Model_1_Analysis

April 3, 2019

In [2]:
```
# Mount Google Drive
"""
No need to execute this block when working on local system.
"""
from google.colab import drive
drive.mount("/content/vdrive", force_remount = True)
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/vdrive/
```

In [0]:
```
# Files to process
"""
Modify the locations below as per your directory struture.
"""
sp_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/"
root_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/"
data_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/raw/"
prep_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/prep/"
model_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/model
```

In [0]:
```
# Loading the csv tickers, train_tickers and test_tickers file
import pandas as pd
ticker_list_df = pd.read_csv(root_dir + "ticker_list.csv", header = None, names = ["Ti
train_tickers_df = pd.read_csv(root_dir + "train_tickers.csv", header = None, names =
test_tickers_df = pd.read_csv(root_dir + "test_tickers.csv", header = None, names = ["
```

In [0]:
```
def get_actual_data(ticker):
    # INCOME STATEMENT
    income_statement = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "income_
    income_statement = income_statement.loc[["Gross Profit", "Operating Income", "Net I
    income_statement.rename(index = {
        "Gross Profit": "gross_profit",
        "Operating Income": "op_income",
        "Net Income": "net_income"
```

```
    }, inplace = True)

    # BALANCE SHEET
    balance_sheet = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "balance_sl
    balance_sheet = balance_sheet.loc[["Total current assets", "Total non-current asse
    balance_sheet.rename(index = {
        "Total current assets": "crr_asst",
        "Total non-current assets": "ncrr_asst",
        "Total current liabilities": "crr_libt",
        "Total non-current liabilities": "ncrr_libt"
    }, inplace = True)

    df = pd.concat([income_statement, balance_sheet])
    df = df[df.columns[::-1]]
    df = df.transpose()
    df = df[["net_income", "op_income", "gross_profit", "crr_asst", "ncrr_asst", "crr_
    df["Ticker"] = ticker
    df.set_index("Ticker", inplace = True)
#     print(df)
    return df
```

In [0]:
```
# the companies for which balance sheet without current and non-current assets and lia
def get_actual_data_2(ticker):
    # INCOME STATEMENT
    income_statement = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "income_
    income_statement = income_statement.loc[["Gross Profit", "Operating Income", "Net I
    income_statement.rename(index = {
        "Gross Profit": "gross_profit",
        "Operating Income": "op_income",
        "Net Income": "net_income"
    }, inplace = True)

    # BALANCE SHEET
    balance_sheet = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "balance_sl
    balance_sheet = balance_sheet.loc[["Total assets", "Total liabilities"]]
    balance_sheet.rename(index = {
        "Total assets": "ncrr_asst",
        "Total liabilities": "ncrr_libt"
    }, inplace = True)

    df = pd.concat([income_statement, balance_sheet])
    df = df[df.columns[::-1]]
    df = df.transpose()
    df["Ticker"] = ticker
    df.set_index("Ticker", inplace = True)
    df.insert(0, "crr_asst", 0)
    df.insert(0, "crr_libt", 0)
    df = df[["net_income", "op_income", "gross_profit", "crr_asst", "ncrr_asst", "crr_
```

```
        return df
```

```
In [100]: df = pd.DataFrame(columns = ["net_income", "op_income", "gross_profit", "crr_asst", "
          df.index.name = "Ticker"
          counter = 0
          for ticker in test_tickers_df["Test Tickers"]:
              counter += 1
              print(str(counter) + ". Getting data for: " + ticker)
              try:
                  df = df.append(get_actual_data(ticker))
              except:
                  df = df.append(get_actual_data_2(ticker))
```

```
1. Getting data for: HSIC
2. Getting data for: ALXN
3. Getting data for: KR
4. Getting data for: BBT
5. Getting data for: DIS
6. Getting data for: MMC
7. Getting data for: MAR
8. Getting data for: CELG
9. Getting data for: VMC
10. Getting data for: RHI
11. Getting data for: MKC
12. Getting data for: PGR
13. Getting data for: ILMN
14. Getting data for: AMAT
15. Getting data for: LEG
16. Getting data for: STI
17. Getting data for: GS
18. Getting data for: RTN
19. Getting data for: KMI
20. Getting data for: CRM
21. Getting data for: STZ
22. Getting data for: INFO
23. Getting data for: AAP
24. Getting data for: EXC
25. Getting data for: MCO
26. Getting data for: AGN
27. Getting data for: C
28. Getting data for: NTRS
29. Getting data for: TMK
30. Getting data for: EW
31. Getting data for: NEE
32. Getting data for: BBY
33. Getting data for: RCL
34. Getting data for: VIAB
35. Getting data for: TTWO
```

```
36. Getting data for: AWK
37. Getting data for: MO
38. Getting data for: WAT
39. Getting data for: EQR
40. Getting data for: MA
41. Getting data for: TGT
42. Getting data for: DG
43. Getting data for: JPM
44. Getting data for: IT
45. Getting data for: LYB
46. Getting data for: ISRG
47. Getting data for: ABC
48. Getting data for: FCX
49. Getting data for: ETR
50. Getting data for: LB
51. Getting data for: GWW
52. Getting data for: GT
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54. Getting data for: DVA
55. Getting data for: CAH
56. Getting data for: ADP
57. Getting data for: CAG
58. Getting data for: YUM
59. Getting data for: D
60. Getting data for: CL
61. Getting data for: PRGO
62. Getting data for: AZO
63. Getting data for: ETFC
64. Getting data for: IP
65. Getting data for: COF
66. Getting data for: GPS
67. Getting data for: FL
68. Getting data for: GD
69. Getting data for: CVS
70. Getting data for: ED
71. Getting data for: CI
72. Getting data for: PNC
73. Getting data for: BLK
74. Getting data for: HUM
75. Getting data for: MMM
76. Getting data for: ALGN
77. Getting data for: AFL
78. Getting data for: CHTR
79. Getting data for: CSX
80. Getting data for: ORLY
81. Getting data for: CNC
82. Getting data for: MDLZ
```

In [104]:
```
df = df.dropna()
df
```

Out[104]:

