Stock Price Relation to News-Based Health Scores

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Introduction

The objective of this report is to determine whether there is a correlation between a company's corporate stock price and their news-based Manzama Insights Health Score (MIHS). In other words, the goal is to ascertain whether there is a quantitative relationship between (A) the collective behavior of investors when choosing to buy, sell or hold stock, as measured by stock price movements, and (B) the collective behavior of news editors when choosing whether or not to publish a corporate news event, as measured by the MIHS. By conceiving these two wisdom-of-crowds metrics as valuation estimates, we intend to provide a more holistic understanding of a company's health.

The relationship between new information and stock price movements has been extensively researched by behavioral psychologists, accounting researchers, financial mathematicians and financial economists. Although the interaction between investor behavior and price fluctuations has been modeled since the early 20th century (Bachelier, 1900), the Efficient Market Hypothesis (EMH) is often considered the starting point of the theoretical framework underlying market reactions to news (Mizuno, 2017). A main exponent of the EMH was the Nobel prize winner Friedrich August Hayek, who described the efficiency of markets in his 1945 essay "The Use of Knowledge in Society". By comparing price movements to "a system of telecommunications which enables individuals to watch... merely the hands of a few dials in order to adjust their activities" (Hayek, 1945), Hayek applauds the time efficiency of market responses to new information, and the information efficiency of market price as a summary of all information. The EMH considers that stock prices incorporate new information as soon as it is available, and that price movements reliably summarize the information available to all market participants (Kuepper, 2019; Chen, 2019).

The Efficient Market Hypothesis has faced intense yet sensible criticism, particularly by Daniel Kahneman and Amos Tversky's Prospect Theory challenging human rationality[1] and Benoit Mandelbrot's Chaos Theory challenging market stability[2]. However, the fundamental notion that new information influences stock prices, albeit inefficiently, has not lost support (Mizuno, 2017). On the contrary, the availability of massive datasets and new algorithmic approaches like Word Embeddings, Support Vector Regression and Deep Learning have allowed researchers to experimentally capture the interaction between news and stock price changes, yielding significant results (Liu, 2018; Shah, 2018; Schumaker, 2018; Mizuno, 2017; Li, 2014; Gidofalvi, 2001). Several researchers reported above 54% directional accuracy on stock price predictions, and some detected significant correlations approximately 20 minutes before and 20 minutes after relevant news was released. Most research obtained numerical signals from news by relying on financial dictionaries[3] or the stock price itself to arduously train deep networks. The Manzama Insights Health Score, on the other hand, uses tens of thousands of manually labeled articles to train a neural network to discriminate between positive, negative and neutral corporate events.

The algorithm to compute the MIHS operates as follows (Chart A): First, we gather all articles that mention a company name, product or CEO in the headline. Second, we preprocess each headline by making all words lower-case, removing uninformative and misleading words, and tokenizing remaining words. Third, we input each headline through a Long-Short Term Memory (LSTM) Neural Network with attentional and fully connected layers, which in turn outputs two pieces of information — the Category and the Valence — for each headline[4]. The Category takes one of twenty-five possible values, where each Category is a member of one of six Factors. For instance, the Financials Factor is made up of four Categories: Stock News, Analyst, Bankruptcy and Financials. The Operations Factor is made up of five Categories: Attacks & Disasters, Cyber Issues, Expansions & Contractions, Labor, and Supply Chain. The other four Factors are Management, which refers to news about executives and shareholders; Government, which takes into account political

[1] See Kahneman and Tversky's 1979 paper "Prospect Theory: An Analysis of Decision under Risk".
[2] See Mandelbrot's 2004 book "The Misbehavior of Markets" or Nassim Nicholas Taleb's 2010 book "The Black Swan: the Impact of the Highly Improbable".
[3] Dictionary methods consist of assigning a fixed score of +1 or -1 to specific words like "buy" or "sell", irrespective of the context.
[4] Manzama has an evolving set of Category-Valence Guidelines for analysts to use to classify headlines which are then used as a teaching signal.

issues and regulatory news; Products & Services, which includes product news and customer reactions; and lastly, Partners & Competitors, which includes merger and acquisition activity and dealings with other companies. The Valence can be one of three possible values: Positive, Negative or Neutral--- depending on whether the corporate event is good, bad or neither good nor bad for the company mentioned in the headline. The teaching signal for the network is a single Category-Valence pair.

Once all headlines have a Factor and a Valence, the next step in the algorithm is to group all headlines by Factor and feed these Valences into a function. The function assigns a score of +10 to a positive valence headline, a -10 to a negative valence headline and a 0 to a neutral valence headline[5], and in turn computes the aggregate score for each Factor: six numbers between -10 and +10. These aggregates are the Manzama Insights Factor Health Scores (FHS's). The headlines classified under all six Factors are then aggregated into the overall Manzama Insights Health Score (MIHS) by using the same function. Although this aggregation function weighs all headlines equally, resyndication and similar headlines are classified similarly, and therefore combine to have an additive impact on the Health Scores. In other words, the quantity of repeated and similar headlines, which theoretically represents news editors' perceived importance of that corporate event, is proportional to the impact of those headlines on the Health Scores.

