

Bedrock AI

Price impact of Bedrock AI Risk Scores - Backtest

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Executive Summary

Bedrock AI uses deep learning based language models to find associations between content in unstructured text in securities filings and downside outcomes like SEC Enforcement actions. We quantify this association using our machine learned Bedrock AI Risk Scores. Our Risk Scores represent a normalized prediction of whether or not a downside event will occur.

Critical information disclosed in the form of unstructured text in quarterly and annual filings takes months to be incorporated into share price, as demonstrated here. Companies take advantage of grey areas in accounting and estimates to bolster earnings in the short term. In the long-term these effects reverse.

In this paper, we use a simplistic test to demonstrate that high risk filers (as defined by Bedrock AI Risk Scores) significantly underperform their peers in the months and years following a high risk filing. Our basic question:

How would you expect returns to differ between high and low risk company shares at various intervals following the filing of their annual reports (10-K)?

In this paper, we've calculated the historical return on investment for equity securities, as described below in [Approach](#). This simplistic approach demonstrates the value of Bedrock AI Risk Scores even in the most basic investment strategies.

Summarized Results and Conclusions

We demonstrated results for two strategies, a Long-Short strategy and an Index-Exclusionary strategy. Refer to [Approach](#), in the Testing section of this whitepaper, for the details of each strategy. The results for both strategies support the hypothesis that information disclosed in 10-Ks is not incorporated into stock price in a timely manner. Under both investment strategies, the Bedrock AI Risk-Score based strategies provide superior returns long-term.

As expected, high risk companies often slightly outperform lower risk companies in the short term but dramatically under-perform lower risk companies in the long term.

Long-Short Strategy

The median ROI for the High Risk group (top 7 percent by Risk Score) underperformed that of the Standard group by 11%, after 24 months. Median returns of the Standard group exceed those of the High Risk group for all intervals of at least 3 months or longer, on average.

- ▶ Year 2021 demonstrated significant outperformance despite the short measurement period with performance differentials of 14% to 26% at the 9 month mark (for the 7% and 5% groups), where available.
- ▶ In all of 2017-2019 the Long-Short strategy tests demonstrated significant performance differentials in all intervals of 9 months or longer for both the 7% and 5% test groups.
- ▶ Year 2020 demonstrated price impact differentials from the 15 month interval (7% group), reflecting a longer time to price impact. The 2020 year test was anomalous. The 2020 results were due, at least in part, to the timing of the stock market crash that occurred during the busiest period for filing 10-Ks, in February 2020. Slightly differing measurement start dates impact ROI figures significantly in this year. The 2020 year had markedly more outlier returns than any other year in this test, with multiple stocks earning more than 500 percent returns from the date of measurement during multiple intervals.

Performance differential is calculated as the difference between Median ROI (%) for the Standard Group and High Risk Groups.

Long-Short Strategy - 7% Group

	Performance Differential ($\Delta\%$)								
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
2017	0.4	(0.3)	1.0	5.5	7.1	11.0	5.7	8.4	5.2
2018	1.0	1.6	(0.4)	5.1	6.2	6.1	6.1	8.1	11.1
2019	0.3	(2.2)	(3.1)	1.3	10.5	8.6	11.9	9.0	11.0
2020	(6.9)	(2.0)	(0.4)	(8.0)	(2.0)	1.5	4.6		
2021	3.2	7.2	11.8	13.9					
Median	0.4	(0.3)	(0.4)	5.1	6.7	7.4	5.9	8.4	11.0

Long-Short Strategy - 5% Group

	Performance Differential ($\Delta\%$)								
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
2017	0.0	(2.3)	(0.8)	4.0	9.9	13.7	8.4	18.4	11.1
2018	3.0	3.0	0.5	10.2	13.5	15.9	26.4	21.4	22.8
2019	0.1	(3.3)	(3.1)	0.1	12.0	11.1	12.0	12.5	11.2
2020	(5.1)	(4.5)	(0.3)	(13.2)	(7.0)	(7.2)	(9.7)		
2021	5.4	8.6	14.3	26.1					
Median	0.1	(2.3)	(0.3)	4.0	11.0	12.4	10.2	18.4	11.2

Index-Exclusionary Strategy

The Bedrock AI “exclusionary” group outperforms the “index” group at all intervals, on average. Outperforming an index-style strategy is challenging and valuable. Consistent with the long-short strategy, the performance differential increases with time.

