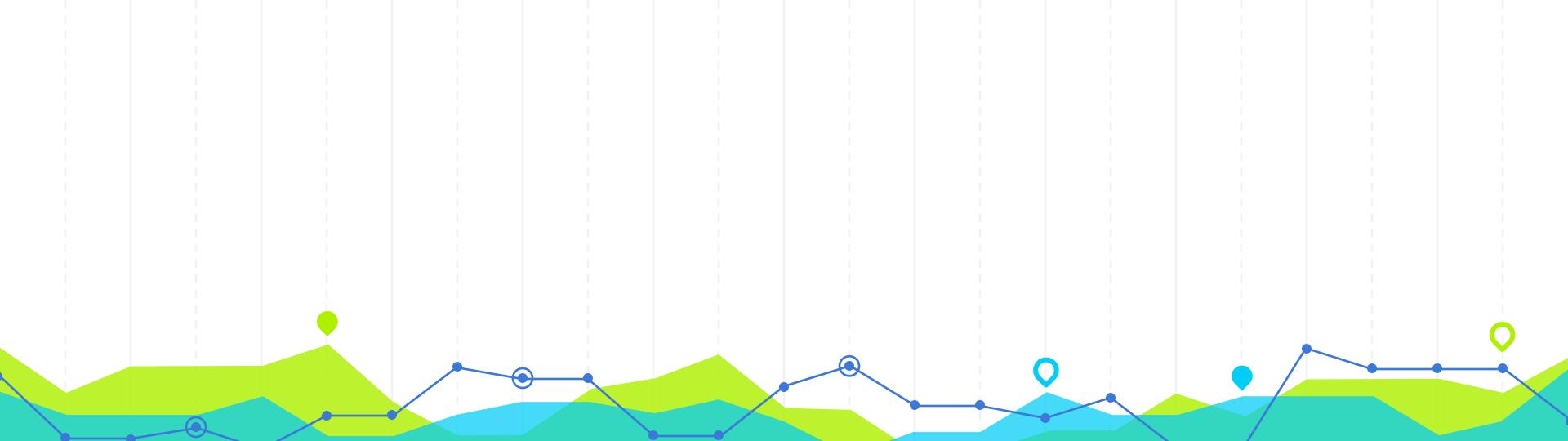


Exploratory Data Analysis



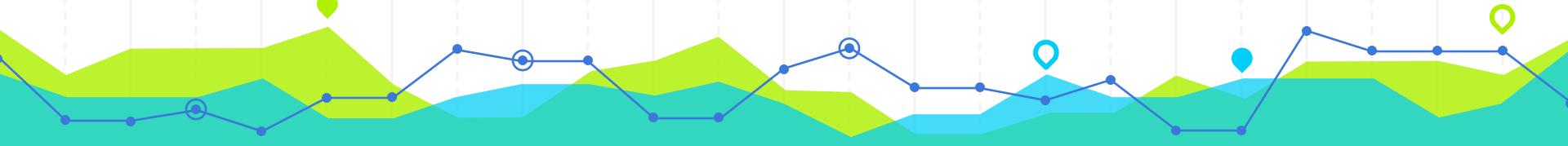
Team 4

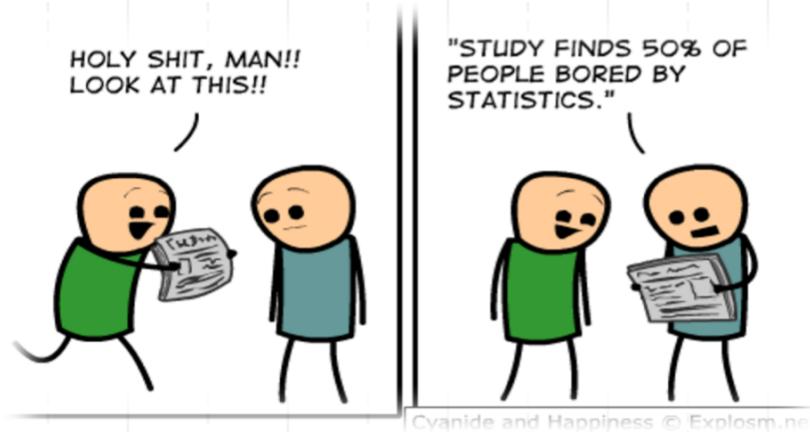
Ashish Dass - dass.s@husky.neu.edu

Anamika Jha - jha.a@husky.neu.edu

Shruti Narain - narain.s@husky.neu.edu

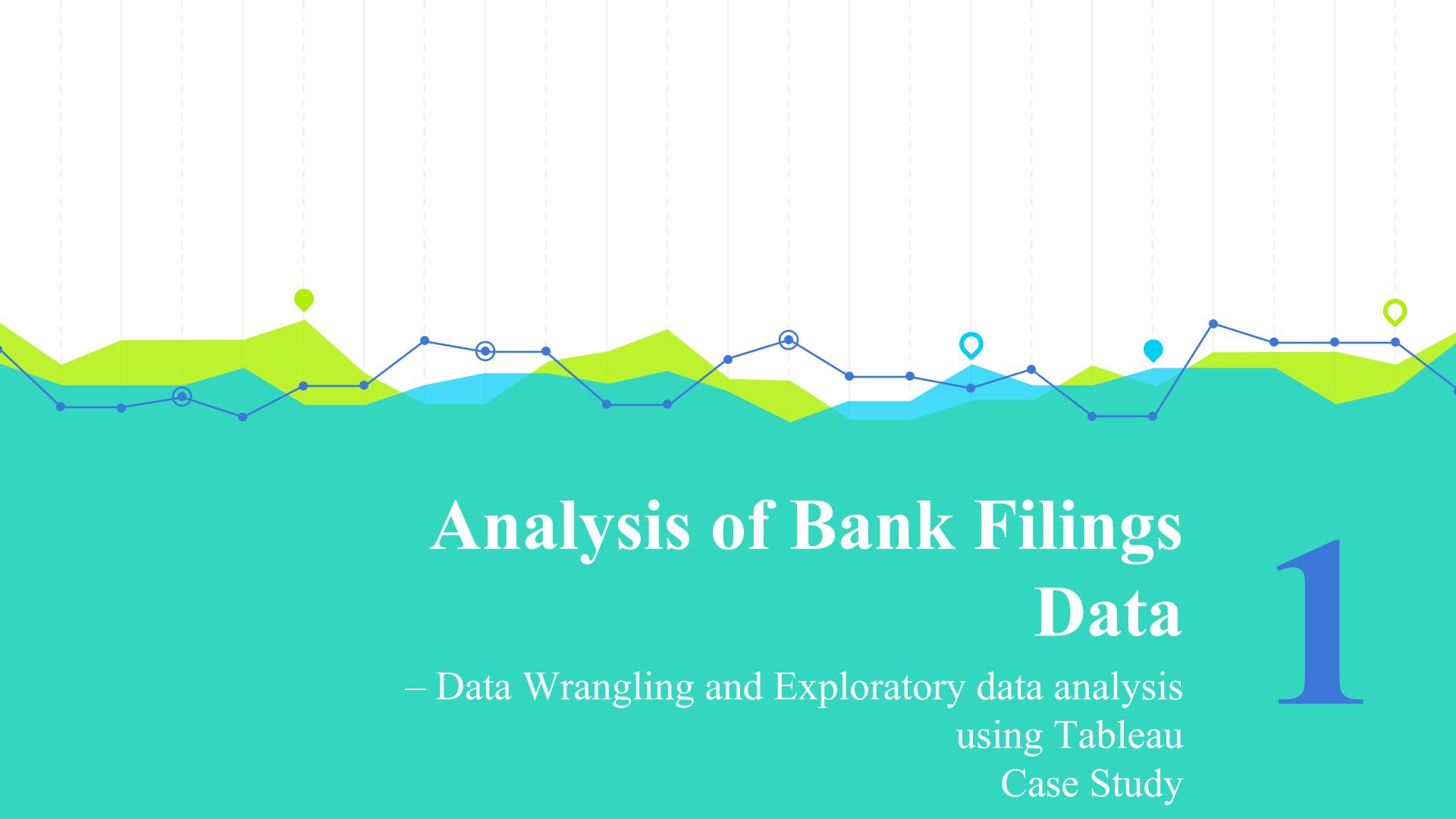
In DATA we TRUST!!





Every day, three times per second, we produce the equivalent of the amount of data that the Library of Congress has in its entire print collection, right? But most of it is like cat videos on YouTube or 13-year-olds exchanging text messages about the next Twilight movie.

— Nate Silver



Analysis of Bank Filings Data

– Data Wrangling and Exploratory data analysis
using Tableau
Case Study

1

Step1:

Scraping data from the below url for 15 quarters into 15 different csv files using R

<https://www.ffiec.gov/nicpubweb/nicweb/HCSGreaterThan10B.aspx>

- ```
install.packages("rvest")
install.packages("RSelenium")
```
- ```
remDrv <- remoteDriver(remoteServerAddr = "localhost", port = 4444, browserName = "firefox")
```
- ```
remDrv$navigate("https://www.ffiec.gov/nicpubweb/nicweb/HCSGreaterThan10B.aspx")
```
- ```
timeframe <- xpathSApply(html page, "//option", function(u) xmlAttrs(u)["value"])
```
- ```
for(i in timeframe){
 option <- remDrv$findElement(using = 'xpath', paste('//*[@option[@value=',i,']]'))
 option$clickElement()
 xt <- readHTMLTable(tables[[3]].....)
 write.csv(xt, file = paste("quarter_",i,'.csv'))}
```

## Step2:

Cleaning and merging data from all 15 csv files into a single csv file in the form of stacked data and unstacked data

- Merging all 15 csv files (**STACKED**) and renaming column header for the purpose of merging  
for (i in timeframe){

```
y <- data.frame(read.csv(paste("quarter_",i,".csv"), header = TRUE))
x<-replicate(nrow(y),i)
y$quarter <- as.Date(x,"%Y%m%d")
colnames(y) <- c('SNo', 'Rank','Company', 'Location', 'Assets', 'Quarter')
w <- rbind(w,y) }
```

- Splitting company ID and Location  
install.packages('reshape2')

```
w1 <- with(w, cbind(Rank, colsplit(w$Company, pattern = "\\" , names = c('Institution
Name', 'RSSDId')),colsplit(w$Location, pattern = "\\", names = c('City', 'State')), Assets,
Quarter))
```

```
w2 <- as.data.frame(sapply(w1,gsub,pattern=")",replacement=""))
```

- Merging all 15 csv files (**UNSTACKED**) and renaming column header for the purpose of merging

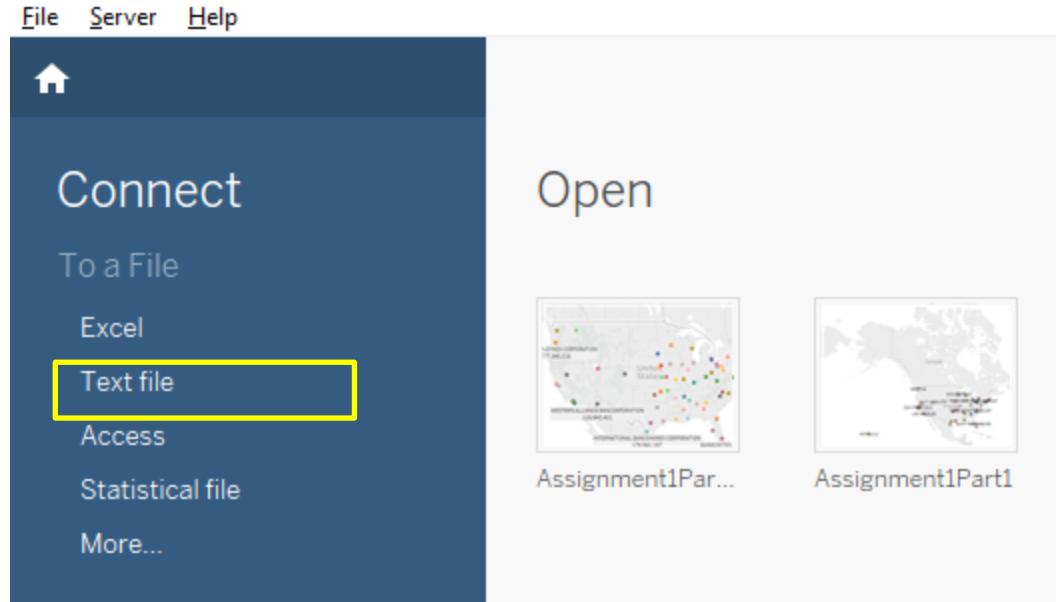
```
unstacked = NULL
counter <- 1
for (i in timeframe){
 unstacked_ <- data.frame(read.csv(paste("quarter_",i,".csv"), header = TRUE))
 quarter_row<-replicate(nrow(unstacked_),i)
 unstacked_$quarter <- as.Date(quarter_row,"%Y%m%d")
 colnames(unstacked_) <- c('SNo', 'Rank','Company', 'Location', 'Assets', 'Quarter')

 if (counter == 1){
 unstacked <- unstacked_
 counter <- 2
 } else{
 unstacked <- merge(unstacked,unstacked_, by="Company" , all.unstacked
 =TRUE , all.unstacked_= TRUE)
 }
}
}
```



