CSSS 569 · Visualizing Data and Models

VISUAL DISPLAYS IN THE SOCIAL SCIENCES

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Why Scientific Visualization Should Matter to Social Scientists

Good visuals help social science researchers uncover patterns and relationships we'd otherwise miss

Ever more sophisticated statistical models cry out for clear, easy-to-understand visual representations of model findings

Casual observation suggests good visuals have a big impact on audiences for papers and job talks

Puzzle: Social scientists seldom put as much care into designing visual displays as they devote to crafting effective prose – but this is changing

Plan of the Course

Part I	Weeks	Principles of Effective Information Visualization
Ideas	1–3	Cognitive Science and Visualization
		Graphical Programming in R
Part II	Weeks	Exploratory Data Analysis
Tools	4–7	Visualizing Model Inference
		Visualizing Model Robustness and Interactions
Part III	Weeks	Interactive Graphics
Applications	8–10	Tools for Scientific Writing and Presentations
		Final Presentations

Three Examples of Visual Data Analysis

Success! Stopping infectious disease

Failure. The *Challenger* disaster

Confusion? Deciphering models of monetary policymaking

As we go, consider three uses of visuals:

to explore *data*

to understand *model implications*

to test *model fit*

John Snow Saves London

Cholera outbreaks were common in 19th century London; 10,000s of deaths

Contemporary theories:

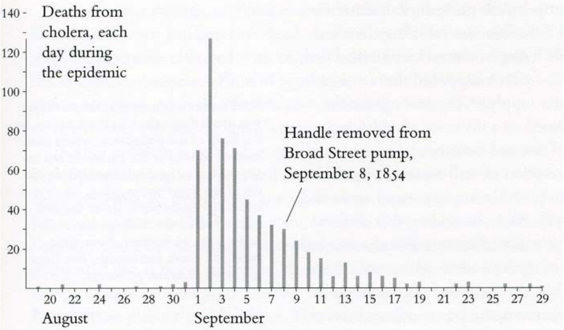
1. Cholera caused by "miasma" in the air coming from swamps...
2. Or a "poison" slowly losing strength as it passed from victim to victim...
3. London doctor John Snow thought contaminated water the cause

Outbreak in 1854: 500 deaths in 10 days in Soho

Snow collects real-time data; has Broad Street water pump handle removed

Did he stop the epidemic? And prove disease can be spread by germs?

A newspaper visually "analyzes" John Snows's intervention?



Source: Tufte, *Visual Explanations*

Overwhelming tendency to view time series data this way

A first step, but doesn't help us make inferences about the data

The mortality data aren't being compared to any other variables: time series plots aren't models of the data generating process

Snow’s spatial analysis

In 1854, London water was provided by competing private firms

Each had its own network and reputation for cleanliness

Residents typically walked to the nearest street pump for water

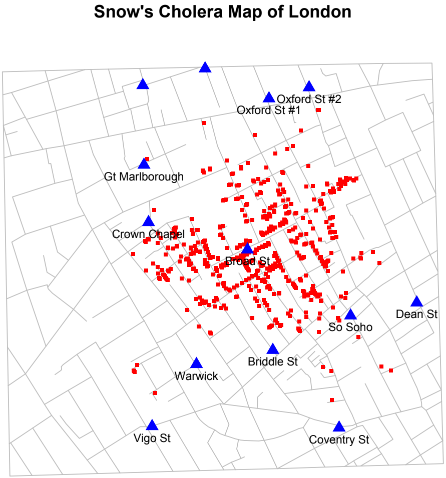
Snow recorded the location of each death in real time

Placed these spatial data on a map along with the *water pumps*

Was one company’s network – or even just one pump – contaminated with cholera “germs”?

Reproduced from *Visual and Statistical Thinking*, ©E.R. Tufte 1997, based on Snow's drawing .

Snow's spatial analysis: Slide friendly version



Deaths are concentrated around Broad Street pump, not other pumps

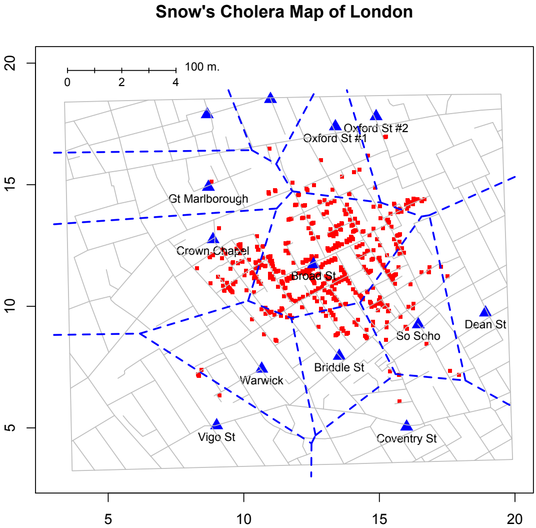
Was it the source of the epidemic?

Or could this evidence be consistent with a different story?

How might the map be misleading? What does the map hide?

What other evidence would you like to have?

Snow's spatial analysis: A simple visual model (Tobler 1994)



Fact: For any spot x on the map, there is a closest pump A

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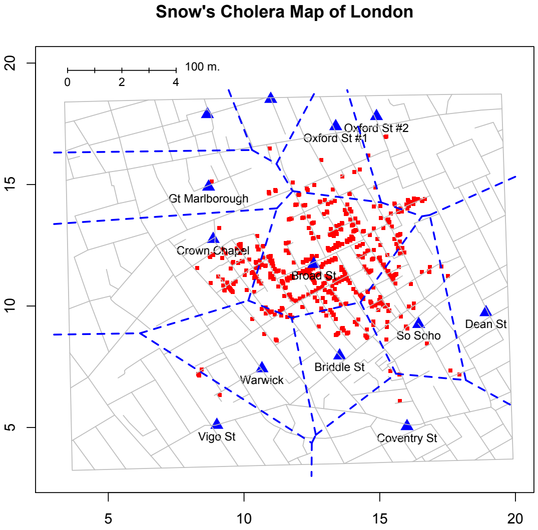

Fact: For any spot *x* on the map, there is a closest pump *A*

Definition: The set of all points *x* closest to pump *A* is the *Voronoi cell* of pump *A*

