A Bloomberg Professional Services Offering

Bloomberg Terminal

Quant

Predictive Analysis of Bloomberg Automated Intelligence

Mohammad Fesanghary and Arun Verma
Bloomberg Quant Research

Bloomberg

Contents

Executive summary

This white paper investigates the predictive abilities of Bloomberg Automated Intelligence (BAI) news stories. The results show that corporate actions such as mergers & acquisitions follow certain combinations of these automated stories far more than would be expected in a random sampling. For example, when BAI stories showing insider buying, high implied volatility, and unusual bond trading volume about a single large-cap company are published in close proximity to each other, M&A events are announced in the next few days about 16% of the time, which is more than 3 times the expected amount of announcements. BAI stories have been ahead of major announcements by a diverse range of companies, including 3M Co., Tiffany & Co., LogMeIn Inc., and Expedia Group Inc.

A few examples of BAI types and their signal strength:

Combination	Precision
Insider buying + implied volatility + high bond trading……………………..	16.7%
Insider buying + "news heat" + high bond trading………………...………..	16.1%
CDS moves + social velocity alerts + high stock volume...………………….	20.0%

Abstract

In this paper, a non-parametric method is proposed to study the predictive power of Bloomberg automated news. The basic idea is to randomize the publication date of the news and compare the distribution of randomized publications with the observed distribution. If the observed rate of publication of a news type before corporate events or major price movements is substantially different from the randomized rate, then this news type carries some signal. This method is also used to study triggers and co-publication of different news types. Results reveal that certain types of automated news such as social velocity and news heat carry a fairly strong signal and can be useful in predicting future corporate actions and price movements.

Keywords: BAI; News; Automated Intelligence; Corporate Actions; Price Move; Machine Learning

1. Introduction

Bloomberg Automated Intelligence (BAI) is a fully automated news service that explores Bloomberg's vast proprietary data sets to identify market irregularities. Currently, the BAI universe covers dozens of story types ranging from hedge fund positions to anomalies in individual equities and indices. Looking back over the past few years, we observe numerous cases where major price movements (PXMOVs) and corporate actions (CAs) such as mergers & acquisitions (M&A) have been preceded by the publication of automated news. The question at hand is whether stories produced by Bloomberg Automated Intelligence, which we will refer to as "BAIs," carry predictive power and, if so, what kind of corporate events can be predicted most accurately.

One of the easiest ways to address this question is to use a suitable Machine Learning (ML) model in which the desired corporate actions are predicted using BAIs as predictors. The feature importance then can be extracted from the ML model and used as a proxy for the relative predictive power of BAIs. However, it should be noted that this approach may suffer from several shortcomings. In linear ML models (i.e., logistic regression), the assumption is that the relation between all predictors and the target variable is linear. If the relation between BAIs and corporate actions is not linear, the feature importance values are not reliable. One remedy is to use nonlinear ML methods (i.e., random forests). Unfortunately, the lack of interpretability of nonlinear models makes it quite difficult for us to trust the model and explain why it made a certain decision. Also, since these models are quite flexible and powerful, they can easily fit the noise. Several precautionary steps must be taken into account to avoid this overfitting problem.

In this study, we propose a simple non-parametric method that is highly interpretable and purely data-driven. It is able to tackle the abovementioned problems and can discover the strength of signals as well as co-occurrence in BAIs.

2. Events of Interest

2.1. BAIs

We focus on 12 BAI categories, as listed in Table 1. The data used in this study incorporate all of these BAIs and corporate actions published/announced for almost 5,000 companies from May 2018 to January 2020. In order to account for the earnings effect, we exclude all BAIs published 2 days before and after earnings announcements. Since different BAIs cover different regions, we only focus on companies listed in the United States. This will ensure that all of the companies are potentially included in each BAI universe.

Table 1: BAI types

ANACHG	Analyst recommendations and context of how stocks performed relative to the ratings.
BLKTRD	Instant updates on major block trades and trading spikes.
NHEAT	News heat highlights when market participants are searching for news on a company even though news publication is relatively low.
SVEL	Social velocity alerts are published when there is a significant increase in social media postings about a company.
CDSMOV	CDS movers are published intraday when spreads on single-name contracts move 3 standard deviations based on 90-day historical volatility.
OPTSPK	Options alerts are produced intraday when trading in options is greater than 3 times its 20-day average volume for that time of day, and a minimum of 500 contracts have traded.
IMPVOL	Implied volatility alerts are published during trading hours when there is a significant change in 1-month at-the-money implied volatility for companies around the world.
VOLSPK	Volume spike articles are published intraday when trading in a liquid stock is at least 3 times above its 20-day average volume for that time of day for large-cap companies and 5 times above for small-cap companies.
TRACE	TRACE volume spike articles highlight when U.S. trading in a company's bonds is at least double the average for that time of day.
IBSBAI	Insider sale alerts are published when an insider discloses a significant open-market purchase or sale in a Form4 filing with the SEC. These are published intraday when the SEC releases the filing.
SHRTPOS	Short position alerts are published intraday when short-sellers in Europe and Japan report significant changes in their positions to regulators and exchanges.
SI	Short interest alerts are produced when a U.S. or Canadian company's short interest ratio or the percentage of total float sold short reaches the highest level in at least a year.

The company coverage for each BAI type is shown in Figure 1 (lower left section). It shows that about 4,000 out of 5,000 companies have had ANACHG news and this ratio drops to around 2,300/5,000 for NHEAT and IBSBAI. Figure 1, which can be seen as a high-dimensional Venn diagram, also shows the joint publication of BAIs. The lower matrix of Figure 1 shows the most frequent sets of BAIs (highlighted with connected black circles), followed by the frequency (intersection size) on the top bar chart. For example, the first column of Figure 1 shows that there are 733 companies that just had ANACHG publication and nothing else. The second column shows that there are 233 companies that have ANACHG and IBSBAI publications.
The majority of companies have a few types of BAI published about them.

2.2. Corporate Actions (CAs)

The corporate action events of interest for this study are mergers and acquisitions (M&A) and spinoffs (SPIN). We only consider cases where either the target company or its seller is a public company listed on a U.S. stock exchange. There are 2,700 M&A announcements in our universe.