## Step 3:

Importing the csv file (which has stacked data) as a “text” file in Tableau for the purpose of analysis

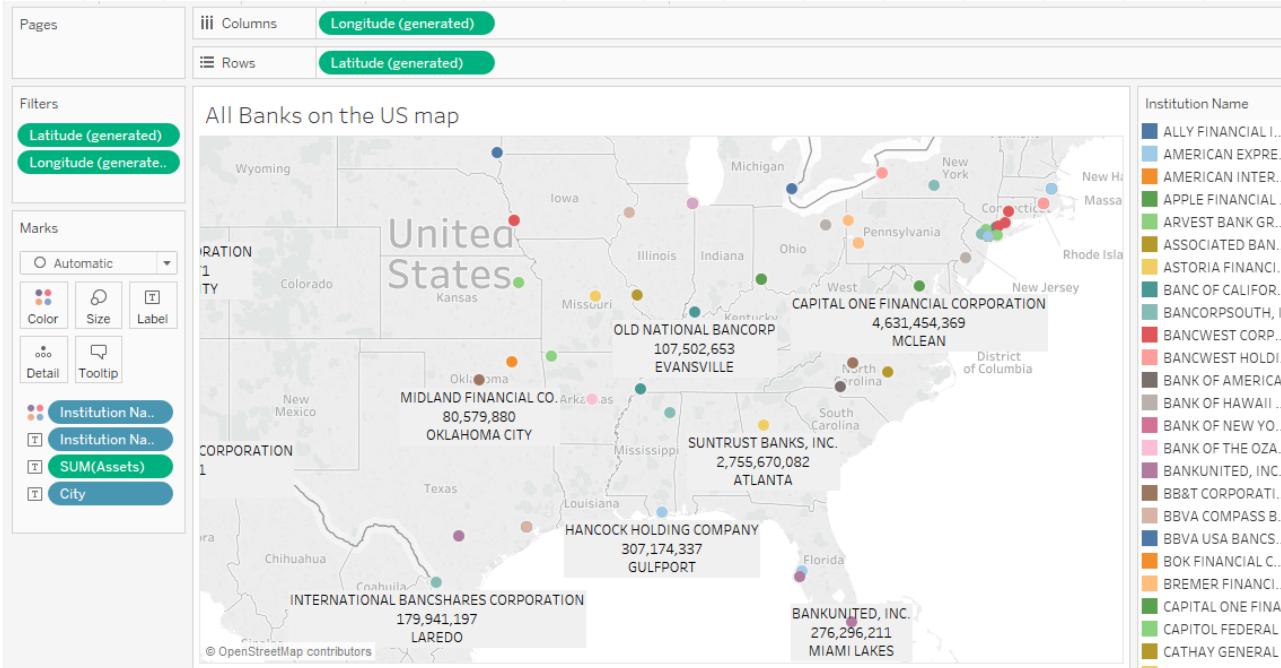


# Dashboards



# All banks on the US Map using location information

All the banks with their total assets and city , highlighted with different colors on the map

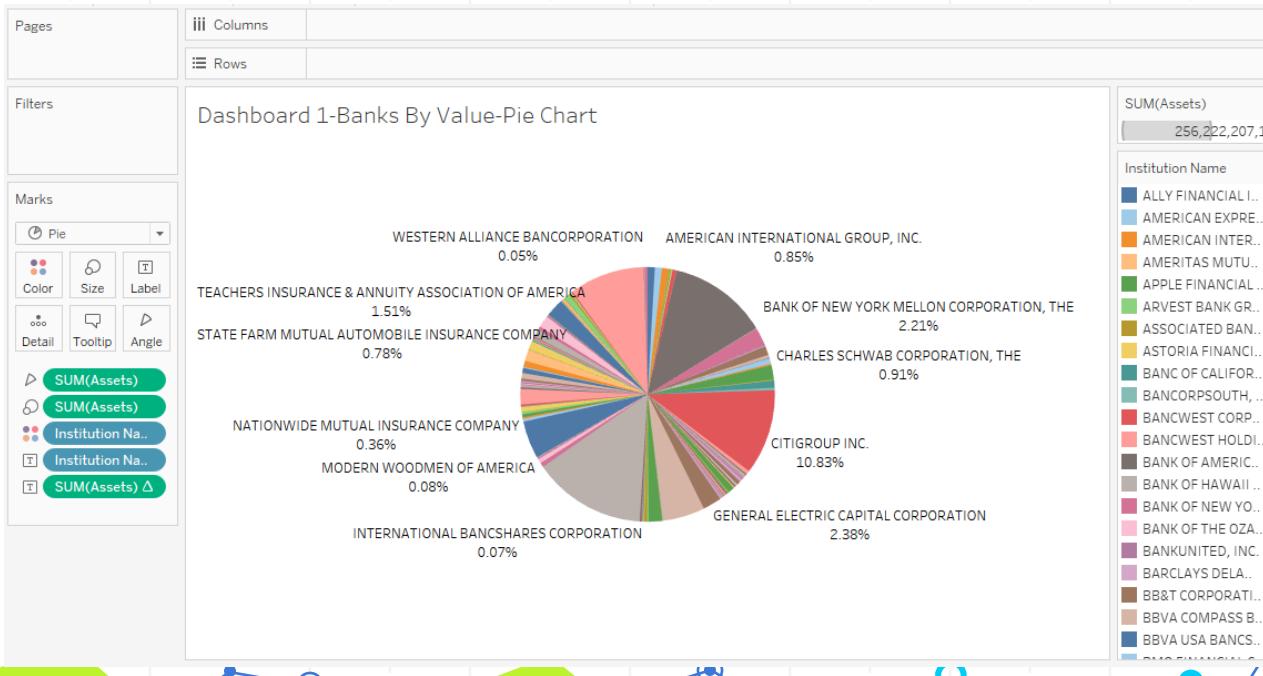


# 1.a: Histogram describing the banks by value



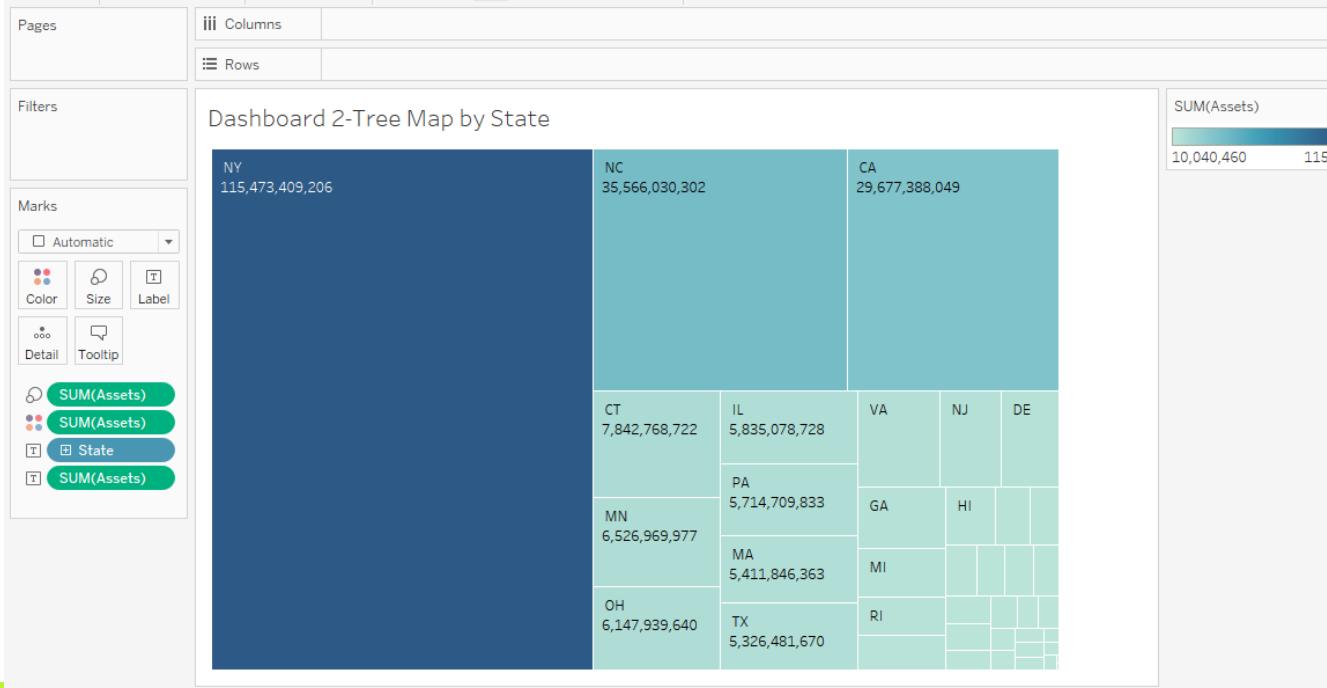
## 1.b: Pie Chart describing the banks by value

Based on 15 quarters, the pie chart represents that, the major portion is occupied by companies like JP Morgan(14%), Bank of America(12%), Citi group(10%), etc.



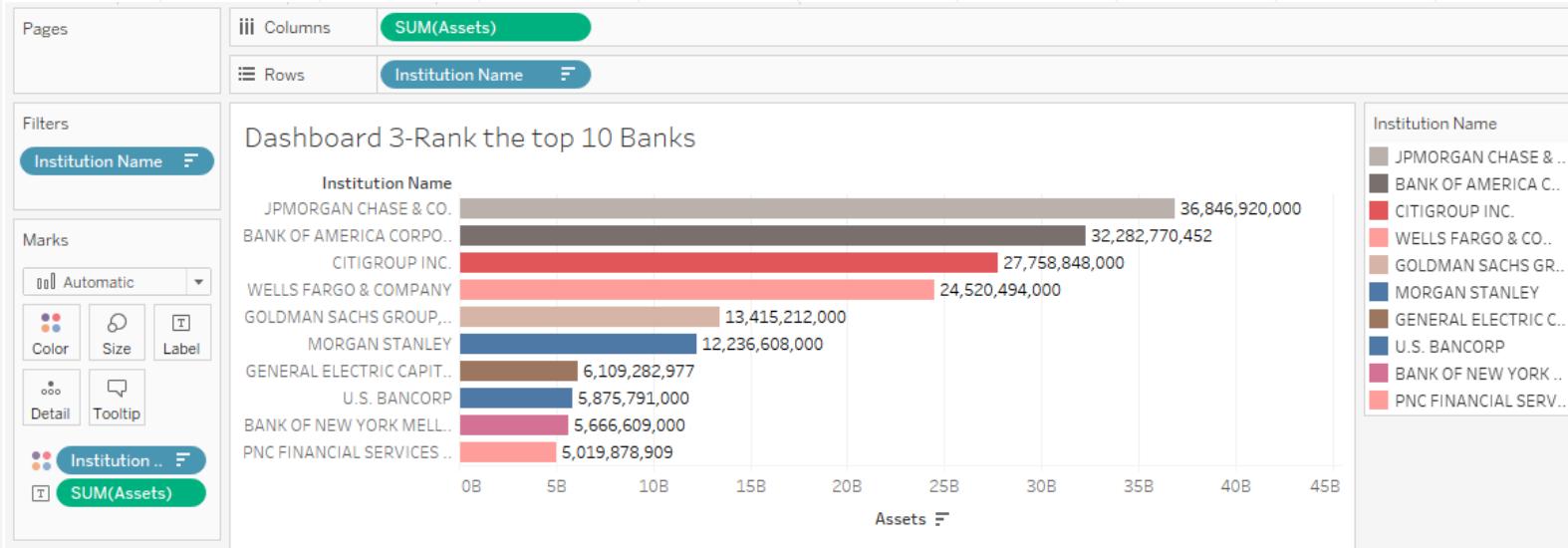
## 2: Tree Map by State

The chart represents that the states with almost similar assets have similar size and color.  
The size of the rectangle decreases with decrease in the total asset value .



