Correlation between stock price change and weather

Feng Ding

Jan 2018

Introduction

Common senses tells us the mood of human being are influenced by the weather around us, some more while others less - a pleasant and optimistic felling in a sunny morning, and tend to be blue and pessimistic in a dark stormy afternoon. Individuals are more predisposed towards either optimistic and pessimistic expectations depending on their mood, according to psychological studies (Arkes et al., 1988; Etzioni, 1988; Romer, 2000).it is also well researched that human beings a influenced by their mood when making decisions, trading decision or daily routine ones. But, is it true that feelings towards weather conditions attributed to stock trading and cause stock price fluctuated with the mood of the trader and the weather of that day? Or, the market is not affected but driven by rational decision based on available information , made by rational investors? Or, simply the market or individual stock investors population is diversified enough not to be affected by the mood of investors. Or, is weather conditions in major cities strong enough to affect investors mood and then individual stock or sector price change?

This paper will test the correlation between the daily return of individual stocks and sectors and the weather of that day. Specifically, the daily return and sector of S&P 500 and the daily weather indicators of Chicago, New York and San Francisco: temperature, humidity, pressure, and wind.

Data description

This research consider the daily price change of S&P 500 individuals stocks as well as it's sectors, from January 2016 to December 2017. They are gathered from Yahoo. 2016 and 2017 weather data are gathered from weather stations from Chicago, New York and San Francisco.

Table 1 return data general description:

Daily price change for individual S&P 500 stocks with column names for company stock tickers and stock sectors.

```
[3]: print(sp500_changes.head())
...:
      Date  MMM&industrials  ABT&health_care  ABBV&health_care  \
2016-11-01              NaN              NaN               NaN
2016-11-02         0.008970        -0.009003          0.006005
2016-11-03         0.006615        -0.008303         -0.015975
2016-11-04        -0.002100         0.018330          0.002680
2016-11-07         0.019393         0.019507          0.049945
```

```
In [18]: sp500_changes.describe()
    ...:
Out[18]:
       MMM&industrials  ABT&health_care  ABBV&health_care  \
count       265.000000       265.000000        265.000000
mean          0.001388         0.001399          0.002043
std           0.007997         0.009538          0.012658
min          -0.051845        -0.042647         -0.036771
25%          -0.002325        -0.003911         -0.003494
50%           0.000951         0.001121          0.001488
75%           0.004999         0.007135          0.007295
max           0.057447         0.028323          0.063092
```

Stock price change is calculated as follows:
The difference of log of current close price and the price of the past trading day: np.log(x) - np.log(x.shift(1))

And, according to Olha Z, they believe that stock price changes presents relatively no volatility and stock returns exhibit non-normality.

This research focus on these parameters of weather data: daily average temperature, humidity, pressure, and wind, with the same date range as stock price change. The range of variable temperature is 9-91, with 91 as the strongest. The range of variable humidity is 23 to 96, with 96 as the strongest. The range of variable pressure is 29 to 31, with 31 as the strongest. The range of variable wind is 3.5 to 28, with 28 as the strongest.

Table 2: Weather data sample:

```
In [19]: print(df_weather1.head())
    ...:
           Date  DAILYAverageDryBulbTemp  DAILYAverageRelativeHumidity  \
32   2016-01-01                     40.0                          53.0
65   2016-01-02                     38.0                          49.0
98   2016-01-03                     42.0                          49.0
132  2016-01-04                     26.0                          53.0
165  2016-01-05                     22.0                          46.0
```

Table 3: weather condition general description

```
    ...:
Out[20]:
       DAILYAverageDryBulbTemp  DAILYAverageRelativeHumidity  \
count               689.000000                    534.000000
mean                 59.416546                     59.964419
std                  16.643730                     14.829002
min                   9.000000                     23.000000
25%                  46.000000                     49.000000
50%                  60.000000                     59.000000
75%                  74.000000                     71.000000
max                  91.000000                     96.000000

       DAILYAverageStationPressure  DAILYAverageWindSpeed
count                   689.000000             685.000000
mean                     29.979158              10.723796
std                       0.216129               4.016243
min                      29.280000               3.500000
25%                      29.850000               8.000000
50%                      29.970000               9.900000
75%                      30.120000              12.400000
max                      30.630000              28.000000
```

