Tufte Without Tears

Flexible tools for visual exploration and presentation of statistical models

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In several beautifully illustrated books Edward Tufte gives the following advice:

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Edward Tufte & Scientific Visuals

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4. Use **small multiples**: repetitions of a basic design

Tufte’s recommended medical chart illustrates many of these ideas:
This chart is annotated for pedagogical purposes

Lots of information; little distracting scaffolding

A model that can be repeated once learned...
Surname, Forename M. admitted 3.24.93
Right lower lobe pneumonia, hallucinations, new onset diabetes, history of manic depressive illness

-1yr 3.24 4.4.93 1yr 3.24 4.4.93 1yr 3.24 4.4.93 1yr 3.24 4.4.93
WBC 11100 c/µl Psychosis 0 Glucose 237 mg/dl Mood 0

T 98.8°F Haloperidol 6.0 mg Reg Insulin 3 units Li 0.56 mmol/l

4.4.93 7-South, Bed 5
Discharge. PB MD 1200 4.4.93
No delirium. JT MD 900 4.4.93
Enema given. PAC RN 1100 4.3.93
Will treat for probable constipation. MBM 2245 4.2.93
Vomited three times. RW RN 2230 4.2.93
Left lower lobe infiltrate or atelectasis. AL MD 1500 4.2.93
Alert and oriented. No complaints. PAC RN 1100 4.1.93
Attending to activities of daily living. PAC RN 1100 3.31.93

A complete layout using small multiples to convey lots of info
Elegant, information-rich... and hard to make
What most discussions of statistical graphics leave out

Tufte’s books have had a huge impact on information visualization

However, they have two important limits:

**Modeling**  Most examples are either exploratory or very simple models;

  Social scientists want cutting edge applications

**Tools**  Need to translate aesthetic guidelines into software

  Social scientists are unlikely to do this on their own—and shouldn’t have to!
Key problem  Ready-to-use techniques to visually present model results:

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**Key problem**  Ready-to-use techniques to visually present model results:

- for many variables
- for many robustness checks
- showing uncertainty
- without accidental extrapolation
- for an audience without deep statistical knowledge

**Not covered here**  The theory behind effective visual display of data

Visual displays for data (not model) exploration

For these and other topics, and a reading list, see my course at https://faculty.washington.edu/cadolph/vis

**Lots of examples...**  Too many if we need to discuss methods in detail
Who votes in American elections?

Source: King, Tomz, and Wittenberg
Method: Logistic regression

What do alligators eat?

Source: Agresti
Method: Multinomial logit

How do Chinese leaders gain power?

Source: Shih, Adolph, and Liu
Method: Bayesian model of partially observed ranks

When do governments choose liberal or conservative central bankers?

Source: Adolph
Method: Zero-inflated compositional data model

What explains the tier of European governments controlling health policies?

Source: Adolph, Greer, and Fonseca
Method: Multilevel multinomial logit
Presenting Estimated Models in Social Science

Most empirical work in social science is regression model-driven, with a focus on conditional expectation.

Our regression models are:

- full of covariates
- often non-linear
- usually involve interactions and transformations

If there is anything we need to visualize well, it is our models.

Yet we often just print off tables of parameter estimates.

Limits readers’ and analysts’ understanding of the results.
Coefficients are not enough

Some limits of typical presentations of statistical results:

- Everything written in terms of arcane intermediate quantities (for most people, this includes logit coefficients)

- Little effort to transform results to the scale of the quantities of interest → really want the conditional expectation, $E(y|x)$

- Little effort to make informative statements about estimation uncertainty → really want to know how uncertain is $E(y|x)$

- Little visualization at all, or graphs with low data-ink ratios
Voting Example (Logit Model)

We will explore a simple dataset using a simple model of voting

People either vote \((\text{Vote}_i = 1)\), or they don’t \((\text{Vote}_i = 0)\)