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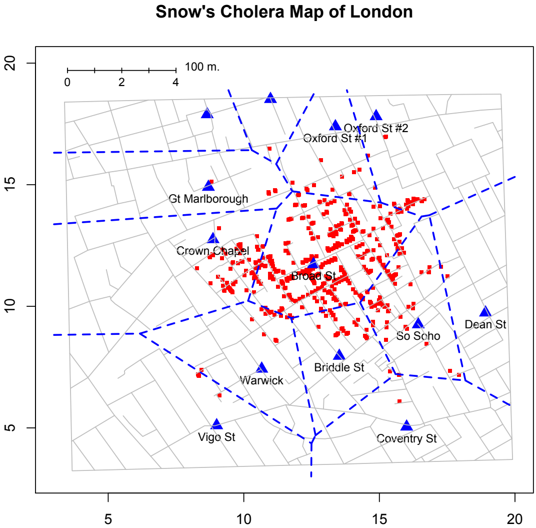

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Modeling Assumptions:

Some (not all) pumps are contaminated

People use the closest pump

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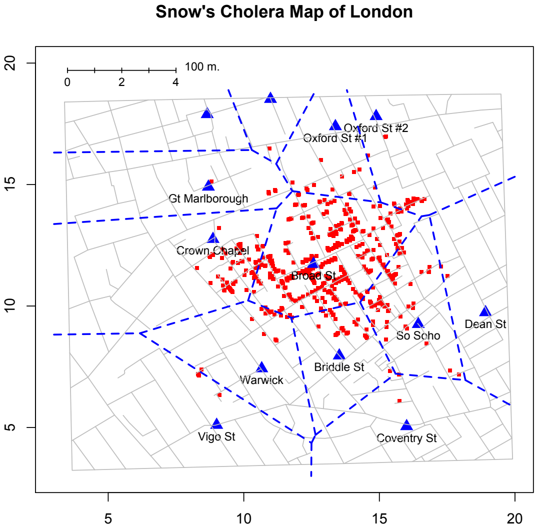

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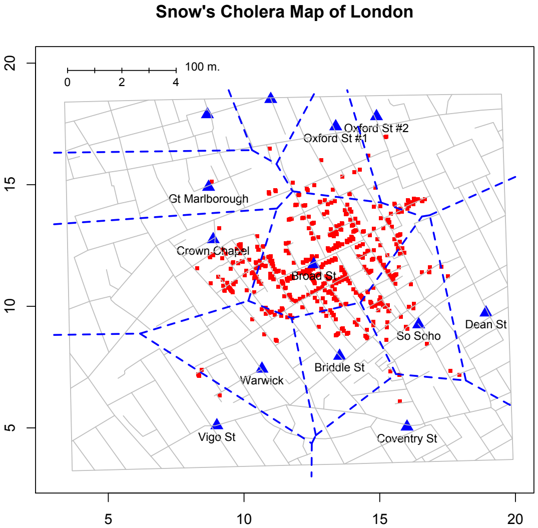
Model prediction: Pattern of deaths should match Voronoi cell boundaries


Snow's Cholera Map of London
100 m.
0
2
4
Oxford St #2
Oxford St #1
Gt Marlborough
Crown Chapel
Broad St
So Soho
Dean St
Briddle St
Warwick
Vigo St
Coventry St
5
10
15
20
5
10
15
20

Problems?

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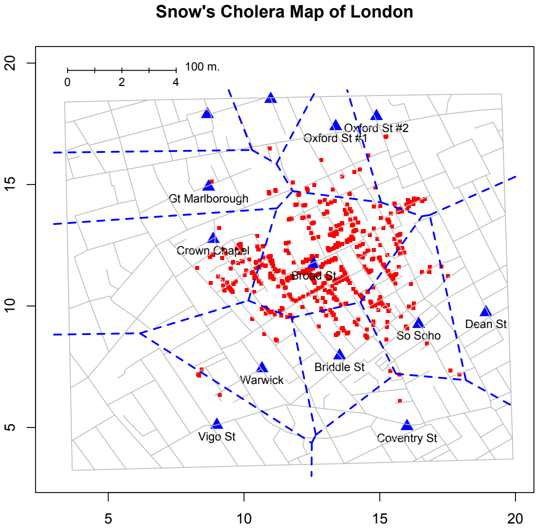

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Distance in a city isn't really Euclidian – the built environment lengthens some paths.

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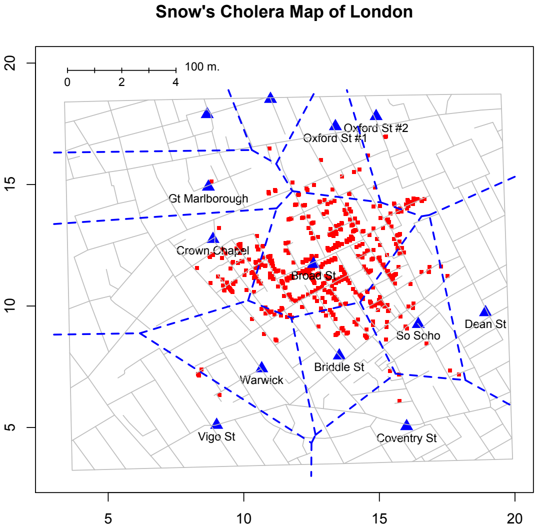

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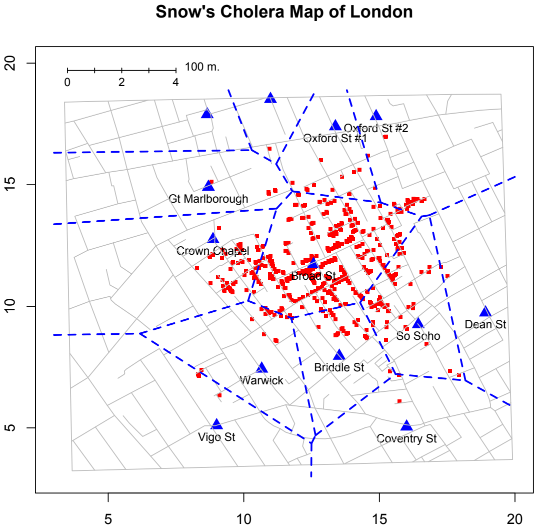

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Outliers could point to missing variables or simple randomness

Reproduced from *Visual and Statistical Thinking*, ©E.R. Tufte 1997, based on Snow's drawing .