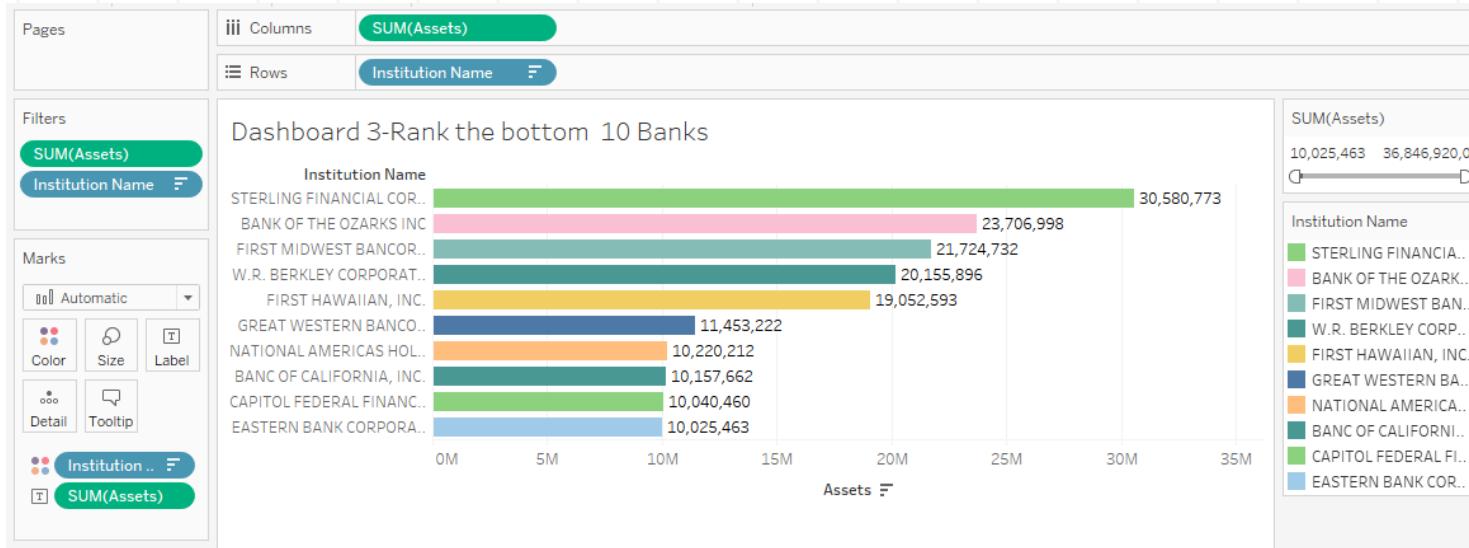
## 3.1: Ranking the top 10 banks

The ranking of top 10 banks is based on total assets combined using 15 quarters.



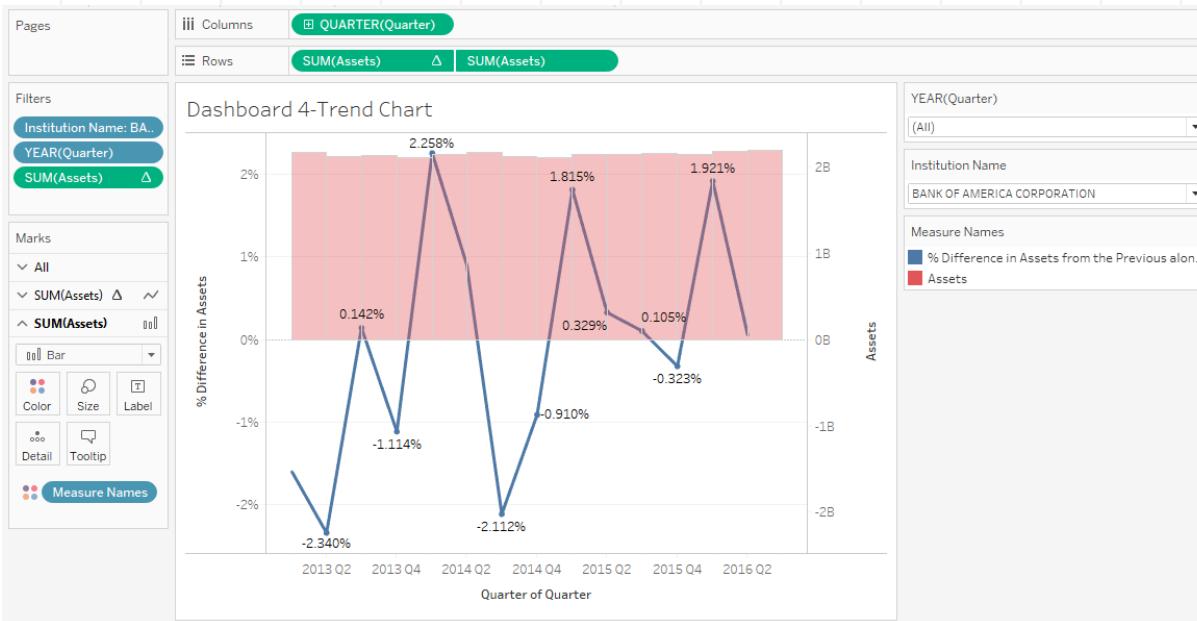
## 3.2: Ranking the bottom 10 banks

The ranking of bottom 10 banks is based on total assets combined using 15 quarters.



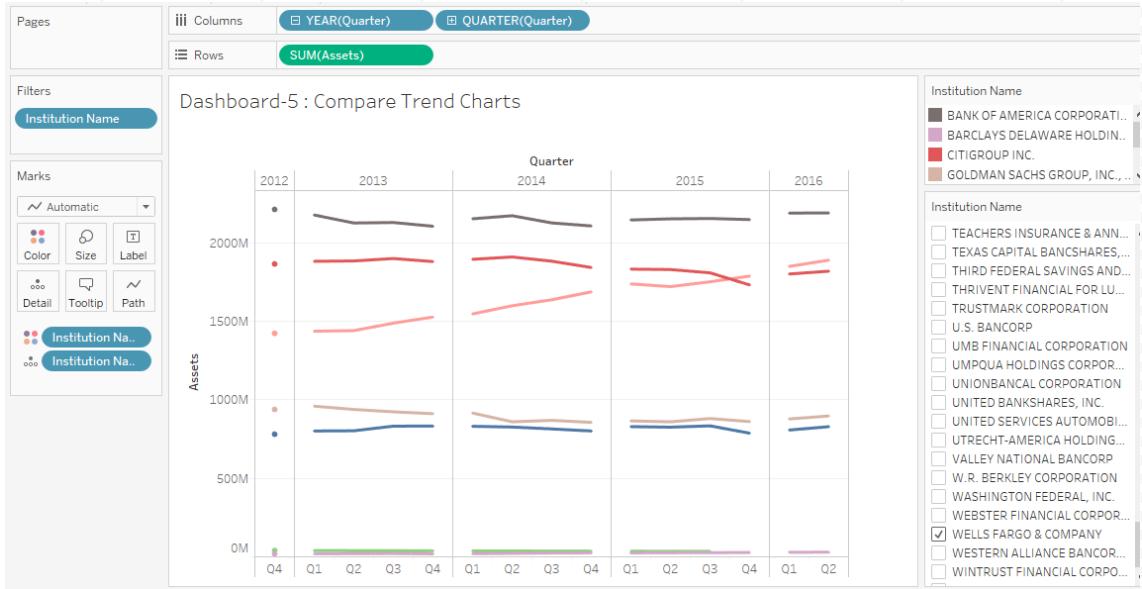
## 4: Trend Charts - per company

The chart consists of trend lines that represent growth rate.  
With decrease in asset value for a particular quarter, the line goes in the negative quadrant.



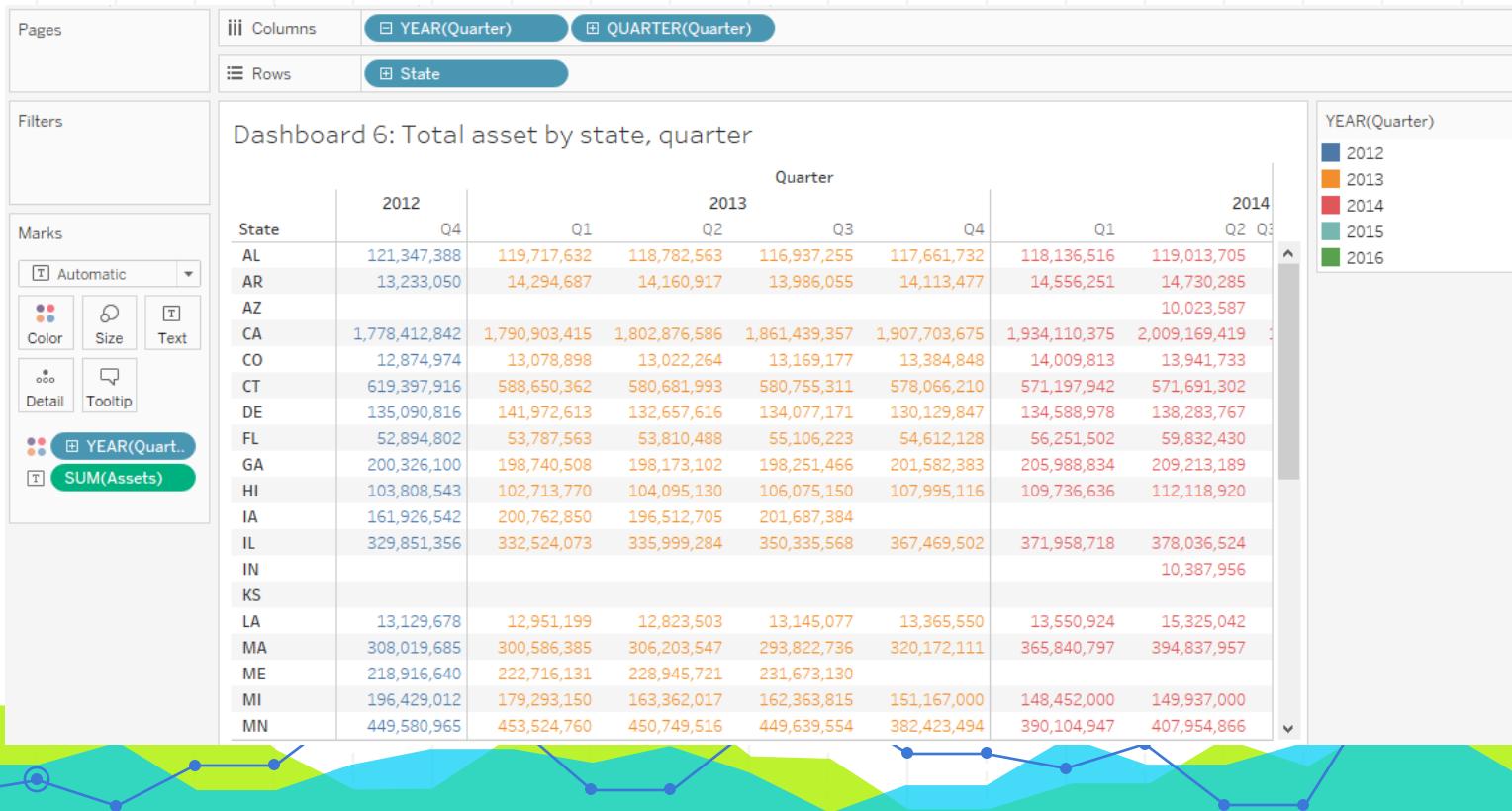
# 5: Comparing companies using Trend Charts

