Dataminr SignalS Analysis

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# Executive Summary

In this study we analyze asset returns around the time of Dataminr signals. In particular, our study includes the following analyses:

1. Comparison of end of day returns with Dataminr signals including lagged effects ;
2. Comparison of intraday pre-signal and post-signal returns;
3. Enhancement of equity short-term reversal strategy by Dataminr signals.

Using Dataminr signal data classified as either Alerts or Flashes and Notables and intra-day asset prices provided by DataMinr, along with publicly available asset price information, we find that assets had significantly higher absolute return values on days with both Dataminr signals. This effect is amplified for higher volatility stocks and is particularly strong in sectors like pharmaceuticals.

Our study of intra-day price dynamics concluded that stock prices movement co-occur with Dataminr signals most strongly in the first half an hour after the signal and that abnormal returns continue over the next three days after the signal. We find that abnormal returns are much higher for Flashes and Notables than for Alerts.

In addition we back-tested a reversal strategy that involves shorting past week winner stocks and rebalancing this portfolio on weekly basis. We have used event volume count by adding up the number of Dataminr signals over the past week and discovered that winner reversal strategy is significantly enhanced by filtering on high event volume stocks.

# Introduction

The following report provides details of the analysis carried out by FNA to analyse Dataminr signals data and its relationship with returns of the associated assets. We first describe the data used and then detail analysis carried out.

# Dataminr Signals Data

The results presented here are based on signal data provided by DataMinr in the files:

* alerts.3.1.2014-11.30.2014.dateString.tsv which includes Alert signals
* notable\_and\_flash.3.1.201411.30.2014.dateString.tsv which includes Flashes and Notables -signals

From these files we used only columns A and D, which provide the date/time of the signal and the associated asset ticker(s), respectively.

Since we are only counting the number of signals associated with each ticker within a given time span, the content of the tweets themselves was not used. We ignored any signals that had no ticker provided in column D.

As a coarse way to deal with time zone incompatibilities (e.g., European markets close much earlier than US markets, yet the timing of all signals is in EDT), we limited analysis to only signals associated with US tickers (those with no periods in the ticker).

Finally, any signals made after 4pm EDT (closing time of markets) were considered to have their impact on the next day prices. We also removed from the data set 7 rows that had a tweet in the column where the date and time should have been[[1]](#footnote-1).

From here we created a file with the number of signals per ticker per day, a sample of which is shown below.

Date,duk,gm,orcl,cvx,nok,lmt,ibm,twc,cmcsa,ba,...

20141128,0,0,0,2,0,0,0,0,1,0,...

20141127,0,1,0,0,0,0,0,0,0,0,...

20141126,0,1,0,0,0,0,1,1,4,0,...

20141125,0,1,0,3,0,0,0,0,2,0,...

20141124,0,3,0,2,0,0,1,0,0,0,...

20141123,0,0,0,0,0,0,0,0,1,0,...

20141121,0,0,0,1,0,0,0,1,3,0,...

20141120,0,2,0,0,0,0,0,0,0,0,...

20141119,0,0,0,0,0,0,0,0,1,0,...

20141118,0,0,0,1,0,0,1,0,0,0,...

20141117,1,3,0,0,0,0,0,0,0,4,...

...

We first limited the price and signal files to those tickers and dates common to both. In particular, 55 of the 1993 US tickers in the signal data did not have prices available on Yahoo, so these tickers were excluded from the analysis[[2]](#footnote-2). There were also a few dates that were not common to both files (for example, there were some tweets on Sundays), and those data were removed as well. This yielded 182 days of data on 2065 assets, with 18368 signals in total.

## Yahoo Price Data

Using Yahoo Finance, we downloaded price data for all US tickers between 13 March, 2014 and 28 November, 2014. From these data we calculated returns for the period between 14 March, 2014 and 28 November, 2014, which corresponds to the dates available in the DataMinr data. Any missing return values during this period were excluded from the analysis.

## Intraday Price data

Our intra-day analysis is based on the minute by minute price data taken from the file price.1min.march.dec.tgz . We have divided the trading day into hour-long intervals into which we have binned the signal counts.

# Analysis of Alert Signals

### End of day Analysis

We first consider whether there is any relationship between Dataminr signal activity and asset returns by comparing average absolute return values on “high" and “low" signal days. We consider two definitions of high and low activity: signals vs. no signals and many signals vs. fewer signals.

