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Is Inclusion of the Words AI or Artificial Intelligence in 10-K and 10-Q Reports Enough to Cause Abnormal Returns?

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Abstract

Many factors cause abnormal returns among stocks. The rise of news coverage on Artificial Intelligence (aka AI) and the inclusion of these terms in 10-K and 10-Q reports in recent years raises the question, does inclusion of these terms in 10-K and 10-Q reports lead to abnormal returns among companies? To investigate this question 10-K and 10-Q reports, both those mentioning and not mentioning AI and/or Artificial Intelligence, from 695 and 507 companies respectively were collected along with other relevant company information. Ultimately these terms held no significant impact on abnormal returns.

Keywords: Abnormal Returns, AI/Artificial Intelligence, 10-K reports, 10-Q reports

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I. Introduction

Research surrounding biases in investor decision-making and the impact of terminology and sentiment on stock returns are both well-established fields. It has long been determined that for a multitude of reasons investors do not always make logical choices and that to a certain degree, the language used and associated sentiment in corporation-expressed textual information, social media posts, news articles, etc can influence stock price (Coelho et al. 2019; Hájek 2017). This research aims to determine if the inclusion of the terms AI/Artificial Intelligence in 10-K and 10-Q reports[1] impacts abnormal returns. While the overarching themes of terminology and sentiment in corporation-expressed textual information and corresponding stock price impacts has been well researched, the impact of the terms AI/Artificial Intelligence in company-related reports has not been. Thus, this research aims to fill the current gap. This research focuses on U.S. companies due to the financial position the U.S. stock market holds in the global economy. However, this research could be applied to any country where the information is available.

There are five sections in this research paper. The first section is the introduction, followed by the second section, the literature review. The literature review dives into previous research on abnormal stock price returns, investor biases/decision making, and AI and the perceptions associated with the technology that may contribute to how investors perceive AI investments. The third section is data description and methodology, which explores the data used in the research and collection process and chosen methodology for analyzing the data. Section four is the results section, and it covers the specific results and findings of the research while section five, the discussion, addresses what the results could mean and their potential implications along with limitations of the research and what future research into

[1] A 10-K report is an annual financial performance report that is mandated by the Securities and Exchange Commission (SEC) for public U.S. companies. A 10-Q report is also a SEC mandated financial performance report for public U.S. companies but is submitted quarterly (Griffin 2003).

the topic may look like.

II. Literature Review

Establishing a well-thought-out research question and methodology involves examining the previous research related to the topic being investigated. To understand how the terms AI/Artificial Intelligence may be impacting abnormal returns, it is important to look at prior research regarding abnormal stock returns and investor-decision making, as well as what AI/Artificial Intelligence is and the public perceptions of the technology.

II.a. Abnormal Stock Returns

Stock price changes are everyday occurrences and can be attributed to a multitude of factors, including the return on assets ratio and debt to equity ratio of the company (Akbar and Afiezan 2018). Abnormal stock returns occur when stock prices differ from their "… fundamental value then… gradually revert to the fundamental values" (Cherono, Olweny, and Nasieku 2019, 150). There are several reasons that a company's stock may see abnormal changes, including changes in leadership, volatility levels, and investor sentiment (Mohan et al. 2019). Investors' roles in these abnormal changes should not be underestimated since high investor sentiment has been linked to overvalued stock prices, while low investor sentiment has been linked to undervalued stock prices (Shi et al. 2018). The relationship between investor sentiment and stock prices makes understanding the drivers behind investor sentiment important.

Unfortunately, the drivers behind investor sentiment are a complex mix of both company/stock related factors and the investors' personal/unique factors. Some known company factors that contribute to investor sentiment include dividends, cash flow projections, and discount rates (Bennet 2011). Personal factors that contribute to investor sentiment include the investors' objectives and goals, their knowledge of investing, and their biases which combined with all the other factors makes it very hard to properly understand and gauge investor sentiment (Bennet 2011; Cherono, Olweny, and Nasieku 2019).

II.b. Investor Bias

A wide range of literature shows that investor sentiment has a significant and long-lasting impact on prices (Polat 2022). As previously established, investor sentiment can be driven by many factors including bias. Biases refer to beliefs that interfere with a person's ability to make a rational decision (Hayes 2021). Investor biases are simply biases that impact the way investors make their choices. While many biases exist, three common ones that affect investors are overconfidence bias, herding bias, and disposition effect (Prasetyo, Sumiati, and Ratnawati 2023). In the context of investing, overconfidence bias refers to when investors believe that they understand the financial markets, investment strategies, or even company financials better than experts (Aguilar 2023). Herding bias refers to investors copying other investors' investment choices (Ah Mand et al. 2021). Meanwhile, the disposition effect is when investors sell winning stocks quickly and hold onto losing stocks in the hopes they will rebound (Gutiérrez-Nieto, Ortiz, and Vicente 2022). The biases most relevant to this research are the herding and overconfidence biases (Cherono, Olweny, and Nasieku 2019).

On a capital investment level, it is known that optimism surrounding technology increases value perception of companies (Dunne et al. 2019). It is possible that this value perception also occurs with stock market investors. Herding bias could lead to investors flocking towards companies that are talking about investing in AI if they see other investors doing the same thing. They may feel it is the next important advancement for companies even if they are not very familiar with AI technology themselves. Overconfidence bias could then lead investors to then hold onto stocks of companies they invested in longer than they should, even if they realize the AI technology is taking longer than expected to develop, is unable to fulfill its intended use, is not as innovative as the they thought, and so forth.

II.c. AI/Artificial Intelligence & Surrounding Perceptions

For those not in the technology space, it may seem like AI is a relatively new and revolutionary technology, but it is not. The term AI and the associated technology date back to the 1950s, and over the past 70 years researchers have been working on different AI technologies (European Commission et al. 2020). What is new and are two of the main reasons AI has been able to take off in the past seven to eight years, is the large creation of data and the rise in quality and quantity of Graph Processing Units, which in turn allow programs to train on large data samples (Reynolds et al. 2019). The long history of AI and its range of capabilities developed, and being developed, by researchers and scientists in a variety of fields is part of what makes AI such a complex topic (European Commission et al. 2020). AI contains subsections such as Machine Learning, and those subsections have subsections such as Deep Learning (European Commission et al. 2020). Outside of these different sections, AI is also split into three different stages of development: Artificial Narrow Intelligence 'ANI', Artificial General Intelligence 'AGI', and Artificial Super Intelligence 'ASI' (Mou 2019). The different stages of AI technology lend themselves to different purposes along with different levels of accessibility. Artificial Narrow Intelligence for example, which is the most basic of the different AI stages, has been available for quite some time, while AGI is newer, and ASI has not yet been achieved (Mou 2019). These different applications naturally influence the perception of the technology, which leads to competing understandings of AI.

Complex technology such as AI and all it encompasses naturally makes it difficult for many individuals to understand the technology and its nuances. Research led by Brauner et al. (2023) led the team to conclude that AI is, "… a 'black box' for many…which can lead to biased and irrational control beliefs in the public perception of AI" (1). This idea that AI is a 'black box' for many is supported by a 2022 survey from the PEW Research Center that found roughly one-third of respondents in the U.S. had a high level of awareness regarding AI in day-to-day life, based on a six-question survey they created (Kennedy, Tyson, Saks 2023). However, the complex topic of AI goes beyond simple awareness of AI, a 2023 survey by Ipsos found that of those surveyed over sixty percent reported that they had a good grasp on the concept of AI but only about fifty percent knew which companies and their products were using AI (Carmichael 2023). This suggests many consumers overestimate their understanding of AI.

But it is not just consumers who appear to have cognitive disconnects regarding AI; these disconnects between perceptions and reality affect businesses as well. A survey from McKinsey found that approximately forty percent of respondents were so optimistic about generative AI they were planning to increase their investments in AI (Chui et al. 2023). But despite their plans to increase investments in AI technology, "… few companies seem fully prepared for the widespread use of gen AI—or the business risks these tools may bring" (Chui et al. 2023, 6). This juxtaposition is perhaps best exemplified by the fact that the same report found that the consumer goods/retail industry and the business, legal, and professional services industry are two with the highest rate of non-exposure to generative AI tools despite being two industries that may see the greatest impact of generative AI (Chui et al. 2023).

Overall, there is no one report or study clearly showing companies are investing in AI technology that they do not need or fully understand out of fear of being left behind, and/or that investors are not properly able to assess company investments in AI because they lack the proper understanding of the technology. But what is clear is that companies are planning on investing more in AI, particularly generative AI. If companies and individuals begin to invest in a technology they do not understand and cannot properly assess for risks, there may be abnormal returns in the stock market.

