FINC-672 – WORKSHOP IN FINANCE: EMPIRICAL RESEARCH

TABULAR DATA

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GOALS

Tabular Data in Julia using DataFrames
Load and Save Files
Index Tabular Data
Filter and Subset DataFrames
Select Columns of DataFrames
Missing Data and Data Types

SETTING UP DATAFRAMES

- First, we need to step up the Julia DataFrames package.
- Start Julia and enter the following commands at the "REPL".

```
julia> using Pkg
julia> Pkg.add("DataFrames")
julia> using DataFrames
```

TABULAR DATA

- Data comes mostly in a tabular format.
- By tabular, we mean that the data consists of a table containing rows and columns.
- Columns are usually of the same data type, whereas rows have different types.
- The rows, in practice, denote observations while columns denote variables.
- For example, we can have a table of TV shows containing in which country it was produced and our personal rating.

Name	Country	Rating
Game of Thrones	United States	8.2
The Crown	England	7.3
Friends	United States	7.8

• Here, the dots mean that this could be a very long table and we only show a few rows.

- When we analyze data, often we come up with interesting questions about the data, also known as data queries.
- Examples of, so called **queries**, for this data could be:
 - Which TV show has the highest rating?
 - Which TV shows were produced in the United States?
 - Which TV shows were produced in the same country?
- To answer questions like "Which TV show has the highest rating?" we use **data transformation**.

- Let's take the first three shows in the table and see how we model this using DataFrames in Julia.
- In a Julia DataFrame, we would set this up as follows

```
julia> tv_shows = DataFrame(
          name=["Game of Thrones", "The Crown", "Friends"],
          country=["United States", "England", "United States"],
          rating=[8.2, 7.3, 7.8]
);
```

julia> tv_shows

3×3 Da	3×3 DataFrame							
Row	name	country	rating					
	String	String	Float64					
1	Game of Thrones	United States	8.2					
2	The Crown	England	7.3					
3	Friends	United States	7.8					

• As a second example, suppose we have data on bonds of four firms with (full) price and coupon rate (expressed in percentage points, and paid semi-annually).

firm	price	coupon
firmA	70.0	5.00
$_{ m firmB}$	80.0	3.75
$\operatorname{firm} C$	100.0	2.50
$\operatorname{firm} D$	110.0	2.00

• Here, the column with the firm name (firm) has type string, price (price) and coupon rate (coupon) have type float.

GETTING DATA INTO A DATAFRAME

- With DataFrames, we can define a DataFrame to hold our tabular data.
- The following code gives us a variable df containing our data in table format.

```
julia> frm = ["firmA","firmB","firmC","firmD"];
julia> px = [70.0, 80.0, 100.0, 110.0];
julia> cpn = [5.00, 3.75, 2.50, 2.00];
julia> df = DataFrame(; firm=frm, price=px, coupon=cpn);
```

GETTING DATA INTO A DATAFRAME (CONT'D)

• Let's display our DataFrame.

julia> df

4×3 DataFrame						
Row	firm	price	coupon			
	String	Float64	Float64			
1	firmA	70.0	5.0			
2	firmB	80.0	3.75			
3	firmC	100.0	2.5			
4	firmD	110.0	2.0			

DATAFRAME CONSTRUCTOR

- We construct a DataFrame is simply to pass vectors as arguments into the DataFrame constructor.
- You can come up with any valid Julia vector and it will work as long as the vectors have the same length.
- Duplicates, Unicode symbols and any sort of numbers are fine.
- Another example:

LOADIND AND SAVING FILES

- We need to be able to store files and load files from disk.
- We focus on CSV and Excel file formats since those are the most common data storage formats for tabular data.
- Comma-separated values (CSV) files are are very effective way to store tables. CSV files have two advantages over other data storage files.
- First, it does exactly what the name indicates it does, namely storing values by separating them using commas ,
- This acronym is also used as the file extension (you save your files using the ".csv" extension such as "myfile.csv").
- To demonstrate how a CSV file looks, we can install the CSV jl package.

```
julia> using Pkg
julia> Pkg.add("CSV")
julia> using CSV
```

SAVING TO CSV FILES

• We can now use our previous data on bonds and write it to CSV.