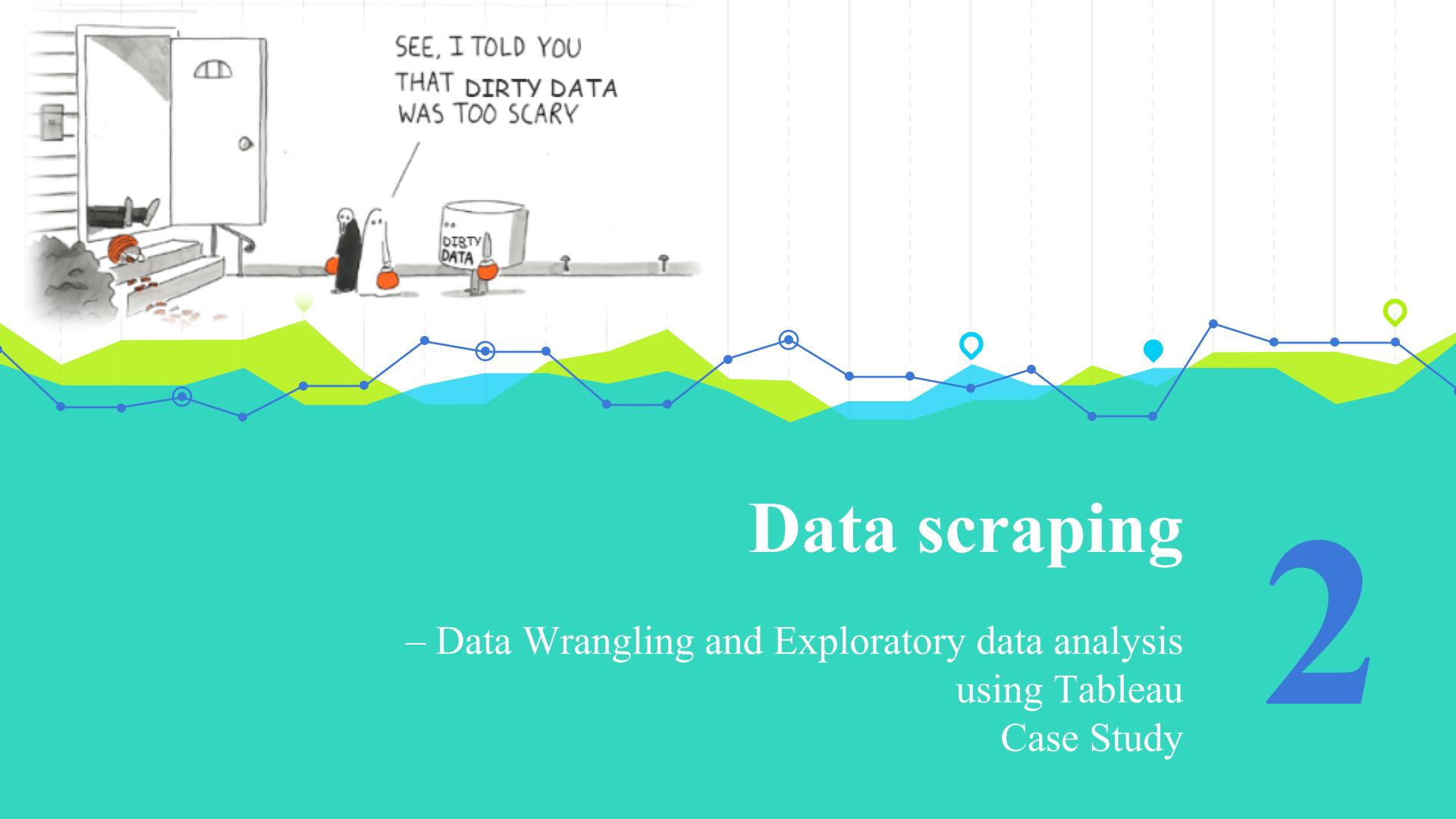
Different trend lines represent different companies for all 15 quarters.



## 6: Pivot table- total asset by state, quarter

The table represents total assets for all the states, year wise and quarter wise





# Data scraping

– Data Wrangling and Exploratory data analysis  
using Tableau  
Case Study

# 1: Very Unclean Data

|    | BHCP.R.PERCENTILE.DISTRIBUTION.REPORT | ALLOWANCE.AND.NET.LOAN.AND.LEASE.LOSSES | X      | X.1    | X.2    | X.3 | PAGE.6 |
|----|---------------------------------------|-----------------------------------------|--------|--------|--------|-----|--------|
| 1  | PEER GROUP 1                          | NA                                      | NA     | NA     | NA     | NA  | NA     |
| 2  | NA                                    | PEER                                    | NA     | NA     | NA     | NA  | BHC    |
| 3  | ANALYSIS RATIOS                       | RATIO5%10%25%50%                        | 75%    | 90%    | 95%    | NA  | COUNT  |
| 5  | Provision for Ln&Ls Losses/Avg Assets | 0.24-0.060.000.070.15                   | 0.31   | 0.58   | 1.41   | NA  | 93     |
| 6  | Provision for Ln&Ls Losses/Avg Lns&Ls | 0.40-0.100.000.100.27                   | 0.57   | 1.07   | 1.93   | NA  | 93     |
| 7  | Provision for Ln&Ls Losses/Net Losses | 163.62 -325.8719.8695.14119.44          | 195.48 | 388.01 | 775.77 | NA  | 93     |
| 9  | Ln&Ls Allowance/Total Loans & Leases  | 1.150.290.530.851.12                    | 1.34   | 1.96   | 2.57   | NA  | 93     |
| 10 | Ln&Ls Allowance/Net Ln&Ls Losses (X)  | 7.151.151.482.684.63                    | 9.76   | 18.31  | 32.00  | NA  | 83     |
| 11 | ALLL/Nonaccrual Assets                | 153.4542.9065.1493.75129.26             | 200.63 | 298.26 | 395.35 | NA  | 91     |
| 12 | Ln&Ls Allow/90+ Days PD+Nonaccr Ln&Ls | 124.4626.4742.4874.5997.36              | 155.13 | 290.04 | 327.89 | NA  | 93     |
| 14 | Gross Ln&Ls Losses/Avg Loans & Leases | 0.400.050.060.120.29                    | 0.55   | 1.02   | 2.19   | NA  | 93     |
| 15 | Recoveries/Avg Loans and Leases       | 0.120.000.010.040.09                    | 0.18   | 0.34   | 0.46   | NA  | 93     |
| 16 | Net Losses/Avg Loans and Leases       | 0.28-0.07-0.000.050.18                  | 0.41   | 0.73   | 1.72   | NA  | 93     |
| 17 | Write-downs, Trans Lns HFS/Avg Lns&Ls | 0.000.000.000.000.00                    | 0.00   | 0.00   | 0.01   | NA  | 93     |
| 18 | Recoveries/Prior Year-End Losses      | 9.870.902.955.768.50                    | 13.06  | 22.44  | 32.80  | NA  | 92     |
| 19 | Earnings Coverage of Net Losses (X)   | 12.61 -117.95-15.153.738.29             | 21.99  | 44.71  | 72.39  | NA  | 93     |
| 21 | NET LOAN AND LEASE LOSSES BY TYPE     | NA                                      | NA     | NA     | NA     | NA  | NA     |
| 23 | Real Estate Loans                     | 0.04-0.21-0.03-0.000.01                 | 0.08   | 0.18   | 0.26   | NA  | 92     |
| 24 | RE Loans Secured By 1-4 Family        | 0.09-0.10-0.030.000.05                  | 0.15   | 0.30   | 0.50   | NA  | 90     |
| 25 | Revolving                             | 0.12-0.10-0.020.000.00                  | 0.33   | 0.60   | 1.06   | NA  | 89     |
| 26 | Closed-End                            | 0.07-0.09-0.05-0.000.04                 | 0.11   | 0.27   | 0.45   | NA  | 90     |

## Step1:

Package to read pdf's not in cran as a library yet, but a project extracted from github  
<https://github.com/ropenscilabs/tabulizer>

```
install.packages("devtools", dependencies = TRUE)
library(devtools)
devtools::install_github(c("ropenscilabs/tabulizerjars", "ropenscilabs/tabulizer"), args = "--no-
multiarch")
```

## Step 2:

Set this to your jre link in the system

```
Sys.setenv(JAVA_HOME='C://Program Files//Java//jre1.8.0_101')
install.packages("rJava")
library(rJava)
```

## Step3:

To read tables from pdf, data manipulation and string splitting of column cells to clean dirty/combined data

```
install.packages("devtools", dependencies = TRUE)
library(devtools)
devtools::install_github(c("ropenscilabs/tabulizerjars", "ropenscilabs/tabulizer"), args = "--no-
multiarch")
```

## Step 4:

**Extracting the file**

```
f <- system.file("examples", "PeerGroup_1_March2016.pdf", package="tabulizer")
```

## Step 5:

**Making tabular structure of each page [list of 28 pages as 28 tables]**

```
out1 <- extract_tables(f, guess=FALSE, method = "data.frame")
```

## Step 6:

**Initialize the final result data set**

```
dfresult <- NULL
```

## Step 7:

Now the pdf structure is such that the pdf's each table is broken in 2 halves

set 1:- page 1- page 13

set 2:- page 14- page 26

set 3:- page 27,28

j <- 14

i<-1

## Step 8:

for(i in length(out1)/2-1)



## Step 9:

**Logic to replace empty values as na, if "all" cell values are na we "remove" the row also remove the rows havin '---' as the values first for 2nd half of pdf's, second for 1st half**

```
df2 <- as.data.frame(apply(out1[[j]], 2, function(x) gsub("^$|^ $", NA, x)))
row.has.na <-(apply(df2, 1, function(x){all(is.na(x))}))
sum(row.has.na)
df2 <- as.data.frame(df2[!row.has.na,])
del<-which(apply(df2, 1, function(x) any(grepl("\>--", x))))
df2<-df2[-del,]
```

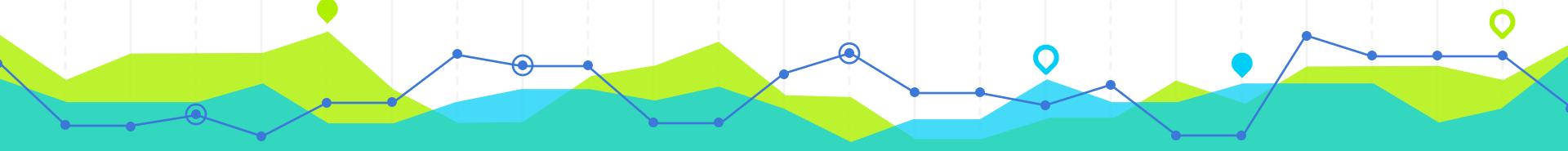
## Step 10:

Logic to unlist the values and flatten out the common cell values as a single list basically done to merge the 2 subsets of data to form 1 logical table logic to match the 'number of rows' to be able to do 'bind by column'

```
df2<-df2[-c(1:2),]
names(df2)=unlist(df2[c(1),])
names(df2)

df2 <- as.data.frame(df2[-1,])
```

```
df1<-df1[-c(1:2),]
names(df1)=unlist(df1[c(1),])
names(df2)
df1 <- as.data.frame(df1[-1,])
```



## Step 11:

Clean the data by using regex patterns for subset 2 values that are stuck in 1 column  
used 'gsub' function to be able to remove columns with entire 'na' values

```
df2.trial <- data.frame(t(sapply(df2[,2], function(y) gsub('(^-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})', '\\1d\\2d\\3d\\4d\\5d\\6d\\7d\\8', y)))
divisions<-8
```

## Step 12:

Clean the data by using regex patterns for subset 1 values that are stuck in 1 column  
used 'gsub' function to be able to remove columns with entire 'na' values

```
df1.trial <- data.frame(t(sapply(df1[,2], function(y) gsub('(^-*[0-9]*.[0-9]{2})(-*[0-9]*.[0-9]{2})', '\\1d\\2', y)))
divisions<-2
```

## 2: Semi Clean And Structured

|    | ANALYSIS RATIOS                        | Ratio                          | 5%    | 10%   | 25%   | 50%    | 75%    | 90%    | 95%    | BHC COUNT |
|----|----------------------------------------|--------------------------------|-------|-------|-------|--------|--------|--------|--------|-----------|
| 5  | Provision for Ln&Ls Losses/Avg Assets  | 0.24                           | -0.06 | 0.00  | 0.07  | 0.15   | 0.31   | 0.58   | 1.41   | 93        |
| 6  | Provision for Ln&Ls Losses/Avg Lns&Ls  | 0.40                           | -0.10 | 0.00  | 0.10  | 0.27   | 0.57   | 1.07   | 1.93   | 93        |
| 7  | Provision for Ln&Ls Losses/Net Losses  | 163.62 -325.8719.3695.14119.44 |       |       |       |        | 195.48 | 388.01 | 775.77 | 93        |
| 9  | Ln&Ls Allowance/Total Loans & Leases   | 1.15                           | 0.29  | 0.53  | 0.85  | 1.12   | 1.34   | 1.96   | 2.57   | 93        |
| 10 | Ln&Ls Allowance/Net Ln&Ls Losses (X)   | 7.15                           | 1.15  | 1.48  | 2.68  | 4.63   | 9.76   | 18.31  | 32.00  | 83        |
| 11 | ALLL/Nonaccrual Assets                 | 153.45                         | 42.00 | 65.14 | 93.75 | 120.26 | 200.63 | 208.26 | 305.35 | 91        |
| 12 | Ln&Ls Allow/90+ Days PD+NonaccrLn&Ls   | 124.46                         | 26.47 | 42.48 | 74.59 | 97.36  | 155.13 | 290.04 | 327.89 | 93        |
| 14 | Gross Lr&Ls Losses//Avg Loans & Leases | 0.10                           | 0.05  | 0.06  | 0.12  | 0.20   | 0.55   | 1.02   | 2.10   | 93        |
| 15 | Recoveries/Avg Loans and Leases        | 0.12                           | 0.00  | 0.01  | 0.04  | 0.09   | 0.18   | 0.34   | 0.46   | 93        |
| 16 | Net Losses/Avg Loans and Leases        | 0.28                           | -0.07 | -0.00 | 0.05  | 0.18   | 0.41   | 0.73   | 1.72   | 93        |
| 17 | Write-downs, Trans Lris HFS/Avg Lns&Ls | 0.00                           | 0.00  | 0.00  | 0.00  | 0.00   | 0.00   | 0.00   | 0.01   | 93        |
| 18 | Recoveries/Prior Year-End Losses       | 9.87                           | 0.90  | 2.95  | 5.76  | 8.50   | 13.06  | 22.44  | 32.80  | 92        |
| 19 | Earnings Coverage of Net Losses (X)    | 12.61 -117.95-15.153.738.29    |       |       |       |        | 21.99  | 44.71  | 72.39  | 93        |
| 21 | NET LOAN AND LEASE LOSSES BY TYPE      |                                |       |       |       |        | NA     | NA     | NA     | NA        |
| 23 | Real Estate Loans                      | 0.04                           | -0.21 | -0.03 | -0.00 | 0.01   | 0.08   | 0.18   | 0.26   | 92        |
| 24 | RE Loans Secured By 1-4 Family         | 0.09                           | -0.10 | -0.03 | 0.00  | 0.05   | 0.15   | 0.30   | 0.50   | 90        |
| 25 | Revolving                              | 0.18                           | -0.19 | -0.08 | 0.00  | 0.09   | 0.33   | 0.60   | 1.06   | 89        |
| 26 | Closed-End                             | 0.07                           | -0.09 | -0.05 | -0.00 | 0.04   | 0.11   | 0.27   | 0.45   | 90        |
| 27 | Commercial Real Estate Loans           | -0.00                          | -0.31 | -0.09 | -0.03 | -0.00  | 0.00   | 0.07   | 0.18   | 91        |
| 28 | Construction and Land Dev              | -0.03                          | -0.65 | -0.22 | -0.08 | -0.01  | 0.00   | 0.16   | 0.31   | 87        |