It is especially interesting to relate the MIHS to the stock price because they are both wisdom-of-crowds proxies for the perceived value of a company, albeit according to different crowds: the former algorithmically combines the perspectives of the news editor crowd about a company and distills them into one number (the Health Score), while the latter uses the "invisible hand"[6] of supply and demand to combine the actions of the investor crowd and distills them into one number (the stock price). The differences in the way these values come to exist, however, makes the comparison even more compelling. According to the wisdom of crowds theory, four conditions characterize wise crowds: diversity of opinion (different interpretations of the same information), decentralization (specialization and local knowledge), aggregation (a mechanism that turns private judgments into a collective judgment), and independence (opinions are not determined by others' opinions) (Surowiecki, 2004). While the stock market is characterized as having diversity of opinion, decentralization and an aggregation method built in via the mechanisms of the "invisible hand", there is no self-organizational equivalent for the News Industry. Manzama incorporates diversity of opinion and decentralization by extracting information from tens of thousands of online sources from different geographic locations and political inclinations and uses a mathematical aggregation function to convert the multiplicity of headlines into one statistic. In the present report, we intend to determine whether the aggregate decisions of news editors are correlated with the aggregate decisions of investors, and ultimately, find evidence for a relationship between two distinct wisdom-of-crowds metrics: the news-based Manzama Insights Health Score and the corporate stock price.

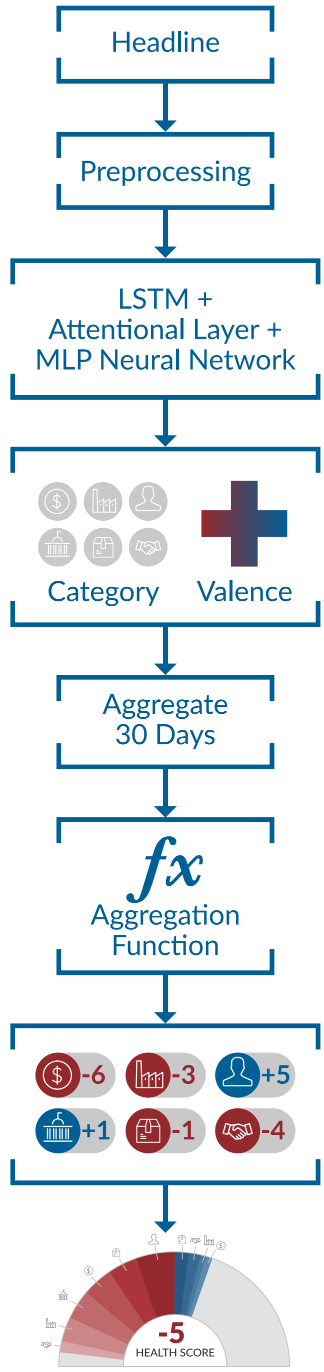

Chart A. Manzama Insights Health Score Computation

[5] This mapping of valence to scores is valid when the article volume for a Company or a Factor is above 100 articles in 30 days.

[6] The "marvelous" self-regularization of market forces to reach equilibrium is dubbed "the invisible hand".

Data
We selected the 99 companies with the largest headline volume from Manzama's company database (Appendix I). We extracted 90 days' worth of FHS's and MIHS's from Manzama's database for the companies listed in Appendix I. Then, we obtained the 62 stock closing prices between June 30th, 2019 and September 26th, 2019 from Yahoo Finance.

We standardized the stock prices by computing the percent change in the closing price since the last trading day, and standardized MIHS and FHS using the absolute change in value since the last trading day. This resulted in 61 unique data points for each health score per company, or 42,273 health score representations from an aggregate count of 173,327 headlines and 6,039 stock price representations.

Methods
An understanding of lags, leads and correlations is necessary to comprehend the analysis. Consider the following 4 arbitrary variables: **X** which takes on values [1, 6, 2, 8, 3] on January 1 through January 5; **W**, defined as the one-day lag of **X**, which constitutes all of the values of **X** the day before; **Z**, defined as the one-day lead of **X**, which constitutes the value of **X** the day after; and **Y** which takes on the values [14, 20, 10, 17, 14] during those same 5 days. Notice that the value of **X** on January 2nd corresponds to the value of **W** on January 3rd, and the value of **Z** on January 1st.

Table 1.

