Hiding in Plain Sight – Risks That Are Overlooked

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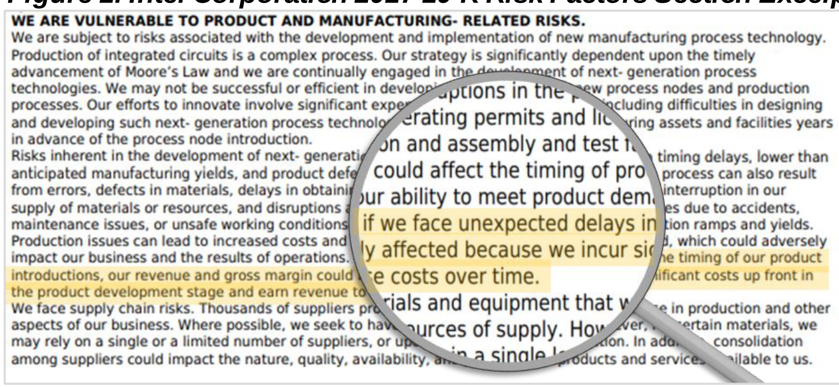
Company quarterly (10-Q) and annual (10-K) filings have traditionally been a vital source of information for investment decisions. However, the increasing length and complexity of these filings can result in investors overlooking new and important details in these reports. For example, Intel Corporation ("INTC") updated the "Risk Factors" section of its 2017 10-K filing released on February 16, 2018 with the following: "*if we face unexpected delays in the timing of our product introductions, our revenue and gross margin could be adversely affected*" (Figure 1). Investors appeared not to have noticed this update as the stock climbed 5% in the week following the earnings release. INTC eventually disclosed a significant delay in the launch of its new 10-nanometer processor during its 2018 2Q earnings call held on July 26, 2018. The company's stock dropped by 8% that day (despite earnings and revenue beats), and fell by another 6% over the next 3 months.

Figure 1: Intel Corporation 2017 10-K Risk Factors Section Excerpt



Source: Intel Corporation 10-K Filing. S&P Global Market Intelligence Quantamental Research. Data as of 02/28/2021.

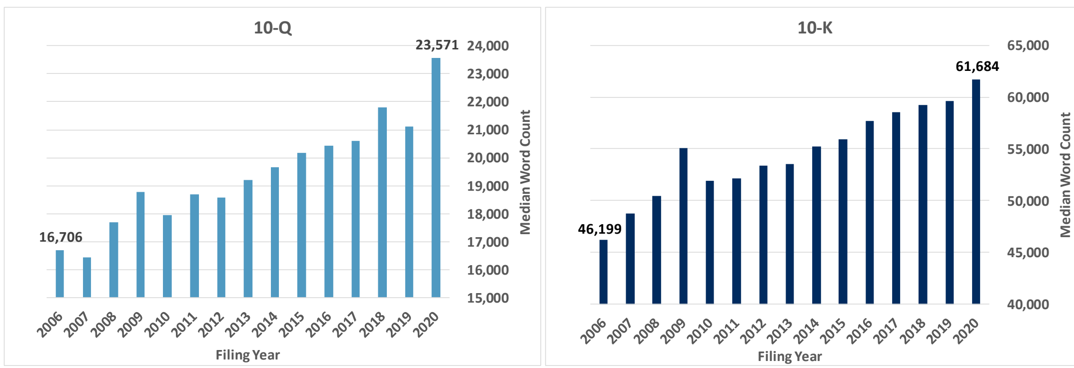
This report uses three metrics (Minimum Edit Distance, Jaccard Similarity, and Cosine Similarity) to identify companies that made significant changes to the "Risk Factors" section of their filings. These metrics can serve as alpha signals or be used to quickly identify a pool of companies that require further investigation. Our findings include:

- Updates to risk disclosures may indicate a structural change in a company's business or new threats to its existing businesses. **A quintile portfolio strategy that buys (sells) companies with small (large) changes in the "Risk Factors" section of 10-K and 10-Q regulatory filings yields an annualized return of up to 5.36% (Table 1).**
- Given that most companies make little or no changes to risk disclosures, a quintile approach may include companies with small changes in the short portfolio. **A process that targets only companies with "significant" changes (outliers) in the short portfolio produces an annualized long-short return of 6.59% (Table 2).**
- Information conveyed by changes to the risk disclosures by large cap companies are quickly incorporated into their stock prices, as large caps are more widely followed by analysts and receive more news coverage. **Therefore, as shown in Table 3, the performance is stronger in the small cap space (6.42%) compared to the large cap segment (2.37%).**
- Slow signal decay is consistent with the view that updates to risk disclosures act as a proxy for risks yet to be revealed, which will materialize over time. **Annualized long-short return (3.32%) remains significant with a 12-month signal implementation lag (Table 4).**

