SmartMarketData
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Axiomatic Data ThriveScores and Stock Price Performance

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Axiomatic higher/lower ThriveScores correlate with higher/lower stock price performance

Abstract

This white paper builds on Axiomatic Data's 2020 white paper "Pension Contributions & Financial Performance"[i], which looked at Pension Contribution impact on company revenue, among other things.

Over the past year Axiomatic Data has developed and tested a new metric – ThriveScores - which facilitate the comparison of public and private company financial health and growth potential. We take a high-level look at the relationship between company ThriveScores and a company's stock performance.

We hypothesize that higher ThriveScores will translate to higher stock price returns, and lower ThriveScores translate to weaker stock price returns.

To test the hypothesis, we segment, by ThriveScores, a large subset of Russell 3000 constituents into quintiles – High, Medium High, Medium, Medium Low, Low. We then create three portfolios and look at the alpha generated by each across annual investing periods, with constituent companies rebalanced each calendar year.

The results do confirm the hypothesis. Higher ThriveScores do correlate with higher stock price performance, and lower ThriveScores do correlate with weaker stock price performance.

Axiomatic ThriveScore

Axiomatic Data is the market leader in the development of investment data gleaned from Form 5500 filings, which contain detailed information on employee benefit plans. Axiomatic Data provides a point-in-time database with seven years of history that contains the key attributes from these filings for about 700,000 US companies used by quantitative hedge funds and traditional asset managers.

Using corporate growth attributes extracted from Form 5500 filings, Axiomatic Data has created a proprietary company level metric called the ThriveScore, which provides insight into recent and expected corporate growth. Variables incorporated in the ThriveScore include growth rates of employees and active pension plan participants, employer and employee pension fund contributions, and contributions per employee. ThriveScores range from 1 to 1000 and the median ThriveScore for the Russell 3000 companies in 2020 was 610.

Hypothesis

Intuitively, companies that are experiencing employee count growth and growth in employee benefits metrics such as pension contributions would see greater than average financial performance, which would in turn translate to greater than average stock price performance all else being equal. Research has shown, for example, that public companies that sponsor ESOP plans show financial performance that significantly outperforms those that do not.[ii]

In this whitepaper, we examine the impact of company 401(k), profit sharing, and related company benefits that are included in Form 5500, on a company's stock price. We answer the question "Do companies with superior Form 5500 metrics, as defined by the proprietary Axiomatic ThriveScore described above, outperform those with inferior ThriveScores, in terms of stock price return?"

We hypothesize that ***high ThriveScores correlate to relatively higher stock price returns, and low ThriveScores correlate to relatively lower stock price returns***.

Methodology

To test the above hypothesis, we first obtained ThriveScores from Axiomatic Data. We then looked at a large subset of the Russell 3000 Index "constituent companies"[iii], a broad US market index representing 98% of the investable US market, for the ThriveScore periods 2016, 2017, 2018, and 2019, with the results current through calendar year end 2020 (e.g. 2020 Stock Prices are used to test 2019 ThriveScores).

We then created a sample panel that consisted of companies that had stock prices in year t_1 matching companies with ThriveScores in calendar year t_0, where each company was a constituent of the Russell 3000 in calendar year t_0.

The Constituents

The below *Table 1- Benchmark Constituent Counts* shows the number of company constituents in each year in the sample.

Table 1- Benchmark Constituent Counts

Year	Benchmark Constituents
2016	2,361
2017	2,390
2018	2,459
2019	2,667

We rebalanced the constituents annually based on the constituent changes in the Russell 3000. If a company was a constituent in 2016, but not in 2017, it was ***excluded*** from the 2017 constituents. If a company started a year as a constituent of the Russell 3000, but went out of business or was acquired etc. during that year, it was ***included*** in that year's sample. This assured no look ahead bias.

Company Stock Return

We created company annual stock price returns as follows:

$$r_t = \left[\frac{Price_{t1}}{Price_{t0}} - 1\right] x\ 100$$

where

$$r_t = stock\ price\ return\ for\ the\ calendar\ year\ t$$

$$Price_{t1} = stock\ price\ at\ the\ end\ of\ calendar\ year\ t$$

$$Price_{t0} = stock\ price\ at\ the\ beginning\ of\ calendar\ year\ t$$

Benchmark Portfolio

The next step was to create a Benchmark Portfolio to represent the "market". To do this we merely used ALL the constituents available in each year, as outlined in *Table 1- Benchmark Constituent Counts*. For example, in 2019, our benchmark portfolio consisted of 2,667 constituents of the Russell 3000 Index.