What explains outliers in this map?

Three cases:

1. A prison (work house) with its own well.
2. A brewery with its own water source. Saved by the beer.
3. Some distant deaths attributed to preference for Broad St. water.

John Snow stops the Cholera epidemic

Snow used his data and map to convince officials to remove the handle from the Broad Street pump.

Credited with stopping the outbreak & providing 1st experimental evidence for germs

Some questions to consider later:

1. Did the Broad Street Pump really cause the cholera outbreak?
2. Did removing the handle stop it?
3. How could Snow's map be improved
   as a visual display of scientific information (VDSI)?

Steven Johnson (*The Ghost Map*, Riverhead Press, 2007) notes forensic evidence supporting Snow – final case occurred next to Broad St. Pump but didn't spread

One way to think about data graphics is as a set of tools:

Maps, scatterplots, time series plots, histograms...

Another view: visuals can explore relationships and tell stories

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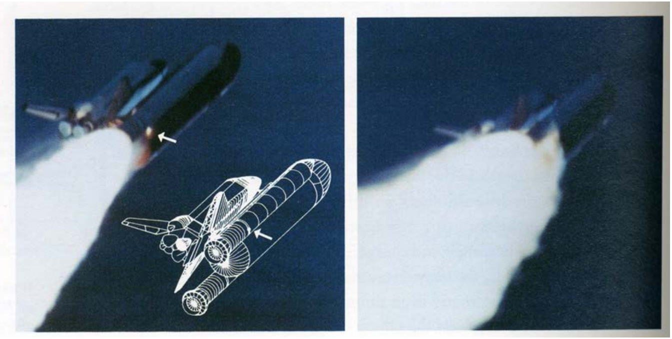
2. find ways to usefully *juxtapose variables* within a visual display
3. *be creative:* move beyond rote applications of the most obvious tool
4. *take care with details:* annotations, use of color, scales, and so on



In 1986, the Challenger space shuttle exploded moments after liftoff

The decision to launch is one of the most scrutinized in history

Failure of O-rings in the solid-fuel rocket boosters blamed for explosion

Could this failure have been foreseen?

The *Challenger* launch decision

Flights with O-ring damage	
Flt Number	Temp (F)
2	70
41b	57
41c	63
41d	70
51c	53
61a	79
61c	58

Data on O-ring failures
at different launch temperatures,
provided to NASA by Morton-Thiokol
hours before launch

Engineers who made this table worried about launching below 53 degrees (Why?)

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Failed to convince administrators of danger
Counter-argument:
"damages at low and high temps"

Are there problems with this presentation?
With the use of data?

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With the use of data?

Selection on the dependent variable

Why sort by launch number?

The *Challenger* launch decision

O-ring damage pre-Challenger, by temperature at launch

Damage?	Temp (F)	Damage?	Temp (F)
Yes	53	**Yes**	70
Yes	57	No	70
Yes	58	No	70
Yes	63	No	72
No	66	No	73
No	67	No	75
No	67	No	76
No	67	No	76
No	68	No	78
No	69	**Yes**	79
Yes	70	No	81

After fixing these two problems, the evidence begins to speak for itself.

What if Morton-Thiokol engineers had made this table before the launch?

The *Challenger* launch decision

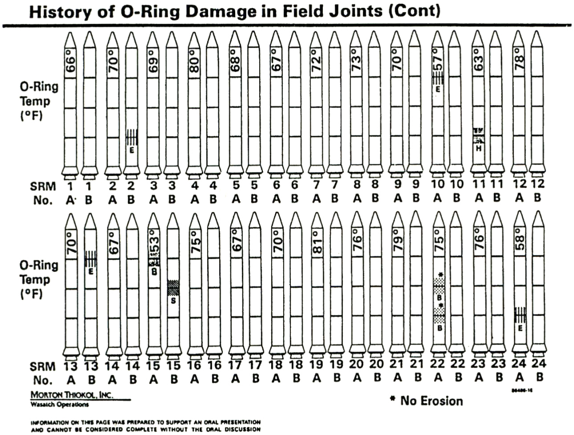
Why didn't NASA make the right decision?

Many answers in the literature:
bureaucratic politics; group think; bounded rationality, etc.

But Edward Tufte thinks it may have been a matter of presentation & modeling:

- Never made the right tables or graphics
- Selected only failure data
- Never considered a simple statistical model

What Morton-Thiokol presented months *after* the disaster



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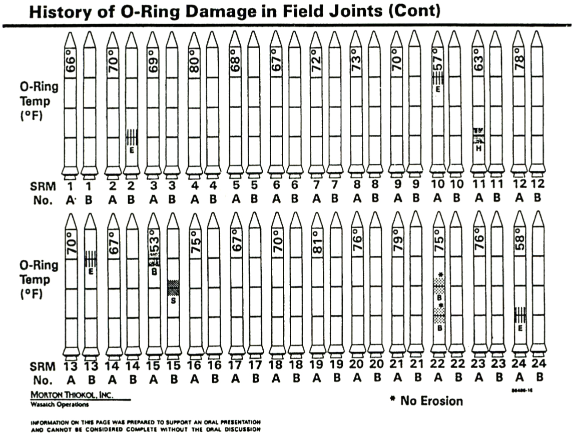
A marvel of poor design – obscures the data, makes analysis *harder*



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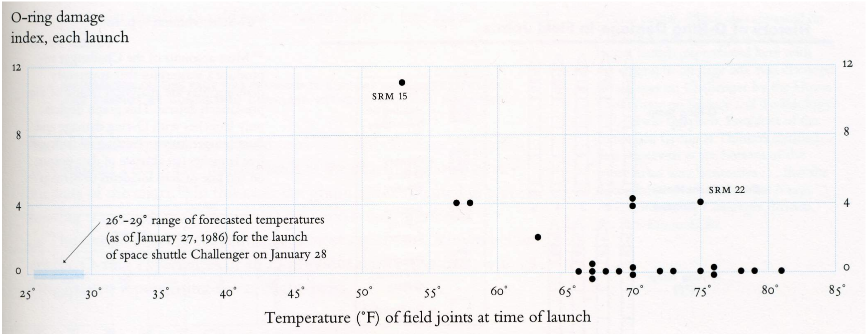
Can methods commonly used in social science do better?