READING DATA FROM CSV FILES

- Next, let's read the data from the CSV file we have just created and put it into a DataFrame.
- Conveniently, CSV jl will automatically infer column types for us.

```
julia> path = "bonds.csv"
"bonds.csv"
```

julia> CSV.File(path) |> DataFrame

4×3 DataFrame

Row	firm String7	price Float64	coupon Float64
1	firmA	70.0	5.0
2	firmB	80.0	3.75
3	firmC	100.0	2.5
4	firmD	110.0	2.0

• Here we use the |> operator to "send" the CSV file into a DataFrame.

WRITING DATA TO EXCEL FILES

• To load an Excel file, we first need to add the XLSX.jl package.

```
julia> using Pkg
julia> Pkg.add("XLSX")
julia> using XLSX
```

¹Note that in the Julia codeblock the using Pkg is only needed once. That is if you have Julia opened and entered it before, you do not need to enter it again.

WRITING DATA TO EXCEL FILES (CONT'D)

• Let's now write the bonds data to an Excel file.

```
julia> path==="bonds.xlsx";
julia> data===collect(eachcol(df));
julia> cols===names(df);
julia> XLSX.writetable(path,=data,=cols)
```

- Here, we need to provide the tabular data (data) and the column names (cols) individually to writetable.
- We get the data by *collecting* EACH column. This is what collect(eachcol(df)) does.
- We get the column names by using names(df).

READING DATA FROM EXCEL FILES

• Let's now read the bond data in the Excel file we have just created back into a DataFrame.

• Note that the ... in the code above is again the splat operator we have encountered before. Here it basically unpacks the Excel worksheet so that we can put it into a DataFrame.

INDEXING AND SUMMARIZING DATA

- Let's continue to use our bond data as an example.
- Suppose we want to know all names of the firms in our dataset.
- To retrieve a vector for firm names, we can access the DataFrame with the operator.

```
julia> df.firm
4-element Vector{Any}:
   "firmA"
   "firmB"
   "firmC"
   "firmD"
```

• Alternatively, we can index a DataFrame much like an Array with symbols and special characters. The second index is the column indexing.

```
julia> df[!, :firm]
4-element Vector{Any}:
   "firmA"
   "firmB"
   "firmC"
   "firmD"
```

• Here, we use the ! operator to indicate that we want to get all rows.

- Let's suppose, you want to get the price and coupon rate for the second bond in our data.
- For any row, in our case the second row, we can use the first index as row indexing (in the codeblock below, this is the 2 before the comma).
- The colon: just means that we want to get all columns (in our case the firm name, bond price, and coupon rate).

- How would we get the price and dividend for the third stock in our data?
- Simply use a 3 as the row index.

julia> df[3, :] DataFrameRow Row | firm price coupon | Any Any Any | 3 | firmC 100.0 2.5

• How about the firm name for the second and the third bond?

```
julia> df[1:2, :firm]
2-element Vector{Any}:
   "firmA"
   "firmB"
```

• How can we get the price and coupon rate of the second and third bond?

• Note that we write the column names with a colon : and put them between brackets ([and]) and separate the column names with a comma ,

FILTER AND SUBSET DATAFRAMES

- The DataFrame functions filter and subset subset allow us to "filter" out rows from a DataFrame, or, in other words, allow us to take a subset of a DataFrame.
- We can filter rows by using filter(source => f::Function, df)
- Let's illustrate this with an example using our bond data from before.

firm	price	coupon
firmA	70.0	5.00
$_{ m firmB}$	80.0	3.75
$_{\rm firmC}$	100.0	2.50
firmD	110.0	2.00

• Let's find the bond that is trading at par (i.e. its price is 100.0).