Many factors could influence turn-out; we focus on age and education

Data from National Election Survey in 2000. “Did you vote in 2000 election?”

```
vote00  age  hsdeg  coldeg
[1,]   1  49    1    0
[2,]   0  35    1    0
[3,]   1  57    1    0
[4,]   1  63    1    0
[5,]   1  40    1    0
[6,]   1  77    0    0
[7,]   0  43    1    0
[8,]   1  47    1    1
[9,]   1  26    1    1
[10,]  1  48    1    0
...```
Age enters as a quadratic to allow the probability of voting to first rise and eventually fall over the life course.

Results look sensible, but what do they mean?

Which has the bigger effect, age or education?

What is the probability a specific person will vote?
Run your model as normal. Treat the output as an intermediate step.
An alternative to printing eye-glazing tables

1. Run your model as normal. Treat the output as an intermediate step.

2. Translate your model results back into the scale of the response variable
   - Modeling war? Show the change in probability of war associated with $X$
   - Modeling counts of crimes committed? Show how those counts vary with $X$
   - Unemployment rate time series? Show how a change in $X$ shifts the unemployment rate over the following $t$ years
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4. Present visually as many scenarios calculated from the model as needed
A bit more formally...

We want to know the behavior of $E(y|x)$ as we vary $x$.

In non-linear models with multiple regressors, this gets tricky.

The effect of $x_1$ depends on all the other $x$’s and $\hat{\beta}$’s.

Generally, we will need to make a set of “counterfactual” assumptions:

$$x_1 = a, \quad x_2 = b, \quad x_3 = c, \quad \ldots$$

- Choose $a, b, c, \ldots$ to match a particular counterfactual case of interest *or*
- Hold all but one of the $x$’s at their mean values (or other reference baseline), then systematically vary the remaining $x$.

The same trick works if we are after differences in $y$ related to changes in $x$, such as $E(y_{\text{scen1}} - y_{\text{scen2}} | x_{\text{scen1}}, x_{\text{scen2}})$.
Calculating quantities of interest

Our goal to obtain “quantities of interest,” like

- **Expected Values:** $E(Y|X_c)$
- **Differences:** $E(Y|X_{c2}) - E(Y|X_{c1})$
- **Risk Ratios:** $E(Y|X_{c2})/E(Y|X_{c1})$

or any other function of the above

for some counterfactual $X_c$’s.

For our Voting example, that’s easy—just plug $X_c$ into

$$E(Y|X_c) = \frac{1}{1 + \exp(-X_c/\beta)}$$
Getting confidence intervals is harder, but there are several options:

- For maximum likelihood models, simulate the response conditional on the regressors
  These simulations can easily be summarized as CIs: sort them and take percentiles

- For Bayesian models, usual model output *is* a set of posterior draws

Once we have the quantities of interest and confidence intervals, we’re ready to make some graphs...but how?
Here is the graph that King, Tomz, and Wittenberg created for this model.
How would we make this?
We could use the default graphics in Zelig or Clarify (limiting, not as nice as the above)

Or we could do it by hand (hard)
Wanted: an easy-to-use R package that

1. takes as input the *output* of estimated statistical models
2. makes a variety of plots for model interpretation
3. plots “triples” (lower, estimate, upper) from estimated models well
4. lays out these plot in a tiled arrangement (small multiples)
5. takes care of axes, titles, and other fussy details
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With considerable work, one could
  - coerce \texttt{R}'s basic graphics to do this badly
  - \texttt{or} get \texttt{lattice} to do this fairly well for a specific case

But an easy-to-use, general solution is lacking
The \texttt{tile} package

My answer is the \texttt{tile} package, written using \texttt{R}'s \texttt{grid} graphics

Some basic tile graphic types:

- \texttt{scatter}: Scatterplots with fits, CIs, and extrapolation checking
- \texttt{lineplot}: Line plots with fits, CIs, and extrapolation checking
- \texttt{ropeladder}: Dot plots with CIs and extrapolation checking

Each can take as input draws from the posterior of a regression model

A call to a tile function makes a multiplot layout:

ideal for small multiples of model parameters
Plot simulations of QoI

Generally, we want to plot triples: lower, estimate, upper
We could do this for specific discrete scenarios, e.g.

Pr(Voting) given five distinct sets of x’s

Recommended plot: Dotplot with confidence interval lines
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We could do this for specific discrete scenarios, e.g.

\[ \text{Pr(Voting)} \text{ given five distinct sets of } x's \]

**Recommended plot:** Dotplot with confidence interval lines

Or for a continuous stream of scenarios, e.g.,

Hold all but Age constant, then calculate \( \text{Pr(Voting)} \) at every level of Age

**Recommended plot:** Lineplot with shaded confidence intervals
This example is obviously superior to the table of logit coefficients

But is there anything wrong or missing here?
18 year old college grads?! And what about high school dropouts?
tile helps us systematize plotting model results, and helps avoid unwanted extrapolation by limiting results to the convex hull.
Three steps to make tile plots

Create data traces. Each trace contains the data and graphical parameters needed to plot a single set of graphical elements to one or more plots.
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Three steps to make tile plots

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   - Could be the marginal data for a rug
   - **All** annotation must happen in this step

2. **Basic traces:** `linesTile()`, `pointsTile()`, `polygonTile()`, `polylinesTile()`, and `textTile()`

3. **Complex traces:** `lineplot()`, `scatter()`, `ropeladder()`, and `rugTile()`
Trace functions in tile

**Primitive trace functions:**

- **linesTile**  Plot a set of connected line segments
- **pointsTile**  Plot a set of points
- **polygonTile**  Plot a shaded region
- **polylinesTile**  Plot a set of unconnected line segments
- **textTile**  Plot text labels

**Complex traces for model or data exploration:**

- **lineplot**  Plot lines with confidence intervals, extrapolation warnings
- **ropeladder**  Plot dotplots with confidence intervals, extrapolation warnings, and shaded ranges
- **rugTile**  Plot marginal data rugs to axes of plots
- **scatter**  Plot scatterplots with text and symbol markers, fit lines, and confidence intervals
Three steps to make tile plots

1. **Create data traces.** Each trace contains the data and graphical parameters needed to plot a single set of graphical elements to one or more plots.

2. **Plot the data traces.** Using the `tile()` function, simultaneously plot all traces to all plots.
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2. **Plot the data traces.** Using the `tile()` function, simultaneously plot all traces to all plots.
   - This is the step where the scaffolding gets made: axes and titles
   - Set up the rows and columns of plots
   - Titles of plots, axes, rows of plots, columns of plots, etc.
   - Set up axis limits, ticks, tick labels, logging of axes
Three steps to make tile plots

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2. **Plot the data traces.** Using the `tile()` function, simultaneously plot all traces to all plots.

3. **Examine output and revise.** Look at the graph made in step 2, and tweak the input parameters for steps 1 and 2 to make a better graph.
# Using simcf and tile to explore an estimated logistic regression
# Voting example using 2000 NES data after King, Tomz, and Wittenberg
# Chris Adolph

# Load libraries
library(RColorBrewer)
library(MASS)
library(simcf)  # Download simcf and tile packages
library(tile)   # from faculty.washington.edu/cadolph

# Load data (available from faculty.washington.edu/cadolph)
file <- "nes00.csv"
data <- read.csv(file, header=TRUE)
# Set up model formula and model specific data frame
model <- vote00 ~ age + I(age^2) + hsdeg + coldeg
mdata <- extractdata(model, data, na.rm=TRUE)

# Run logit & extract results
logit.result <- glm(model, family=binomial, data=mdata)
pe <- logit.result$coefficients # point estimates
vc <- vcov(logit.result) # var-cov matrix

# Simulate parameter distributions
sims <- 10000
simbetas <- mvrnorm(sims, pe, vc)
# R Syntax for Lineplot of Voting Logit