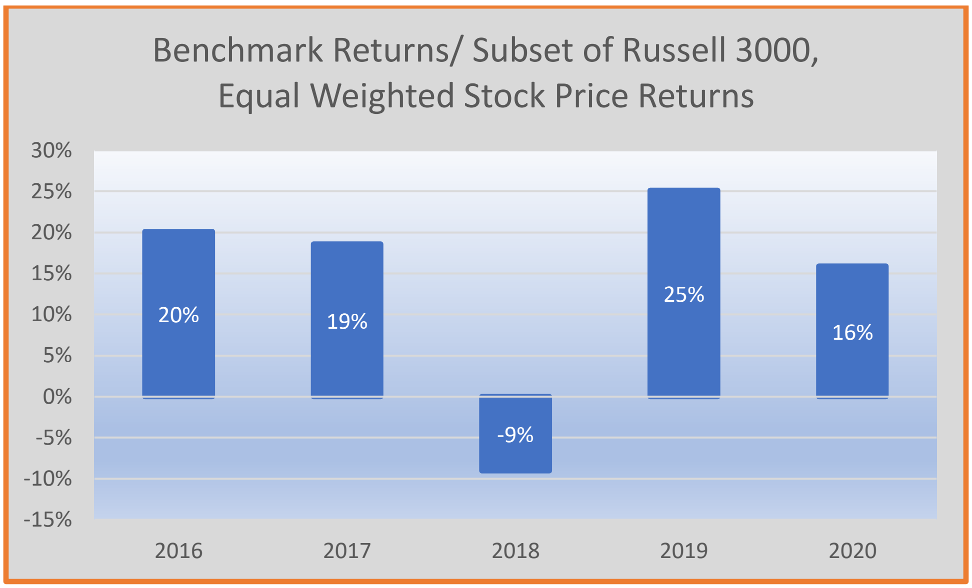
Benchmark Return

We then calculated a Benchmark Return for each Benchmark Portfolio, for each year. Because this is an equal weighted portfolio, we merely sum each constituent's stock price return, for each year (Table 2 - Benchmark Returns, Figure 1 - Benchmark Returns).

Table 2 - Benchmark Returns

Axiomatic Data Date	Benchmark Date	Constituent Count	Benchmark Return
2015	2016	2,344	0.201
2016	2017	2,361	0.186
2017	2018	2,390	-0.090
2018	2019	2,459	0.251
2019	2020	2,667	0.159

Figure 1 - Benchmark Returns



Quintiles

For each year, we separated each group of constituents based on their ThriveScores. Quintiles were determined by slicing into 5 equal-sized buckets the Benchmark constituents, based on their ThriveScores. Duplicates on a bucket's edge would fall into the nearest bucket that established the closest "near-equal" size buckets. These buckets were then labeled for further use in allocation and discussion in our analysis. Each bucket ranges in size from ~450-~550 constituents.

High = H
Medium High = MH
Medium = M
Medium Low = ML
Low = L

Sample Portfolios

For this analysis, we chose to create 3 portfolios.

Portfolio 1 – Long Only

The long only portfolio consists of all companies in each Benchmark Portfolio for each year.

Portfolio 2 – 50% Allocation Long, 50% Allocation Short

Long the Highest (“H”) quintile ThriveScore constituents, and Short the Lowest (“L”) quintile ThriveScore constituents of the Benchmark Portfolio for each year.

Portfolio 3 – 50% Allocation Long, 50% Allocation Short, Further Split Long and Short allocations

Long the Highest (“H”) and the 2nd Highest (“MH”) quintiles ThriveScore constituents, and Short the Lowest (“L”) and the 2nd Lowest (“ML”) quintile ThriveScore constituents of the Benchmark Portfolio for each year.