Ticker	net_income	op_income	gross_profit	crr_asst	ncrr_asst \
HSIC	5.358810e+08	7.530520e+08	3.595084e+09	4.175220e+09	4.325307e+09
ALXN	7.760000e+07	3.861000e+08	3.756900e+09	3.385000e+09	1.054690e+10
KR	1.907000e+09	2.085000e+09	2.700000e+10	1.111700e+10	2.608000e+10
BBT	3.237000e+09	4.060000e+09	1.099200e+10	0.000000e+00	2.256970e+11
DIS	1.259800e+10	1.480400e+10	2.670800e+10	1.682500e+10	8.177300e+10
MMC	1.650000e+09	2.761000e+09	1.495000e+10	5.934000e+09	1.564400e+10
MAR	1.907000e+09	2.366000e+09	3.674000e+09	2.706000e+09	2.099000e+10
CELG	4.046000e+09	5.191000e+09	1.469400e+10	9.067000e+09	2.641300e+10
VMC	5.158050e+08	7.477130e+08	1.100945e+09	1.079145e+09	8.752985e+09
RHI	4.342880e+08	5.872200e+08	2.410014e+09	1.473610e+09	4.294870e+08
MKC	8.986000e+08	9.033000e+08	2.371600e+09	1.479900e+09	8.776500e+09
PGR	2.615300e+09	3.330100e+09	1.025800e+10	0.000000e+00	4.657500e+10
ILMN	8.260000e+08	8.830000e+08	2.300000e+09	4.490000e+09	2.469000e+09
AMAT	3.313000e+09	4.796000e+09	7.817000e+09	1.060400e+10	7.029000e+09
LEG	3.059000e+08	4.377000e+08	8.887000e+08	1.524600e+09	1.857400e+09
STI	2.775000e+09	3.332000e+09	9.005000e+09	0.000000e+00	2.155430e+11
GS	1.045900e+10	1.315500e+10	3.661600e+10	0.000000e+00	9.317960e+11
RTN	2.909000e+09	4.538000e+09	7.485000e+09	1.213600e+10	1.972800e+10
KMI	1.609000e+09	3.794000e+09	6.856000e+09	5.722000e+09	7.314400e+10
CRM	1.110000e+09	5.350000e+08	9.831000e+09	1.068300e+10	2.005400e+10
STZ	2.318900e+09	2.284500e+09	3.817200e+09	3.474000e+09	1.706470e+10
AAP	4.238470e+08	6.042750e+08	4.219413e+09	6.082454e+09	2.958194e+09
EXC	2.010000e+09	3.898000e+09	8.195000e+09	1.336000e+10	1.063060e+11
MCO	1.309600e+09	1.868200e+09	4.442700e+09	3.386900e+09	6.139300e+09
AGN	-5.096400e+09	-6.247600e+09	1.359600e+10	6.475400e+09	9.531220e+10
C	1.804500e+10	2.344500e+10	6.528600e+10	0.000000e+00	1.917383e+12
NTRS	1.556400e+09	1.957800e+09	5.974700e+09	0.000000e+00	1.322125e+11
TMK	7.014660e+08	9.537470e+08	2.028509e+09	0.000000e+00	2.309572e+10
EW	7.222000e+08	7.496000e+08	2.783400e+09	2.286900e+09	3.036800e+09
NEE	6.638000e+09	4.280000e+09	9.665000e+09	6.393000e+09	9.730900e+10
...	...	...	...	...	...
GT	7.080000e+08	1.158000e+09	3.514000e+09	5.925000e+09	1.094700e+10
CF	2.900000e+08	7.300000e+08	9.170000e+08	1.274000e+09	1.138700e+10
DVA	1.593940e+08	1.530308e+09	3.209338e+09	8.424159e+09	1.068609e+10
CAH	2.560000e+08	1.030000e+08	7.181000e+09	2.455300e+10	1.539800e+10
ADP	1.620800e+09	2.511700e+09	5.483200e+09	3.182330e+10	7.025800e+09
CAG	8.084000e+08	1.033500e+09	2.351500e+09	1.938900e+09	8.450600e+09
YUM	1.542000e+09	2.296000e+09	2.658000e+09	1.207000e+09	2.923000e+09
D	2.447000e+09	3.601000e+09	5.624000e+09	5.161000e+09	7.275300e+10
CL	2.400000e+09	3.694000e+09	9.231000e+09	3.793000e+09	8.368000e+09
PRGO	1.310000e+08	2.365000e+08	1.831500e+09	2.902200e+09	8.081200e+09
AZO	1.337536e+09	1.810856e+09	5.973746e+09	4.635869e+09	4.711111e+09
ETFC	1.052000e+09	1.422000e+09	2.873000e+09	0.000000e+00	6.500300e+10

IP	2.012000e+09	2.933000e+09	7.751000e+09	6.996000e+09	2.658000e+10
COF	6.015000e+09	7.318000e+09	2.222000e+10	0.000000e+00	3.725380e+11
GPS	1.003000e+09	1.362000e+09	6.322000e+09	4.251000e+09	3.798000e+09
FL	2.840000e+08	5.710000e+08	2.456000e+09	2.551000e+09	1.410000e+09
GD	3.345000e+09	4.457000e+09	6.715000e+09	1.818900e+10	2.721900e+10
CVS	-5.940000e+08	4.021000e+09	3.153800e+10	4.524300e+10	1.512130e+11
ED	1.382000e+09	2.664000e+09	6.237000e+09	3.864000e+09	5.005600e+10
CI	2.237000e+09	3.606000e+09	1.375400e+10	0.000000e+00	6.175900e+10
PNC	5.301000e+09	6.836000e+09	1.713200e+10	0.000000e+00	3.823150e+11
BLK	4.305000e+09	5.457000e+09	1.152500e+10	0.000000e+00	1.595730e+11
HUM	1.683000e+09	3.100000e+09	1.103000e+10	1.694800e+10	8.465000e+09
MMM	5.349000e+09	7.207000e+09	1.608300e+10	1.370900e+10	2.279100e+10
ALGN	4.002350e+08	4.665640e+08	1.447867e+09	1.302479e+09	7.499790e+08
AFL	2.920000e+09	4.205000e+09	9.758000e+09	0.000000e+00	1.404060e+11
CSX	3.309000e+09	4.773000e+09	4.773000e+09	2.565000e+09	3.416400e+10
ORLY	1.324487e+09	1.815184e+09	5.039966e+09	3.543102e+09	4.437687e+09
CNC	9.000000e+08	1.458000e+09	8.421000e+09	1.199800e+10	1.890300e+10
MDLZ	3.381000e+09	3.312000e+09	1.035200e+10	7.604000e+09	5.512500e+10