```r
# Set up counterfactuals: all ages, each of three educations
xhyp <- seq(18, 97, 1)
nscen <- length(xhyp)
nohsScen <- hsScen <- collScen <- cfMake(model, mdata, nscen)
for (i in 1:nscen) {
    # No High school scenarios (loop over each age)
    nohsScen <- cfChange(nohsScen, "age", x = xhyp[i], scen = i)
    nohsScen <- cfChange(nohsScen, "hsdeg", x = 0, scen = i)
    nohsScen <- cfChange(nohsScen, "coldeg", x = 0, scen = i)

    # HS grad scenarios (loop over each age)
    hsScen <- cfChange(hsScen, "age", x = xhyp[i], scen = i)
    hsScen <- cfChange(hsScen, "hsdeg", x = 1, scen = i)
    hsScen <- cfChange(hsScen, "coldeg", x = 0, scen = i)

    # College grad scenarios (loop over each age)
    collScen <- cfChange(collScen, "age", x = xhyp[i], scen = i)
    collScen <- cfChange(collScen, "hsdeg", x = 1, scen = i)
    collScen <- cfChange(collScen, "coldeg", x = 1, scen = i)
}
```
R Syntax for Lineplot of Voting Logit

```r
# Simulate expected probabilities for all scenarios
nohsSims <- logitsimev(nohsScen, simbetas, ci=0.95)
hsSims <- logitsimev(hsScen, simbetas, ci=0.95)
collSims <- logitsimev(collScen, simbetas, ci=0.95)

# Get 3 nice colors for traces
col <- brewer.pal(3,"Dark2")

# Set up lineplot traces of expected probabilities
nohsTrace <- lineplot(x=xhyp,
    y=nohsSims$pe,
    lower=nohsSims$lower,
    upper=nohsSims$upper,
    col=col[1],
    extrapolate=list(data=mdata[,2:ncol(mdata)],
        cfact=nohsScen$x[,2:ncol(hsScen$x)],
        omit.extrapolated=TRUE),
    plot=1)
```
R Syntax for Lineplot of Voting Logit

```r
hsTrace <- lineplot(x=xhyp,
                     y=hsSims$pe,
                     lower=hsSims$lower,
                     upper=hsSims$upper,
                     col=col[2],
                     extrapolate=list(data=mdata[,2:ncol(mdata)],
                                      cfact=hsScen$x[,2:ncol(hsScen$x)],
                                      omit.extrapolated=TRUE),
                     plot=1)

