CSSS 569: Visualizing Data

Visualizing Robustness

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Robustness Checks

Last time: 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
- e.g., we 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
<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>
<td>X.XX</td>
<td>X.XX</td>
<td>X.XX</td>
<td>X.XX</td>
</tr>
<tr>
<td></td>
<td>(X.XX)</td>
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</tr>
<tr>
<td>A control</td>
<td>X.XX</td>
<td>X.XX</td>
<td>X.XX</td>
<td>X.XX</td>
<td>X.XX</td>
</tr>
<tr>
<td>I ”need“</td>
<td>(X.XX)</td>
<td>(X.XX)</td>
<td>(X.XX)</td>
<td>(X.XX)</td>
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<td>(X.XX)</td>
<td>(X.XX)</td>
<td>(X.XX)</td>
</tr>
<tr>
<td>A candidate control</td>
<td>X.XX</td>
<td></td>
<td>X.XX</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(X.XX)</td>
<td></td>
<td>(X.XX)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A candidate control</td>
<td></td>
<td></td>
<td>X.XX</td>
<td>X.XX</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(X.XX)</td>
<td>(X.XX)</td>
<td></td>
</tr>
<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>
<td></td>
<td></td>
<td></td>
<td>(X.XX)</td>
</tr>
</tbody>
</table>
Robustness Checks

Problems with the approach above?

1. Lots of space to show a few permutations of the model

   Most space wasted or devoted to ancillary info
Robustness Checks

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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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   E.g., because of nonlinearities, interactions, scale differences, etc.

3. The selection of permutations is 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 $X$, 
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   - a functional form, $g(\cdot)$
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   - a measure of $\mathcal{Y}$, denoted $Y$,
   - a set of confounders, $Z$,
   - a functional form, $g(\cdot)$
   - a probability model of $Y$, $f(\cdot)$

3. Estimate the probability model $Y \sim f(\mu, \alpha), \mu = g(\text{vec}(X, Z), \beta)$. 
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4. Simulate the quantity of interest, e.g., $E(Y \mid X)$ or $E(Y_1 - Y_2 \mid X_1 - X_2)$, to obtain a point estimate and confidence interval.
Robustness Checks: An algorithm

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4. Simulate the quantity of interest, e.g., $\mathbb{E}(Y|X)$ or $\mathbb{E}(Y_1 - Y_2|X_1 - X_2)$, to obtain a point estimate and confidence interval.

5. Repeat above steps, changing at each iteration one of the choices in step 2.
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6. Compile the results in a variant of the dot plot (ropeladder).
## Kitchen sink models of 1960 US crime rates

