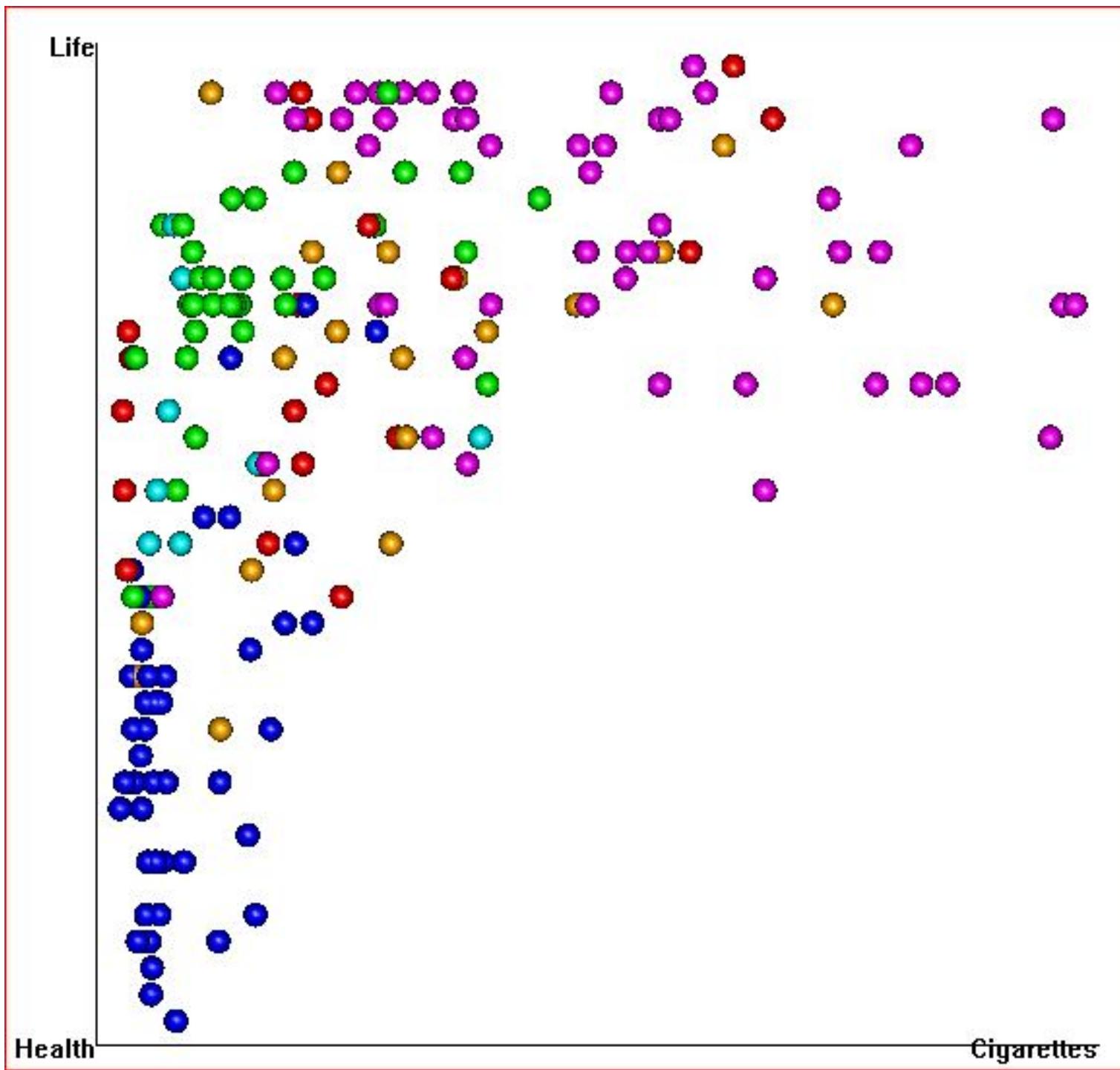
Answering an important question:

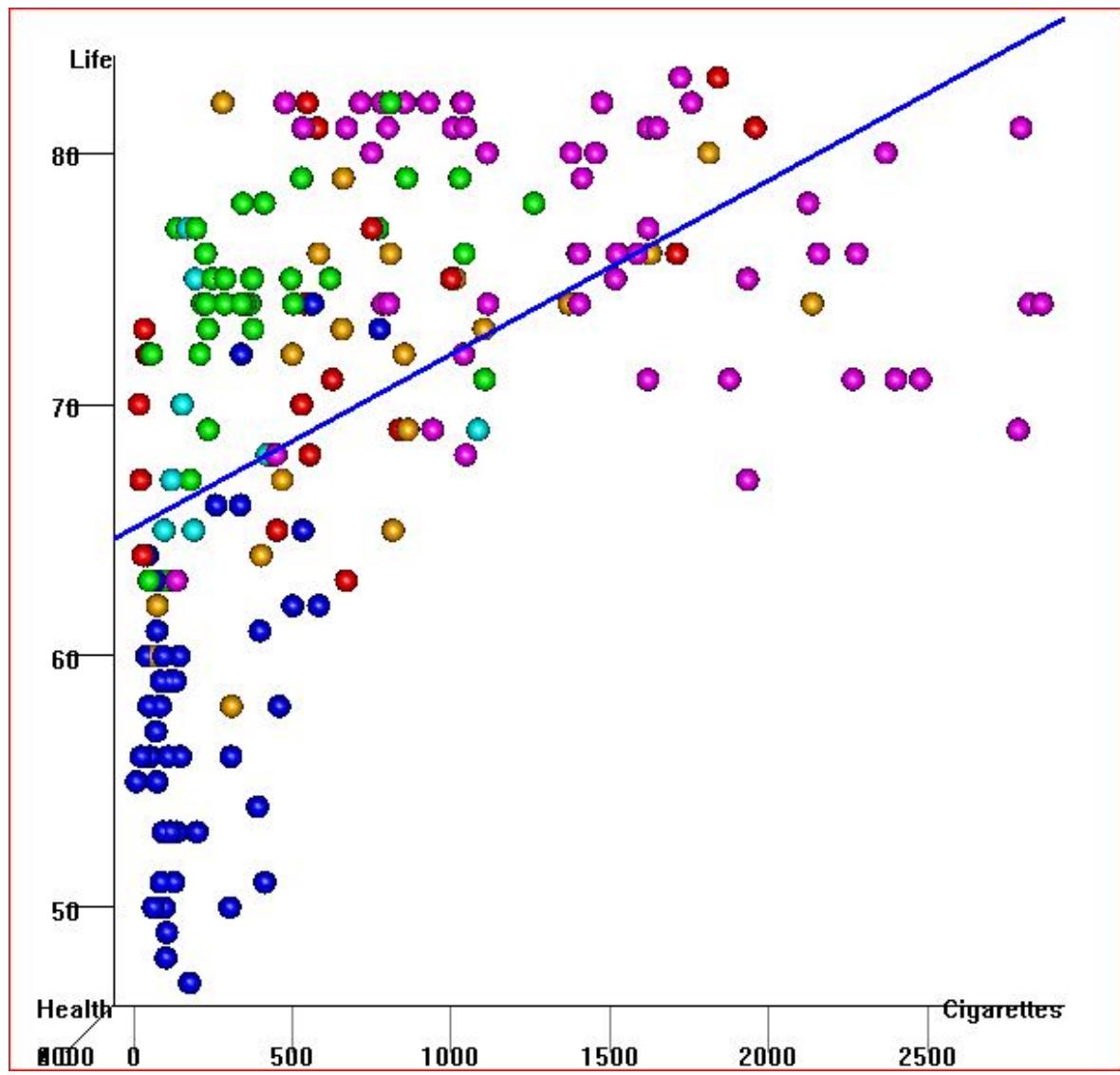
Just how harmful is smoking anyways?

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**





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

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

What does this actually mean?

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

What does this actually mean?

One extra **cigarette per year** adds
0.006915 years to your life,

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

What does this actually mean?

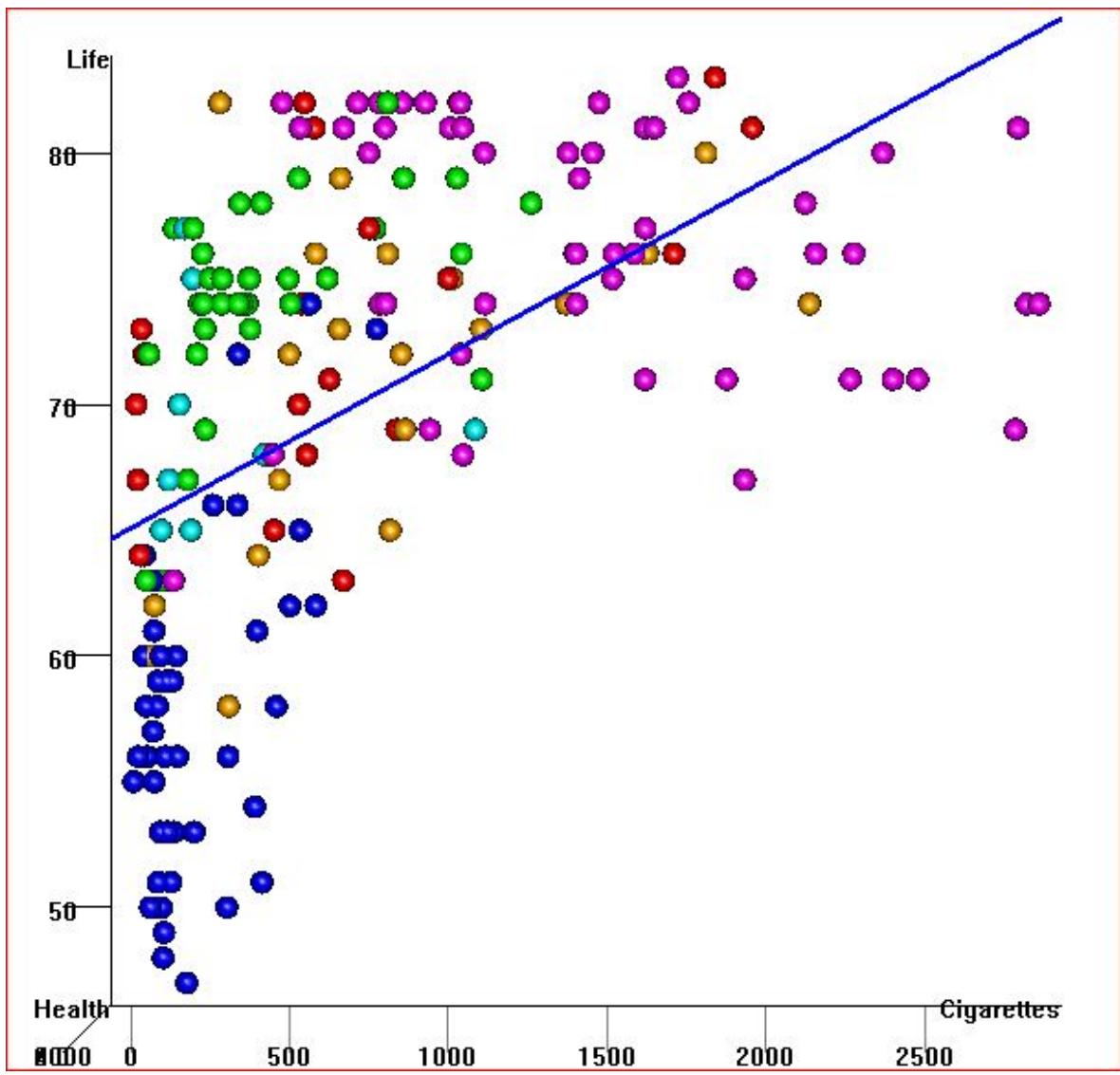
One extra **cigarette per year** adds

0.006915 years to your life,

Not very impressive but in better units:

