ACCT 420: Linear Regression

Session 3

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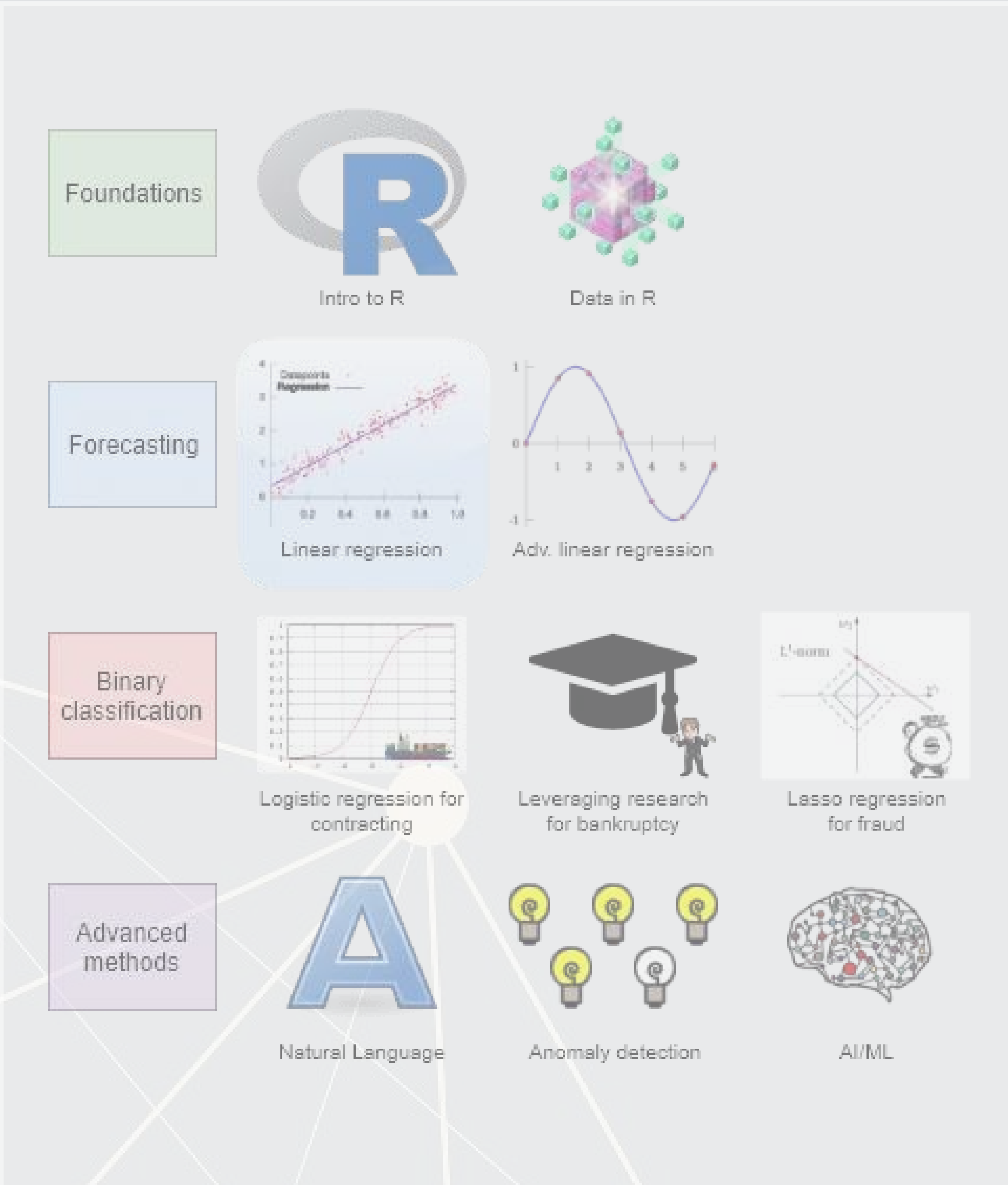
Front matter

Learning objectives



- **Theory:**
  - Develop a logical approach to problem solving with data
    - Hypothesis testing
- **Application:**
  - Predicting revenue for real estate firms
- **Methodology:**
  - Univariate stats
  - Linear regression
  - Visualization

Datacamp

- For next week:
  - Just 1 chapter on linear regression
- The full list of Datacamp materials for the course is up on eLearn

R Installation

- If you haven't already, make sure to install R and R Studio!
  - Instructions are in Session 1's slides
  - You will need it for this week's individual
- Please install a few packages using the following code
  - These packages are also needed for the first assignment
  - You are welcome to explore other packages as well, but those will not be necessary for now

```r
# Run this in the R Console inside RStudio
install.packages(c("tidyverse","plotly","tufte","reshape2"))
```

- The individual assignment will be provided as an R Markdown file

> The format will generally all be filled out – you will just add to it, answer questions, analyze data, and explain your work. Instructions and hints are in the same file

R Markdown: A quick guide

- Headers and subheaders start with # and ##, respectively
- Code blocks starts with ```{r} and end with ```
  - By default, all code and figures will show up in the document
- Inline code goes in a block starting with `r ` and ending with `
- Italic font can be used by putting * or _ around text
- Bold font can be used by putting ** around text
  - E.g.: **bold text** becomes **bold text**
- To render the document, click Knit
- Math can be placed between $ to use LaTeX notation
  - E.g. $\frac{revt}{at}$ becomes $\frac{revt}{at}$
- Full equations (on their own line) can be placed between $$
- A block quote is prefixed with >
- For a complete guide, see R Studio's R Markdown::Cheat Sheet

Application: Revenue prediction

The question

> How can we predict revenue for a company, leveraging data about that company, related companies, and macro factors

- Specific application: Real estate companies

More specifically…

- Can we use a company's own accounting data to predict it's future revenue?
- Can we use other companies' accounting data to better predict all of their future revenue?
- Can we augment this data with macro economic data to further improve prediction?
  - Singapore business sentiment data

Linear models

What is a linear model?

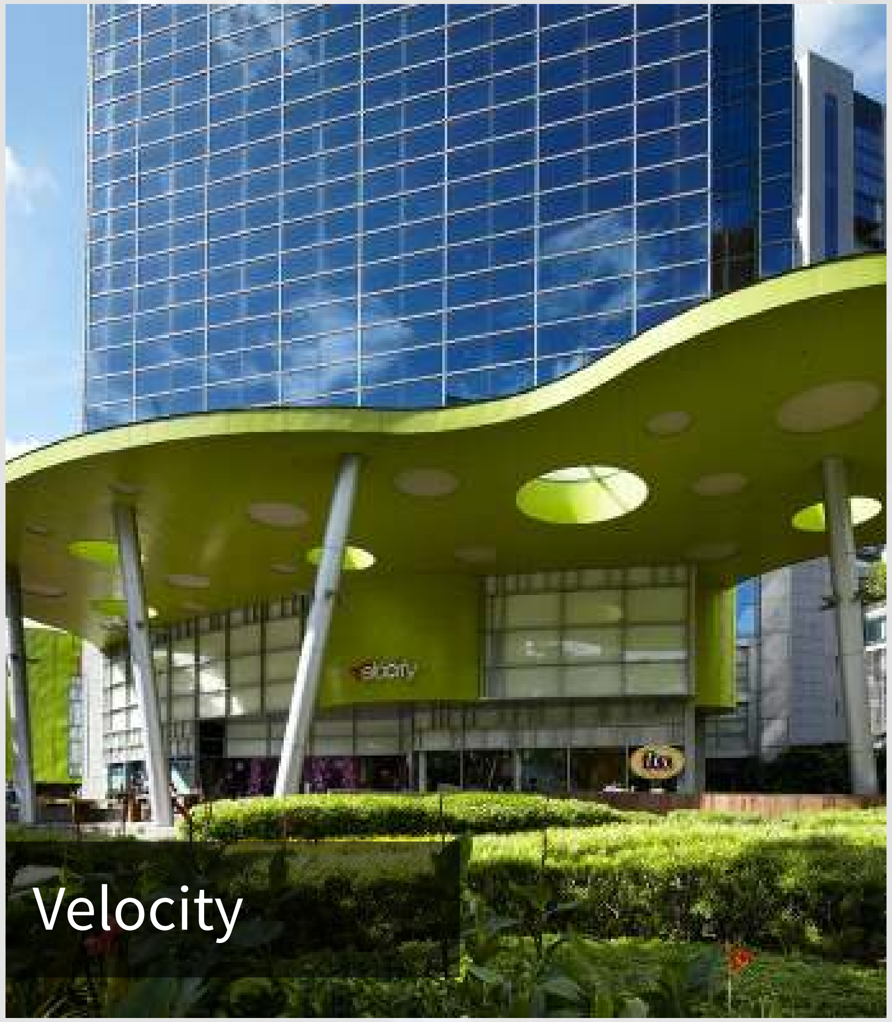
$$\hat{y} = \alpha + \beta\hat{x} + \varepsilon$$