	crr_libt	ncrr_libt
Ticker		
HSIC	3.218827e+09	1.427756e+09
ALXN	1.174000e+09	3.592600e+09
KR	1.419700e+10	1.609500e+10
BBT	0.000000e+00	1.955190e+11
DIS	1.786000e+10	2.790600e+10
MMC	4.924000e+09	9.070000e+09
MAR	6.437000e+09	1.503400e+10
CELG	4.057000e+09	2.526200e+10
VMC	6.025500e+08	4.026677e+09
RHI	8.195360e+08	2.036300e+07
MKC	2.001700e+09	5.072500e+09
PGR	0.000000e+00	3.553870e+10
ILMN	1.804000e+09	1.310000e+09
AMAT	3.922000e+09	6.866000e+09
LEG	8.157000e+08	1.408700e+09
STI	0.000000e+00	1.912630e+11
GS	0.000000e+00	8.416110e+11
RTN	8.288000e+09	1.210400e+10
KMI	7.557000e+09	3.611200e+10
CRM	1.125500e+10	3.877000e+09
STZ	2.039600e+09	1.050740e+10
AAP	3.885950e+09	1.603885e+09
EXC	1.140400e+10	7.519200e+10
MCO	2.098500e+09	6.771200e+09
AGN	5.727900e+09	3.092870e+10
C	0.000000e+00	1.720309e+12
NTRS	0.000000e+00	1.217042e+11

```
TMK     0.000000e+00  1.768054e+10
EW      8.766000e+08  1.306700e+09
NEE     1.756300e+10  4.872600e+10
...              ...           ...
GT      4.781000e+09  7.021000e+09
CF      7.050000e+08  6.225000e+09
DVA     4.891161e+09  9.186052e+09
CAH     2.289300e+10  1.099900e+10
ADP     3.041270e+10  3.700500e+09
CAG     2.336200e+09  4.296700e+09
YUM     1.301000e+09  1.075500e+10
D       7.647000e+09  4.821900e+10
CL      3.341000e+09  8.623000e+09
PRGO    1.537400e+09  3.777900e+09
AZO     5.028681e+09  5.838654e+09
ETFC    0.000000e+00  5.844100e+10
IP      4.694000e+09  2.149900e+10
COF     0.000000e+00  3.208700e+11
GPS     2.174000e+09  2.322000e+09
FL      6.160000e+08  8.260000e+08
GD      1.473900e+10  1.893700e+10
CVS     4.400900e+10  9.390400e+10
ED      6.207000e+09  3.087400e+10
CI      0.000000e+00  4.799900e+10
PNC     0.000000e+00  3.345450e+11
BLK     0.000000e+00  1.260330e+11
HUM     1.007700e+10  5.175000e+09
MMM     7.244000e+09  1.940800e+10
ALGN    6.920730e+08  1.074940e+08
AFL     0.000000e+00  1.169440e+11
CSX     1.915000e+09  2.223400e+10
ORLY    3.894020e+09  3.733102e+09
CNC     1.197100e+10  7.907000e+09
MDLZ    1.673700e+10  2.027900e+10

[80 rows x 7 columns]
```

```
In [0]: df.to_csv(model_dir + "actual_data.csv")
```

```
In [0]: def get_prev_data(ticker):
            # INCOME STATEMENT
            income_statement = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "income_
            income_statement = income_statement.loc[["Gross Profit", "Operating Income", "Net I
            income_statement.rename(index = {
                "Gross Profit": "gross_profit",
                "Operating Income": "op_income",
                "Net Income": "net_income"
            }, inplace = True)
```

```
    # BALANCE SHEET
    balance_sheet = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "balance_sl
    balance_sheet = balance_sheet.loc[["Total current assets", "Total non-current asset
    balance_sheet.rename(index = {
        "Total current assets": "crr_asst",
        "Total non-current assets": "ncrr_asst",
        "Total current liabilities": "crr_libt",
        "Total non-current liabilities": "ncrr_libt"
    }, inplace = True)

    df = pd.concat([income_statement, balance_sheet])
    df = df[df.columns[::-1]]
    df = df.transpose()
    df = df[["net_income", "op_income", "gross_profit", "crr_asst", "ncrr_asst", "crr_l
    df["Ticker"] = ticker
    df.set_index("Ticker", inplace = True)
#     print(df)
    return df

# get_prev_data("HSIC")
```