	January 1st	January 2nd	January 3rd	January 4th	January 5th	Mean
W (lag one of X)	NA -	1 ↓	6 ↑	2 ↓	8 ↑	4.25
X	1 ↓	6 ↑	2 ↓	8 ↑	3 ↓	4
Z (lead one of X)	6 ↑	2 ↓	8 ↑	3 ↓	NA -	4.75
Y	14 ↓	20 ↑	10 ↓	17 ↑	14 ↓	15

The arrow next to each number represents the position of the variable with respect to its mean. The arrow is important, because *the correlation between **X** and **Y** is a measure that quantifies how synchronized **X** and **Y** are with respect to their means.* If the correlation is 1, it means that **X** and **Y** move up and down with respect to their means in complete synchrony; if the correlation is -1, it means **X** moves above (or below) its mean and **Y** moves below (or above) its mean in synchrony. If the correlation is 0, it means that there is no relationship between the movement of **X** and **Y** about their means. The correlation of **X** and **Y** comes down to 0.73, which makes sense because the arrows are pointing in the same direction on all 5 days. However, the correlation of **W** and **Y** is -0.78 and that of **Z** and **Y** is -0.98, because the arrows are pointing in different directions on each day. While the correlation quantifies the synchrony of **X** and **Y** moving about their means, *the cross-correlation computes the synchrony of X and Y for various different lags and leads of X with respect to their means.*

The methodology I used to compare the corporate stock price with the MIHS was to compute the cross-correlation between the percent change in the stock price with the absolute change in the MIHS, resulting in one correlation estimate per company per lag/lead. I consequently computed the average cross-correlation and the standard deviation of the cross-correlation at each lag/lead.

Results
Chart B presents the average cross-correlation at each lag/lead, with **error bars representing 3 standard deviations of the mean** (99.6% confidence level; p-value = 0.004). On the x-axis is the lag/lead in days with respect to the stock price. On the y-axis is the average cross-correlation for the sample of 99 companies. Consider the leftmost point in the chart located at coordinates (-30, -0.006). This means that the percent change in the stock price has an average correlation of -0.006 with respect to the change in the MIHS thirty days before. Since the error bars for the correlation estimate cross 0, there is not enough evidence to support the claim that the percent change in the stock price and the change in the health score thirty days before are correlated. In fact, the only error bars that do not cross 0 are at a lag of 1 and at a lag of 0. This constitutes the first finding of the report: on average, the percent change in the stock price has a positive correlation with the absolute change of the Health Score **the day before and on the same day**. More specifically, the correlation point estimate at a lag of 1 was 0.045 ± 0.042, and the point estimate at a lag of 0 was 0.085 ± 0.052.