- The simplest model is trying to predict some outcome $\hat{y}$ as a function of an input $\hat{x}$
  - $\hat{y}$ in our case is a firm's revenue in a given year
  - $\hat{x}$ could be a firm's assets in a given year
  - α and β are solved for
  - ε is the error in the measurement

> I will refer to this as an *OLS* model – **O**rdinary **L**east **S**quare regression

Example

Let's predict UOL's revenue for 2016

- 

- Compustat has data for them since 1989
  - Complete since 1994
    - Missing CapEx before that

```r
# revt: Revenue, at: Assets
summary(uol[,c("revt", "at")])
```

```
##       revt               at
##  Min.   :  94.78   Min.   : 1218
##  1st Qu.: 193.41   1st Qu.: 3044
##  Median : 427.44   Median : 3478
##  Mean   : 666.38   Mean   : 5534
##  3rd Qu.:1058.61   3rd Qu.: 7939
##  Max.   :2103.15   Max.   :19623
```

Linear models in R

- To run a linear model, use `lm()`
  - The first argument is a formula for your model, where `~` is used in place of an equals sign
    - The left side is what you want to predict
    - The right side is inputs for prediction, separated by `+`
  - The second argument is the data to use
- Additional variations for the formula:
  - Functions transforming inputs (as vectors), such as `log()`
  - Fully interacting variables using `*`
    - I.e., `A*B`includes, A, B, and A times B in the model
  - Interactions using `:`
    - I.e., `A:B` just includes A times B in the model

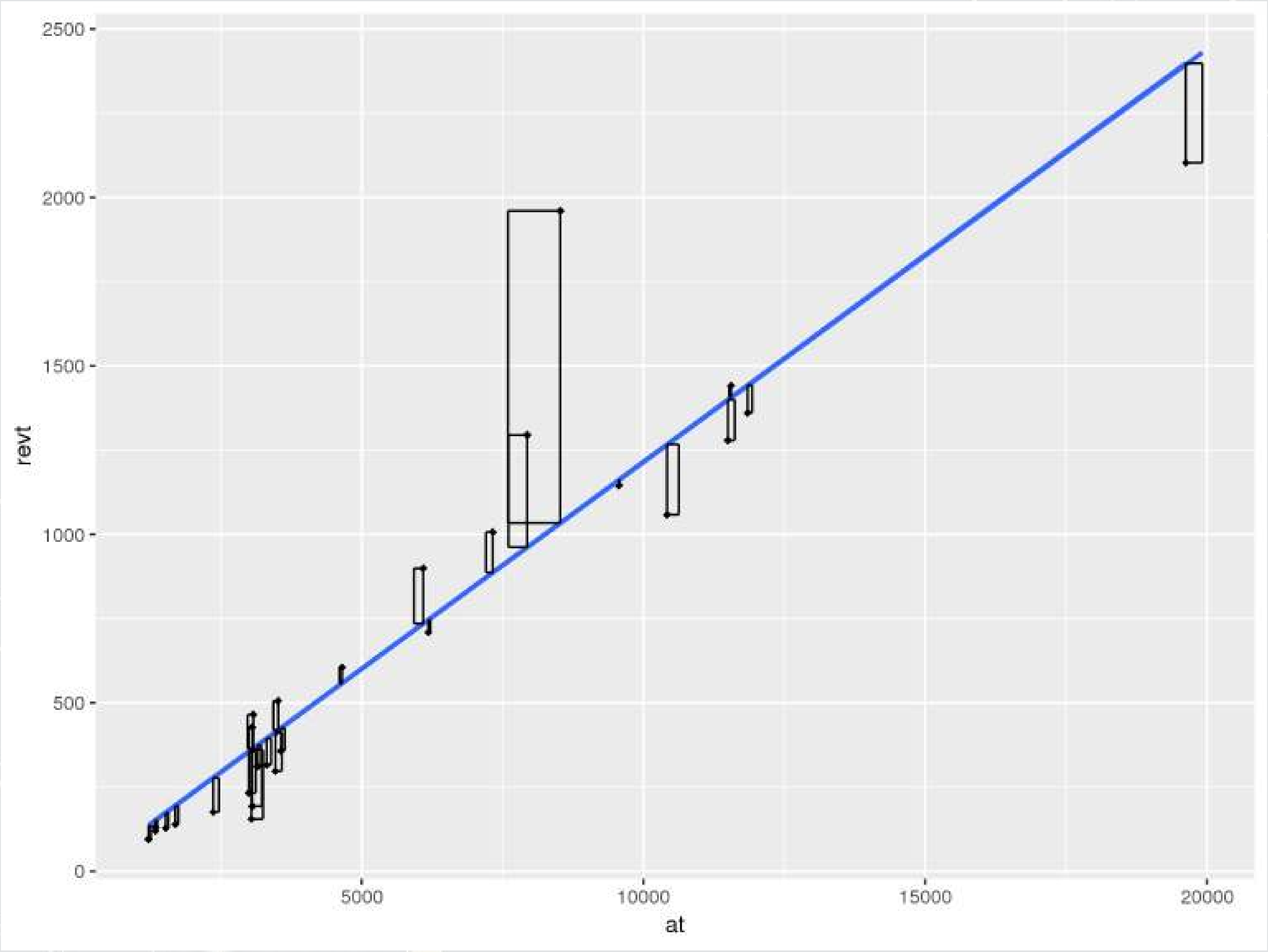
```
# Example:
lm(revt ~ at, data = uol)
```

Example: UOL

```r
mod1 <- lm(revt ~ at, data = uol)
summary(mod1)
```

```
##
## Call:
## lm(formula = revt ~ at, data = uol)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -295.01 -101.29  -41.09   47.17  926.29
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -13.831399  67.491305  -0.205    0.839
## at            0.122914   0.009678  12.701  6.7e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 221.2 on 27 degrees of freedom
## Multiple R-squared:  0.8566, Adjusted R-squared:  0.8513
## F-statistic: 161.3 on 1 and 27 DF,  p-value: 6.699e-13
```

Why is it called Ordinary Least Squares?