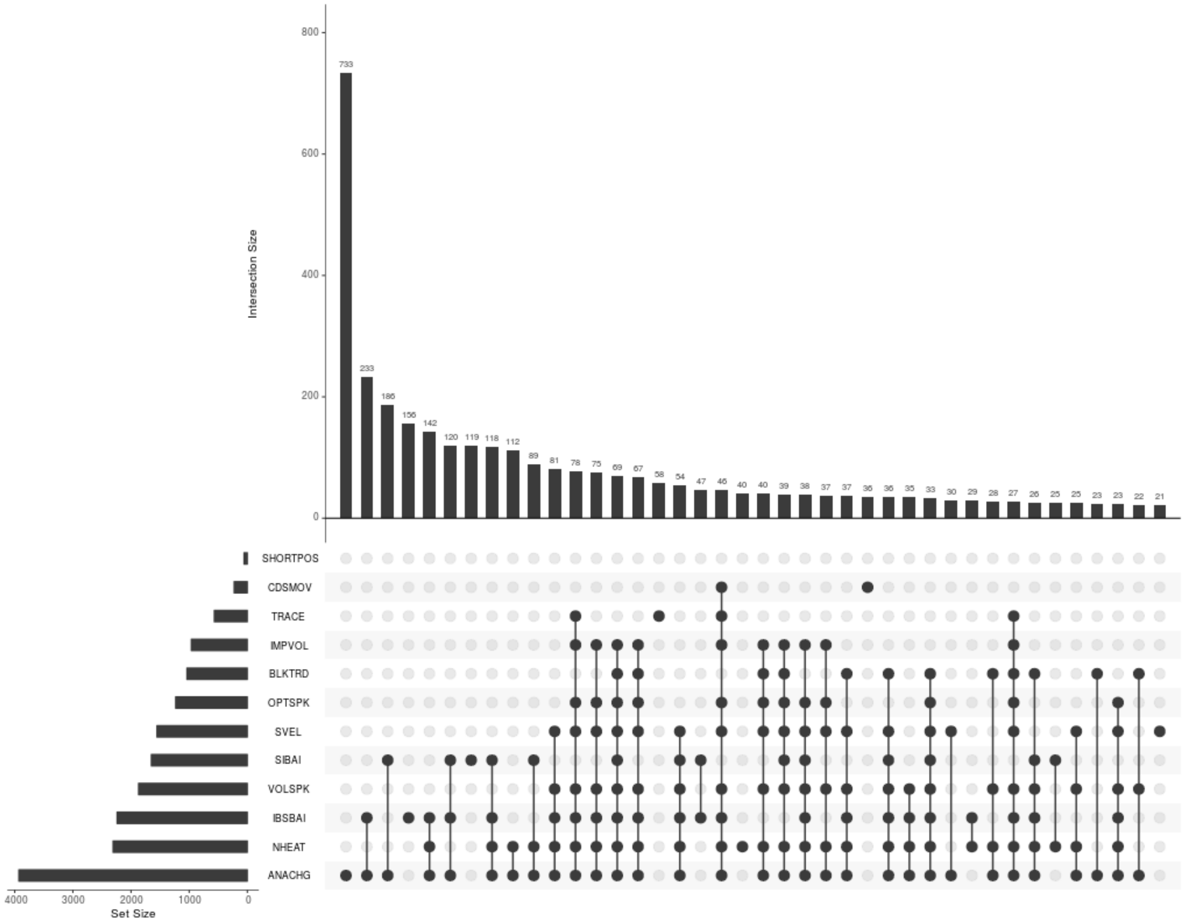

Figure 1 – BAI Publications.

2.3. Price Movements (PXMOVs)

In this study, we are also interested in prediction of major price movements after BAI publications. We consider a price movement to be extreme if the maximum draw down (MDD) or draw up in given period normalized by 30 day volatility is more than 2.5 as specified below:

$$\frac{\max \mathit{drawdown\ or\ drawup}}{vol_{30d} * \sqrt{duration}} \geq 2.5$$

Figure 2a shows periods of extreme price movements highlighted in green for a sample company. On average, we expect to observe 8-9 major price movements for each stock (Figure 2b). The majority of price movements happen in 1 day (Figure 2c). However, longer durations are also common.

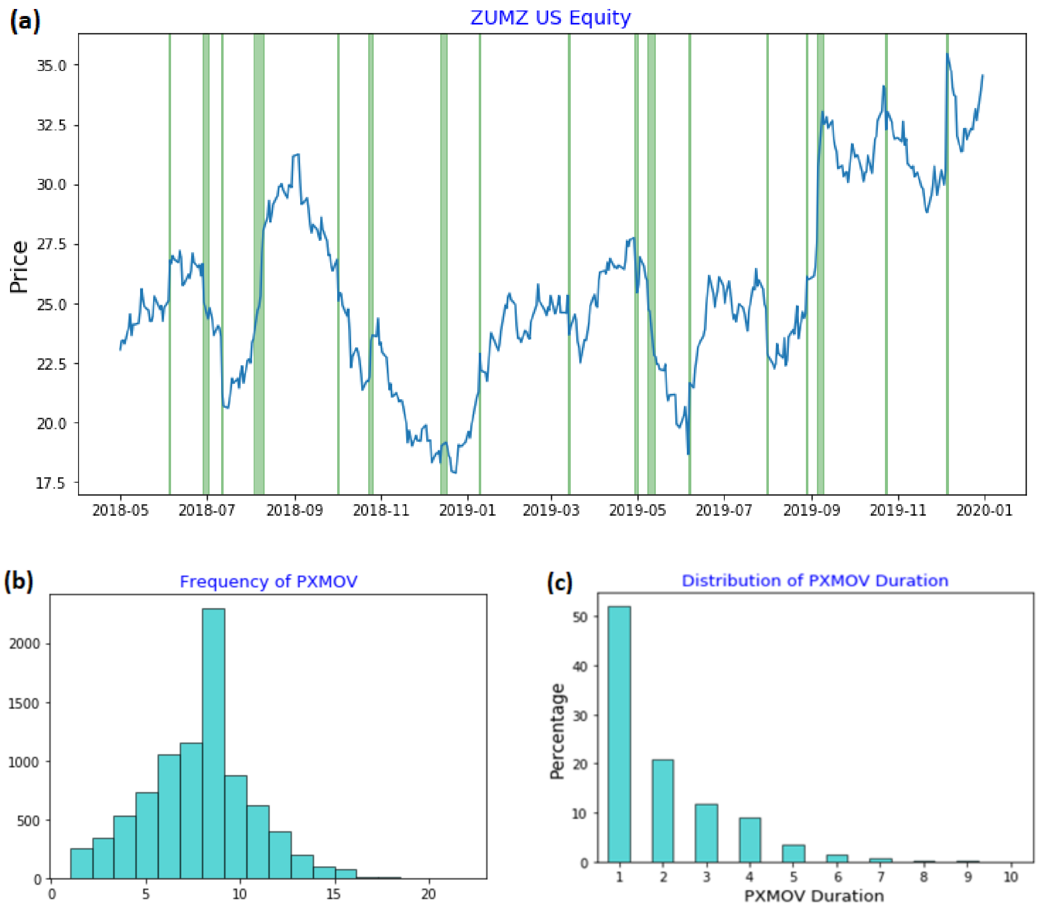

Figure 2 – Major price movements: (a) time series; (b) frequency of occurrence; (c) duration.

3. Methodology

The basic idea is to observe the rate of occurrence of BAIs before CAs and PXMOVs within a fixed time window and compare it with a scenario in which all BAIs are published randomly. In this study, we are focusing on immediate and short-term effects. Consequently, we only consider events (i.e., BAIs, CAs, and PXMOV) in a time window of 5 business days. The idea is similar to permutation tests [1,2] in which we seek to break whatever statistical relationship that might be preset in a data, and quantify the kinds of patterns one expects to see purely by chance. In this way we can characterize the null distribution of the occurrence rates, that is, the distribution we would expect if there were no relationship between BAI publications before major CAs and PXMOVs. We seek to permute the data in a way that it removes the time structure while preserving the publication volume of BAIs for individual companies. To make the methodology clear, we start with a simple example. Consider a company where we monitor all BAI publications, CA announcements, and the start of major price movements (PXMOVs) within given time period, as shown in Figure 3a.