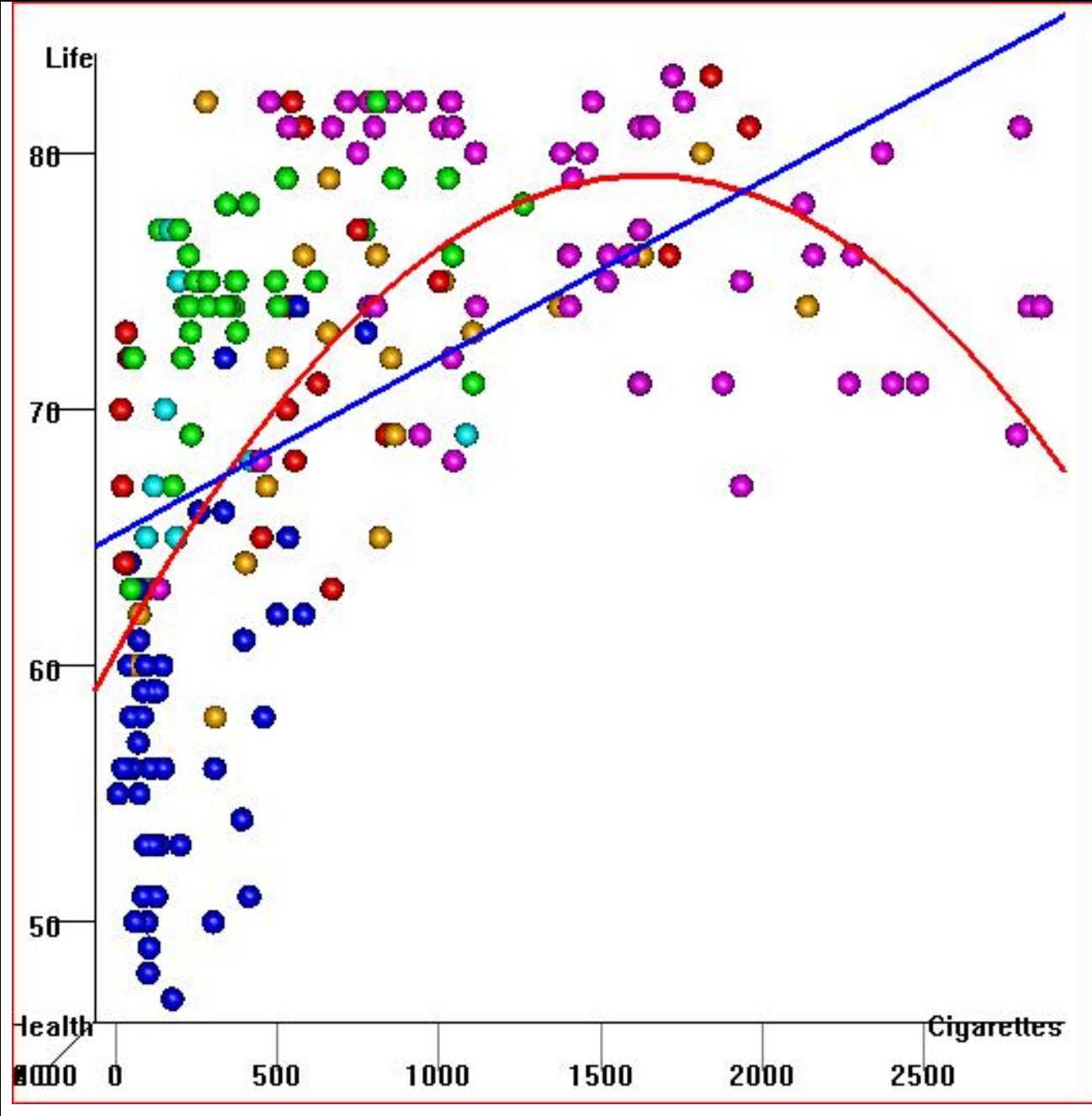
All it takes is 4 cigarettes a day

to add 10 years to your life



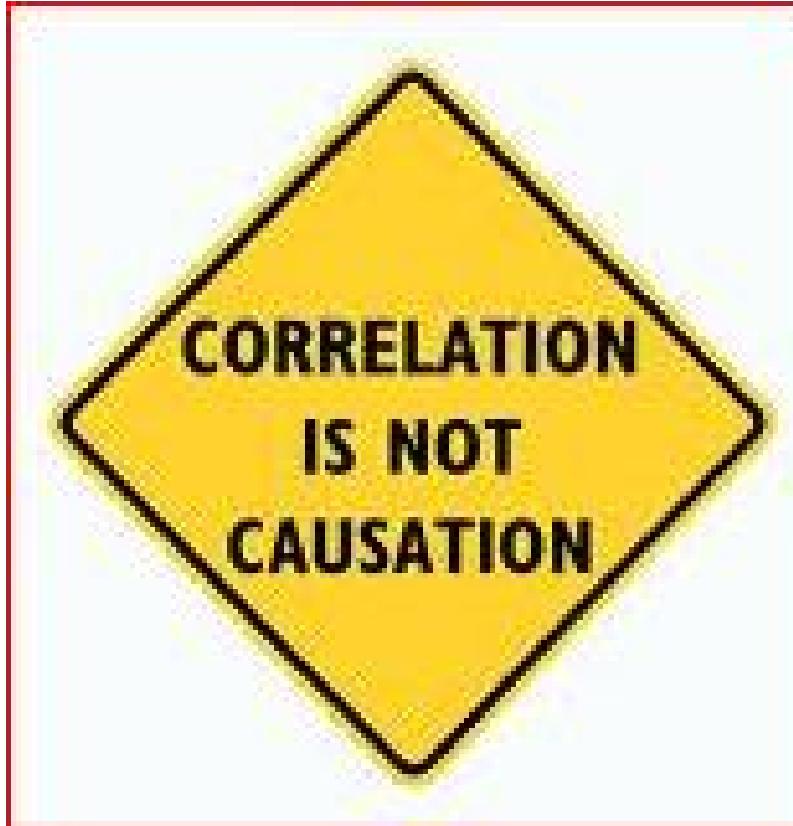
A good statistician would tell you
that this is ridiculous.

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?



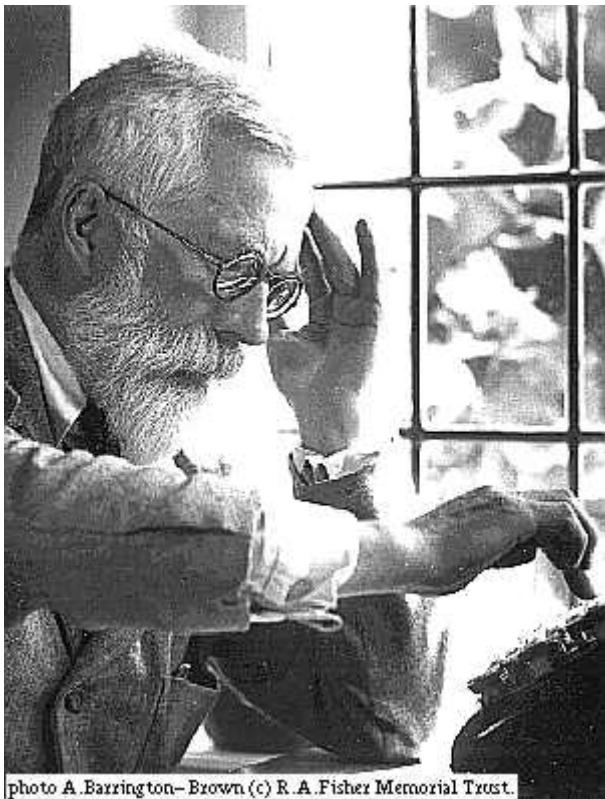
1

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 **effectiveness** 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:

*The fundamental
2 x 2 table of statistics*

Questions			

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	
Questions	Causal	Experimental	Observational
	what would happen if ...?	random assignment to treatments (X)	X is not controlled
Predictive	passive guessing		

Understanding the problem:

*The fundamental
2 x 2 table of statistics*

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

Understanding the problem:

*The fundamental
2 x 2 table of statistics*

		Data	
Questions	Causal what would happen if ...?	Experimental random assignment to treatments (X)	Observational X is not controlled
	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.

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.

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

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

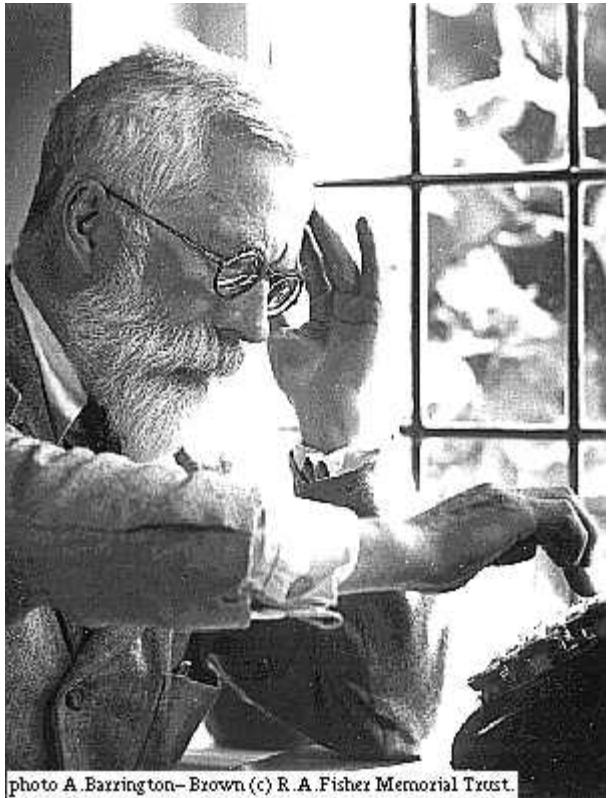


photo A. Barrington-Brown (c) R.A. Fisher Memorial Trust.