In [0]:
```
# the companies for which balance sheet without current and non-current assets and lia
def get_prev_data_2(ticker):
    # INCOME STATEMENT
    income_statement = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "income_
    income_statement = income_statement.loc[["Gross Profit", "Operating Income", "Net I
    income_statement.rename(index = {
        "Gross Profit": "gross_profit",
        "Operating Income": "op_income",
        "Net Income": "net_income"
    }, inplace = True)

    # BALANCE SHEET
    balance_sheet = pd.read_excel(data_dir + ticker + ".xlsx", sheet_name = "balance_sl
    balance_sheet = balance_sheet.loc[["Total assets", "Total liabilities"]]
    balance_sheet.rename(index = {
        "Total assets": "ncrr_asst",
        "Total liabilities": "ncrr_libt"
    }, inplace = True)

    df = pd.concat([income_statement, balance_sheet])
    df = df[df.columns[::-1]]
    df = df.transpose()
    df["Ticker"] = ticker
    df.set_index("Ticker", inplace = True)
    df.insert(0, "crr_asst", 0)
    df.insert(0, "crr_libt", 0)
```

```
        df = df[["net_income", "op_income", "gross_profit", "crr_asst", "ncrr_asst", "crr_l
        return df
```

```
In [121]: df2 = pd.DataFrame(columns = ["net_income", "op_income", "gross_profit", "crr_asst",
          df2.index.name = "Ticker"
          counter = 0
          for ticker in test_tickers_df["Test Tickers"]:
              counter += 1
              print(str(counter) + ". Getting data for: " + ticker)
              try:
                  df2 = df2.append(get_prev_data(ticker))
              except:
                  df2 = df2.append(get_prev_data_2(ticker))
```

```
1. Getting data for: HSIC
2. Getting data for: ALXN
3. Getting data for: KR
4. Getting data for: BBT
5. Getting data for: DIS
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7. Getting data for: MAR
8. Getting data for: CELG
9. Getting data for: VMC
10. Getting data for: RHI
11. Getting data for: MKC
12. Getting data for: PGR
13. Getting data for: ILMN
14. Getting data for: AMAT
15. Getting data for: LEG
16. Getting data for: STI
17. Getting data for: GS
18. Getting data for: RTN
19. Getting data for: KMI
20. Getting data for: CRM
21. Getting data for: STZ
22. Getting data for: INFO
23. Getting data for: AAP
24. Getting data for: EXC
25. Getting data for: MCO
26. Getting data for: AGN
27. Getting data for: C
28. Getting data for: NTRS
29. Getting data for: TMK
30. Getting data for: EW
31. Getting data for: NEE
32. Getting data for: BBY
33. Getting data for: RCL
34. Getting data for: VIAB
```

```
35. Getting data for: TTWO
36. Getting data for: AWK
37. Getting data for: MO
38. Getting data for: WAT
39. Getting data for: EQR
40. Getting data for: MA
41. Getting data for: TGT
42. Getting data for: DG
43. Getting data for: JPM
44. Getting data for: IT
45. Getting data for: LYB
46. Getting data for: ISRG
47. Getting data for: ABC
48. Getting data for: FCX
49. Getting data for: ETR
50. Getting data for: LB
51. Getting data for: GWW
52. Getting data for: GT
53. Getting data for: CF
54. Getting data for: DVA
55. Getting data for: CAH
56. Getting data for: ADP
57. Getting data for: CAG
58. Getting data for: YUM
59. Getting data for: D
60. Getting data for: CL
61. Getting data for: PRGO
62. Getting data for: AZO
63. Getting data for: ETFC
64. Getting data for: IP
65. Getting data for: COF
66. Getting data for: GPS
67. Getting data for: FL
68. Getting data for: GD
69. Getting data for: CVS
70. Getting data for: ED
71. Getting data for: CI
72. Getting data for: PNC
73. Getting data for: BLK
74. Getting data for: HUM
75. Getting data for: MMM
76. Getting data for: ALGN
77. Getting data for: AFL
78. Getting data for: CHTR
79. Getting data for: CSX
80. Getting data for: ORLY
81. Getting data for: CNC
82. Getting data for: MDLZ
```

```
In [122]: df2 = df2.dropna()
          df2
```

```
Out[122]:           net_income     op_income  gross_profit      crr_asst     ncrr_asst  \
          Ticker
          HSIC    4.062990e+08  8.593690e+08  3.399103e+09  4.086020e+09  3.777975e+09
          ALXN    4.433000e+08  6.684000e+08  3.096900e+09  2.953900e+09  1.062940e+10
          KR      1.975000e+09  3.436000e+09  2.583500e+10  1.034000e+10  2.616500e+10
          BBT     2.394000e+09  3.718000e+09  1.077000e+10  0.000000e+00  2.216420e+11
          DIS     8.980000e+09  1.377500e+10  2.483100e+10  1.588900e+10  7.990000e+10
          MMC     1.492000e+09  2.655000e+09  1.402400e+10  5.562000e+09  1.486700e+10
          MAR     1.459000e+09  2.504000e+09  3.813000e+09  2.740000e+09  2.110600e+10
          CELG    2.940000e+09  4.707000e+09  1.254200e+10  1.489200e+10  1.524900e+10
          VMC     6.011850e+08  6.390440e+08  9.935130e+08  1.180101e+09  8.324790e+09
          RHI     2.905840e+08  5.157170e+08  2.163812e+09  1.431869e+09  4.355850e+08
          MKC     4.435000e+08  7.024000e+08  2.010200e+09  1.617000e+09  8.768800e+09
          PGR     1.592200e+09  2.292000e+09  8.031000e+09  0.000000e+00  3.870120e+10
          ILMN    7.260000e+08  6.060000e+08  1.826000e+09  2.980000e+09  2.277000e+09
          AMAT    3.434000e+09  3.868000e+09  6.532000e+09  1.291800e+10  6.501000e+09
          LEG     2.926000e+08  4.563000e+08  8.824000e+08  1.766500e+09  1.784300e+09
          STI     2.273000e+09  2.814000e+09  8.578000e+09  0.000000e+00  2.059620e+11
          GS      4.286000e+09  1.178900e+10  3.273000e+10  0.000000e+00  9.167760e+11
          RTN     2.024000e+09  4.231000e+09  7.008000e+09  1.132600e+10  1.953400e+10
          KMI     1.830000e+08  3.529000e+09  6.490000e+09  2.715000e+09  7.634000e+10
          CRM     3.600000e+08  4.540000e+08  7.767000e+09  9.584000e+09  1.240000e+10
          STZ     1.535100e+09  2.137000e+09  3.529400e+09  3.230000e+09  1.537240e+10
          INFO    1.394000e+08  2.301000e+08  9.479000e+08  3.110000e+08  2.785700e+09
          AAP     4.755050e+08  5.702120e+08  4.085049e+09  5.426892e+09  3.055409e+09
          EXC     3.786000e+09  4.162000e+09  7.774000e+09  1.189600e+10  1.048740e+11
          MCO     1.000600e+09  1.820800e+09  4.204100e+09  2.580600e+09  6.013600e+09
          AGN    -4.125500e+09 -5.921200e+09  1.377270e+10  1.137670e+10  1.069652e+11
          C      -6.798000e+09  2.276100e+10  6.499300e+10  0.000000e+00  1.842465e+12
          NTRS    1.199000e+09  1.633900e+09  5.403300e+09  0.000000e+00  1.385905e+11
          TMK     1.454494e+09  9.151800e+08  1.927698e+09  0.000000e+00  2.347498e+10
          EW      5.836000e+08  1.029300e+09  2.560000e+09  2.549200e+09  3.117200e+09
          ...              ...           ...           ...           ...           ...
          CF      3.580000e+08  2.250000e+08  4.340000e+08  1.465000e+09  1.199800e+10
          DVA     6.636180e+08  1.821395e+09  3.236629e+09  8.770701e+09  1.020384e+10
          CAH     1.288000e+09  2.125000e+09  6.544000e+09  2.834500e+10  1.176700e+10
          ADP     1.733400e+09  2.326800e+09  5.110000e+09  3.265870e+10  4.521300e+09
          CAG     6.393000e+08  9.250000e+08  2.342100e+09  2.013200e+09  8.083100e+09
          YUM     1.340000e+09  2.761000e+09  2.687000e+09  2.507000e+09  2.804000e+09
          D       2.999000e+09  3.937000e+09  5.710000e+09  4.334000e+09  7.225100e+10
          CL      2.024000e+09  3.707000e+09  9.280000e+09  4.639000e+09  8.037000e+09
          PRGO    1.196000e+08  5.982000e+08  1.979500e+09  2.819600e+09  8.809200e+09
          AZO     1.280869e+09  2.080069e+09  5.739620e+09  4.611255e+09  4.648526e+09
```

ETFC	6.140000e+08	1.122000e+09	2.366000e+09	0.000000e+00	6.336500e+10
IP	2.144000e+09	1.953000e+09	6.941000e+09	8.277000e+09	2.562600e+10
COF	1.982000e+09	5.492000e+09	1.968600e+10	0.000000e+00	3.656930e+11
GPS	8.480000e+08	1.479000e+09	6.066000e+09	4.568000e+09	3.421000e+09
FL	6.640000e+08	1.000000e+09	2.636000e+09	2.633000e+09	1.207000e+09
GD	2.912000e+09	4.236000e+09	6.242000e+09	1.832800e+10	1.671800e+10
CVS	6.622000e+09	9.538000e+09	2.852800e+10	3.122900e+10	6.390200e+10
ED	1.525000e+09	2.774000e+09	6.269000e+09	3.537000e+09	4.457400e+10
CI	1.867000e+09	2.979000e+09	1.271400e+10	0.000000e+00	5.936000e+10
PNC	5.338000e+09	5.931000e+09	1.632900e+10	0.000000e+00	3.807680e+11
BLK	4.952000e+09	5.254000e+09	1.104200e+10	0.000000e+00	2.202410e+11
HUM	2.448000e+09	4.262000e+09	1.027100e+10	1.740200e+10	9.776000e+09
MMM	4.858000e+09	7.692000e+09	1.560200e+10	1.427700e+10	2.371000e+10
ALGN	2.314180e+08	3.536110e+08	1.116947e+09	1.158367e+09	6.256420e+08
AFL	4.604000e+09	4.258000e+09	9.486000e+09	0.000000e+00	1.372170e+11
CHTR	-2.370000e+08	1.020000e+09	7.059000e+09	3.560000e+08	1.538100e+10
CSX	5.471000e+09	3.501000e+09	3.741000e+09	1.915000e+09	3.382400e+10
ORLY	1.133804e+09	1.725400e+09	4.720683e+09	3.397672e+09	4.174213e+09
CNC	8.280000e+08	1.199000e+09	5.801000e+09	8.703000e+09	1.315200e+10
MDLZ	2.828000e+09	3.276000e+09	1.003400e+10	7.520000e+09	5.543700e+10