1. Introduction

Annual and quarterly filings have become longer over time due to new disclosure requirements by regulators, increased business complexity, and an expansion of risk disclosures as companies seek to manage litigation risks. The median length of 10-Qs increased from approximately 17,000 words in 2006 to 24,000 words in 2020 (41% increase), while the median length of 10-Ks increased from approximately 46,000 words to 62,000 words (34% increase) in the same time period (Figure 2).[1] Although increased disclosures provide more transparency to market participants, the volume of new information requires investors to dedicate more time and resources to process corporate reports. You and Zhang (2009) document a positive relationship between the length of 10-K filings and a delay in market reaction to the information in those reports. More recently Loughran and McDonald (2013) found that larger 10-Ks are significantly associated with high return volatility, earnings forecast errors, and earnings forecast dispersion.

Figure 2: Russell 3000 Median 10-Q and 10-K Length



Source: S&P Global Market Intelligence Quantamental Research. Data as of 02/28/2021.

The Securities and Exchange Commission (SEC) began requiring risk factors to be disclosed in 10-Ks and updated in 10-Qs in 2005.[2] The SEC rule requires firms to disclose material factors that may adversely affect the company's operations, business or financial condition. This report examines the relationship between year-over-year changes in the "Risk Factors" section of corporate filings and future stock returns. This analysis focuses on risk disclosures as updates in this section can indicate future changes in business and financial risks. Cohen et al. (2020) also found the "Risk Factors" section to be indicative of future stock returns.

[1] Median word count of Russell 3000 companies' 10-Q and 10-K filings. Does not include text of tables and exhibits.
[2] The 2005 amendment to the Securities Act of 1933 could be found on the SEC website https://www.sec.gov/news/press/2005-99.htm.

2. Signal Construction

Every month, the "Risk Factors" section of the most recent quarterly or annual filing is compared to that of the same period the prior year. The difference between current and prior year risk disclosures are captured and quantified by three textual similarity metrics – Minimum Edit Distance, Jaccard Similarity, and Cosine Similarity.

- Minimum Edit Distance simply counts the number of word additions and deletions to get from one document to the other (Equation 1). The measure is normalized by the length[3] of the risk disclosures to facilitate company-to-company comparisons.

$$Minimum\ Edit\ Distance = \frac{Deletions + Additions}{TotalWords} \qquad \text{Equation 1}$$

- Jaccard Similarity measures the number of unique common words proportional to the total number of unique words within two documents. Mathematically Jaccard Similarity is defined as the intersection of two word sets $|T_A \cap T_B|$, divided by the union of two word sets $|T_A \cup T_B|$, as shown in Equation 2. Jaccard Similarity can range from 0 to 1.

$$Jaccard\ Similarity = \frac{|T_A \cap T_B|}{|T_A \cup T_B|} \qquad \text{Equation 2}$$

- Cosine Similarity measures the cosine of the angle between the vector representation of two documents. It compares the proportion of the words represented in each document. Mathematically the Cosine Similarity is calculated using Equation 3, where $\bar{a} \cdot \bar{b}$ is the scalar product of the two vectors and $||\bar{a}||$ is the Euclidean norm. Cosine Similarity can range from 0 to 1.

$$Cosine\ Similarity = \frac{\bar{a} \cdot \bar{b}}{||\bar{a}||\,||\bar{b}||} \qquad \text{Equation 3}$$

Key preprocessing steps for textual similarity calculations include 1) tag removal, 2) numerical value removal, 3) punctuation removal, and 4) lemmatization. For a complete list of preprocessing steps, please refer to Appendix A. **All returns in this report are equal weighted, winsorized to 3 standard deviations, and (FF4) adjusted for market, size, value, and price momentum risk factors.**

[3] The length of risk disclosures refers to the word count of "Risk Factors" section of company filings. The word count is measured after preprocessing is conducted on the textual data to be consistent with when Minimum Edit Distance is measured.

