

Explore data

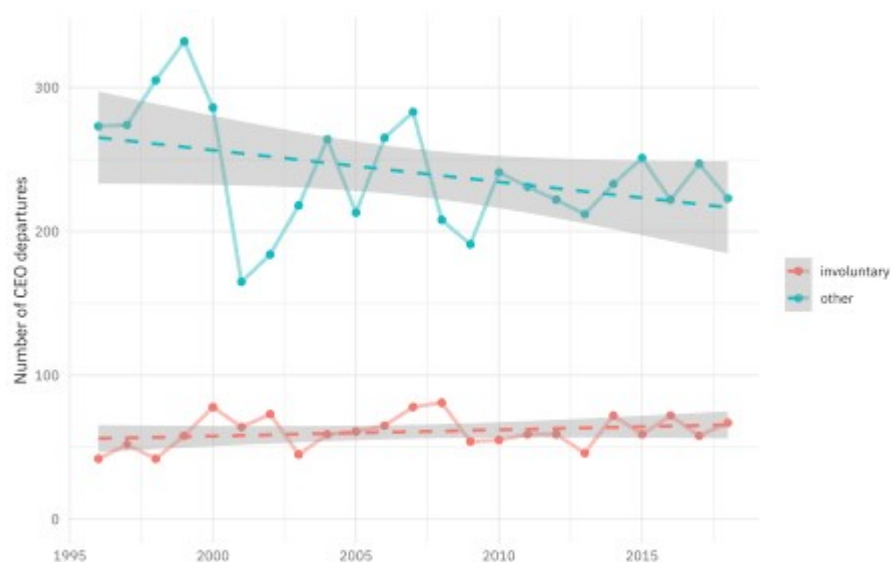
Our modeling goal is to estimate how [involuntary CEO departures](#) are changing with time. Let's start by reading in the data.

```
library(tidyverse)
```

```
departures_raw <- read_csv("https://raw.githubusercontent.com/rfordatascience/tidytuesday/master/data/2021/2021-04-27/departures.csv")
```

How are involuntary departures changing with time? What about the rest of the CEO departures?

```
departures_raw %>%
  filter(departure_code < 9) %>%
  mutate(involuntary = if_else(departure_code %in% 3:4, "involuntary",
    "other")) %>%
  filter(fyear > 1995, fyear < 2019) %>%
  count(fyear, involuntary) %>%
  ggplot(aes(fyear, n, color = involuntary)) +
  geom_line(size = 1.2, alpha = 0.5) +
  geom_point(size = 2) +
  geom_smooth(method = "lm", lty = 2) +
  scale_y_continuous(limits = c(0, NA)) +
  labs(x = NULL, y = "Number of CEO departures", color = NULL)
```



Looks like proportionally more departures are involuntary over time, but that is what we'll work on estimating. Let's create a data set to use for modeling.

```
departures <- departures_raw %>%
  filter(departure_code < 9) %>%
  mutate(involuntary = if_else(departure_code %in% 3:4, "involuntary",
    "other")) %>%
  filter(fyear > 1995, fyear < 2019)
```

```
departures
```

```
## # A tibble: 6,942 x 20
##   dismissal_datase... coname   gvkey fyear co_per_rol exec_fullname
departure_code
##
##   1           559043 SONICB... 27903  2002           -1 L. Gregory B...
7
##   2           12 AMERIC...  1045  1997           1 Robert L. Cr...
5
##   3           13 AMERIC...  1045  2002           3 Donald J. Ca...
3
##   4           31 ABBOTT...  1078  1998           6 Duane L. Bur...
5
##   5           43 ADVANC...  1161  2001          11 Walter Jerem...
5
##   6           51 AETNA ...  1177  1997          16 Ronald Edwar...
5
##   7           63 AHMANS...  1194  1997          22 Charles R. R...
7
##   8           65 AIR PR...  1209  2000          28 Harold A. Wa...
5
##   9           76 ALBERT...  1239  2007          34 Howard B. Be...
5
## 10          78 ALBERT...  1240  2000          38 Gary Glenn M...
3
## # ... with 6,932 more rows, and 13 more variables: ceo_dismissal ,
## #   interim_cocceo , tenure_no_ceodb , max_tenure_ceodb ,
## #   fyear_gone , leftofc , still_there , notes ,
## #   sources , eight_ks , cik , _merge , involuntary
```