The *Challenger* launch decision

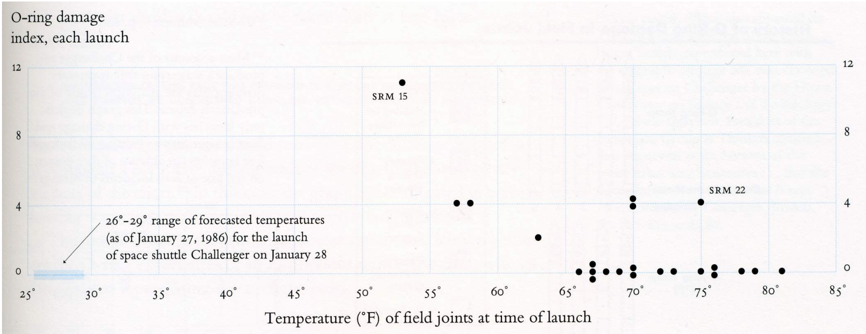


What was the forecast temperature for launch?

26 to 29 degrees Fahrenheit (−2 to −3 degrees C)!

The shuttle was launched in unprecendented cold

The *Challenger* launch decision

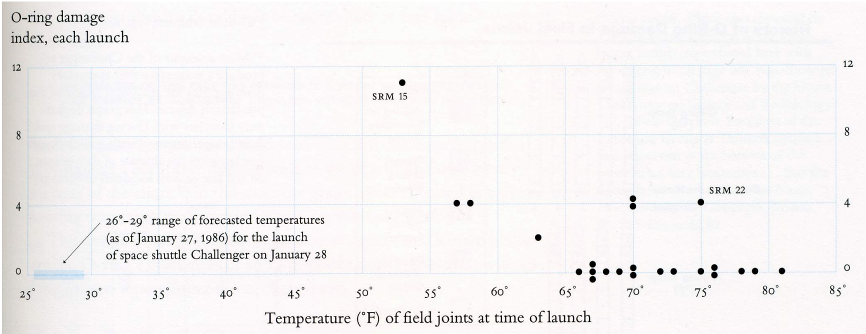


Imagine you are the analyst making the launch recommendation.

You've made the scatterplot above. What would you add to it?

Put another way, what do you is the first question you expect to hear?

The *Challenger* launch decision



"What's the chance of failure at 26 degrees?"

The scatterplot suggests the answer is "high," but that's vague.

But what if the next launch is at 58 degrees? Or 67 degrees?

We need a *probability model* and a way to convey that model to the public

Let's estimate a simple logit model of damage as a function of temperature:

$$\Pr(\text{Damage}|\text{Temp}) = \text{logit}^{-1}(\hat{\beta}_0 + \hat{\beta}_1 \text{Temp})$$

R gives us this lovely logit output...

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Variable	est.	s.e.	p
Temperature (F)	-0.18	0.09	0.047
Constant	11.9	6.34	0.062
N	22		
log-likelihood	-10.9		

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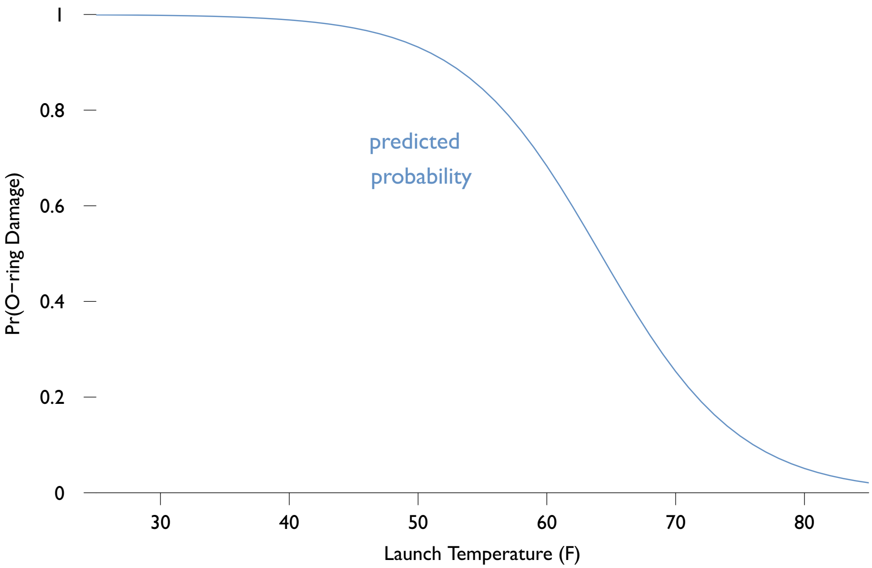
log-likelihood	-10.9		

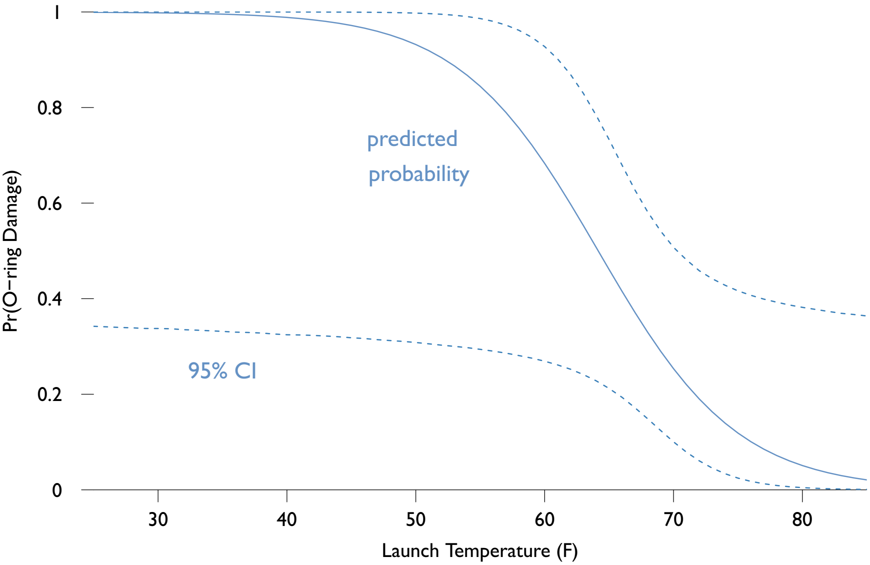
...which most social scientists read as
"a significant negative relationship b/w temperature and probability of damage"

...but that's pretty vague too

Is there a more persuasive/clear/useful way to present these results?