The 2020 test year demonstrated positive performance differentials at all but one interval despite the onset of the global pandemic and significant outlier returns.

Performance differential is calculated as the difference between Median ROI (%) for Bedrock AI's "exclusionary" group and the complete group of tradable securities, the "index" group.

	Median Performance Differential ($\Delta\%$)								
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
2017	0.0	(0.2)	(0.5)	0.5	0.9	1.1	1.1	1.0	1.1
2018	0.3	0.6	0.5	0.5	0.7	1.0	1.1	1.6	1.7
2019	0.0	0.3	0.2	0.7	0.9	1.0	0.8	1.5	0.9
2020	0.5	0.4	0.4	0.4	0.2	(0.2)	0.4		
2021	0.7	1.0	2.3	0.6					
Median	0.3	0.4	0.4	0.5	0.8	1.0	1.0	1.5	1.1

The results of both tests demonstrate that significant red flags in a 10-K (as measured through the Bedrock AI Risk Score) are predictive of underperformance in the long term. Results are consistent across years. Within test years, the price impact magnifies as time increases. The Bedrock AI Risk Score is an early and powerful precedent of price impact.

About Bedrock AI

Bedrock AI is software that extracts red flags from SEC filings and predicts crisis. Bedrock AI finds material information in a matter of seconds, allowing analysts to cut research time by over 1/3rd and to find forensic flags they would otherwise never see. Our platform supports over 100,000 filings, 8,000 issuers and updates in real-time. Our customers include asset managers with over \$30B in AUM.

The Bedrock AI founding team includes CPAs and machine learning researchers with over 20 years of combined experience. Bedrock AI is a **Y Combinator** company.

In the news:

- [Bedrock AI receives \\$1 million to extract hidden information from financial documents](#) | **BetaKit**
- [Securities regulators announce Canadian firm selected for cross-border testing](#) | **Ontario Securities Commission**
- [Short Sellers and Hedge Funds Sign On to Fintech Company...](#) | **Institutional Investor**
- [Fixing Audit Won't Fix Fraud](#) | **Alex Danco**

Bedrock AI covers SEC filing types 10-K, 10-Q, 20-F and 8-K, with additional filings types coming soon. Results are available via our web dashboard **in real-time** and/or via email notifications. Learn more at our website, www.bedrock-ai.com and our newsletter, <https://bedrock.substack.com/>.

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Testing

Approach

How would you expect returns to differ between high-risk and lower risk companies at various intervals following the filing of their annual reports?

We performed identical tests for each year from 2017 through 2021 to find an answer. In each year we measured returns for a tradeable population of companies that filed a 10-K in that year. We analyzed returns on investment against the price at the time of filing the 10-K. Return on investment was measured at 1, 3, 6, 9, 12, 15 and 24 months after the date of the 10-K.

Price & Return on Investment

Historical price data: We used *monthly* adjusted close price throughout the test. Our hypothesis is that information disclosed in 10-Ks is an indicator of long-term value. Therefore, backtesting results should not be dependent on daily price fluctuations. Historical pricing information was provided by AlphaVantage.

Initial price: The monthly adjusted close price for each ticker for the month in which the 10-K was filed. For instance, Alphabet Inc (GOOG) filed their 10-K on February 3rd, 2021. For the purposes of our test, the “initial price” (the price at month 0) for Alphabet for the test performed in 2021 was the adjusted close price on February 26th, 2021.

Price at X months: The monthly adjusted close price for the equity, X months after the 10-K was filed. For instance, as above, the initial price for Alphabet Inc (GOOG)'s 2021 10-K was the adjusted close price on February 26th, 2021. The price at six months after the 2021 initial price for Alphabet was measured at August 31st, 2021.

Return on Investment (ROI) at X months: Return on Investment (ROI) at each measurement date was calculated as $(\text{price at X months} - \text{initial price}) / (\text{initial price}) * 100$.

Unless otherwise noted, median results are reported.

Test Population

We performed identical tests for each year from 2017 through 2021. In each year we determined the population for the test by restricting available equities to a tradeable population using volume and pricing information. We performed the following steps for each year:

- ▶ We limited our population of equities to only those issuers who filed a 10-K during the calendar year in question. Amended filings (10-K/As) were not included in this analysis. For the 2017 dataset this means an issuer must have filed a 10-K between January 1, 2017 and December 31, 2017. In practice, the vast majority of companies file their 10-K after February 1st.