In both cases we test whether the mean absolute return value is significantly different on high versus low activity days. We find that the mean absolute return on days with any signals is 3.0% and the mean absolute return on days with no signals is 1.6%. The p-value for testing equality of the two means is less than 10-16.

For comparing many signals versus fewer signals, we calculate for each ticker the 90th percentile of number of signals per day. All days where the number of signals was higher than the 90th percentile for the given ticker were considered high signal days for that ticker. Defined this way, the mean absolute return value on high signal days is equal to 3.6% and the mean absolute return on days with low signal is equal to 1.6%, with p-value again less than 10-16.

Figure 1: Mean absolute returns for Alert -signals

|  |  |  |  |
| --- | --- | --- | --- |
|  | High Signal | Low/no Signal | p-value |
| Signals vs no signals | 3.0% | 1.6% | 10-16 |
| 90th percentile | 3.6% | 1.6% | 10-16 |

Thus we see significantly higher returns on high aignal days for both definitions of high and low signal. Because the difference in mean returns on high versus low activity days is greater for our second definition, we will use the 90% percentile definition of signal in the subsequent analyses, unless otherwise noted.

### Lagged Effects

We have just shown that absolute return values are higher on signal days. Now we consider whether absolute returns on the days following the signal are also elevated. The table below summarizes results for comparing returns zero (as in the previous section), one, two, and three days following the signal.

Figure 2: Lagged effects of Alert signals

|  |  |  |  |
| --- | --- | --- | --- |
| Days Lagged | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| 0  1  2  3 | 3.6%  2.2%  2.1%  1.9% | 1.6%  1.7%  1.7%  1.7% | < 10-16  < 10-16  < 10-16  < 10-16 |

We see that while mean absolute returns remain significantly higher up to three days following a high activity day, the magnitude of the difference gets smaller as the lag increases. Since we see the most impact on returns on the same day as the high activity, subsequent analyses for sectors, volatility and returns prior to the signal will consider returns on the same day, unless otherwise noted.

### Sector Analysis

Now we consider how signals are associated with asset returns across different sectors. The table below shows absolute returns on signal and no-signal days across GICS industry groups. We show results for all groups with at least 50 tickers, ordered by the magnitude of the impact. We find that mean absolute returns are significantly higher (p < 0.05) on high activity days in all sectors and particularly in Pharmaceuticals.

Figure 3: Returns by sector

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sector | # of Tickers | Signal day | No-signal day | p-value |
| Pharmaceuticals, Biotechnology & Life Sciences | 257 | 5.70% | 2.40% | < 10-16 |
| Consumer Services | 79 | 3.50% | 1.50% | 0.0001 |
| Software & Services | 183 | 3.70% | 1.80% | < 10-11 |
| Consumer Durables & Apparel | 73 | 3.40% | 1.50% | < 10-7 |
| Health Care Equipment & Services | 105 | 3.40% | 1.60% | < 10-5 |
| Technology Hardware & Equipment | 87 | 3.60% | 1.90% | 0.0001 |
| Retailing | 107 | 3.20% | 1.60% | < 10-13 |
| Semiconductors & Semiconductor Equipment | 70 | 3.20% | 1.70% | < 10-6 |
| Capital Goods | 122 | 2.90% | 1.40% | < 10-9 |
| Materials | 89 | 2.60% | 1.40% | < 10-7 |
| Real Estate | 54 | 1.90% | 0.80% | 0.0037 |
| Food, Beverage & Tobacco | 51 | 1.90% | 1.00% | < 10-4 |
| Energy | 154 | 2.60% | 1.80% | < 10-6 |
| Banks | 62 | 1.90% | 1.10% | 0.0042 |
| Media | 56 | 2.00% | 1.30% | < 10-4 |
| Diversified Financials | 93 | 1.80% | 1.20% | 0.0009 |

### Volatility Analysis

To study how the relationship between tweet signals and asset returns is impacted by asset volatility, we grouped the tickers into two categories -high and low realized volatility - based on a year of returns between 28 November 2013 and 28 November 2014. We split the groups at the median volatility value so to have the same number of low volatility and high volatility tickers.

Figure 4: Mean absolute returns by volatility

|  |  |  |  |
| --- | --- | --- | --- |
| Volatility | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| Low  High | 1.6%  5.7% | 1.0%  2.3% | < 10-15  < 10-15 |

While the difference in mean absolute returns is significantly different from zero for both high and low volatility assets, the impact is much greater for the high volatility assets.