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

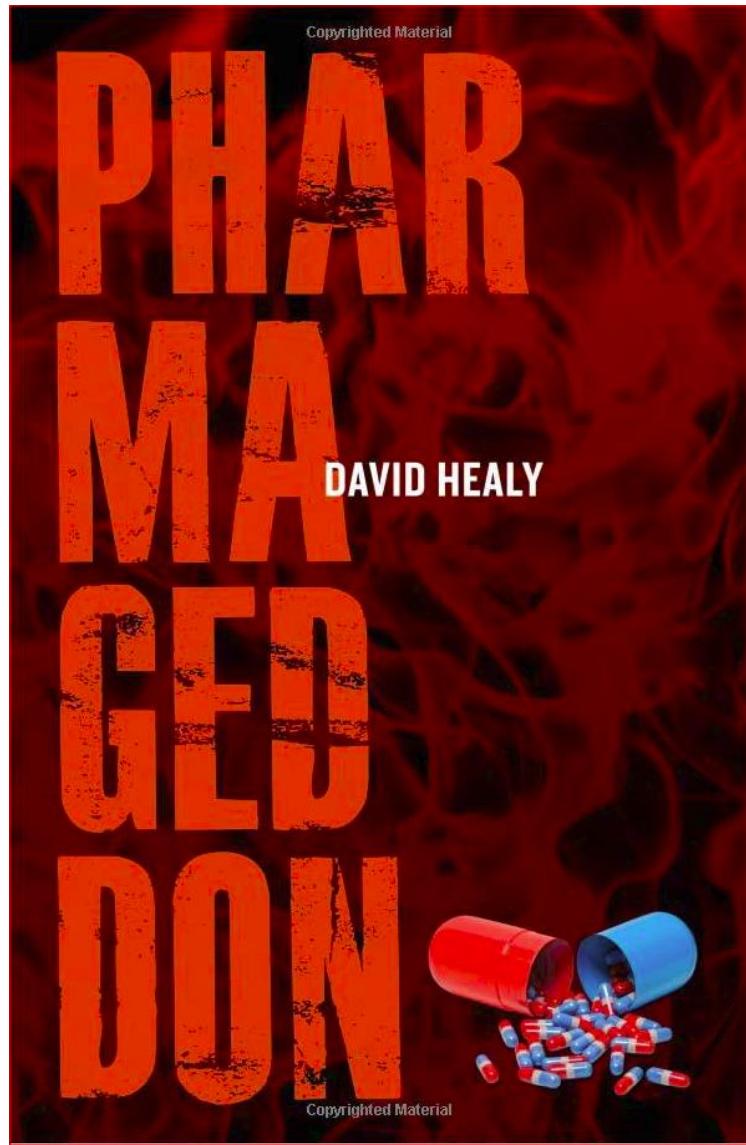
Experimental Data

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

Data

<p><i>On relationships between X and Y:</i></p> <p>The fundamental 2 x 2 table of statistics</p>	Experimental Levels of X decided by tossing a coin	Observational Levels of X observed as they occur without intervention
<p>Causal Should I or Shouldn't I do X?</p>	Gold standard: Fisher insists on this for causal inference	The main challenge of statistics and research
<p>Predictive Will I or Won't I be Y?</p>	Problematic but rarely an issue	OK

Questions



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 col-

lect 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



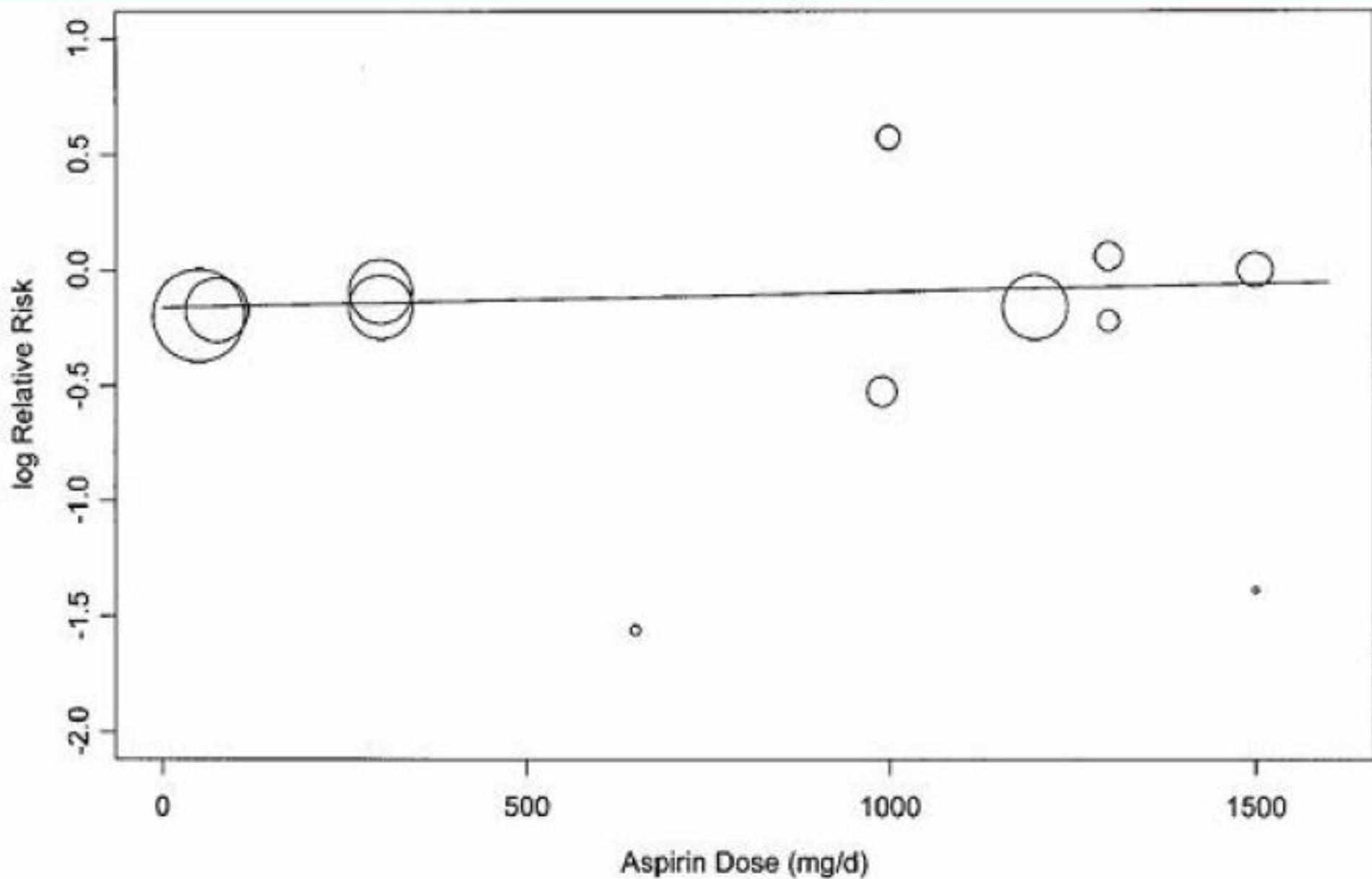


Figure 1. Log relative risk of stroke in 13 trials of aspirin versus placebo [6], according to aspirin dose, together with a summary random effects meta-regression. The area of each circle is inversely proportional to the variance of the log relative risk estimate.

Meet the man whose big idea felled Wall Street

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

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."

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
- 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

For example: clinical trials are used to assess the **effectiveness** 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*.

This is not a perfect solution and judgment must be used in applying it and in assessing 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.

Why does choosing treatments at random work?

The fundamental 2 x 2 table of statistics:

Caution:

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

PHILLIES CRUSHED
Phillies on verge
of winning Series
SPORTS — S1

U.S. shock, sadness spread hit to over senseless shooting inside

8 killed as militia
‘takes matters
into own hands’
insurgents’ line

ALBERT AJI
ASSOCIATED PRESS

DAMASCUS—U.S. militaries yesterday attack side Syria close to Iraq, killing eight people. The Syrian government as “serious aggressor.” A U.S. military of by special forces, a fighter net through Syria is where the Americans unable to shut was out of the. “We are taking our hands,” Associated Press anonymity.

A Syrian carried by News Agency attacked the town of metres in

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 charged with murdering Brampton teenager Rajiv Dharamdial, government printing presses were gearing up to publish a major new report on preventing youth crime.

Commissioned last year by Premier Dalton McGuinty after 16-year-old Jordan Manners was killed in a Toronto school, the report examines the “root causes” of youth criminal behaviour. It took months of work by Justice Minister McMurtry, Ontario’s former justice, and former Liberal cabinet minister Alvin Curling.

“I’m sure the premier ... is going to take the report seriously,” McMurtry said in an interview. “But there will certainly be some people in government who may be quite happy to see it buried.”

While McMurtry doesn’t doubt the sincerity of McGuinty or his cabinet in wanting to do something about youth crime, a lowering of expectations might be prudent.

In recent years, the province

“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

Does Death Penalty Save Lives? A New Debate



Joe Raedle/Getty Images

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

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 intense new debate about one of the central justifications

E-MAIL

PRINT

SINGLE PAGE

REPRINTS

SAVE

USES AND ABUSES OF EMPIRICAL EVIDENCE IN THE DEATH PENALTY DEBATE

John J. Donohue* and Justin Wolfers**

INTRODUCTION.....	791
I. THEORY: WHAT ARE THE IMPLICATIONS OF THE DEATH PENALTY FOR HOMICIDE RATES?	795
II. A CENTURY OF MURDERS AND EXECUTIONS	796
III. THE IMPORTANCE OF COMPARISON GROUPS	798
A. <i>Canada Versus the United States</i>	798
B. <i>Non-Death Penalty States Versus Other States in the United States</i> ...	800
IV. PANEL DATA METHODS.....	804
A. <i>Katz, Levitt, and Shustorovich</i>	811
B. <i>Deshbakhsh and Shepherd</i>	813
C. <i>Mocan and Gittings</i>	816
D. <i>Other Studies</i>	818
V. INSTRUMENTAL VARIABLES ESTIMATES.....	821
A. <i>Problems with Invalid Instruments</i>	827