A picture of the logistic regression shows model predictions *and* uncertainty



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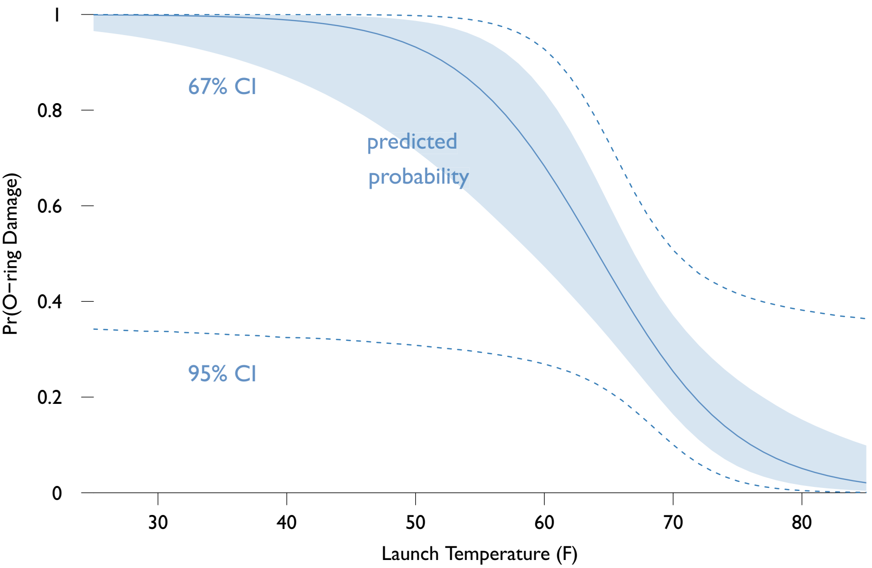

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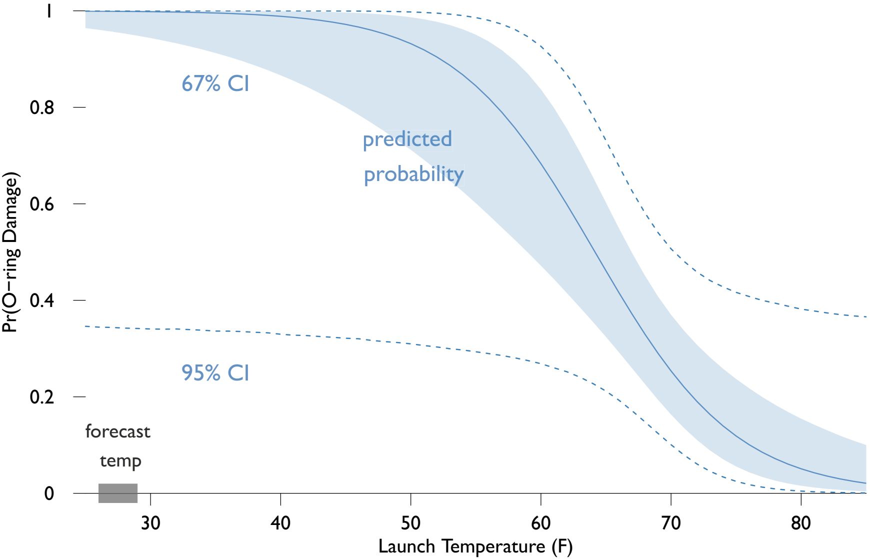
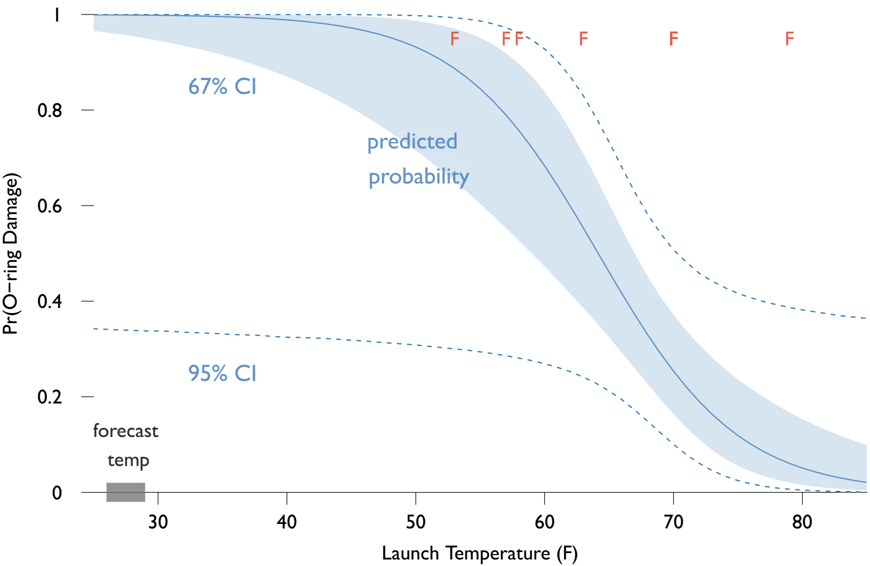
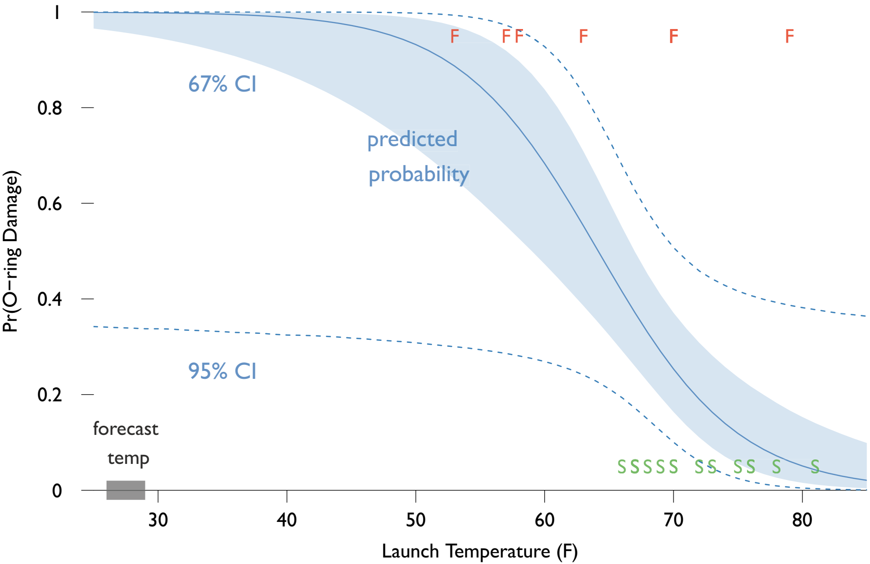