Research shows GARCH model could be a better tool for analysis due to heteroscedasticity as Chang et al. (2006) argued and so called 'volatility-clustering' pointed out by Engle (2006). As Engle(2001) explained GARCH uses heteroscedasticity to generate robust variance estimators by updating the formula with weighted average of the unconditional variance, the square residual for the first observation and the starting variance and estimating the variance of the second observation. Eventually, an entire time series of variance of is constructed. However, this research will use linear models to analyze the potential relationship between stock price changes and weather. And, like what Olha Z stressed in the research all weather variables represent exogenous influence on stock returns as stock returns obviously can not influence the weather. I agree with him that omitted variable won't be an issue based on the assumption that weather variables are not correlated with other potential factors that affect stock returns.

Again, this analysis tries to demonstrate whether there is possible statistically significant correlation between stock price change and weather, as it's a strong psychological factor affects investors' mood. In general, if such statistically significant relationship exists between certain individual stocks or certain sectors, investor can take those weather variables in to consideration for their strategy modeling.

Table 4: Correlation of individual stocks and weather conditions table sample:

```
In [28]: print(corr_ny.head())
    ...:
                         stocks          corr_tempe_ny       corr_humidity_ny  \
0               MMM&industrials  0.040689764022298874   -0.01313335703935984
1               ABT&health_care  0.015435814891446792  -0.006040903197934687
2              ABBV&health_care   0.02416309107710931   -0.05483539929583637
3   ACN&information_technology   0.0392101919089813     0.23036344424272034
4  ATVI&information_technology  -0.07217774670400717    0.12836599481803967

        corr_preassure_ny           corr_wind_ny
0    0.035279833772934935  -0.02009078201271687
1   -0.004839067069646986  -0.03565222657614037
2    0.008045486173243707  -0.04717228515344916
3    -0.06127752743718058   0.05835619607537703
4  0.00042630310772237545  0.030336233497807785
```

Table 5: Correlation of stock sectors and weather conditions table sample:

```
n [29]: print(corr_ny_sec.head())
  ...:
                  sector      corr_tempe_ny_sec  corr_humidity_ny_sec  \
 consumer_discretionary    -0.05047830134869494    0.13188576156852788
       consumer_staples    -0.10850742367617533   0.050478489070360996
                 energy    0.017188270280445773    0.13720556630340225
             financials    -0.01559437244586297    0.11961186278889263
            health_care   -0.051940803482675976   0.002519698134349137

 corr_preassure_ny_sec       corr_wind_ny_sec
   -0.0633235989720105    0.05818412953612455
   0.04471739106988957   0.029361907465594868
   -0.14352551238097083     0.0541252188040345
   -0.0712010049639195   0.030422209220796147
 -0.008540173171714913  -0.004885768772788842
```

Table 6: Correlation matrix between individual stock and New York temperature, and humidity

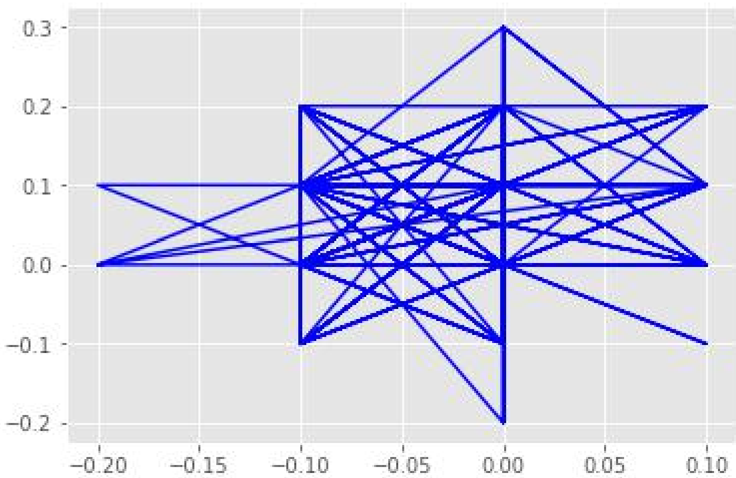


Table 7:Correlation matrix between individual stock and New York pressure and wind speed