To compute the average rate of publication of BAIs before CAs and PXMOVs, we start by creating a table in which we list all the events related to the company, as shown in Table 2. The first 2 columns show the type of events, as well as the date on which they occurred. Then, for each row of the table (i.e., days with CA announcements or BAI publication) we look back 5 business days and count all the BAIs that have been published and the events that have occurred. On day 7, for example, when an M&A was announced, we see there had been 1 NHEAT, 1 SVEL, and 1 PXMOVs in the past 5 days. We reflect this by putting 1 in the corresponding columns for them, as shown in row 4 of Table 2. We construct the same table for all 5,000 companies in this study. A giant table is then formed by merging the tables for the individual companies. The average rate of occurrence of all events can now be determined by conditioning on a specific type of event and calculating the mean for each column. For instance, in order to calculate the average rate of all events observed before M&A announcements, we only select rows that have M&A in the type column and then calculate the average for each column. The average rate for each column will show the observed rate of occurrence of that type before any M&A announcements.

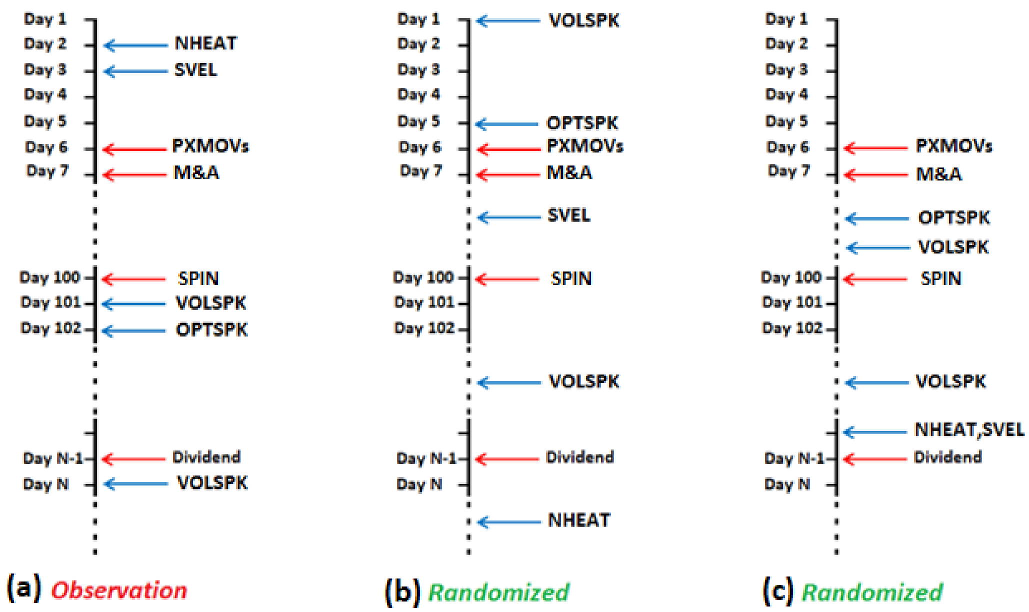

Figure 3 – BAI publications, PXMOVs, and CAs for a company: (a) observation, (b) randomized.

Table 2: 5-day running sum of events for each BAI publication or CA

	TYPE	NHEAT	OPTSPK	SVEL	VOLSPK	....		PXMOVs	SPIN	M&A	Dividend
Day 2	NHEAT	1									
Day 3	SVEL	1		1							
Day 6	PXMOVs	1		1				1			
Day 7	M&A	1		1				1		1	
Day 100	SPIN								1		
Day 101	VOLSPK				1				1		
Day 102	OPTSPK		1		1				1		
Day 153	Dividend										1
Day 154	VOLSPK				1						1

Once we have the average observed rates, the next step is to randomize the BAI publication dates to calculate the expected average rates. To do this, we propose a randomization procedure as follows. For each company, we start from the observed sequence of events and shuffle BAIs randomly, as shown in Figure 3b. It should be noted that the CAs or PXMOVs will not be randomized. The randomization at the company level ensures that no unrealistic combination of events can occur. For example, a company that does not have credit default swaps will not get CDSMOV after randomizations. After shuffling the BAIs for all of the companies, we calculate the average rates for each event type. The randomization procedure will be repeated several thousand times and each time we will record the average rates. At the end of this process, we can plot a histogram of these randomized average rates for each pair of events, as shown in Figure 4.

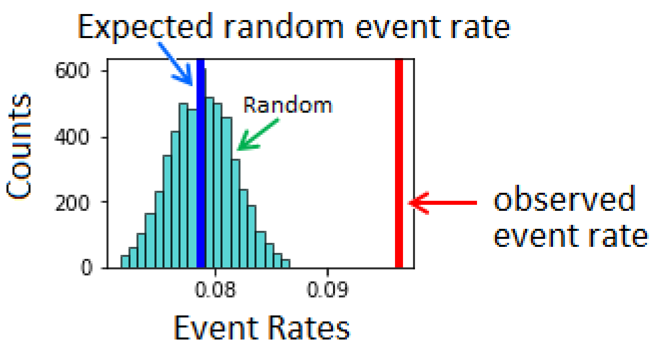

Figure 4 – Randomized event rates.

The vertical red line in Figure 4 shows the observed average rate and the green bars show the possible event rates if BAIs had been published randomly. Some rates are less likely than the others, as indicated by the shorter green bars. The expected rate of event rates in a random scenario is shown by the vertical blue line. The further away the red line is from the blue line, the stronger the evidence that the observed event rates differ from random. If the red line is within the green bars (i.e., distribution of rates that could happen by chance), there is strong evidence that our observation is simply by chance and it cannot be distinguished from random. For the sake of simplicity, we can summarize Figure 4 in a single Z value defined as the observed rate minus the expected random rate divided by the standard deviation of the random rates.

4. Results and Discussion

A total of 30,000 of randomized simulations were performed. Since large-cap companies can behave differently from small-cap companies, we divided the companies by market cap size. The following subsections summarize the results.

4.1. Predictive Power

4.1.1. Single BAI

To assess the predictive power of different BAI types, in Figure 5, we have plotted the observed/random occurrence rates for each BAI category in the 5 business days preceding CAs, start of major price movements (PXMOVs), and end of price movements (PXMOVe). In the subplots, the Z-scores for each BAI are provided.