Investment Process

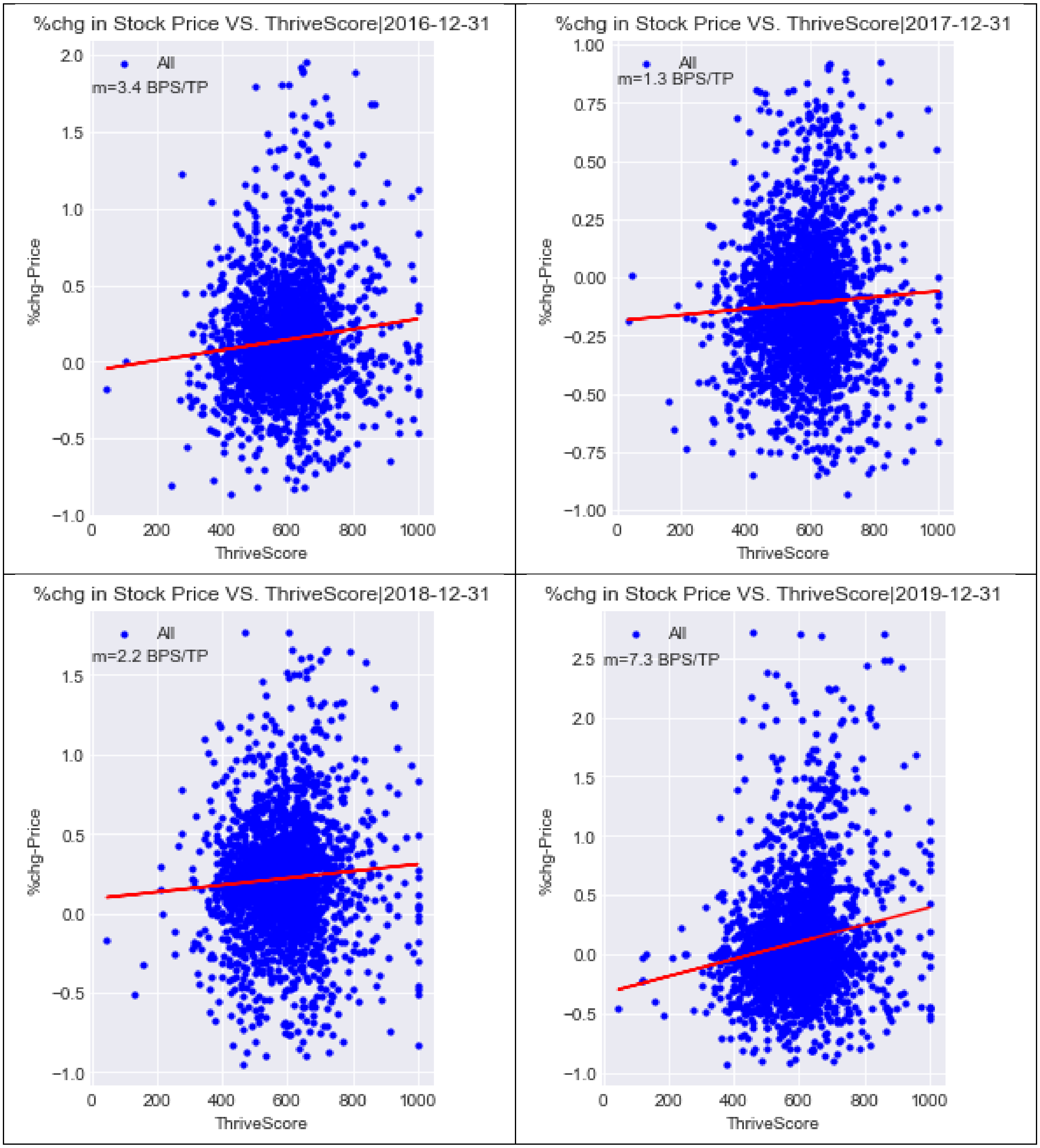
Our analysis consists of us going Long (and Short) on December 31st (t_0)(or the last trading day of the year) of the year the ThriveScore is for (the Axiomatic Data Date in Table 2 - Benchmark Returns) - at the market Close. We then close the position on the last trading day of the following year (t_1), establishing a return for each position, as well as for the portfolio. The process:

1) Determine constituents
2) Determine Portfolio Quintiles
3) Long/Short at t_0 the Portfolio
4) Sell/Cover at t_1 the Portfolio
5) Determine the return of the Portfolio by summing the constituent stock price returns
6) Determine the Alpha by subtracting the Benchmark Return from the Portfolio Return

Results

The first thing we looked at was a high-level correlation examining the % change in Stock Price compared to ThriveScores for each year. For our hypothesis to be true, you would expect to see stock returns correlated to ThriveScores – Lower ThriveScores would correlate with lower stock returns, and Higher ThriveScores would correlate with higher stock returns. In each year, we do see this when looking at the entire sample, as represented in the below Figure 2 - %Chg in price vs. ThriveScore, with linear regression. The results show an expected positive slope in the **red** regression line, implying a positive correlation. The signal appears to be getting stronger, with an increase of 3.4 bps of stock return for each ThriveScore point in 2016, 1.3 bps in 2018, 2.2 bps in 2019, and 7.3 in 2020.