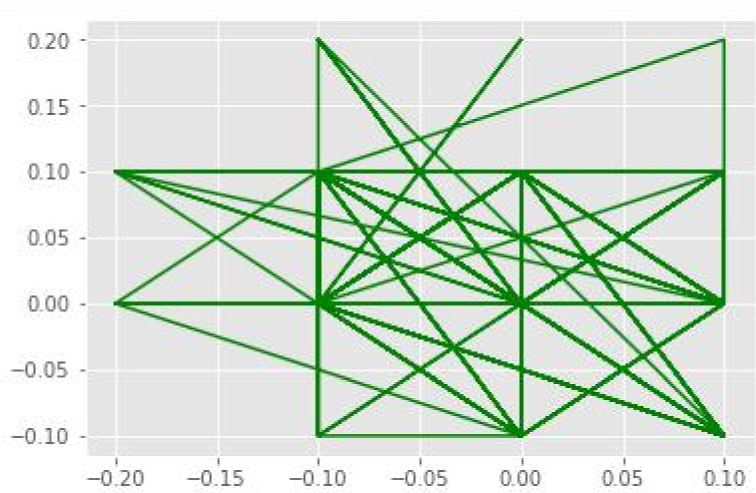


Table 8:Correlation matrix between individual stock and Chicago temperature, and humidity

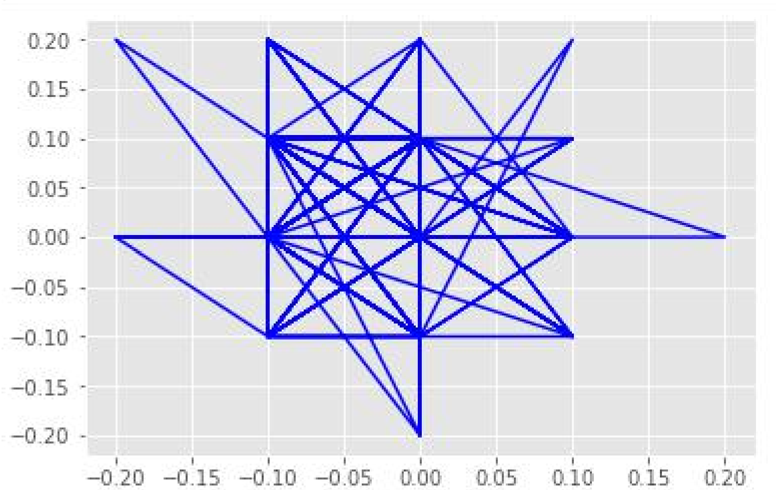


Table 9:Correlation matrix between individual stock and Chicago pressure and wind speed

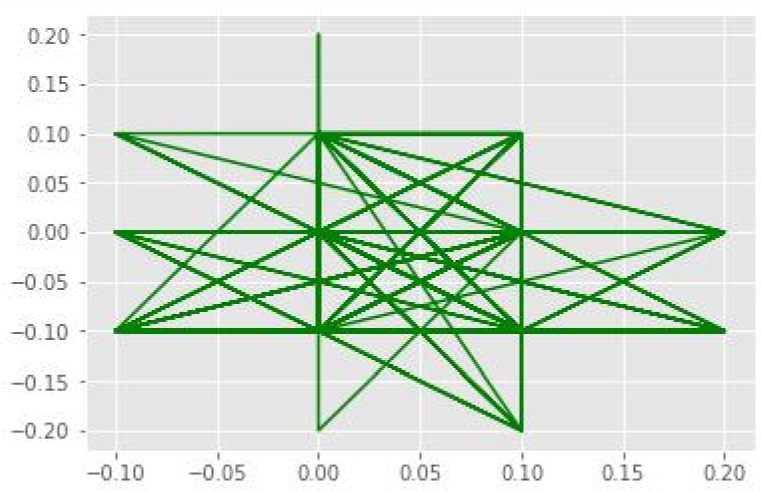


Table 10: Correlation matrix measure between individual stock and San Francisco temperature, and humidity