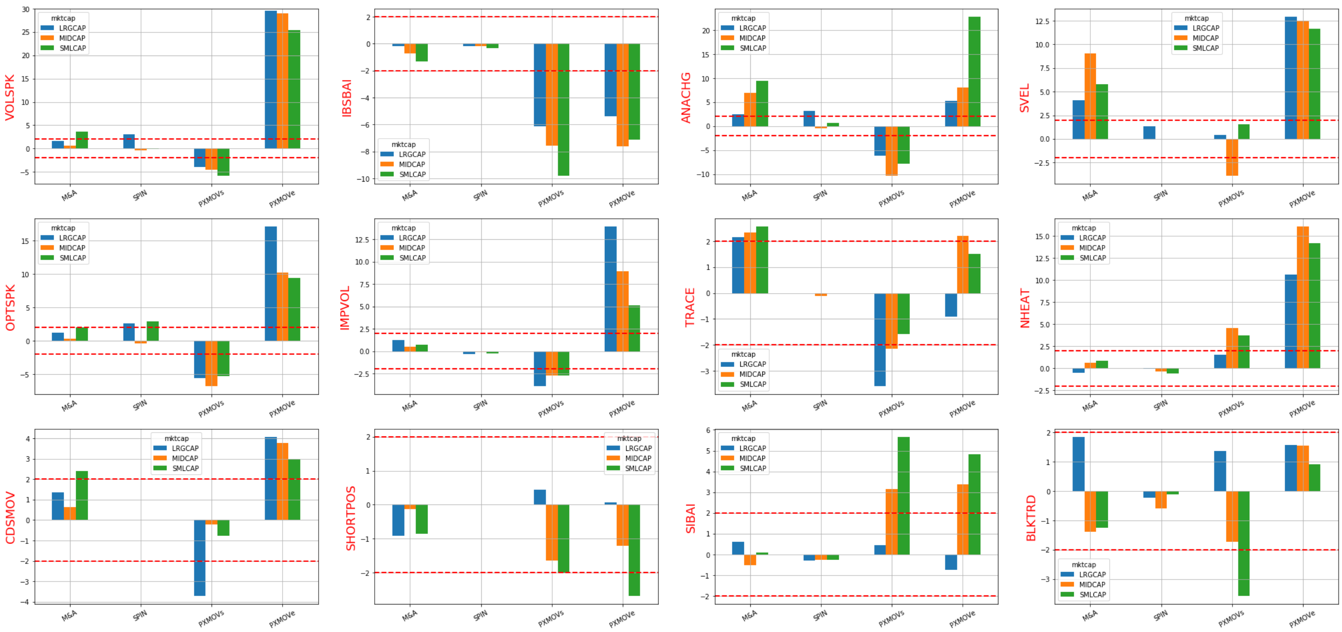

Figure 5 – Predictive power of single BAIs.

The results show that SVEL, TRACE, and ANACHG are good predictors for M&A. The observed rate of these BAIs before M&A announcements is much higher than one can expect from random variation. We find that for SPIN, OPTSPK and VOLSPK also have some predictive powers.

Predicting major price movements using a single BAI is more difficult. Looking at Figure 5, most types, with the exception of NHEAT and SIBAI, will miss the start of PXMOVs, as seen by negative Z-scores. However, most BAI types are good predictors of the end of price movements. This means these BAIs are getting published after the price started to move, but before the end of price movement, suggesting that a momentum-based trading strategy might be effective.

In general, this kind of plot is quite useful for determining what a particular BAI type is good for. The results can also help us determine what BAIs to use in ML models (i.e., feature selection) and how to interpret the ML variable importance results.

4.1.2. Combination of BAIs

There is anecdotal evidence showing that when we observe certain types of BAIs in the vicinity of each other, there is a higher chance of a major corporate event in the near future. See the following examples.

Example: EXPEDIA

From mid-February to mid-March, Expedia Group Inc. shares fell more than 60% amid the Covid-19 crisis. On February 24, the company announced that it would cut 12% of its direct workforce. There was no news about the company seeking a cash infusion. In mid-April, Bloomberg Automated Intelligence published a series of stories:

April 15: Expedia Class A 645,000 Share Block Trades at $58.90
April 16: Expedia Social Media Volume Surges
April 17: Expedia Bond Trading Jumps to More Than Three Times Average
April 20: Expedia Class A 540,800 Share Block Trades at $61
April 21: Expedia Reader Interest Increases; Stock Declines 4.5%
April 21: Expedia Option Volume Rises, Led by May 15, $35 Puts

After the close of trading on April 21, Dow Jones reported that Expedia was in talks to sell a stake to Silver Lake and Apollo and, 2 days later, the company announced the transaction, raising $3.2 billion of new capital.

Example: 3M

There was no M&A news about 3M Co. in early December as the company prepared to sell most of its drug delivery business. Bloomberg Automated Intelligence published multiple stories of unusual market and reader activity from Dec. 2 to early on Dec. 6. Later on Dec. 6, Bloomberg News reported that 3M was planning to sell the drugs unit:

*3M Is Said To Plan $1 Billion Sale Of Drug Delivery Systems Arm.

The company announced the sale less than a week later:

*3M To Sell Drug Delivery Assets To Altaris For About $650m

Here are the publication dates and the headlines of the stories that preceded the M&A news:

Dec. 2: 3M Co Implied Volatility Surges as Shares Rise
Dec. 4: 3M Co Reader Interest Increases
Dec. 6: 3M Co Option Volume Rises, Led by Dec. 6, $162.50 Puts

Example: RANGE RESOURCES

In the week before Range Resources announced plans to sell drilling royalties, Bloomberg Automated Intelligence published 8 stories. On July 19, the company announced plans to sell interests for $634 million:

Range Sells Shale Royalties, Assets for $634 Million to Cut Debt

The company's shares rose as much as 9.9% that day.

Here are the publication dates and headlines of the stories that preceded the announcement:

July 12: Range Resources Option Volume Rises, Led by Jan. 17, $7 Calls
July 15: Range Resources Downgraded to Hold at Jefferies; PT $7
July 16: Range Resources News Demand Surges; Shares Drop 3.7%
July 16: Range Resources Social Media Volume Surges; Sentiment Negative
July 16: Range Resources Option Volume Surges, Led by Aug. 16, $5 Puts
July 17: Range Resources Option Volume Surges, Led by Jan. 17, $13 Puts
July 17: Range Resources Social Media Volume Surges
July 18: Range Resources Implied Volatility Up, Reaches 100th Percentile

To validate the hypothesis that proximity shows a higher probability of major corporate events, in this section, we focus on the joint predictive power of BAIs. The procedure is the same as previous section except that we look at BAI combinations of up to 3 types, instead of a single BAI. For example, ANACHG_TRACE_VOLSP shows a combination of 3 BAI types (analyst ratings change, unusually active bond trading, and a sharp rise in stock trading volume). For the sake of brevity, we only show the results for top 5 BAI combinations in terms of the Z-scores for M&A and PXMOVs in Figures 6-7, respectively. We have filtered those top combinations that have fewer than 15 successful event predictions (i.e., the total number of cases with this BAI combination times the observed precision is less than 15). A more complete list of top BAI combinations can be found in Table A1 in the appendix.