### Returns Prior to Tweet Signals

Finally, we test whether absolute returns are higher on the day before a high activity day. We find results very similar to those for the day after a high activity day: The mean absolute return prior to a high activity day is equal to 2.2% and the mean prior to a low activity day is equal to 1.7%, with p-value less than 10-15.

Combining this result with those from the lagged analysis, we see a trend where returns are elevated the day before a high activity day, are elevated even more on the high activity day, and remain elevated, to a decreasing extent, on the days following the high activity day. The figure below shows this trend. We interpret the trend as new information first being reflected

in somewhat elevated absolute returns, then being tweeted about as absolute returns are elevated even further, and the elevation of absolute returns diminishing on subsequent days.

Figure 5: Lagged returns around Alert signals

|  |  |  |  |
| --- | --- | --- | --- |
| Days Lagged | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| -1  0  1  2  3 | 2.2%  3.6%  2.2%  2.1%  1.9% | 1.7%  1.6%  1.7%  1.7%  1.7% | < 10-15  < 10-16  < 10-16  < 10-16  < 10-16 |

## Flashes and Notable Signals

Overall, the results for flashes and notables data are very similar to those for Alerts Data.

### Lagged Effects

Lagged effects are higher on high activity days, peaking on the signal day with absolute returns having very similar values as for the alert file. The results are statistically significant, but the p-values are smaller than those seen with alerts data because of the smaller sample size for flashes and notables.

Figure 6: Returns around Flashes and Notable signals

|  |  |  |  |
| --- | --- | --- | --- |
| Days Lagged | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| -1  0  1  2  3 | 2.4%  3.3%  2.1%  2.2%  2% | 1.7%  1.7%  1.7%  1.7%  1.7% | 2.27\*10-7  < 10-16  1.23\*10-8  0.0004  3.25\*10-5 |

### Sector Analysis

Pharmaceuticals again show the highest difference in absolute returns between the high and low activity days. The results consistently show higher returns on high activity days in all sectors.

Sectors with higher volatility highlight the effect a lot more with absolute returns almost doubling on high activity days. Lower volatility sectors show higher absolute returns on high activity days however the effect is not nearly as strong.

Results are mostly statistically significant, but again with smaller p-values due to the smaller sample size.

Figure 7: Mean absolute returns by sector

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Group | # Tickers | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| |  | | --- | | Pharmaceuticals, Biotechnology & Life Sciences | | Software & Services | | Energy | | Capital Goods | | Retailing | | Health Care Equipment & Services | | Diversified Financials | | Materials | | Technology Hardware & Equipment | | Consumer Services | | Consumer Durables & Apparel | | Semiconductors & Semiconductor Equipment | | Banks | | Media | | Real Estate | | Food, Beverage & Tobacco | | |  | | --- | | 257 | | 183 | | 154 | | 122 | | 107 | | 105 | | 93 | | 89 | | 87 | | 79 | | 73 | | 70 | | 62 | | 56 | | 54 | | 51 | | |  | | --- | | 4.9% | | 2.9% | | 2.5% | | 2.1% | | 2.8% | | 2.1% | | 2% | | 2.4% | | 2.4% | | 3.2% | | 4.3% | | 2.8% | | 1.6% | | 2.1% | | 1.2% | | 2.8% | | |  | | --- | | 2.4% | | 1.8% | | 1.5% | | 1.4% | | 1.6% | | 1.4% | | 1.1% | | 1.4% | | 1.7% | | 1.5% | | 1.5% | | 2% | | 1.2% | | 1.3% | | 0.9% | | 1% | | |  | | --- | | 4.5\*10-8 | | 0.0002 | | 0.0032 | | 0.0333 | | 1.4\*10-8 | | 0.1186 | | 0.0750 | | 0.1343 | | 0.0113 | | 0.0418 | | 0.0002 | | 0.1044 | | 0.2686 | | 0.0058 | | 0.3121 | | 0.0019 | |

Results for the sectors listed below are not statistically significant at level 0.05.

Health Care Equipment & Services

Diversified Financials

Materials

Semiconductors & Semiconductor Equipment

Banks

Real Estate

### Volatility Analysis

Analysis based on stock volatility percentiles looks almost identical to alerts file.