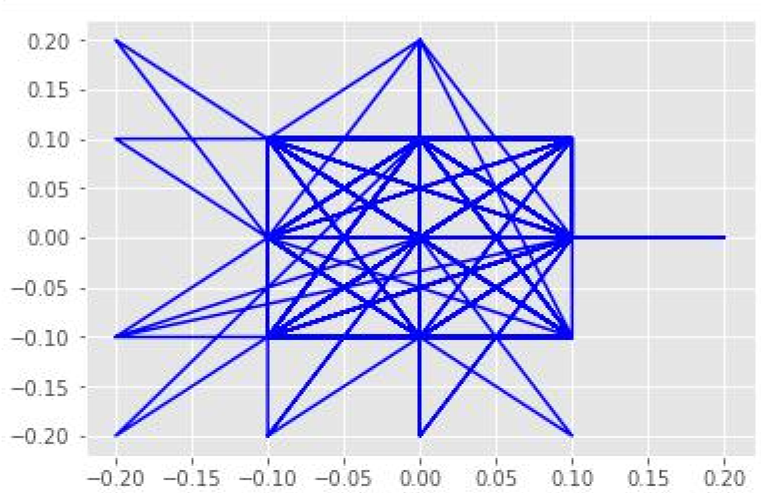


Table 11: Correlation between individual stock and San Francisco pressure and wind speed

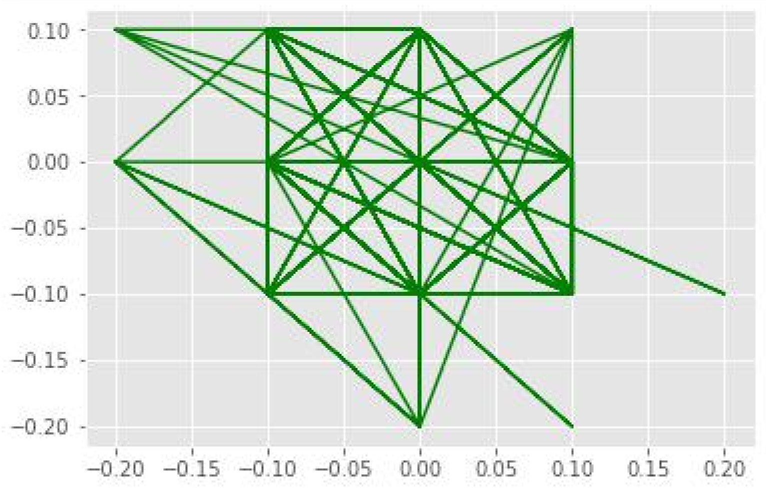


Table 12: Correlation matrix between sector and New York temperature, and humidity