3. Test Results

The results in Table 1 confirm that companies with large changes in risk disclosures underperform companies with small changes. The long-short returns of Minimum Edit Distance, Jaccard Similarity, and Cosine Similarity metrics are 4.51%, 4.74%, and 5.36% respectively, and are significant at the 1% level. It is also worth noting that the hit rates (a measure of strategy consistency) of the long-short returns of all metrics are above 65%, which are also significant at the 1% level. The results suggest that the signal is robust to different textual similarity constructions.

Table 1: Risk Factor Section Textual Similarity Quintile Performance (Russell 3000, January 2008 – December 2020)

Factors	Factor Rank Order	Average Constituent Count	Average IC (1-month)	Annualized Long-Only Active Return	Annualized Short-Only Active Return	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Minimum Edit Distance	Ascending	508	0.013***	2.01%***	-2.50%***	4.51%***	1.25	65%***
Jaccard Similarity	Descending	508	0.012***	2.14%***	-2.60%***	4.74%***	1.47	67%***
Cosine Similarity	Descending	508	0.012***	2.86%***	-2.50%***	5.36%***	1.38	65%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/28//2021.

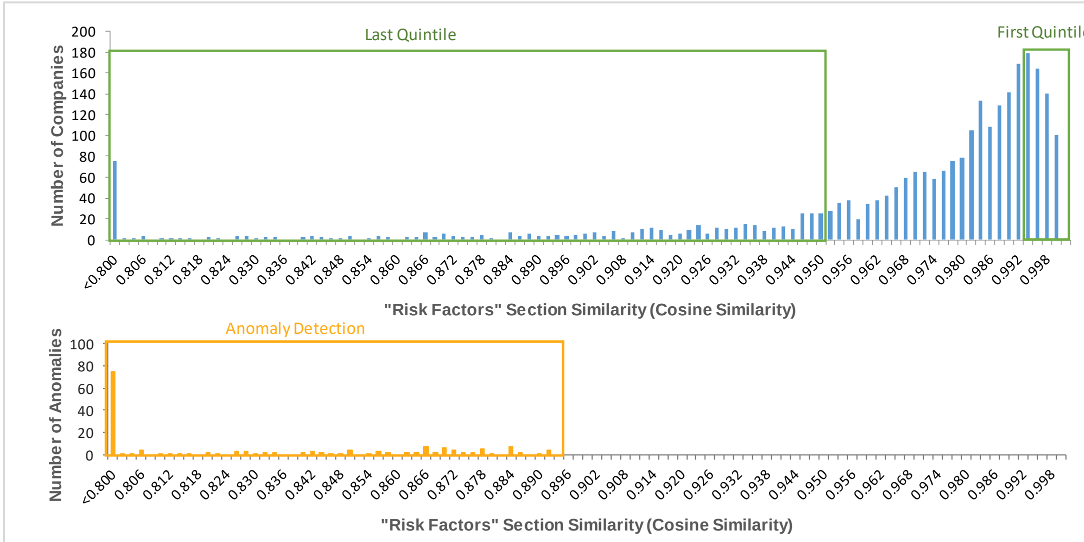
For the following sections 4 and 5, Cosine Similarity will be used as a benchmark measure for additional tests.

4. Anomaly Detection

Companies are not likely to rewrite the entire risk disclosures every year. Updates are usually made to specific sentences or paragraphs, with the bulk of the risk disclosures remaining unchanged. Measuring year-over-year textual similarity in the "Risk Factors" section will therefore result in a distribution with a long left tail, with most companies scoring highly on similarity measures (Figure 3). A quintile approach may lead to companies with minimal changes being grouped in the same bucket as companies with large changes, as shown with the green box in Figure 3.

One way to target outliers is to use an anomaly detection technique. Anomaly detection considers how far away a data point is relative to others, and only picks values with the greatest separation. The lower chart in Figure 3 shows the companies identified by an anomaly detection approach called Isolation Forest (for a description refer to Appendix B). As shown with the orange box in the chart, anomaly detection is better at capturing companies with "significant" changes in their risk disclosures.

Figure 3: Sample "Risk Factors" Section Cosine Similarity Distribution Quintile vs Anomaly Detection (Russell 3000, May 2010)



Source: S&P Global Market Intelligence Quantamental Research. Data as of 02/28//2021.