III. Data Description & Methodology

To conduct the research the data needed for the regressions was obtained through Wharton Research Data Services. The 'WRDS SEC Analytics Suite' was first employed to find all reports classified as 10-K and 10-Q containing either the words 'AI' or 'Artificial Intelligence' between the years 2013 and 2023. Reports such as 10-K405 and NT 10-Q/A were not included in the initial data set to try to ensure that there were no other factors, such as late filing, to impact the data. The reports were stored separately to ensure that the reports and corresponding data could be analyzed separately as filing type can act as a proxy for. "… difference in the informativeness…" (Christensen, Heninger, and Stice 2013, 139) which may impact investors' reactions. Analyzing the data separately provided the opportunity to see if the type of report impacted the effect of the mention of AI/Artificial Intelligence on abnormal returns later in the regressions.

Once the reports mentioning AI/Artificial Intelligence were collected, the CIK codes tied to each report were extracted and consolidated and used to find each company's other 10-K and 10-Q reports that did not contain the words AI or Artificial Intelligence to provide a control in the regression. A dummy variable 1 (if AI or Artificial Intelligence was mentioned) and 0 (if AI or Artificial Intelligence was not mentioned) was introduced for later use in the regressions. After collecting the reports, the CIK codes of each company were used in the CIK-CUSIP link table to retrieve the relevant CUSIP codes.

Using the CUSIP codes eight key financial ratios for each company from the 'Financial Ratios Firm-level by WRDS (Beta)' database were obtained. The key ratios were book-to-market, price-earnings ratio excluding extraordinary items (P/E), return on assets (ROA), return on equity (ROE), debt-to-equity (D/E), current ratio, asset turnover, and dividend yield[2]. These

[2] The ratios from the database were provided as ratios not percents and were not changed to percents in the research.

ratios were selected based on the findings of two recent research papers. The first paper by Yulianty, Mugayat, and Nur'aeni (2023) found that the return on equity ratio, price earnings ratio and debt-to-equity ratio all have an impact on stock prices. The second research paper by Mei et al. (2023) found that ratios such as dividend yield, return on assets, book-to-market ratio, assets turnover, and the current ratio play an important role in stock returns. Each set of ratios was matched to each company's 10-K or 10-Q filing based on the date closest to when the report was filed.

After obtaining the eight key financial ratios, the CUSIP codes for each company were used to obtain the SIC code and yearly market value[3] of each company from the 'Compustat Daily Updates-Fundamentals Annual' database. Market value was of particular importance as it could not only indicate if the impact of these terms was partially dependent on firm size, but also because firm size can be a proxy for the, "… level of pre-disclosure information… and political scrutiny" (Christensen, Heninger, and Stice 2013, 139) which may also impact the reaction investors have when the companies they have invested in mention AI. The SIC codes were important as they allowed for later classification of each company report into one of twelve categories which assisted in deeper analysis of the data.

The final step in the data collection process was to find the cumulative abnormal returns related[4] to the event. To obtain the relevant cumulative abnormal returns the 'U.S. Daily Event Study: Upload Your Own Events' database was employed. The database requires an input file, risk model, estimation parameters, and query variables. The input file was the relevant filing dates and associated tickers. The risk model selected was the Fama French Three Factor Model as it was employed in a similar line of research by Thomas (2001). The estimation parameters for the model included 255 days for the estimation window, 70 minimum number of

[3] The database provided market value in millions of USD.
[4] The database provided cumulative abnormal returns in percentage format.

observations, 35 gap days, and a -1 event window start and +1 event window end. The 70 minimum number of observations was chosen based on the WRDS standard protocol while the 255 estimation days were chosen based on recommendations set forth by Offenberg and Officer (2012). The 35 gap days were selected based on the fact that previous literature by Langh (2022) suggests 50 gap days while Lipson and Mortal (2007) suggest 20 gap days, hence the median period of 35 gap days. Meanwhile, the start and end of the event window were selected based on research which suggests that it takes 1-2 days after important news is released to see changes in stock prices (Christensen, Heninger, and Stice 2013).

Having obtained the relevant data, the next step was to remove any companies that had no- or missing- financial ratio information[5], had the terms AI/Artificial Intelligence in their title or as their ticker, or had filed more than one 10-K report each year or more than three 10-Q reports each year. Ultimately this left 6,221 instances for 695 companies among the 10-K reports and 11,267 instances for 507 companies among 10-Q reports which would provide the two sets of panel data for further analysis in the regressions. Summary statistics and quantile-quantile plots of the raw data of each of the variables in both the 10-K and 10-Q reports' data were then created[6].

[5] There were missing financial ratios among the 10-K and 10-Q reports, however, it was only around 10% for each variable except for dividend yield which was noticeably higher at just under 50% for both the 10-K and 10-Q data. Due to the high number of missing dividend yields a zero was put in place of missing values. The assumption was that if a company is not paying a dividend, it may be omitted from the 10-K or 10-Q report thus leading to the missing value.

[6] The summary statistics for the 10-K and 10-Q data before any transformations were applied can be found in Appendix A Tables 1A and 2A respectively. An example of the quantile-quantile plot made for each variable can be seen in Appendix A Figure 1A.

Table 1: Frequency of Fama-French Industry Code (12 Industries) Among the Reports

Industry Classification	Frequency Among 10-K Reports' Data	Frequency Among 10-Q Reports' Data
Consumer NonDurables -- Food, Tobacco	313	453
Consumer Durables -- Cars, TV's, Furniture	235	449
Manufacturing -- Machinery, Trucks, Planes	663	1033
Oil, Gas, and Coal Extraction and Production	175	307
Chemicals and Allied Products	181	340
Business Equipment -- Computers, Software	1838	3135
Telephone and Television Transmission	136	204
Utilities	210	507
Wholesale, Retail, and Some Services	605	1071
Healthcare, Medical Equipment, and Drug	644	1613
Finance	272	551
Other -- Mines, Construction, Building Materials	949	1604
Total	6221	11267

Table 1: Displays the number of reports among the 10-K reports and 10-Q reports' data that are in each of the 12 Fama-French industry categories.

Upon further examination of the data, the log of the market value was taken to make the interpretation of the data easier by normalizing the scale of the data. The cumulative abnormal return data was also converted from percent to basis points[7] to make interpretation of the results easier.

In addition to the initial summary statistics four tests for normal distribution were used for the eight financial ratios, market value, and cumulative abnormal returns for both the 10-K

[7] A basis point is one hundredth of one percent, so to convert to basis points a percent is multiplied by 100.

reports' data and 10-Q reports' data. The Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), Shapiro-Wilk, and Anderson-Darling tests all indicated that every variable suffered from non-normal distribution based on the fact that the p-values were consistently less than 0.001 for the Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), and Shapiro-Wilk tests with the Anderson-Darling p-value usually coming in at 1 when it could be calculated. But despite the higher Anderson-Darling p-value did show normal distribution under the three other tests[8]. Quantile-quantile plots of each variable supported these findings of non-normally distributed data. Almost identical results for both the four normality tests and quantile-quantile graphs were found when analyzing the 10-Q reports' data[9].

The first step in addressing both the non-normal distribution of the data and general data integrity was to winsorize the variables with outliers. The book-to-market, price-to-earnings excluding extraordinary items, return on assets, return on equity, debt-to-equity, current ratio, asset turnover, and dividend yield were winsorized at the 1% and 99% level for both the 10-K and 10-Q data. No improvements in the Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), Shapiro-Wilk, and Anderson-Darling tests were found, and the graphs showed minimal improvement, but the new summary statistics had smaller standard deviation values and showed more appropriate minimum and maximum values.

[8] The results of the normality tests for the 10-K reports' data before any transformations were applied to the data can be found in Appendix A Table 3A.
[9] The results of the normality tests for the 10-Q reports' data before any transformations or were applied to the data can be found in Appendix A Table 4A.

Table 2: Summary Statistics for the 10-K Reports' Data After Transforming the Data

	Mean	Median	Mode	Std. deviation	Minimum	Maximum
Cumulative Abnormal Return	0.164	0.054	6.710	6.702	-61.841	79.943
AI/Artificial Intelligence	0.250	0.000	0.000	0.428	0.000	1.000
Market Value	4.319	3.458	6.425	5.004	1.000	6.425
Book-to-Market	0.470	0.367	0.000	0.396	0.022	2.335
P/E	16.491	18.264	19.000	66.401	-277.200	309.889
ROA	0.096	0.115	0.000	0.144	-0.632	0.398
ROE	0.060	0.093	0.000	0.346	-1.644	1.231
D/E	2.025	1.140	1.000	3.749	-16.044	29.966
Current Ratio	2.567	1.891	1.000	2.228	0.451	14.867
Asset Turnover	0.962	0.781	1.000	0.664	0.029	3.392
Dividend Yield	0.010	0.000	0.000	0.014	0.000	0.067

Table 2: Summary statistics for the data of the 10-K reports after all variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points.