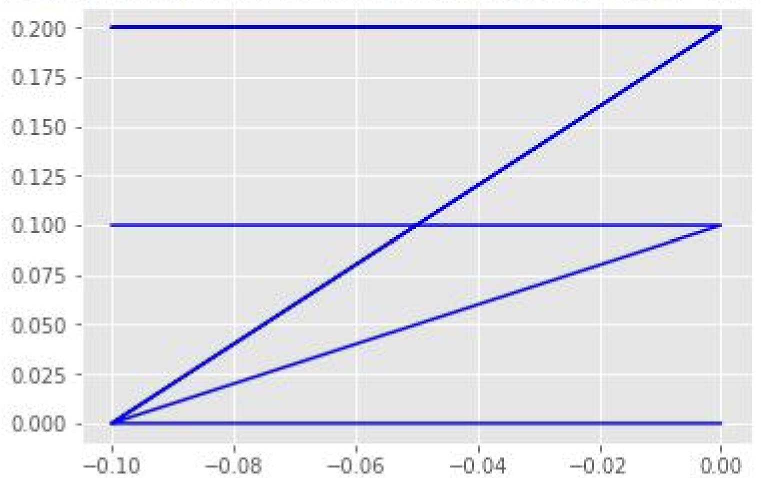


Table 13: Correlation matrix between sector and New York pressure and wind speed

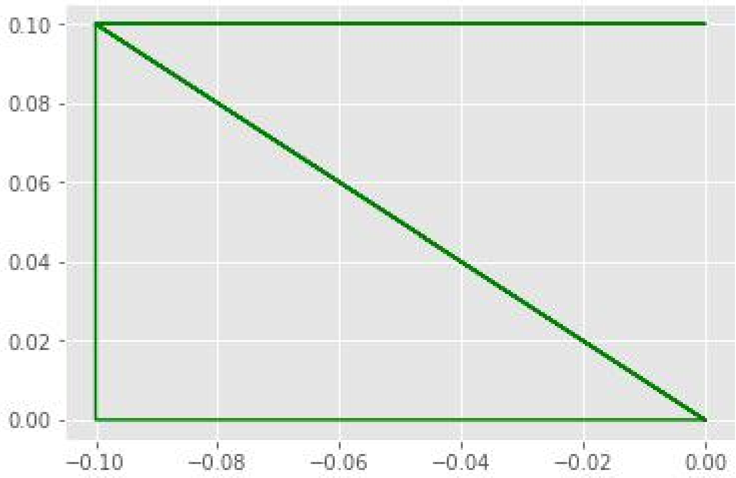


Table 14: Correlation matrix between sector and Chicago temperature, and humidity

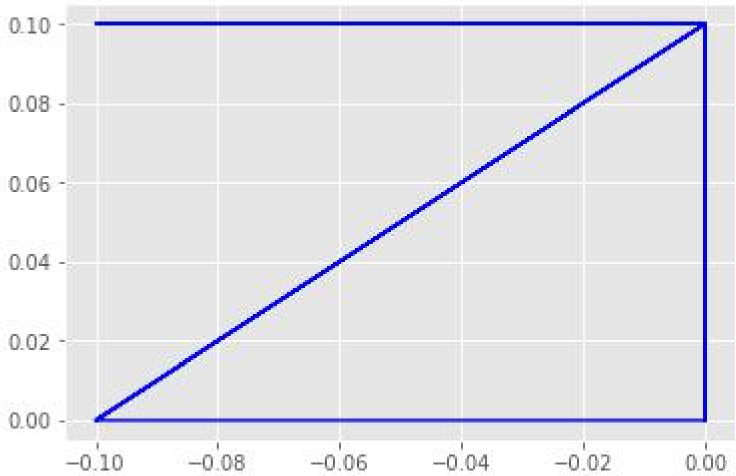


Table 15: Correlation matrix between sector and Chicago pressure and wind

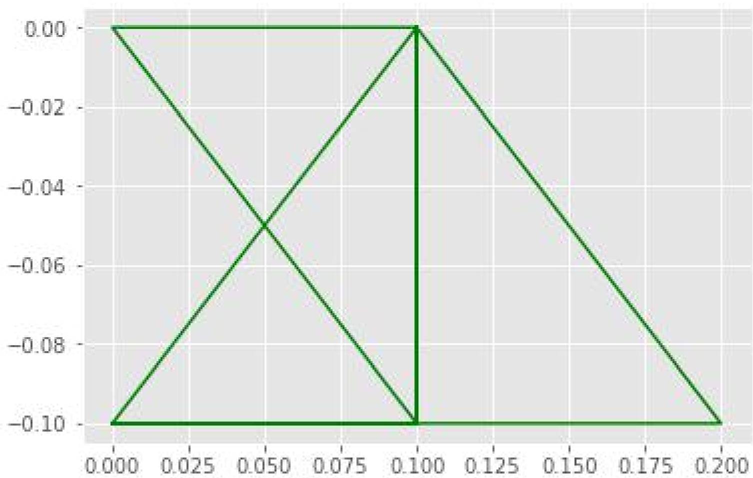


Table 16: Correlation matrix between sector and San Francisco temperature, and humidity