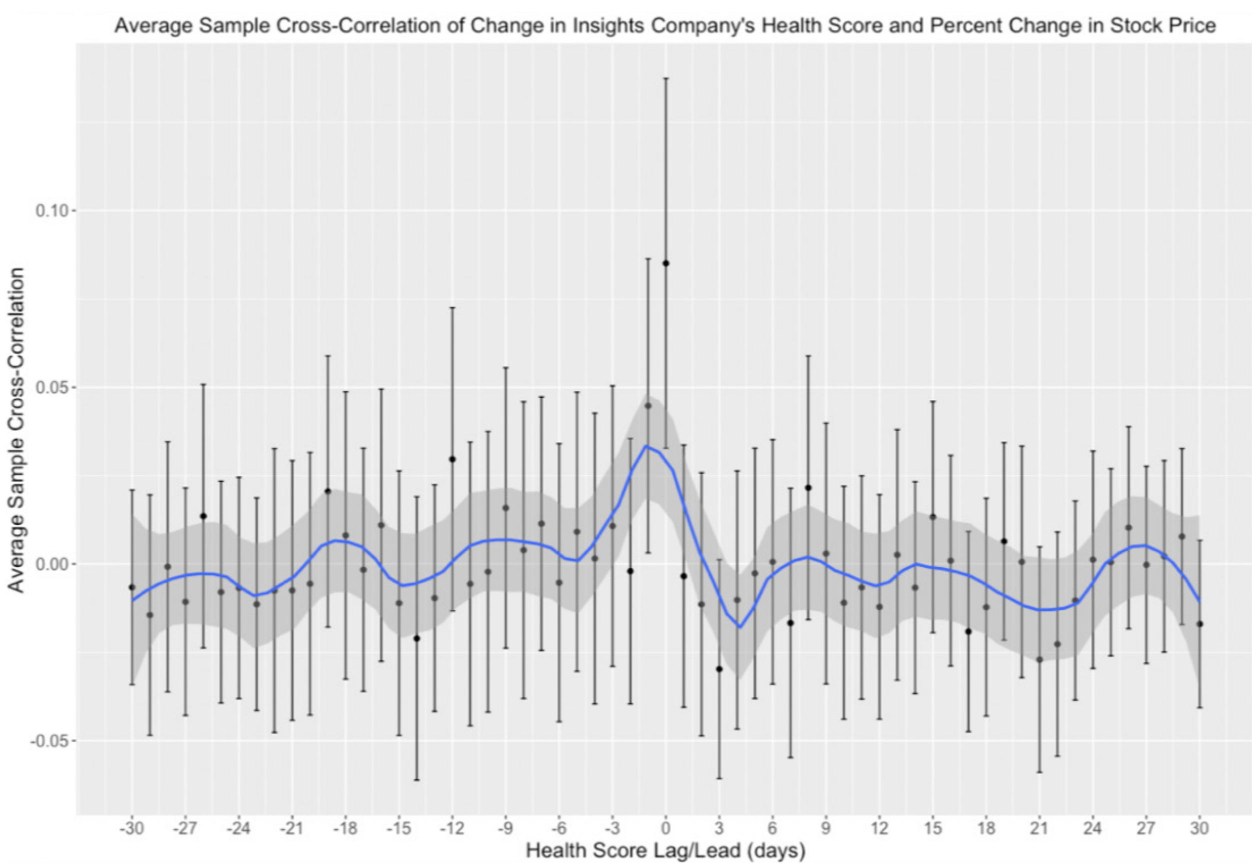

Chart B. Average Cross-Correlations of Change in MIHS and Percent Change in Stock Price

In addition to computing cross-correlations for the company health score overall, we also computed cross-correlations for all 6 Factors. The cross-correlations for these 6 Factors are presented in Chart C.

The second finding of the report is that three FHS's stand out as having statistically significant (p-value = 0.01) **positive** correlations on the same day as the stock price change: (1) Financials (0.120 ± 0.055); (2) Operations (0.056 ± 0.045); (3) Products & Services (0.037 ± 0.041). One interpretation of this finding is that when headlines about earnings, expansions into new markets or product releases are printed by news editors, there are corresponding responses by investors. Conversely, another interpretation is that stock price movements impact news editors' decisions on what to publish, since news editors retroactively publish headlines about stock price changes, categorized under Financials. Also, stock price movements could cause companies to make decisions regarding their Products or Operations, consequently generating news on these fronts.

The third finding of the report is that there is a significant relationship between stock price and the Financials Health Score *the day before*, namely, a **positive** correlation significant at a 99.4% confidence level (p-value = 0.006), with a point estimate of 0.048 ± 0.051. This implies that, on average, the Financials Health Score weakly leads the stock price by one day. This correlation could be caused by the fact that the Stock Exchange closes at 4PM ET, 4 hours before 24:00 GMT, which is the end of the day for Health Scores. Therefore, new articles could impact the Health Scores during those 4 hours, which would be interpreted as occurring the day before. An alternative interpretation is that news published the day before about Analysts' opinions about what will occur, or specific news about funds buying or selling assets might trigger stock prices to rise or fall.