4.1. Anomaly Detection Test Results

The backtest results from a strategy that shorts the "significant" changers captured by anomaly detection, and longs small changers are displayed in Table 2 below.[4] The results confirm that investors should focus on outliers, as the negative market reaction is stronger for companies that had "significant" changes in risk disclosures. The annualized average short portfolio return for anomaly detection is -4.09% compared to -2.50% for the quintile approach. The difference of -1.59% is significant at the 1% level.

Table 2: Risk Factors Section Cosine Similarity Anomaly Detection Performance (Russell 3000, January 2008 – December 2020)

Factor	Methodology	Average Constituent Count - Long	Average Constituent Count - Short	Annualized Long-Only Active Return	Annualized Short-Only Active Return	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Cosine Similarity	(A) Quintile	518	504	2.86%***	-2.50%***	5.36%***	1.38	65%***
	(B) Anomaly Detection (iForest)	316	233	2.50%***	-4.09%***	6.59%***	1.44	68%***
	(B) - (A) Difference	N/A	N/A	-0.36%	-1.59%***	1.23%	N/A	N/A

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/28//2021.

[4] Small changers are defined by a hard cutoff in the Cosine Similarity score so that the number of companies in the long portfolio is close to the number of companies in the short portfolio.

5. Robustness Checks

In this section additional robustness checks were conducted that address concerns around:

- Difference in signal performance in the large cap vs small cap spectrum.
- Signal decay.

5.1. Large Cap vs Small Cap

Long-only and long-short returns are about 3 times larger in the small cap universe (Russell 2000) compared to the large cap universe (Russell 1000). Because large cap companies are widely followed by analysts and investors, information conveyed by changes to the risk section may be quickly incorporated into their stock prices.

Table 3: Risk Factors Section Cosine Similarity Quintile Performance
Large Cap vs Small Cap (Russell 1000,2000,3000, January 2008 – December 2020)

Factor	Universe	Average Constituent Count	Average IC (1-month)	Annualized Long-Only Active Return	Annualized Short-Only Active Return	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Cosine Similarity	Russell 1000	170	0.006*	0.80%	-1.57%**	2.37%**	0.66	56%*
	Russell 2000	338	0.014***	3.55%***	-2.87%***	6.42%***	1.34	67%***
	Russell 3000	508	0.012***	2.86%***	-2.50%***	5.36%***	1.38	65%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/28//2021.

5.2. Signal Decay

The signal remains effective even when strategy implementation is delayed by up to 12 months (Table 4). Long-only and long-short returns remain statistically significant for lags between 1 months to 12 months. The signal decay results are consistent with the view that updates to “Risk Factors” are a proxy for risks soon to be revealed (i.e. INTC delays new processor), and these risks will materialize over time.

Table 4: Risk Factors Section Cosine Similarity Quintile Performance
Signal Decay (Russell 3000, January 2008 – December 2020)

Factor	Signal Lag	Average IC (1-month)	Annualized Long-Only Active Return	Annualized Short-Only Active Return	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Cosine Similarity	No Lag	0.012***	2.86%***	-2.50%***	5.36%***	1.38	65%***
	1 Month	0.011***	2.71%***	-2.38%***	5.09%***	1.32	63%***
	3 Months	0.010***	2.11%***	-2.01%***	4.12%***	1.17	62%***
	6 Months	0.007***	1.59%***	-1.90%***	3.49%***	1.09	58%**
	12 Months	0.008***	1.56%**	-1.76%***	3.32%***	0.90	62%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/28//2021.

6. Data

The data used to construct textual similarity signal in this report is from the S&P Global Market Intelligence's U.S. Machine Readable Filings dataset. The U.S. Machine Readable Filings dataset was added to the S&P Global Market Intelligence's Xpressfeed product in April 2020. This dataset includes textual data derived from filings (10-Ks, 10-Qs, 8-Ks, 20-Fs) to the Securities and Exchange Commission (SEC) on 30,000 companies, with history dating back to 2006.

The U.S. Machine Readable Filings feed provides all of the textual portions of public filings, broken down into the various sections identified by the company, with extraneous information such as page numbers, images, and tables removed. The data is delivered in a structured and machine readable format through Xpressfeed. The textual data is also cleansed and parsed into sections (i.e., Business Overview, Risk Factors, Management Discussion & Analysis, etc.) so users can leverage Natural Language Processing (NLP) to extract insights without having to do the document cleanup and structuring themselves.