Table 3: Summary Statistics for the 10-Q Reports' Data After Transforming the Data

	Mean	Median	Mode	Std. deviation	Minimum	Maximum
Cumulative Abnormal Return	-0.040	-0.090	-51.960	7.840	-51.960	124.425
AI/Artificial Intelligence	0.140	0.000	0.000	0.338	0.000	1.000
Market Value	4.296	3.450	6.403	4.945	1.530	6.403
Book-to-Market	0.460	0.360	0.020	0.400	0.022	2.340
P/E	16.510	17.340	317.070	72.190	-290.750	317.070
ROA	0.090	0.110	-0.600	0.140	-0.600	0.390
ROE	0.040	0.090	1.040	0.36	-1.960	1.040
D/E	2.080	1.200	29.890	3.770	-20.270	29.890
Current Ratio	2.560	1.930	0.450	2.020	0.450	12.630
Asset Turnover	0.910	0.730	3.510	0.650	0.020	3.510
Dividend Yield	0.010	0.000	0.000	0.010	0.000	0.070

Table 3: Summary statistics for the data of the 10-Q after all variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points.

But as there was still non-normal distribution, three separate transformations were applied to all the variables except the dummy variable to see if improvements in the distribution could be made. The transformations applied were a log function, square root, and Box-Cox function. The most noticeable improvement among all the transformations applied was among the book-to-market ratio and current ratio when using the Box-Cox function than any other function, even though their Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), Shapiro-Wilk tests, and Anderson-Darling results did not improve and the quantile-quantile graphs still failed to show normal distribution most likely due to the fact that the data as a whole suffered from being highly peaked rather than a right or left skew.

Despite normal distribution not being obtained, an initial t-Test for independent samples was run to test the null hypothesis and alternative hypothesis for the 10-K and 10-Q reports' data.

Table 4: Hypotheses for Both the 10-K and 10-Q Reports' Data

Null hypothesis	Alternative hypothesis
There is no difference between the 0 and 1 groups with respect to the dependent variable Cumulative Abnormal Return	There is a difference between the 0 and 1 groups with respect to the dependent variable Cumulative Abnormal Return

Table 4: Hypotheses for both the 10-K and 10-Q report data used in the hypothesis testing.

The t-Test for independent samples for the 10-K reports' data being 0.529 for equal variances and 0.555 for unequal variance means that the null hypothesis fails to be rejected under both tests[10]. The results of the t-Test for independent samples for the 10-Q reports' data also revealed that the null hypothesis fails to be rejected. As evidenced by the fact that the p-values were not significant for either the equal or unequal variances as they were much greater than 0.05 at 0.797 for both equal variance and unequal variances[11].

However, knowing that the t-Test for independent samples test assumption of normal distribution of the AI/Artificial Intelligence dummy variable could not be met, the Mann-Whitney U-test, which is a nonparametric hypothesis test, was performed. The Mann-Whitney U-test also indicated that the null hypothesis failed to be rejected for the 10-K reports' data as evidenced by the fact that both the asymptotic and exact p-values were well over 0.05 at 0.628 for the asymptotic and 0.629 for the exact p.

[10] The results for the t-Test for independent samples for 10-K reports' data can be found in Appendix A Table 5A.
[11] The results for the t-Test for independent samples for 10-Q reports' data can be found in Appendix A Table 6A.

Table 5: Mann-Whitney U Test: 10-K Reports' Data

	U	z	Asymptotic p	Exact p	r
Cumulative Abnormal Return	3607463.000	-0.480	0.628	0.629	0.010

Table 5: Results of the Mann-Whitney U test for the 10-K reports' data.

The Mann-Whitney U-test for the 10-Q reports' data also confirmed that the null hypothesis fails to be rejected since the asymptotic and exact p-values were well above 0.05 at 0.708 for both the asymptotic p and exact p.

Table 6: Mann-Whitney U Test: 10-Q Reports' Data

	U	z	Asymptotic p	Exact p	r
Cumulative Abnormal Return	7502487.000	-0.370	0.708	0.708	0.000

Table 6: Results of the Mann-Whitney U test for the 10-Q reports' data.

Together these results indicated that there was in fact no difference between the 0 and 1 groups with respect to the dependent variable cumulative abnormal return. Even though the initial hypothesis testing indicated the mention of AI/Artificial Intelligence in 10-K and 10-Q reports did not affect cumulative abnormal returns, regressions were performed to explore the full relationship of the dependent variable and independent variable of interest along with exploring how introducing additional independent variables may impact the relationship.

To perform the appropriate regression, the first step was to find whether a fixed effects model or random effects model was more appropriate. In order to make this determination a Hausman test was performed for both the 10-K and 10-Q reports' data. The p-value equaled 0.004 for the 10-K reports and 0.000 for the 10-Q reports' data indicated that the null hypothesis is rejected and thus a fixed effects model was preferred[12]. To validate the findings of the

[12] The results of the Hausman test for the 10-K and 10-Q reports' data can be found in Appendix A Table 7A and Table 8A respectively.

Hausman test the Breusch and Pagan Lagrangian multiplier test for random effects was used[13]. The Breusch and Pagan Lagrangian multiplier test for random effects indicated that both sets of data would benefit from a fixed effects model as the p-value for the 10-K reports' data was significantly higher than 0.05 at 0.432 and the p-value for the 10-Q reports' data was 0.288. These results mean that the null hypothesis fails to be rejected.

Once the fixed effects model was determined to be more appropriate than the random effects model it was important to check if clustering and robust standard errors were needed. A Modified Wald test for groupwise heteroskedasticity revealed that there was indeed groupwise heteroskedasticity for the 10-K and 10-Q regressions as observed from the fact that the p-value equaled 0.000 for both the 10-K reports' data and the 10-Q reports' data which leads to a rejection of the null hypothesis[14]. To control for groupwise heteroskedasticity 'vce (cluster permno)' was introduced to the fixed effects regression model for cluster-robust standard errors at the firm-level (StataCorp 2023). Once it was determined that clustered-robust standard errors were appropriate the last step was to see if a two-way model was necessary to control for time effects and well as firm effects. A joint F-test was conducted for both the 10-K and 10-Q reports' data to test whether the time variables jointly equaled zero (Torres-Reyna 2007). The p-values of the tests equaled 0.099 and 0.005 for the 10-K reports and 10-Q reports' data respectively[15]. This indicated a two-way fixed effects model was not needed for the 10-K reports' data but was needed for the 10-Q reports' data.

The final step in making sure the model was appropriate was to plot the residuals of not only the fixed effects regression model with clustered robust standard errors, but two alternative

[13] The results from the Breusch and Pagan Lagrangian multiplier test for random effects for the 10-K and 10-Q reports' data can be found in Appendix A Table 9A and 10A respectively.
[14] Appendix A Table 11A and Table 12A respectively show the results of the Modified Wald test for groupwise heteroskedasticity in fixed effect regression model for the 10-K reports' data and 10-Q reports' data.
[15] Results of the joint F-tests for the 10-K and 10-Q reports data can be found in Appendix A Tables 13A and 14A respectively.

models as well. The generalized linear regression model with robust standard errors and the quantile regression model with fixed effects and robust standard errors were chosen as alternative models due to the GLM model not requiring equal variance and handling the non-normal distribution of data within the dependent variable well (PennState n.d.) while the quantile regression model is able to handle non-normal distribution and is robust to outliers (Gibbs n.d.). The results of the residual plots provided further evidence that the linear fixed effects regression model with firm-level clustered robust standard errors was an appropriate regression model as the residuals were mostly linear with minimal outliers and no slope[16]. The GLM model was the least appropriate as the residuals showed a clear positive slope[17]. The quantile model residuals at first glance appear to be very similar to the linear model but upon closer inspection, a negative slope can be seen along with a wider variance in the outliers[18].

IV. Results

Having determined that the fixed effects model with firm-level clustered robust standard errors was the most appropriate out of the models tested for the 10-K reports' data, and the two-way fixed effects linear regression model with firm-level clustered robust standard errors was the most appropriate for the 10-Q reports' data, three regressions for each set of data were conducted in line with the procedure outlined in Thomas (2001). The first regression only considered the impact of the mention of AI/Artificial Intelligence on the dependent variable of cumulative abnormal returns. The second regression builds on the first by also considering the eight previously outlined key financial ratios. The final regression examines all the factors from the second regression while also considering market value.