Example: UOL

- This model wasn't so interesting…
  - Bigger firms have more revenue – this is a given
- How about… revenue *growth*?
- And *change* in assets
  - i.e., Asset growth

$$\Delta x_t = \frac{x_t}{x_{t-1}} - 1$$

Calculating changes in R

- The easiest way is using tidyverse's dplyr
  - lag() function along with mutate()
- The default way to do it is to create a vector manually

```
# tidyverse
uol <- uol %>%
  mutate(revt_growth1 = revt / lag(revt) - 1)

# R way
uol$revt_growth2 = uol$revt / c(NA, uol$revt[-length(uol$revt)]) - 1

identical(uol$revt_growth1, uol$revt_growth2)
```

```
## [1] TRUE
```

```
# faster with in place creation
library(magrittr)
uol %<>% mutate(revt_growth3 = revt / lag(revt) - 1)
identical(uol$revt_growth1, uol$revt_growth3)
```

```
## [1] TRUE
```

> You can use whichever you are comfortable with

A note on mutate()

- mutate() adds variables to an existing data frame
  - Also mutate_all(), mutate_at(), mutate_if()
  - mutate_all() applies a transformation to all values in a data frame and adds these to the data frame
  - mutate_at() does this for a set of specified variables
  - mutate_if() transforms all variables matching a condition
    - Such as is.numeric
- Mutate can be very powerful when making more complex variables
  - For instance: Calculating growth within company in a multi-company data frame
  - It’s way more than needed for a simple ROA though.

Example: UOL with changes

```r
# Make the other needed change
uol <- uol %>%
  mutate(at_growth = at / lag(at) - 1)  # From dplyr
# Rename our revenue growth variable
uol <- rename(uol, revt_growth = revt_growth1)  # From dplyr
# Run the OLS model
mod2 <- lm(revt_growth ~ at_growth, data = uol)
summary(mod2)
```

```
##
## Call:
## lm(formula = revt_growth ~ at_growth, data = uol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.57736 -0.10534 -0.00953  0.15132  0.42284
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.09024    0.05620   1.606   0.1204
## at_growth    0.53821    0.27717   1.942   0.0631 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2444 on 26 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1267, Adjusted R-squared:  0.09307
## F-statistic: 3.771 on 1 and 26 DF,  p-value: 0.06307
```

Example: UOL with changes

- ΔAssets doesn't capture ΔRevenue so well
- Perhaps change in total assets is a bad choice?
- Or perhaps we need to expand our model?

Scaling up!

$$\hat{y} = \alpha + \beta_1 \hat{x}_1 + \beta_2 \hat{x}_2 + \ldots + \varepsilon$$

- OLS doesn't need to be restricted to just 1 input!
  - Not unlimited though (yet)
    - Number of inputs must be less than the number of observations minus 1
- Each $\hat{x}_i$ is an input in our model
- Each β_i is something we will solve for
- $\hat{y}$, α, and ε are the same as before

Scaling up our model

We have… 464 variables from Compustat Global alone!

- Let's just add them all?

- We only have 28 observations…
  - 28 << 464…

Now what?

Scaling up our model

> Building a model requires careful thought!

- What makes sense to add to our model?

> This is where having accounting and business knowledge comes in!

Formalizing testing

Why formalize?

- Our current approach has been ad hoc
  - What is our goal?
  - How will we know if we have achieved it?
- Formalization provides more rigor

Scientific method

1. Question
   - What are we trying to determine?
2. Hypothesis
   - What do we think will happen? Build a model
3. Prediction
   - What exactly will we test? Formalize model into a statistical approach
4. Testing
   - Test the model
5. Analysis
   - Did it work?

Hypotheses

- Null hypothesis, a.k.a. H_0
  - The status quo
  - Typically: The model *doesn't* work
- Alternative hypothesis, a.k.a. H_1 or H_A
  - The model *does* work (and perhaps how it works)

> We will use test statistics to test the hypotheses

Test statistics

- Testing a coefficient:
  - Use a t or z test
- Testing a model as a whole
  - F-test, check *adjusted* R squared as well
    - Adj R^2 tells us the amount of variation captured by the model (higher is better), after adjusting for the number of variables included
      - Otherwise, more variables (almost) always equals a higher amount of variation captured
- Testing across models
  - Chi squared (χ^2) test
  - Vuong test (comparing R^2)
  - Akaike Information Criterion (AIC) (Comparing MLEs, lower is better)

Revisiting the previous problem

Formalizing our last test

1. Question
    -
2. Hypotheses
    - H_0:
    - H_1:
3. Prediction
    -
4. Testing:
    -
5. Statistical tests:
    - Individual variables:
    - Model:

Is this model better?

```
anova(mod2, mod3, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_growth ~ at_growth
## Model 2: revt_growth ~ lct_growth + che_growth + ebit_growth
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     26 1.5534
## 2     24 1.1918  2   0.36168   0.0262 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> A bit better at
> $p < 0.05$

- This means our model with change in current liabilities, cash, and EBIT appears to be better than the model with change in assets.

Panel data

Expanding our methodology

- Why should we limit ourselves to 1 firm's data?
- The nature of data analysis is such:

> Adding more data usually helps improve predictions

- Assuming:
  - The data isn't of low quality (too noisy)
  - The data is relevant
  - Any differences can be reasonably controlled for

Expanding our question

- Previously: Can we predict revenue using a firm's accounting information?
  - This is simultaneous, and thus is not forecasting
- Now: Can we predict *future* revenue using a firm's accounting information?
  - By trying to predict ahead, we are now in the realm of forecasting
  - What do we need to change?
    - $\hat{y}$ will need to be 1 year in the future

First things first

- When using a lot of data, it is important to make sure the data is clean
- In our case, we may want to remove any very small firms

```
# Ensure firms have at least $1M (local currency), and have revenue
# df contains all real estate companies excluding North America
df_clean <- filter(df, df$at>1, df$revt>0)

# We cleaned out 578 observations!
print(c(nrow(df), nrow(df_clean)))
```

```
## [1] 5161 4583
```

```
# Another useful cleaning funtion:
# Replaces NaN, Inf, and -Inf with NA for all numeric variables in the data!
df_clean <- df_clean %>%
  mutate_if(is.numeric, funs(replace(., !is.finite(.), NA)))
```

Looking back at the prior models

```r
uol <- uol %>% mutate(revt_lead = lead(revt))  # From dplyr
forecast1 <-
  lm(revt_lead ~ lct + che + ebit, data=uol)
library(broom)  # Let's us view bigger regression outputs in a tidy fashion
tidy(forecast1)  # present regression output
```

```
## # A tibble: 4 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   87.4     124.        0.707  0.486
## 2 lct            0.213     0.291     0.731  0.472
## 3 che            0.112     0.349     0.319  0.752
## 4 ebit           2.49      1.03      2.42   0.0236
```

```r
glance(forecast1)  # present regression statistics
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic p.value    df logLik   AIC   BIC
## *     <dbl>         <dbl> <dbl>     <dbl>   <dbl> <int>  <dbl> <dbl> <dbl>
## 1     0.655         0.612  357.      15.2 9.39e-6     4  -202.  414.  421.
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
```

This model is ok, but we can do better.

Expanding the prior model

```r
forecast2 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit , data=uol)
tidy(forecast2)
```

```
## # A tibble: 7 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  15.6       97.0       0.161 0.874
## 2 revt          1.49       0.414     3.59  0.00174
## 3 act           0.324      0.165     1.96  0.0629
## 4 che           0.0401     0.310     0.129 0.898
## 5 lct          -0.198      0.179    -1.10  0.283
## 6 dp            3.63       5.42      0.669 0.511
## 7 ebit         -3.57       1.36     -2.62  0.0161
```

- Revenue to capture stickiness of revenue
- Current assest & Cash (and equivalents) to capture asset base
- Current liabilities to capture payments due
- Depreciation to capture decrease in real estate asset values
- EBIT to capture operational performance

Expanding the prior model

```
glance(forecast2)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic p.value    df logLik   AIC   BIC
## *     <dbl>         <dbl> <dbl>     <dbl>   <dbl> <int>  <dbl> <dbl> <dbl>
## 1     0.903         0.875  203.      32.5 1.41e-9     7  -184.  385.  396.
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
```