Bootstrapping a model

We can count up the two kinds of departures per financial year and fit the model once, for the whole data set.

```
library(broom)
```

```
df <- departures %>%
  count(fyear, involuntary) %>%
  pivot_wider(names_from = involuntary, values_from = n)
```

```
mod <- glm(cbind(involuntary, other) ~ fyear, data = df, family =
"binomial")
summary(mod)
```

```
##
## Call:
## glm(formula = cbind(involuntary, other) ~ fyear, family =
"binomial",
##   data = df)
##
## Deviance Residuals:
```

```
##      Min      1Q   Median      3Q      Max
## -2.9858 -1.2075 -0.1947   0.7302   3.6816
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -33.236731    8.949722  -3.714 0.000204 ***
## fyear         0.015875    0.004459   3.560 0.000370 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 78.421  on 22  degrees of freedom
## Residual deviance: 65.722  on 21  degrees of freedom
## AIC: 200.86
##
## Number of Fisher Scoring iterations: 4
```

```
tidy(mod, exponentiate = TRUE)
```

```
## # A tibble: 2 x 5
##   term          estimate std.error statistic  p.value
##
## 1 (Intercept) 3.68e-15     8.95         -3.71 0.000204
## 2 fyear       1.02e+ 0     0.00446         3.56 0.000370
```

When we use `exponentiate = TRUE`, we get the model coefficients on the linear scale instead of the logistic scale.

What we want to do is fit a model like this a whole bunch of times, instead of just once. Let's create bootstrap resamples.

```
library(rsample)

set.seed(123)
ceo_folds <- bootstraps(departures, times = 1e3)
ceo_folds

## # Bootstrap sampling
## # A tibble: 1,000 x 2
##   splits          id
##
## 1 Bootstrap0001
## 2 Bootstrap0002
## 3 Bootstrap0003
## 4 Bootstrap0004
## 5 Bootstrap0005
## 6 Bootstrap0006
## 7 Bootstrap0007
## 8 Bootstrap0008
## 9 Bootstrap0009
## 10 Bootstrap0010
```

```
## # ... with 990 more rows
```

Now we need to make a function to count up the departures by year and type, fit our model, and return the coefficients we want.

```
fit_binom <- function(split) {
  df <- analysis(split) %>%
    count(fyear, involuntary) %>%
    pivot_wider(names_from = involuntary, values_from = n)

  mod <- glm(cbind(involuntary, other) ~ fyear, data = df, family =
"binomial")
  tidy(mod, exponentiate = TRUE)
}
```

We can apply that function to all our bootstrap resamples with `purrr::map()`.

```
boot_models <- ceo_folds %>% mutate(coef_info = map(splits, fit_binom))
boot_models
```

```
## # Bootstrap sampling
## # A tibble: 1,000 x 3
##   splits          id      coef_info
##
## 1 Bootstrap0001
## 2 Bootstrap0002
## 3 Bootstrap0003
## 4 Bootstrap0004
## 5 Bootstrap0005
## 6 Bootstrap0006
## 7 Bootstrap0007
## 8 Bootstrap0008
## 9 Bootstrap0009
## 10 Bootstrap0010
## # ... with 990 more rows
```

Explore results

What did we find? We can compute bootstrap confidence intervals with `int_pctl()`.

```
percentile_intervals <- int_pctl(boot_models, coef_info)
percentile_intervals
```

```
## # A tibble: 2 x 6
##   term          .lower .estimate      .upper .alpha .method
##
## 1 (Intercept) 6.03e-23 0.0000273 0.000000246 0.05 percentile
## 2 fyear      1.01e+ 0 1.02      1.03      0.05 percentile
```

We can also visualize the results as well.

```
boot_models %>%
  unnest(coef_info) %>%
  filter(term == "fyear") %>%
```

```
ggplot(aes(estimate)) +  
  geom_vline(xintercept = 1, lty = 2, color = "gray50", size = 2) +  
  geom_histogram() +  
  labs(  
    x = "Annual increase in involuntary CEO departures",  
    title = "Over this time period, CEO departures are increasingly  
involuntary",  
    subtitle = "Each passing year corresponds to a departure being 1-2%  
more likely to be involuntary"  
  )
```