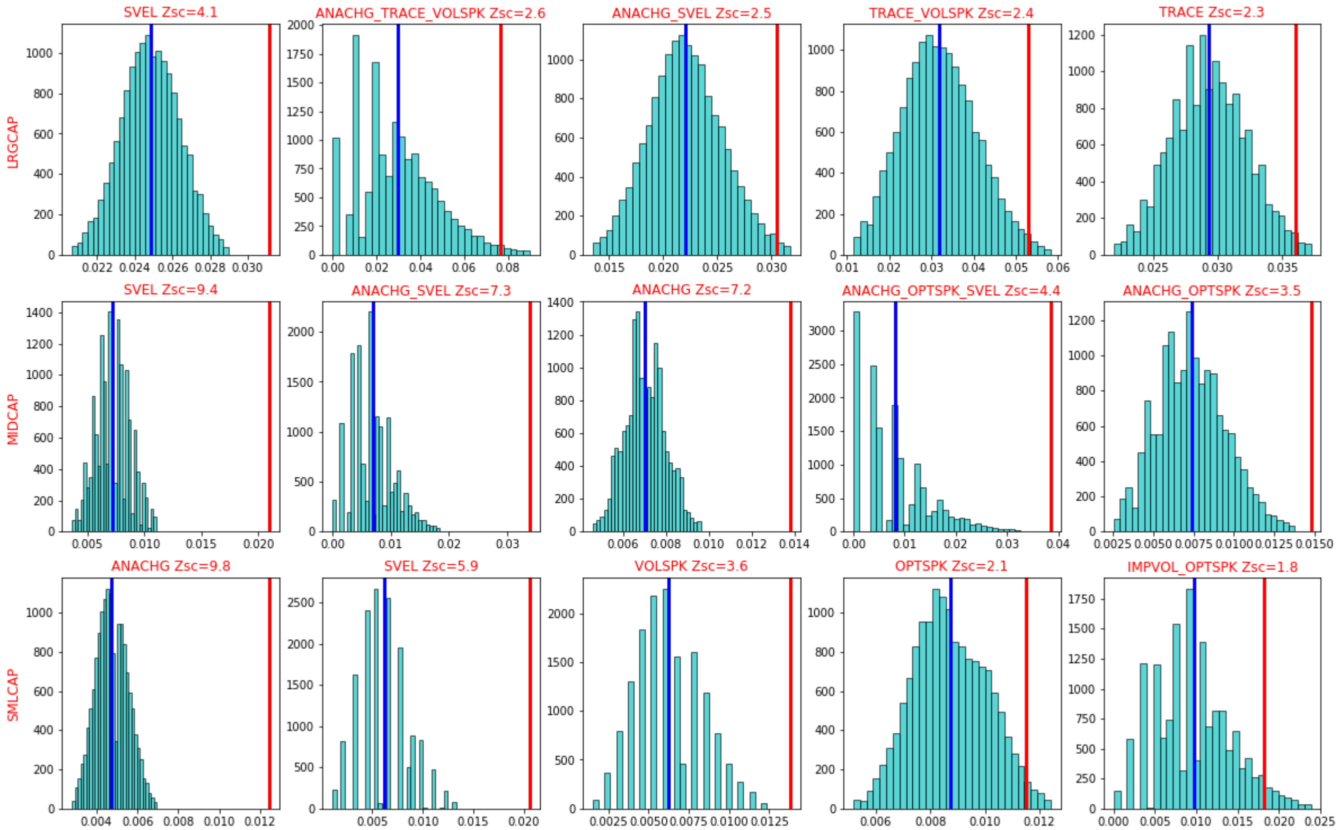

Figure 6 – Top 5 significant combinations for M&A.

One interesting observation is that combined BAIs show higher predictive power than single BAIs. As an example, for large-cap companies, the chance of observing an M&A announcement within 5 days of publication of an SVEL is 3.1% (vertical red line); this chance jumps to near 8% if we observe a combination of ANACHG, TRACE, and VOLSPK. We observe a similar trend for mid-cap companies. The predictive power of ANACHG will improve if it is combined with SVEL, and it will be further enhanced if it is observed with OPTSPK and SVEL. Figure 7 confirms that the best predictors for price movement are NHEAT, or SIBAI, or a combination of them. The combination of the two is a stronger predictor.

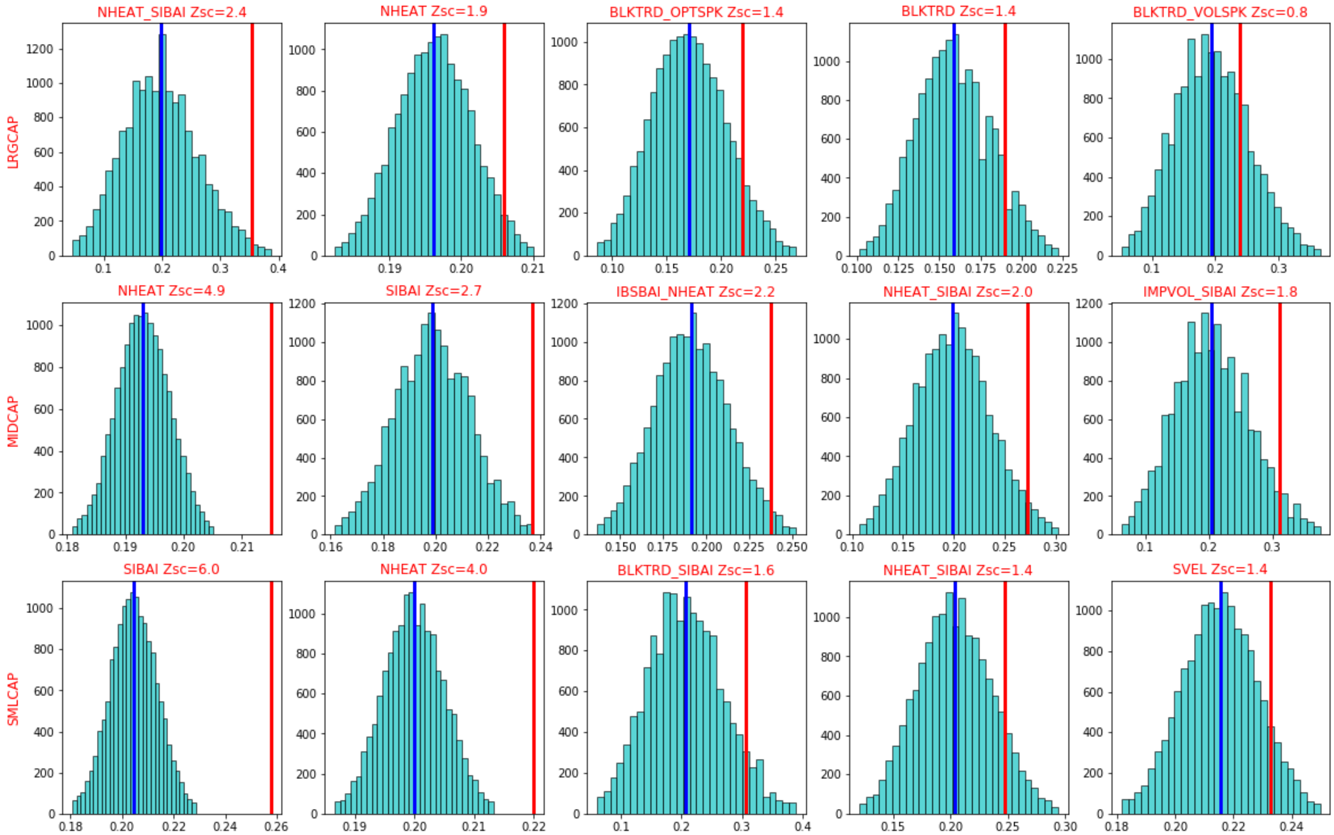

Figure 7 – Top 5 significant combinations for PXMOVs.

