Final_Project_Proposal

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1 The Effect of Data Breaches on Stock Price

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Using data from Morningstar, I will explore the way in which data breaches affect on the shareholder values of 11 companies in various industries. Through an analysis of stock prices in the 10-day period surrounding the report of the data breach of each company, the research will illustrate the effect of the data breach on the company's stock performance before, during, and after the breach as well as each industry's trends in reaction to breaches.

Data breaches are the subject of today's news, with people resorting to boycotting Facebook to protect their data from being shared with unauthorized third parties, whether intentionally or not. Facebook has reported reduced advertising revenues following large breaches and even a shift towards more user-produced content rather than branded and sponsored content.

The stock data for this project will come from Morningstar, specifically for an 11 day period, with the data breach report placed at the center of the date range, or timeline. Each company will have its data extracted from morningstar and placed alongside that of the others for individual as well as comparative analysis across companies and industries.

In this project, I will answer three questions: 1. How do data breaches affect shareholder value in general? 2. How do the effects of data breaches on shareholder value vary across industries? 3. Does the size of the breach have any effect on the change in stock price following the breach?

I will use line graphs to illustrate the behavior of each company's stock, while also calculating the percent change in stock price, whether positive or negative, following each breach. I will also calculate the mean percent change in stock price for each industry and company to compare averages. The size of each breach, or number of users affected by it, will be retreieved for further analysis comparing those numbers to the percent change in stock price.

The companies that will be analyzed in this project include:

Adobe: A software company.
Anthem: A health insurance company.
eBay: An online retailer.
Equifax: A credit reporting agency.
Facebook: An online social media platform.
Home Depot: A home improvement retailer.
JP Morgan: A multinational financial services firm.
SONY: A gaming and electronics company.
Target: A discount goods department store.
TJX: A discount goods department store.
Yahoo: An online news, search, media outlet.

The industries they represent include:
Finance
Insurance
Retail
Technology

1.1 1. Retreiving the Data

The data will be imported from Morningstar. I will take data specifically for each company and the 10 days surrounding the date of the breach. Each company will then have 11 rows of stock data, labeled from -5 to 5, representing the date's location before and after the breach report date. I have done this so that the data for each company can be merged cohesively and also presented more clearly on a graph. The number 0 on each timeline will represent the date that the breach was reported.

```
In [2]: import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        import datetime as dt
        import pandas_datareader as dr
```