SEMI CLEAN  
DATA  
AND  
STRUCTURED  
DATA

## Step 13:

**cbind to form the original data tables that were distorted while being written on pdf's**

```
if(nrow(df1.yo1)==nrow(df2.yo2))
dffinal1 <-(cbind(as.data.frame(df1.yo1),as.data.frame(df2.yo2)))
```

```
write.csv(dffinal1, file = paste("page_",i,'.csv'))
dffinal1.new<- dffinal1[,-7]
```

```
to_be_removed <- names(dffinal1.new)[1]
colnames(dffinal1.new)[1] <- "Parameters"
```

**final row binding of all the data frames to make 1 csv**

```
dfresult <- bind_rows(dfresult,dffinal1.new)
```

**outputting the csv**

```
write.csv(dfresult, file = paste("PEER1_2016","_Q1','.csv'))
```

```
i<-i+1
```

```
j<-j+1
```



### 3: Clean, structured and beautiful data

| Parameters                            | 03/31/2016 | 03/31/2015 | 12/31/2015 | 12/31/2014 | 12/31/2013 | Ratio                          | 5%    | 10%   | 25%   | 50%    | 75%    | 90%    | 95%    | BHC COUNT |
|---------------------------------------|------------|------------|------------|------------|------------|--------------------------------|-------|-------|-------|--------|--------|--------|--------|-----------|
| Provision for Ln&Ls Losses/Avg Assets | 0.24       | 0.13       | 0.17       | 0.14       | 0.19       | 0.24                           | -0.06 | 0.00  | 0.07  | 0.15   | 0.31   | 0.58   | 1.41   | 93        |
| Provision for Ln&Ls Losses/Avg Lns&Ls | 0.40       | 0.20       | 0.28       | 0.23       | 0.32       | 0.40                           | -0.10 | 0.00  | 0.10  | 0.27   | 0.57   | 1.07   | 1.93   | 93        |
| Provision for Ln&Ls Losses/Net Losses | 163.63     | 89.81      | 109.43     | 105.35     | 64.28      | 163.62 -325.8719.8695.14119.44 |       |       |       |        | 195.48 | 388.01 | 775.77 | 93        |
| Ln&Ls Allowance/Total Loans & Leases  | 1.16       | 1.22       | 1.14       | 1.23       | 1.40       | 1.15                           | 0.29  | 0.53  | 0.85  | 1.12   | 1.34   | 1.96   | 2.57   | 93        |
| Ln&Ls Allowance/Net Ln&Ls Losses (X)  | 7.15       | 10.34      | 9.29       | 11.58      | 7.42       | 7.15                           | 1.15  | 1.48  | 2.68  | 4.63   | 9.76   | 18.31  | 32.00  | 83        |
| ALLL/Nonaccrual Assets                | 153.45     | 166.35     | 164.24     | 165.18     | 147.71     | 153.45                         | 42.90 | 65.14 | 93.75 | 129.26 | 200.63 | 298.26 | 395.35 | 91        |
| Ln&Ls Allow/90+ Days PD+Nonaccr Ln&Ls | 124.47     | 128.45     | 125.86     | 130.23     | 114.92     | 124.46                         | 26.47 | 42.48 | 74.59 | 97.36  | 155.13 | 290.04 | 327.89 | 93        |
| Gross Ln&Ls Losses/Avg Loans & Leases | 0.41       | 0.36       | 0.44       | 0.45       | 0.63       | 0.40                           | 0.05  | 0.06  | 0.12  | 0.29   | 0.55   | 1.02   | 2.19   | 93        |
| Recoveries/Avg Loans and Leases       | 0.13       | 0.13       | 0.14       | 0.15       | 0.18       | 0.12                           | 0.00  | 0.01  | 0.04  | 0.09   | 0.18   | 0.34   | 0.46   | 93        |
| Net Losses/Avg Loans and Leases       | 0.28       | 0.23       | 0.31       | 0.30       | 0.44       | 0.28                           | -0.07 | -0.00 | 0.05  | 0.18   | 0.41   | 0.73   | 1.72   | 93        |
| Write-downs, Trans Lns HFS/Avg Lns&Ls | 0.00       | 0.00       | 0.01       | 0.01       | 0.01       | 0.00                           | 0.00  | 0.00  | 0.00  | 0.00   | 0.00   | 0.00   | 0.01   | 93        |
| Recoveries/Prior Year-End Losses      | 9.88       | 9.39       | 39.28      | 33.44      | 23.10      | 9.87                           | 0.90  | 2.95  | 5.76  | 8.50   | 13.06  | 22.44  | 32.80  | 92        |
| Earnings Coverage of Net Losses (X)   | 12.61      | 16.67      | 15.90      | 32.42      | 19.55      | 12.61 -117.95-15.153.738.29    |       |       |       |        | 21.99  | 44.71  | 72.39  | 93        |
| NET LOAN AND LEASE LOSSES BY TYPE     |            |            |            | NA         | NA         |                                |       |       |       |        | NA     | NA     | NA     | NA        |
| Real Estate Loans                     | 0.04       | 0.11       | 0.09       | 0.17       | 0.34       | 0.04                           | -0.21 | -0.03 | -0.00 | 0.01   | 0.08   | 0.18   | 0.26   | 92        |
| RE Loans Secured By 1-4 Family        | 0.09       | 0.15       | 0.12       | 0.22       | 0.45       | 0.09                           | -0.10 | -0.03 | 0.00  | 0.05   | 0.15   | 0.30   | 0.50   | 90        |
| Revolving                             | 0.18       | 0.25       | 0.19       | 0.30       | 0.57       | 0.18                           | -0.19 | -0.08 | 0.00  | 0.09   | 0.33   | 0.60   | 1.06   | 89        |
| Closed-End                            | 0.07       | 0.12       | 0.10       | 0.18       | 0.39       | 0.07                           | -0.09 | -0.05 | -0.00 | 0.04   | 0.11   | 0.27   | 0.45   | 90        |
| Commercial Real Estate Loans          | -0.01      | 0.01       | 0.00       | 0.07       | 0.20       | -0.00                          | -0.31 | -0.09 | -0.03 | -0.00  | 0.00   | 0.07   | 0.18   | 91        |

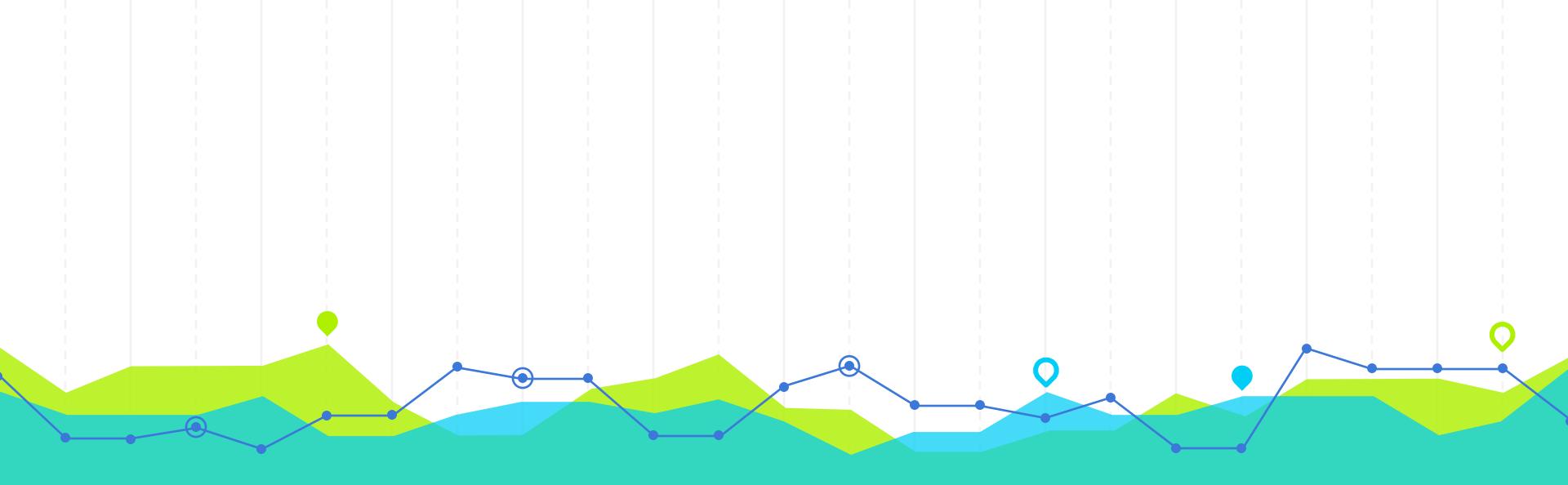
CLEAN AND WELL STRUCTURED DATA WITH COMMON COLUMNS FOR 'rbind'



# Analysis of Banking Organization

3

Risk Reports for the years 2012, 2013 and 2014

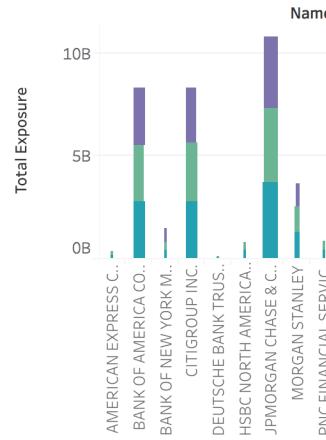


# Graphs Dashboard

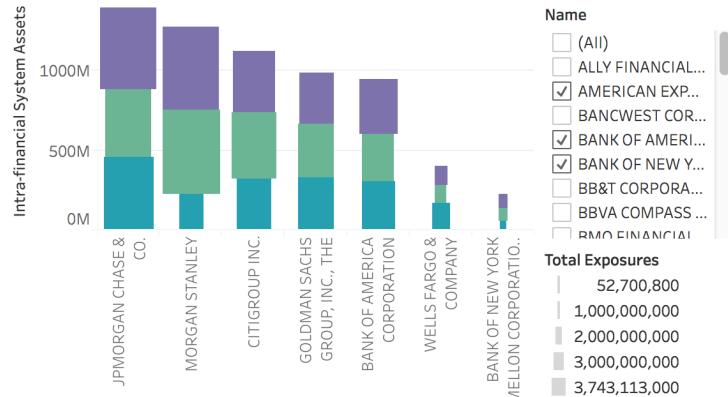
The charts are designed in the “Marimekko” design which represents the change in total exposure and Intra-financial system assets

The height along with the width represents the change in values over time.