Figure 2 - %Chg in price vs. ThriveScore, with linear regression



The results for each portfolio are as follows:

Portfolio 1 Results– Long Only

A portfolio consisting of just going long every constituent, should return little if any alpha as it nearly replicates the benchmark. In our specific case, that means going long the good "H" ThriveScore companies, as well as the bad "L". This is a good sanity check, and the results in Table 3 - Portfolio 1 - Long Only Alpha, are as expected and show basically zero alpha for each year.

Table 3 - Portfolio 1 - Long Only Alpha

datarun_date	alpha
2016	0.00162
2017	-0.00355
2018	-0.0027
2019	-0.00356

Portfolio 2 Results – 50% Allocation Long, 50% Allocation Short

The long "H", and short "L" portfolio, we expected to show positive alpha if our hypothesis is valid. The results are found in the below Table 4 - Portfolio 2 - Long H/Short L - Alpha, and confirm our hypothesis with greater than benchmark returns.

Table 4 - Portfolio 2 - Long H/Short L - Alpha

datarun_date	alphals2
2016	0.04806
2017	0.03562
2018	0.03644
2019	0.11390

Portfolio 3 Results – 50% Allocation Long, 50% Allocation Short, Further Split Long and Short allocations

The long "H" and long "MH", short "L" and short "ML" portfolio, we expected to show positive alpha if our hypothesis is valid. The results are found in the below Table 5 - Portfolio 3 - Long H,MH/Short L,ML - alpha, and confirm our hypothesis with solid positive alpha returns. This also tangentially confirms the hypothesis with slightly lower alphas in general compared to Portfolio 2, as we expect because we diluted the strongest longs and shorts with more of the "middle of the road" ThriveScores.

Table 5 - Portfolio 3 - Long H,MH/Short L,ML - alpha

datarun_date	alphals4
2016	0.05094
2017	0.02220
2018	0.01776
2019	0.08415

Summary and Conclusion

Axiomatic Data, the market leader in the development of investment data gleaned from Form 5500 filings has created a proprietary "ThriveScore" which looks at company IRS Form 5500 data, and combined with other factors, provides insight into recent and future corporate growth.

This white paper examined the impact of company ThriveScores on a company's stock performance. We hypothesized that higher ThriveScores yield higher stock returns, and lower ThriveScores would yield lower stock price returns.

To test the hypothesis, we segmented into ThriveScore quintiles, a large subset of Russell 3000 constituents – High, Medium High, Medium, Medium Low, Low. We then created three portfolios and looked at the alpha generated by each across annual investing periods, rebalancing each calendar year.

The results confirm the hypothesis. Higher ThriveScores do correlate with higher stock performance, and lower ThriveScores correlate with lower stock price performance. The test portfolios performed as theorized, with both the Long H/Short L and long H/MH and short L/ML providing positive alpha.

Future Research

We will be following up this white paper with a deeper analysis that segments the ThriveScore across various other factors such as Sectors, Industries, Employee counts, Benefit types and more, seeing if there are possibly even stronger alpha signals.

About SmartMarketData, LLC

SmartMarketData (SMD) was founded in 2014 by SMD President - Larry Green. SMD finds unique and relevant alternative data and helps productize that data for consumption by Wall Street. Key services to both data providers and data consumers include:

- Product Development
- Operations
- Identifier/Reference Data Mapping
- Business Development
- Client Admin
- Data Science and Research
- Custom Data Science and Research for customers

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[i] https://axiomaticdata.com/blogPosts/whitepaper-pension-contributions-and-finance-performance

[ii] Michael A. Conte, Joseph Blasi, Douglas Kruse & Rama Jampani (1996) Financial Returns of Public ESOP Companies: Investor Effects vs. Manager Effects, Financial Analysts Journal, 52:4, 51-61, DOI: 10.2469/faj.v52.n4.2011

[iii] https://research.ftserussell.com/Analytics/FactSheets/temp/6bba8e08-5d4e-430e-98e3-60919116c2cb.pdf