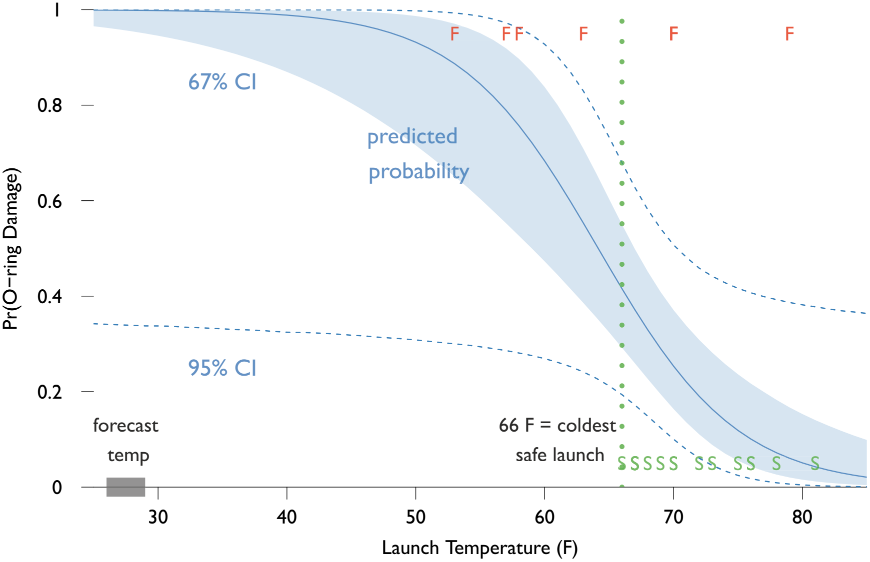
...and gives a more precise sense of how reckless it was to launch at 29 F



When possible, it's good to show the data giving rise to the model

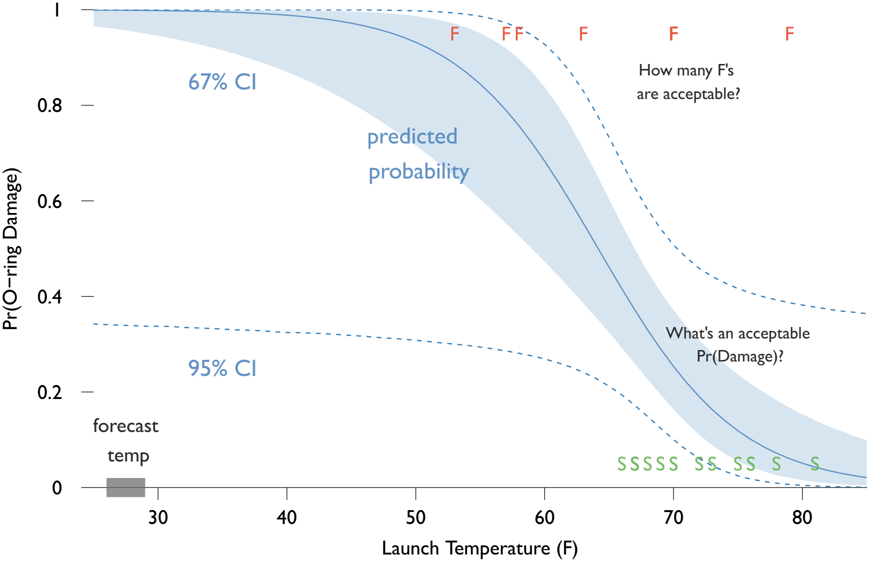


Remembering that the **Failures** are only meaningful compared to **Successes**



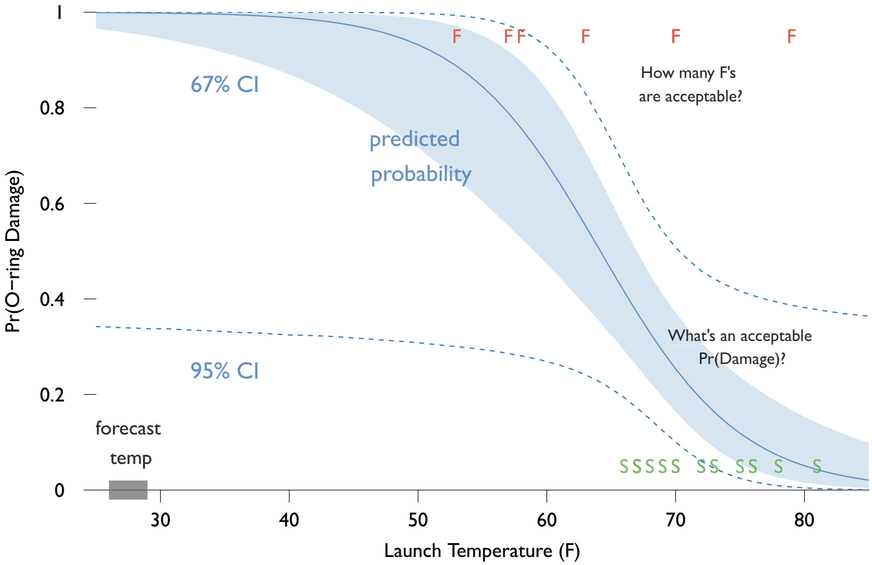
Looking *only* at the data we might think launches <66 F are "certain failures"

This inference is based on an unstated (and flawed) model



The estimated logit model should give us pause

There is a significant risk of failure across the board



What is an acceptable risk of O-ring failure?

Was the shuttle safe at any temperature?

In a hearing, Richard Feynmann dramatically showed O-rings lose resilence when cold by dropping one in his ice water.