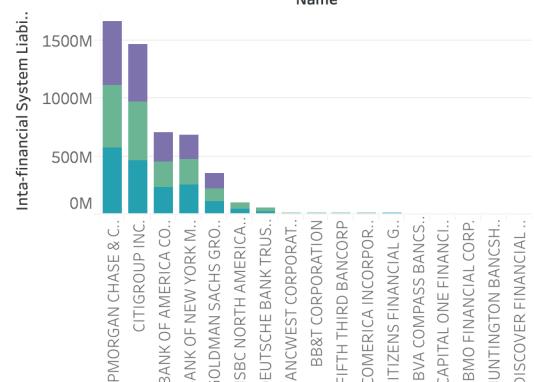
Total Exposure (In Billions)



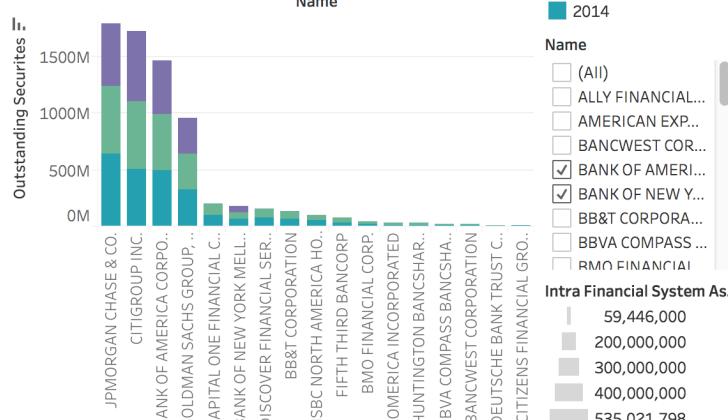
Intra-financial System Assets (In millions)



Intra-financial System Liabilities (In millions)



Securities Outstanding (In Millions)



date  
12/31/12 12/31/14  
D

Name  
(All) ALLY FINANCIAL... AMERICAN EXP... BANCWEST COR... BANK OF AMERI... BANK OF NEW Y... BB&T CORPORA... BBVA COMPASS ... RMO FINANCIAI  
Total Exposures  
52,700,800 1,000,000,000 2,000,000,000 3,000,000,000 3,743,113,000

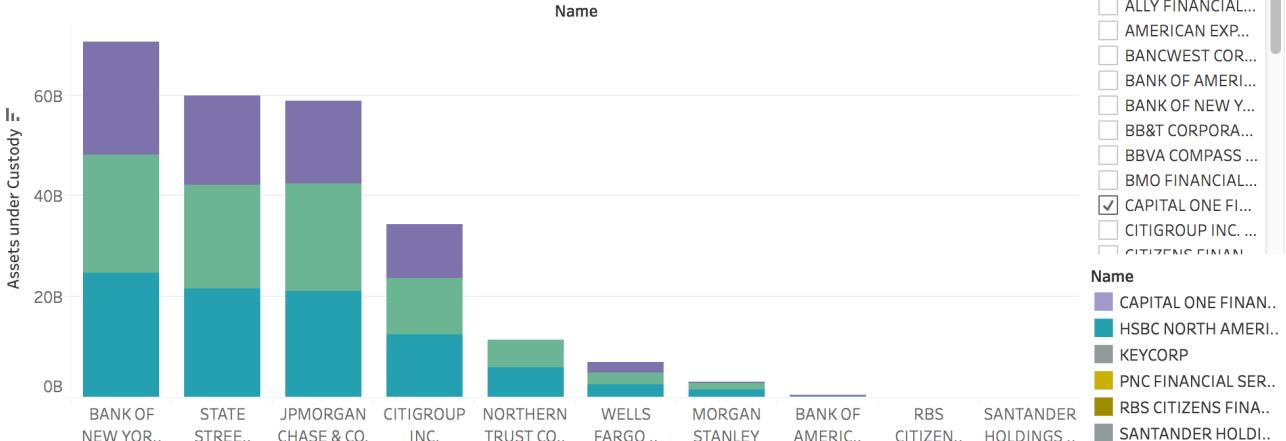
Year of Date  
2012 2013 2014  
Name  
(All) ALLY FINANCIAL... AMERICAN EXP... BANCWEST COR... BANK OF AMERI... BANK OF NEW Y... BB&T CORPORA... BBVA COMPASS ... RMO FINANCIAI

Name  
(All) ALLY FINANCIAL... AMERICAN EXP... BANCWEST COR... BANK OF AMERI... BANK OF NEW Y... BB&T CORPORA... BBVA COMPASS ... RMO FINANCIAI  
Intra Financial System Asse...

Intra Financial System Asse...  
59,446,000 200,000,000 300,000,000 400,000,000 535,021,798

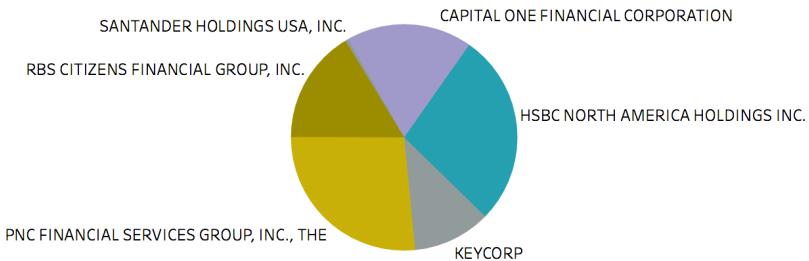
## Assets under Custody (In Billions)

The bar chart represents the value of the clients assets held by the company over the period of 3 years.



## Payments

The pie chart depicts the total payment value of different companies combined for all 3 years.



Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC...
- CITIZENS FINAN...

Name

- CAPITAL ONE FINAN...
- HSBC NORTH AMERI...
- KEYCORP
- PNC FINANCIAL SER...
- RBS CITIZENS FINA...
- SANTANDER HOLDI...
- SUNTRUST BANKS, I...

Payments

17,302,077,972

Name

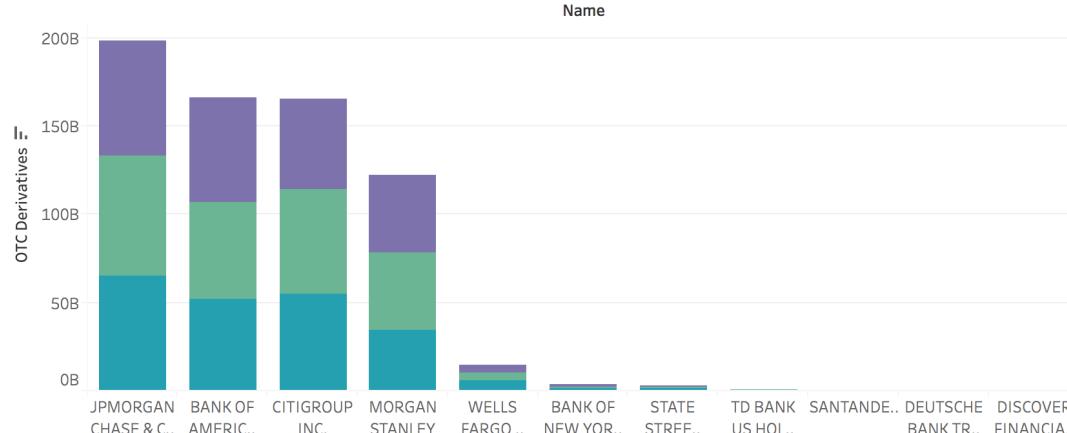
- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC...
- CITIZENS FINAN...

Year of Date

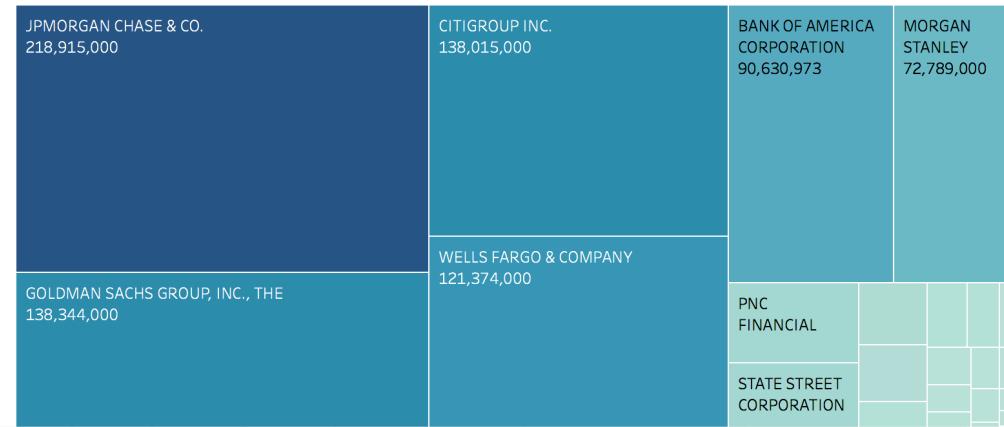
- 2012
- 2013
- 2014

“Over-the-counter” (OTC) Derivatives refers to the derivatives that are traded through a dealer network as opposed to a centralized exchange such as New York Stock Exchange (NYSE). Different colors represent values for 3 different years.

### OTC Derivatives (In Millions)



### Level 3 Assets (In Millions)



From the tree map we see that JP Morgan holds the maximum level three assets for all the 3 years.

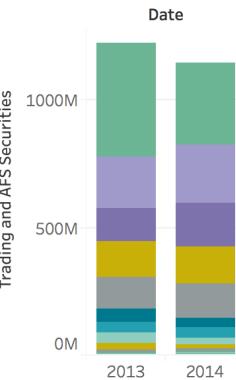
- Name
- (All)
  - ALLY FINANCIAL IN...
  - AMERICAN EXPRE...
  - BANCWEST CORPO...
  - BANK OF AMERICA...
  - BANK OF NEW YOR...
  - BB&T CORPORATIO...
  - BBVA COMPASS B...
  - BMO FINANCIAL C...
  - CAPITAL ONE FINA...
  - CITIGROUP INC. ...
  - CITIZENS FINANCI...
  - COMERICA INCORP...
  - DEUTSCHE BANKT...
  - DISCOVER FINANC...
  - FIFTH THIRD BANC...
  - GOLDMAN SACHS ...
  - HSBC NORTH AME...
  - HUNTINGTON BAN...
  - JPMORGAN CHASE...
  - KEYCORP ...
  - M&T BANK CORPO...
  - MORGAN STANLEY...
  - MUFG AMERICAS ...
  - NORTHERN TRUST ...
  - PNC FINANCIAL SE...
  - RBS CITIZENS FIN...
  - REGIONS FINANCI...
  - SANTANDER HOLD...
  - STATE STREET COR...
  - SUNTRUST BANKS...
  - TD BANK US HOLDI...
  - U.S. BANCORP ...
  - UNIONBANCAL CO...
  - WELLS FARGO & C...
  - ZIONS BANCORPO...

Level 3 assets

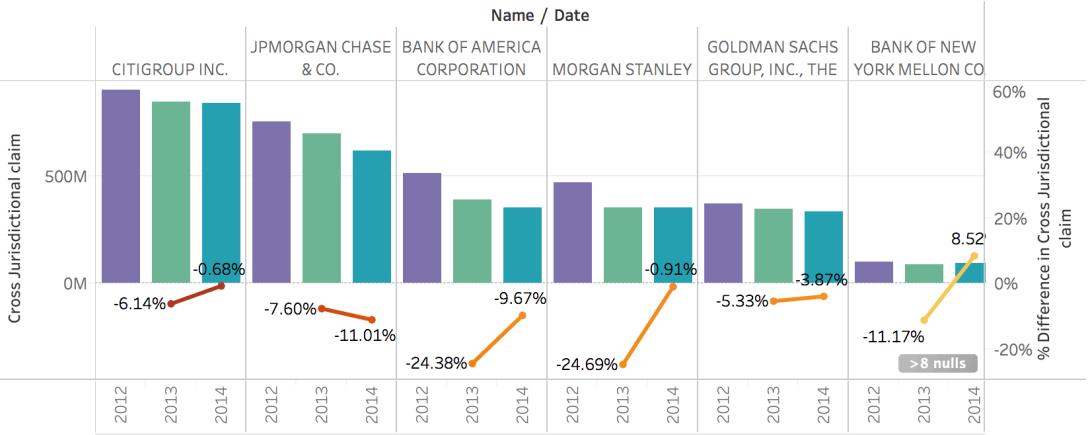
0 219M

The bubble chart is showing the investment capital that each firm raised on behalf of their corporation. As JPMorgan has the highest value it is occupying the biggest bubble.