• Let's figure out what is going on here.

```
filter(:price \Rightarrow (x->x==100.0), df)
```

- We take the price column and use the => operator to pass this column to a function.
- Why? Because we are looking for the bond with price=100.0.
- Then, we use a so-called **anonymous function** to check when the bond price is equal to 100.0
- This is the (x->x==100.0)
- The filter function then returns the row for which the condition x==100.0 is true

- We often want to subset data using multiple conditions.
- For instance, we would like to know which bond trades at a discount to par and has a coupon rate greater than four percent.
- In these cases, we do not use an anonymous function as in the previous example ((x->x==100.0)), but we define a function.
- To illustrate this, let's use a function in the previous example.

```
julia> function isPar(x)
    if x==100.0
        return true
    else
        return false
    end
end;
julia>
df2 = filter(:price => (x->isPar(x)), df)
1x3 DataFrame
 Row | firm price coupon
      Anv
             Anv
                    Anv
       firmC 100.0 2.5
```

- We can build a more complex filter
- Suppose we want to get the bonds that trade at a discount to par value and with coupon rate of at least four percent.
- Let's first build the function

```
julia> function getBond(price,coupon)
   if price<100.0 && coupon>=4.00
      return true
   else
      return false
   end
end;
```

• Now, let's use our getBond function.

• Let's figure out what is going on here.

```
df2 = filter([:price, :coupon] => ( (x,y)->getBond(x,y)), df)
```

- Here, we need to check the price (price) and coupon rate (coupon) of the bonds.
- We get these two columns by using the colon: operator and by putting them between brackets ([and]), seperated by a comma, i.e. [:price, :coupon]
- We then use => to "send" these two columns to our function.
- To call our function, we need two inputs: the price and the coupon rate.
- Thus, we use x,y) make sure to use the parentheses (and)).
- Then, we send these two input to our function getBond(x,y).

SELECTING COLUMNS

- We select specific columns using the function select
- To illustrate, lets suppose we have the following bond dataset.
- Note that we have the same bonds as before, but we now know the year when the bonds were issued and the year of maturity of the bonds. We also have bid and ask prices.

$_{ m firm}$	${\bf bidprice}$	askprice	coupon	issueyear	maturityyear
$_{ m firm}$ A	69.00	70.0	5.00	2018	2023
$_{ m firmB}$	79.50	80.0	3.75	2020	2030
$\operatorname{firm} C$	99.75	100.0	2.50	2021	2024
$\operatorname{firm} D$	109.00	110.0	2.00	2015	2025

SELECTING COLUMNS

• First, let's create a DataFrame.

```
julia> frm = ["firmA", "firmB", "firmC", "firmD"];
julia> pxbid = [69.00, 79.50, 99.75, 109.00];
julia> pxask = [70.0, 80.0, 100.0, 110.0];
julia> cpn = [5.00, 3.75, 2.50, 2.00];
julia> issyr = [2018, 2020, 2021, 2015];
julia> matyr = [2023, 2030, 2024, 2025];
julia> df = DataFrame(firm=frm, bidprice=pxbid, askprice=pxask, coupon=cpn, issueyear=issyr, maturityyear=matyr);
```

SELECTING COLUMNS (CONT'D)

• Let's display the DataFrame

julia> df

4×6 Da	ataFrame firm String	bidprice Float64	askprice Float64		issueyear Int64	maturityyear Int64
1	firmA	69.0	70.0	5.0	2018	2023
2	firmB	79.5	80.0	3.75	2020	2030
3	firmC	99.75	100.0	2.5	2021	2024
4	firmD	109.0	110.0	2.0	2015	2025

SELECTING COLUMNS (CONT'D)

• First, we want to select the column with all firm names.

- Note that our DataFrame df comes first, i.e. select(df
- Also note that we could get the same result by using df.firm
- However, select is powerful when we select multiple columns

• Next, suppose we want to get back the original bond dataset that we started with (i.e. where we have the firm name, askprice, and the coupon rate).

```
julia> df2 = select(df, [:firm, :askprice, :coupon])
4×3 DataFrame
Row
      firm askprice
                       coupon
      String Float64 Float64
      firmA
                 70.0
                          5.0
      firmB
                 80.0
                          3.75
      firmC
                100.0 2.5
      firmD
                110.0
                          2.0
```

• Let's discuss what is going on here.

```
df2 = select(df, [:firm, :askprice, :coupon])
```

- As before, we use the column names with a colon : and put them between brackets ([and]), separated by a comma ,
- Then we simply use this as the second argument after df in the function call to select

- Suppose now that we want all columns, except the issue year.
- To exclude one (or more columns), we use Not() as shown below.

julia> df2 = select(df, Not(:issueyear))