	crr_libt	ncrr_libt
Ticker		
HSIC	2.828975e+09	1.378472e+09
ALXN	9.525000e+08	3.737700e+09
KR	1.286000e+10	1.693500e+10
BBT	0.000000e+00	1.919470e+11
DIS	1.959500e+10	3.119000e+10
MMC	4.262000e+09	8.725000e+09
MAR	5.807000e+09	1.445700e+10
CELG	2.987000e+09	2.023300e+10
VMC	4.428720e+08	4.093126e+09
RHI	7.478960e+08	1.429300e+07
MKC	1.947300e+09	5.867600e+09
PGR	0.000000e+00	2.891270e+10
ILMN	7.460000e+08	1.762000e+09
AMAT	4.115000e+09	5.955000e+09
LEG	9.762000e+08	1.383800e+09
STI	0.000000e+00	1.808080e+11
GS	0.000000e+00	8.345330e+11
RTN	7.348000e+09	1.354900e+10
KMI	6.181000e+09	3.775000e+10
CRM	1.006700e+10	1.541000e+09
STZ	2.697600e+09	9.020000e+09
INFO	5.008000e+08	5.400000e+08
AAP	3.480097e+09	1.587008e+09
EXC	1.079800e+10	7.378500e+10
MCO	2.063300e+09	6.645800e+09

```
AGN     9.848100e+09  3.465670e+10
C       0.000000e+00  1.640793e+12
NTRS    0.000000e+00  1.283743e+11
TMK     0.000000e+00  1.724356e+10
EW      1.420000e+09  1.290200e+09
...              ...           ...
CF      5.800000e+08  6.199000e+09
DVA     3.067520e+09  1.000959e+10
CAH     2.122100e+10  1.206300e+10
ADP     2.981590e+10  3.387100e+09
CAG     1.720500e+09  4.298000e+09
YUM     1.512000e+09  1.013300e+10
D       9.636000e+09  4.757900e+10
CL      3.408000e+09  9.025000e+09
PRGO    1.436000e+09  4.022200e+09
AZO     4.766301e+09  5.921857e+09
ETFC    0.000000e+00  5.643400e+10
IP      5.102000e+09  2.226000e+10
COF     0.000000e+00  3.169630e+11
GPS     2.461000e+09  2.384000e+09
FL      6.120000e+08  5.180000e+08
GD      1.309900e+10  1.051200e+10
CVS     3.064800e+10  2.678800e+10
ED      4.902000e+09  2.778400e+10
CI      0.000000e+00  4.557500e+10
PNC     0.000000e+00  3.331830e+11
BLK     0.000000e+00  1.879770e+11
HUM     9.406000e+09  7.930000e+09
MMM     7.687000e+09  1.867800e+10
ALGN    5.000510e+08  1.296700e+08
AFL     0.000000e+00  1.126190e+11
CHTR    1.049000e+09  1.321000e+10
CSX     1.894000e+09  1.912400e+10
ORLY    3.647366e+09  3.271473e+09
CNC     9.332000e+09  5.647000e+09
MDLZ    1.579300e+10  2.109000e+10

[82 rows x 7 columns]
```

In [0]:
```
df2.to_csv(model_dir + "prev_data.csv")
```

In [0]:
```
def prepare_test_data(data, n_steps):
    for i in range(1, len(data)):
        end_ix = i + n_steps
        if(end_ix > len(data) - 1):
            seq_x = data[i-1:end_ix-1, :]
            return seq_x
```

In [0]:
```
def read_data_from_file(ticker):
```

```
    df = pd.read_csv(prep_dir + ticker + ".csv")
    return df[["net_income", "op_income", "gross_profit", "crr_asst", "ncrr_asst", "cr
```

In [0]:
```
# Load trained model
from keras.models import load_model
model = load_model(sp_dir + "bondai_model_1.1.h5")
```