collTrace <- lineplot(x=xhyp,
                      y=collSims$pe,
                      lower=collSims$lower,
                      upper=collSims$upper,
                      col=col[3],
                      extrapolate=list(data=mdata[,2:ncol(mdata)],
                                       cfact=collScen$x[,2:ncol(hsScen$x)],
                                       omit.extrapolated=TRUE),
                      plot=1)
```
# Set up traces with labels and legend
labelTrace <- textTile(labels=c("Less than HS", "High School", "College"),
                       x=c(55, 49, 30),
                       y=c(0.26, 0.56, 0.87),
                       col=col,
                       plot=1)

legendTrace <- textTile(labels=c("Logit estimates:", "95% confidence", "interval is shaded"),
                         x=c(82, 82, 82),
                         y=c(0.2, 0.16, 0.12),
                         plot=1)
R Syntax for Lineplot of Voting Logit

# Plot traces using tile
tile(nohsTrace,
    hsTrace,
    collTrace,
    labelTrace,
    legendTrace,
    width=list(null=5),
    limits=c(18,94,0,1),
    xaxis=list(at=c(20,30,40,50,60,70,80,90)),
    xaxistitle=list(labels="Age of Respondent"),
    yaxistitle=list(labels="Probability of Voting"),
    frame=TRUE
)
Agresti offers the following example of a multinominal data analysis

Alligators in a certain Florida lake were studied, and the following data collected:

Principal Food 1 = Invertebrates,  
2 = Fish,  
3 = “Other” (!!! Floridians?)

Size of alligator in meters  
Sex of alligator male or female

The question is how alligator size influences food choice.

We fit the model in \( \mathbb{R} \) using multinominal logit and get . . .
Chomp! Coefficient tables can hide the punchline

### Multinomial Logit of Alligator’s Primary Food Source

<table>
<thead>
<tr>
<th></th>
<th>$\ln(\frac{\pi_{\text{Invertebrates}}}{\pi_{\text{Fish}}})$</th>
<th>$\ln(\frac{\pi_{\text{Other}}}{\pi_{\text{Fish}}})$</th>
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<tr>
<td>Intercept</td>
<td>4.90</td>
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<td>(1.71)</td>
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Direct interpretation?
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Direct interpretation?

We could do it, using odds ratios and a calculator.

Invertebrates vs Fish: A 1 meter increase in length makes the odds that an alligator will eat invertebrates rather than fish $\exp(-2.53 - 0) = 0.08$ times smaller.
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Invertebrates vs Other: A 1 meter increase in length makes the odds that an alligator will eat invertebrates rather than “other” food $\exp(-2.53 - 0.13) = 0.07$ times smaller.
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*No reader is going to do this*
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Fish vs Other: A 1 meter increase in length makes the *odds* that an alligator will eat fish rather than “other” food $\exp(0 - 0.13) = 0.87$ times smaller.

*There has to be a better way*
A simple lineplot made with \texttt{tile} shows the whole covariate space

Much more dramatic than the table
We can also add easy to interpret measures of uncertainty

Above are standard error regions
Easy to highlight where the model is interpolating into the observed data

... and where it’s extrapolating into Hollywood territory
When simulation is the only option: Chinese leadership


Explain (partially observed) ranks of the top 300 to 500 Chinese Communist Party leaders as a function of:

- Demographics: age, sex, ethnicity
- Education: level of degree
- Performance: provincial growth, revenue
- Faction: birth, school, career, and family ties to top leaders

Bayesian model of partially observed ranks of CCP officials

Model parameters difficult to interpret: on a latent scale and individual effects are conditioned on all other ranked members

Only solution:
Simulate ranks of hypothetical officials as if placed in the observed hierarchy
Black circles show expected ranks for otherwise average Chinese officials with the characteristic listed at left.
Thick black horizontal lines are 1 std error bars, and thin lines are 95% CIs.
Blue triangles are officials with random effects at ±1 sd; how much unmeasured factors matter.
Helps to sort rows of the plot from smallest to largest effect.
Shih, Adolph, and Liu re-estimate the model for each year, leading to a large number of results.

A complex lineplot helps organize them and facilitate comparisons.
Note that these results are now first differences:
the expected percentile change in rank for an otherwise average official who gains the characteristic noted
Over time, officials’ economic performance never matters, but factions often do.

Runs counter to the conventional wisdom that meritocratic selection of officials lies behind Chinese economic success.
Robustness Checks

So far, we’ve presenting conditional expectations & differences from regressions

But are we confident that these were the “right” estimates?

The language of inference usually assumes we

- correctly specified our model
- correctly measured our variables
- chose the right probability model
- don’t have influential outliers, etc.
Robustness Checks

So far, we’ve presenting conditional expectations & differences from regressions

But are we confident that these were the “right” estimates?

The language of inference usually assumes we

- correctly specified our model
- correctly measured our variables
- chose the right probability model
- don’t have influential outliers, etc.

We’re never completely sure these assumptions hold.