This is where I begin extracting the data, using morningstar. The data includes the company's ticker, the eleven days surrounding the breach as well as the timeline number for each respective day, the day's close price, the day's high, the day's low, it's opening price, and trading volume. I have also included the type of industry each company is in, labeled as "Type." I will use this column to compare the effect of breaches across industries.

```
In [3]: breachdate = "3/16/2018" # Here, I identify the date the breach was reported.

        #The following two lines set the range of dates I will be looking at.
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        fb = dr.DataReader("FB", 'morningstar', start, end)
        #This brings in the stock information from morningstar for the specified dates.

        fb.reset_index(inplace=True)
        fb["Type"] = ("Tech")
        #This column identifies the industry the company is in.
        fb["Company"] = ("Facebook")
        #This column identifies the company.
        fb["Timeline"] = pd.RangeIndex(-5,6)
        #This column numbers the dates according to a timeline.
        fb
```

```
Out[3]:   Symbol       Date   Close    High     Low    Open    Volume  Type  \
        0     FB 2018-03-09  185.23  185.51  183.21  183.91  18526292  Tech
        1     FB 2018-03-12  184.76  186.10  184.22  185.23  15301229  Tech
        2     FB 2018-03-13  181.88  185.99  181.11  185.61  18067477  Tech
        3     FB 2018-03-14  184.19  184.25  181.85  182.60  16821728  Tech
```

```
4       FB 2018-03-15  183.86  184.00  182.19  183.24   15645035  Tech
5       FB 2018-03-16  185.09  185.33  183.41  184.49   24403438  Tech
6       FB 2018-03-19  172.56  177.17  170.06  177.01   88140060  Tech
7       FB 2018-03-20  168.15  170.20  161.95  167.47  129851768  Tech
8       FB 2018-03-21  169.39  173.40  163.30  164.80  106598834  Tech
9       FB 2018-03-22  164.89  170.27  163.72  166.13   73742979  Tech
10      FB 2018-03-23  159.39  167.10  159.02  165.44   53609706  Tech

     Company  Timeline
0   Facebook        -5
1   Facebook        -4
2   Facebook        -3
3   Facebook        -2
4   Facebook        -1
5   Facebook         0
6   Facebook         1
7   Facebook         2
8   Facebook         3
9   Facebook         4
10  Facebook         5
```

```
In [4]: breachdate = "9/7/2017"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        efx = dr.DataReader("EFX", 'morningstar', start, end)
        efx.reset_index(inplace=True)
        efx["Type"] = ("Financial")
        efx["Company"] = ("Equifax")
        efx["Timeline"] = pd.RangeIndex(-5,6)
        efx
```

```
Out[4]:    Symbol       Date   Close    High     Low    Open    Volume       Type  \
        0     EFX 2017-08-31  142.47  143.27  141.77  141.78    425417  Financial
        1     EFX 2017-09-01  141.59  143.37  141.59  142.73    363111  Financial
        2     EFX 2017-09-04  141.59  141.59  141.59  141.59         0  Financial
        3     EFX 2017-09-05  141.10  142.49  140.57  141.42    495148  Financial
        4     EFX 2017-09-06  141.39  142.14  141.02  141.58    452154  Financial
        5     EFX 2017-09-07  142.72  143.27  141.35  141.45    499797  Financial
        6     EFX 2017-09-08  123.23  125.50  117.25  121.82  16848398  Financial
        7     EFX 2017-09-11  113.12  122.00  111.17  121.53   9820487  Financial
        8     EFX 2017-09-12  115.96  116.08  112.18  112.97   6937090  Financial
        9     EFX 2017-09-13   98.99  116.75   98.04  116.55  17494316  Financial
        10    EFX 2017-09-14   96.66  100.75   89.59   98.69  34565048  Financial

            Company  Timeline
        0   Equifax        -5
        1   Equifax        -4
        2   Equifax        -3
```

```
3   Equifax        -2
4   Equifax        -1
5   Equifax         0
6   Equifax         1
7   Equifax         2
8   Equifax         3
9   Equifax         4
10  Equifax         5
```

```
In [5]: breachdate = "12/14/2016"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        yhoo = dr.DataReader("YHOO", 'morningstar', start, end)
        yhoo.reset_index(inplace=True)
        yhoo["Type"] = ("Tech")
        yhoo["Company"] = ("Yahoo")
        yhoo["Timeline"] = pd.RangeIndex(-5,6)
        yhoo
```

```
Out[5]:    Symbol       Date  Close   High      Low   Open    Volume  Type Company  \
        0    YHOO 2016-12-07  40.52  40.57  39.7500  39.98   7208492  Tech   Yahoo
        1    YHOO 2016-12-08  41.41  41.60  40.4168  40.66   9171707  Tech   Yahoo
        2    YHOO 2016-12-09  41.76  41.80  41.4400  41.52   6836112  Tech   Yahoo
        3    YHOO 2016-12-12  41.30  41.53  41.1250  41.45   4451709  Tech   Yahoo
        4    YHOO 2016-12-13  41.47  41.79  41.1400  41.35   6564552  Tech   Yahoo
        5    YHOO 2016-12-14  40.91  41.53  40.8300  41.44  19555694  Tech   Yahoo
        6    YHOO 2016-12-15  38.41  40.00  38.2500  40.00  43669990  Tech   Yahoo
        7    YHOO 2016-12-16  38.61  39.22  38.4200  38.62  21694081  Tech   Yahoo
        8    YHOO 2016-12-19  38.42  38.79  38.2700  38.66  13615511  Tech   Yahoo
        9    YHOO 2016-12-20  39.16  39.18  38.2400  38.40  25008427  Tech   Yahoo
        10   YHOO 2016-12-21  39.15  39.32  38.9700  39.08   8296514  Tech   Yahoo

            Timeline
        0         -5
        1         -4
        2         -3
        3         -2
        4         -1
        5          0
        6          1
        7          2
        8          3
        9          4
        10         5
```

```
In [6]: breachdate = "9/8/2014"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        hd = dr.DataReader("HD", 'morningstar', start, end)
        hd.reset_index(inplace=True)
        hd["Type"] = ("Retail")
        hd["Company"] = ("Home Depot")
        hd["Timeline"] = pd.RangeIndex(-5,6)
        hd
```

```
Out[6]:    Symbol       Date  Close   High      Low   Open    Volume    Type  \
        0      HD 2014-09-01  93.50  93.50  93.5000  93.50         0  Retail
        1      HD 2014-09-02  91.15  93.31  89.8500  93.04  20753212  Retail
        2      HD 2014-09-03  89.00  91.31  88.9800  91.11  15413898  Retail
        3      HD 2014-09-04  89.93  90.75  89.0000  89.00   8453181  Retail
        4      HD 2014-09-05  91.61  91.64  89.2809  89.66   7748251  Retail
        5      HD 2014-09-08  90.82  91.78  90.5700  91.38   4888298  Retail
        6      HD 2014-09-09  88.93  90.33  88.7750  90.21   8105283  Retail
        7      HD 2014-09-10  89.25  89.40  88.3300  88.66   6245512  Retail
        8      HD 2014-09-11  89.22  89.42  88.6200  89.07   4538983  Retail
        9      HD 2014-09-12  88.84  89.50  88.4600  89.38   4593705  Retail
        10     HD 2014-09-15  89.38  89.54  88.6000  89.18   3935032  Retail

               Company  Timeline
        0   Home Depot        -5
        1   Home Depot        -4
        2   Home Depot        -3
        3   Home Depot        -2
        4   Home Depot        -1
        5   Home Depot         0
        6   Home Depot         1
        7   Home Depot         2
        8   Home Depot         3
        9   Home Depot         4
        10  Home Depot         5
```

```
In [7]: breachdate = "12/19/2013"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        tgt = dr.DataReader("TGT", 'morningstar', start, end)
        tgt.reset_index(inplace=True)
        tgt["Type"] = ("Retail")
        tgt["Company"] = ("Target")
        tgt["Timeline"] = pd.RangeIndex(-5,6)
        tgt
```

```
Out[7]:    Symbol       Date  Close   High      Low   Open   Volume    Type Company  \
        0     TGT 2013-12-12  62.89  63.24  62.7500  62.94  4029226  Retail  Target
        1     TGT 2013-12-13  62.36  63.24  62.2900  63.23  4751040  Retail  Target
        2     TGT 2013-12-16  62.17  62.51  61.7300  62.44  4776792  Retail  Target
        3     TGT 2013-12-17  61.65  62.15  61.4400  62.12  5315422  Retail  Target
```

```
4     TGT 2013-12-18  63.55  63.59  62.4300  62.52  8305331  Retail  Target
5     TGT 2013-12-19  62.15  62.89  61.9800  62.22  7903937  Retail  Target
6     TGT 2013-12-20  62.49  62.66  62.0200  62.12  6869129  Retail  Target
7     TGT 2013-12-23  61.88  62.15  61.5349  62.00  5726545  Retail  Target
8     TGT 2013-12-24  61.71  61.75  61.2600  61.60  3356284  Retail  Target
9     TGT 2013-12-25  61.71  61.71  61.7100  61.71        0  Retail  Target
10    TGT 2013-12-26  62.48  62.59  61.7400  61.74  3972228  Retail  Target

    Timeline
0         -5
1         -4
2         -3
3         -2
4         -1
5          0
6          1
7          2
8          3
9          4
10         5
```

```
In [8]: breachdate = "5/21/2013"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        ebay = dr.DataReader("EBAY", 'morningstar', start, end)
        ebay.reset_index(inplace=True)
        ebay["Type"] = ("Retail")
        ebay["Company"] = ("Ebay")
        ebay["Timeline"] = pd.RangeIndex(-5,6)
        ebay
```

```
Out[8]:    Symbol       Date    Close     High      Low     Open    Volume    Type  \
        0    EBAY 2013-05-14  23.6828  23.7417  23.2072  23.2325  21924170  Retail
        1    EBAY 2013-05-15  23.8427  23.8554  23.5944  23.6828  20357669  Retail
        2    EBAY 2013-05-16  23.4850  23.9480  23.4513  23.9059  20246798  Retail
        3    EBAY 2013-05-17  23.8680  24.0342  23.7670  23.7754  27464373  Retail