In [178]:
```
df3 = pd.DataFrame(columns = ["net_income", "op_income", "gross_profit", "crr_asst",
df3.index.name = "Ticker"
test_df = pd.DataFrame(columns = ["net_income", "op_income", "gross_profit", "crr_as
test_df.index.name = "Ticker"
counter = 0
for ticker in test_tickers_df["Test Tickers"]:
    counter += 1
    print(str(counter) + ". Predicting values for: " + ticker)
    test_array = prepare_test_data(read_data_from_file(ticker), 2)
    test_input = test_array.reshape(1, 2, 7)
    pred_array = model.predict(test_input, verbose = 1)
    df_temp = pd.DataFrame(pred_array.tolist(), columns = ["net_income", "op_income"
    df_temp["Ticker"] = ticker
    df_temp.set_index("Ticker", inplace = True)
    test_df = test_df.append(df_temp)
    df_temp = df_temp.loc[ticker]*df2.loc[ticker]
    df3 = df3.append(df_temp)
```

```
1. Predicting values for: HSIC
1/1 [==============================] - 0s 293ms/step
2. Predicting values for: ALXN
1/1 [==============================] - 0s 1ms/step
3. Predicting values for: KR
1/1 [==============================] - 0s 2ms/step
4. Predicting values for: BBT
1/1 [==============================] - 0s 1ms/step
5. Predicting values for: DIS
1/1 [==============================] - 0s 2ms/step
6. Predicting values for: MMC
1/1 [==============================] - 0s 2ms/step
7. Predicting values for: MAR
1/1 [==============================] - 0s 3ms/step
8. Predicting values for: CELG
1/1 [==============================] - 0s 1ms/step
9. Predicting values for: VMC
1/1 [==============================] - 0s 5ms/step
10. Predicting values for: RHI
1/1 [==============================] - 0s 3ms/step
11. Predicting values for: MKC
1/1 [==============================] - 0s 1ms/step
```

```
12. Predicting values for: PGR
1/1 [==============================] - 0s 1ms/step
13. Predicting values for: ILMN
1/1 [==============================] - 0s 1ms/step
14. Predicting values for: AMAT
1/1 [==============================] - 0s 2ms/step
15. Predicting values for: LEG
1/1 [==============================] - 0s 2ms/step
16. Predicting values for: STI
1/1 [==============================] - 0s 1ms/step
17. Predicting values for: GS
1/1 [==============================] - 0s 2ms/step
18. Predicting values for: RTN
1/1 [==============================] - 0s 2ms/step
19. Predicting values for: KMI
1/1 [==============================] - 0s 1ms/step
20. Predicting values for: CRM
1/1 [==============================] - 0s 1ms/step
21. Predicting values for: STZ
1/1 [==============================] - 0s 2ms/step
22. Predicting values for: INFO
1/1 [==============================] - 0s 2ms/step
23. Predicting values for: AAP
1/1 [==============================] - 0s 1ms/step
24. Predicting values for: EXC
1/1 [==============================] - 0s 2ms/step
25. Predicting values for: MCO
1/1 [==============================] - 0s 3ms/step
26. Predicting values for: AGN
1/1 [==============================] - 0s 1ms/step
27. Predicting values for: C
1/1 [==============================] - 0s 1ms/step
28. Predicting values for: NTRS
1/1 [==============================] - 0s 2ms/step
29. Predicting values for: TMK
1/1 [==============================] - 0s 2ms/step
30. Predicting values for: EW
1/1 [==============================] - 0s 1ms/step
31. Predicting values for: NEE
1/1 [==============================] - 0s 2ms/step
32. Predicting values for: BBY
1/1 [==============================] - 0s 2ms/step
33. Predicting values for: RCL
1/1 [==============================] - 0s 1ms/step
34. Predicting values for: VIAB
1/1 [==============================] - 0s 2ms/step
35. Predicting values for: TTWO
1/1 [==============================] - 0s 2ms/step
```

```
36. Predicting values for: AWK
1/1 [==============================] - 0s 1ms/step
37. Predicting values for: MO
1/1 [==============================] - 0s 2ms/step
38. Predicting values for: WAT
1/1 [==============================] - 0s 2ms/step
39. Predicting values for: EQR
1/1 [==============================] - 0s 3ms/step
40. Predicting values for: MA
1/1 [==============================] - 0s 3ms/step
41. Predicting values for: TGT
1/1 [==============================] - 0s 5ms/step
42. Predicting values for: DG
1/1 [==============================] - 0s 2ms/step
43. Predicting values for: JPM
1/1 [==============================] - 0s 1ms/step
44. Predicting values for: IT
1/1 [==============================] - 0s 1ms/step
45. Predicting values for: LYB
1/1 [==============================] - 0s 4ms/step
46. Predicting values for: ISRG
1/1 [==============================] - 0s 1ms/step
47. Predicting values for: ABC
1/1 [==============================] - 0s 1ms/step
48. Predicting values for: FCX
1/1 [==============================] - 0s 1ms/step
49. Predicting values for: ETR
1/1 [==============================] - 0s 2ms/step
50. Predicting values for: LB
1/1 [==============================] - 0s 5ms/step
51. Predicting values for: GWW
1/1 [==============================] - 0s 1ms/step
52. Predicting values for: GT
1/1 [==============================] - 0s 1ms/step
53. Predicting values for: CF
1/1 [==============================] - 0s 2ms/step
54. Predicting values for: DVA
1/1 [==============================] - 0s 1ms/step
55. Predicting values for: CAH
1/1 [==============================] - 0s 1ms/step
56. Predicting values for: ADP
1/1 [==============================] - 0s 1ms/step
57. Predicting values for: CAG
1/1 [==============================] - 0s 3ms/step
58. Predicting values for: YUM
1/1 [==============================] - 0s 1ms/step
59. Predicting values for: D
1/1 [==============================] - 0s 3ms/step
```

```
60. Predicting values for: CL
1/1 [==============================] - 0s 2ms/step
61. Predicting values for: PRGO
1/1 [==============================] - 0s 2ms/step
62. Predicting values for: AZO
1/1 [==============================] - 0s 1ms/step
63. Predicting values for: ETFC
1/1 [==============================] - 0s 2ms/step
64. Predicting values for: IP
1/1 [==============================] - 0s 4ms/step
65. Predicting values for: COF
1/1 [==============================] - 0s 4ms/step
66. Predicting values for: GPS
1/1 [==============================] - 0s 1ms/step
67. Predicting values for: FL
1/1 [==============================] - 0s 5ms/step
68. Predicting values for: GD
1/1 [==============================] - 0s 2ms/step
69. Predicting values for: CVS
1/1 [==============================] - 0s 4ms/step
70. Predicting values for: ED
1/1 [==============================] - 0s 2ms/step
71. Predicting values for: CI
1/1 [==============================] - 0s 3ms/step
72. Predicting values for: PNC
1/1 [==============================] - 0s 1ms/step
73. Predicting values for: BLK
1/1 [==============================] - 0s 1ms/step
74. Predicting values for: HUM
1/1 [==============================] - 0s 3ms/step
75. Predicting values for: MMM
1/1 [==============================] - 0s 1ms/step
76. Predicting values for: ALGN
1/1 [==============================] - 0s 1ms/step
77. Predicting values for: AFL
1/1 [==============================] - 0s 4ms/step
78. Predicting values for: CHTR
1/1 [==============================] - 0s 1ms/step
79. Predicting values for: CSX
1/1 [==============================] - 0s 3ms/step
80. Predicting values for: ORLY
1/1 [==============================] - 0s 1ms/step
81. Predicting values for: CNC
1/1 [==============================] - 0s 3ms/step
82. Predicting values for: MDLZ
1/1 [==============================] - 0s 4ms/step
```

In [179]: test_df

Out[179]:

Ticker	net_income	op_income	gross_profit	crr_asst	ncrr_asst \
HSIC	90.567238	35.086239	14.530129	3.199066	12.404232
ALXN	11.829369	29.504908	6.072799	5.710222	9.407384
KR	6.805795	20.842474	0.706779	6.696035	9.308869
BBT	4.631532	7.631013	4.076230	4.039822	6.841225
DIS	6.123345	-3.027328	3.794250	4.097010	6.743133
MMC	23.680965	13.961922	6.381871	4.081548	8.549265
MAR	278.247192	19.505434	38.074577	21.264244	39.012157
CELG	2.759505	6.238966	4.803248	4.299804	6.992246
VMC	1.012426	1.713614	3.753136	3.853374	6.492170
RHI	-16.500957	22.620205	6.634981	3.216424	7.109317
MKC	44.851856	54.633381	12.268779	6.913266	8.424918
PGR	-22.359821	-30.774036	-0.918028	5.315338	6.155030
ILMN	24.232273	-21.696569	6.372759	6.993613	13.137230
AMAT	-39.677147	-48.804760	3.526615	4.078002	5.533684
LEG	84.898415	38.331421	15.286839	2.685039	12.308332
STI	5.329725	-1.177359	3.946419	4.137344	6.873646
GS	141.891342	19.214287	6.992815	5.306882	0.039634
RTN	8.814200	8.301688	4.792628	3.941169	7.808271
KMI	140.190170	66.064644	9.009709	8.582937	7.205617
CRM	-4.347672	71.355286	18.989914	17.506184	34.478912
STZ	16.871347	1.731304	6.574644	5.122755	8.874253
INFO	-88.488770	-167.708755	-0.058043	10.298864	4.550863
AAP	-237.654007	-34.885979	0.533802	-5.439468	3.720004
EXC	102.606873	75.571060	18.690868	12.941171	-1.032147
MCO	229.797852	-227.544067	-2.176387	20.765575	15.108139
AGN	-754.913513	-219.685608	-28.087549	0.103294	12.548471
C	62.903969	292.381195	27.323601	5.517290	4.894373
NTRS	7.758569	5.147412	4.659198	4.006699	8.151949
TMK	-14.267471	-8.295863	3.830308	3.400224	5.832761
EW	69.738274	58.002121	17.697083	7.901003	20.296350
...	...	...	...	...	...
CF	-52.760147	190.646027	7.333159	-9.596813	-17.028282
DVA	69.615120	18.823231	8.143291	6.502781	10.997393
CAH	47.119205	58.475464	14.313903	8.094099	12.451889
ADP	6.835963	3.941001	5.064887	4.495402	7.109206
CAG	-94.807930	15.300156	14.766015	-4.935698	29.091955
YUM	13.718836	-23.878765	4.004870	5.379927	7.986770
D	6.640142	2.789119	4.828179	4.552726	6.477331
CL	3.283488	1.473836	4.073280	4.027480	6.686031
PRGO	493.345337	1115.858154	82.202499	60.797508	-10.241606
AZO	1.048150	-4.571373	4.246134	4.335862	7.230009
ETFC	0.445210	6.779930	3.764673	3.821513	6.615489
IP	34.668022	14.521718	6.415457	5.072599	6.320753
COF	326.315033	219.281219	12.965794	20.009697	8.147700

