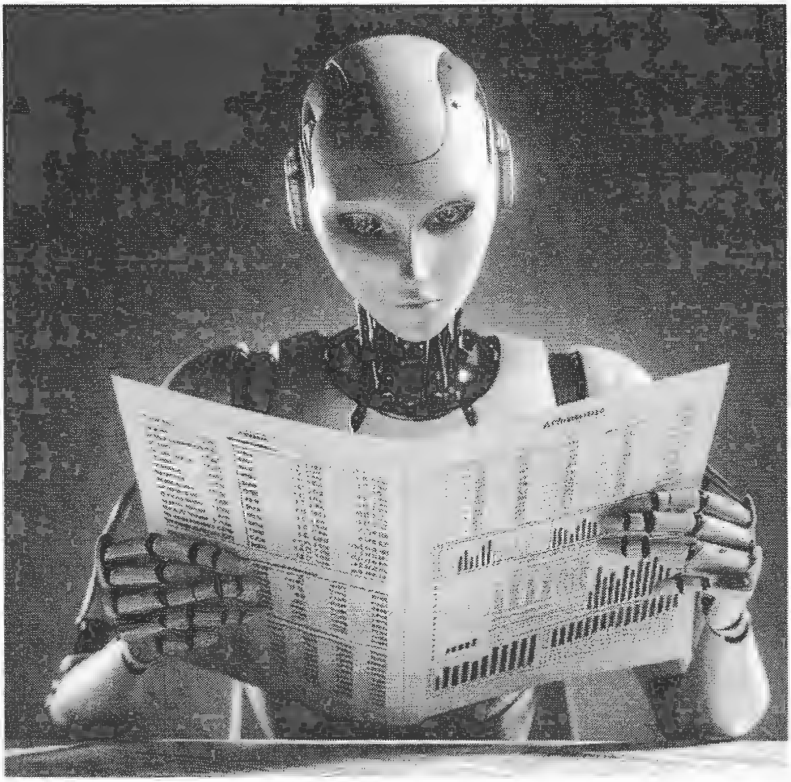
Chapter 11 | Financial Analysis

> "The investor who buys securities when the market price looks cheap on the basis of the company's statements, and sells them when they look high on this same basis, probably will not make spectacular profits. But on the other hand, he will probably avoid equally spectacular and more frequent losses." ~ Benjamin Graham



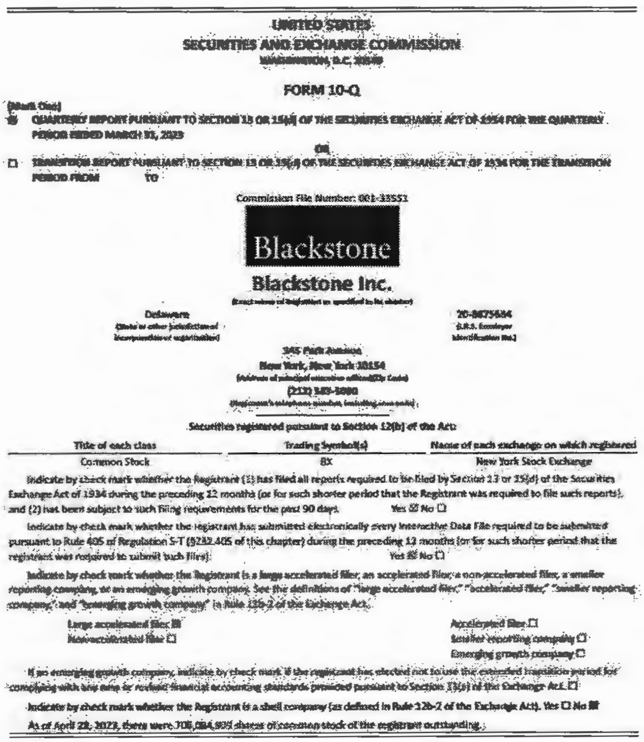
11.1 Theory of Financial Analysis

11.1.1 Financial Information

In the US, public firms (listed in the stock market) are required to file financial reports following Section 13 or 15(d) of the Securities Exchange Act of 1934 (SEC, n.d.). They file forms 10-K once a year, typically at the end of a fiscal year, and three forms 10-Q for the other quarters. In addition to the 10-K and the 10-Q forms, companies have to report information on significant events, corporate changes like mergers and acquisitions, proxy statements for the shareholders' annual meetings, registration documents of public securities, and trades by insiders.