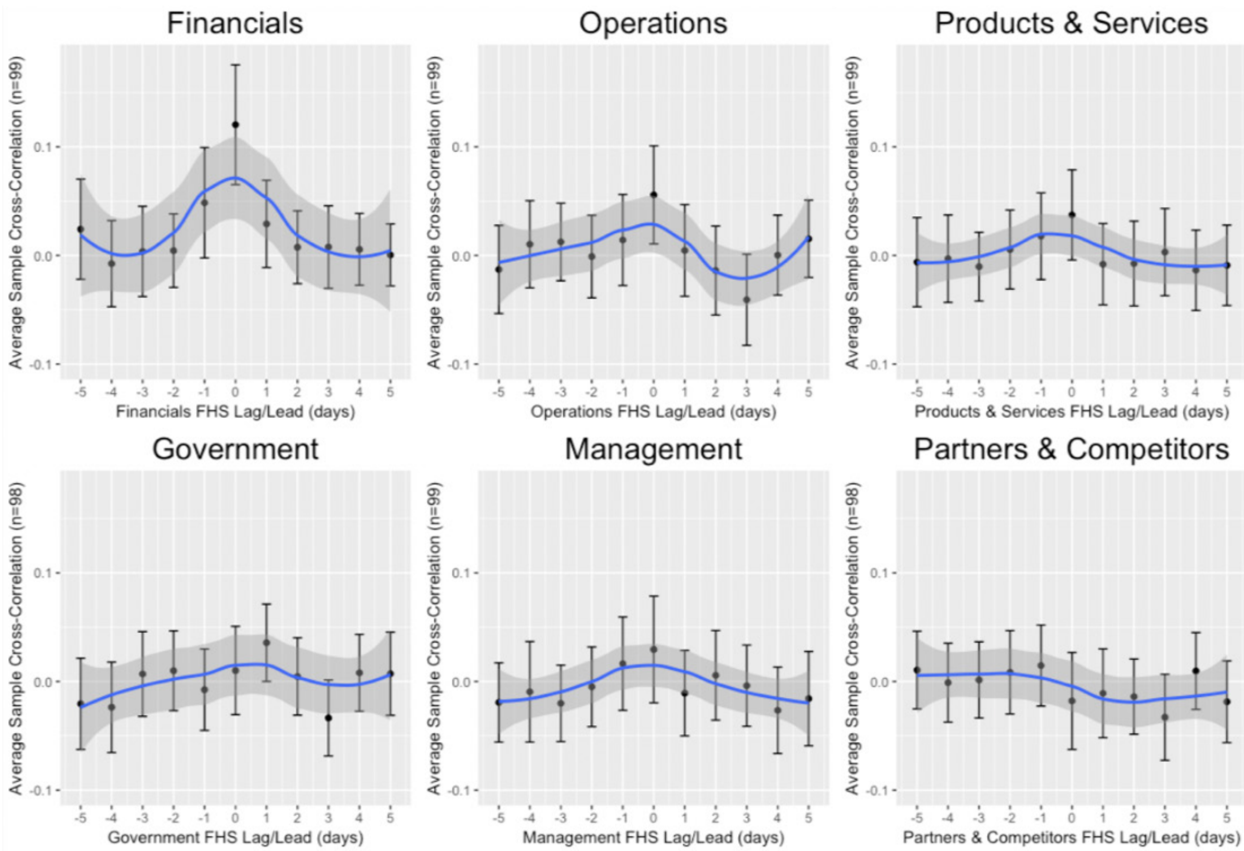

Chart C. Average Cross-Correlations of Change in 6FHS's and Percent Change in Stock Price

The fourth finding is that there are significant relationships between stock prices and Factor Health Scores *the day after*. Specifically, stock price is **positively** correlated with the Financials health score *the day after*, significant at a 96.6% confidence level (p-value = 0.04), and also **positively** correlated with the Government health score *the day after*, significant at a 99.8% confidence level (p-value = 0.002). One possible interpretation for the positive correlation with Financials is the effect of delayed or reprinted stock news. With regard to the correlation with the Government score, a reasonable explanation would be that investors find out about regulatory actions or government involvement before news editors print their headlines.

The fifth finding of the report is that there is a significant anti-correlation between the stock price and some Factor Health Scores *three days after*. Specifically, the Operations score *three days after* has a point estimate of -0.041 ± 0.042, and Government score *three days after* has a point estimate of -0.034 ± 0.035. A possible interpretation for this correlation is that health changes caused by Operations or Government news tend to revert after 3 days.

Limitations

This report has limitations that must be recognized. The Manzama Insights Health Score is generated from the output of a Neural Network Classifier that has a Valence accuracy of 83%, and Factor accuracy of 90%. For this reason, the Health Scores could be off by 15% or more, depending on the rarity of the headlines' syntax or word choice. Another limitation of this study is that we used the Pearson correlation statistic to relate stock prices and Health Scores, which is sensitive to outliers because of its reliance on the average percent change in stock price for each company. Since financial statistics tend to have heavy-tailed distributions, their average can be unstable, and therefore, the correlation coefficient can also be unstable (Mandelbrot, 1997). In future research, we could use median-based correlation coefficients to increase estimator stability.

There are some limitations to the stock price and the Manzama Insights Health Score from a wisdom-of-crowds theory perspective. From the four properties that characterize wise crowds --- diversity of opinion, decentralization, aggregation, and independence --- market investors are most frequently criticized for their lack of independence. The decisions of investors on whether to buy, sell and hold are influenced by the decisions of other investors during the same time, causing bubbles (Surowiecki, 2004). The same could be true for the decisions of news editors, which would cause the quantity of reprinted headlines to rise without a proportional increase in the importance of the information contained in the headlines, resulting in the equivalent of a bubble in Health Scores. While stock prices automatically integrate the other characteristics through market forces, the MIHS incorporates these characteristics programmatically and algorithmically. Our aggregation function additively combines all headline scores, meaning that “minority” news editors’ points of view on an event, which tend to have few headline occurrences, have a smaller impact on the Health Score than the headlines coming from “mainstream” news organizations, which are well-connected and take advantage of resyndication. Although this ensures that the majority’s vote wins, we risk presenting a statistic that does not represent the opinions of the news editor crowd overall.

Another limitation is that our aggregation function utilizes a 30-day window of headline news to compute the Health Scores, after which the headlines are omitted from the calculation. The effect of this algorithmic design choice can be appreciated by looking at the *negative average correlation* of stock prices and Health Scores at a lead of 21 and 22 days (the approximate number of trading days in a 30-day interval) in Chart B. Although this makes Health Scores more interpretable, it adds noise to the impact of novel headlines on the Health Scores. For this same reason, the absolute change in the Health Score, the variable selected to compute correlations against stock prices, is a function of *the difference between the impact of headlines today and the impact of headlines exactly 30 days ago*. This implies that a company that gets 60 new negative headlines and 40 new positive headlines every day will have an MIHS fixed at -2, even though the 60 new negative headlines today could have been more important than the 60 old negative headlines printed 30 days ago that are now being forgotten. Despite all of these limitations and the fact that the algorithmic design choices for the Health Score computations were not intended to converse well with stock prices, correlations were found, generating exciting prospects for future research directions.