GPS	4.164483	2.801186	7.154431	4.550849	6.165731
FL	0.033799	-0.243920	3.334037	3.723461	6.018923
GD	-19.551931	-0.638254	1.315832	4.709514	6.749040
CVS	9.458874	14.278608	5.295164	5.329990	9.393739
ED	8.864672	3.252520	3.760813	3.671202	7.492142
CI	-20.038069	-11.917254	2.348321	3.612511	7.372001
PNC	3.807448	1.187793	3.997733	3.691278	6.107180
BLK	-0.181906	3.171088	4.399975	3.880582	5.727203
HUM	10.173508	-15.633470	2.405644	3.394741	4.856322
MMM	26.686396	13.186875	7.995681	4.374392	8.845362
ALGN	93.567940	-6.044254	19.191267	9.676134	20.929417
AFL	3.479529	4.972035	4.142946	4.038532	6.740419
CHTR	108.851677	27.181824	29.480879	4.534270	6.922085
CSX	4.655613	-0.001982	4.069959	2.971053	6.472765
ORLY	-1.098833	-10.375491	3.918644	4.268546	6.872735
CNC	40.988697	-54.546623	13.914059	13.093858	15.929489
MDLZ	-34.439030	21.967449	4.324399	5.888249	5.309289

	crr_libt	ncrr_libt
Ticker		
HSIC	9.485085	6.233299
ALXN	7.486669	18.218327
KR	8.750217	14.008575
BBT	7.078929	6.557758
DIS	7.032441	6.772195
MMC	7.774268	7.294129
MAR	25.189312	-5.472239
CELG	7.321340	6.957475
VMC	6.870212	6.646871
RHI	7.145907	9.579412
MKC	9.480685	2.504369
PGR	7.560374	5.983315
ILMN	9.809477	15.808467
AMAT	5.715414	6.000074
LEG	8.880333	0.662446
STI	7.182800	7.324257
GS	7.070748	-2.266990
RTN	7.276250	5.928930
KMI	7.086630	5.341793
CRM	9.979552	152.972015
STZ	8.009127	7.188514
INFO	16.299294	-9.776512
AAP	4.423370	2.267954
EXC	9.963234	12.306341
MCO	15.387785	45.914356
AGN	24.451839	-15.454521
C	6.366542	0.221878
NTRS	7.374359	8.047464

```
TMK      6.117756    6.386825
EW      10.623949    2.504603
...           ...         ...
CF      -5.290913    6.349937
DVA      7.787979   16.983440
CAH     10.439190    8.568964
ADP      7.434902    7.403680
CAG      3.352486  -15.117414
YUM      7.312113    6.884905
D        7.302917    6.532606
CL       7.135282    6.881402
PRGO    12.224224    3.851890
AZO      7.179330    8.037186
ETFC     6.955028    6.220142
IP       7.385159    6.671010
COF      9.458015    2.655196
GPS      7.237342    4.318239
FL       6.853255    7.385875
GD       6.897113    6.459259
CVS      8.157414   17.640574
ED       7.036551    6.400068
CI       6.561469    8.737535
PNC      6.908329    7.551773
BLK      6.907135    5.663427
HUM      6.146457    5.599200
MMM      8.020289    8.033869
ALGN    12.703783   10.517294
AFL      7.121217    6.561082
CHTR     8.173641   11.869499
CSX      6.404769    6.629484
ORLY     7.226124    6.875263
CNC     15.514424    4.651995
MDLZ     8.031281   13.849812

[82 rows x 7 columns]
```

```
In [180]: df3
```

```
Out[180]:         net_income     op_income  gross_profit      crr_asst     ncrr_asst  \
Ticker
HSIC    3.679738e+10  3.015203e+10  4.938941e+10  1.307145e+10  4.686288e+10
ALXN    5.243959e+09  1.972108e+10  1.880685e+10  1.686743e+10  9.999485e+10
KR      1.344144e+10  7.161474e+10  1.825964e+10  6.923701e+10  2.435666e+11
BBT     1.108789e+10  2.837211e+10  4.390100e+10  0.000000e+00  1.516303e+12
DIS     5.498764e+10 -4.170145e+10  9.421502e+10  6.509739e+10  5.387763e+11
MMC     3.533200e+10  3.706890e+10  8.949936e+10  2.270157e+10  1.271019e+11
MAR     4.059627e+11  4.884161e+10  1.451784e+11  5.826403e+10  8.233906e+11
CELG    8.112943e+09  2.936682e+10  6.024234e+10  6.403268e+10  1.066248e+11
```