Figure 1. Homicides and Execution in the United States

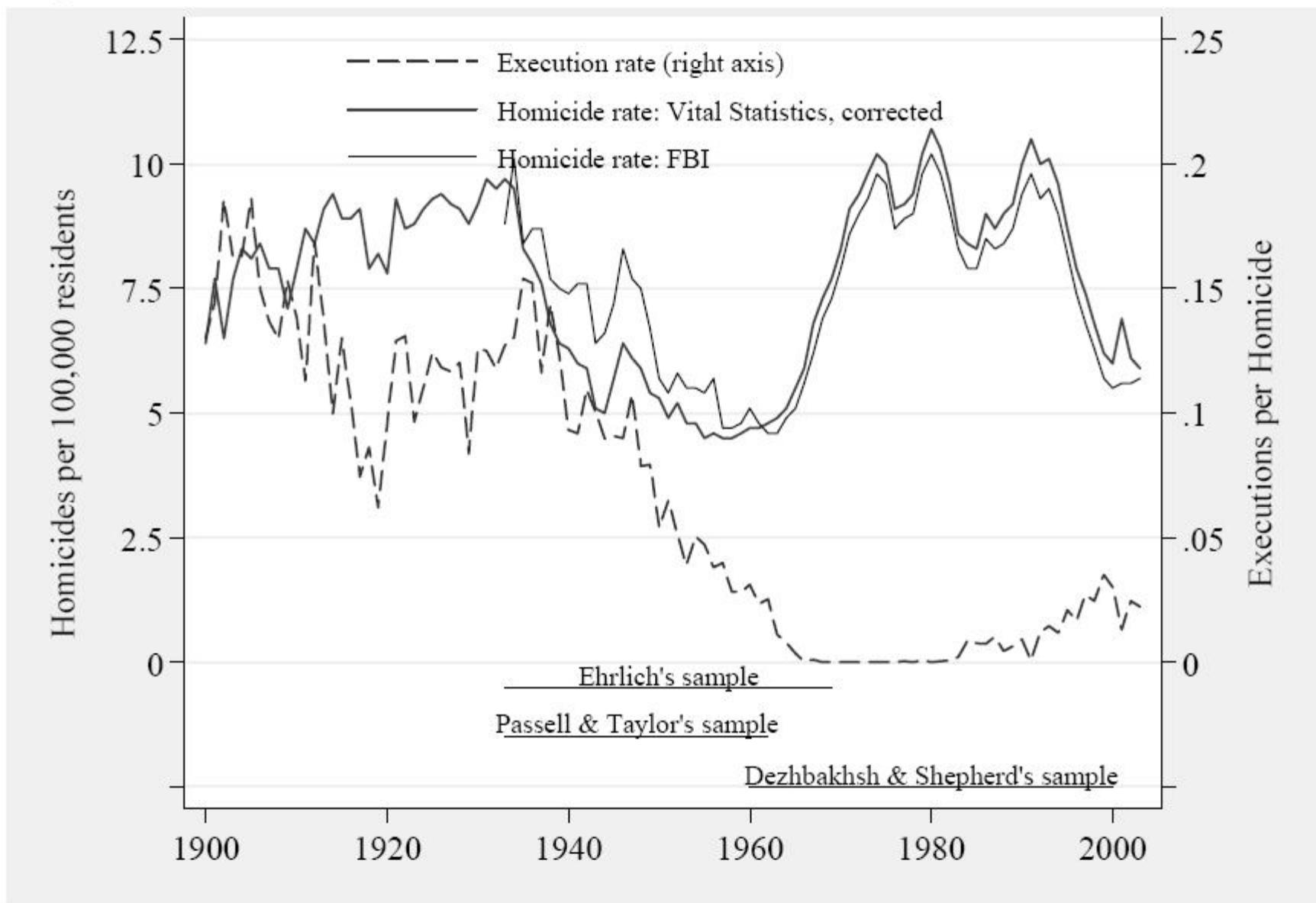
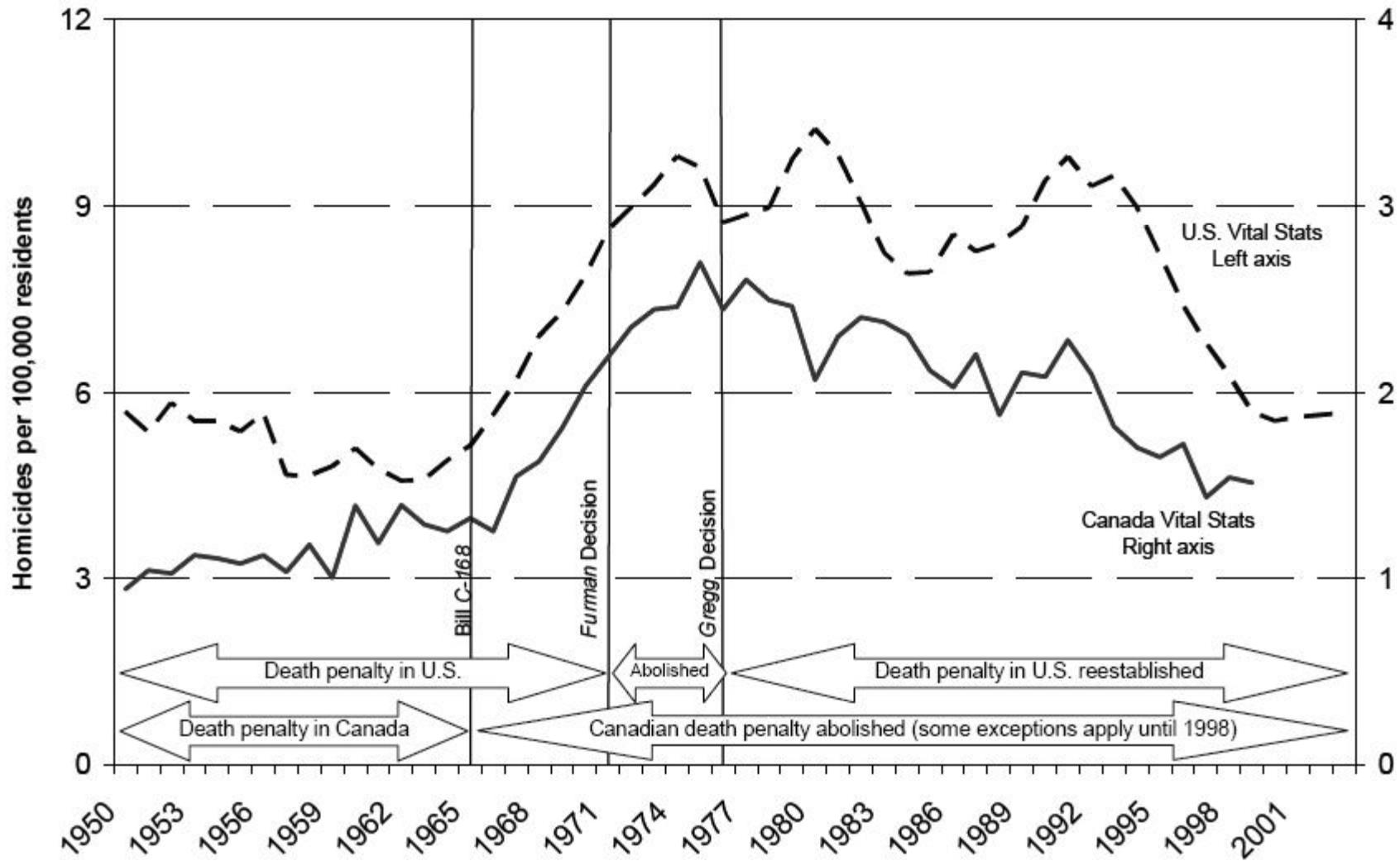
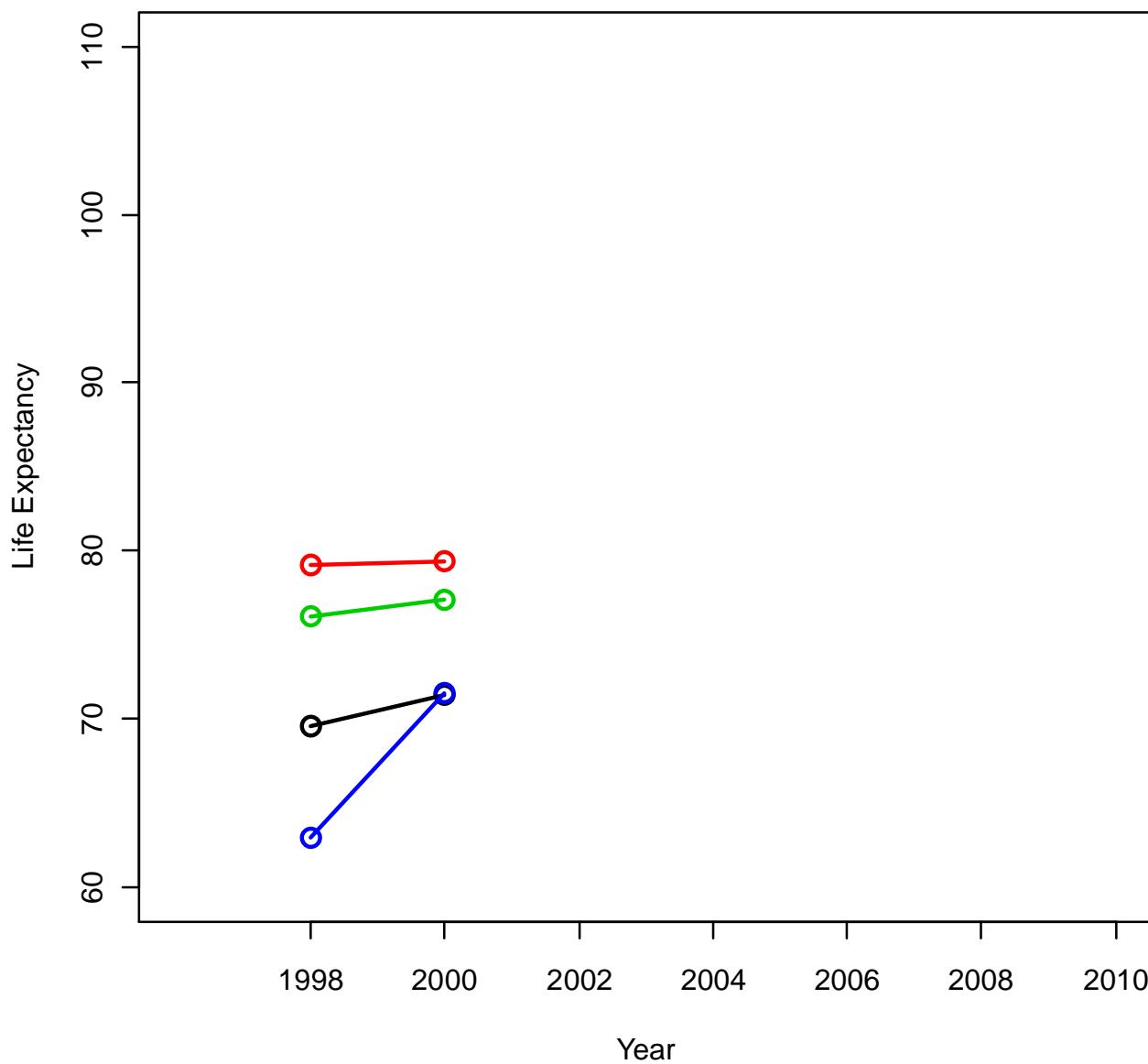
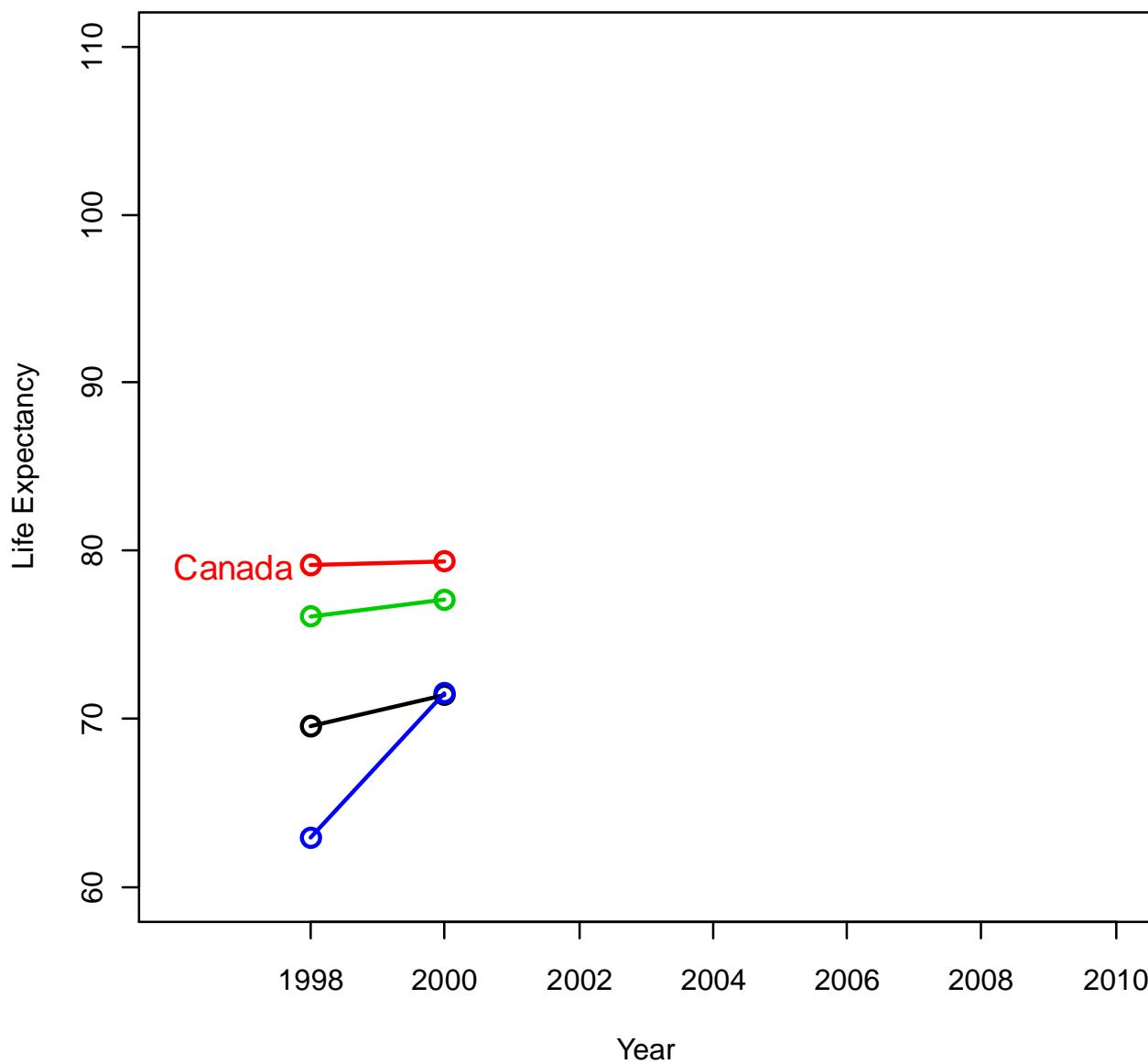