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Robust</th>
<th>Poisson</th>
<th>Neg Bin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−28820.91</td>
<td>−17784.56</td>
<td>−19.08</td>
<td>−15.43</td>
</tr>
<tr>
<td></td>
<td>(10199.82)</td>
<td>(8158.71)</td>
<td>(1.77)</td>
<td>(7.81)</td>
</tr>
<tr>
<td>% males aged 14–24</td>
<td>1156.49</td>
<td>2480.55</td>
<td>1.1</td>
<td>1.53</td>
</tr>
<tr>
<td></td>
<td>(522.98)</td>
<td>(418.32)</td>
<td>(0.1)</td>
<td>(0.4)</td>
</tr>
<tr>
<td>Southern state</td>
<td>0.97</td>
<td>138.11</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(141.49)</td>
<td>(113.18)</td>
<td>(0.02)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Mean education (yrs)</td>
<td>1802.64</td>
<td>1413.62</td>
<td>1.84</td>
<td>2.11</td>
</tr>
<tr>
<td></td>
<td>(590.84)</td>
<td>(472.61)</td>
<td>(0.11)</td>
<td>(0.45)</td>
</tr>
<tr>
<td>Police spending 1960</td>
<td>897.54</td>
<td>422.45</td>
<td>0.81</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>(813.8)</td>
<td>(650.95)</td>
<td>(0.15)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>Police spending 1959</td>
<td>6.66</td>
<td>651.14</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(823.35)</td>
<td>(658.59)</td>
<td>(0.15)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>Labor participation</td>
<td>143.91</td>
<td>2235.29</td>
<td>0.63</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>(727.79)</td>
<td>(582.15)</td>
<td>(0.13)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Males per 1000</td>
<td>94.71</td>
<td>−3469.7</td>
<td>−1.46</td>
<td>−2.3</td>
</tr>
<tr>
<td></td>
<td>(1943.8)</td>
<td>(1554.82)</td>
<td>(0.36)</td>
<td>(1.49)</td>
</tr>
<tr>
<td>State population</td>
<td>−79.39</td>
<td>−138.58</td>
<td>−0.08</td>
<td>−0.07</td>
</tr>
<tr>
<td></td>
<td>(51.4)</td>
<td>(41.12)</td>
<td>(0.01)</td>
<td>(0.04)</td>
</tr>
</tbody>
</table>
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<thead>
<tr>
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<th>Linear</th>
<th>Robust</th>
<th>Poisson</th>
<th>Neg Bin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonwhites per 1000</td>
<td>61.25</td>
<td>32.47</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(47.85)</td>
<td>(38.28)</td>
<td>(0.01)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Unem, males 14–24</td>
<td>−325.65</td>
<td>−444.95</td>
<td>−0.18</td>
<td>−0.18</td>
</tr>
<tr>
<td></td>
<td>(336.46)</td>
<td>(269.13)</td>
<td>(0.06)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Unem, males 35–39</td>
<td>475.14</td>
<td>895.28</td>
<td>0.39</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>(239.62)</td>
<td>(191.67)</td>
<td>(0.04)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Gross state product, pc</td>
<td>282.31</td>
<td>−196.44</td>
<td>0.69</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>(420.2)</td>
<td>(336.11)</td>
<td>(0.08)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Income inequality</td>
<td>1461.68</td>
<td>943.27</td>
<td>1.68</td>
<td>1.56</td>
</tr>
<tr>
<td></td>
<td>(386.64)</td>
<td>(309.27)</td>
<td>(0.07)</td>
<td>(0.3)</td>
</tr>
<tr>
<td>Pr(imprisonment)</td>
<td>−226.39</td>
<td>−443.28</td>
<td>−0.29</td>
<td>−0.31</td>
</tr>
<tr>
<td></td>
<td>(103.39)</td>
<td>(82.7)</td>
<td>(0.02)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>E(time in prison)</td>
<td>−69.91</td>
<td>−294.41</td>
<td>−0.16</td>
<td>−0.27</td>
</tr>
<tr>
<td></td>
<td>(184.13)</td>
<td>(147.29)</td>
<td>(0.03)</td>
<td>(0.14)</td>
</tr>
</tbody>
</table>
Pr(Prison) +0.5 sd
Police Spending +0.5 sd
Unemployment (t-2) +0.5 sd
Non-White Pop +0.5 sd
Male Pop +0.5 sd
Education +0.5 sd
Inequality +0.5 sd
Pr(Prison) +0.5 sd
Police Spending +0.5 sd
Unemployment (t-2) +0.5 sd
Non-White Pop +0.5 sd
Male Pop +0.5 sd
Education +0.5 sd
Inequality +0.5 sd

Linear
\[ E(\text{crime rate per 100,000}) / \text{average} \]

Robust
\[ E(\text{crime rate per 100,000}) / \text{average} \]
- Linear
  - E(criminal rate per 100,000) / average
  - Pr(Prison) + 0.5 sd
  - Police Spending + 0.5 sd
  - Unemployment (t-2) + 0.5 sd
  - Non-White Pop + 0.5 sd
  - Male Pop + 0.5 sd
  - Education + 0.5 sd
  - Inequality + 0.5 sd

- Robust
  - E(criminal rate per 100,000) / average

- Poisson
  - E(criminal rate per 100,000) / average

- Neg Bin
  - E(criminal rate per 100,000) / average
Ropeladder example

# Linear, Poisson, and Negative Binomial regression using UScrime data

# Uses ropeladders to show how the expected crime rate varies in response to changes in 7 covariates under each of four estimation methods.

# Plot 1 shows a four plot set up, one plot per method. This approach highlights differences in effects across covariates

# Plot 2 squeezes all four ropeladders into a single plot. This approach gives equal attention to differences across covariates and models

# Plot 3 creates a plot for each covariate. This approach highlights differences across models.
Ropeladder example

# Load data and libraries; set up specification
library(tile)
library(simcf)
library(MASS)
data(UScrime)
model <- (y ~ log(M) + So + log(Ed) + log(Po1) + log(Po2)
          + log(LF) + log(M.F) + log(Pop) + log(NW) + log(U1)
          + log(U2) + log(GDP) + log(Ineq) + log(Prob) +
          log(Time))
# Estimate Linear regression model

```r
lm1.res <- lm(model, data = UScrime)
```

```r
lm1.pe <- lm1.res$coefficients  # point estimates
```

```r
lm1.vc <- vcov(lm1.res)  # var-cov matrix
```