```
anova(forecast1, forecast2, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_lead ~ lct + che + ebit
## Model 2: revt_lead ~ revt + act + che + lct + dp + ebit
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     24 3059182
## 2     21  863005  3   2196177 1.477e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

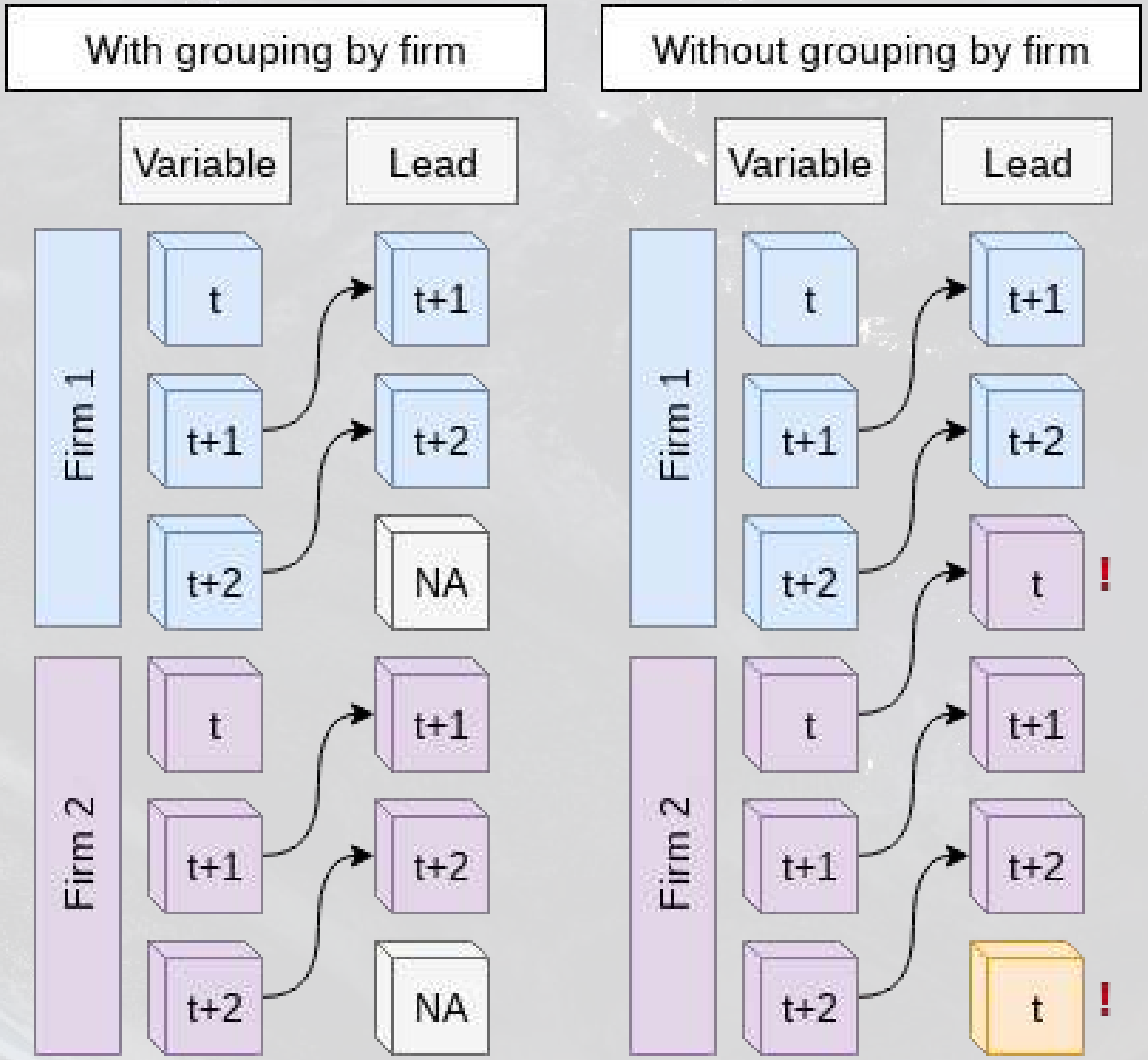
> This is better (Adj. R^2, χ^2, AIC).

Panel data

- Panel data refers to data with the following characteristics:
  - There is a time dimension
  - There is at least 1 other dimension to the data (firm, country, etc.)
- Special cases:
  - A panel where all dimensions have the same number of observations is called *balanced*
    - Otherwise we call it *unbalanced*
  - A panel missing the time dimension is *cross-sectional*
  - A panel missing the other dimension(s) is a *time series*
- Format:
  - Long: Indexed by all dimensions
  - Wide: Indexed only by other dimensions

All Singapore real estate companies

```r
# Note the group_by -- without it, lead() will pull from the subsequent firm!
# ungroup() tells R that we finished grouping
df_clean <- df_clean %>%
  group_by(isin) %>%
  mutate(revt_lead = lead(revt)) %>%
  ungroup()
```



All Singapore real estate companies

```
forecast3 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit , data=df_clean[df_clean$fic=="SGP",])
tidy(forecast3)
```

```
## # A tibble: 7 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  25.0      13.2         1.89 5.95e- 2
## 2 revt          0.505     0.0762      6.63 1.43e-10
## 3 act          -0.0999    0.0545     -1.83 6.78e- 2
## 4 che           0.494     0.155       3.18 1.62e- 3
## 5 lct           0.396     0.0860      4.60 5.95e- 6
## 6 dp            4.46      1.55        2.88 4.21e- 3
## 7 ebit         -0.951     0.271      -3.51 5.18e- 4
```

All Singapore real estate companies

```r
glance(forecast3)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
## *     <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl> <dbl>
## 1     0.844         0.841  210.      291. 2.63e-127     7 -2237. 4489.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

> Lower adjusted R^2 – This is worse? Why?

- Note: χ^2 can only be used for models on the same data
  - Same for AIC

Worldwide real estate companies

```
forecast4 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit , data=df_clean)
tidy(forecast4)
```

```
## # A tibble: 7 x 5
##   term         estimate std.error statistic  p.value
##   <chr>           <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  222.      585.          0.379 7.04e- 1
## 2 revt           0.997     0.00655   152.    0.
## 3 act           -0.00221   0.00547    -0.403 6.87e- 1
## 4 che           -0.150     0.0299     -5.02  5.36e- 7
## 5 lct            0.0412    0.0113      3.64  2.75e- 4
## 6 dp             1.52      0.184       8.26  1.89e-16
## 7 ebit           0.308     0.0650      4.74  2.25e- 6
```

Worldwide real estate companies

```
glance(forecast4)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared  sigma statistic p.value    df  logLik    AIC
## *     <dbl>         <dbl>  <dbl>     <dbl>   <dbl> <int>   <dbl>  <dbl>
## 1     0.944         0.944 36459.    11299.       0     7 -47819. 95654.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

> Higher adjusted R^2 – better!

- Note: χ^2 can only be used for models on the same data
  - Same for AIC

Model accuracy

> Why is 1 model better while the other model is worse?

- Ranking:
  1. Worldwide real estate model
  2. UOL model
  3. Singapore real estate model

Noise

> Statistical noise is random error in the data

- Many sources of noise:
  - Other factors not included in
  - Error in measurement
    - Accounting measurement!
  - Unexpected events / shocks

> Noise is OK, but the more we remove, the better!