[16] The residual plot of linear fixed effects regression model with firm-level clustered robust standard errors can be seen in Appendix A Figure 2A.
[17] The residual plot of the generalized linear regression model with robust standard errors can be seen in Appendix A Figure 3A.
[18] The residual plot of the quantile regression model with fixed effects and robust standard errors can be seen in Appendix A Figure 4A.

IV.a. 10-K Reports' Data Regression Results

Table 7: Fixed Effects Linear Regression with Firm-Level Clustered Robust Standard Errors for 10-K Reports' Data

	Dependent Variable:		
	Cumulative Abnormal Return		
	(1)	(2)	(3)
AI/Artificial Intelligence	0.103	0.225	0.011
	(0.440)	(0.930)	(0.040)
Book-to-Market		0.696	1.276*
		(1.250)	(2.200)
P/E		-0.002	-0.002
		(-1.070)	(-1.070)
ROA		-0.642	-2.097
		(-0.310)	(-1.100)
ROE		-0.485	-0.709
		(-0.770)	(-1.100)
D/E		0.063	0.076
		(1.610)	(1.930)
Current Ratio		0.063	0.074
		(0.670)	(0.790)
Asset Turnover		1.270*	1.854**
		(2.400)	(3.260)
Dividend Yield		14.630	17.860
		(1.340)	(1.630)
Market Value			0.809***
			(3.590)
Constant	0.138*	-1.749**	-8.857***
	(2.360)	(-2.610)	(-4.250)
N	6221	6221	6221
Adjusted R^2	-0.000	0.002	0.005

Table 7: Results of 3 linear fixed effects regression with firm-level clustered robust standard errors. The first regression only included the dependent variable Cumulative Abnormal Return and the independent variable AI/Artificial Intelligence. The second regression built on the first one by adding Book-to-Market (BM), Price/Earnings Ratio Excluding EI (P/E), Return on Assets (ROA), Return on

*Equity (ROE), Debt-to-Equity, Current Ratio, Asset Turnover, and Dividend Yield as independent variables. The third regression built on the second by adding Market Value as an independent variable. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. Cumulative Abnormal Returns were changed from percents to basis points before running the regressions. The logarithm of the Market Value was also taken. T-statistics are in the parenthesis and *, **, *** represent significance at the 10%, 5%, and 1% levels respectively.*

Regression number one for the 10-K reports' data shows that the inclusion of the term AI/Artificial Intelligence does not have a significant impact on cumulative abnormal returns. The low adjusted r-squared value of -0.000 also indicates that the model does not have strong predictive power. The results of the second regression are similar to the findings in the first regression; not only does the low adjusted r-squared value of 0.002 indicate that the model has poor predictive power but only the asset turnover ratio is significant at the 10% level. The third regression is slightly better than the previous two in terms of predictive power. The adjusted r-squared is higher than before but still only 0.005, however unlike the two previous regressions there is significance among some of the independent variables. Market value shows significance at the 1% level while the asset turnover and book-to-market ratio show significance at the 5% and 10% level respectively. In the final regression model the significance of market value suggests that for a one percent increase in market value the cumulative abnormal returns will increase by 0.00809 basis points. When looking at the asset turnover and book-to-market ratios a one unit increase in each of these variables will lead to a 1.854 basis point increase and 1.276 basis point increase in cumulative abnormal returns for each variable respectively.

IV.b. 10-Q Reports' Data Regression Results

Table 8: Two-Way Fixed Effects Linear Regression Model with Firm-Level Clustered Robust Standard Errors for 10-Q Reports' Data

	Dependent Variable:		
	Cumulative Abnormal Return		
	(1)	(2)	(3)
AI/Artificial Intelligence	0.211	0.241	0.128
	(0.780)	(0.900)	(0.480)
Book-to-Market		1.732***	2.648***
		(3.330)	(4.750)
P/E		0.000	-0.000
		(0.060)	(-0.140)
ROA		-2.229	-3.598*
		(-1.330)	(-2.050)
ROE		-1.302**	-1.549**
		(-2.590)	(-3.050)
D/E		0.050	0.067
		(1.470)	(1.960)
Current Ratio		-0.055	-0.0746
		(-0.550)	(-0.740)
Asset Turnover		0.522	0.918
		(0.870)	(1.490)
Dividend Yield		1.973	7.360
		(0.150)	(0.570)
Market Value			0.985***
			(5.630)
Constant	-0.527	-1.748**	-10.03***
	(-1.620)	(-2.110)	(-5.810)
N	11267	11267	11267
Adjusted R^2	0.001	0.006	0.010

Table 8: Results of 3 two-way fixed effects linear regression with firm-level clustered robust standard errors. The first regression only included the dependent variable Cumulative Abnormal Return and the independent dummy variable AI/Artificial Intelligence. The second regression builds on the first one by adding Book-to-Market (BM), Price/Earnings Ratio Excluding EI (P/E), Return on Assets

*(ROA), Return on Equity (ROE), Debt-to-Equity, Current Ratio, Asset Turnover, and Dividend Yield as independent variables. The third regression built on the second by adding Market Value as an independent variable. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. Cumulative Abnormal Returns were changed from percents to basis points before running the regressions. The logarithm of the Market Value was also taken. T-statistics are in the parenthesis and *, **, *** represent significance at the 10%, 5%, and 1% levels respectively.*

The results of the 10-Q reports' data were similar to those of the 10-K reports' data regressions. The first regression did not indicate that the terms AI/Artificial Intelligence had any effect on cumulative abnormal returns. The adjusted r-squared of the model was also low at 0.001, indicating it did not have strong predictive power. The second model did have a higher adjusted r-squared than the first model at 0.006, indicating it has more predictive power than the previous model, but the adjusted r-squared is still relatively low. However, the second model did indicate that the book-to-market ratio was significant at the 1% level and the return on equity ratio was significant at the 5% level. The final regression[19] showed an improvement in predictive power compared to the first two regressions with an adjusted r-squared of 0.010, however, it is still a low r-squared value. Despite the low predictive power of the regression model, several independent variables show significance. The book-to-market ratio and market value show significance at the 1% level, while return on equity ratio shows significance at the 5% level and the return on assets ratio shows significance at the 10% level. These results of the final regression model indicate that a one percent increase in market value increases cumulative abnormal returns by 0.00985 basis points, while a one unit increase in the book to market ratio leads to a 2.648 basis point increase in cumulative abnormal returns. It also indicates that a one unit increase in the return on equity and return on assets ratios lead to a 1.549 and 3.598 basis point decrease in cumulative abnormal returns for each variable respectively.

[19] The coefficients for each period of time can be seen in Appendix A Table 15A. The results of the 3 linear fixed effects regression with firm-level clustered robust standard errors for the 10-Q reports' data can also be seen in the Appendix A Table 16A.

V. Discussion

The main research question explored in the paper was whether the inclusion of the terms AI/Artificial Intelligence in 10-K and 10-Q reports led to abnormal returns, and the results of the regressions indicate that there is no significant relationship between these terms and abnormal returns. This does not mean that these terms are not important, but rather that in this context they do not have a significant role. This research only focused on U.S. companies, so it is possible that in other markets these terms do impact abnormal returns. Additionally, despite the significance of several variables in the final regression models, the adjusted r-squared remained low. This may indicate that there are additional factors that could be included in the regression model to increase its predictive power. Exploring potential additional factors in future research could help build a more robust model and provide more accurate insight into the relationship these variables have with abnormal returns.

Additional factors that may be worth looking at in future research include; whether it was the first time AI/Artificial Intelligence was mentioned in a 10-K or 10-Q report for the company, and/or the overall sentiment of the reports. These factors may help isolate the impact of the term on abnormal returns. Continuous mentions of AI, for example, may remove the novelty of the idea and the term leading to more rational behavior. Meanwhile, for sentiment, it may be that the mention of these terms does not have an impact until the report's sentiment crosses a certain positive or negative threshold.