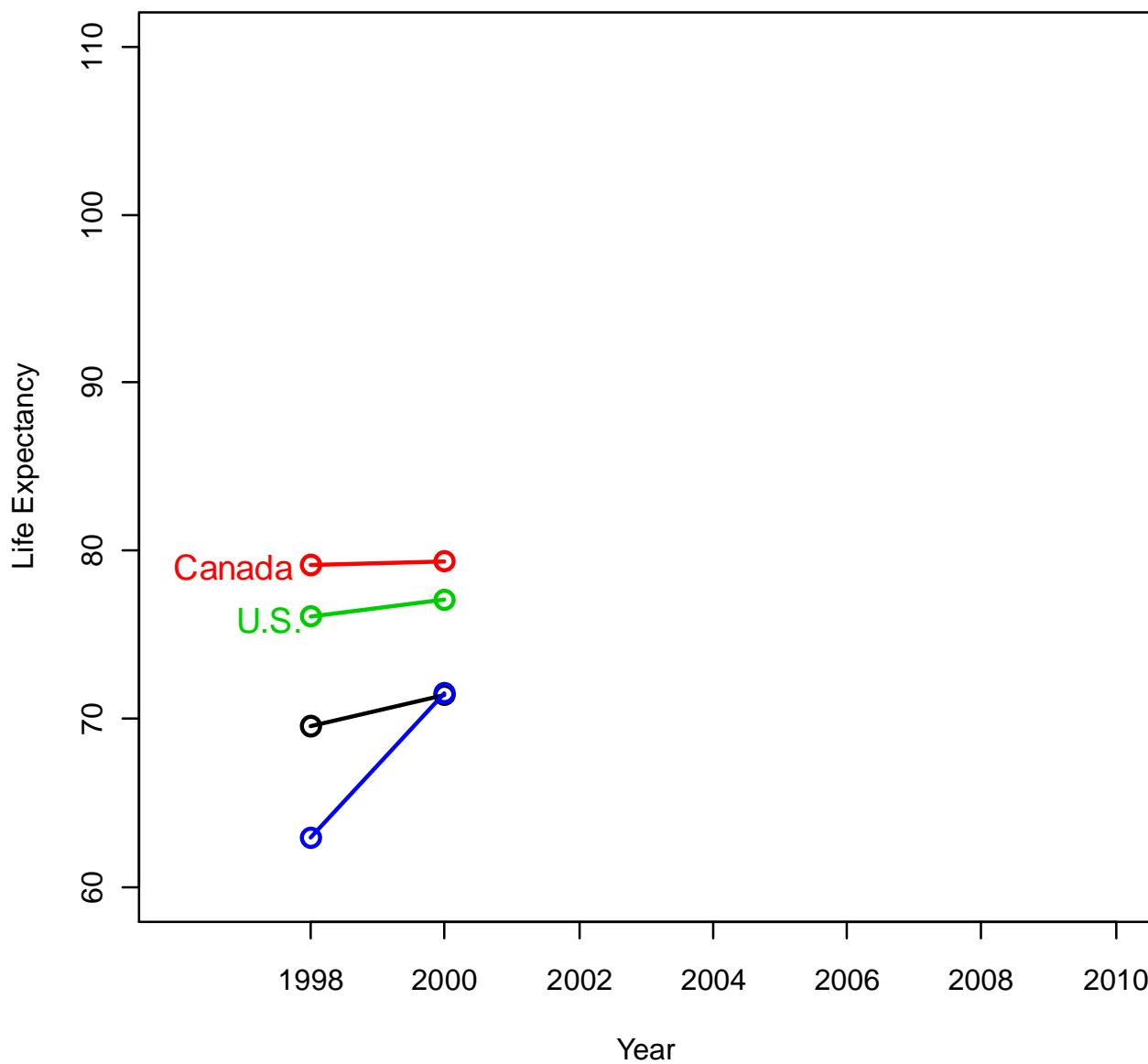
Figure 2. Homicide Rates and the Death Penalty in the United States and Canada