        4    EBAY 2013-05-20  23.5481  23.8469  23.4660  23.8049  20813269  Retail
        5    EBAY 2013-05-21  23.1272  23.6155  23.1230  23.5523  30956267  Retail
        6    EBAY 2013-05-22  22.8958  23.4934  22.7821  23.2451  27209575  Retail
        7    EBAY 2013-05-23  22.9294  22.9631  22.4412  22.5591  22583084  Retail
        8    EBAY 2013-05-24  22.9968  23.0010  22.5464  22.6306  17368809  Retail
        9    EBAY 2013-05-27  22.9968  22.9968  22.9968  22.9968         0  Retail
        10   EBAY 2013-05-28  23.3713  23.6744  23.2367  23.2535  23160436  Retail

           Company  Timeline
        0     Ebay        -5
        1     Ebay        -4
        2     Ebay        -3
```

```
3     Ebay        -2
4     Ebay        -1
5     Ebay         0
6     Ebay         1
7     Ebay         2
8     Ebay         3
9     Ebay         4
10    Ebay         5
```

```
In [9]: breachdate = "2015-2-4"
        start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
        end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
        antm = dr.DataReader("ANTM", 'morningstar', start, end)
        antm.reset_index(inplace=True)
        antm["Type"] = ("Insurance")
        antm["Company"] = ("Anthem")
        antm["Timeline"] = pd.RangeIndex(-5,6)
        antm
```

```
Out[9]:    Symbol       Date   Close    High     Low    Open   Volume       Type  \
        0    ANTM 2015-01-28  133.58  139.28  133.03  138.21  3476169  Insurance
        1    ANTM 2015-01-29  137.10  137.37  133.76  134.62  1950356  Insurance
        2    ANTM 2015-01-30  134.96  137.40  134.14  135.41  2246853  Insurance
        3    ANTM 2015-02-02  135.50  135.59  132.94  134.96  1819776  Insurance
        4    ANTM 2015-02-03  136.96  137.24  135.50  136.08  1710527  Insurance
        5    ANTM 2015-02-04  137.65  138.67  135.40  136.49  1674628  Insurance
        6    ANTM 2015-02-05  137.23  138.37  135.40  135.50  2314611  Insurance
        7    ANTM 2015-02-06  135.69  137.23  135.09  136.95  2244555  Insurance
        8    ANTM 2015-02-09  134.88  135.69  134.38  134.79  1745541  Insurance
        9    ANTM 2015-02-10  138.74  139.04  135.61  136.38  2100226  Insurance
        10   ANTM 2015-02-11  141.49  141.72  138.56  138.60  2104377  Insurance

           Company  Timeline
        0   Anthem        -5
        1   Anthem        -4
        2   Anthem        -3
        3   Anthem        -2
        4   Anthem        -1
        5   Anthem         0
        6   Anthem         1
        7   Anthem         2
        8   Anthem         3
        9   Anthem         4
        10  Anthem         5
```

```
In [10]: breachdate = "2014-10-2"
         start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
         end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
         jpm = dr.DataReader("JPM", 'morningstar', start, end)
         jpm.reset_index(inplace=True)
         jpm["Type"] = ("Financial")
         jpm["Company"] = ("JP Morgan")
         jpm["Timeline"] = pd.RangeIndex(-5,6)
         jpm

Out[10]:    Symbol       Date  Close    High     Low   Open    Volume       Type  \
         0     JPM 2014-09-25  60.15  61.500  60.150  61.49  16346723  Financial
         1     JPM 2014-09-26  60.56  60.880  60.320  60.33  11948887  Financial
         2     JPM 2014-09-29  60.33  60.500  59.730  60.03  10694938  Financial
         3     JPM 2014-09-30  60.24  60.740  60.130  60.40  14384783  Financial
         4     JPM 2014-10-01  59.77  60.400  59.730  60.24  18995987  Financial
         5     JPM 2014-10-02  58.84  59.490  58.610  59.15  24561606  Financial
         6     JPM 2014-10-03  60.30  60.385  59.050  59.25  18321078  Financial
         7     JPM 2014-10-06  60.18  60.800  60.000  60.78  11578147  Financial
         8     JPM 2014-10-07  59.27  59.920  59.185  59.92  14542010  Financial
         9     JPM 2014-10-08  60.40  60.430  59.180  59.36  15834553  Financial
         10    JPM 2014-10-09  59.08  60.330  58.890  60.33  19191404  Financial

               Company  Timeline
         0   JP Morgan        -5
         1   JP Morgan        -4
         2   JP Morgan        -3
         3   JP Morgan        -2
         4   JP Morgan        -1
         5   JP Morgan         0
         6   JP Morgan         1
         7   JP Morgan         2
         8   JP Morgan         3
         9   JP Morgan         4
         10  JP Morgan         5

In [574]: breachdate = "2007-1-17"
          start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
          end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
          tjx = dr.DataReader("TJX", 'morningstar', start, end)
          tjx.reset_index(inplace=True)
          tjx["Type"] = ("Retail")
          tjx["Company"] = ("TJX")
          tjx["Timeline"] = pd.RangeIndex(-5,6)
          tjx

Out[574]:    Symbol       Date   Close    High     Low    Open   Volume    Type  \
          0     TJX 2007-01-10  14.745  14.805  14.485  14.585  3447200  Retail
          1     TJX 2007-01-11  14.970  14.990  14.750  14.750  5143600  Retail
          2     TJX 2007-01-12  14.970  15.080  14.800  14.845  8109600  Retail
          3     TJX 2007-01-15  14.970  15.080  14.800  14.845        0  Retail
```

```
4     TJX 2007-01-16  14.925  15.000  14.655  14.970   5418400  Retail
5     TJX 2007-01-17  14.815  15.050  14.425  14.865  10458400  Retail
6     TJX 2007-01-18  14.750  14.795  14.500  14.775  10340200  Retail
7     TJX 2007-01-19  15.015  15.035  14.595  14.915   8891600  Retail
8     TJX 2007-01-22  14.975  15.020  14.760  14.985   9597200  Retail
9     TJX 2007-01-23  14.920  15.040  14.815  14.975   5838600  Retail
10    TJX 2007-01-24  15.020  15.120  14.910  14.935   4578800  Retail

   Company  Timeline
0      TJX        -5
1      TJX        -4
2      TJX        -3
3      TJX        -2
4      TJX        -1
5      TJX         0
6      TJX         1
7      TJX         2
8      TJX         3
9      TJX         4
10     TJX         5
```

```
In [575]: breachdate = "2011-4-20"
          start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
          end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
          sne = dr.DataReader("SNE", 'morningstar', start, end)
          sne.reset_index(inplace=True)
          sne["Type"] = ("Tech")
          sne["Company"] = ("SONY")
          sne["Timeline"] = pd.RangeIndex(-5,6)
          sne
```

```
Out[575]:    Symbol       Date  Close   High    Low    Open   Volume  Type Company  \
          0     SNE 2011-04-13  29.78  29.99  29.610  29.960  1460889  Tech    SONY
          1     SNE 2011-04-14  29.69  29.80  29.581  29.690   515569  Tech    SONY
          2     SNE 2011-04-15  29.69  29.72  29.520  29.540   591641  Tech    SONY
          3     SNE 2011-04-18  29.25  29.32  28.910  28.950   876065  Tech    SONY
          4     SNE 2011-04-19  29.71  29.78  29.410  29.420   560330  Tech    SONY
          5     SNE 2011-04-20  30.14  30.15  29.940  30.030   909392  Tech    SONY
          6     SNE 2011-04-21  30.50  30.63  30.350  30.620  1276821  Tech    SONY
          7     SNE 2011-04-22  30.50  30.63  30.350  30.620        0  Tech    SONY
          8     SNE 2011-04-25  30.09  30.26  29.910  30.260   595962  Tech    SONY
          9     SNE 2011-04-26  29.79  29.79  29.560  29.755   773682  Tech    SONY
          10    SNE 2011-04-27  29.03  29.11  28.860  29.060  1517514  Tech    SONY

              Timeline
          0         -5
          1         -4
          2         -3
```

```
3          -2
4          -1
5           0
6           1
7           2
8           3
9           4
10          5
```

```
In [576]: breachdate = "2013-10-3"
          start = pd.to_datetime(breachdate) + pd.DateOffset(days=-7)
          end = pd.to_datetime(breachdate) + pd.DateOffset(days=7)
          adbe = dr.DataReader("ADBE", 'morningstar', start, end)
          adbe.reset_index(inplace=True)
          adbe["Type"] = ("Tech")
          adbe["Company"] = ("Adobe")
          adbe["Timeline"] = pd.RangeIndex(-5,6)
          adbe
```

```
Out[576]:    Symbol       Date   Close   High     Low   Open   Volume  Type Company  \
          0    ADBE 2013-09-26  52.100  52.38  51.810  52.00  2902916  Tech   Adobe
          1    ADBE 2013-09-27  52.030  52.48  51.650  51.71  2382014  Tech   Adobe
          2    ADBE 2013-09-30  51.940  52.15  51.202  51.50  2748601  Tech   Adobe
          3    ADBE 2013-10-01  52.430  52.48  51.840  52.10  3243476  Tech   Adobe
          4    ADBE 2013-10-02  51.520  52.28  51.290  51.88  3691656  Tech   Adobe
          5    ADBE 2013-10-03  50.880  51.65  50.540  51.61  3862291  Tech   Adobe
          6    ADBE 2013-10-04  51.570  51.67  50.020  50.09  3881470  Tech   Adobe
          7    ADBE 2013-10-07  50.820  51.34  50.790  51.05  2582671  Tech   Adobe
          8    ADBE 2013-10-08  49.580  50.97  49.440  50.93  4953841  Tech   Adobe
          9    ADBE 2013-10-09  49.450  49.87  48.870  49.62  4347529  Tech   Adobe
          10   ADBE 2013-10-10  51.165  51.22  49.860  50.06  3740948  Tech   Adobe

              Timeline
          0         -5
          1         -4
          2         -3
          3         -2
          4         -1
          5          0
          6          1
          7          2
          8          3
          9          4
          10         5
```