Despite the terms AI/Artificial Intelligence not having a significant impact on abnormal returns, the research does indicate the there are several variables that do have a significant impact. Market value and the asset turnover and book-to-market ratios have a significant impact on abnormal returns related to 10-K reports; while market value and the book-to-market, return on equity, and return on assets ratios have a significant impact on abnormal returns related to 10-Q reports. These results largely make sense on several levels. On a holistic level it makes sense that these factors would influence abnormal returns based on work done by Yulianty, Mugayat, and Nur'aeni (2023) and Mei et al. (2023). At an individual level; higher book-to-market ratios have been linked with higher distress risks and therefore higher abnormal returns (Griffin and Lemon 2002). Asset turnover, in conjunction with profit margin, has been used to proxy for earnings management and has been found to signal downward earnings management when the ratio has increased while profit margin has decreased (Jansen, Ramnath, and Yohn 2011). Increases in return on assets and return on equity have been linked to higher profitability metrics (Truong 2011) which may initially appear to contradict the results found in the research, but what may be happening is that the fundamental value of the stock is rising as these metrics improve, which is causing fewer abnormal returns. The only result that does not appear to be in line with previous findings is that a higher market value leads to increased abnormal returns. Previous research suggests that the opposite usually occurs (Tseng 1988). It may be that because the companies in the sample had higher market values, they receive more attention and are perhaps at a certain point are expected to be stagnant in their growth. Thus, any change apart from what is expected leads to abnormal returns, but it is a question that may be worth exploring in the future.

Overall, the terms AI/Artificial Intelligence do not have a significant impact on abnormal returns, but the research does open up several avenues for further research while also providing further insight into the roles financial ratios and metrics have on abnormal returns.

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Appendix A

Tables

Table 1A: Summary Statistics for the 10-K Reports' Data Before Transformations Were Applied

	Mean	Median	Mode	Std. deviation	Minimum	Maximum
Cumulative Abnormal Return	0.002	0.001	0.007	0.067	-0.618	0.080
AI/Artificial Intelligence	0.250	0.000	0.000	0.428	0.000	1.000
Market Value	20856.260	2868.220	2662327.00	100953.460	0.000	2662327.000
Book-to-Market	0.480	0.370	0.090	0.460	0.000	7.360
P/E	14.700	18.260	-45.200	96.690	-1872.800	633.500
ROA	0.100	0.120	0.130	0.160	-2.300	1.010
ROE	0.060	0.090	0.080	0.630	-8.230	24.430
D/E	3.130	1.140	2.440	50.450	-391.270	2691.670
Current Ratio	2.630	1.890	2.320	2.800	0.170	63.620
Asset Turnover	0.970	0.780	0.540	0.720	0.000	8.360
Dividend Yield	0.010	0.000	0.000	0.010	0.000	0.140

Table 1A: Summary statistics for the data of the 10-K reports before any transformations were applied.

Table 2A: Summary Statistics for the 10-Q Reports' Data Before Transformations Were Applied

	Mean	Median	Mode	Std. deviation	Minimum	Maximum
Cumulative Abnormal Return	-0.000	-0.001	-0.519	0.078	-0.520	1.244
AI/Artificial Intelligence	0.140	0.000	0.000	0.338	0.000	1.000
Market Value	19752.530	2820.729	2530893.000	88201.660	0.000	2530893.000
Book-to-Market	0.480	0.360	0.180	0.540	0.000	18.300
P/E	14.550	17.340	-45.200	106.130	-4266.670	633.500
ROA	0.090	0.110	0.130	0.150	-1.290	0.700
ROE	0.010	0.090	-0.110	2.730	-90.020	92.930
D/E	2.650	1.280	2.440	48.650	-1760.72	2691.670
Current Ratio	2.630	1.930	2.320	2.440	0.200	68.710
Asset Turnover	0.920	0.730	0.320	0.690	0.000	8.490
Dividend Yield	0.010	0.000	0.000	0.020	0.000	0.240

Table 2A: Summary statistics for the data of the 10-Q reports before any transformations were applied.

Table 3A: Tests for Normal Distribution of the 10-K Reports' Data Before Transformations Were Applied

	Kolmogorov-Smirnov		Kolmogorov-Smirnov (Lilliefors Corr.)		Shapiro-Wilk		Anderson-Darling	
	Statistics	p-value	Statistics	p-value	Statistics	p-value	Statistics	p-value
Cumulative Abnormal Return	0.160	<.001	0.160	<.001	0.840	<.001	258.920	<.001
Market Value	0.420	<.001	0.420	<.001	0.160	<.001	1618.180	1.000
Book-to-Market	0.410	<.001	0.410	<.001	0.650	<.001	1054.910	1.000
P/E	0.200	<.001	0.200	<.001	0.730	<.001	536.250	1.000
ROA	0.530	<.001	0.530	<.001	0.080	<.001	Infinity	aN
ROE	0.470	<.001	0.470	<.001	0.400	<.001	1777.030	1.000
D/E	0.310	<.001	0.310	<.001	0.460	<.001	965.510	1.000
Current Ratio	0.270	<.001	0.270	<.001	0.670	<.001	572.890	1.000
Asset Turnover	0.310	<.001	0.310	<.001	0.800	<.001	572.550	<.001
Dividend Yield	0.280	<.001	0.280	<.001	0.720	<.001	581.12	<.001

Table 3A: Displays the results of the Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), Shapiro-Wilk, and Anderson-Darling tests for the 10-K reports' data before any transformations were applied.

Table 4A: Tests for Normal Distribution of the 10-Q Reports' Data Before Transformations Were Applied

	Kolmogorov-Smirnov		Kolmogorov-Smirnov (Lilliefors Corr.)		Shapiro-Wilk		Anderson-Darling	
	Statistics	p-value	Statistics	p-value	Statistics	p-value	Statistics	p-value
Cumulative Abnormal Return	0.110	<.001	0.110	<.001	0.890	<.001	313.100	1.000
Market Value	0.410	<.001	0.410	<.001	0.180	<.001	2839.120	1.000
Book-to-Market	0.190	<.001	0.190	<.001	0.580	<.001	778.910	1.000
P/E	0.250	<.001	0.250	<.001	0.510	<.001	Infinity	aN
ROA	0.180	<.001	0.180	<.001	0.790	<.001	Infinity	aN
ROE	0.390	<.001	0.390	<.001	0.040	<.001	Infinity	aN
D/E	0.480	<.001	0.480	<.001	0.030	<.001	3878.650	1.000
Current Ratio	0.180	<.001	0.180	<.001	0.610	<.001	918.390	1.000
Asset Turnover	0.140	<.001	0.140	<.001	0.820	<.001	456.330	1.000
Dividend Yield	0.290	<.001	0.290	<.001	0.680	<.001	1165.910	1.000

Table 4A: Displays the results of the Kolmogorov-Smirnov, Kolmogorov-Smirnov (Lilliefors Corr.), Shapiro-Wilk, and Anderson-Darling tests for the 10-Q reports' data before any transformations were applied.

Table 5A: t-Test for Independent Samples for the 10-K Reports' Data

		t	df	p	Cohen's d
Cumulative Abnormal Return	Equal Variances	0.635	6219.000	0.529	0.020
	Unequal Variances	0.595	2415.550	0.555	0.020

Table 5A: Results of the t-Test for independent samples for the 10-K reports' data.

Table 6A: t-Test for Independent Samples for the 10-Q Reports' Data

		T	df	p	Cohen's d
Cumulative Abnormal Return	Equal Variances	0.260	11265.000	0.797	0.010
	Unequal Variances	0.260	2084.210	0.797	0.010

Table 6A: Results of the t-Test for independent samples for the 10-Q reports' data.

Table 7A: Hausman Test for 10-K Reports' Data

	---------Coefficients---------			sqrt(diag(V_b-V_B))
	(b)	(B)	(b-B)	
	fe_model	re_model	Difference	Std. error
AI/Artificial Intelligence	0.011	-0.103	0.115	0.131
Market Value	0.809	0.175	0.635	0.176
Book-to-Market	1.276	0.655	0.621	0.332
P/E	-0.002	-0.002	-0.000	0.001
ROA	-2.097	-0.616	-1.480	1.362
ROE	-0.709	-0.257	-0.452	0.323
D/E	0.076	0.041	0.035	0.024
Current Ratio	0.074	0.071	0.003	0.057
Asset Turnover	1.854	0.159	1.695	0.447
Dividend Yield	17.864	-0.652	18.516	7.784

b = Consistent under H0 and Ha;

B = Inconsistent under Ha, efficient under H0;

Test of H0: Difference in coefficients not systematic

chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) 30.38

Prob > chi2 = 0.004

Table 7A: Displays the results of the Hausman test for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 8A: Hausman Test for 10-Q Reports' Data