4×5 Da		bidprice Float64			maturityyear Int64
1	firmA	69.0	70.0	5.0	2023
2	firmB	79.5	80.0	3.75	2030
3	firmC	99.75	100.0	2.5	2024
4	firmD	109.0	110.0	2.0	2025

• What if we want all columns except the issue year and the bid price?

```
julia> df2 = select(df, Not([:issueyear,:bidprice]))
4×4 DataFrame
      firm
             askprice
                       coupon maturityvear
Row
      String Float64 Float64 Int64
      firmA
                 70.0
                          5.0
                                       2023
      firmB
                 80.0
                          3.75
                                       2030
      firmC
                100.0 2.5
                                       2024
      firmD
                110.0
                          2.0
                                       2025
```

• Note that we need to put the two column names between brackets ([and]), separated by a comma ,

- We can also "mix and match"
- Suppose we want the firm name, all other columns, but not the bid price.

julia> df2 = select(df, :firm, Not(:bidprice))

Row	firm String	askprice Float64		issueyear Int64	maturityyear Int64
1	firmA	70.0	5.0	2018	2023
2	firmB	80.0	3.75	2020	2030
3	firmC	100.0	2.5	2021	2024
4	firmD	110.0	2.0	2015	2025

- Can we **rename** columns using the **select** function?
- The answer is yes. Suppose we want to rename the **firm** column to **firmname**.

```
julia> df2 = select(df, :firm => :firmname, :)
4×7 DataFrame
 Row
       firmname
                firm
                        bidprice
                                 askprice
                                            coupon
                                                    issuevear
                                                                maturityyear
                                 Float64
      Strina
                Strina
                        Float64
                                            Float64 Int64
                                                                Tnt64
       firmA
                firmA
                           69.0
                                      70.0
                                               5.0
                                                          2018
                                                                        2023
      firmB
                firmB
                           79.5
                                      80.0
                                               3.75
                                                          2020
                                                                        2030
      firmC
                firmC
                           99.75
                                               2.5
                                     100.0
                                                          2021
                                                                        2024
       firmD
                firmD
                          109.0
                                     110.0
                                               2.0
                                                          2015
                                                                        2025
```

• What is happening here?

```
df2 = select(df, :firm => :firmname, :)
```

- the first part :firm => :firmname means that we assign the new name "firmname" to the existing column firm.
- The colon: (which is separated by a comma,) means that we want to select all other columns as well (except the one we just renamed).

MISSING DATA AND DATA TYPES

- CSV. jl will typically work quite well in guessing what kind of types our data have as columns.
- However, this won't always work perfectly. Let's see how we fix wrong data types and what data types we should use.
- We work with the following bond dataset.

id	\mathbf{firm}	${\bf bidprice}$	${\bf ask price}$	coupon	is sued at e	${\bf maturity date}$
1	$_{\mathrm{firmA}}$	69.00	70.0	5.00	31-01-2018	31-01-2023
2	$_{ m firmB}$	79.50	80.0	3.75	31-03-2020	31-03-2030
3	$_{\rm firmC}$	99.75	100.0	2.50	30-09-2021	30-09-2024
4	firmD	109.00	110.0	2.00	31-10-2015	31-10-2025

• Suppose someone created the DataFrame as shown below.

```
julia> idno = ["1","2","3","4"];
julia> frm = ["firmA","firmB","firmC","firmD"];
julia> pxbid = [69.00, 79.50, 99.75, 109.00];
julia> pxask = [70.0, 80.0, 100.0, 110.0];
julia> cpn = [5.00, 3.75, 2.50, 2.00];
julia> issdt = ["31-01-2018","31-03-2020","30-09-2021","31-10-2015"];
julia> matdt = ["31-01-2023","31-03-2030","30-09-2024","31-10-2025"];
julia> df = DataFrame(id=idno, firm=frm, bidprice=pxbid, askprice=pxask, coupon=cpn, issuedate=issdt, maturitydate=matds
```

• Let's display the DataFrame.

julia> df

Row	ataFrame id String	firm String	bidprice Float64	askprice Float64	coupon Float64	issuedate String	maturitydate String
1	1	firmA	69.0	70.0	5.0	31-01-2018	31-01-2023
2	2	firmB	79.5	80.0	3.75	31-03-2020	31-03-2030
3	3	firmC	99.75	100.0	2.5	30-09-2021	30-09-2024
4	4	firmD	109.0	110.0	2.0	31-10-2015	31-10-2025

• What could be wrong here?