VMC	6.086551e+08	1.095075e+09	3.728789e+09	4.547371e+09	5.404595e+10
RHI	-4.794914e+09	1.166562e+10	1.435685e+10	4.605498e+09	3.096712e+09
MKC	1.989180e+10	3.837449e+10	2.466270e+10	1.117875e+10	7.387642e+10
PGR	-3.560131e+10	-7.053409e+10	-7.372684e+09	0.000000e+00	2.382071e+11
ILMN	1.759263e+10	-1.314812e+10	1.163666e+10	2.084097e+10	2.991347e+10
AMAT	-1.362513e+11	-1.887768e+11	2.303585e+10	5.267963e+10	3.597448e+10
LEG	2.484128e+10	1.749063e+10	1.348911e+10	4.743122e+09	2.196176e+10
STI	1.211447e+10	-3.313087e+09	3.385239e+10	0.000000e+00	1.415710e+12
GS	6.081463e+11	2.265172e+11	2.288748e+11	0.000000e+00	3.633571e+10
RTN	1.783994e+10	3.512444e+10	3.358674e+10	4.463768e+10	1.525268e+11
KMI	2.565480e+10	2.331421e+11	5.847301e+10	2.330267e+10	5.500768e+11
CRM	-1.565162e+09	3.239530e+10	1.474947e+11	1.677793e+11	4.275385e+11
STZ	2.589921e+10	3.699796e+09	2.320455e+10	1.654650e+10	1.364186e+11
INFO	-1.233533e+10	-3.858978e+10	-5.501919e+07	3.202947e+09	1.267734e+10
AAP	-1.130057e+11	-1.989240e+10	2.180606e+09	-2.951941e+10	1.136613e+10
EXC	3.884696e+11	3.145268e+11	1.453028e+11	1.539482e+11	-1.082454e+11
MCO	2.299357e+11	-4.143122e+11	-9.149749e+09	5.358764e+10	9.085430e+10
AGN	3.114396e+12	1.300802e+12	-3.868414e+11	1.175146e+09	1.342250e+12
C	-4.276212e+11	6.654888e+12	1.775843e+12	0.000000e+00	9.017712e+12
NTRS	9.302524e+09	8.410357e+09	2.517505e+10	0.000000e+00	1.129783e+12
TMK	-2.075195e+10	-7.592208e+09	7.383677e+09	0.000000e+00	1.369240e+11
EW	4.069926e+10	5.970158e+10	4.530453e+10	2.014124e+10	6.326778e+10
...	...	...	...	...	...
CF	-1.888813e+10	4.289536e+10	3.182591e+09	-1.405933e+10	-2.043053e+11
DVA	4.619785e+10	3.428454e+10	2.635681e+10	5.703395e+10	1.122156e+11
CAH	6.068954e+10	1.242604e+11	9.367018e+10	2.294272e+11	1.465214e+11
ADP	1.184946e+10	9.169922e+09	2.588157e+10	1.468140e+11	3.214285e+10
CAG	-6.061071e+10	1.415264e+10	3.458348e+10	-9.936546e+09	2.351532e+11
YUM	1.838324e+10	-6.592927e+10	1.076109e+10	1.348748e+10	2.239490e+10
D	1.991379e+10	1.098076e+10	2.756890e+10	1.973152e+10	4.679937e+11
CL	6.645780e+09	5.463510e+09	3.780004e+10	1.868348e+10	5.373563e+10
PRGO	5.900410e+10	6.675063e+11	1.627198e+11	1.714247e+11	-9.022035e+10
AZO	1.342543e+09	-9.508770e+09	2.437120e+10	1.999376e+10	3.360889e+10
ETFC	2.733586e+08	7.607082e+09	8.907217e+09	0.000000e+00	4.191905e+11
IP	7.432824e+10	2.836092e+10	4.452969e+10	4.198591e+10	1.619756e+11
COF	6.467564e+11	1.204292e+12	2.552446e+11	0.000000e+00	2.979557e+12
GPS	3.531481e+09	4.142954e+09	4.339878e+10	2.078828e+10	2.109297e+10
FL	2.244281e+07	-2.439203e+08	8.788522e+09	9.803873e+09	7.264840e+09
GD	-5.693522e+10	-2.703642e+09	8.213421e+09	8.631597e+10	1.128304e+11
CVS	6.263666e+10	1.361894e+11	1.510604e+11	1.664503e+11	6.002787e+11
ED	1.351862e+10	9.022491e+09	2.357653e+10	1.298504e+10	3.339547e+11
CI	-3.741107e+10	-3.550150e+10	2.985656e+10	0.000000e+00	4.376020e+11
PNC	2.032416e+10	7.044803e+09	6.527898e+10	0.000000e+00	2.325419e+12
BLK	-9.008008e+08	1.666090e+10	4.858452e+10	0.000000e+00	1.261365e+12
HUM	2.490475e+10	-6.662985e+10	2.470837e+10	5.907528e+10	4.747541e+10
MMM	1.296425e+11	1.014334e+11	1.247486e+11	6.245319e+10	2.097235e+11
ALGN	2.165331e+10	-2.137315e+09	2.143563e+10	1.120851e+10	1.309432e+10
AFL	1.601975e+10	2.117093e+10	3.929998e+10	0.000000e+00	9.249001e+11

CHTR	-2.579785e+10	2.772546e+10	2.081055e+11	1.614200e+09	1.064686e+11
CSX	2.547086e+10	-6.940559e+06	1.522572e+10	5.689567e+09	2.189348e+11
ORLY	-1.245861e+09	-1.790187e+10	1.849868e+10	1.450312e+10	2.868826e+10
CNC	3.393864e+10	-6.540140e+10	8.071545e+10	1.139558e+11	2.095046e+11
MDLZ	-9.739358e+10	7.196536e+10	4.339102e+10	4.427963e+10	2.943311e+11

	crr_libt	ncrr_libt
Ticker		
HSIC	2.683307e+10	8.592428e+09
ALXN	7.131052e+09	6.809464e+10
KR	1.125278e+11	2.372352e+11
BBT	0.000000e+00	1.258742e+12
DIS	1.378007e+11	2.112248e+11
MMC	3.313393e+10	6.364128e+10
MAR	1.462743e+11	-7.911217e+10
CELG	2.186884e+10	1.407706e+11
VMC	3.042625e+09	2.720648e+10
RHI	5.344396e+09	1.369185e+08
MKC	1.846174e+10	1.469464e+10
PGR	0.000000e+00	1.729938e+11
ILMN	7.317870e+09	2.785452e+10
AMAT	2.351893e+10	3.573044e+10
LEG	8.668981e+09	9.166935e+08
STI	0.000000e+00	1.324284e+12
GS	0.000000e+00	-1.891878e+12
RTN	5.346588e+10	8.033108e+10
KMI	4.380246e+10	2.016527e+11
CRM	1.004642e+11	2.357299e+11
STZ	2.160542e+10	6.484040e+10
INFO	8.162686e+09	-5.279317e+09
AAP	1.539376e+10	3.599261e+09
EXC	1.075830e+11	9.080234e+11
MCO	3.174962e+10	3.051376e+11
AGN	2.408042e+11	-5.356027e+11
C	0.000000e+00	3.640560e+11
NTRS	0.000000e+00	1.033088e+12
TMK	0.000000e+00	1.101316e+11
EW	1.508601e+10	3.231439e+09
...	...	...
CF	-3.068729e+09	3.936326e+10
DVA	2.388978e+10	1.699973e+11
CAH	2.215300e+11	1.033674e+11
ADP	2.216783e+11	2.507700e+10
CAG	5.767953e+09	-6.497465e+10
YUM	1.105592e+10	6.976475e+10
D	7.037090e+10	3.108149e+11
CL	2.431704e+10	6.210466e+10
PRGO	1.755399e+10	1.549307e+10

```
AZO     3.421885e+10  4.759506e+10
ETFC    0.000000e+00  3.510275e+11
IP      3.767908e+10  1.484967e+11
COF     0.000000e+00  8.415989e+11
GPS     1.781110e+10  1.029468e+10
FL      4.194192e+09  3.825883e+09
GD      9.034529e+10  6.789973e+10
CVS     2.500084e+11  4.725557e+11
ED      3.449317e+10  1.778195e+11
CI      0.000000e+00  3.982132e+11
PNC     0.000000e+00  2.516122e+12
BLK     0.000000e+00  1.064594e+12
HUM     5.781358e+10  4.440166e+10
MMM     6.165196e+10  1.500566e+11
ALGN    6.352539e+09  1.363778e+09
AFL     0.000000e+00  7.389025e+11
CHTR    8.574150e+09  1.567961e+11
CSX     1.213063e+10  1.267822e+11
ORLY    2.635632e+10  2.249224e+10
CNC     1.447806e+11  2.626981e+10
MDLZ    1.268380e+11  2.920925e+11

[82 rows x 7 columns]
```

In [0]:
```
df3.to_csv(model_dir + "pred_data.csv")
```