4.2. Co-Occurrence

In this section, we study the co-occurrence of different BAIs. These results can be useful in updating the BAI triggers to improve their relevancy and to decrease publication of non-informative/repetitive BAIs. For large-cap companies, the average event rate for each BAI type observed within 5 business days after publication of BAIs has been shown in Figure 8.

The results show strong co-occurrence between most BAI types. This means that the same underlying phenomenon can trigger publication of different type of BAIs. The co-occurrence between the same kinds of news is also quite strong. The strongest co-occurrence is observed in SVEL. For each social velocity story we publish, we observe 0.9 occurrences of the same story type within a 5-day period. The same pattern can be observed in options volume (OPTSPK) stories.

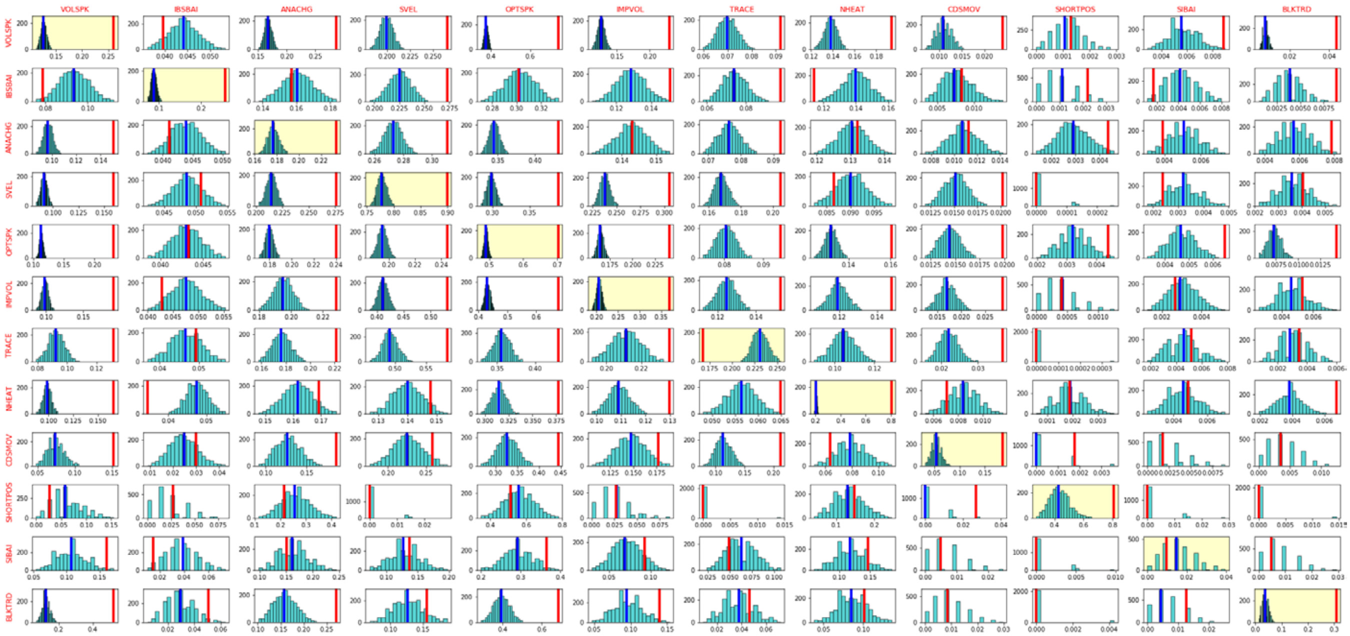

Figure 8 – Co-occurrence of different BAIs for large-cap companies.

We can also summarize the significance of co-occurrence as a Z-score for all market caps, as shown in Figure 9. Overall, the co-occurrence trend is similar for large and small companies.

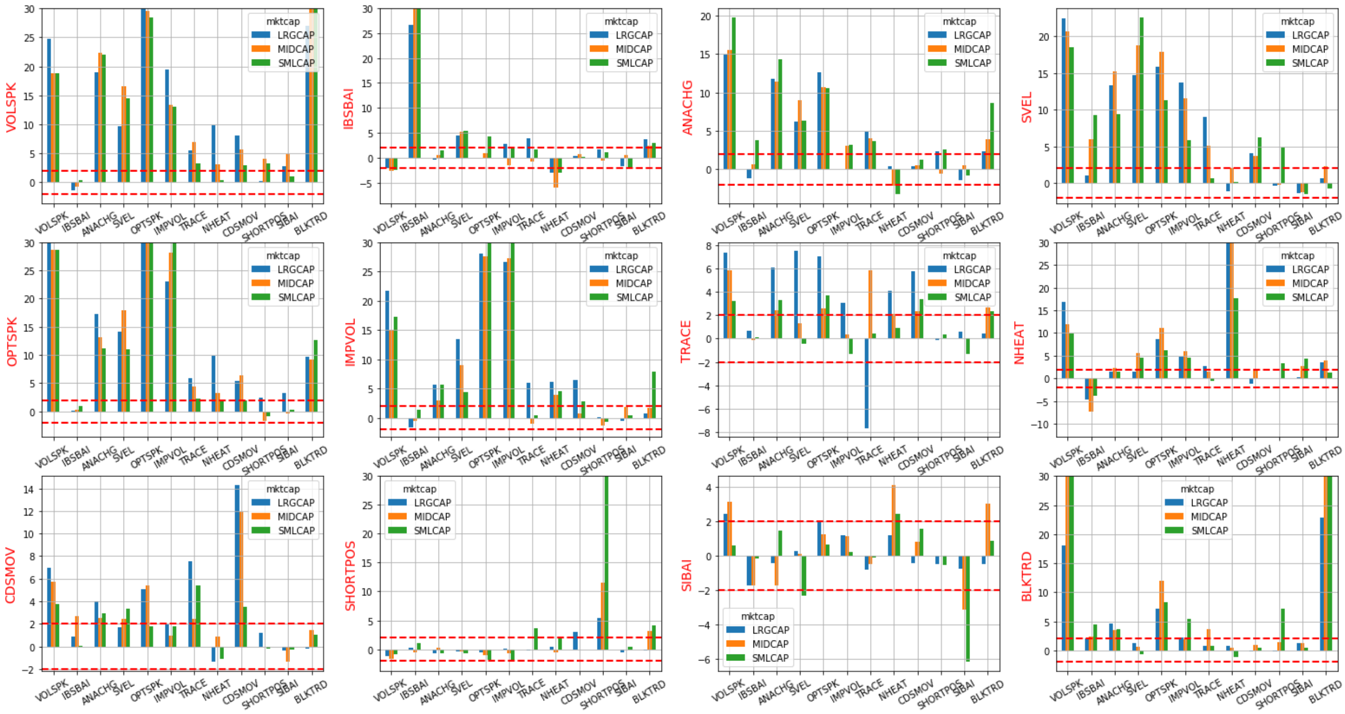

Figure 9 – Z-score of BAI co-occurrence.

4.3. Triggers and Filters

In this section, we focus on PXMOVs and CA announcements before BAI publications. The objective is to investigate whether or not these events can trigger the publication of BAIs, and if they do, whether we should filter their effects out or not. We utilize the results of the randomization simulations performed earlier, look at all BAIs, and count the number of PXMOVs and M&A before their publication. The results for PXMOVs and M&A are shown in Figs. 10-11, respectively. In general, observing a red line to the right of the green bars indicates that the corresponding PXMOVs or M&A over-triggers the publication of BAI.