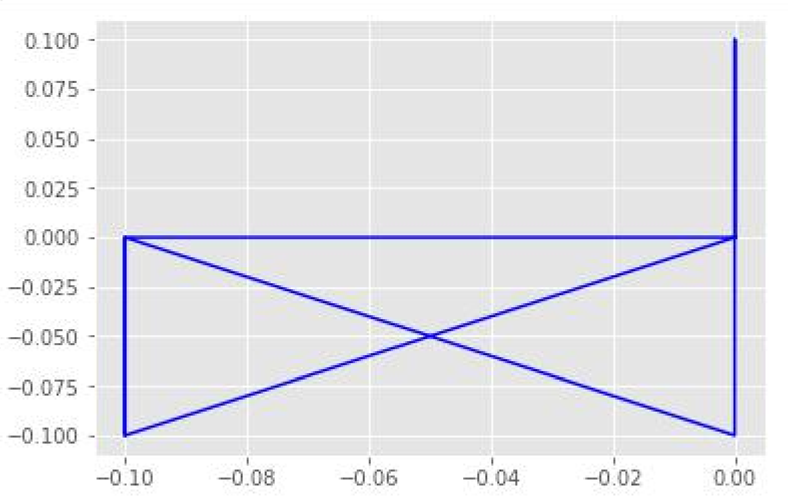
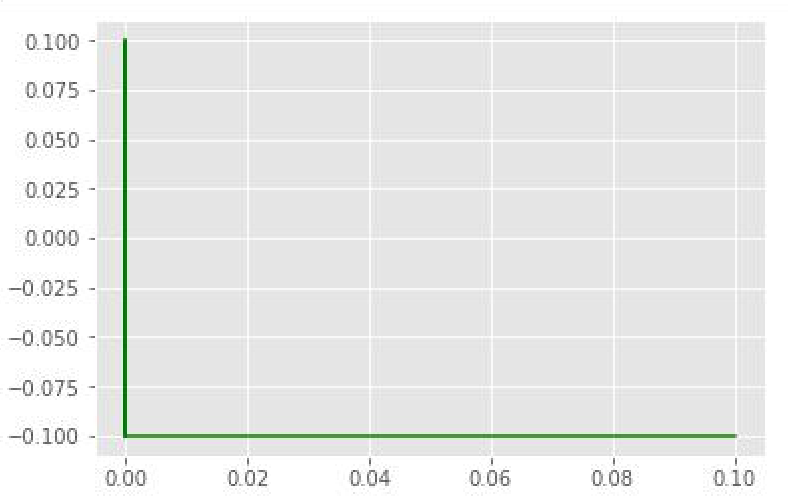


Table 17: Correlation matrix between sector and San Francisco pressure and wind speed



Conclusion

It is logically and physiologically understandable that mood affect investors' and traders' decision making; it is also common sense and well researched that weather affect people's mood. But is there a strong correlation between weather condition , as a proxy for investors' mood, and stock price changes?

This paper used correlation as a statistic tool and tested the correlation between weather conditions like temperature, pressure, humidity, and wind speed and S&P 500 individual stock daily price change and sector price changes. As you can see from individual stock correlation charts, table6 to table 11, the range of correlation is -0.2 to 0.3, which means there is not strong correlation between stock daily price changes and daily weather condition. As you can see from those sector correlation charts, table 12 to table 17, that the range of correlation is -0.1 to 0.2, even narrower than the range of individual stock correlation. These two narrow ranges calls no need to test the significance of correlation.

To sum up, there is little evidence show that there is a strong correlation between weather condition and stock price change or sector price change. It's either the stock market is big enough not to be affected by investors' mood, or the investors population is diversified enough not to be affected by weather in individual cities. In other words, it not a good strategy to invest base solely on weather conditions from individual cities,not even major cities like New York or Chicago, as there is no significantly strong correlation between return and weather conditions in those cities. Weather may affect investors' mood, some more some less, but it is not strong enough to guide the whole population's decision making.

Appendix

1. Olha Z, “Does weather affect stock returns across emerge markets’, Kyiv school of economics
2. David H, Tyler S, “Good day sunshine: stock returns and the weather
3. Weather station records: https://www.ncdc.noaa.gov/cdo-web/datatools/lcd

Python for finance
https://pythonprogramming.net/handling-stock-data-graphing-python-programming-for-finance/?completed=/getting-stock-prices-python-programming-for-finance/

4. Stock returns:
https://ntguardian.wordpress.com/2016/09/19/introduction-stock-market-data-python-1/