2 2. Organizing the Data

Now I will take all of the data extracted from morningstar above, create common columns, and then place all dataframes on top of eachother to make on large dataframe. I will then perform operations on the larger dataframe to sort and group by the variables I would like to analyze.

```
In [577]: all_dfs = [fb, efx, tgt,jpm,adbe,hd,sne,tjx,antm,ebay,yhoo]

          # Give all df's common column names so that they can be concatenated cohesively.
          for df in all_dfs:
              df.columns = ['Symbol', 'Date', 'Close', 'High', 'Low', 'Open', 'Volume', 'Indus

          bigdata = pd.concat(all_dfs).reset_index(drop=True)

          bigdata
```

```
Out[577]:     Symbol        Date     Close      High       Low      Open     Volume  \
          0       FB  2018-03-09  185.2300  185.5100  183.2100  183.9100   18526292
          1       FB  2018-03-12  184.7600  186.1000  184.2200  185.2300   15301229
          2       FB  2018-03-13  181.8800  185.9900  181.1100  185.6100   18067477
          3       FB  2018-03-14  184.1900  184.2500  181.8500  182.6000   16821728
          4       FB  2018-03-15  183.8600  184.0000  182.1900  183.2400   15645035
          5       FB  2018-03-16  185.0900  185.3300  183.4100  184.4900   24403438
          6       FB  2018-03-19  172.5600  177.1700  170.0600  177.0100   88140060
          7       FB  2018-03-20  168.1500  170.2000  161.9500  167.4700  129851768
          8       FB  2018-03-21  169.3900  173.4000  163.3000  164.8000  106598834
          9       FB  2018-03-22  164.8900  170.2700  163.7200  166.1300   73742979
          10      FB  2018-03-23  159.3900  167.1000  159.0200  165.4400   53609706
          11     EFX  2017-08-31  142.4700  143.2700  141.7700  141.7800     425417
          12     EFX  2017-09-01  141.5900  143.3700  141.5900  142.7300     363111
          13     EFX  2017-09-04  141.5900  141.5900  141.5900  141.5900          0
          14     EFX  2017-09-05  141.1000  142.4900  140.5700  141.4200     495148
          15     EFX  2017-09-06  141.3900  142.1400  141.0200  141.5800     452154
          16     EFX  2017-09-07  142.7200  143.2700  141.3500  141.4500     499797
          17     EFX  2017-09-08  123.2300  125.5000  117.2500  121.8200   16848398
          18     EFX  2017-09-11  113.1200  122.0000  111.1700  121.5300    9820487
          19     EFX  2017-09-12  115.9600  116.0800  112.1800  112.9700    6937090
          20     EFX  2017-09-13   98.9900  116.7500   98.0400  116.5500   17494316
          21     EFX  2017-09-14   96.6600  100.7500   89.5900   98.6900   34565048
          22     TGT  2013-12-12   62.8900   63.2400   62.7500   62.9400    4029226
          23     TGT  2013-12-13   62.3600   63.2400   62.2900   63.2300    4751040
          24     TGT  2013-12-16   62.1700   62.5100   61.7300   62.4400    4776792
          25     TGT  2013-12-17   61.6500   62.1500   61.4400   62.1200    5315422
          26     TGT  2013-12-18   63.5500   63.5900   62.4300   62.5200    8305331
          27     TGT  2013-12-19   62.1500   62.8900   61.9800   62.2200    7903937
          28     TGT  2013-12-20   62.4900   62.6600   62.0200   62.1200    6869129
          29     TGT  2013-12-23   61.8800   62.1500   61.5349   62.0000    5726545
          ..     ...         ...       ...       ...       ...       ...        ...
```

```
91    ANTM 2015-02-02  135.5000  135.5900  132.9400  134.9600    1819776
92    ANTM 2015-02-03  136.9600  137.2400  135.5000  136.0800    1710527
93    ANTM 2015-02-04  137.6500  138.6700  135.4000  136.4900    1674628
94    ANTM 2015-02-05  137.2300  138.3700  135.4000  135.5000    2314611
95    ANTM 2015-02-06  135.6900  137.2300  135.0900  136.9500    2244555
96    ANTM 2015-02-09  134.8800  135.6900  134.3800  134.7900    1745541
97    ANTM 2015-02-10  138.7400  139.0400  135.6100  136.3800    2100226
98    ANTM 2015-02-11  141.4900  141.7200  138.5600  138.6000    2104377
99    EBAY 2013-05-14   23.6828   23.7417   23.2072   23.2325   21924170
100   EBAY 2013-05-15   23.8427   23.8554   23.5944   23.6828   20357669
101   EBAY 2013-05-16   23.4850   23.9480   23.4513   23.9059   20246798
102   EBAY 2013-05-17   23.8680   24.0342   23.7670   23.7754   27464373
103   EBAY 2013-05-20   23.5481   23.8469   23.4660   23.8049   20813269
104   EBAY 2013-05-21   23.1272   23.6155   23.1230   23.5523   30956267
105   EBAY 2013-05-22   22.8958   23.4934   22.7821   23.2451   27209575
106   EBAY 2013-05-23   22.9294   22.9631   22.4412   22.5591   22583084
107   EBAY 2013-05-24   22.9968   23.0010   22.5464   22.6306   17368809
108   EBAY 2013-05-27   22.9968   22.9968   22.9968   22.9968          0
109   EBAY 2013-05-28   23.3713   23.6744   23.2367   23.2535   23160436
110   YHOO 2016-12-07   40.5200   40.5700   39.7500   39.9800    7208492
111   YHOO 2016-12-08   41.4100   41.6000   40.4168   40.6600    9171707
112   YHOO 2016-12-09   41.7600   41.8000   41.4400   41.5200    6836112
113   YHOO 2016-12-12   41.3000   41.5300   41.1250   41.4500    4451709
114   YHOO 2016-12-13   41.4700   41.7900   41.1400   41.3500    6564552
115   YHOO 2016-12-14   40.9100   41.5300   40.8300   41.4400   19555694
116   YHOO 2016-12-15   38.4100   40.0000   38.2500   40.0000   43669990
117   YHOO 2016-12-16   38.6100   39.2200   38.4200   38.6200   21694081
118   YHOO 2016-12-19   38.4200   38.7900   38.2700   38.6600   13615511
119   YHOO 2016-12-20   39.1600   39.1800   38.2400   38.4000   25008427
120   YHOO 2016-12-21   39.1500   39.3200   38.9700   39.0800    8296514

      Industry   Company  Timeline
0         Tech  Facebook        -5
1         Tech  Facebook        -4
2         Tech  Facebook        -3
3         Tech  Facebook        -2
4         Tech  Facebook        -1
5         Tech  Facebook         0
6         Tech  Facebook         1
7         Tech  Facebook         2
8         Tech  Facebook         3
9         Tech  Facebook         4
10        Tech  Facebook         5
11   Financial   Equifax        -5
12   Financial   Equifax        -4
13   Financial   Equifax        -3
14   Financial   Equifax        -2
15   Financial   Equifax        -1
```

```
16   Financial   Equifax         0
17   Financial   Equifax         1
18   Financial   Equifax         2
19   Financial   Equifax         3
20   Financial   Equifax         4
21   Financial   Equifax         5
22      Retail    Target        -5
23      Retail    Target        -4
24      Retail    Target        -3
25      Retail    Target        -2
26      Retail    Target        -1
27      Retail    Target         0
28      Retail    Target         1
29      Retail    Target         2
..         ...       ...       ...
91   Insurance    Anthem        -2
92   Insurance    Anthem        -1
93   Insurance    Anthem         0
94   Insurance    Anthem         1
95   Insurance    Anthem         2
96   Insurance    Anthem         3
97   Insurance    Anthem         4
98   Insurance    Anthem         5
99      Retail      Ebay        -5
100     Retail      Ebay        -4
101     Retail      Ebay        -3
102     Retail      Ebay        -2
103     Retail      Ebay        -1
104     Retail      Ebay         0
105     Retail      Ebay         1
106     Retail      Ebay         2
107     Retail      Ebay         3
108     Retail      Ebay         4
109     Retail      Ebay         5
110       Tech     Yahoo        -5
111       Tech     Yahoo        -4
112       Tech     Yahoo        -3
113       Tech     Yahoo        -2
114       Tech     Yahoo        -1
115       Tech     Yahoo         0
116       Tech     Yahoo         1
117       Tech     Yahoo         2
118       Tech     Yahoo         3
119       Tech     Yahoo         4
120       Tech     Yahoo         5

[121 rows x 10 columns]
```

```
In [578]: bigdata['Percent_Change'] = bigdata.groupby('Company')['Close'].pct_change()*100
          # Include a percent change column to analyze the magnitude of daily price changes.

          bigdata.sort_values(["Industry","Company"], inplace=True)  # Sort dada by Type and C

          bigdata.set_index(["Industry","Company"]) # Set the main index as Type, but also by 
          # With this model, I can make better inferences about the behavior within
          #each industry with respect to each company.
```

```
Out[578]:                     Symbol       Date   Close     High       Low     Open  \
          Industry  Company