- ▶ We further limited the population to equities with a minimum price of US\$3 and a minimum average daily volume traded of 60,000. These limiting values were measured using the January month-end price and volume information each year.
Specifically, we used the monthly adjusted close price for January, and the volume of the last day of trading in January of the year of the dataset. (That is, the closing share price on January 31, 2017 and daily traded volume on January 31, 2017 were used to determine inclusion in the population for the 2017 data-set).
- ▶ We were further limited by availability of ticker symbols for securities and/or dropped filings from historical filings collection. We have not excluded any securities for which there was available data through our data providers. Omissions, if any, were unintentional.

This process resulted in a population of 2500 to 3000 equities for each of the years.

Risk Score Model:

The backtesting included herein predates our company, and therefore we were not able to use live, published scores. In creating Risk Scores for historical data we had two objectives

- (1) To remove look-ahead bias
- (2) To minimize any difference in methodology from live Risk Scores as published on the Bedrock AI platform.

To this end, we used the same training methodology as used in our live models, but limited training sets to data available before the start of the testing period. This resulted in “point-in-time” models for each year to avoid look-ahead bias. Training data included only information available filed before January 1 of the year of the applicable dataset (e.g. training data to create models used for the 2017 dataset was limited to training set information available as at January 1, 2017).

Strategies:

We performed two distinct tests in each year. The first was designed to understand the efficacy of the scores in informing a long-short strategy and the second to do so for an index-based exclusionary strategy.

Long-short strategy: We assessed whether returns for high risk companies significantly underperform lower risk company returns, as measured by the Bedrock AI Risk Score. In assessing performance, we compared the performance of the top 7% of highest risk companies to the bottom 93%. We chose to analyze the top 7 percent based on our estimate of the true rate of malfeasance in the tradeable population. We also compared the top 95th and bottom 95th percentiles for reference purposes.

Index-Exclusionary strategy: An index exclusionary strategy is a strategy where, instead of purchasing interest in a share of all stocks in a certain population as is done by popular index-based ETFs like SPY, a subset of these stocks is excluded based on specified criteria. In this test we excluded stocks with Bedrock AI Risk Scores in the top 35% of scores in that filing year. In an index exclusionary strategy, a larger number of excluded stocks is required to have an impact on a large, diversified portfolio. Therefore, we exclude a higher proportion of high-risk filings for the purposes of this test, as compared to the “long-short” tests.

Exclusionary strategies are commonly evaluated against a formal index such as the Russell 3000 or S&P 500. Acquiring accurate historical index and sizing data is costly, however. Our approach is designed to represent a facsimile of the Russell 3000 (without considering sizing) vs. a Bedrock AI portfolio which excludes higher risk companies. Regularly outperforming an index by even half a point is valuable.

Below we refer to the portfolio representing the entire population included for that year as the “index” portfolio and to the portfolio that excludes stocks whose filing ranked in the 35th percentile by Risk Score as the “exclusionary” portfolio.

Data Sources & Limitations

We obtained monthly adjusted close pricing data from [AlphaVantage](#). We obtained 10-Ks from EDGAR, the Securities Exchange Commission (SEC)'s “Electronic Data Gathering, Analysis, and Retrieval” system. 10-Ks were obtained either from EDGAR itself or from EDGAR via the SEC-API or through the [Attain PDS](#) service. Some 10-Ks may have been dropped during collection. Any drops were random.

The AlphaVantage historical equities dataset, while better than other datasets we investigated, is still missing coverage of some now delisted tickers, particularly pre-2019. This is one reason you see more data loss in earlier years in our analysis. Missing coverage of delisted tickers leads to what is called “survivorship bias”. In this case, survivorship bias likely underrepresents the power of our Risk Scores rather than vice versa. Higher risk companies are more likely to be delisted due to bankruptcy and cease trade orders. If we were to use a complete historical dataset with all now defunct tickers we would expect even better results.

We mapped filings to tickers based on the Central Index Key (CIK) assigned via EDGAR at the time of the filing. Our CIK to ticker mapping is derived by mappings published by the SEC at specific points in time as well as historical mapping obtained from “rankandfiled.com”, [a website that is now defunct](#).

Note that we have not attempted to address sizing of trades as part of this test.