	---------Coefficients---------			sqrt(diag(V_b-V_B))
	(b)	(B)	(b-B)	
	fe_model	re_model	Difference	Std. error
AI/Artificial Intelligence	-0.097	-0.005	-0.092	0.114
Market Value	0.821	0.268	0.553	0.120
Book-to-Market	2.407	0.866	0.866	0.262
P/E	-0.000	0.000	-0.000	0.000
ROA	-3.800	-1.327	-2.473	1.030
ROE	-1.564	-0.910	-0.655	0.230
D/E	0.056	0.017	0.039	0.018
Current Ratio	-0.034	-0.022	-0.012	0.048
Asset Turnover	1.384	0.342	1.042	0.430
Dividend Yield	8.721	-8.088	16.809	7.624

b = Consistent under H0 and Ha;

B = Inconsistent under Ha, efficient under H0;

Test of H0: Difference in coefficients not systematic

chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) 71.090

Prob > chi2 = 0.000

Table 8A: Displays the results of the Hausman test for the 10-Q reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 9A: Breusch and Pagan Lagrangian Multiplier Test for Random Effects for 10-K Reports' Data

CumulativeAbnormalReturn[permno,t] = Xb + u[permno] + e[permno,t]		
Estimated results:	Var	SD = sqrt(Var)
Cumulative Abnormal Return	44.916	6.702
e	44.255	6.652
u	1.669	1.292
Test: Var(u) = 0.000		
chibar2(01) = 0.030		
Prob > chibar2 = 0.432		

Table 9A: Results of the Breusch and Pagan Lagrangian multiplier test for random effects for 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 10A: Breusch and Pagan Lagrangian Multiplier Test for Random Effects for 10-Q Reports' Data

CumulativeAbnormalReturn[permno,t] = Xb + u[permno] + e[permno,t]		
Estimated results:	Var	SD = sqrt(Var)
Cumulative Abnormal Return	61.736	7.857
e	61.091	7.816
u	2.567	1.603
Test: Var(u) = 0.000		
chibar2(01) = 0.310		
Prob > chibar2 = 0.288		

Table 10A: Results of the Breusch and Pagan Lagrangian multiplier test for random effects for 10-Q reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 11A: Modified Wald Test for Groupwise Heteroskedasticity in Fixed Effect Regression Model for the 10-K Reports' Data

H0: sigma(i)^2 = sigma^2 for all i
chi2 (695) = 9.800e+30
Prob>chi2 = 0.000

Table 11A: Results of the Modified Wald test for groupwise heteroskedasticity in fixed effect regression model for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 12A: Modified Wald Test for Groupwise Heteroskedasticity in Fixed Effect Regression Model for the 10-Q Reports' Data

H0: sigma(i)^2 = sigma^2 for all i
chi2 (507) = 1.2e+34
Prob>chi2 = 0.000

Table 12A: Results of the Modified Wald test for groupwise heteroskedasticity in fixed effect regression model for the 10-Q reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 13A: Joint F-test for 10-K Reports' Data

Year	Result
2014	0
2015	0
2016	0
2017	0
2018	0
2019	0
2020	0
2021	0
2022	0
2023	0
$F(10, 694) = 1.61$	
Prob > F = 0.099	

Table 13A: The joint F-test to test whether all the years equal zero for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 14A: Joint F-test for 10-Q Reports' Data

Quarter and Year	Result
Quarter 2 2013	0
Quarter 3 2013	0
Quarter 1 2014	0
Quarter 2 2014	0
Quarter 3 2014	0
Quarter 1 2015	0
Quarter 2 2015	0
Quarter 3 2015	0
Quarter 1 2016	0
Quarter 2 2016	0
Quarter 3 2016	0
Quarter 1 2017	0
Quarter 2 2017	0
Quarter 3 2017	0
Quarter 1 2018	0
Quarter 2 2018	0
Quarter 3 2018	0
Quarter 1 2019	0
Quarter 2 2019	0
Quarter 3 2019	0
Quarter 1 2020	0
Quarter 2 2020	0
Quarter 3 2020	0
Quarter 1 2021	0
Quarter 2 2021	0
Quarter 3 2021	0
Quarter 1 2022	0
Quarter 2 2022	0
Quarter 3 2022	0
Quarter 1 2023	0

Quarter 2 2023	0
Quarter 3 2023	0
F(32, 506) = 1.800	
Prob>F = 0.005	

Table 14A: The joint F-test to test whether all the years equal zero for the 10-Q reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points before running the test.

Table 15A: Two-Way Fixed Effects Linear Regression Model with Firm-level Clustered Robust Standard Errors for 10-Q Reports' Data – Quarters and Years

	Dependent Variable:		
	Cumulative Abnormal Return		
	(1)	(2)	(3)
Quarter 2 2013	0.534	0.639	0.624
	(1.280)	(1.540)	(1.500)
Quarter 3 2013	0.489	0.620	0.680
	(1.130)	(1.440)	(1.590)
Quarter 1 2014	0.071	0.287	0.248
	(0.150)	(0.620)	(0.540)
Quarter 2 2014	0.420	0.687	0.660
	(0.990)	(1.610)	(1.560)
Quarter 3 2014	0.644	0.897	0.870
	(1.430)	(1.900)	(1.850)
Quarter 1 2015	0.591	0.843	0.876
	(1.310)	(1.850)	(1.950)
Quarter 2 2015	0.972*	1.273*	1.328**
	(1.980)	(2.510)	(2.640)
Quarter 3 2015	0.472	0.724	0.761
	(0.870)	(1.340)	(1.410)
Quarter 1 2016	0.789	0.933*	0.881
	(1.71)	(2.000)	(1.890)
Quarter 2 2016	0.582	0.714	0.656
	(1.170)	(1.420)	(1.300)
Quarter 3 2016	-0.050	0.071	0.007
	(-0.100)	(0.140)	(0.010)
Quarter 1 2017	0.956*	1.154*	0.942
	(2.010)	(2.350)	(1.950)
Quarter 2 2017	0.614	0.835	0.640
	(1.210)	(1.630)	(1.250)
Quarter 3 2017	0.613	0.819	0.625
	(1.110)	(1.470)	(1.130)

Quarter 1 2018	0.523	0.801	0.703
	(0.950)	(1.410)	(1.240)
Quarter 2 2018	1.138*	1.371*	1.263*
	(2.150)	(2.530)	(2.350)
Quarter 3 2018	0.579	0.865	0.770
	(0.980)	(1.450)	(1.300)
Quarter 1 2019	-0.386	-0.282	-0.631
	(-0.780)	(-0.570)	(-1.250)
Quarter 2 2019	1.035	1.251*	0.963
	(1.770)	(2.140)	(1.640)
Quarter 3 2019	1.316*	1.476	1.161
	(2.050)	(2.230)	(1.740)
Quarter 1 2020	0.825	0.972	0.523
	(1.390)	(1.590)	(0.850)
Quarter 2 2020	1.021	0.893	0.322
	(1.490)	(1.290)	(0.470)
Quarter 3 2020	-0.002	-0.000	-0.469
	(-0.000)	(-0.000)	(-0.840)
Quarter 1 2021	0.059	0.352	-0.219
	(0.120)	(0.670)	(-0.400)
Quarter 2 2021	0.220	0.642	0.129
	(0.480)	(1.260)	(0.250)
Quarter 3 2021	-0.185	0.285	-0.202
	(-0.310)	(0.470)	(-0.330)
Quarter 1 2022	-0.302	0.0765	-0.291
	(-0.570)	(0.140)	(-0.510)
Quarter 2 2022	-0.819	0.131	-0.294
	(-0.330)	(0.220)	(-0.500)
Quarter 3 2022	0.882	1.040	0.557
	(1.440)	(1.640)	(0.88)
Quarter 1 2023	1.097	1.175	0.681
	(1.690)	(1.800)	(1.030)

Quarter 2 2023	-0.108	-0.059	-0.538
	(-0.160)	(-0.090)	(-0.790)
Quarter 3 2023	-0.227	-0.149	-0.613
	(-0.370)	(-0.240)	(-0.960)

*Table 15A: The coefficients of each time period for the 3 two-way fixed effects linear regression with firm-level clustered robust standard errors. The first regression only included the dependent variable Cumulative Abnormal Return and the independent variable AI/Artificial Intelligence. The second regression builds on the first one by adding Book-to-Market (BM), Price/Earnings Ratio Excluding EI (P/E), Return on Assets (ROA), Return on Equity (ROE), Debt-to-Equity, Current Ratio, Asset Turnover, and Dividend Yield as independent variables. The third regression built on the second by adding Market Value as an independent variable. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. Cumulative Abnormal Returns were changed from percents to basis points before running the regressions. The logarithm of the Market Value was also taken. T-statistics are in the parenthesis and *, **, *** represent significance at the 10%, 5%, and 1% levels respectively.*