# Estimate Robust and resistant regression model

```r
mm1.res <- rlm(model, data = UScrime, method="MM")
```

```r
mm1.pe <- mm1.res$coefficients  # point estimates
```

```r
mm1.vc <- vcov(mm1.res)  # var-cov matrix
```

# Estimate Poisson model

```r
po1.res <- glm(model, family=poisson, data = UScrime)
```

```r
po1.pe <- po1.res$coefficients  # point estimates
```

```r
po1.vc <- vcov(po1.res)  # var-cov matrix
```

# Estimate Negative Binomial model

```r
nb1.res <- glm.nb(model, data = UScrime)
```

```r
nb1.pe <- nb1.res$coefficients  # point estimates
```

```r
nb1.vc <- vcov(nb1.res)  # var-cov matrix
```
Ropeladder example

# Initialize 7 different scenarios to mean values of covariates
xscen <- cfMake(model, data=UScrime, nscen=7)

# Configure scenario 1: Raise Probability of Imprisonment by 1/2 sd
xscen <- cfName(xscen, "Pr(Prison) +0.5 sd", scen=1)
xscen <- cfChange(xscen, "Prob",
    x = mean(UScrime$Prob) + 0.5*sd(UScrime$Prob),
    scen=1)

Notes:

Unlike the lineplot example, no longer looping over a continuous covariate

Now considering discrete changes in a series of covariates, each time holding others constant at their means

Result similar to table of linear regression coefficients (partial derivatives)

cfName() lets us name each scenario; we’ll use these later to label the plot
Ropeladder example

# Configure scenario 2: Raise Police Spending by 1/2 sd
xscen <- cfName(xscen, "Police Spending +0.5 sd", scen=2)
xscen <- cfChange(xscen, "Po1",
                   x = mean(UScrime$Po1) + 0.5*sd(UScrime$Po1),
                   scen=2)

# Configure scenario 3: Raise Unemployment (Age 35-39) by 1/2 sd
xscen <- cfName(xscen, "Unemployment (t-2) +0.5 sd", scen=3)
xscen <- cfChange(xscen, "U2",
                   x = mean(UScrime$U2) + 0.5*sd(UScrime$U2),
                   scen=3)

# Configure scenario 4: Raise Non-white population by 1/2 sd
xscen <- cfName(xscen, "Non-White Pop +0.5 sd", scen=4)
xscen <- cfChange(xscen, "NW",
                   x = mean(UScrime$NW) + 0.5*sd(UScrime$NW),
                   scen=4)
Ropeladder example

# Configure scenario 5: Raise Male Pop by 1/2 sd
xscen <- cfName(xscen, "Male Pop +0.5 sd", scen=5)
xscen <- cfChange(xscen, "M",
    x = mean(UScrime$M) + 0.5*sd(UScrime$M),
    scen=5)

# Configure scenario 6: Raise Education by 1/2 sd
xscen <- cfName(xscen, "Education +0.5 sd", scen=6)
xscen <- cfChange(xscen, "Ed",
    x = mean(UScrime$Ed) + 0.5*sd(UScrime$Ed),
    scen=6)

# Configure scenario 7: Raise Inequality by 1/2 sd
xscen <- cfName(xscen, "Inequality +0.5 sd", scen=7)
xscen <- cfChange(xscen, "Ineq",
    x = mean(UScrime$Ineq) + 0.5*sd(UScrime$Ineq),
    scen=7)
Ropeladder example

# Simulate conditional expectations for these counterfactuals
sims <- 10000

# Linear regression simulations
simbetas.lm <- mvrnorm(sims, lm1.pe, lm1.vc)
lm1.qoi <- linearsimfd(xscen, simbetas.lm, ci=0.95)

# Robust regression simulations
simbetas.mm <- mvrnorm(sims, mm1.pe, mm1.vc)
mm1.qoi <- linearsimfd(xscen, simbetas.mm, ci=0.95)

# Poisson simulations
simbetas.po <- mvrnorm(sims, po1.pe, po1.vc)
po1.qoi <- loglinsimfd(xscen, simbetas.po, ci=0.95)

# Negative Binomial simulations
simbetas.nb <- mvrnorm(sims, nb1.pe, nb1.vc)
b1.qoi <- loglinsimfd(xscen, simbetas.nb, ci=0.95)
Ropeladder example

```r
# Create ropeladder traces of first differences from each model
trace1 <- ropeladder(x=lm1.qoi$pe,
                     lower=lm1.qoi$lower,
                     upper=lm1.qoi$upper,
                     labels=row.names(xscen$x),
                     plot=1)
```

Notes:

Ropeladder trace needs 4 inputs:

The points themselves, the lower bound, the upper bound, and a label for each point