Results & Analysis

Detailed Results by Year

For detailed results, refer to [Appendix I - Long-Short Strategy - Detailed results by year](#) and [Appendix II - Index-Exclusionary Strategy - Detailed results by year](#).

Refer to the [Executive Summary](#) for summary results.

The Power of Human Judgment - FOI Results

A quantamental approach improves the already strong results of our algorithms. Once a week we send a report to our institutional holders, containing a curated list of high risk companies with red flags that are persuasive and/or interesting. The list is curated by internal expert CPAs. These companies are a subset of companies that our algorithms rate as high risk. We report on companies that have been rated medium-high to high risk by our algorithms and that have a market capitalization of \$300M or higher at the time of the report. Since our launch in April, we have sent curated reports containing 86 different medium-high to high risk names. We measured ROI against the date of our subscribers-only report. Consistent with the analysis above, the price impact of our Risk Scores increases as time increases. Find the detailed analysis of the results from our quantamental picks in our newsletter here -

<https://bedrock.substack.com/p/weve-picked-our-features-well>.

Our quantamental results suggest that human review magnifies the power of the Bedrock AI Risk Scores.

Future Tests and Analysis

In the upcoming iteration of this test we will assess information gain and momentum by analyzing how changes in Bedrock AI Risk Score impact the succeeding stock price. We will also assess which red flag categories have the highest predictive value for stock price impact, irrespective of Risk Score.

Conclusion

Our analysis presents persuasive evidence that information disclosed in 10-Ks is not incorporated into stock price in a timely manner. Understanding and using information in long-form securities filings represents a significant trading advantage in the long term. Bedrock AI facilitates this process through both Risk Scores and red flag extraction.

Bedrock AI is on a mission to improve corporate accountability through transparency. Join us. To see a demo of our institutional product, email us at info@bedrock-ai.com.

Sign up for our free newsletter - bedrock.substack.com.

Appendix I - Long-Short Strategy

Detailed results by year

As described in [Approach](#), the “93rd percentile grouping” compares the top 7% of riskiest equities, as measured by the Bedrock AI Risk Score, to the remaining 93% of equities. We analyzed the top 7% based on our estimate of the true proportion of malfeasance among public issuers.

The “95th percentile grouping” compares the top 5% of highest risk equities, as measured by the Bedrock AI Risk Score, to the bottom 5% i.e. the lowest risk. This analysis is done for comparison purposes.

Refer to [Approach](#) for further details.

Long-Short Strategy (93rd percentile grouping) - Comparative Data 2017									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Mean ROI - Standard (%)	0.1	(0.2)	2.8	8.0	6.2	10.2	12.8	2.9	7.4
Median ROI - High risk (%)	(0.3)	0.1	1.8	2.5	(0.9)	(0.8)	7.1	(5.5)	2.2
Performance differential (Δ%)	0.4	(0.3)	1.0	5.5	7.1	11.0	5.7	8.4	5.2
Standard count	2532	2519	2498	2462	2439	2417	2396	2375	2349
High risk count	190	188	182	181	180	177	175	173	169

Long-Short Strategy (95th percentile grouping) - Comparative Data 2017									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Median ROI - Standard (%)	(0.2)	(2.2)	0.2	5.2	5.5	10.2	11.3	4.5	7.0
Median ROI - High risk (%)	(0.2)	0.1	1.0	1.2	(4.4)	(3.5)	2.9	(13.9)	(4.1)
Performance differential (Δ%)	0.0	(2.3)	(0.8)	4.0	9.9	13.7	8.4	18.4	11.1

Long-Short Strategy (93rd percentile grouping) - Comparative Data 2018									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Median ROI - Standard (%)	0.6	5.3	7.7	(3.7)	1.2	(3.3)	(3.7)	4.1	(11.8)
Median ROI - High risk (%)	(0.4)	3.7	8.1	(8.8)	(5.0)	(9.4)	(9.8)	(4.0)	(22.9)
Performance differential (Δ%)	1.0	1.6	(0.4)	5.1	6.2	6.1	6.1	8.1	11.1
Standard count	2654	2638	2617	2601	2570	2550	2532	2508	2483
High risk count	198	196	194	192	187	185	183	180	178