Removing noise: Singapore model

- Different companies may behave slightly differently
  - Control for this using a *Fixed Effect*
  - Note: ISIN uniquely identifies companies

```
forecast3.1 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit + factor(isin),
     data=df_clean[df_clean$fic=="SGP",])
# n=7 to prevent outputting every fixed effect
print(tidy(forecast3.1), n=7)
```

```
## # A tibble: 27 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)   1.58     39.4       0.0401 0.968
## 2 revt          0.392     0.0977    4.01   0.0000754
## 3 act          -0.0538    0.0602   -0.894  0.372
## 4 che           0.304     0.177     1.72   0.0869
## 5 lct           0.392     0.0921    4.26   0.0000276
## 6 dp            4.71      1.73      2.72   0.00687
## 7 ebit         -0.851     0.327    -2.60   0.00974
## # ... with 20 more rows
```

Removing noise: Singapore model

```
glance(forecast3.1)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
## *     <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl> <dbl>
## 1     0.856         0.844  208.      69.4 1.15e-111    27 -2223. 4502.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

```
anova(forecast3, forecast3.1, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_lead ~ revt + act + che + lct + dp + ebit
## Model 2: revt_lead ~ revt + act + che + lct + dp + ebit + factor(isin)
##   Res.Df      RSS Df Sum of Sq Pr(>Chi)
## 1    324 14331633
## 2    304 13215145 20   1116488   0.1765
```

> This isn't much different. Why? There is another source of noise within Singapore real estate companies

Another way to do fixed effects

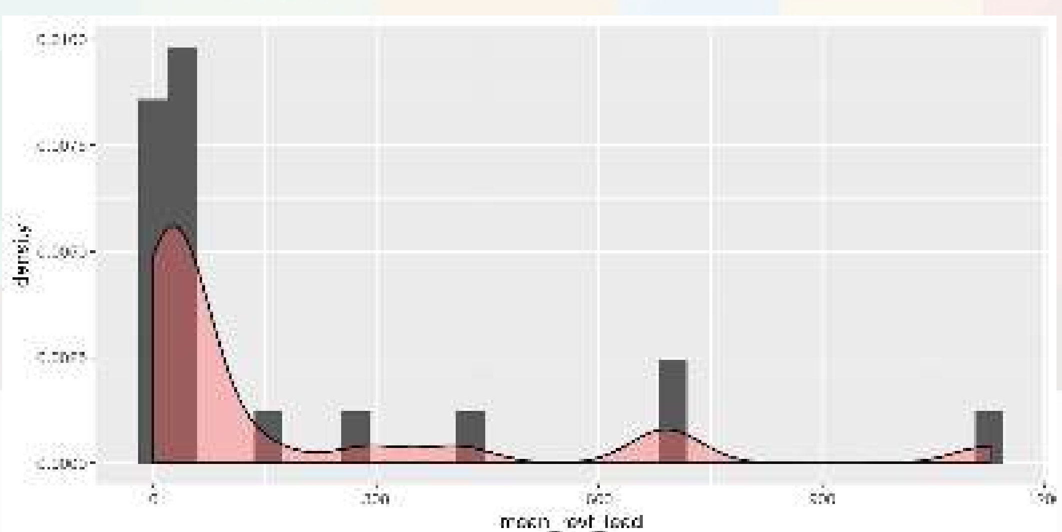
- The library lfe has felm(): fixed effects linear model
  - Better for complex models

```
library(lfe)
forecast3.2 <-
  felm(revt_lead ~ revt + act + che + lct + dp + ebit | factor(isin),
       data=df_clean[df_clean$fic=="SGP",])
summary(forecast3.2)
```

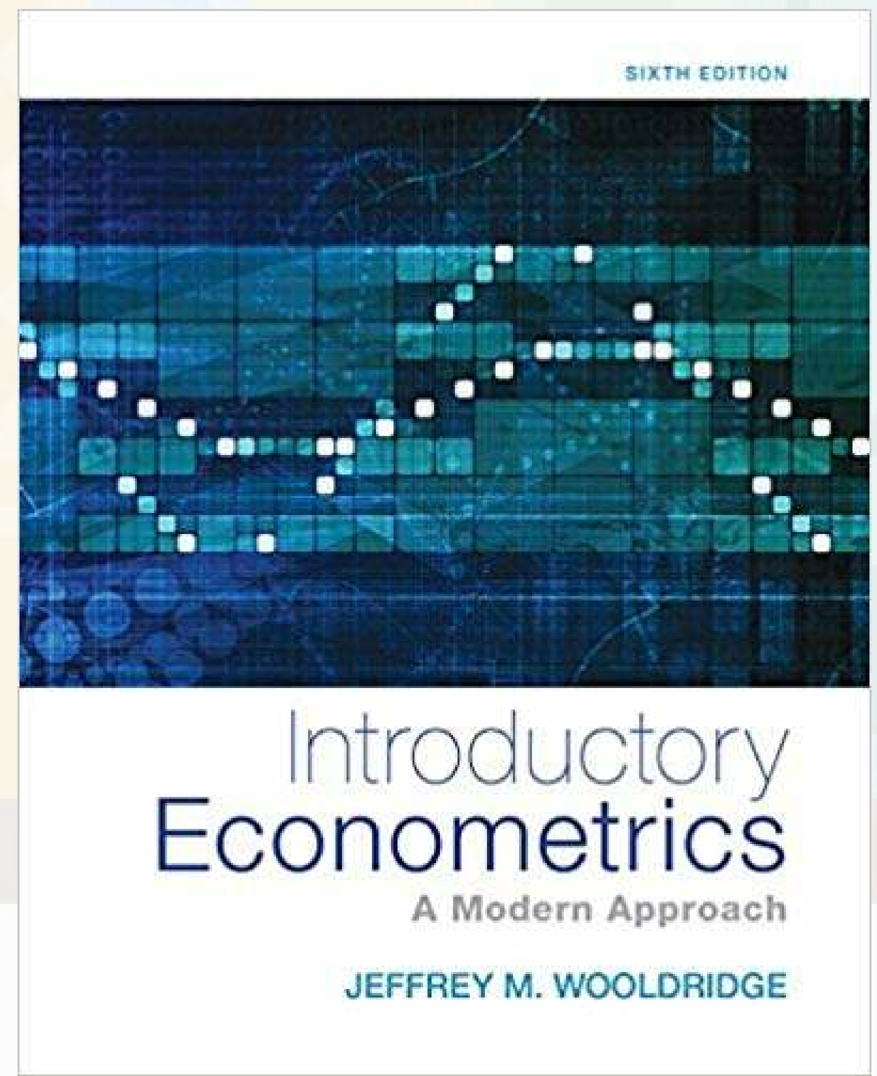
```
##
## Call:
##    felm(formula = revt_lead ~ revt + act + che + lct + dp + ebit |      factor(isin), data = df_clean[df_clean$
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1181.88   -23.25    -1.87    18.03  1968.86
##
## Coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## revt  0.39200    0.09767   4.013 7.54e-05 ***
## act  -0.05382    0.06017  -0.894  0.37181
## che   0.30370    0.17682   1.718  0.08690 .
## lct   0.39209    0.09210   4.257 2.76e-05 ***
## dp    4.71275    1.73168   2.721  0.00687 **
## ebit -0.85080    0.32704  -2.602  0.00974 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Why exactly would we use fixed effects?