          Financial Equifax      EFX 2017-08-31  142.47  143.270  141.7700  141.780
                    Equifax      EFX 2017-09-01  141.59  143.370  141.5900  142.730
                    Equifax      EFX 2017-09-04  141.59  141.590  141.5900  141.590
                    Equifax      EFX 2017-09-05  141.10  142.490  140.5700  141.420
                    Equifax      EFX 2017-09-06  141.39  142.140  141.0200  141.580
                    Equifax      EFX 2017-09-07  142.72  143.270  141.3500  141.450
                    Equifax      EFX 2017-09-08  123.23  125.500  117.2500  121.820
                    Equifax      EFX 2017-09-11  113.12  122.000  111.1700  121.530
                    Equifax      EFX 2017-09-12  115.96  116.080  112.1800  112.970
                    Equifax      EFX 2017-09-13   98.99  116.750   98.0400  116.550
                    Equifax      EFX 2017-09-14   96.66  100.750   89.5900   98.690
                    JP Morgan    JPM 2014-09-25   60.15   61.500   60.1500   61.490
                    JP Morgan    JPM 2014-09-26   60.56   60.880   60.3200   60.330
                    JP Morgan    JPM 2014-09-29   60.33   60.500   59.7300   60.030
                    JP Morgan    JPM 2014-09-30   60.24   60.740   60.1300   60.400
                    JP Morgan    JPM 2014-10-01   59.77   60.400   59.7300   60.240
                    JP Morgan    JPM 2014-10-02   58.84   59.490   58.6100   59.150
                    JP Morgan    JPM 2014-10-03   60.30   60.385   59.0500   59.250
                    JP Morgan    JPM 2014-10-06   60.18   60.800   60.0000   60.780
                    JP Morgan    JPM 2014-10-07   59.27   59.920   59.1850   59.920
                    JP Morgan    JPM 2014-10-08   60.40   60.430   59.1800   59.360
                    JP Morgan    JPM 2014-10-09   59.08   60.330   58.8900   60.330
          Insurance Anthem      ANTM 2015-01-28  133.58  139.280  133.0300  138.210
                    Anthem      ANTM 2015-01-29  137.10  137.370  133.7600  134.620
                    Anthem      ANTM 2015-01-30  134.96  137.400  134.1400  135.410
                    Anthem      ANTM 2015-02-02  135.50  135.590  132.9400  134.960
                    Anthem      ANTM 2015-02-03  136.96  137.240  135.5000  136.080
                    Anthem      ANTM 2015-02-04  137.65  138.670  135.4000  136.490
                    Anthem      ANTM 2015-02-05  137.23  138.370  135.4000  135.500
                    Anthem      ANTM 2015-02-06  135.69  137.230  135.0900  136.950
          ...                    ...        ...     ...      ...       ...      ...
          Tech      Facebook      FB 2018-03-14  184.19  184.250  181.8500  182.600
                    Facebook      FB 2018-03-15  183.86  184.000  182.1900  183.240
                    Facebook      FB 2018-03-16  185.09  185.330  183.4100  184.490
                    Facebook      FB 2018-03-19  172.56  177.170  170.0600  177.010
                    Facebook      FB 2018-03-20  168.15  170.200  161.9500  167.470
                    Facebook      FB 2018-03-21  169.39  173.400  163.3000  164.800
          Facebook      FB 2018-03-22  164.89  170.270  163.7200  166.130
          Facebook      FB 2018-03-23  159.39  167.100  159.0200  165.440
          SONY         SNE 2011-04-13   29.78   29.990   29.6100   29.960
          SONY         SNE 2011-04-14   29.69   29.800   29.5810   29.690
          SONY         SNE 2011-04-15   29.69   29.720   29.5200   29.540
          SONY         SNE 2011-04-18   29.25   29.320   28.9100   28.950
          SONY         SNE 2011-04-19   29.71   29.780   29.4100   29.420
          SONY         SNE 2011-04-20   30.14   30.150   29.9400   30.030
          SONY         SNE 2011-04-21   30.50   30.630   30.3500   30.620
          SONY         SNE 2011-04-22   30.50   30.630   30.3500   30.620
          SONY         SNE 2011-04-25   30.09   30.260   29.9100   30.260
          SONY         SNE 2011-04-26   29.79   29.790   29.5600   29.755
          SONY         SNE 2011-04-27   29.03   29.110   28.8600   29.060
          Yahoo       YHOO 2016-12-07   40.52   40.570   39.7500   39.980
          Yahoo       YHOO 2016-12-08   41.41   41.600   40.4168   40.660
          Yahoo       YHOO 2016-12-09   41.76   41.800   41.4400   41.520
          Yahoo       YHOO 2016-12-12   41.30   41.530   41.1250   41.450
          Yahoo       YHOO 2016-12-13   41.47   41.790   41.1400   41.350
          Yahoo       YHOO 2016-12-14   40.91   41.530   40.8300   41.440
          Yahoo       YHOO 2016-12-15   38.41   40.000   38.2500   40.000
          Yahoo       YHOO 2016-12-16   38.61   39.220   38.4200   38.620
          Yahoo       YHOO 2016-12-19   38.42   38.790   38.2700   38.660
          Yahoo       YHOO 2016-12-20   39.16   39.180   38.2400   38.400
          Yahoo       YHOO 2016-12-21   39.15   39.320   38.9700   39.080

                        Volume  Timeline  Percent_Change
Industry  Company
Financial Equifax       425417        -5             NaN
          Equifax       363111        -4       -0.617674
          Equifax            0        -3        0.000000
          Equifax       495148        -2       -0.346070
          Equifax       452154        -1        0.205528
          Equifax       499797         0        0.940661
          Equifax     16848398         1      -13.656110
          Equifax      9820487         2       -8.204171
          Equifax      6937090         3        2.510608
          Equifax     17494316         4      -14.634357
          Equifax     34565048         5       -2.353773
          JP Morgan   16346723        -5             NaN
          JP Morgan   11948887        -4        0.681629
          JP Morgan   10694938        -3       -0.379789
          JP Morgan   14384783        -2       -0.149180
          JP Morgan   18995987        -1       -0.780212
          JP Morgan   24561606         0       -1.555965
          JP Morgan   18321078         1        2.481305
          JP Morgan   11578147         2       -0.199005
          JP Morgan   14542010         3       -1.512130
          JP Morgan   15834553         4        1.906529
          JP Morgan   19191404         5        -2.185430
Insurance Anthem       3476169        -5              NaN
          Anthem       1950356        -4         2.635125
          Anthem       2246853        -3        -1.560904
          Anthem       1819776        -2         0.400119
          Anthem       1710527        -1         1.077491
          Anthem       1674628         0         0.503797
          Anthem       2314611         1        -0.305122
          Anthem       2244555         2        -1.122204
...                        ...       ...              ...
Tech      Facebook    16821728        -2         1.270068
          Facebook    15645035        -1        -0.179163
          Facebook    24403438         0         0.668987
          Facebook    88140060         1        -6.769680
          Facebook   129851768         2        -2.555633
          Facebook   106598834         3         0.737437
          Facebook    73742979         4        -2.656591
          Facebook    53609706         5        -3.335557
          SONY         1460889        -5              NaN
          SONY          515569        -4        -0.302216
          SONY          591641        -3         0.000000
          SONY          876065        -2        -1.481980
          SONY          560330        -1         1.572650
          SONY          909392         0         1.447324
          SONY         1276821         1         1.194426
          SONY               0         2         0.000000
          SONY          595962         3        -1.344262
          SONY          773682         4        -0.997009
          SONY         1517514         5        -2.551192
          Yahoo        7208492        -5              NaN
          Yahoo        9171707        -4         2.196446
          Yahoo        6836112        -3         0.845206
          Yahoo        4451709        -2        -1.101533
          Yahoo        6564552        -1         0.411622
          Yahoo       19555694         0        -1.350374
          Yahoo       43669990         1        -6.110975
          Yahoo       21694081         2         0.520698
          Yahoo       13615511         3        -0.492100
          Yahoo       25008427         4         1.926080
          Yahoo        8296514         5        -0.025536

[121 rows x 9 columns]
```