Long-Short Strategy (95th percentile grouping) - Comparative Data 2018									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Median ROI - Standard (%)	2.1	6.7	6.8	(0.8)	5.7	1.2	3.4	8.2	(3.5)
Median ROI - High risk (%)	(0.9)	3.7	6.3	(11.0)	(7.8)	(14.7)	(23.0)	(13.2)	(26.3)
Performance differential (Δ%)	3.0	3.0	0.5	10.2	13.5	15.9	26.4	21.4	22.8

Long-Short Strategy (93rd percentile grouping) - Comparative Data 2019									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Median ROI - Standard (%)	0.7	(2.6)	(3.0)	4.2	(10.5)	(11.8)	(4.8)	8.0	19.9
Median ROI - High risk (%)	0.4	(0.4)	0.1	2.9	(21.0)	(20.4)	(16.7)	(1.0)	8.9
Performance differential (Δ%)	0.3	(2.2)	(3.1)	1.3	10.5	8.6	11.9	9.0	11.0
Standard count	2637	2628	2611	2584	2557	2538	2519	2495	2440
High risk count	199	199	196	194	191	190	188	185	179

Long-Short Strategy (95th percentile grouping) - Comparative Data 2019									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Median ROI - Standard (%)	0.5	(3.0)	(1.7)	3.3	(9.0)	(6.6)	(1.2)	12.9	21.7
Median ROI - High risk (%)	0.4	0.3	1.4	3.2	(21.0)	(17.7)	(13.2)	0.4	10.5
Performance differential ($\Delta\%$)	0.1	(3.3)	(3.1)	0.1	12.0	11.1	12.0	12.5	11.2

Long-Short Strategy (93rd percentile grouping) - Comparative Data 2020							
	1m after	3m after	6m after	9m after	12m after	15m after	18m after
Median ROI - Standard (%)	(6.4)	3.7	9.8	23.2	38.2	49.1	49.9
Median ROI - High risk (%)	0.5	5.7	10.2	31.2	40.2	47.6	45.3
Performance differential ($\Delta\%$)	(6.9)	(2.0)	(0.4)	(8.0)	(2.0)	1.5	4.6
Standard count	2694	2683	2668	2645	2583	2428	2261
High risk count	202	201	196	195	190	181	167

Long-Short Strategy (95th percentile grouping) - Comparative Data 2020							
	1m after	3m after	6m after	9m after	12m after	15m after	18m after
Median ROI - Standard (%)	(4.7)	1.4	8.0	19.8	32.2	37.8	36.9
Median ROI - High risk (%)	0.4	5.9	8.3	33.0	39.2	45.0	46.6
Performance differential ($\Delta\%$)	(5.1)	(4.5)	(0.3)	(13.2)	(7.0)	(7.2)	(9.7)

Long-Short Strategy (93rd percentile grouping) - Comparative Data 2021				
	1m after	3m after	6m after	9m after
Median ROI - Standard (%)	2.0	5.5	4.1	8.6
Median ROI - High risk (%)	(1.2)	(1.7)	(7.7)	(5.3)
Performance differential ($\Delta\%$)	3.2	7.2	11.8	13.9
Standard count	2987	2928	2745	1600
High risk count	226	222	207	78

Long-Short Strategy (95th percentile grouping) - Comparative Data 2021				
	1m after	3m after	6m after	9m after
Median ROI - Standard (%)	2.9	6.3	4.5	10.0
Median ROI - High risk (%)	(2.5)	(2.3)	(9.8)	(16.1)
Performance differential ($\Delta\%$)	5.4	8.6	14.3	26.1

Appendix II - Index-Exclusionary Strategy

Detailed results by year

As described in [Approach](#), the “index” group includes the entire population of test equities in that year and the “exclusionary” group is the test population for the year, excluding the top 35% of riskiest equities as measured by the Bedrock AI Risk Score. Refer to [Approach](#) for further details.

Index-Exclusionary Strategy - Comparative Data 2017									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Mean ROI "exclusionary" (%)	0.2	0.5	4.5	10.9	11.9	18.5	23.4	9.7	18.4
Mean ROI "index" (%)	0.1	0.5	4.7	10.6	10.9	17.2	21.5	7.2	15.4
Mean Performance Differential (%)	0.1	0.0	(0.2)	0.3	1.0	1.3	1.9	2.5	3.0
Median ROI "exclusionary" (%)	0.1	(0.3)	2.2	8.2	6.5	10.7	13.2	3.2	8.3
Median ROI "index" (%)	0.1	(0.1)	2.7	7.7	5.6	9.6	12.1	2.2	7.2
Median Performance Differential (%)	0.0	(0.2)	(0.5)	0.5	0.9	1.1	1.1	1.0	1.1
Count "index"	2,722	2,707	2,680	2,643	2,619	2,594	2,571	2,548	2,518
Count "exclusionary"	1,771	1,763	1,749	1,726	1,719	1,705	1,691	1,679	1,659