Often best to sort these based on the size of the point estimate (clearest comparisons)
Ropeladder example

trace2 <- ropeladder(x=mm1.qoi$pe, 
    lower=mm1.qoi$lower, 
    upper=mm1.qoi$upper, 
    plot=2
)

trace3 <- ropeladder(x=po1.qoi$pe, 
    lower=po1.qoi$lower, 
    upper=po1.qoi$upper, 
    plot=3
)

trace4 <- ropeladder(x=nb1.qoi$pe, 
    lower=nb1.qoi$lower, 
    upper=nb1.qoi$upper, 
    plot=4
)

Note: Can leave out labels argument to save space in adjacent ropeladders

Make sure they line up with the same scenarios though!
Ropeladder example

rug1 <- rugTile(x = UScrime$y - mean(UScrime$y),
    plot = 1:4
)

vertmark <- linesTile(x = c(0,0),
    y = c(0,1),
    lty = "solid",
    plot = 1:4
)

Note:

We don't really need a rug here. Might be best to not show it.

A vertical reference line, though, is usually very helpful.

For first diffs, a line at 0 is best.

For expected values, a line at the mean is best.
Ropeladder example

# Create Plot 1 (focus on covariates) and save to pdf

tc <- tile(trace1, trace2, trace3, trace4,
  rug1, vertmark,
  #output = list(file = "ropeladderEx1"),
  xaxistitle = list(labels="E(crime rate per 100,000)"),
  topaxis= list(at = mean(UScrime$y)*c(0.5, 1, 1.5, 2) - mean(UScrime$y),
                 labels = c("0.5x","1x","1.5x","2x"),
                 add = rep(TRUE,4)
  ),
  topaxistitle = list(labels="E(crime rate) / average"),
  plottitle = list(labels1 = "Linear",
                  labels2 = "Robust",
                  labels3 = "Poisson",
                  labels4 = "Neg Bin"),
  gridlines=list(type="t")
)
Ropeladder example

What’s going on with this?

topaxis= list(at = mean(UScrime$y)*c(0.5, 1, 1.5, 2) - mean(UScrime$y),
   labels = c("0.5x","1x","1.5x","2x"),
   add = rep(TRUE,4)
 ),

We plot the absolute change in crime rates on the x-axis

Want the relative change on the top-axis

We want to mark where our FDs have halved the crime rate, increased it by 50%, or doubled it.
Ropeladder example

What’s going on with this?

topaxis= list(at = mean(UScrime$y)*c(0.5, 1, 1.5, 2) - mean(UScrime$y),
labels = c("0.5x","1x","1.5x","2x"),
add = rep(TRUE,4)
),

We make labels for these points, but where to put them?

The levels of crime corresponding to half, the same, +50%, and double the mean are: mean(UScrime$y)*c(0.5, 1, 1.5, 2)

But our x-axis is on a first differenced scale, so we need to subtract off the expected value of crime for the average case: -mean(UScrime$y)
Linear
E(crime rate per 100,000)
E(crime rate) / average
Pr(Prison) +0.5 sd
Police Spending +0.5 sd
Unemployment (t-2) +0.5 sd
Non-White Pop +0.5 sd
Male Pop +0.5 sd
Education +0.5 sd
Inequality +0.5 sd

Robust
E(crime rate per 100,000)
E(crime rate) / average

Poisson
E(crime rate per 100,000)
E(crime rate) / average

Neg Bin
E(crime rate per 100,000)
E(crime rate) / average
Pr(Prison) +0.5 sd

Non–White Pop +0.5 sd

Unemployment (t−2) +0.5 sd

Male Pop +0.5 sd

Education +0.5 sd

Police Spending +0.5 sd

Inequality +0.5 sd
Ropeladder example

# Plot all four models together:
# equal focus on covariates and models

# Revise traces to place on same plot
trace1$plot <- trace2$plot <- trace3$plot <- trace4$plot <- 1
vertmark$plot <- 1

# Revise traces to make symbols different
trace1$pch <- 19
trace2$pch <- 15
trace3$pch <- 17
trace4$pch <- 23

Note: Tricky re-use and modification of traces. Just changing a few elements of each trace
Ropeladder example

# Add sublabels to each trace
trace1$sublabels <- "linear"
trace2$sublabels <- "robust"
trace3$sublabels <- "poisson"
trace4$sublabels <- "negbin"

# Widen space between entries to make labels visible
trace1$entryheight <- 0.25

# Shift sublabels to left side of plot to avoid overlap
trace1$sublabelsX <- 0.07
trace2$sublabelsX <- 0.07
trace3$sublabelsX <- 0.07
trace4$sublabelsX <- 0.07