Figure 8: Mean absolute returns by volatility

|  |  |  |  |
| --- | --- | --- | --- |
| Volatility | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| Low  High | 1.6%  5.1% | 1.0%  2.3% | < 10-15  < 10-15 |

# Intraday Analysis

The goal here was to see whether tweet signals activity is related to intraday returns.  Both signal timing and asset prices are available down to the minute. However, since the signal data is fairly sparse, we coarsen the data to hourly values.  That is, we consider the number of tweet signals between 9am and 10am, between 10am and 11am, etc., and prices at 9am, 10am, 11am, etc.  The hour that had the most tweet signals was between 9am and 10am, so we begin by focusing on that hour. Specifically, we only consider tweet signals between 09:30:00 and 09:59:59.  For each asset in the signal data we also calculate an intraday return comparing the asset price at 10am with the price at 4pm.  To assess the impact of tweet signal activity on these intraday returns, we compare the mean absolute intraday return on days where the asset had one or more tweet signals between 9:30am and 10am versus days where the asset had no signals between 9:30am and 10am. Because it was rare for tickers to have more than one tweet signal in such a short time period, high activity here is defined as one or more tweet signals.

Table 1: Alerts signals from 9:30 am -10 am

|  |  |  |  |
| --- | --- | --- | --- |
|  | Signal  Mean abs(return) | No Signal  Mean abs(return) | p-value |
| 10:00 am – 4:00 pm | 1.9% | 1.2% | 0.0003163 |

Table 2: Notable and Flash signals from 9:30 am -10 am

|  |  |  |  |
| --- | --- | --- | --- |
|  | Signal  Mean abs(return) | No Signal  Mean abs(return) | p-value |
| 10:00 am – 4:00 pm | 1.9% | 1.3% | 0.0002623 |

Now let us look at the second hour that had the most tweet signals, the hour between 10 am and 11 am. We can compare returns during the pre-tweet signal hour, i.e. from the market open until 10 am, and returns from 11 am until the market closing at 4 pm. In addition we will also consider returns from after the tweet signal at 11 am until 4pm the following day (holding the stock for 2 days) and until 4pm two days later (holding stock for 3 days). It looks like it makes sense to hold stocks for more than 1 day since the excess return compared with the day when there are no news keeps growing.

Figure 9: Intraday returns around Alert signals

|  |  |  |  |
| --- | --- | --- | --- |
| Return period | Signal  Mean abs(return) | No Signal  Mean abs(return) | p-value |
| 9:30 am – 9:59 am | 2.1% | 1.0% | 2.2\*10-16 |
| 11:00 am – 4:00 pm | 1.5% | 1.0% | 1.655\*10-10 |
| 11:00 am – +1 day | 2.9% | 2.2% | 5.82\*10-6 |
| 11:00 am – +2 days | 4% | 3% | 1.883\*10-6 |

This effect is especially pronounced for Flashes and Notables where excess return reaches 1.6 % by the 3rd day.

Figure 10: Returns around Flashes and Notable signals

|  |  |  |  |
| --- | --- | --- | --- |
| Return period | News  Mean abs(return) | No News  Mean abs(return) | p-value |
| 9:30 am – 9:59 am | 2.1% | 1.2% | 0.0028 |
| 11:00 am – 4:00 pm | 2.0% | 1.1% | 0.0001 |
| 11:00 am – +1 day | 4% | 2.4% | 0.0122 |
| 11:00 am – +2 days | 5% | 3.4% | 0.0068 |

## Volatility Analysis

Now we can separate the stocks by volatility type and analyze the results in high and low volatility groups. We notice that on high activity days returns are a lot higher both pre- and post-tweet signal for high volatility stocks whereas for low volatility stocks the difference in returns on low activity vs high activity days is not very pronounced. Nearly all results are statistically significant, with p-values smaller for alerts.