Conclusion

The objective of finding a correlation between the changes in stock prices and the changes in Manzama Insights Health Scores was fulfilled. Specifically, the change in the company Health Score overall is positively correlated to the changes in stock prices, primarily due to three Factors: Financials, Operations, and Products and Services. The implication of this finding is that the decisions of news editors and those of investors are interrelated: new information injected into the market results in coordinated responses by news editors and investors alike. However, the most important finding of this report is the evidence of a correlation beyond a short time window of 20 minutes before and after news releases. Specifically, we discovered that, on average, the Operations FHS is positively correlated with stock price on the same day and the Government FHS a day later, but both FHS’s are negatively correlated three days later. Due to the fact that stock price changes and Health Score changes are correlated but are not numerically or deterministically related, they can be used in conjunction to verify their signals and to ultimately provide a more holistic assessment of a company’s health.

Several interesting research questions emerge from this report. First, what sort of algorithmic design choices and data transformation choices should be adopted to strengthen the signal between news headlines and stock prices? Regarding algorithmic design choices: (1) the 30-day aggregation time interval could be shrunk to better match the stock price time scale; (2) the Health Score formula could be tweaked to deliver a signal that is more dependent on new information than old information; (3) we could adopt correlation metrics that are robust against outliers. Regarding Health Score data choices, instead of using 6 FHS’s, we could use Manzama’s 25 Category Health Scores (CHS’s) to provide more topic granularity and to pinpoint the types of articles that are correlated with investors’ decisions. Regarding stock data choices, instead of using the percent change of closing price, we could use the Sharpe Ratio to standardize the volatility of each stock and the increase in the index price. Another question left unanswered by this report is whether there are some company profiles for which the correlations are more reliable. We could group companies into industries, or we could group companies according to their predominant Factor, and then conduct statistical tests on correlation quality and stability.

A broader question we ask ourselves is what metrics besides stock prices could we analyze to validate Manzama Insights Health Scores’ relation to the health of a company? Identifying and compiling various correlated corporate health metrics, extracted from different data forms and originating from different crowds, could be an important first step in modernizing Hayek’s metaphor of a time-efficient and information-efficient “system of telecommunications” about corporate health and the economy overall.

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Appendices
Appendix I: Companies

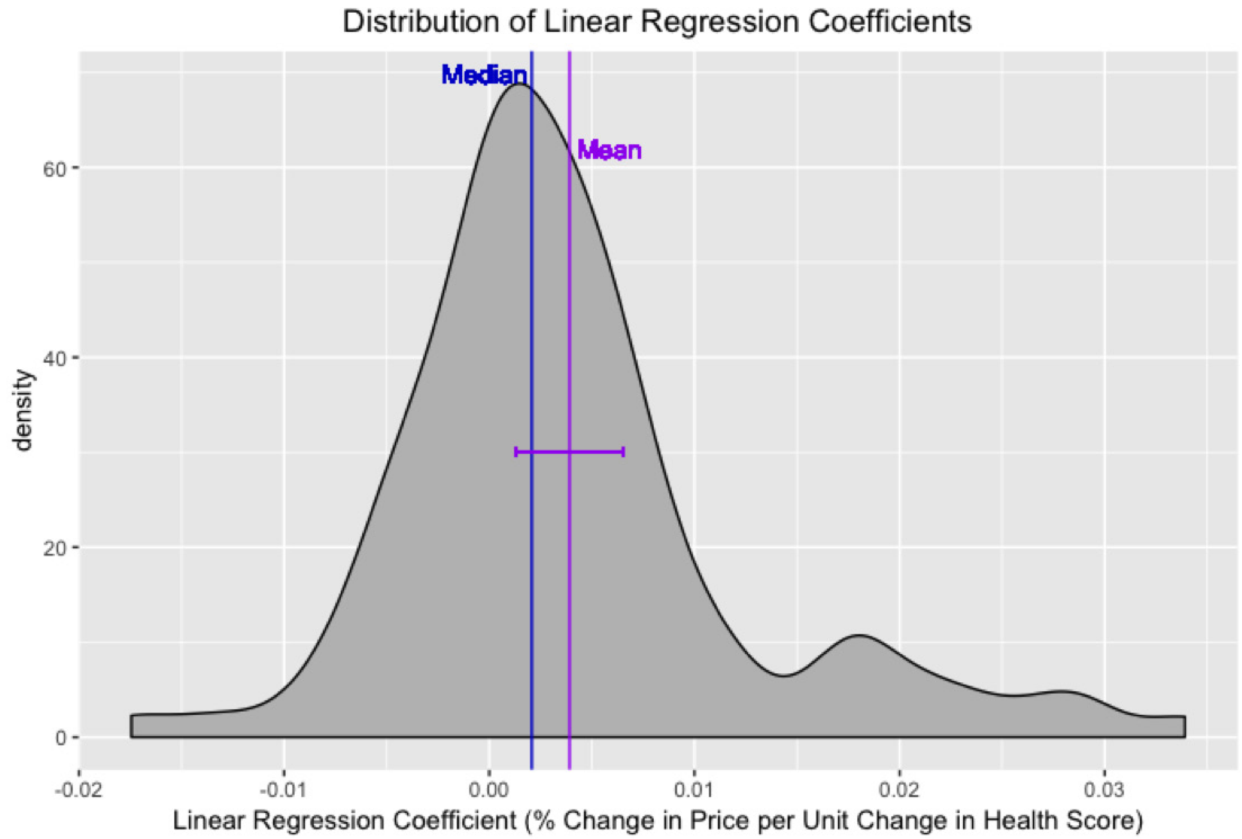
	Company Name	Stock	Articles
1	Apple	AAPL	11220
2	Facebook	FB	9734
3	Amazon.com	AMZN	7977
4	Google	GOOG	7151
5	Boeing	BA	6138
6	The Walt Disney Company	DIS	5717
7	General Motors	GM	4609
8	Microsoft	MSFT	4566
9	Walmart	WMT	4378
10	Netflix	NFLX	3456
11	Tesla Motors	TSLA	3306
12	AT&T	T	3156
13	Ford Motor Company	F	2512
14	Nike	NKE	2464
15	Deutsche Bank	DB	2285
16	General Electric	GE	2282
17	Capital One	COF	2257
18	Starbucks	SBUX	2174
19	JP Morgan Chase	JPM	2171
20	Intel	INTC	2133
21	American Airlines	AAL	2086
22	BlackRock	BLK	1842
23	Pfizer	PFE	1804
24	FedEx	FDX	1799
25	Cisco Systems	CSCO	1712
26	Qualcomm	QCOM	1700
27	Comcast	CMCSA	1679
28	Wells Fargo	WFC	1671
29	Verizon	VZ	1637
30	Bank of America Merrill Lynch	BAC	1633
31	Johnson & Johnson	JNJ	1600
32	Goldman Sachs	GS	1511
33	Citigroup	C	1476
34	McDonald's Corporation	MCD	1449
35	Delta Air Lines	DAL	1446
36	Exxon Mobil	XOM	1440
37	Mastercard Incorporated	MA	1418
38	BP	BP	1408
39	Visa Inc.	V	1393
40	The Procter & Gamble Company	PG	1364
41	Advanced Micro Devices	AMD	1329