3 3. Visualizing the Data

Now that I have this raw data organized and sorted, I would like to reproduce it as a graph so that I can visualize the effect of a data breach on each company. I will create a line graph, plotting the percent change in stock price for each company during its timeline.

3.1 The Effects of Data Breaches Across Companies

This section will explore the effects of data breaches across the companies presented in this research, giving a general overview of what the effects of data breaches look like.

```
In [579]: fig, ax = plt.subplots(figsize = (30,18))

          companies = bigdata[["Company","Timeline","Percent_Change"]]
          # Here, I make a new dataframe so that it is easier to plot the specific data I need
          by_comp = companies.groupby('Company')
          # I group by Company so that the percent change and timeline
          # for each company is represented graphically.

          for name, group in by_comp:
              plt.plot(group['Timeline'], group['Percent_Change'], label=name, linewidth = 7)
          # This for loop specifies which variables I would like plotted for each
          # company identified by name.

          plt.legend(loc="lower left", prop={'size': 22})
          # This command asks for a legend placed in the lower left
          # corner of the graph, and to be a larger size.

          plt.show


          ax.set_ylim(-15,3.5) # I set the y limits to -15% and 3.5%.
          ax.set_xlim(-4,5) # I set the x limits to -4 and 5 because -5 has no
                            # percent change data.

          plt.setp(ax.get_xticklabels(),fontsize=25,fontname = "Arial")
          plt.setp(ax.get_yticklabels(),fontsize=25,fontname = "Arial")
          # Here, I customize the x and y axis tick labels with font and size.

          ax.set_title("Stock Price Changes Following Data Breach", size = 38, fontweight = "bo
                       fontname = "Arial") # I customize the title.

          ax.set_ylabel("Percent Change in Stock Price",size = 30,fontname = "Arial")
          ax.set_xlabel("Timeline",size = 30,fontname = "Arial")
          # I add axis titles and customizations.

          ax.title.set_position([.5, 1.04])
          # This spaces the title a little bit further above the graph.

          # Now, I will produce a dotted line that indicates the breach date
          # for the entire graph.
```

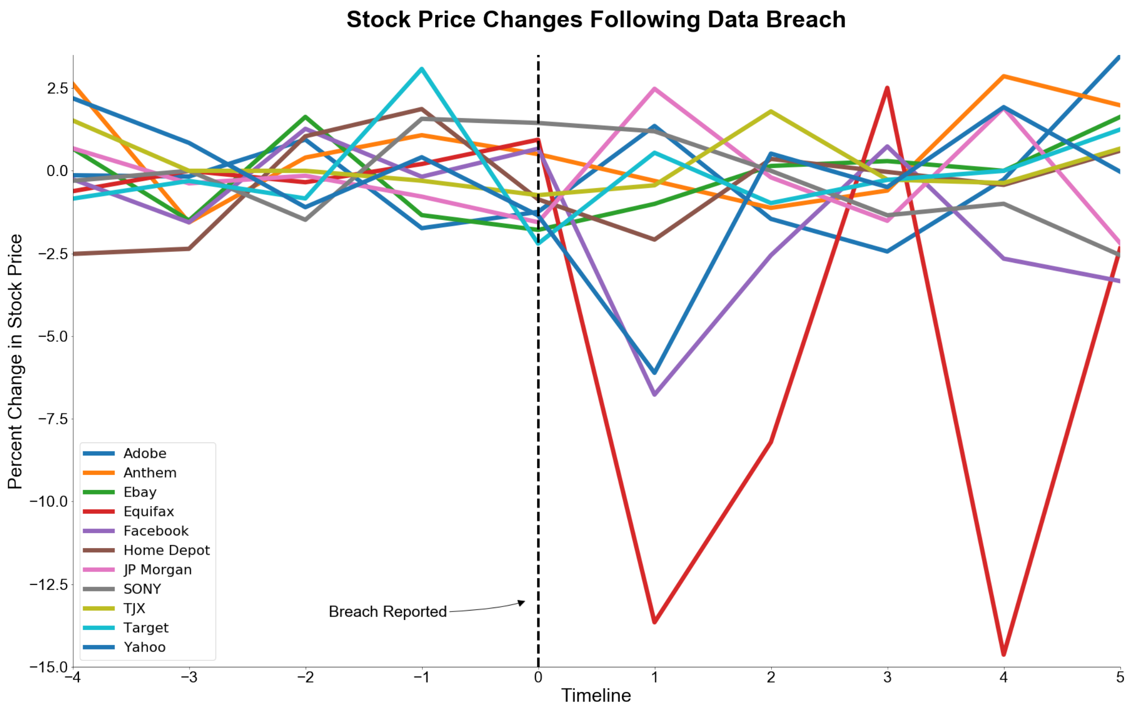
```
brch = 0 # This identifies the breach timeline value.

ax.axvline(x=brch,              # Set the value equal to the average
           color='black',       # Make the color black
           linestyle='--',      # The line style is dotted
           linewidth=4)         # Thickness of the line

ax.spines["right"].set_visible(False) # Removes the right border of the graph
ax.spines["top"].set_visible(False)   # Removes the top border of the graph

#The following commands create the arrow that points to the breach line.
ax.annotate("Breach Reported",
          xy=(-0.1,-13),            # The location of the arrow
          xycoords = 'data',
          xytext = (-1.8,-13.5),    # Location of the arrow's text
          horizontalalignment = 'left', # Left alignement
          arrowprops = {'arrowstyle':'-|>', # Skinny arrow
                        "connectionstyle": "angle3,angleA=180,angleB=20", # Angle cus
                        "color":"black"}, # Black color arrow
           fontsize = 25, fontname = "Arial") # Font and size of arrow text
```

```
Out[579]: Text(-1.8,-13.5,'Breach Reported')
```



```
In [580]: import matplotlib.font_manager
          matplotlib.font_manager.findSystemFonts(fontpaths=None, fontext='ttf')
```

```
# This was used to show which fonts were available on matplotlib.
```

```
Out[580]: ['/Library/Fonts/STIXNonUniBol.otf',
           '/Library/Fonts/Bodoni 72 Smallcaps Book.ttf',
           '/Library/Fonts/Apple Chancery.ttf',
           '/System/Library/Fonts/SFCompactRounded-Light.otf',
           '/System/Library/Fonts/Symbol.ttf',
           '/Library/Fonts/Arial Narrow Bold.ttf',
           '/System/Library/Fonts/SFNSDisplayCondensed-Medium.otf',
           '/Library/Fonts/AppleGothic.ttf',
           '/Library/Fonts/Courier New Bold Italic.ttf',
           '/Library/Fonts/Comic Sans MS Bold.ttf',
           '/Library/Fonts/STIXGeneral.otf',
           '/Library/Fonts/Georgia Italic.ttf',
           '/Library/Fonts/STIXNonUni.otf',
           '/System/Library/Fonts/SFCompactText-Bold.otf',
           '/Library/Fonts/Webdings.ttf',
           '/System/Library/Fonts/SFCompactText-Semibold.otf',
           '/Library/Fonts/Chalkduster.ttf',
           '/Library/Fonts/STIXIntDBol.otf',
           '/Library/Fonts/Arial Unicode.ttf',
           '/System/Library/Fonts/SFNSDisplayCondensed-Regular.otf',
           '/Library/Fonts/STIXIntUpDBol.otf',
           '/Library/Fonts/Arial Bold.ttf',
           '/Library/Fonts/STIXSizOneSymBol.otf',
           '/System/Library/Fonts/SFNSTextItalic.ttf',
           '/Library/Fonts/Arial Narrow Bold Italic.ttf',
           '/System/Library/Fonts/SFNSDisplayCondensed-Light.otf',
           '/Library/Fonts/Georgia Bold.ttf',
           '/Library/Fonts/STIXIntSmReg.otf',
           '/System/Library/Fonts/SFCompactRounded-Medium.otf',
           '/Library/Fonts/Brush Script.ttf',
           '/Library/Fonts/Times New Roman Bold Italic.ttf',
           '/System/Library/Fonts/SFNSTextCondensed-Semibold.otf',
           '/Library/Fonts/Arial Bold Italic.ttf',
           '/Library/Fonts/STIXSizFourSymReg.otf',
           '/System/Library/Fonts/SFNSDisplayCondensed-Bold.otf',
           '/Library/Fonts/STIXGeneralItalic.otf',
           '/System/Library/Fonts/SFNSTextCondensed-Medium.otf',
           '/System/Library/Fonts/SFCompactText-RegularItalic.otf',
           '/Library/Fonts/Arial.ttf',
           '/System/Library/Fonts/SFCompactRounded-Heavy.otf',
           '/Library/Fonts/Herculanum.ttf',
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           '/System/Library/Fonts/SFCompactDisplay-Heavy.otf',
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           '/Library/Fonts/Arial Black.ttf',
           '/Library/Fonts/Trebuchet MS Bold Italic.ttf',
           '/System/Library/Fonts/Apple Symbols.ttf',
           '/Library/Fonts/Kokonor.ttf',
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           '/System/Library/Fonts/Apple Braille.ttf',
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           '/Library/Fonts/Courier New Italic.ttf',
           '/Library/Fonts/Mishafi.ttf',
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           '/System/Library/Fonts/SFCompactDisplay-Regular.otf',
           '/Library/Fonts/STIXGeneralBolIta.otf',
           '/System/Library/Fonts/SFCompactText-Regular.otf',
           '/Library/Fonts/Khmer Sangam MN.ttf',
           '/Library/Fonts/Verdana.ttf',
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           '/Library/Fonts/STIXIntDReg.otf',
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           '/Library/Fonts/Silom.ttf',
           '/System/Library/Fonts/Apple Braille Outline 8 Dot.ttf',
           '/Library/Fonts/Times New Roman Bold.ttf',
           '/System/Library/Fonts/SFCompactText-LightItalic.otf',
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           '/System/Library/Fonts/Apple Braille Pinpoint 6 Dot.ttf',
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           '/Library/Fonts/Wingdings 2.ttf',
           '/Library/Fonts/Microsoft Sans Serif.ttf',
           '/System/Library/Fonts/SFCompactText-HeavyItalic.otf',
           '/Library/Fonts/Zapfino.ttf']
```

As shown in the graph, the largest data breach effects in terms of the percent change in stock price from the breach report date to the following days were from Equifax, Facebook, and Adobe. Equifax is a financial services technology firm, while both Facebook and Adobe are tech companies. Now, I would like to explore how data breach effects behave across the different industries of this dataframe.