### Trading and AFS Securities (In Millions)



### Cross Jurisdictional Claims (In Millions)



A cross claim jurisdiction represents a demand that is filed against a party on the same side of lawsuit. The trend chart clearly represents that over time the claims have declined for almost all the companies

### Underwriting



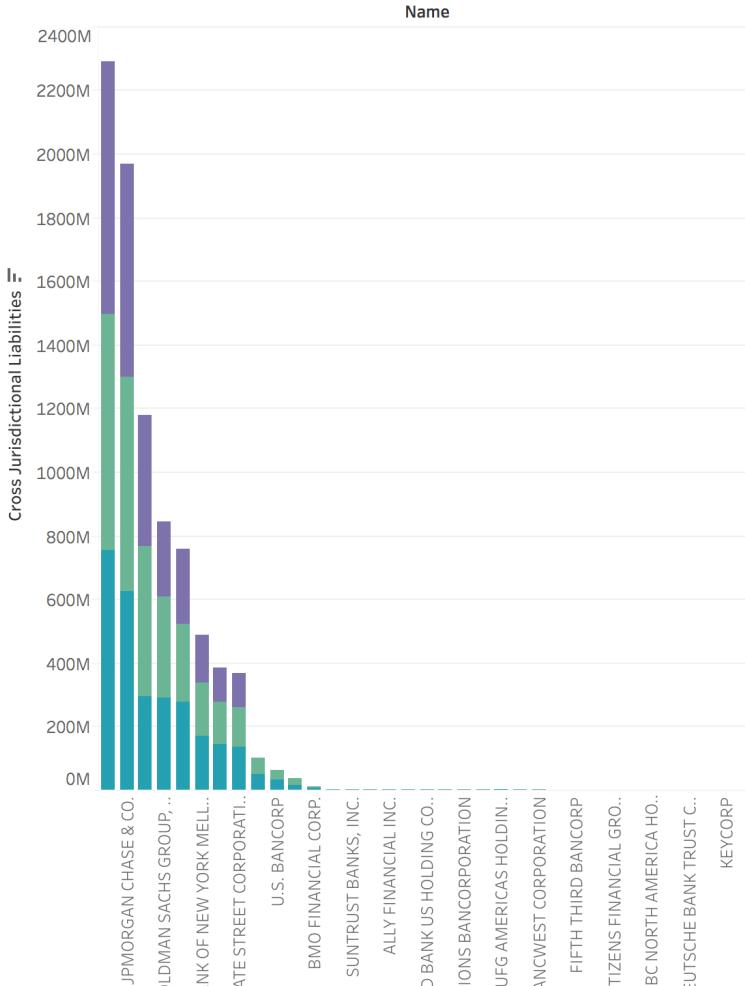
- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORAT...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC ...
- CITIZENS FINAN...
- COMMERCIAL INCS

- Name
- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORAT...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC ...
- CITIZENS FINAN...
- COMMERCIAL INCS

- Name
- BANK OF AMERIC..
- BB&T CORPORATI..
- BBVA COMPASS B...
- CITIGROUP INC.
- CITIZENS FINANC..
- DEUTSCHE BANK..
- DISCOVER FINAN..
- GOLDMAN SACHS..
- HSBC NORTH AM..
- HUNTINGTON BA..
- JPMORGAN CHAS..
- MORGAN STANLEY

The table highlights the cross jurisdictional liabilities in different range. The green shows the maximum value and the yellow is minimum.

### Cross Jurisdictional Liabilities (In Millions)

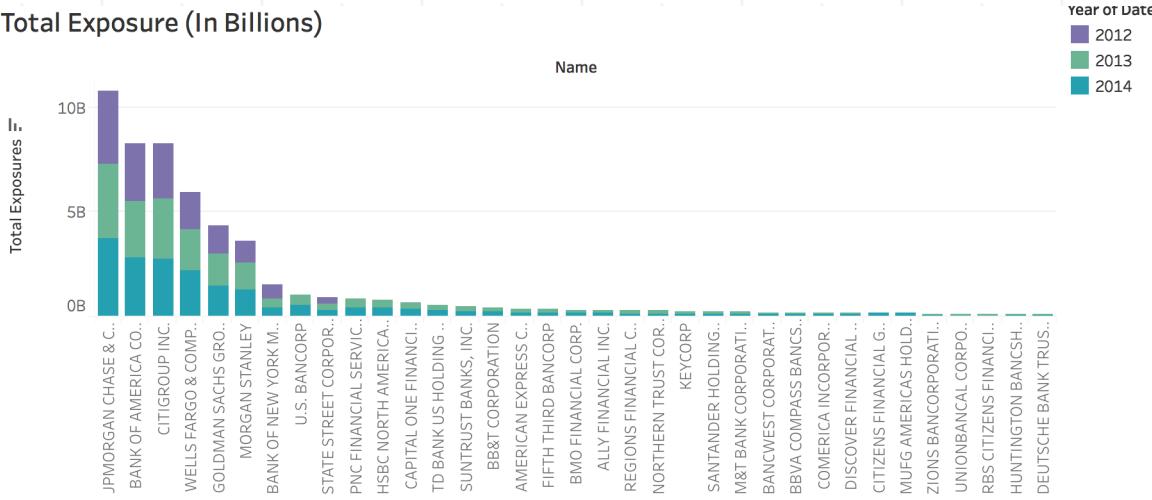


### Cross Jurisdictional Liabilities

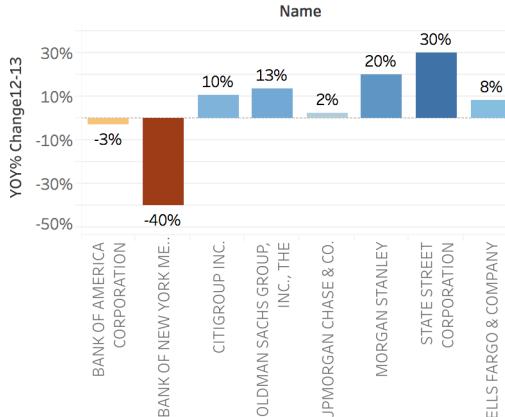


# Time Series Dashboard:

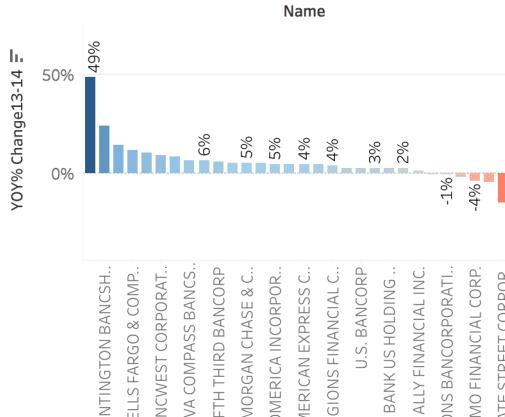
## Total Exposure (In Billions)



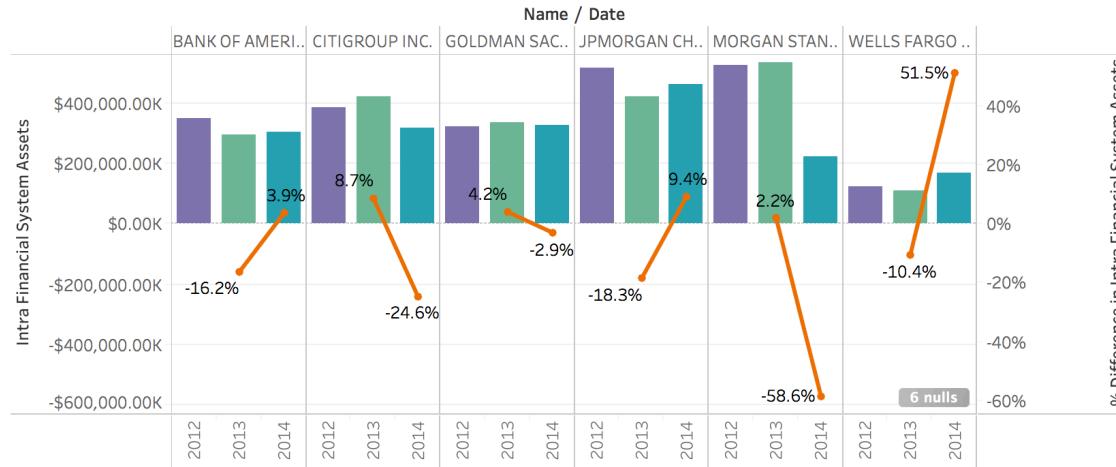
## % Change 2012-2013



## % Change 2013-2014



## Intra financial System Assests



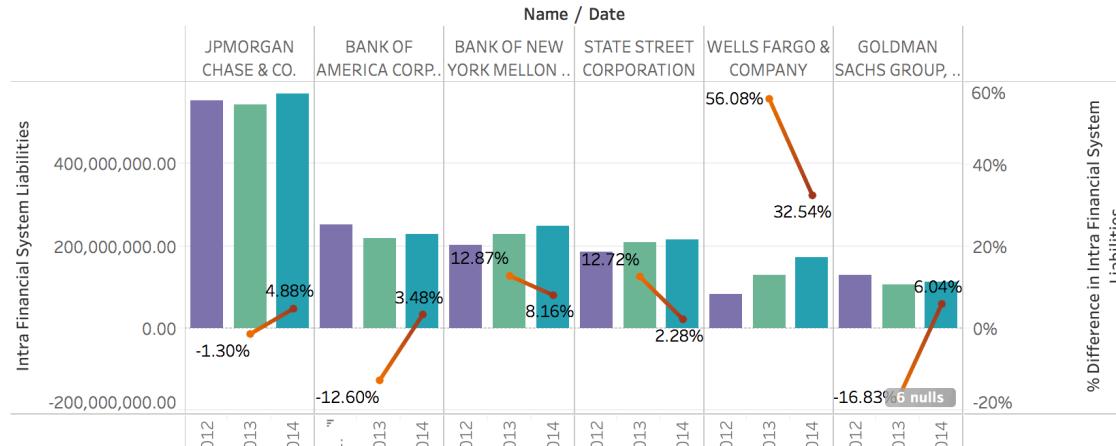
Year of Date

- (All)
- 2012
- 2013
- 2014

Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...

## Intra Financial System Liabilities



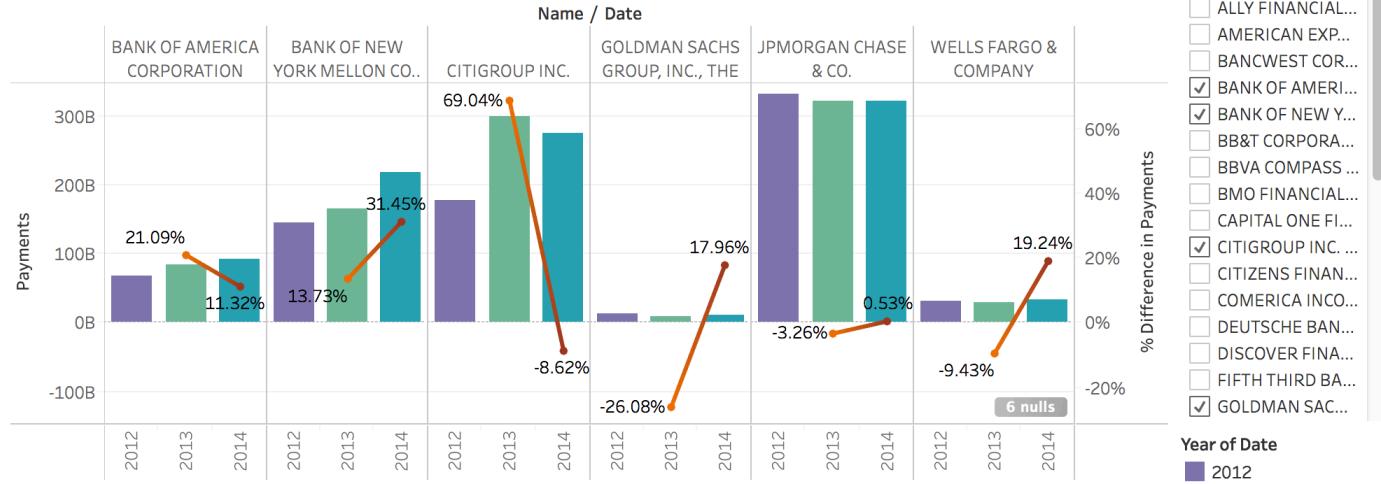
Year of Date

- 2012
- 2013
- 2014

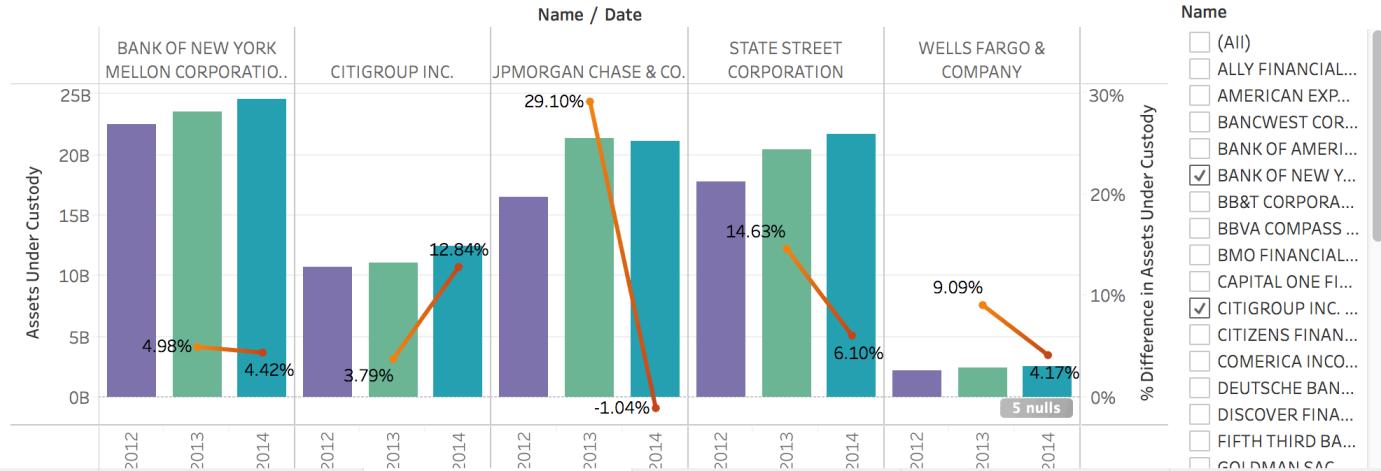
Name

- (All)
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...