It is clear from Figure 10 that major price movements strongly trigger all types of BAIs, with the exception of TRACE and SHORTPOS. For example, considering the number of OPTSPK news published for large-cap companies, one would expect to see only 30% of them having a price movement event within 5 business days before publication. However, we observe that 42% of OPTSPK news for large-cap companies is published after a major price movement.

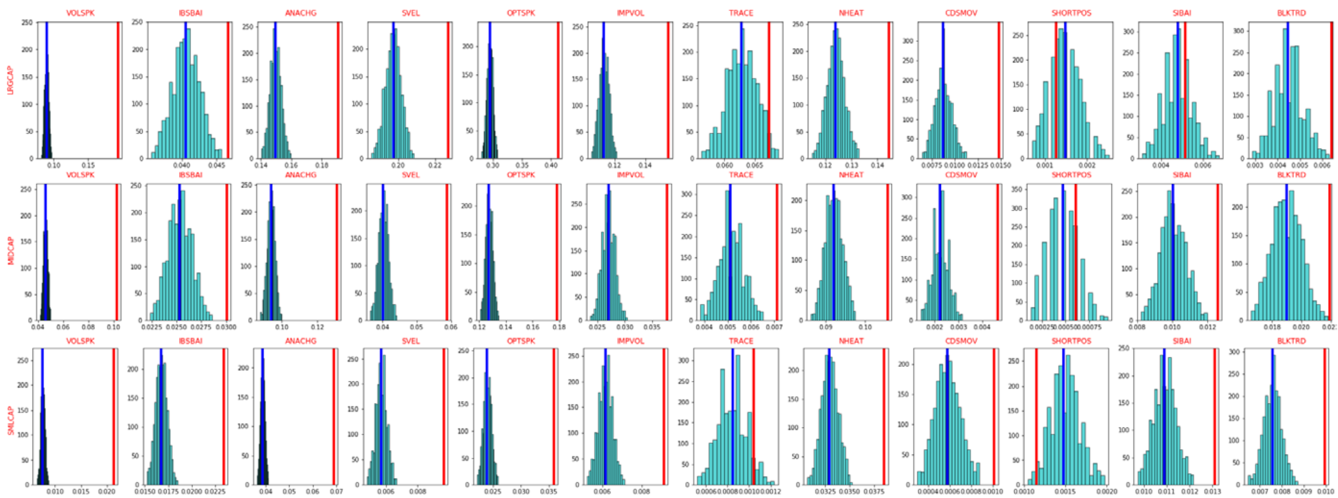

Figure 10 – Major price movements before BAI publication.

If we look at M&A in Figure 11, we will see that the observed rate of occurrence is quite normal (the red observation line is within the random range) before the publication of most types of BAIs. This means that there is no need to filter for M&A, since these events do not over-trigger BAI publication. The observation rate of M&A before ANACHG and SVEL is higher than expected. This can be easily explained by the fact that after M&A people discuss them on social media and analysts update their ratings. However, this means that BAIs published after these events have little predictive power in identifying immediate future M&A.

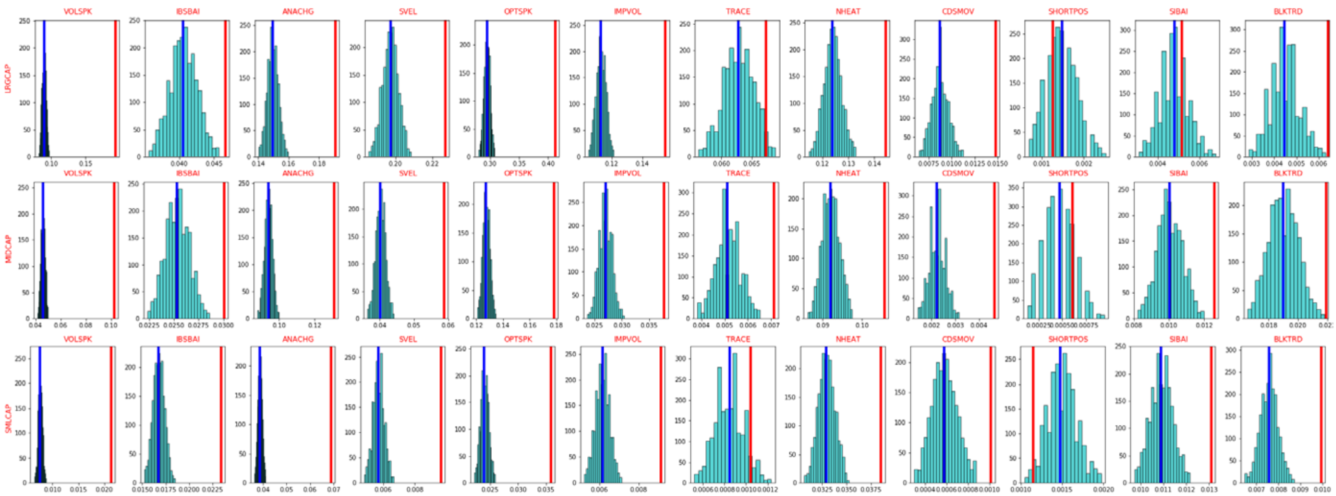

Figure 11 – CA announcements before BAI publication.

5. Optimal Prediction Horizon

So far, we limited our analysis to 5 business days before and after publication. This number can be quite arbitrary. Looking at past events has shown us that even though this number might be optimal for certain type of BAIs, either alone or in combination with other events, it might not be optimal for all types. Sometimes, it may take more than a week for us to see the events and sometimes we may want to look at 2-3 day horizons.

In this section, to find the optimal horizon for BAIs, we perform an experiment. We will perform the same simulations described in section 2 for different horizons ranging from 3 to 15 business days. For each of these dates, we obtain the observed rate and compare it with the corresponding random range. We then calculate the Z-scores and plot them against the number of days. We observe that most BAI signals (i.e., Z-scores) normally start to rise to a point and then drop to insignificant levels. In some cases, they start to drop quickly, as we increase the number of days. We can consider the peak of these curves as the best horizon in which the BAI, either alone or in combination with other BAIs, has predictive power.

We studied several hundred combinations (including PXMOVs). It is not possible to present the results for all sets, so we only present a handful of them in Table 3.

6. Conclusion

The predictive power and co-occurrence of BAIs were investigated in this study. Results are quite promising, showing that some BAI types such as SVEL and NHEAT are good predictors for future CA actions and major price movements. The co-occurrence analysis shows that there is systematic dependency between publications of different news types. It is also apparent that the co-publication of BAIs of the same type can be quite common. An analysis of triggers also shows that publication of some BAI types is strongly affected by certain major price movements. In order to avoid excess publication, we suggest updating current trigger rules by filtering on those events.