Index-Exclusionary Strategy - Comparative Data 2018									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Mean ROI "exclusionary" (%)	1.1	6.9	11.3	(2.1)	5.0	1.5	1.6	9.2	(3.6)
Mean ROI "index" (%)	0.8	6.5	10.8	(3.2)	3.9	0.1	(0.2)	7.1	(5.8)
Mean Performance Differential (%)	0.3	0.4	0.5	1.1	1.1	1.4	1.8	2.1	2.2
Median ROI "exclusionary" (%)	0.8	5.8	8.3	(3.5)	1.6	(2.7)	(2.9)	5.3	(10.9)
Median ROI "index" (%)	0.5	5.2	7.8	(4.0)	0.9	(3.7)	(4.0)	3.7	(12.6)
Median Performance Differential (%)	0.3	0.6	0.5	0.5	0.7	1.0	1.1	1.6	1.7
Count "index"	2,852	2,834	2,811	2,793	2,757	2,735	2,715	2,688	2,661

Count "exclusionary"	1,856	1,848	1,838	1,829	1,809	1,791	1,780	1,760	1,742
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Index-Exclusionary Strategy - Comparative Data 2019									
	1m after	3m after	6m after	9m after	12m after	15m after	18m after	21m after	24m after
Mean ROI "exclusionary" (%)	0.5	(2.8)	(2.8)	4.9	(8.1)	(1.8)	8.9	29.1	42.5
Mean ROI "index" (%)	0.4	(3.4)	(3.7)	3.6	(10.2)	(3.2)	6.9	26.5	40.7
Mean Performance Differential (%)	0.1	0.6	0.9	1.3	2.1	1.4	2.0	2.6	1.8
Median ROI "exclusionary" (%)	0.7	(2.1)	(2.8)	4.7	(10.1)	(11.4)	(4.4)	8.5	20.5
Median ROI "index" (%)	0.7	(2.4)	(3.0)	4.0	(11.0)	(12.4)	(5.2)	7.0	19.6
Median Performance Differential (%)	0.0	0.3	0.2	0.7	0.9	1.0	0.8	1.5	0.9
Count "index"	2,836	2,827	2,807	2,778	2,748	2,728	2,707	2,680	2,619
Count "exclusionary"	1,844	1,840	1,834	1,813	1,794	1,783	1,770	1,754	1,714

Index-Exclusionary Strategy - Comparative Data 2020							
	1m after	3m after	6m after	9m after	12m after	15m after	18m after
Mean ROI "exclusionary" (%)	(5.3)	10.2	22.2	45.6	70.4	82.9	82.8
Mean ROI "index" (%)	(5.6)	11.1	23.9	47.7	72.1	85.4	85.2
Mean Performance Differential (%)	0.3	(0.9)	(1.7)	(2.1)	(1.7)	(2.5)	(2.4)
Median ROI "exclusionary" (%)	(5.3)	4.2	10.2	23.7	38.4	48.8	49.7
Median ROI "index" (%)	(5.8)	3.8	9.8	23.3	38.2	49.0	49.3
Median Performance Differential (%)	0.5	0.4	0.4	0.4	0.2	(0.2)	0.4
Count "index"	2,896	2,884	2,864	2,840	2,773	2,609	2,428
Count "exclusionary"	1,883	1,878	1,869	1,852	1,812	1,703	1,575

Index-Exclusionary Strategy - Comparative Data 2021				
	1m after	3m after	6m after	9m after
Mean ROI "exclusionary" (%)	2.1	6.5	7.0	9.6
Mean ROI "index" (%)	2.0	6.1	4.7	8.3
Mean Performance Differential (%)	0.1	0.4	2.3	1.3
Median ROI "exclusionary" (%)	2.3	5.8	5.2	8.6
Median ROI "index" (%)	1.6	4.8	2.9	8.0
Median Performance Differential (%)	0.7	1.0	2.3	0.6
Count "index"	3,213	3,150	2,952	1,678
Count "exclusionary"	2,088	2,047	1,913	1,146