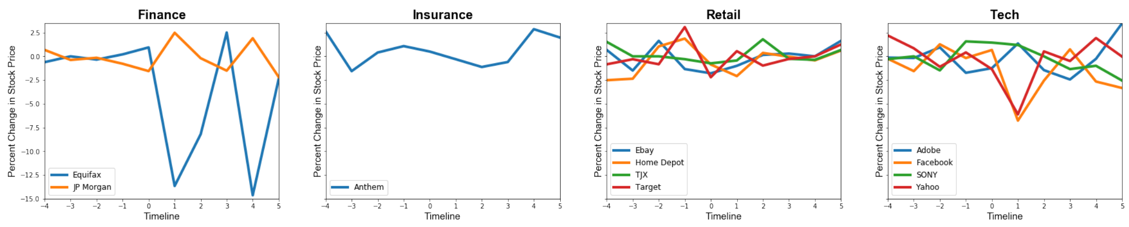
3.2 The Effects of Data Breaches Across Industries

```
In [587]: finance = bigdata.set_index("Industry").loc["Financial"].groupby("Company")
          # This allows me to grab data through 3 layers.
          insurance = bigdata.set_index("Industry").loc["Insurance"].groupby("Company")
          retail = bigdata.set_index("Industry").loc["Retail"].groupby("Company")
          tech = bigdata.set_index("Industry").loc["Tech"].groupby("Company")

          by_ind = finance, insurance, retail, tech
          by_ind
```

```
Out[587]: (<pandas.core.groupby.DataFrameGroupBy object at 0x12f3d22b0>,
           <pandas.core.groupby.DataFrameGroupBy object at 0x12f3d2b00>,
           <pandas.core.groupby.DataFrameGroupBy object at 0x12f3d24a8>,
           <pandas.core.groupby.DataFrameGroupBy object at 0x12f3d2860>)
```

```
In [582]: fig, axs = plt.subplots(1,4, figsize = (30,5), sharex = True, sharey = True)


          for name, group in finance:
              axs[0].plot(group['Timeline'], group['Percent_Change'], label=name, linewidth =
          # This for loop specifies which variables I would like plotted for each
          # company identified by name.
          axs[0].legend(loc="lower left", prop={'size': 12})
          axs[0].set_ylim(-15,3.5)
          axs[0].set_xlim(-4,5)
          axs[0].set_title("Finance", size = 20, fontweight = "bold",
                       fontname = "Arial")
          axs[0].set_ylabel("Percent Change in Stock Price",size = 15,fontname = "Arial")
          axs[0].set_xlabel("Timeline",size = 15,fontname = "Arial")



          for name, group in insurance:
              axs[1].plot(group['Timeline'], group['Percent_Change'], label=name, linewidth =
          axs[1].legend(loc="lower left", prop={'size': 12})
          axs[1].set_title("Insurance", size = 20, fontweight = "bold",
                       fontname = "Arial")
          axs[1].set_ylabel("Percent Change in Stock Price",size = 15,fontname = "Arial")
          axs[1].set_xlabel("Timeline",size = 15,fontname = "Arial")



          for name, group in retail:
              axs[2].plot(group['Timeline'], group['Percent_Change'], label=name, linewidth =
          axs[2].legend(loc="lower left", prop={'size': 12})
          axs[2].set_title("Retail", size = 20, fontweight = "bold",
                       fontname = "Arial")
          axs[2].set_ylabel("Percent Change in Stock Price",size = 15,fontname = "Arial")
          axs[2].set_xlabel("Timeline",size = 15,fontname = "Arial")



          for name, group in tech:
              axs[3].plot(group['Timeline'], group['Percent_Change'], label=name, linewidth =
          axs[3].legend(loc="lower left", prop={'size': 12})
          axs[3].set_title("Tech", size = 20, fontweight = "bold",
                       fontname = "Arial")
          axs[3].set_ylabel("Percent Change in Stock Price",size = 15,fontname = "Arial")
          axs[3].set_xlabel("Timeline",size = 15,fontname = "Arial")
```

```
Out[582]: Text(0.5,0,'Timeline')
```



While the sample size is not large because of the specificity of the project (companies had to be publicly traded stocks and have data breaches that affected more than 10 million users), these juxtaposed graphs illustrate the behavior of each industry in response to the data breaches presented in this project.

In the finance industry, while Equifax exhibited a dramatic decrease in stock price following a breach, JP Morgan's stock price actually increased. This was likely due to the fact that the breach report mentioned no hacking of valuable data. Hackers only obtained names, emails, and addresses of the company's clients. It is difficult to say that the Anthem case is relevant to all insurance companies, but Anthem did not show a significant decrease in stock price. Retail also lacked significant stock price changes following the breaches for its companies. Tech, like finance, exhibited mixed reviews, with two companies, Facebook and Yahoo's respective prices declining, while Adobe increased and Sony remained consistent in its decline from before the time of the breach.

To better understand the effect of data breaches aross industries, I will take the average percent change in stock price for each industry and compare.

```
In [583]: ind_mean = bigdata.groupby("Industry").Percent_Change.describe()
          ind_mean
```

```
Out[583]:            count      mean       std        min       25%       50%       75%  \
          Industry
          Financial   20.0 -1.892380  4.758188 -14.634357 -1.713331 -0.362929  0.324553
          Insurance   10.0  0.587528  1.539510  -1.560904 -0.523992  0.451958  1.755966
          Retail      40.0 -0.108146  1.257235  -2.513369 -0.847644 -0.150007  0.623436
          Tech        40.0 -0.548736  2.019344  -6.769680 -1.461246 -0.216451  0.764379

                          max
          Industry
          Financial  2.510608
          Insurance  2.861803
          Retail     3.081914
          Tech       3.468150
```

The largest percent change in stock price is among the data's financial and tech firms, but as we learned above, Equifax is a significant outlier in the data and has shown the largest percent change out of any firm in the data set. Retail exhibited the least amount of change in stock price.

Why did this pattern occur?

Retail consumers are not as concerned with retail data breaches as they are with technology related data (social media, search). Perhaps it is because these consumers believe that data held by retailers is not nearly as significant as the data collected by tech firms. Tech firms have arsenals of information related to payment, addresses, associations, behavior, personal preferences, and search history. While retailers may also have this information on file, consumers may not associate retail breaches with the same severity as they might associate with technology related breaches. Investors have also caught on to this idea and do not quickly sell off their shares as soon as a data breach is reported; they do not expect consumers to change their shopping behavior or relationship with the breached retailer in a significant way.

This raises an important issue: what will motivate retailers to enhance their security measures if their investors hardly bugde when something like this happens?

3.3 Breach Size and Stock Price Change

Now, I would like to analyze the relationship between the size of the breach (how many people were affected) and the magnitude of the percent change in stock price. It seems intuitive that a company with more users to be affected by a data breach would be a larger company and therefore have more investors to influence stock prices. This section will explore that relationship and help me understand how breach size affects investor decisions.