Figure 11: Mean absolute returns by volatility for Alert signals

|  |  |  |  |
| --- | --- | --- | --- |
| Return period | Signal  Mean abs(return) | No Signal  Mean abs(return) | p-value |
| Low volatility assets |  |  |  |
| 9:30 am – 9:59 am | 1.11% | 0.65% | 1.28\*10-12 |
| 11:00 am – 4:00 pm | 0.73% | 0.6% | 1.42\*10-5 |
|  |  |  |  |
| High volatility assets |  |  |  |
| 9:30 am – 9:59 am | 3.38% | 1.39% | 2.09\*10-13 |
| 11:00 am – 4:00 | 2.41% | 1.42% | 9.89\*10-10 |

Figure 12: Mean absolute returns by volatility for Flash and Notable signals signals

|  |  |  |  |
| --- | --- | --- | --- |
| Volatility | High Activity  Mean abs(return) | Low Activity  Mean abs(return) | p-value |
| Low volatility assets  9:30 am – 9:59 am  11:00 am – 4:00 pm  High volatility assets  9:30 am – 9:59 am  11:00 am – 4:00 pm | 1.02%  0.76%  3.35%  3.34% | 0.73%  0.66%  1.61%  1.64% | 0.01074  0.06064  0.008211  0.0001795 |

## Sector Analysis

Similarly to previous section we can analyze intra-day results within the industry sector. For the second hour that had the most tweet signals (10 am - 11 am), we can compare absolute returns during the pre-tweet signal hour, i.e. from the market open until 10 am and returns from 11 am until the market closing at 4 pm.

In nearly all cases the mean absolute return is higher when there was at least one tweet signal vs. when there were no tweet signals, both before and after the 10am-11am window.  But note that for many sectors the results are not statistically significant.

Figure 13: Mean absolute returns (9:30am – 10am) by sector

Figure 14: Mean absolute returns (11am– 4pm) by sector

Table 3: Alerts (tweet signals from 10 am -11 am)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | Signal | No Signal |  |
| 9:30 am – 9:59 am | # of tickers | Mean abs(return) | Mean abs(return) | p-value |
| Consumer Durables & Apparel | 73 | 2.33 | 0.9 | 0.0049 |
| Consumer Services | 79 | 4 | 0.96 | 0.0845 |
| Pharmaceuticals, Biotechnology & Life Sciences | 257 | 3.52 | 1.44 | 4.12\*10-10 |
| Semiconductors & Semiconductor Equipment | 70 | 2.05 | 1.23 | 0.0202 |
| Health Care Equipment & Services | 105 | 2.13 | 0.99 | 0.2454 |
| Capital Goods | 122 | 2.15 | 0.91 | 0.0133 |
| Energy | 154 | 1.82 | 0.95 | 0.0729 |
| Materials | 89 | 1.33 | 0.89 | 0.1705 |
| Software & Services | 183 | 1.47 | 1.09 | 0.0611 |
| Retailing | 107 | 1.42 | 0.96 | 0.1005 |
| Real Estate | 54 | 4.69 | 0.56 | 0.1346 |
| Diversified Financials | 93 | 1.26 | 0.76 | 0.294 |
| Media | 56 | 1.67 | 0.78 | 0.0232 |
| Technology Hardware & Equipment | 87 | 1.36 | 1 | 0.2216 |
| Banks | 62 | 1.02 | 0.73 | 0.0568 |
| Food, Beverage & Tobacco | 51 | 1.85 | 0.63 | 0.002 |
|  |  |  |  |  |
| 11:00 am – 4:00 pm |  |  |  |  |
| Consumer Durables & Apparel | 73 | 1.65 | 0.84 | 0.0295 |
| Consumer Services | 79 | 1.71 | 0.96 | 0.1433 |
| Pharmaceuticals, Biotechnology & Life Sciences | 257 | 2.13 | 1.49 | 0.0004 |
| Semiconductors & Semiconductor Equipment | 70 | 1.76 | 1.14 | 0.0072 |
| Health Care Equipment & Services | 105 | 1.45 | 0.95 | 0.2015 |
| Capital Goods | 122 | 1.26 | 0.85 | 0.1124 |
| Energy | 154 | 1.36 | 0.99 | 0.1262 |
| Materials | 89 | 1.12 | 0.87 | 0.2996 |
| Software & Services | 183 | 1.28 | 1.07 | 0.0843 |
| Retailing | 107 | 1.05 | 0.87 | 0.1821 |
| Real Estate | 54 | 0.79 | 0.63 | 0.4712 |
| Diversified Financials | 93 | 0.87 | 0.73 | 0.3614 |
| Media | 56 | 0.91 | 0.79 | 0.357 |
| Technology Hardware & Equipment | 87 | 1.04 | 0.95 | 0.6578 |
| Banks | 62 | 0.72 | 0.63 | 0.5095 |
| Food, Beverage & Tobacco | 51 | 0.58 | 0.61 | 0.7585 |

The sectors whose results are statistically significant were:

* Consumer Durables & Apparel
* Pharmaceuticals, Biotechnology & Life Sciences
* Semiconductors & Semiconductor Equipment

For Notable and Flash -signals, most of the sectors don't have enough data for meaningful analysis

# Week 3

## Reversal Strategy

Finally, we consider a reversal strategy and test whether solely returns based strategy can be improved by taking Dataminr signals into consideration.