Table 16A: Fixed Effects Linear Regression with Firm-level Clustered Robust Standard Errors for 10-Q Reports' Data

	Dependent Variable:		
	Cumulative Abnormal Return		
	(1)	(2)	(3)
AI/Artificial Intelligence	0.108	0.126	-0.097
	(0.430)	(0.490)	(-0.380)
Book-to-Market		1.654***	2.407***
		(3.310)	(4.510)
P/E		0.000	-0.000
		(0.050)	(-0.100)
ROA		-2.468	-3.800*
		(-1.460)	(-2.160)
ROE		-1.318**	-1.564**
		(-2.620)	(-3.060)
D/E		0.046	0.056
		(1.350)	(1.640)
Current Ratio		-0.046	-0.034
		(-0.460)	(-0.340)
Asset Turnover		0.726	1.384*
		(1.310)	(2.320)
Dividend Yield		4.019	8.721
		(0.310)	(0.670)
Market Value			0.821***
			(5.160)
Constant	-0.0454	-1.232	-8.648***
	(-1.300)	(-1.950)	(-5.240)
N	11267	11267	11267
Adjusted R^2	-0.000	0.005	0.008

Table 16A: Results of 3 linear fixed effects regression with firm-level clustered robust standard errors. The first regression only included the dependent variable Cumulative Abnormal Return and the independent variable AI/Artificial Intelligence. The second regression built on the first one by adding Book-to-Market (BM), Price/Earnings Ratio Excluding EI (P/E), Return on Assets (ROA), Return on Equity (ROE), Debt-to-Equity, Current Ratio, Asset Turnover, and Dividend Yield as independent variables. The third regression built on the second by adding Market Value as an independent variable. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, *AI/Artificial Intelligence, and Market Value. Cumulative Abnormal Returns were changed from percents to basis points before running the regressions. The logarithm of the Market Value was also taken. T-statistics are in the parenthesis and *, **, *** represent significance at the 10%, 5%, and 1% levels respectively.*

Figures

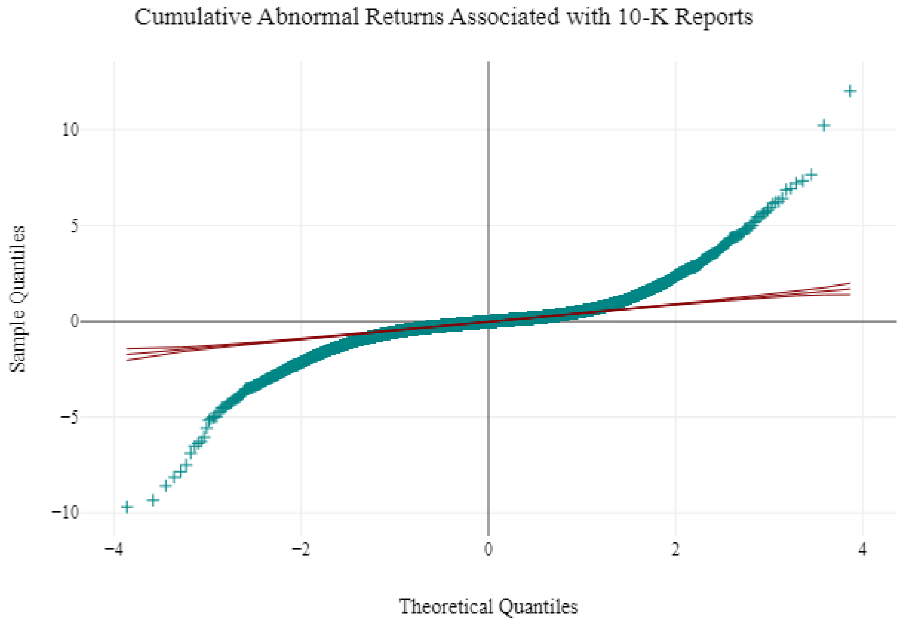

Figure 1A: A quantile-quantile plot of the cumulative abnormal return variable in the 10-K reports' data before any transformations were applied.

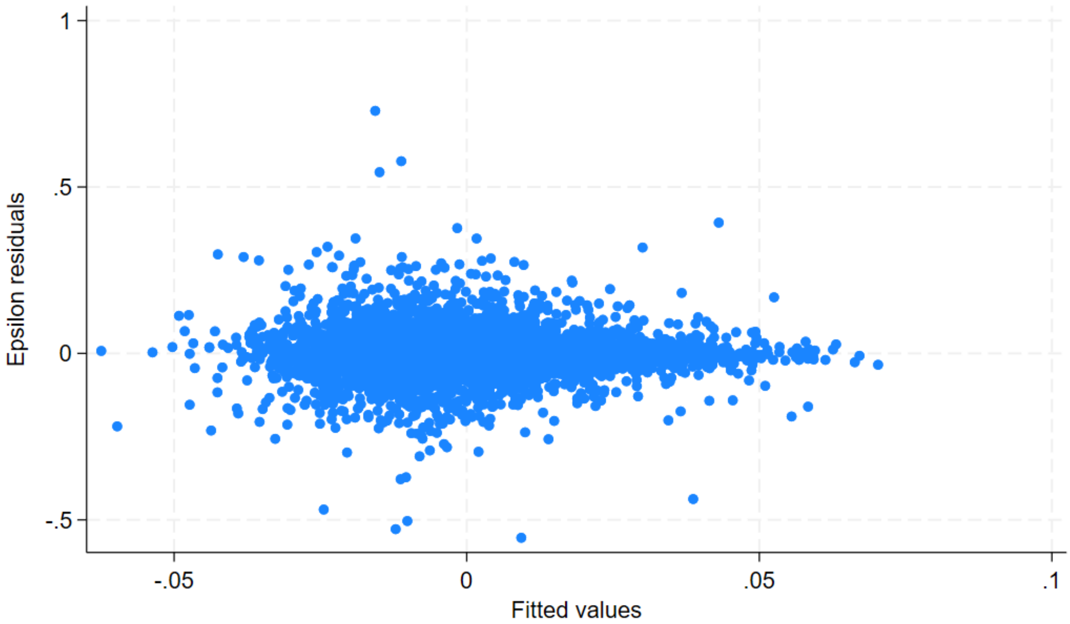

Figure 2A: Residuals from the linear regression with fixed effects and firm-level clustered robust standard errors for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points.

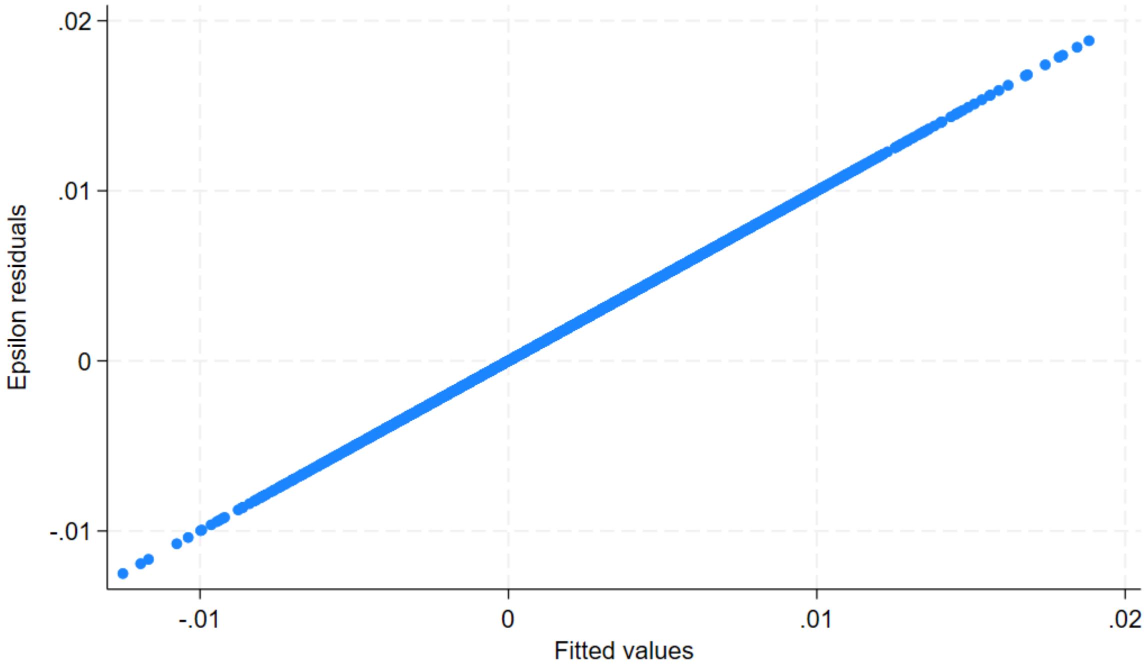

Figure 3A: Residuals from the GLM regression with robust standard errors for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points.