Most people present one model, and argue it was the best choice

Sometimes, a few alternatives are displayed
The race of the variables

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>My variable of interest, $X_1$</td>
<td>X.XX</td>
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<tr>
<td>I &quot;need&quot;</td>
<td>(X.XX)</td>
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<td>A candidate control</td>
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<tr>
<td>Alternate measure of $X_1$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X.XX</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>(X.XX)</td>
</tr>
</tbody>
</table>
Robustness Checks

Problems with the approach above?

- Lots of space to show a few permutations of the model
  
  Most space wasted or devoted to ancillary info
Robustness Checks

Problems with the approach above?

1. Lots of space to show a few permutations of the model
   
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2. What if we’re really interested in $E(Y|X)$, not $\hat{\beta}$?
   
   E.g., because of nonlinearities, interactions, scale differences, etc.
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3. The selection of permutations is \textit{ad hoc}.

We’ll try to fix 1 & 2.

Objection 3 is harder, but worth thinking about.
Robustness Checks: An algorithm

1. Identify a relation of interest between a concept $X$ and a concept $Y$
Robustness Checks: An algorithm

1. Identify a relation of interest between a concept $\mathcal{X}$ and a concept $\mathcal{Y}$

2. Choose:
   - a measure of $\mathcal{X}$, denoted $X$,
Robustness Checks: An algorithm

1. Identify a relation of interest between a concept \( \mathcal{X} \) and a concept \( \mathcal{Y} \)

2. Choose:
   - a measure of \( \mathcal{X} \), denoted \( X \),
   - a measure of \( \mathcal{Y} \), denoted \( Y \),

3. Estimate the probability model \( Y \sim f(\mu, \alpha) \), \( \mu = g(\text{vec}(X, Z), \beta) \).

4. Simulate the quantity of interest, e.g., \( E(Y|X) \) or \( E(Y^2 - Y|X^2, X) \), to obtain a point estimate and confidence interval.

5. Repeat 2–4, changing at each iteration one of the choices in step 2.

6. Compile the results in a variant of the dot plot called a ropeladder.
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Robustness Checks: A central banks example

In *The Dilemma of Discretion*, I argue central bankers’ career backgrounds explain their monetary policy choices.

Central bankers with financial sector backgrounds choose more conservative policies, leading to lower inflation but potentially higher unemployment.

I argue more conservative governments should prefer to appoint more conservative central bankers, e.g., those with financial sector backgrounds.
Robustness Checks: A central banks example

I test this claim using data on central bankers setting monetary policy over 20 countries and 30 years.

Conservatism of central bankers is measured by percentage share in “conservative” careers, and summarized by an index CBCC.

Partisanship of government is measured by PCoG: higher values = more conservative Partisan “Center of Gravity.”

I estimate a zero-inflated compositional regression on career shares and find the expected relationship: conservative governments pick conservative central bankers.
Robustness Checks: A central banks example

Conservative governments pick conservative central bankers

Is this finding robust to specification assumptions?

In my case, the statistical model is so demanding it’s hard to include many regressors at once.

So try one at a time, and show a long “ropeladder” plot...
Robustness Ropeladder: Partisan central banker appointment

Estimated increase in Central Bank Conservatism (CBCC) resulting from . . .

<table>
<thead>
<tr>
<th>Control added</th>
<th>Shifting control from low (µ-1.5 sd) to high (µ+1.5)</th>
<th>Shifting PCoG from From left gov (µ-1.5 sd) to right gov (µ+1.5 sd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[None]</td>
<td></td>
<td></td>
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<tr>
<td>Office appointed to</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBI (3 index avg.)</td>
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<tr>
<td>CBI (Cukierman)</td>
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<tr>
<td>Lagged inflation</td>
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<tr>
<td>Lagged unemployment</td>
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<td>Trade Openness</td>
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<td>Endebtedness</td>
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<tr>
<td>Financial Sector Employment</td>
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<tr>
<td>Financial Sector Score</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Trend</td>
<td></td>
<td></td>
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<tr>
<td>Central Bank staff size</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 8.4: Partisanship of central banker appointment: Robustness, part 2.

Each row presents a different specification, adding to the baseline model the variable listed at the left. To save space, neither the estimated parameters nor the simplex plots of expected values are shown; instead, I plot the first difference in career conservatism (CBCC) for a three standard deviation increase in the control variable (at the left) or partisan center of gravity (at the right). Horizontal bars show 95 percent confidence intervals; the gray box shows the range of point estimates for the partisan effect across all robustness checks. In all cases, partisan effects on appointments are substantively the same as in Figure 8.2.