Experiment cut through weeks of technical gibberish concealing flaws in the O-ring

But it shouldn't have taken a Nobel laureate:

a scientist with a year of statistical training could've used the launch record to reach the same conclusion

And it would take no more than a single graphic to show the result

Visualizing relationships is critical at every stage of statistical analysis

Lessons for social scientists:

Even relatively simple models and data are easier to understand with visuals

Tables can hide strong correlations

Imagine what might be hiding in datasets with dozens of variables?

Or in models with complex functional forms?

Visuals help make discussion more substantive

See the size of the effect, not just the sign

Make relative judgments of the importance of covariates

Make measured assesments of uncertainty – not just "accept/reject"

Coefficients are not enough

Problems arising from "just-the-coefficients" presentations:

- Use of arcane intermediate quantites
  Logit coefficients, odds ratios, but also many interaction and polynomial terms
- Failure to transform results to the scale of the quantities of interest
  here, we really want the conditional expectation: $\mathrm{E}(y|x)$
- Vague, misleading, or indirect measures of uncertainty
  "stars" can be misleading when we want to know the uncertain of $\mathrm{E}(y|x)$
- Results sections with awkward prose focusing more on significance tests than substantive findings

American Interest Rate Policy

Example from my own work on central banking (*Bankers, Bureaucrats, and Central Bank Politics*, Cambridge U.P., 2013, Ch. 4)

Federal Reserve Open Market Committee (FOMC) sets interest rates 10$\times$/year

Members of the FOMC vote on the Chair's proposed interest rate

Dissenting voters signal whether they would like a higher or lower rate

Dissents are rare but may be symptomatic of how the actual rate gets chosen

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Many factors could influence interest rate votes:

Individual	Career background Appointing party Interactions of above
Economy	Expected inflation Expected unemployment
Politics	Election cycles

American Interest Rate Policy

My main concern is the individual determinants,
especially career background

I measure career background as a composite variable

Fractions of career spent in each of 5 categories:

Financial Sector	FinExp
Treasury Department	FMExp
Federal Reserve	CBExp
Other Government	GovExp
Academic Economics	EcoExp

These 5 categories plus an (omitted) "Other" must sum to 1.0

American Interest Rate Policy

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
GovExp	0.3	$=0.15$	
FMExp	0.1		
CBExp	0.2	$\rightarrow$	
EcoExp	0.3		
Sum	1.0		1.000

Because of the composition constraint, to consider the effects of a change in one category, we must adjust the other categories simultaneously

What happens if I increase FinExp by 0.15, but keep all other components the same?

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FinExp	0.1	ΔFinExp	0.250
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CBExp	0.2	$\rightarrow$	
EcoExp	0.3		
Sum	1.0		1.000

What happens if I increase FinExp by 0.15, but keep all other components the same?

Note – this is close to what I *assume* when I interpret the β for a component as the "effect" of raising that component

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
GovExp	0.3	$=0.15$	0.300
FMExp	0.1		0.100
CBExp	0.2	$\rightarrow$	0.200
EcoExp	0.3		0.300
Sum	1.0		1.150

Increasing one component without lowering the combined total of the other components by the same amount leads to a logical fallacy – a career that has 115% total experience!

American Interest Rate Policy

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
GovExp	0.3	$=$0.15	0.300
FMExp	0.1		0.100
CBExp	0.2	$\rightarrow$	0.200
EcoExp	0.3		0.150
Sum	1.0		1.000

Alternatively, if we left out a category (say, EcoExp) as a "reference," we would be implicitly assuming that category alone shrinks to accommodate the increase in FinExp

But that blends the effects of FinExp and EcoExp – so that in our model, the choice of reference category is no longer harmless!

American Interest Rate Policy

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
GovExp	0.3	$=0.15$	0.300
FMExp	0.1		0.100
CBExp	0.4	$\rightarrow$	0.400
EcoExp	0.1		-0.050
Sum	1.0		1.000

And what if EcoExp (still the reference category) starts out smaller than 0.15?

Then our counterfactual would create negative career components!

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
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EcoExp	0.3		
Sum	1.0		1.000

When covariates form a composition, we have two problems:

1. to avoid blending effects across components
2. to avoid impossible counterfactuals

I recommend *ratio-preserving counterfactuals*, which uniquely solve both problems

American Interest Rate Policy

	Initial Composition		Hypothetical New Composition
FinExp	0.1	ΔFinExp	0.250
GovExp	0.3	$=0.15$	0.250
FMExp	0.1		0.083
CBExp	0.2	$\rightarrow$	0.167
EcoExp	0.3		0.250
Sum	1.0		1.000

The transformations above uniquely preserve the ratios among all categories (except FinExp, of course)

Note that now, the effect of a change in one category works through *all* the βs for the composition

American Interest Rate Policy

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While this example raises fairly specific issues of interpretation,
it is an example of a general phenomenon:

Thinking deeply about your research question & counterfactuals often reveals individual coefficients are a poor substantive summary of findings

We'll fit an ordered probit model to the interest rate data:

$$\begin{aligned}
\Pr(Y_i = \text{ease}|\hat{\beta}, \hat{\tau}) &= \Phi\left(0|X_i\hat{\beta}, 1\right) \\
\Pr(Y_i = \text{assent}|\hat{\beta}, \hat{\tau}) &= \Phi\left(\hat{\tau}|X_i\hat{\beta}, 1\right) - \Phi\left(0|X_i\hat{\beta}, 1\right) \\
\Pr(Y_i = \text{tighten}|\hat{\beta}, \hat{\tau}) &= 1 - \Phi\left(\hat{\tau}|X_i\hat{\beta}, 1\right)
\end{aligned}$$

where Φ represents the Normal CDF and τ is a cutpoint

(don't worry if this model is unfamiliar;
suffice it to say we have a nonlinear model and not just linear regression)

Estimating the model yields the following parameters:

Response variable: FOMC Votes (1 = ease, 2 = accept, 3 = tighten)					
EVs	**param.**	**s.e.**	**EVs**	**param.**	**s.e.**
FinExp	−0.021	(0.146)	E(Inflation)	0.019	(0.015)
GovExp	−0.753	(0.188)	E(Unemployment)	−0.035	(0.022)
FMExp	−1.039	(0.324)	In-Party, election year	−0.182	(0.103)
CBExp	−0.142	(0.141)	Republican	−0.485	(0.102)
EcoExp × Repub	0.934	(0.281)	Constant	2.490	(0.148)
EcoExp × Dem	−0.826	(0.202)	Cutpoint (τ)	3.745	(0.067)
N	2957		ln likelihood	−871.68	