	Company Name	Stock	Articles
42	Merck	MRK	1308
43	Viacom Inc.	VIAB	1305
44	IBM	IBM	1287
45	PG&E Corporation	PCG	1258
46	Chevron	CVX	1256
47	Lockheed Martin	LMT	1245
48	CBS Corporation	CBS	1237
49	Oracle	ORCL	1193
50	Home Depot	HD	1181
51	Amgen	AMGN	1148
52	Accenture	ACN	1141
53	Pepsico, Inc.	PEP	1138
54	3M	MMM	1108
55	Marriott International	MAR	1101
56	Broadcom Limited	AVGO	1052
57	United Parcel Service	UPS	1028
58	Hilton Worldwide Holdings Inc.	HLT	1016
59	Kraft Heinz Mondelez	KHC	981
60	Costco Wholesale Corporation	COST	978
61	EBay	EBAY	968
62	Gilead Sciences, Inc.	GILD	960
63	Raytheon	RTN	953
64	Medtronic	MDT	952
65	Allergan	AGN	919
66	Honeywell International	HON	899
67	Adobe Systems	ADBE	880
68	American Express Company	AXP	848
69	Brookfield Asset Management Inc	BAM	830
70	The Kroger Co	KR	827
71	Altria Group	MO	799
72	Target	TGT	798
73	Prudential Financial	PRU	790
74	Eli Lilly	LLY	785
75	Nvidia Corporation	NVDA	771
76	BHP	BHP	759
77	GlaxoSmithKline	GSK	757
78	Enbridge Inc	ENB	753
79	Bristol-Myers Squibb	BMY	749
80	Union Pacific Corporation	UNP	740
81	Moody's Corporation	MCO	733
82	Hewlett-Packard	HPQ	719

	Company Name	Stock	Articles
83	Nokia	NOK	716
84	Coca-Cola	KO	703
85	NextEra Energy, Inc.	NEE	668
86	Dominion Energy, Inc.	D	668
87	Best Buy	BBY	632
88	Motorola Solutions, Inc.	MSI	631
89	Philip Morris International	PM	621
90	General Mills, Inc.	GIS	613
91	Dell	DELL	599
92	The Williams Companies Inc	WMB	592
93	Novartis	NVS	591
94	Credit Suisse Group	CS	581
95	Tyson Foods, Inc.	TSN	580
96	Humana	HUM	531
97	Lloyds Banking Group	LYG	512
98	Dollar General Corporation	DG	483
99	Gamestop Corp.	GME	373

Appendix II: Coefficient Analysis

Another way of interpreting the correlation statistics presented in Charts B and C is as the square root of the coefficient of determination, or R squared value, of a linear regression. Therefore, I computed linear regressions with the percent change in the stock price as y-variable and the change in the Health Score *on the same day* as the x-variable for all 99 companies. Although the linear fits are nowhere close to being predictive, the overall linear trend is still meaningful.