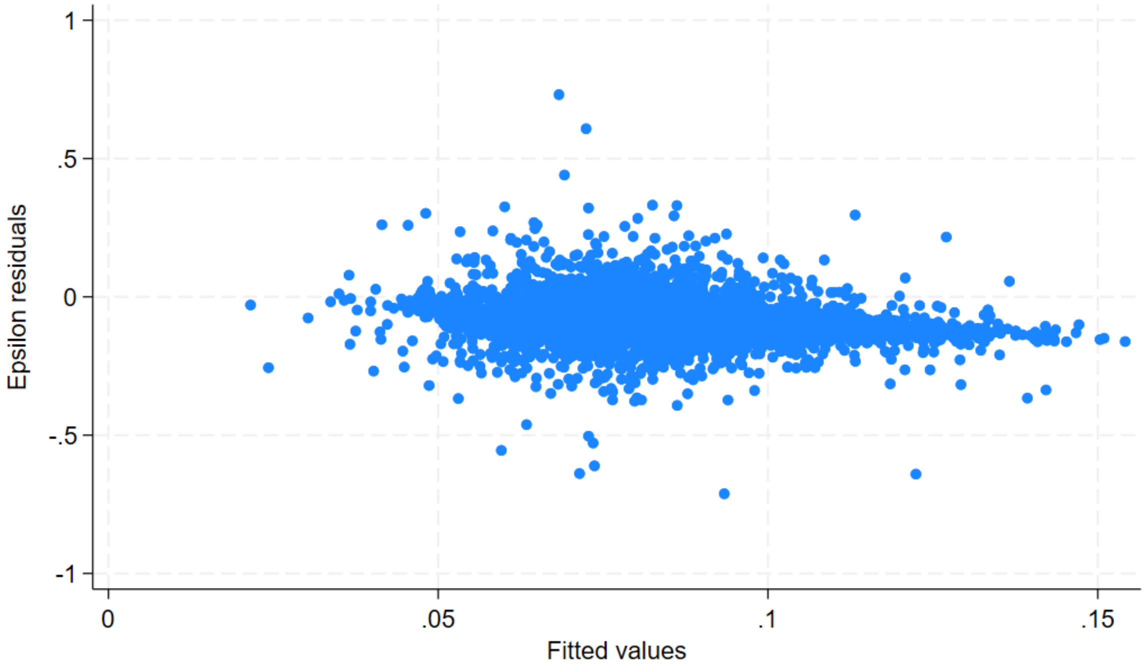

Figure 4A: Residuals from the quantile regression with fixed effects robust standard errors for the 10-K reports' data. All variables were winsorized at the 1% and 99% level except for the Cumulative Abnormal Return, AI/Artificial Intelligence, and Market Value. The logarithm of the Market Value was used and missing values in Dividend Yield were replaced with 0. Cumulative Abnormal Return was also converted from percent format to basis points.

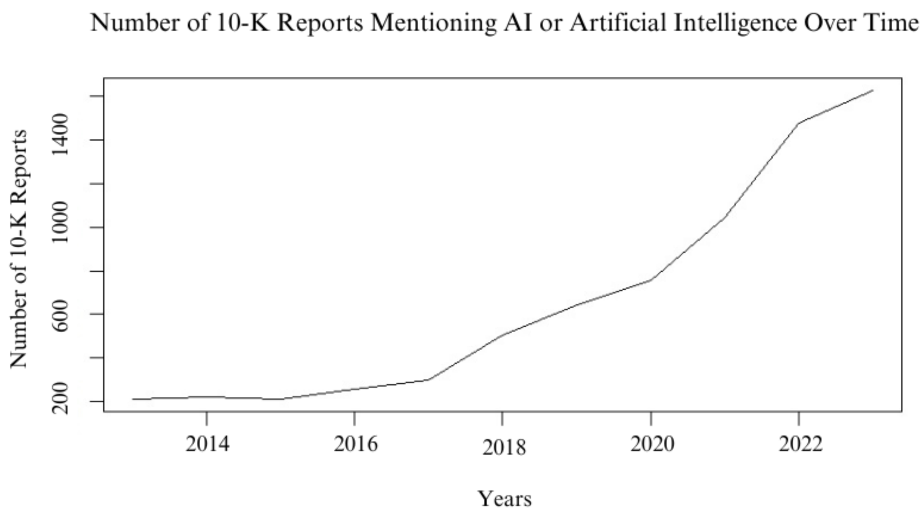

Figure 5A: The number of 10-K Reports from the EDGAR database mentioning AI or Artificial Intelligence from 2013 to 2023.

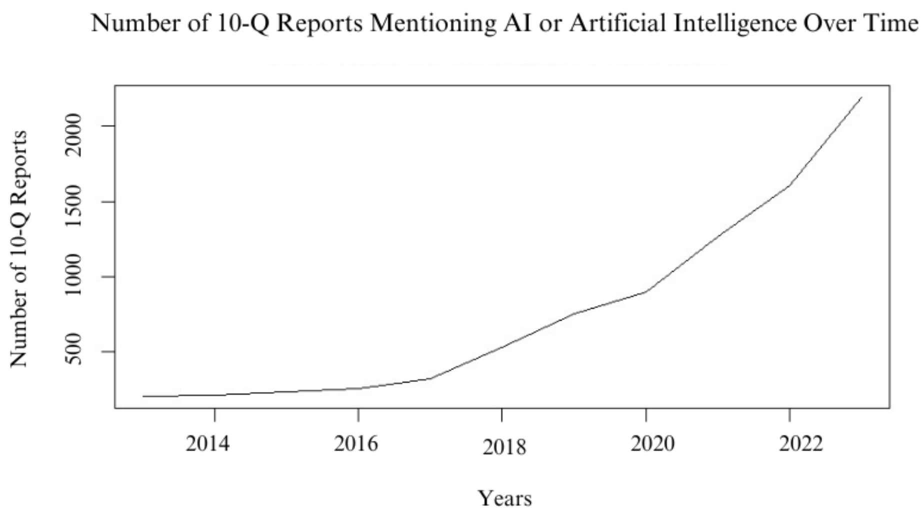

Figure 6A: The number of 10-K Reports from the EDGAR database mentioning AI or Artificial Intelligence from 2013 to 2023.

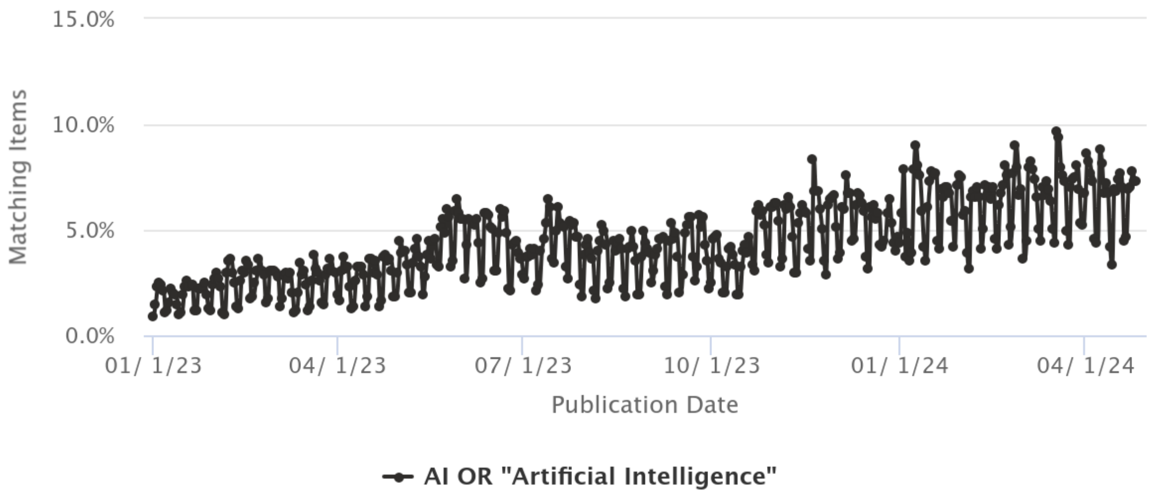

Figure 7A: Displays the news coverage on AI/Artificial Intelligence from limited U.S. news sources from 2023 to 2024 (MediaCloud n.d.)