Note: Tricky re-use and modification of traces. Just changing a few elements of each trace
Ropeladder example

# Add boxes around the results for each covariate
# when traces are plotted to the same graph
# (could add to any of the traces)
trace1$shadowrow <- TRUE

Note: Tricky re-use and modification of traces. Just changing a few elements of each trace
Ropeladder example

# Create Plot 2 and save to pdf
tc <- tile(trace1, trace2, trace3, trace4,
    vertmark,
    limits = c(-230, 460),
    width=list(null=4),
    #output = list(file="ropeladderEx2"),
    xaxistitle = list(labels="E(crime rate per 100,000)"),
    topaxis= list(at = mean(UScrime$y)*c(0.75, 1, 1.25, 1.5) - mean(UScrime$y),
                     labels = c("0.75x","1x","1.25x","1.5x"),
                     add = TRUE),
    topaxistitle = list(labels="E(crime rate) / average"),
    gridlines=list(type="t")
)

Note new limits argument. Got rid of the rugs, so need to set (common) limits on plot(s) now.
Pr(Prison) vs. E(crime rate per 100,000) vs. Pr(Prison) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Police Spending vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Unemployment vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Non-White Pop vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Male Pop vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Education vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial

Inequality vs. E(crime rate per 100,000) vs. E(crime rate) / average
- Linear
- Robust & Resistant
- Poisson
- Negative Binomial
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.

If all the dots line up, with narrow, similar CIs, we say the finding is robust, and reflects the data under a range of reasonable assumptions.

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?

1. 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.”
Why ropeladders?

1. 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.”

2. Investigate robustness more thoroughly.
   
   Traditional tabular presentation can run to many pages, making comparison hard.
   
   Without a compact graphical tool in mind, one might stop specification searches too early.
Ropeladder example

# Plot by coefficient to show variation across models

# Collect in matrix form all first differences and confidence
# intervals across models (columns) and covariates (rows)
allPE <- cbind(lm1.qoi$pe, mm1.qoi$pe, po1.qoi$pe, nb1.qoi$pe)
allLOWER <- cbind(lm1.qoi$lower,
                  mm1.qoi$lower,
                  po1.qoi$lower,
                  nb1.qoi$lower)
allUPPER <- cbind(lm1.qoi$upper,
                  mm1.qoi$upper,
                  po1.qoi$upper,
                  nb1.qoi$upper)
Ropeladder example

# Create a trace for each covariate of the # different models’ estimates # (Save these traces in a vector of traces; # note double bracket indexing)

collectedtraces <- vector("list", nrow(allPE))

for (i in 1: nrow(allPE)) {
  collectedtraces[[i]] <- ropeladder(x = allPE[i,],
          lower = allLOWER[i,],
          upper = allUPPER[i,],
          shadowbox = TRUE,
          plot = i
        )
}

Pay close attention to this code: Making a vector of lists.
Ropeladder example

# Add ropeladder labels to first and fifth plots
# (The first ropeladder in each row of plots;
# note double bracket indexing)
collectedtraces[[1]]$labels <-
collectedtraces[[5]]$labels <-
c("Linear", "Robust & Resistant",
   "Poisson", "Negative Binomial")

# Revise vertical mark to plot on all seven plots
vertmark$plot <- 1:7
Ropeladder example

tc <- tile(collectedtraces, vertmark,
RxC = c(2,4),
limits = c(-230, 460),
width = list(spacer=3),
#output = list(file="ropeladderEx3"),
xaxis = list(at = c(-200, 0, 200, 400)),
xaxistitle = list(labels="E(crime rate per 100,000)")
, topaxis= list(at = mean(UScrime$y)*c(0.75, 1, 1.25, 1.5)
- mean(UScrime$y),
labels = c(".75x","1x","1.25x","1.5x"),
add = rep(TRUE,4)),
topaxistitle = list(labels="E(crime rate) / average"),
plottitle = list(labels1 = "Pr(Prison)",
labels2 = "Police Spending",
labels3 = "Unemployment",
labels4 = "Non-White Pop",
labels5 = "Male Pop",
labels6 = "Education",
labels7 = "Inequality"),
gridlines=list(type="top"))
Pr(Prison)  
E(crime rate) / average

Police Spending  
E(crime rate) / average

Unemployment  
E(crime rate) / average

Non-White Pop  
E(crime rate) / average

Male Pop  
E(crime rate) / average

Education  
E(crime rate) / average

Inequality  
E(crime rate) / average

Linear
Robust & Resistant
Poisson
Negative Binomial

E(crime rate per 100,000)