I will begin by extracting data related to the mean percent change in stock price for each company.

```
In [584]: breach_size = bigdata.groupby("Company").Percent_Change.describe()
          breach_size
```

```
Out[584]:             count      mean       std        min       25%       50%  \
          Company
          Adobe        10.0 -0.167406  1.739025  -2.439984 -1.401309 -0.217590
          Anthem       10.0  0.587528  1.539510  -1.560904 -0.523992  0.451958
          Ebay         10.0 -0.125331  1.245496  -1.787405 -1.255355  0.073376
          Equifax      10.0 -3.615536  6.240664 -14.634357 -6.741572 -0.481872
          Facebook     10.0 -1.463265  2.455436  -6.769680 -2.631352 -0.906259
          Home Depot   10.0 -0.439430  1.501383  -2.513369 -1.776367 -0.229763
          JP Morgan    10.0 -0.169225  1.500684  -2.185430 -1.329151 -0.289397
          SONY         10.0 -0.246226  1.373786  -2.551192 -1.257449 -0.151108
          TJX          10.0  0.188275  0.861715  -0.737018 -0.350609 -0.133200
          Target       10.0 -0.056096  1.441723  -2.202990 -0.841160 -0.289704
          Yahoo        10.0 -0.318047  2.340496  -6.110975 -0.949175  0.193043

                           75%       max
          Company
          Adobe       0.673958  3.468150
          Anthem      1.755966  2.861803
          Ebay        0.579867  1.630828
          Equifax     0.154146  2.510608
          Facebook    0.456950  1.270068
          Home Depot  0.545834  1.868120
          JP Morgan   0.473927  2.481305
          SONY        0.895820  1.572650
          TJX         0.502681  1.796610
          Target      0.410298  3.081914
          Yahoo       0.764079  2.196446
```

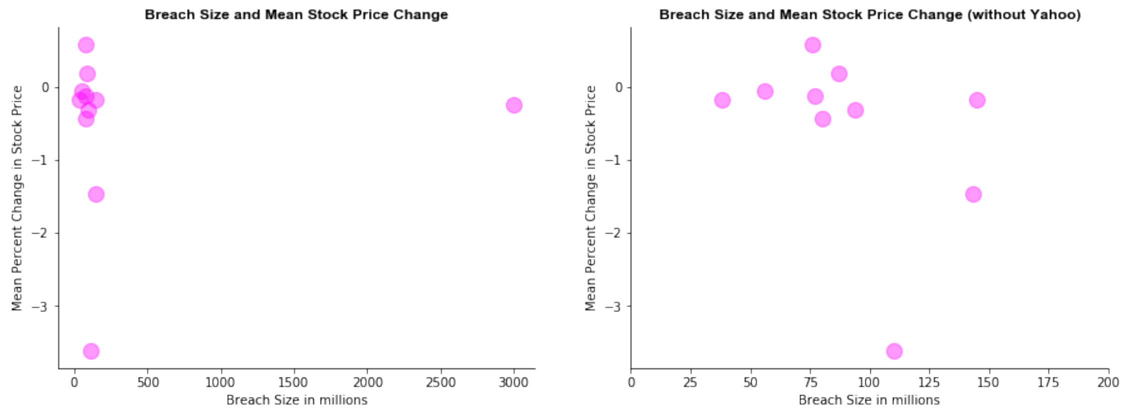
Now, I will create a column in the breach_size data frame that identifies the size of the breach for each company in terms of millions of people affected.

```
In [585]: breach_size["Breach_Size (millions)"] = {38,80,145,143,87,56,76,77,110,94,3000}
          breach_size
```

```
Out[585]:             count      mean       std        min       25%       50%  \
          Company
          Adobe        10.0 -0.167406  1.739025  -2.439984 -1.401309 -0.217590
          Anthem       10.0  0.587528  1.539510  -1.560904 -0.523992  0.451958
          Ebay         10.0 -0.125331  1.245496  -1.787405 -1.255355  0.073376
          Equifax      10.0 -3.615536  6.240664 -14.634357 -6.741572 -0.481872
          Facebook     10.0 -1.463265  2.455436  -6.769680 -2.631352 -0.906259
          Home Depot   10.0 -0.439430  1.501383  -2.513369 -1.776367 -0.229763
          JP Morgan    10.0 -0.169225  1.500684  -2.185430 -1.329151 -0.289397
          SONY         10.0 -0.246226  1.373786  -2.551192 -1.257449 -0.151108
          TJX          10.0  0.188275  0.861715  -0.737018 -0.350609 -0.133200
          Target       10.0 -0.056096  1.441723  -2.202990 -0.841160 -0.289704
          Yahoo        10.0 -0.318047  2.340496  -6.110975 -0.949175  0.193043

                           75%       max  Breach_Size (millions)
          Company
          Adobe       0.673958  3.468150                      38
          Anthem      1.755966  2.861803                      76
          Ebay        0.579867  1.630828                      77
          Equifax     0.154146  2.510608                     110
          Facebook    0.456950  1.270068                     143
          Home Depot  0.545834  1.868120                      80
          JP Morgan   0.473927  2.481305                     145
          SONY        0.895820  1.572650                    3000
          TJX         0.502681  1.796610                      87
          Target      0.410298  3.081914                      56
          Yahoo       0.764079  2.196446                      94
```

I will now create a scatterplot which explores the relationship between percent change in stock price and the size of the breach. Yahoo's breach size is quite an outlier for the data, and so it might distort our perception of the relationship between breach size and stock price changes. As such, I will create two scatterplots; one with Yahoo included and one without.

```
In [586]: fig, ax = plt.subplots(1,2, figsize = (15,5))

          ax[0].scatter(breach_size["Breach_Size (millions)"],breach_size["mean"], s = 150, al
                      color = "magenta" )
          ax[0].set_title('Breach Size and Mean Stock Price Change', loc='center', fontsize=12
                        fontweight = "bold", fontname = "Arial")
          ax[0].set_xlabel("Breach Size in millions")
          ax[0].set_ylabel("Mean Percent Change in Stock Price")
          ax[0].spines["right"].set_visible(False)
          ax[0].spines["top"].set_visible(False)


          ax[1].scatter(breach_size["Breach_Size (millions)"],breach_size["mean"], s = 150, al
                      color = "magenta" )
          ax[1].set_title('Breach Size and Mean Stock Price Change (without Yahoo)', loc='cent
                        fontweight = "bold", fontname = "Arial")
          ax[1].set_xlabel("Breach Size in millions")
          ax[1].set_ylabel("Mean Percent Change in Stock Price")
          ax[1].spines["right"].set_visible(False)
          ax[1].spines["top"].set_visible(False)
          ax[1].set_xlim (0,200)

          plt.show()
```



The second graph (right) is far more clear than first graph, which does contain Yahoo. Based on the available data, we can easily infer from both graphs that there is no significant relationship between the size of a data breach and its effect on the stock price of a company. However, the sample size is not large enough to make any accurate conclusions.

4 Conclusions

While the sample size was too small to make any accurate conclusions or inferences, I do have good visualizations of how data breaches affect different kinds of companies. For example, the dramatic behavior of Equifax, a credit reporting agency, illustrates the severity of a breach of that information. Credit reports influence creditor decisions which affect how individuals can purchase a home, lease a car, take out student loans, and apply for credit cards. If this information were to be stolen or manipulated in any way, the implications would be as significant as the stock price changes the company reported during that time. The graph illustrating retail companies confirmed a theory regarding the nonchalance of consumers toward retail data breaches at their local target or favorite clothing store, which don't influence financial decisions or hold any significant information to do so.

5 Limitations of the Data

The data in this project present several limitations.

1. Sample Size: The sample size is very small, and certainly too small to establish any significant conclusions or inferences about data breaches. The sample size is small for several reasons. The companies presented in this project had to meet two criteria:

a) be an American, publicly traded company

b) be a victim of a data breach which affected at least 10 million users.

Many companies affected by data breaches of larger magnitudes were based outside of the US, including Aadhaar (India), Philippine's Commission on Elections (Philippines), Turkish Citizenship Database (Turkey), and others. Among the database of data breaches, many were not publicly traded companies. Others only affected several hundred thousand users. Friend Finder Network, a strong candidate in my project proposal, actually declared bankruptcy and is no longer publicly traded. It was removed from the data set.

2. Vagueness of Data Breach Reports/Lack of Information: Several companies who issued reports on their data breaches were intentionally vague in their reports, witholding information like the date of the breach or the number of users affected. This affected my sample size, as each company's report for the purposes of this project needed to contain that information. For most of the companies, I had to manually find the breach report date from reading news articles and finding the oldest one, or by looking at the date of the article and counting back to the day of the week the article said the breach was reported by the company.

6 Sources

www.cnnmoney.com
www.csoonline.com
www.forbes.com
www.informationisbeautiful.net
www.washingtonpost.com