7. Conclusion

Quarterly (10-Qs) and annual (10-Ks) filings are long and difficult for investors to digest. Many indicators of changing business fundamentals may be missed by the naked eye. Measuring how much the text within the "Risk Factors" section has changed can be an effective signal in identifying companies with changing risk profiles. This report documents a strategy that longs (shorts) companies with small (large) changes to the "Risk Factors" section is effective in the U.S., with statistically significant long-only and long-short returns. The results suggest that the market is not fully responding to information contained in updates to the "Risk Factors" section at the time of the disclosure. In addition, an anomaly detection method improves the performance of the short portfolio, as this approach is better at identifying companies with "significant" changes compared to a quintile approach.

APPENDIX A

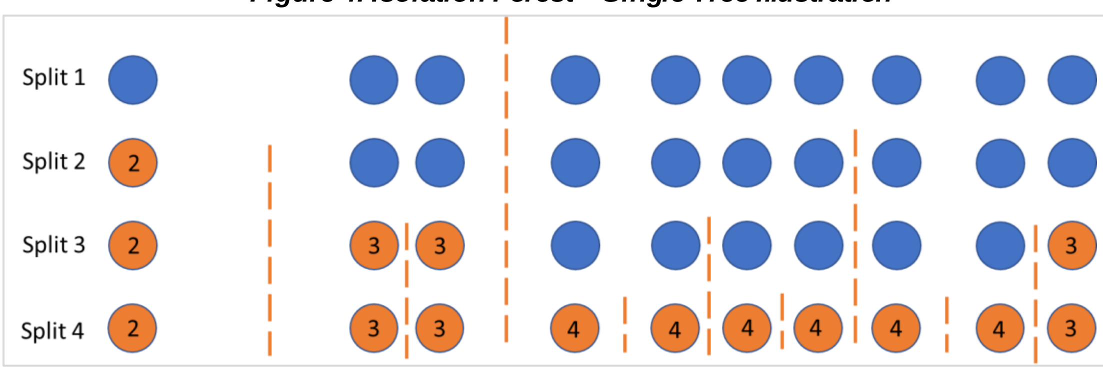
Preprocessing is a noise removal process that helps to bring the textual data into an analyzable form. Steps used to prepare the textual data for similarity calculation include the following:

- Removed all line breaks ('\n')
- Removed all punctuations ('!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~•“”')
- Made lowercase
- Removed numbers
- Removed stop words (Loughran McDonald Stop Words General)
- Filter text through Loughran McDonald Master Words List
- Lemmatized[5] the text

APPENDIX B

Isolation Forest is a popular anomaly detection method that explicitly identifies anomalies. It is based on the idea of decision trees. Within each tree, partitions are created by randomly and uniformly selecting a split between the minimum and maximum values (Figure 4). Splits are more likely where the gap is larger. The method continues to partition the data until one datapoint is isolated and marks that datapoint with the number of splits (path length) it took to isolate (number in orange spheres). Outlier data points (first point in Figure 4) are more separated from the rest of the "regular" observations and are more likely to be isolated with less splits (first data point was isolated on the second split). The method continues to split the data until every data point is isolated, and every data point is assigned a split value. Split values are then averaged across all individual trees (hence "Forest"). The outliers are the datapoints that were isolated with lesser average splits.

Figure 4: Isolation Forest – Single Tree Illustration



Source: S&P Global Market Intelligence Quantamental Research. Blue dots represent fictitious data points for illustration purposes.

[5] Lemmatization refers to the process of reducing word inflection forms to the common base form. Lemmatization uses a deeper analysis than stemming, which only chops off the ends of words (e.g., "studies" to "studi"). Lemmatization removes inflectional endings by returning the word to its base form (e.g., "studies" to "study").

References

Cohen, L., Malloy, C., and Nguyen, Q., 2020, "Lazy Prices", The Journal of Finance Vol.75, pp.1371-1415.

Fama, E., and French, K., 1998, "Value versus Growth: The International Evidence", The Journal of Finance Vol.53, No.6, pp.1975-1999.

Fama, E., and French, K., July 2006, "Profitability, investment and average returns", Journal of Financial Economics Vol.82, pp.491-518.

Loughran, T., and McDonald, B., 2013, "Measuring Readability in Financial Disclosures", https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1920411.

You, H., and Zhang, X., 2009, "Financial Reporting Complexity and Investor Underreaction to 10-K Information", https://papers.ssrn.com/sol3/papers.cfm?abstract_id=985365.

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