Table 1: **Problematic presentation: FOMC member dissenting votes—Ordered probit parameters.** Estimated ordered probit parameters, with standard errors in parentheses, from the regression of a $j = 3$ category variable on a set of explanatory variables (EVs). Although such nonlinear models are often summarized by tables like this one, especially in the social sciences, it is difficult to discern the effects of the EVs listed at right on the probability of each of the j outcomes. Because the career variables *XXX*Exp are logically constrained to a unit sum, even some of the signs are misleading. The usual quantities of interest for an ordered probit model are not the parameters ($\boldsymbol{\beta}$ and τ), but estimates of $\Pr(y_j|\mathbf{x}_c, \boldsymbol{\beta}, \tau)$ for hypothetical levels of the EVs $\mathbf{x}_c$, which I plot in Figure 1.

American Interest Rate Policy

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How do we interpret these results?

American Interest Rate Policy

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Because the model is non-linear,
interpreting coefficients as slopes ($\partial y/\partial\beta$) is grossly misleading

Moreover, the compositional variables are tricky:
If one goes up, the others must go down, to keep the sum =1

Finally, we can't interpret interactive coefficients separately

American Interest Rate Policy

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Looking at this table, two obvious question arise:

What is the effect of each covariate on the probability of each kind of vote?

What are the confidence intervals or standard errors for those effects?

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Cruel to leave this to the reader: it's a lot of work to figure out.

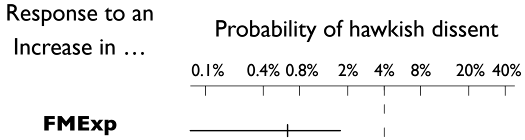
The table above, though conventional, is an intermediate step.

Publishing the table alone is like stopping where Morton-Thiokol did,
with pages of technical gibberish – the answers are there, but buried

As the researcher, I should calculate the effects and uncertainty

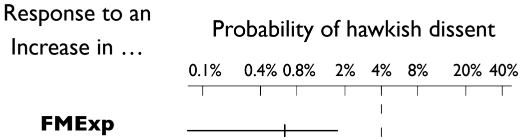
And present them in a readable way

A single graphic achieves both goals

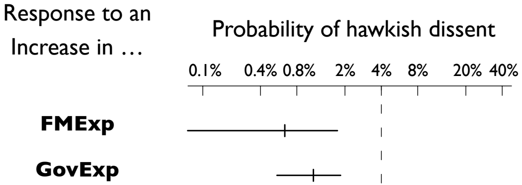


My final graphic will involve small multiples, but explanation should start with a single example

"The average central banker dissents in favor of tighter interest rates 4% of the time. In contrast, former treasury officials in the FOMC dissent 0.6% of the time, with a 95% CI from 0.05% to 2%."



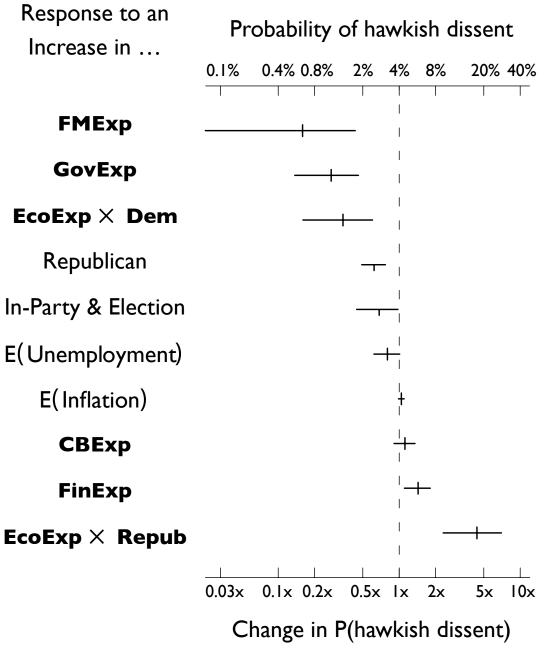
"Other former bureaucrats issue hawkish dissents 1% of the time [95% CI: 0.5 to 2.0], all else equal."



Now that readers understand how to read an individual result, they are ready to explore the graphic on their own.

I can highlight broad trends, then summarize the key findings

But starting by explaining a single instance is critical for effectively using small multiples



Coming later in the course...

No matter how complex the model,
you can always summarize relationships among variables with pictures

Well designed VDSIs make complex models (linear or nonlinear) transparent

For example, for a regression-like model,
you might calculate $\mathrm{E}(y|\mathbf{x}_c, \hat{\beta})$ for interesting cases $\mathbf{x}_c$,
and then plot many such quantities for comparison

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This works no matter how complex your model is –

Any intelligent non-specialist should be able to understand your (simple/fancy/Bayesian/dynamic/hierarchical/nonlinear/interactive) model

If they can't, you're not finished writing it up,
and may be missing some implications yourself!

Scope of the Course

Because visual displays can be woven thoughout all empirical science, it may sound like this course covers all of applied statistics

Course goal: *complement* your other statistical training

Start by defining Visual Displays of Scientific Information & their uses

Almost any representation of information is a VDSI – not just graphics:

- A plot
- A table
- A confection of plots and/or tables
- A schematic
- An equation
- A paragraph
- A movie
- An interactive display

When do we use VDSIs?

VDSIs are woven through the practice of quantitative methods:

- Exploring data
- Interpreting models
- Checking model assumptions & fit
- Persuading an audience
- Making a result memorable

How do VDSIs convey information?

VDSIs can present massive amounts of data for different ends:

- for lookup
- for posterity
- for gestalt impressions
- for exploration
- for rigorous comparison

The appropriate visuals vary by task

Who uses the VDSIs the researcher designs?

- The researcher herself
- The expert reader
- Decision makers
- The general public

Different VDSIs may be best suited for each audience

So how do I choose?

Some VDSIs are generical well suited to some tasks

Tables are usually good for lookup, bad for gestalt impressions

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For fun, type `?pie` in `R`.

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Designing good visuals is more than "Pie charts bad; Dot charts good"

Some VDSIs will be more powerful than others for a particular purpose

Be creative – different visuals can solve the same problem in usefully different ways