In order to have reliable and liquid asset price information and a somewhat uniform tweet signal distribution among the assets we have chosen the stocks in S&P 100 – a broad market index with the most liquid constituents.

We will look into weekly stock returns since our studies have shown that stock prices tend to move in weekly cycles based on news releases. Let us calculate weekly returns from 2014/03/14 till 2014/11/28 and then compute excess returns with respect to the average return for S&P 100 constituents for the corresponding week. We will then look into the stocks that are in the highest quintile based on their excess return and expect their prices to revert back on the following week.

Running such winner reversal portfolio for the time period from 2014/03/14 till 2014/11/28 we find that for that period of time its cumulative return is **0.8524 %.** Since we are supposed to short the winner stocks running this strategy will actually sustain small losses over the above-mentioned period of time.

Let’s also introduce a statistic based on the tweet signals called EV – event volume. Event volume is simply the sum of the tweet signals count for the past week.

If we add EV and narrow down our selection of stocks to be shorted to those that are in the highest quintile of returns and the highest quintile of event volume for the past week then we get the cumulative return of **-12.419 %** over time period from 2014/03/14 till 2014/11/28. This is a significant improvement and in fact presents a good trading opportunity for winner reversal strategy. Therefore taking event volume into account has a strong effect in this case.

Repeating above procedure for winner stocks portfolio but changing the filter to the lowest event volume quintile stocks get a cumulative return of **-1.907%** for the strategy. This is still an improvement over solely return based strategy but the result is not nearly as good as for the stocks in the highest event volume quintile.

Looking into a loser stocks portfolio, i.e. the stocks that showed lowest excess returns for the past week and going long those stocks for the coming week produces a return of **9.5382 %** for the same period of time. This is actually a good result.

If in addition we require the stocks to be in the lowest event volume quintile (EV=0), then we get a **9.1324 %** overall return.This is actually slightly worse that looking into all the stocks without taking the tweet signals into consideration. We think it may be because there are not enough signals that can produce a meaningful low quintile for the event count.

Looking into losing stocks portfolio with highest event volume we get even worse result – overall return is only **2.5266 %.**

**O**ur results are summarized in the following table

Table 4: Reversal strategy returns with and without Dataminr signals

|  |  |  |  |
| --- | --- | --- | --- |
|  | Only returns | Low News | High News |
| Winners | **0.8524 %** | **-1.907%** | **-12.419%** |
| Losers | **9.5382 %** | **9.1324%** | **2.5266%** |

1. These tweets in the date/time column were:

   {Preclinical Programs http://t.co/s2HPShcedCg},

   {Iclusig $14.5M below con of $16M consensus and our lower $15M estimate. <http://t.co/z0MnNwlzrig>},

   {RAISING PRICE TARGET TO $111 ON POSITIVE AG-120 DATA http://t.co/BAaE5ky6FU, Five Incrementals From CS

   Healthcareg},

   {Conference http://t.co/meBzD93aUqg},

   {Technicals Imply Near Floor - Fundamentals Still Attractive <http://t.co/8A3bK9Ay8tg>},

   {We arrive at our $11 pt applying a 20x multiple to our 2022E EPS estimate of $2.70 and discounting at 30%

   <http://t.co/UmH7BKmVj8g> }. [↑](#footnote-ref-1)
2. These tickers are brkb, wpo, nyx, pbra, gnk, peugy, pc, si, ubs, rdsa, bnjaf, jrcc, pcxcq, vrus, rnftf, barc, bcspra, brka, alo, rr, spm, rmg, nvtk, sber, rb, medaa, novob, X7955, X7013, X6, X400, X0, X830, X5, X930, hsba, husiprz, bb, X830.1, X6400, X5930, gazp, gercl, jwa, rrs, kfn, dmp, bacprz, hubb, gwp, rbgpy, hsfcprb, fcea, evkif, and bbplk. [↑](#footnote-ref-2)