Anatomy of a ropeladder plot

I call this a **ropeladder** plot.

The column of dots shows the relationship between $Y$ and a specific $X$ under different model assumptions.

Each entry corresponds to a different assumption about the specification, or the measures, or the estimation method, etc.
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If the ropeladder is “blowing in the wind”, we may be skeptical of the finding. It depends on model assumptions that may be controversial.

The shaded gray box shows the full range of the point estimates for the QoI.

Narrow is better.
Why ropeladders?

Anticipate objections on model assumptions, and have concrete answers.

Avoid: “I ran it that other way, and it came out the ‘same’.”

Instead: “I ran it that other way, and look —it made no substantive or statistical difference worth speaking of.”

Or: “. . . it makes this much difference.”
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1. Anticipate objections on model assumptions, and have concrete answers.

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   Instead: “I ran it that other way, and look —it made no *substantive* or *statistical* difference worth speaking of.”

   Or: “…it makes *this* much difference.”

2. Investigate robustness more thoroughly.

   Traditional tabular presentation would have run to 7 pages, making comparison hard and discouraging a thorough search.
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   Or: “...it makes this much difference.”

2. Investigate robustness more thoroughly.

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3. Find patterns of model sensitivity.

   Two seemingly unrelated changes in specification had the same effect. (Unemployment and Financial Sector Size)

   Turned out to be a missing third covariate. (Time trend)
Robustness for several QoIs at once

Each ropeladder, or column, shows the effect of a different variable on the response.

That is, reading *across* shows the results from a single model.

Reading down shows the results for a single question across different models.
Earlier, I showed the relationship between many different covariates and the expected political rank of Chinese officials.

I also showed how these relationships changed over time, making for a complex plot.

But our findings were controversial: countered the widely accepted belief that Chinese officials are rewarded for economic performance.

Critics asked for lots of alternative specifications to probe our results.

I can use tile to show how exactly what difference these robustness checks made using overlapping lineplots.
Some critics worried that our measures of faction were too sensitive, so we considered a more specific alternative.

This didn’t salvage the conventional wisdom on growth...
But did (unsuprisingly) strengthen our factional results

(Specific measures pick up the strongest ties)
Other critics worried about endogeneity or selection effects flowing from political power to economic performance.

We used measures of unexpected growth to zero in on an official’s own performance in office—which still nets zero political benefit.
But is there a more efficient way to show that our results stay essentially the same?
In our printed article, we show only this plot, which overlaps the full array of robustness checks.
Conveys hundreds of separate findings in a compact, readable form

No knowledge of Bayesian methods or partial rank coefficients required!
Bonus Example: Allocation of Authority for Health Policy

Adolph, Greer, and Fonseca consider the problem of explaining whether local, regional, or national European government have power over specific health policy areas and instruments.

Areas: Pharmaceuticals, Secondary/Tertiary, Primary Care, Public Health

Instruments: Frameworks, Finance, Implementation, Provision

Each combination for each country is a case.
Bonus Example: Allocation of Authority for Health Policy

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Each combination for each country is a case.

Fiscal federalism suggests lower levels for information-intensive policies and higher levels for policies with spillovers or public goods.

Also control for country characteristics and country random effects.

With 3 nominal outcomes for each case, need a multilevel multinomial logit.
Bonus Example: Allocation of Authority for Health Policy

Covariates:

- Policy area: Nominal
- Policy instrument: Nominal
- Regions old or new: Binary
- Country size: Continuous
- Number of regions: Continuous
- Mountains: Continuous
- Ethnic heterogeneity: Continuous

Tricky part to the model:
some cases have structural zeros for regions (when they don’t exist!)
How to set up counterfactuals?

We could set all but one covariate to the mean, then predict the probability of each level of authority given varied levels of the remaining covariate.

We should do this separately for countries with and without regional governments.

Let’s fix everything but policy instrument to the mean values, then simulate the probability of authority at each level for each instrument.

We show the results using a “nested” dot plot, made using ropeladder() in the tile package.
Special plots for compositional data

Probabilities have a special property: they sum to one

Variables that sum to a constraint are compositional

We can plot a two-part composition on a line,

and a three-part composition on a triangular plot

This makes it easier to show more complex counterfactuals, such as every combination of policy area and instrument