- Let's try to sort the DataFrame by issue date.
- We do this by using the function sort as follows

julia> sort(df, :issuedate)

4×/ Da	4×/ DataFrame									
Row	id	firm	bidprice	askprice	coupon	issuedate	maturitydate			
İ	String	String	Float64	Float64	Float64	String	String			
1	3	firmC	99.75	100.0	2.5	30-09-2021	30-09-2024			
2	1	firmA	69.0	70.0	5.0	31-01-2018	31-01-2023			
3	2	firmB	79.5	80.0	3.75	31-03-2020	31-03-2030			
4	4	firmD	109.0	110.0	2.0	31-10-2015	31-10-2025			

- What went wrong?
- Because the issue date column has the wrong type, sorting does not work correctly.

- To fix the sorting, we can use the Date module from Julias standard library.
- To illustrate convert a **String** to **Date**, consider the first date "31-01-2023".

```
julia> using Dates;
julia> date_str = "31-01-2023"
"31-01-2023"

julia> date = Dates.Date(date_str, "dd-mm-yyyy")
2023-01-31
```

- Next, let's convert all issue date to Julia Date type.
- To do this, we first get all issue dates in a **Vector**.
- Then we **broadcast** the Date constructor.
- In the last step, we write the converted dates back to our DataFrame df

```
julia> issue dates str = df.issuedate
4-element Vector{String}:
 "31-01-2018"
 "31-03-2020"
 "30-09-2021"
 "31-10-2015"
julia> issue dates dt = Dates Date (issue dates str, "dd-mm-yyyy")
4-element Vector{Dates.Date}:
2018-01-31
2020-03-31
2021-09-30
 2015 - 10 - 31
```

- Likewise, we repeat the same operations for the maturity dates.
- Note, we will learn how to do this more quickly when we talk about data transformation function in DataFrames.

```
julia> mat dates str = df.maturitydate
4-element Vector{String}:
 "31-01-2023"
 "31-03-2030"
 "30-09-2024"
 "31-10-2025"
julia> mat dates_dt = Dates.Date.(mat_dates_str, "dd-mm-yyyy")
4-element Vector{Dates.Date}:
2023-01-31
2030-03-31
2024-09-30
 2025 - 10 - 31
julia> df.maturitydate = mat dates dt
```

- We are not done yet. Notice that the id column is also recognized as a String.
- An id variable should be of **categorical** type.
- Julia helps us here since it implements functionality for categorical data.
- All we need to do is load CategoricalArrays.jl.

```
julia> using Pkg;
julia> Pkg.add("CategoricalArrays");
julia> using CategoricalArrays;
```

• Now we are all set to convert the id column to categorical.

```
julia> categorical(df[!, :id])
4-element CategoricalArrays.CategoricalArray{String,1,UInt32}:
    "1"
    "2"
    "3"
    "4"
```

- Here we are using a shortcut by directly making the conversion on our DataFrame.
- Note: We must use the ! operator.
- This ensures two things. First, recall that ! gives us the entire id column. Second, by using ! we change the contents of our DataFrame df directly (or in place).

• Finally, let's sort our DataFrame by the issuedate column.

julia> sort(df, :issuedate)

1x7 DataEramo

Row	id String	firm String	bidprice Float64	askprice Float64	coupon Float64	issuedate Date…	maturitydate Date…
1	4	firmD	109.0	110.0	2.0	2015-10-31	2025-10-31
2	1	firmA	69.0	70.0	5.0	2018-01-31	2023-01-31
3	2	firmB	79.5	80.0	3.75	2020-03-31	2030-03-31
4	3	firmC	99.75	100.0	2.5	2021-09-30	2024-09-30

WRAP-UP

- ✓ Tabular Data in Julia using DataFrames
- ✓ Load and Save Files
- ✓ Index Tabular Data
- ✓ Filter and Subset DataFrames
- ✓ Select Columns of DataFrames
- ✓ Missing Data and Data Types