- Fixed effects are used when the average of $\hat{y}$ varies by some group in our data
  - In our problem, the average revenue of each firm is different
- Fixed effects absorb this difference



- Further reading:
  - Introductory Econometrics by Jeffrey M. Wooldridge



Macro data

Macro data sources

- For Singapore: Data.gov.sg
  - Covers: Economy, education, environment, finance, health, infrastructure, society, technology, transport
- For real estate in Singapore: URA's REALIS system
  - Access through the library
- WRDS has some as well
- For US: data.gov, as well as many agency websites
  - Like BLS or the Federal Reserve

Loading macro data

- Singapore business expectations data (from data.gov.sg)

```
# Import the csv file
expectations <- read.csv("general-business-expectations-by-detailed-services-industry-quarterly.csv",
                         stringsAsFactors = FALSE)
# split the year and quarter
expectations$year <- as.numeric(substr(expectations$quarter, 1, 4))
expectations$quarter <- as.numeric(substr(expectations$quarter, 7, 7))
# cast value to numeric
expectations$value <- as.numeric(expectations$value)
```

```
# extract out Q1, finance only
expectations_avg <- filter(expectations, quarter == 1 & level_2 == "Financial & Insurance")

# build a finance-specific measure
expectations_avg <- expectations_avg %>%
  group_by(year) %>%
  mutate(value=mean(value, na.rm=TRUE)) %>%
  slice(1)

# rename the value column to something more meaningful
colnames(expectations_avg)[colnames(expectations_avg) == "value"] <- "fin_sentiment"
```

- At this point, we can merge with our accounting data

R: Merging and sorting

dplyr makes things easy

- For merging, use dplyr's *_join() commands
  - left_join() for merging a dataset into another
  - inner_join() for keeping only matched observations
  - outer_join() for making all possible combinations
- For sorting, dplyr's arrange() command is easy to use
  - For sorting in reverse, combine arrange() with desc()

Merging example

> Merge in the finance sentiment data to our accounting data

```r
# subset out our Singaporean data, since our macro data is Singapore-specific
df_SG <- df_clean[df_clean$fic == "SGP",]

# Create year in df_SG (date is given by datadate as YYYYMMDD)
df_SG$year = round(df_SG$datadate / 10000, digits=0)

# Combine datasets
# Notice how it automatically figures out to join by "year"
df_SG_macro <- left_join(df_SG, expectations_avg[,c("year","fin_sentiment")])
```

```
## Joining, by = "year"
```

Sorting example

```r
expectations %>%
  filter(quarter == 1) %>%  # using dplyr
  arrange(level_2, level_3, desc(year)) %>%  # using dplyr
  select(year, quarter, level_2, level_3, value) %>%  # using dplyr
  datatable(options = list(pageLength = 5), rownames=FALSE)  # using DT
```

Show 5 entries

Search:

year	quarter	level_2	level_3	value
2018	1	Accommodation & Food Services	Accommodation	-7
2017	1	Accommodation & Food Services	Accommodation	-15
2016	1	Accommodation & Food Services	Accommodation	-25
2015	1	Accommodation & Food Services	Accommodation	4
2014	1	Accommodation & Food Services	Accommodation	3

Showing 1 to 5 of 216 entries

Previous 1 2 3 4 5 … 44 Next

Predicting with macro data

Building in macro data

- First try: Just add it in

```
macro1 <- lm(revt_lead ~ revt + act + che + lct + dp + ebit + fin_sentiment,
             data=df_SG_macro)
tidy(macro1)
```

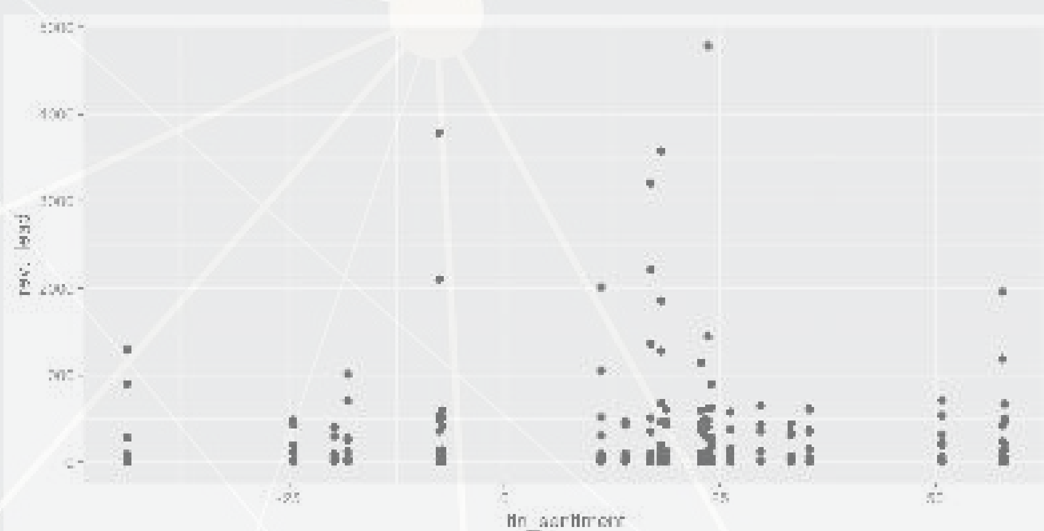
```
## # A tibble: 8 x 5
##   term          estimate std.error statistic       p.value
##   <chr>            <dbl>     <dbl>     <dbl>         <dbl>
## 1 (Intercept)     24.0      15.9        1.50  0.134
## 2 revt             0.497     0.0798     6.22  0.00000000162
## 3 act             -0.102     0.0569    -1.79  0.0739
## 4 che              0.495     0.167      2.96  0.00329
## 5 lct              0.403     0.0903     4.46  0.0000114
## 6 dp               4.54      1.63       2.79  0.00559
## 7 ebit            -0.930     0.284     -3.28  0.00117
## 8 fin_sentiment    0.122     0.472      0.259 0.796
```

> It isn't significant. Why is this?

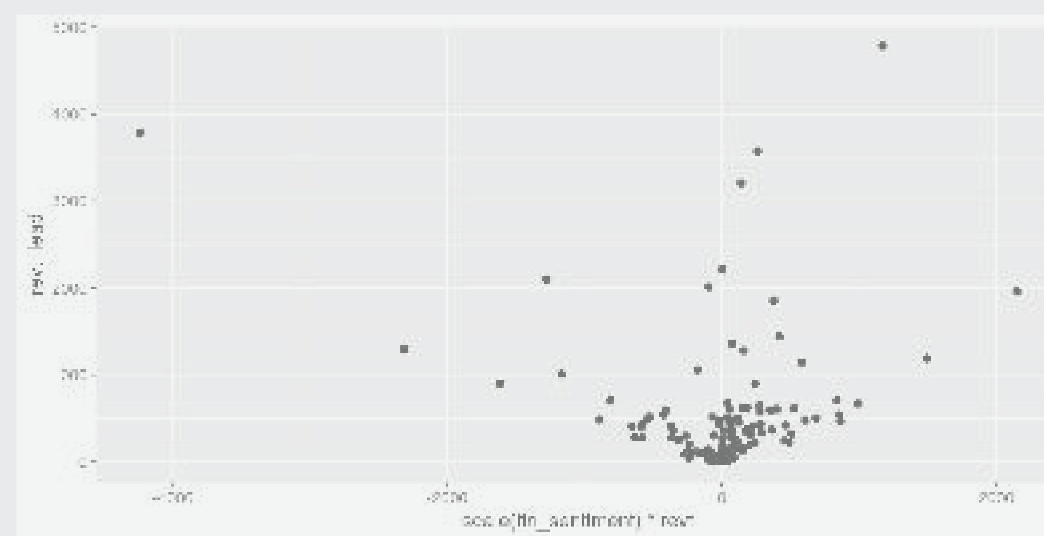
Scaling matters

- All of our firm data is on the same terms as revenue: dollars within a given firm
- But `fin_sentiment` is a constant scale…
  - Need to scale this to fit the problem
    - The current scale would work for revenue growth

```r
df_SG_macro %>%
  ggplot(aes(y=revt_lead,
             x=fin_sentiment)) +
  geom_point()
```



```r
df_SG_macro %>%
  ggplot(aes(y=revt_lead,
    x=scale(fin_sentiment) * revt)) +
  geom_point()
```