But we also need to work harder to explain these plots
Probability of allocation of authority by policy type

Above holds country characteristics at their means
Probability of allocation of authority by country type

Above holds policy area and instrument “at their means”
Residual country effects

Looking at the country random effects might suggest omitted variables
On a previous iteration, mountainous countries clustered as high $\Pr(\text{Regions})$. 

Residual country effects
Lessons for practice of data analysis

Simulation + Graphics can summarize complex models for a broad audience

You might even find something you missed as an analyst

And even for fancy or complex models, we can and should show uncertainty

Payoff to programming: this is hard the first few times, but gets easier

Code is re-usable, and encourages more ambitious modeling
Teaching with tile

tile helps clarify data and models in research

Also helps in teaching statistical models

I incorporate this software throughout our graduate statistics sequence

Greatly aids intuitive understanding of models

Find out much more, and download the software, from:

faculty.washington.edu/cadolph
Building a scatterplot: Supplementary exploratory example

In my graphics class, I have students build a scatterplot “from scratch”

This helps us see the many choices to make, and implications for:

1. perception of the data
2. exploration of relationships
3. assessment of fit

A good warm up for tile before the main event (application to models)

See how tile helps follow Tufte recommendations
Building a scatterplot: Redistribution example

Data on political party systems and redistributive effort from various industrial countries

Source of data & basic plot:

Torben Iversen & David Soskice, 2002, “Why do some democracies redistribute more than others?” Harvard University.
Building a scatterplot: Redistribution example

Concepts for this example (electoral systems and the welfare state):

Effective number of parties:
Building a scatterplot: Redistribution example

Concepts for this example (electoral systems and the welfare state):

Effective number of parties:

- # of parties varies across countries
- electoral rules determine #
  - Winner take all (US) $\rightarrow \sim 2$ parties.
  - Proportional representation $\rightarrow$ more parties
- To see this, need to discount trivial parties.
Building a scatterplot: Redistribution example

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Poverty reduction:
Building a scatterplot: Redistribution example

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Effective number of parties:

- # of parties varies across countries
- electoral rules determine #
  - Winner take all (US) → ~ 2 parties.
  - Proportional representation → more parties

To see this, need to discount trivial parties.

Poverty reduction:

- Percent lifted out of poverty by taxes and transfers.
- Poverty = an income below 50% of mean income.
Initial plotting area is often oddly shaped (I’ve exaggerated)
Plotting area hiding relationship here. Sometimes can even exclude data!
Filled circles: okay for a little data; open is better when data overlap
Sensible, data based plot limits

Appears to be a curvilinear relationship. Can bring that out with...
Log scaling.

But what logarithmic base? And why print the exponents?
Combine a log scale with linear labels. Now everyone can read…

Next: Axis labels people can understand
So what’s going on the data? What are those outliers?
With little data & big outliers, show the name of each case
Now we can try to figure out what makes the US and Switzerland so different
Plot redone using `scatter` (tile package in R)
Scatterplots relate two distributions.
Why not make those marginal distributions explicit?
Rugs accomplish this by replacing the axis lines with the plots.

We could choose any plotting style: from the histogram-like dots...
... to a strip of jittered data...
...to a set of very thin lines marking each observation.

Because we have so few cases, thin lines work best for this example.
Let's add a parametric model of the data: a least squares fit line
tile can do this for us
But we don’t have to be parametric

A local smoother, like loess, often helps show non-linear relationships
M-estimators weight observations by an influence function to minimize the influence of outliers
Even with an M-estimator, every outlier has some influence
Thus any one distant outlier can bias the result
A robust and resistant MM-estimator, shown above, largely avoids this problem.

Only a (non-outlying) fraction of the data influence this fit.

\texttt{rlm(method="MM")}
In our final plot, we add 95 percent confidence intervals for the MM-estimator. A measure of uncertainty is essential to reader confidence in the result.
library(tile)

# Load data
data <- read.csv("iver.csv", header=TRUE)
attach(data)
Syntax for redistribution scatter

# First, collect all the data inputs into a series of "traces"

# The actual scattered points
trace1 <- scatter(x = enp, # X coordinate of the data
                  y = povred, # Y coordinate of the data
                  labels = cty, # Labels for each point
                  
                  # Plot symbol for each point
                  pch = recode(system,"1=17;2=15;3=16"),

                  # Color for each point
                  col = recode(system,"1='blue';2='darkgreen';3='red'"),

                  # Offset text labels
                  labelyoffset = -0.03, # on npc scale

                  # Fontsize
                  fontsize = 9,
Syntax for redistribution scatter