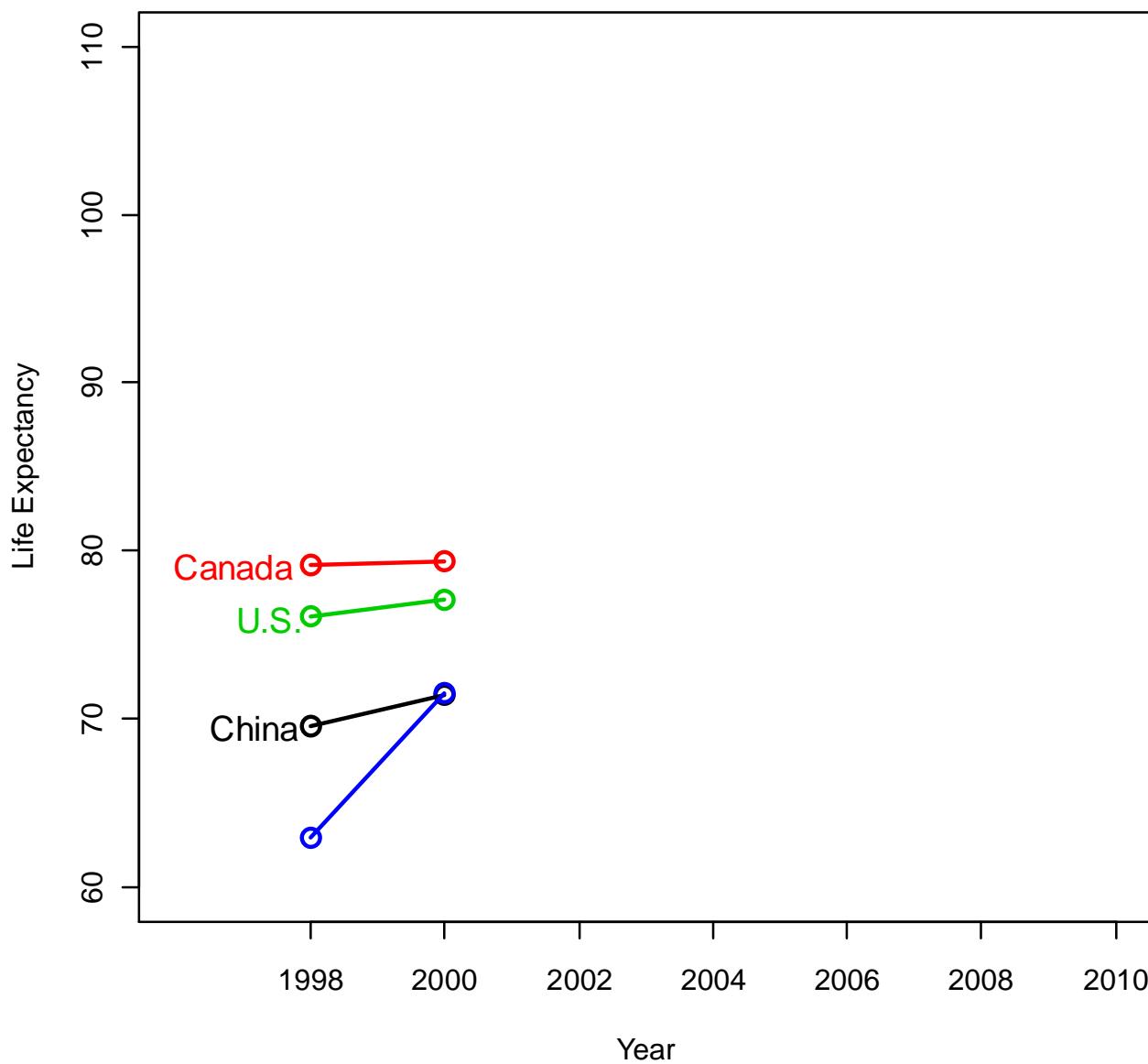


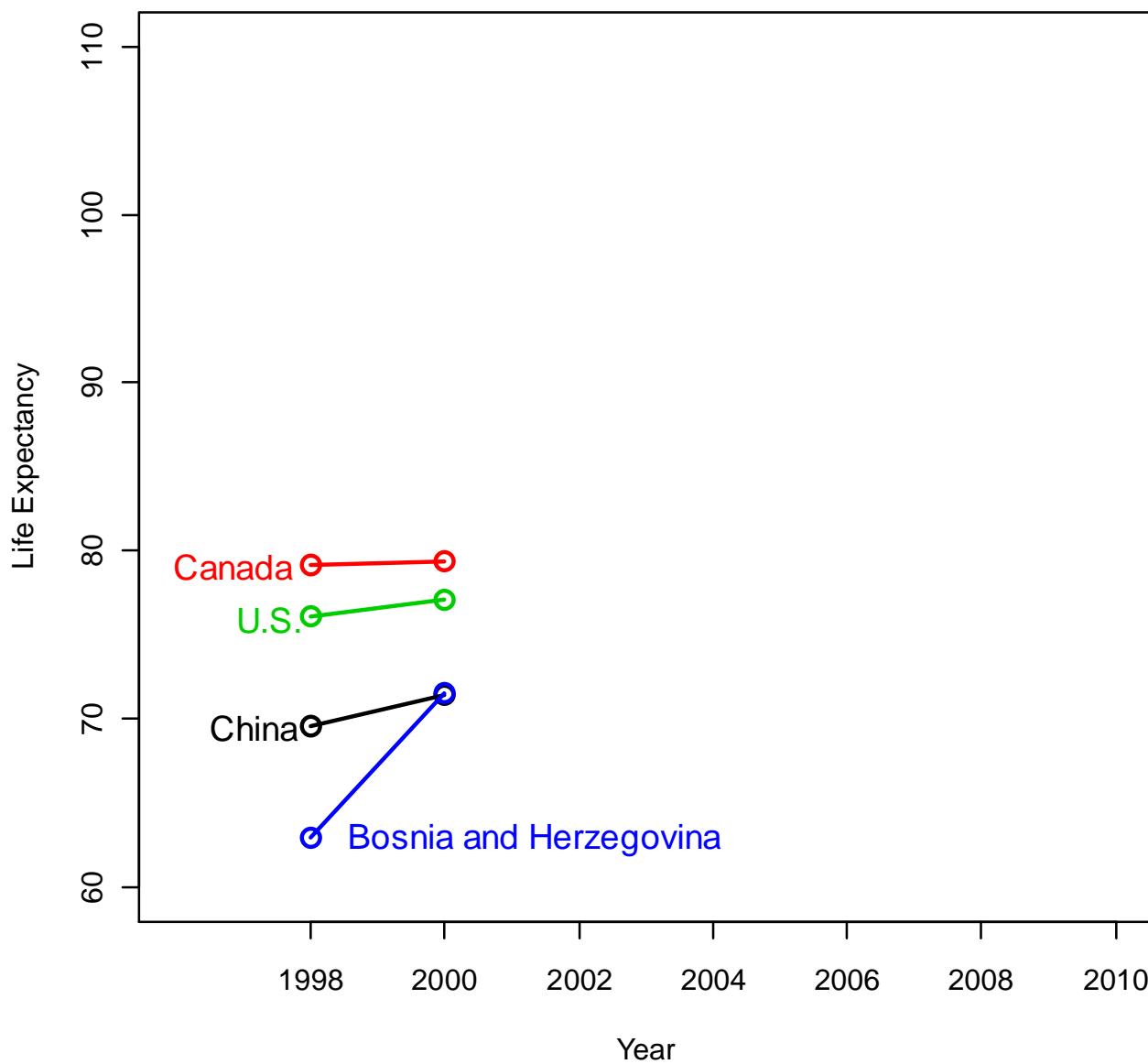
Another common way of thinking
that can mislead:

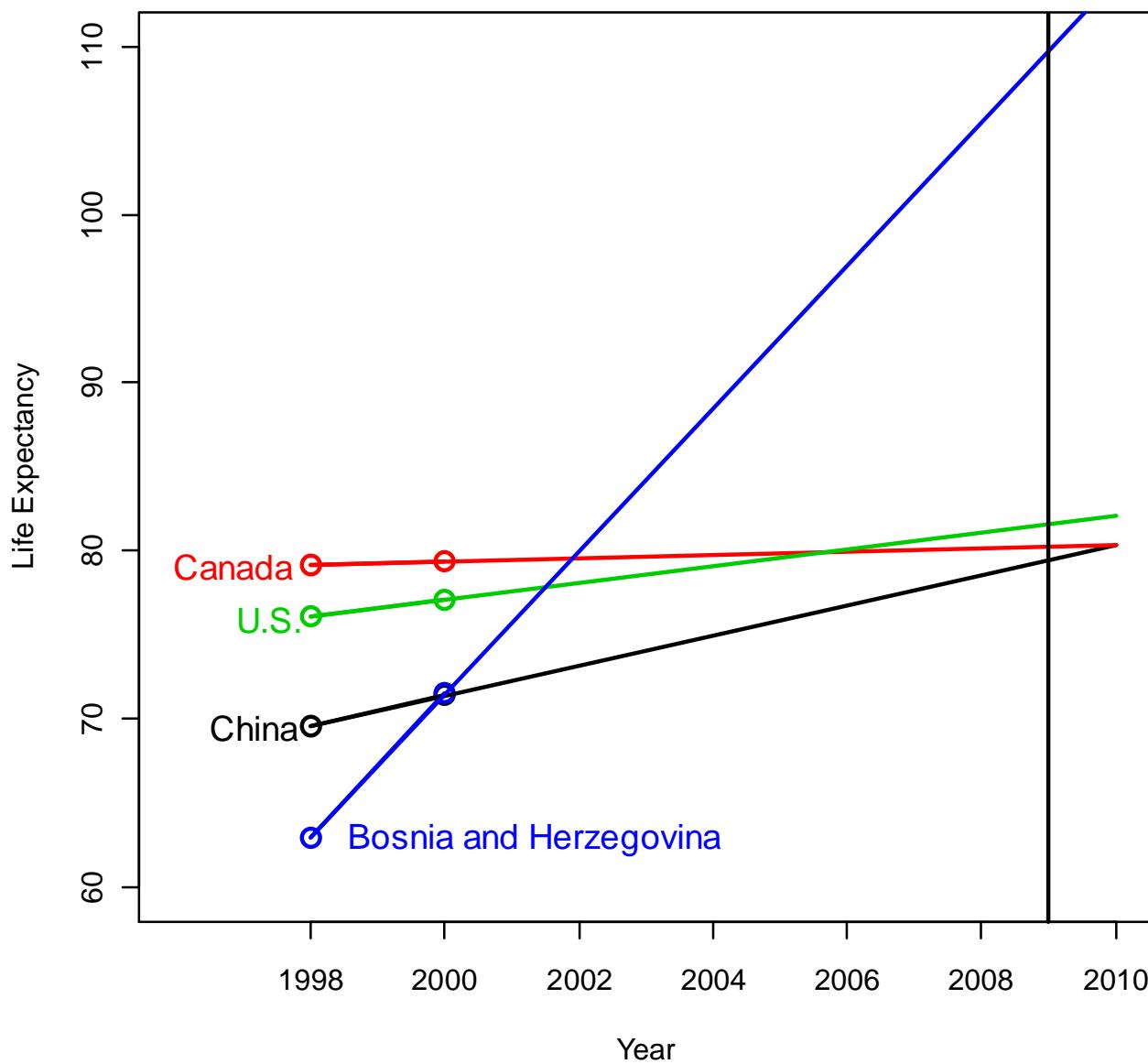








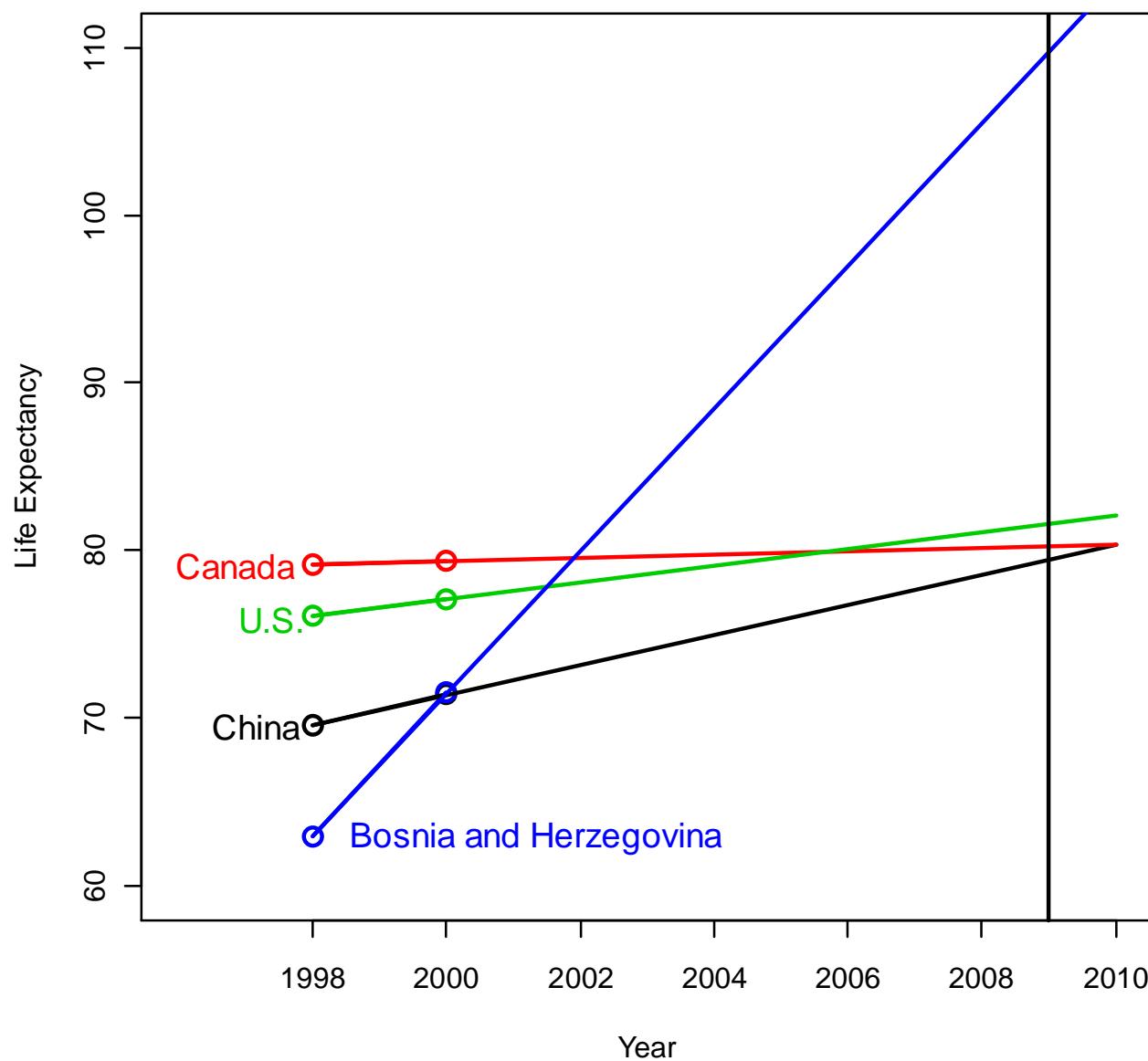


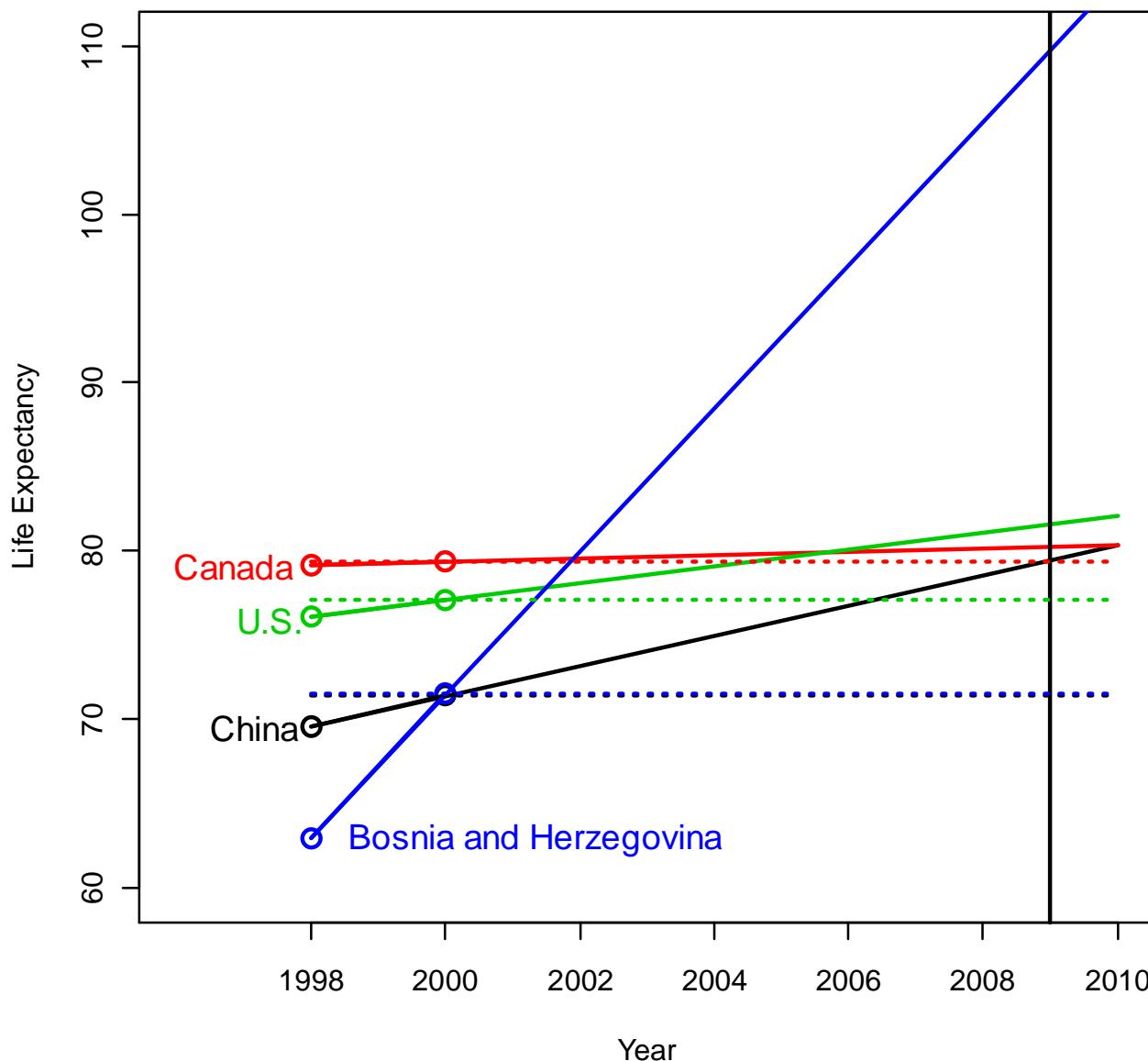


So:

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 last value.

Usually:
something in between.

Do statistics lie?

OR is it misuse of statistics that lies?