Scaled macro data

- Normalize and scale by revenue

```
# Scale creates z-scores, but returns a matrix by default.  [,1] gives a vector
df_SG_macro$fin_sent_scaled <- scale(df_SG_macro$fin_sentiment)[,1]
macro3 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit + fin_sent_scaled:revt,
     data=df_SG_macro)
tidy(macro3)
```

```
## # A tibble: 8 x 5
##   term                 estimate std.error statistic       p.value
##   <chr>                   <dbl>     <dbl>     <dbl>         <dbl>
## 1 (Intercept)           25.5      13.8         1.84 0.0663
## 2 revt                   0.490     0.0789      6.21 0.00000000170
## 3 act                   -0.0677    0.0576     -1.18 0.241
## 4 che                    0.439     0.166       2.64 0.00875
## 5 lct                    0.373     0.0898      4.15 0.0000428
## 6 dp                     4.10      1.61        2.54 0.0116
## 7 ebit                  -0.793     0.285      -2.78 0.00576
## 8 revt:fin_sent_scaled   0.0897    0.0332      2.70 0.00726
```

```
glance(macro3)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
## *     <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl> <dbl>
## 1     0.847         0.844  215.      240. 1.48e-119     8 -2107. 4232.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

Model comparisons

```
baseline <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit,
     data=df_SG_macro[!is.na(df_SG_macro$fin_sentiment),])
glance(baseline)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
## *     <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl> <dbl>
## 1     0.843         0.840  217.      273. 3.13e-119     7 -2111. 4237.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

```
glance(macro3)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
## *     <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl> <dbl>
## 1     0.847         0.844  215.      240. 1.48e-119     8 -2107. 4232.
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

> Adjusted R^2 and AIC are slightly better with macro data

Model comparisons

```
anova(baseline, macro3, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_lead ~ revt + act + che + lct + dp + ebit
## Model 2: revt_lead ~ revt + act + che + lct + dp + ebit + fin_sent_scaled:revt
##   Res.Df      RSS Df Sum of Sq Pr(>Chi)
## 1    304 14285622
## 2    303 13949301  1    336321 0.006875 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

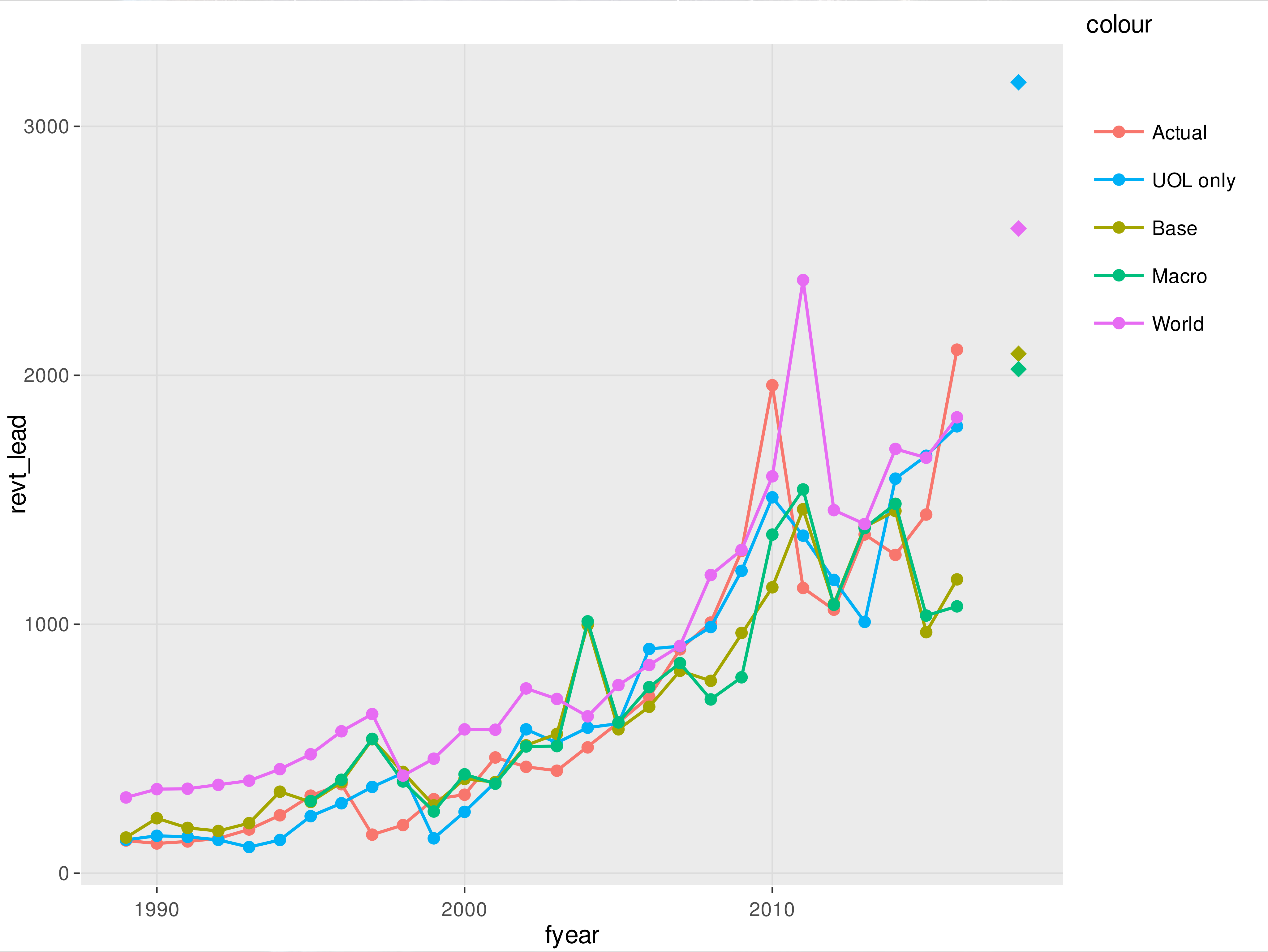
> Macro model definitely fits better than the baseline model!

Takeaway

1. Adding macro data can help explain some exogenous variation in a model
   - Exogenous meaning outside of the firms, in this case
2. Scaling is very important
   - Not scaling properly can suppress some effects from being visible

```
##   UOL 2018 UOL  UOL 2018 Base UOL 2018 Macro UOL 2018 World
##       3177.073       2086.437       2024.842       2589.636
```