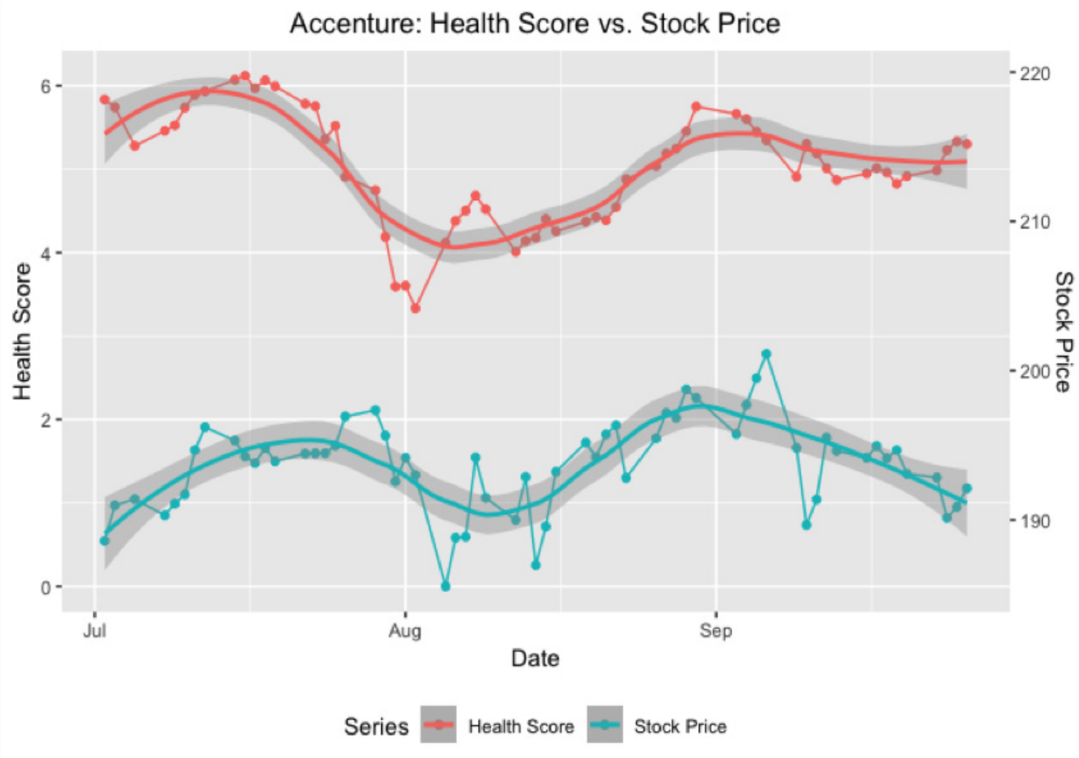


The average coefficient is 0.39%, while the median coefficient is 0.21%. The same analysis was conducted with the MIHS *the day before*, and the average coefficient was positive with a 99.3% confidence level, with a point estimate of 0.17%, and a median coefficient of 0.18%. This means that, on average, a unit change in the Health Score roughly corresponds to a 0.39% change in the stock price on the same day, and a unit change in the Health Score corresponds to a 0.17% change in the stock price the day after.

It is important to highlight that the linear regression coefficients aggregated into the above distribution were not statistically significant. Therefore, the purpose of this coefficient analysis is to aid in the comprehension of the correlation analysis.

Appendix III: Accenture

To make these findings more concrete, let's look at the stock price and the MIHS for Accenture, the leading professional services company headquartered in Ireland. By looking at the trend lines superimposed on both series, we can observe a possible relation between the stock price and the Manzama Insights Health Score. This relationship can be explained by diving into Manzama's raw inputs: news article headlines.



The first peak was prompted by a news release on July 11th, stating that Accenture had appointed Julie Sweet as their new global chief executive, causing an increase of the stock price and an increase of the Management component of the company's MIHS. Subsequently, on July 24th, Manzama picked up on articles stating that Douglas Lane & Associates LLC, Patten Group, and other investment firms were selling Accenture stock, causing a dip in the Financials component of their Health Score. Then, on August 5th, two big stories caused Accenture's Partners & Competitors Health Score to jump: (1) "Accenture Named A Leader in Next-Generation IT Infrastructure Services for Banking, Financial Services, and Insurance by Everest Group"; (2) "Accenture Acquires Northstream, Stockholm-Based Consultancy to Communications Service Providers". Throughout August and September, Accenture's health score was bolstered by additional acquisitions news: on August 12th, they acquired the Design and Innovation firm INSTITUM; on August 15th, Analytics and Data firm Analytics8; on August 19th, the Financial Services company Parker Fitzgerald; on August 28th, the Engineering Services company Fairway Technologies, and on September 10th, the Artificial Intelligence and Big Data company Pragsis Bidoop. In September, Accenture maintained a very healthy score of +6 by: (1) hiring the Cyber Executive Aaron Faulkner and partnering with AXA XL to provide cybersecurity services; (2) earning awards in Digital Technology Innovation and taking the top spot in the Refinitiv Diversity and Inclusivity Index; (3) partnering with Exxaro and Qualtrics.