```r
# Marker size
size = 1, # could be vector for bubble plot

# Add a robust fit line and CI
fit = list(method = "mmest", ci = 0.95),

# Which plot(s) to plot to
plot = 1
)

# The rugs with marginal distributions
rugX1 <- rugTile(x=enp, type="lines", plot = 1)

rugY1 <- rugTile(y=povred, type="lines", plot = 1)
```
Syntax for redistribution scatter

# A legend
legendSymbols1 <- pointsTile(x= c(1.8, 1.8, 1.8),
    y= c(78, 74, 70),
    pch=c(17, 15, 16),
    col=c("blue", "darkgreen", "red"),
    fontsize = 9,
    size=1,
    plot=1
)

legendLabels1 <- textTile(labels=c("Majoritarian",
    "Proportional",
    "Unanimity"),
    x= c(2.05, 2.05, 2.05),
    y= c(78, 74, 70),
    pch=c(17, 15, 16),
    col=c("blue", "darkgreen", "red"),
    fontsize = 9,
    plot=1
)
Syntax for redistribution scatter

# Now, send that trace to be plotted with tile

tile(trace1,  
   rugX1,  # Could list as many
   rugY1,  # traces here as we want
   legendSymbols1,  # in any order
   legendLabels1,

   
   # Some generic options for tile
   RxC = c(1,1),
   #frame = TRUE,
   #output = list(file="iverson1", width=5, type="pdf"),
   height = list(plot="golden"),

   
   # Limits of plotting region
   limits=c(1.6, 7.5, 0, 82),


Syntax for redistribution scatter

# x-axis controls
xaxis=list(log = TRUE,
    at = c(2,3,4,5,6,7)
),

# x-axis title controls
xaxistitle=list(labels=c("Effective number of parties")),

# y-axis title controls
yaxistitle=list(labels=c("% lifted from poverty by taxes & transfers"))

# Plot titles
plottitle=list(labels=("Party Systems and Redistribution"))