Statistics \neq 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*



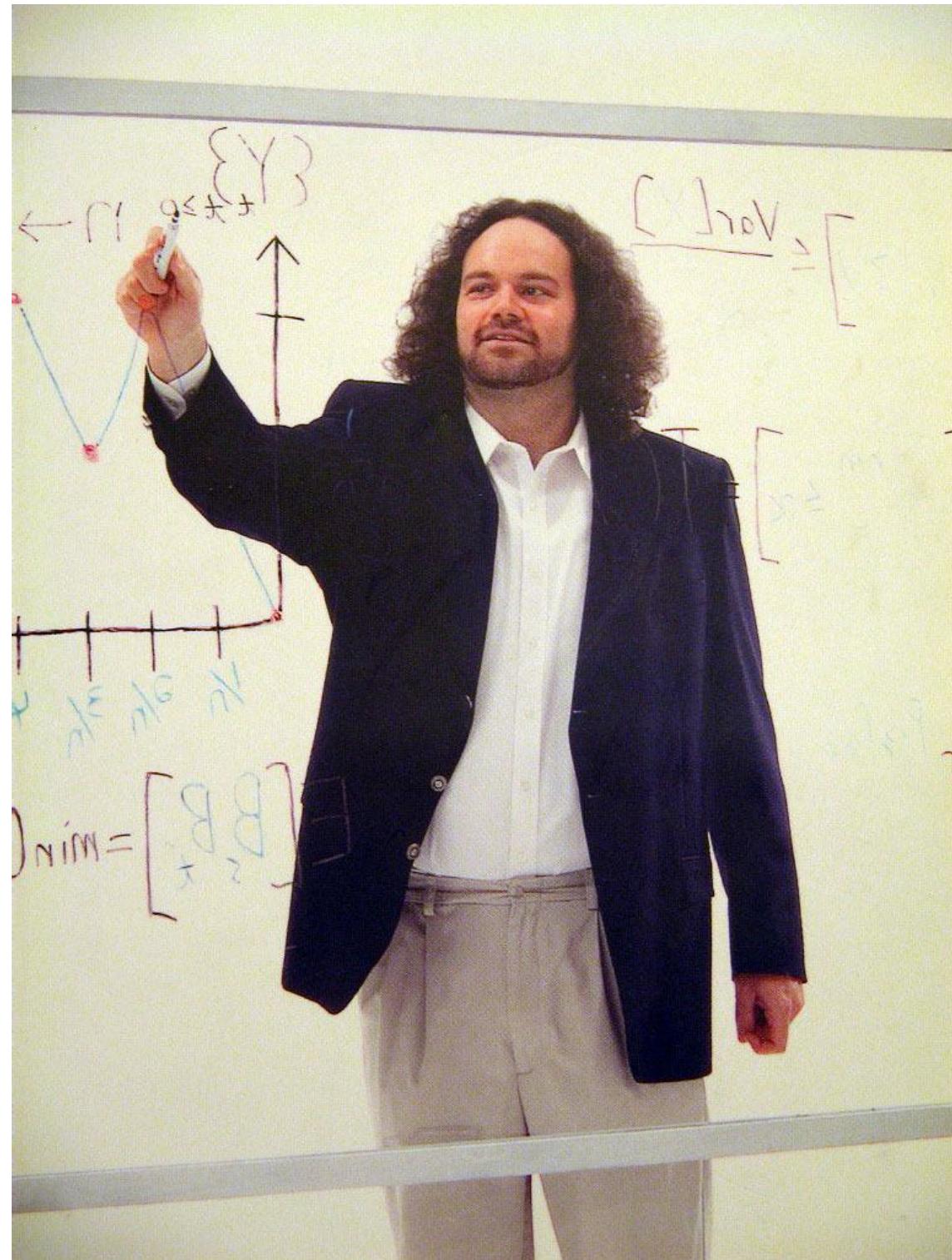


Table 3.5 Average Loss When Betting \$10 at Various Casino Games

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

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

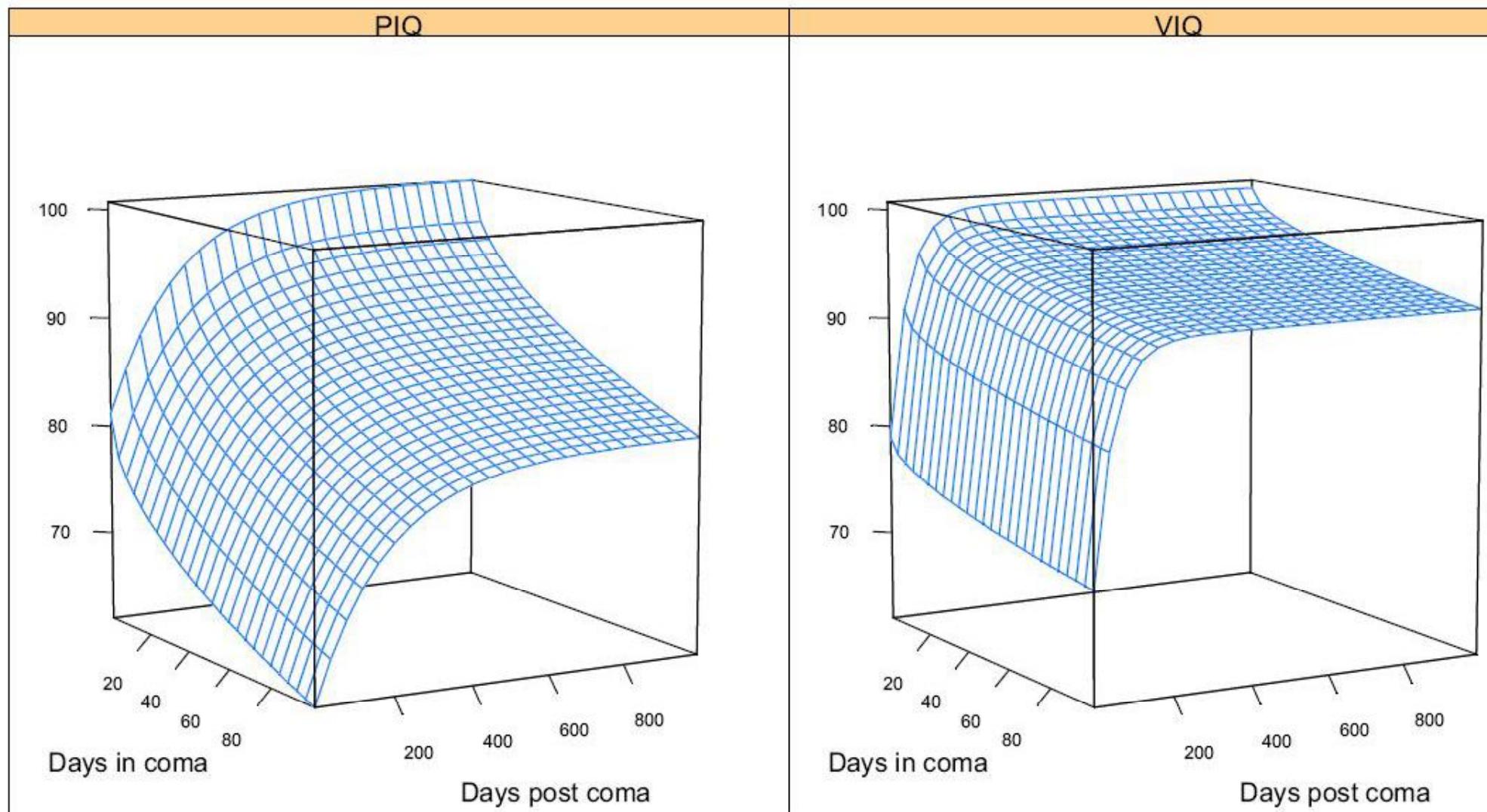
*Specifically, the version of keno described above; others may vary.

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.



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

venues 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:

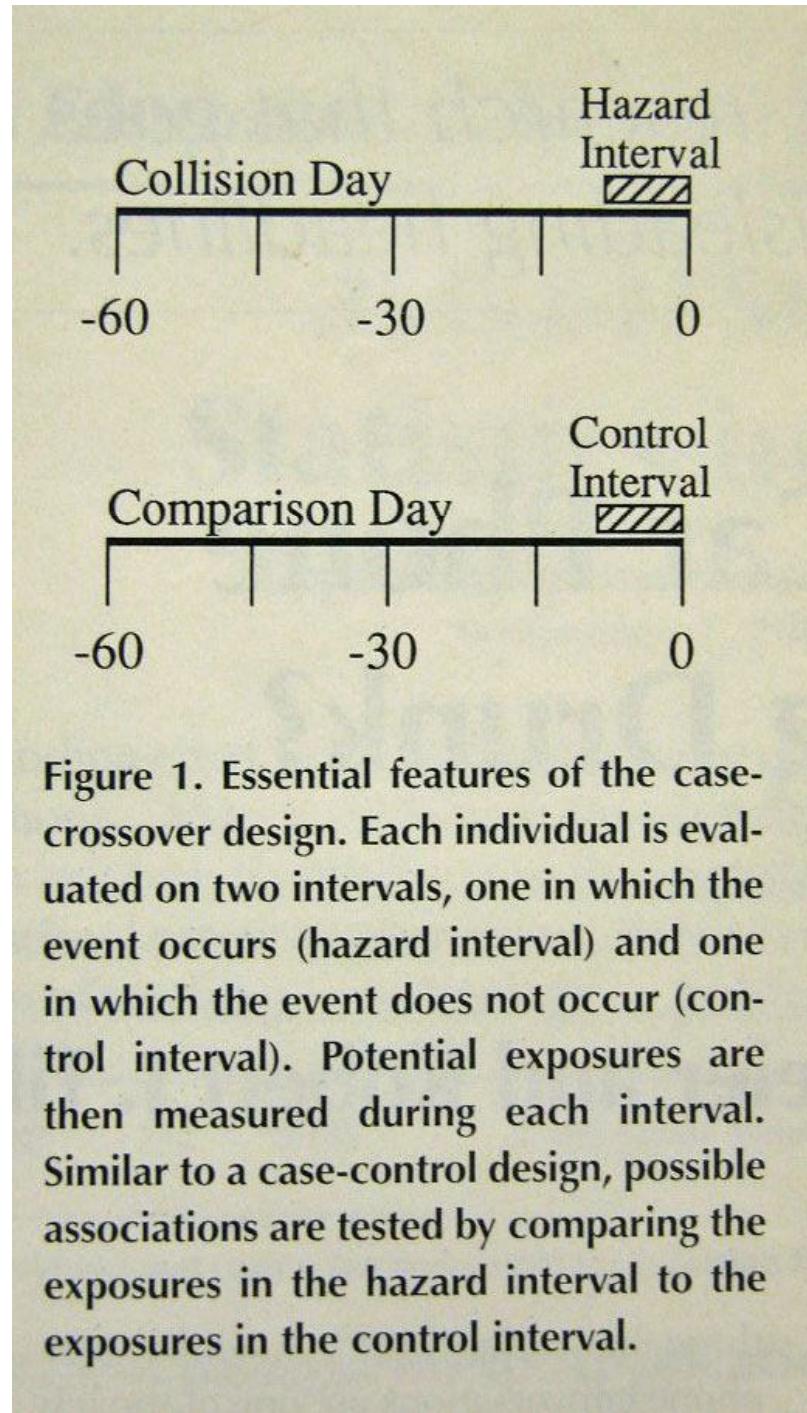


Figure 1. Essential features of the case-crossover design. Each individual is evaluated on two intervals, one in which the event occurs (hazard interval) and one in which the event does not occur (control interval). Potential exposures are then measured during each interval. Similar to a case-control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

individuals had been at the time of the collision selected to risk of encouraging, concerns and might be for driving reck.

which we can an individual days conditional have only vehicle at a tive days alone, we any cellular l interval as therefore, at a relative lysis would e could not probability ducted our ed in a coll ual tele ed an esti of driving

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...**

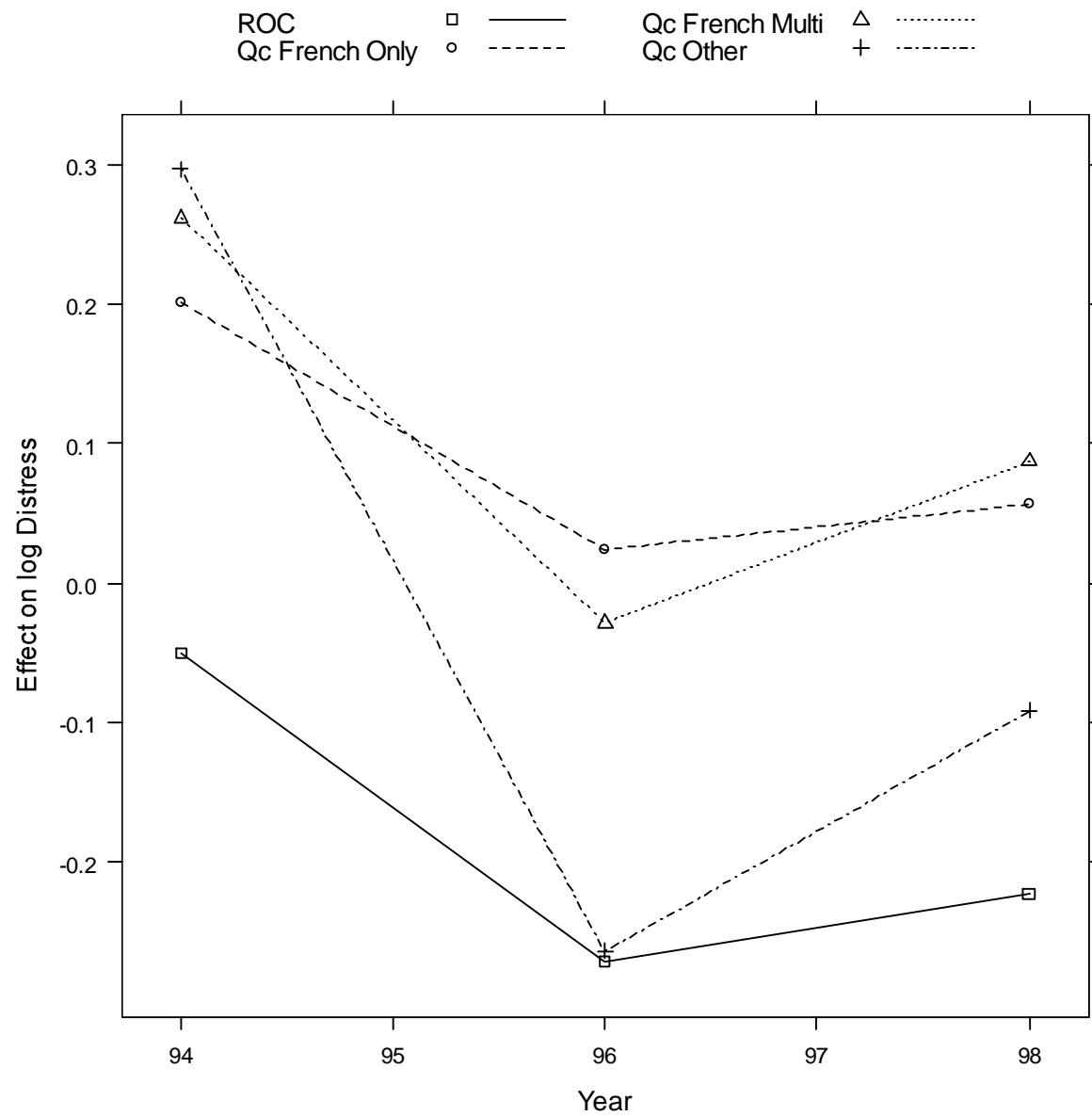
blunder to mislabel these calls made

than five tive risk association inexperienced n performance who used phone ar This sug telephone advantag factor in tions in a ty. A false could als eral attitu telephone selves to hand-hel The a implicate their brain with their hearing, voice-act ly available in o safety ad data base telephone relative r

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



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

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 Courier 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. Courier, 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. Counter, 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

- | | |
|-----------------------------------|-----------------------------------|
| 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. Counter. "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

Copyright © 1991 by [The Johns Hopkins University School of Hygiene and Public Health](#)

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, Philadelphia, 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