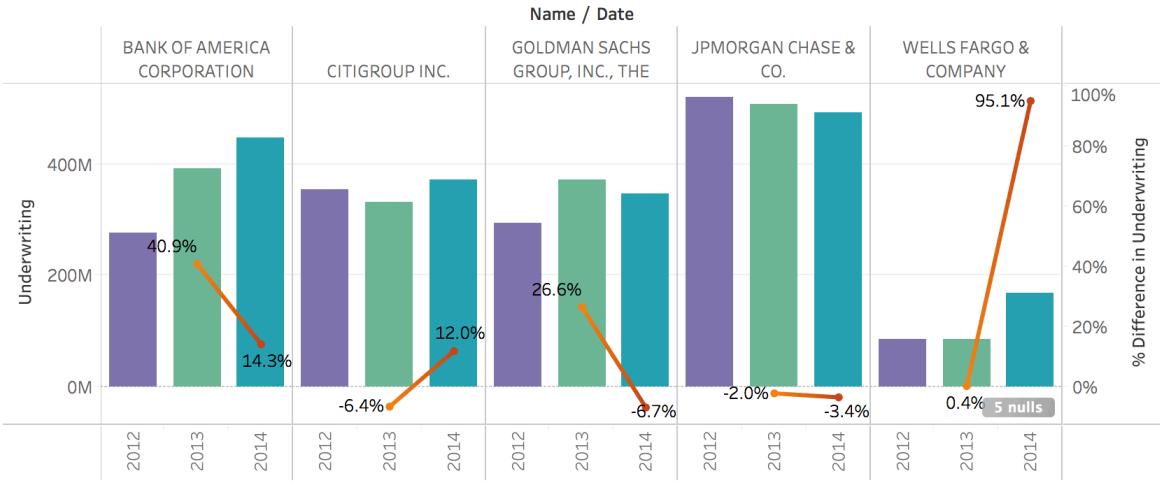
## Payments



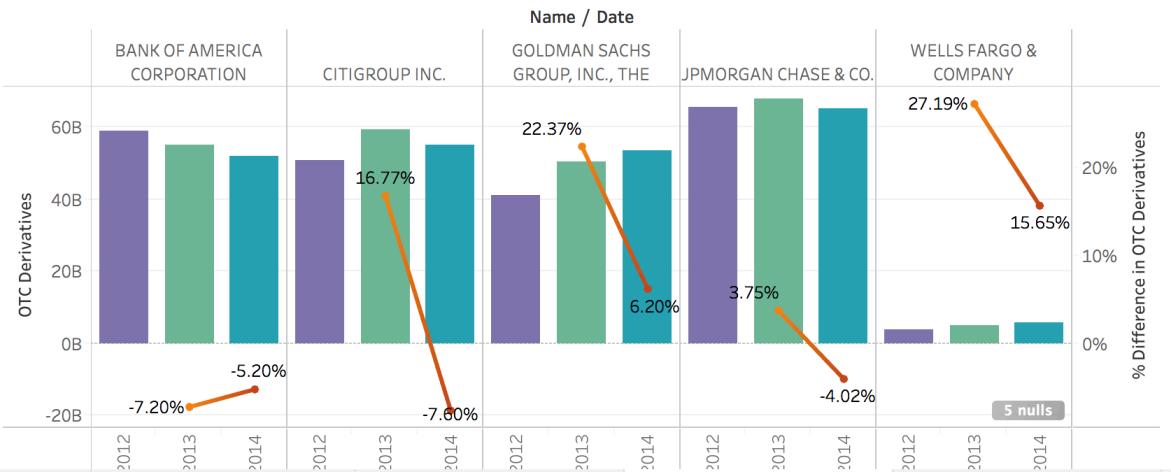
## Assets Under Custody



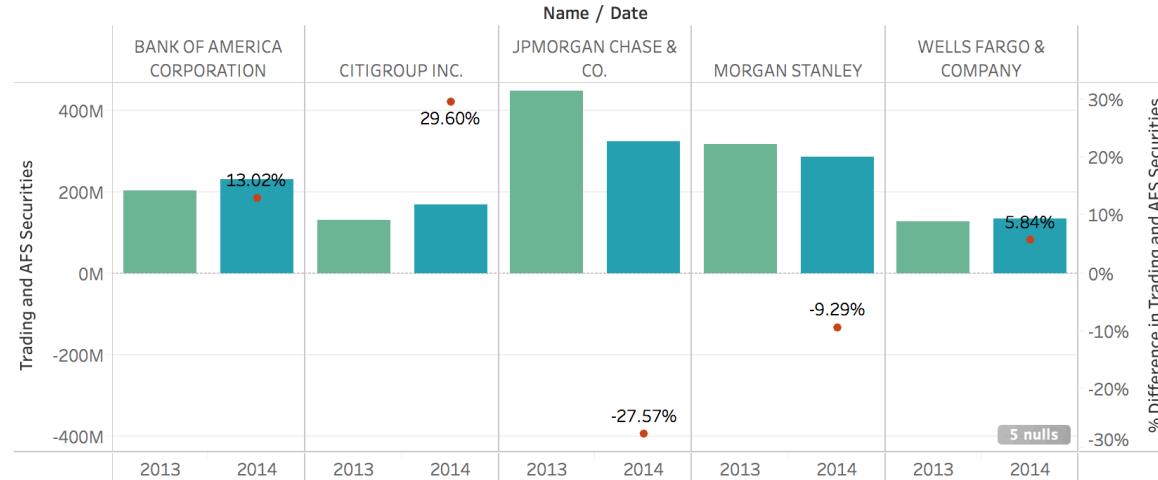
## Underwriting



## OTC Derivatives



# Trading and AFS Securities



Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...
- DISCOVER FINA...
- FIFTH THIRD BA...
- GOLDMAN SAC...
- HSBC NORTH A...

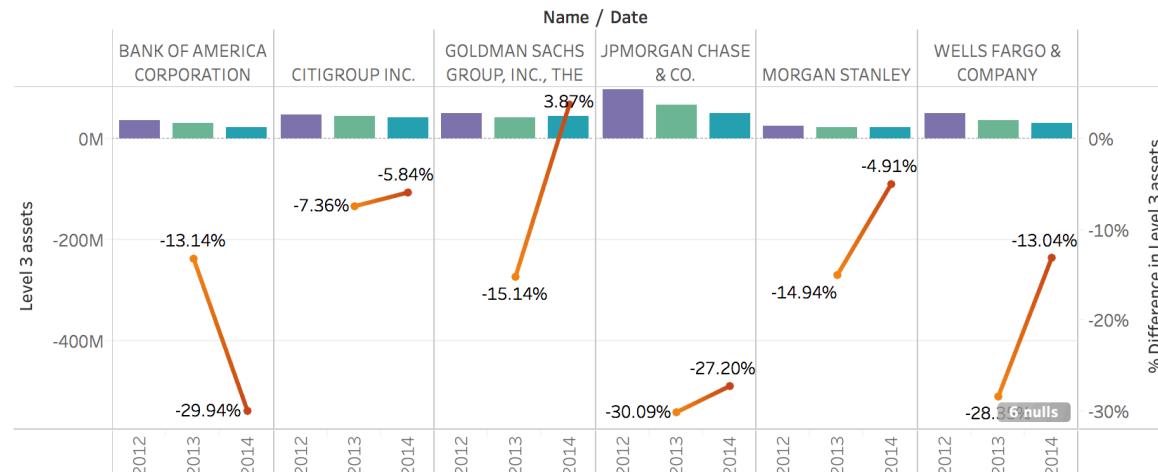
Year of Date

- 2013
- 2014

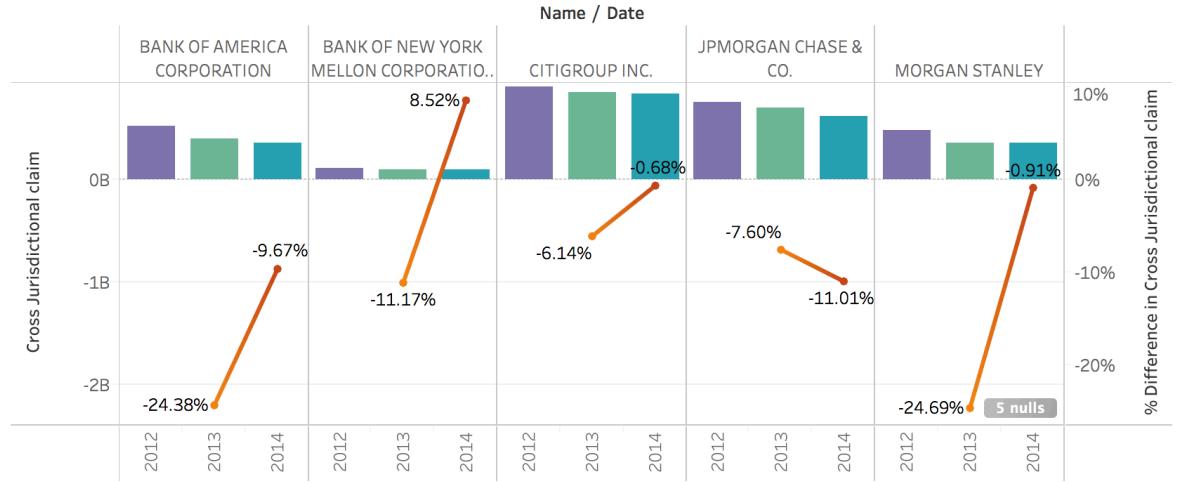
Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...
- DISCOVER FINA...
- FIFTH THIRD BA...
- GOLDMAN SAC...

# Level 3 Assets



## Cross Jurisdictional Claims



Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...
- DISCOVER FINA...
- FIFTH THIRD BA...
- GOLDMAN SAC...

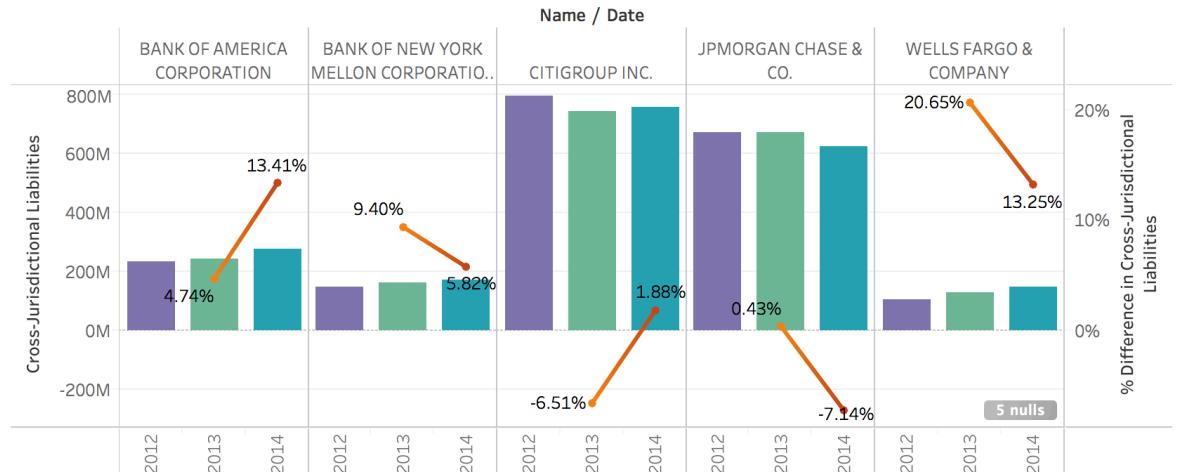
Year of Date

- 2012
- 2013
- 2014

Name

- (All)
- ALLY FINANCIAL...
- AMERICAN EXP...
- BANCWEST COR...
- BANK OF AMERI...
- BANK OF NEW Y...
- BB&T CORPORA...
- BBVA COMPASS ...
- BMO FINANCIAL...
- CAPITAL ONE FI...
- CITIGROUP INC. ...
- CITIZENS FINAN...
- COMERICA INCO...
- DEUTSCHE BAN...
- DISCOVER FINA...
- FIFTH THIRD BA...
- GOLDMAN SAC...

## Cross Jurisdictional Liabilities





# Thank You!