Visualizing our prediction



In Sample Accuracy

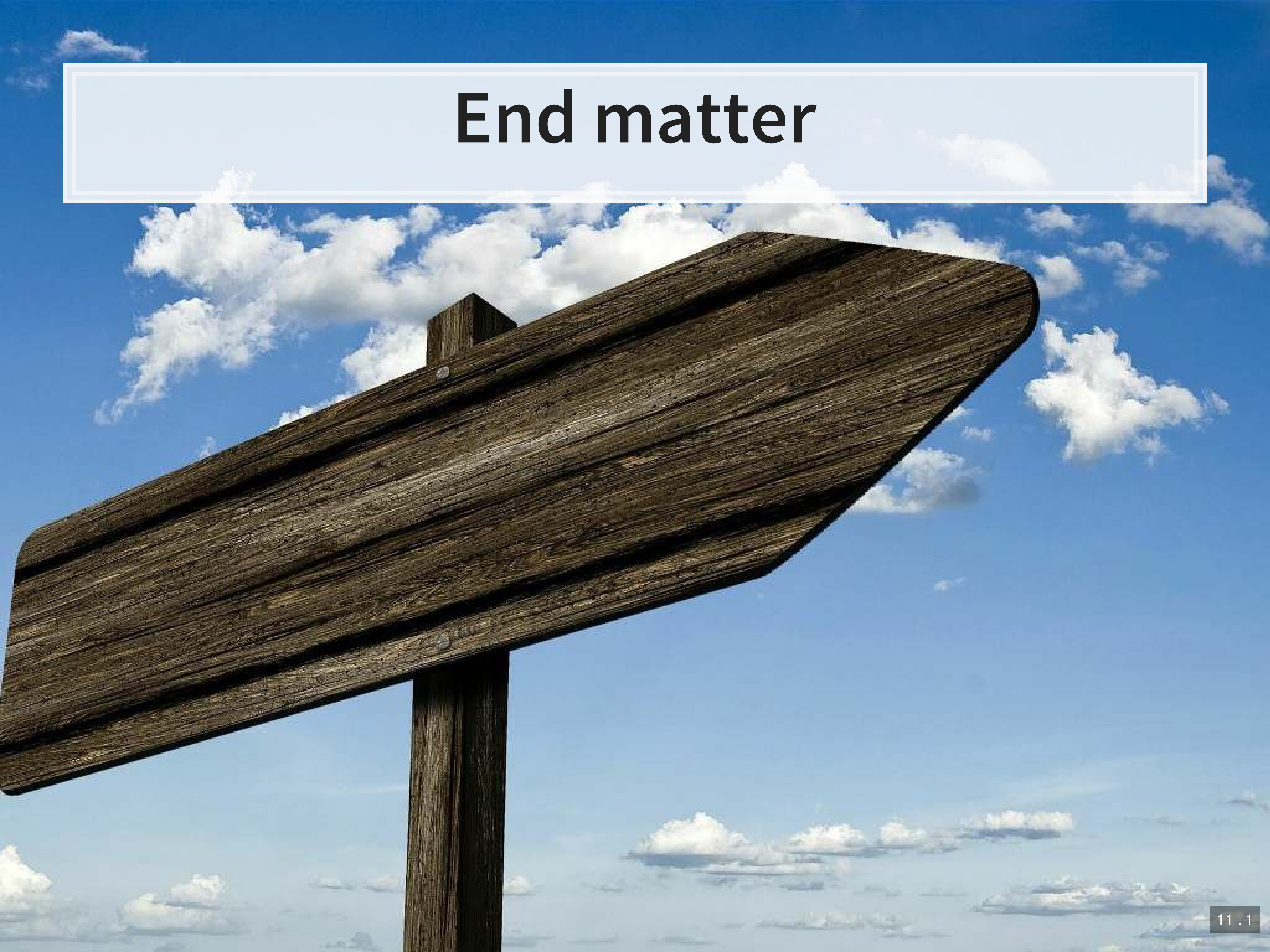
```
# series vectors calculated here -- See appendix
rmse <- function(v1, v2) {
  sqrt(mean((v1 - v2)^2, na.rm=T))
}

rmse <- c(rmse(actual_series, uol_series), rmse(actual_series, base_series),
          rmse(actual_series, macro_series), rmse(actual_series, world_series))
names(rmse) <- c("UOL 2018 UOL", "UOL 2018 Base", "UOL 2018 Macro", "UOL 2018 World")
rmse
```

```
##   UOL 2018 UOL  UOL 2018 Base UOL 2018 Macro UOL 2018 World
##       175.5609       301.3161       344.9681       332.8101
```

> Why is UOL the best for in sample?

End matter



For next week

- For next week:
  - 1 chapter of 1 course on Datacamp
  - First individual assignment
    - Do this one individually!
    - Turn in on eLearn by the end of next Thursday

Packages used for these slides

- broom
- DT
- knitr
- lfe
- magrittr
- plotly
- revealjs
- tidyverse

Custom code

```
# Graph showing squared error (slide 4.6)
uolg <- uol[,c("at","revt")]
uolg$resid <- mod1$residuals
uolg$xleft <- ifelse(uolg$resid < 0,uolg$at,uolg$at - uolg$resid)
uolg$xright <- ifelse(uolg$resid < 0,uolg$at - uolg$resid, uol$at)
uolg$ytop <- ifelse(uolg$resid < 0,uolg$revt - uolg$resid,uol$revt)
uolg$ybottom <- ifelse(uolg$resid < 0,uolg$revt, uolg$revt - uolg$resid)
uolg$point <- TRUE

uolg2 <- uolg
uolg2$point <- FALSE
uolg2$at <- ifelse(uolg$resid < 0,uolg2$xright,uolg2$xleft)
uolg2$revt <- ifelse(uolg$resid < 0,uolg2$ytop,uolg2$ybottom)

uolg <- rbind(uolg, uolg2)

uolg %>% ggplot(aes(y=revt, x=at, group=point)) +
         geom_point(aes(shape=point)) +
         scale_shape_manual(values=c(NA,18)) +
         geom_smooth(method="lm", se=FALSE) +
         geom_errorbarh(aes(xmax=xright, xmin = xleft)) +
         geom_errorbar(aes(ymax=ytop, ymin = ybottom)) +
         theme(legend.position="none")
```

```
# Chart of mean revt_lead for Singaporean firms (slide 7.19)
df_clean %>%                                         # Our data frame
  filter(fic=="SGP") %>%                             # Select only Singaporean firms
  group_by(isin) %>%                                 # Group by firm
  mutate(mean_revt_lead=mean(revt_lead, na.rm=T)) %>%  # Determine each firm's mean revenue (lead)
  slice(1) %>%                                       # Take only the first observation for each group
  ungroup() %>%                                      # Ungroup (we don't need groups any more)
  ggplot(aes(x=mean_revt_lead)) +                    # Initialize plot and select data
  geom_histogram(aes(y = ..density..)) +             # Plots the histogram as a density so that geom_density is visible
  geom_density(alpha=.4, fill="#FF6666")             # Plots smoothed density
```

Custom code

```r
# Chart of predictions (slide 11.4)
library(plotly)
df_SG_macro$pred_base <- predict(baseline, df_SG_macro)
df_SG_macro$pred_macro <- predict(macro3, df_SG_macro)
df_clean$pred_world <- predict(forecast4, df_clean)
uol$pred_uol <- predict(forecast2, uol)
df_preds <- data.frame(preds=preds, fyear=c(2018,2018,2018,2018), model=c("UOL only", "Base", "Macro", "World"))
plot <- ggplot() +
  geom_point(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=revt_lead,x=fyear, color="Actual")) +
  geom_line(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=revt_lead,x=fyear, color="Actual")) +
  geom_point(data=uol[uol$fyear < 2017,], aes(y=pred_uol,x=fyear, color="UOL only")) +
  geom_line(data=uol[uol$fyear < 2017,], aes(y=pred_uol,x=fyear, color="UOL only")) +
  geom_point(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=pred_base,x=fyear, color="Base")) +
  geom_line(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=pred_base,x=fyear, color="Base")) +
  geom_point(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=pred_macro,x=fyear, color="Macro")) +
  geom_line(data=df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,], aes(y=pred_macro,x=fyear, color="Macro")) +
  geom_point(data=df_clean[df_clean$isin=="SG1S83002349" & df_clean$fyear < 2017,], aes(y=pred_world,x=fyear, color="World")) +
  geom_line(data=df_clean[df_clean$isin=="SG1S83002349" & df_clean$fyear < 2017,], aes(y=pred_world,x=fyear, color="World")) +
  geom_point(data=df_preds, aes(y=preds, x=fyear, color=model), size=1.5, shape=18)
ggplotly(plot)
```

```r
# Calculating Root Mean Squared Error (Slide 11.5)
actual_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$revt_lead
uol_series <- uol[uol$fyear < 2017,]$pred_uol
base_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$pred_base
macro_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$pred_macro
world_series <- df_clean[df_clean$isin=="SG1S83002349" & df_clean$fyear < 2017,]$pred_world

rmse <- function(v1, v2) {
  sqrt(mean((v1 - v2)^2, na.rm=T))
}

rmse <- c(rmse(actual_series, uol_series),
          rmse(actual_series, base_series),
          rmse(actual_series, macro_series),
          rmse(actual_series, world_series))
names(rmse) <- c("UOL 2018, UOL only", "UOL 2018 Baseline", "UOL 2018 w/ macro", "UOL 2018 w/ world")
rmse
```