Table 3: Optimal horizon for M&A prediction

BAI combinations	Zsc	Precision	Expected precision	Mktcap	Horizon
ANACHG_SVEL	2.8	2.4%	1.5%	LRGCAP	3
ANACHG_TRACE_VOLSPK	2.6	7.7%	3.0%	LRGCAP	5
IBSBAI_IMPVOL	2.6	5.3%	3.2%	LRGCAP	8
IBSBAI_IMPVOL_TRACE	5.2	16.7%	5.0%	LRGCAP	8
IBSBAI_NHEAT_TRACE	4.6	16.1%	3.9%	LRGCAP	8
IBSBAI_TRACE	2.8	11.4%	7.8%	LRGCAP	15
TRACE_VOLSPK	2.7	8.1%	5.6%	LRGCAP	10
ANACHG_IMPVOL_OPTSPK	2.6	2.8%	1.0%	MIDCAP	5
ANACHG_OPTSPK_SVEL	4.4	3.8%	0.8%	MIDCAP	5
ANACHG_SVEL	8.5	3.6%	0.6%	MIDCAP	4
OPTSPK_SVEL	4.5	3.0%	1.6%	MIDCAP	10
OPTSPK_SVEL_VOLSPK	2.5	4.4%	2.1%	MIDCAP	15
SVEL	11.0	1.8%	0.5%	MIDCAP	3
ANACHG_OPTSPK	3.3	3.0%	1.5%	SMLCAP	10
ANACHG_VOLSPK	3.8	4.2%	1.7%	SMLCAP	15
SVEL	8.1	2.1%	0.4%	SMLCAP	3
VOLSPK	4.0	2.2%	1.1%	SMLCAP	10

Acknowledgments

The authors would like to thank Kenneth Kohn, Rachel Campanelli, Alberta Ofori, and Connie Yee for great comments and discussions, and also teams within ENG News Automation Infrastructure for providing the BAI publication data.

References

1. Ptitsyn, A.A., Zvonic, S., & Gimble, J.M. Permutation test for periodicity in short time series data. BMC Bioinformatics 7, S10 (2006). https://doi.org/10.1186/1471-2105-7-S2-S10

2. Good, P. Permutation Tests. A Practical Guide to Resampling Methods for Testing Hypotheses. Springer Series in Statistics, New York (1994)

Appendix

BAI combinations	Zsc	Precision	Exp. Precision	N	mktcap	target
NHEAT_SIBAI	2.4	35.4%	19.8%	17	LRGCAP	PXMOVs
NHEAT_SIBAI	2	27.3%	19.9%	48	MIDCAP	PXMOVs
IBSBAI_NHEAT	2.2	23.7%	19.1%	47	MIDCAP	PXMOVs
SIBAI	2.7	23.7%	19.9%	173	MIDCAP	PXMOVs
NHEAT	4.9	21.5%	19.3%	1477	MIDCAP	PXMOVs
SIBAI	6	25.8%	20.4%	483	SMLCAP	PXMOVs
NHEAT	4	22.0%	20.0%	1278	SMLCAP	PXMOVs
CDSMOV_SVEL_VOLSPK	2.7	20.0%	5.6%	13	LRGCAP	M&A
CDSMOV_IMPVOL_VOLSPK	2.3	15.1%	3.9%	8	LRGCAP	M&A
CDSMOV_VOLSPK	4	12.6%	3.7%	14	LRGCAP	M&A
IBSBAI_IMPVOL_TRACE	2.6	10.3%	3.5%	9	LRGCAP	M&A
IBSBAI_IMPVOL_NHEAT	4.4	9.7%	1.7%	6	LRGCAP	M&A
CDSMOV_TRACE	2.1	9.2%	4.6%	14	LRGCAP	M&A
ANACHG_TRACE_VOLSPK	2.6	7.7%	3.0%	17	LRGCAP	M&A
CDSMOV_IMPVOL	2.2	7.6%	3.8%	12	LRGCAP	M&A
IMPVOL_NHEAT_TRACE	2	5.7%	2.6%	11	LRGCAP	M&A
TRACE_VOLSPK	2.4	5.3%	3.2%	28	LRGCAP	M&A
IBSBAI_IMPVOL_OPTSPK	2.2	5.0%	2.2%	10	LRGCAP	M&A
IBSBAI_IMPVOL	2.1	3.8%	2.2%	14	LRGCAP	M&A
TRACE	2.3	3.6%	2.9%	104	LRGCAP	M&A
SVEL	4.1	3.1%	2.5%	262	LRGCAP	M&A
ANACHG_SVEL	2.5	3.0%	2.2%	81	LRGCAP	M&A
ANACHG	2.2	2.0%	1.7%	133	LRGCAP	M&A
ANACHG_IMPVOL_SVEL	2.5	4.3%	1.1%	7	MIDCAP	M&A
ANACHG_OPTSPK_SVEL	4.4	3.8%	0.8%	18	MIDCAP	M&A
ANACHG_SVEL	7.3	3.4%	0.7%	28	MIDCAP	M&A
TRACE	2.5	3.0%	1.5%	11	MIDCAP	M&A

BAI combinations	Zsc	Precision	Exp. Precision	N	mktcap	target
ANACHG_IMPVOL_OPTSPK	2.6	2.8%	1.0%	10	MIDCAP	M&A
SVEL	9.4	2.1%	0.7%	59	MIDCAP	M&A
OPTSPK_SVEL	2.5	1.6%	0.9%	24	MIDCAP	M&A
ANACHG_OPTSPK	3.5	1.5%	0.7%	32	MIDCAP	M&A
ANACHG	7.2	1.4%	0.7%	97	MIDCAP	M&A
ANACHG_NHEAT	2.2	1.3%	0.7%	14	MIDCAP	M&A
ANACHG_SVEL	6.1	5.3%	0.6%	10	SMLCAP	M&A
TRACE	2.6	4.5%	1.7%	6	SMLCAP	M&A
ANACHG_VOLSPK	3.1	2.6%	0.6%	9	SMLCAP	M&A
SVEL	5.9	2.1%	0.6%	19	SMLCAP	M&A
ANACHG_OPTSPK	2.1	1.7%	0.8%	12	SMLCAP	M&A
ANACHG_NHEAT	2.3	1.4%	0.6%	8	SMLCAP	M&A
VOLSPK	3.6	1.4%	0.6%	18	SMLCAP	M&A
ANACHG	9.8	1.2%	0.5%	85	SMLCAP	M&A
OPTSPK	2.1	1.2%	0.9%	46	SMLCAP	M&A

About the Bloomberg Terminal.

Since 1981, business and financial professionals have depended on the Bloomberg Terminal® for the real-time data, news and analytics they need to make the decisions that matter. The Terminal provides information on every asset class — from fixed income to equities, foreign exchange to commodities, derivatives to mortgages — all seamlessly integrated with on-demand multimedia content, extensive electronic-trading capabilities and a superior communications network.

Take the next step.

For additional information, press the <HELP> key twice on the Bloomberg Terminal®.

Beijing
+86 10 6649 7500

Dubai
+971 4 364 1000

Frankfurt
+49 69 9204 1210

Hong Kong
+852 2977 6000

London
+44 20 7330 7500

Mumbai
+91 22 6120 3600

New York
+1 212 318 2000

San Francisco
+1 415 912 2960

São Paulo
+55 11 2395 9000

Singapore
+65 6212 1000

Sydney
+61 2 9777 8600

Tokyo
+81 3 4565 8900

bloomberg.com/professional