Private firms are generally not required to publish financials unless they have issued securities such as corporate bonds. Other firms will communicate financial information to banks if they need funding. Internationally, listed companies have similar requirements and must comply with local laws and regulations. The United Kingdom has the Financial Conduct Authority (FCA), the Europe Union, the European Securities and Markets Authority (ESMA) that coordinates the work of the national regulatory agencies such as the Autorité des marchés financiers (AMF) in France and the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) in Germany.

To facilitate reporting, transparency, and accessibility, the SEC now requires public companies to report their financials in the XBRL (eXtensible Business Reporting Language) ("XBRL," n.d.) format, which is a machine-readable and standardized format based on XML. The data and files are also available on its EDGAR (Electronic Data Gathering, Analysis, and Retrieval) database. There are similar international requirements; companies filing in Europe must comply with the European Single Electronic Format (ESEF) and report in the iXBRL format that combines XBRL and XHTML and allows files to be readable by humans and machines. These new machine-readable formats are essential for developing new AI models to analyze financial information from companies.



UNITED STATES
SECURITIES AND EXCHANGE COMMISSION

FORM 10-Q

☒ QUARTERLY REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934 FOR THE QUARTERLY PERIOD ENDED MARCH 31, 2023

OR

☐ TRANSITION REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934 FOR THE TRANSITION PERIOD FROM TO

Commission File Number: 001-33551

Blackstone

Blackstone Inc.

Delaware

New York, New York 10154

Securities registered pursuant to Section 12(b) of the Act:

Title of each class	Trading Symbol(s)	Name of each exchange on which registered
Common Stock	BX	New York Stock Exchange

Indicate by check mark whether the Registrant (1) has filed all reports required to be filed by Section 13 or 15(d) of the Securities Exchange Act of 1934 during the preceding 12 months (or for such shorter period that the Registrant was required to file such reports), and (2) has been subject to such filing requirements for the past 90 days. Yes ☒ No ☐

Indicate by check mark whether the registrant has submitted electronically every Interactive Data File required to be submitted pursuant to Rule 405 of Regulation S-T (§232.405 of this chapter) during the preceding 12 months (or for such shorter period that the registrant was required to submit such files). Yes ☒ No ☐

Indicate by check mark whether the Registrant is a large accelerated filer, an accelerated filer, a non-accelerated filer, a smaller reporting company, or an emerging growth company. See the definitions of "large accelerated filer," "accelerated filer," "smaller reporting company," and "emerging growth company" in Rule 12b-2 of the Exchange Act.

Large accelerated filer ☒ Accelerated filer ☐
Non-accelerated filer ☐ Smaller reporting company ☐
Emerging growth company ☐

If an emerging growth company, indicate by check mark if the registrant has elected not to use the extended transition period for complying with any new or revised financial accounting standards provided pursuant to Section 13(a) of the Exchange Act. ☐

Indicate by check mark whether the Registrant is a shell company (as defined in Rule 12b-2 of the Exchange Act). Yes ☐ No ☒

Figure 11.1. Blackstone form 10-Q

11.1.2 Financial Statements

Financial statements include the balance sheet (Figure 11.2), the income statement (Figure 11.3), the cash flow statement (Figure 11.4), the statement of shareholders' equity (Figure 11.5), and the accompanying notes (Brown et al., 2021). They provide information on the current financial position and the recent trends from the past quarters. They are helpful to evaluate the financial health of a company, to compare with peers of the same industry or other industries, and to predict future financial performance.

11.1.3 Financial Statement Analysis

Financial statement analysis or fundamental analysis is the study of a firm's financial situation and performance that includes measures of profitability, liquidity, solvability, financial strength, financial flexibility, growth rate and financial prospect, and valuation:

- **Profitability**: Gross Profit Margins (revenue minus cost of goods sold, divided by revenue, GPM), Net Income (Gross Profit - Operating Expenses - Taxes - Interest +/- Non-operating Items, NI), Return on Sales (net income divided by sales, ROS), Return on Equity (net income divided by net equity, ROE) or Return on Assets (net income divided by total assets, ROA), or Earnings Per Share (EPS).
- **Liquidity**: Current Ratio (ability to cover short-term liabilities with short-term assets, current assets divided by current liabilities), Quick Ratio (or acid-test Ratio, similar to the current ratio but excludes inventory from current assets, measures the immediate liquidity of a company), Cash Ratio (most conservative liquidity ratio, considers only cash and cash equivalents in relation to current liabilities), Operating Cash Flow Ratio (ability to generate cash from core operations to cover current liabilities, operating cash flow divided by current liabilities).
- **Solvability**: Debt-to-Equity Ratio (total debt divided by total equity), Debt Ratio (total debt divided by total assets), Interest Coverage Ratio: (ability to meet interest obligations on outstanding debt, earnings before interest and taxes (EBIT) divided by interest expenses), Debt-Service Coverage Ratio (ability to meet debt service obligations, including both interest and principal repayments, EBITDA divided by total debt service)
- **Financial strength and flexibility**: in addition to the profitability solvability ratios, Operating Cash Flow Ratio (operating cash flow divided by total liabilities)
- **Growth rate and financial prospect**: Revenue Growth Rate, Earnings Growth Rate, Return on Equity (ROE) Growth, Cash Flow Growth, Asset Growth Rate, and Market Share Growth.
- **Valuation**: Price-to-Earnings Ratio (P/E Ratio, market price per share divided by the earnings per share (EPS)), Price-to-Sales Ratio (P/S Ratio, the market price per share divided by the company's revenue per share), Price-to-Book Ratio (P/B Ratio, market price per share divided by the book value per share), Dividend Yield (annual dividend per share divided by the market price per share), Enterprise Value-to-EBITDA (EV/EBITDA, company's enterprise value (market capitalization plus debt minus cash) divided by EBITDA), Free Cash Flow Yield (free cash flow (operating cash flow minus capital expenditures) per share divided by the market price per share).

Most of these financial indicators can be calculated from numbers extracted from the firm's financial statements.

	31-Mar-23	31-Dec-22
Assets		
Cash and Cash Equivalents	$ 2,830,971	$ 4,252,003
Cash Held by Blackstone Funds and Other	190,322	241,712
Investments	26,365,951	27,563,251
Accounts Receivable	924,934	462,904
Due from Affiliates	4,099,765	4,146,707
Intangible Assets, Net	230,295	217,287
Goodwill	1,890,202	1,890,202
Other Assets	833,232	800,458
Right-of-Use		
Assets	894,067	896,981
Deferred Tax Assets	2,206,700	2,062,722
Total Assets	**$ 41,986,439**	**$ 42,524,227**
Liabilities and Equity		
Loans Payable	$ 12,311,469	$ 12,349,584
Due to Affiliates	1,974,182	2,118,481
Accrued Compensation and Benefits	5,470,773	6,101,801
Securities Sold, Not Yet Purchased	3,881	3,825
Repurchase Agreements	19,563	89,944
Operating Lease Liabilities	1,016,808	1,021,454
Accounts Payable, Accrued Expenses and Other		
Liabilities	1,575,938	1,158,071
Total Liabilities	**22,372,614**	**22,843,160**
Commitments and Contingencies		
Redeemable		
Non-Controlling		
Interests in Consolidated Entities	1,644,697	1,715,006
Equity		
Stockholders' Equity of Blackstone Inc.		
Common Stock, $0.00001 par value, 90 billion shares		
authorized, (712,794,968 shares issued and		
outstanding as of March 31, 2023; 710,276,923 shares		
issued and outstanding as of December 31, 2022)	7	7
Series I Preferred Stock, $0.00001 par value,		
999,999,000 shares authorized, (1 share issued and		
outstanding as of March 31, 2023 and December 31,		
2022)	-	-
Series II Preferred Stock, $0.00001 par value, 1,000		
shares authorized, (1 share issued and outstanding as		
of March 31, 2023 and December 31, 2022)	-	-
Additional		
Paid-in-Capital	5,957,054	5,935,273
Retained Earnings	1,156,109	1,748,106
Accumulated Other Comprehensive Loss	(22,333)	(27,475)
Total Stockholders' Equity of Blackstone Inc.	7,090,837	7,655,911
Non-Controlling		
Interests in Consolidated Entities	5,058,090	5,056,480
Non-Controlling		
Interests in Blackstone Holdings	4,920,201	5,253,670
Total Equity	17,069,128	17,966,061
Total Liabilities and Equity	**$ 41,086,439**	**$ 42,524,227**

Figure 11.2. Blackstone Inc. Consolidated Balance Sheet (Dollars in Thousands, Except Share Data) Q1-2023. Source: 10-Q Quarterly Report https://ir.blackstone.com/sec-filings/default.aspx

	Three Months Ended 31-Mar-23	31-Mar-22
Revenues		
Management and Advisory Fees, Net	$ 1,658,315	$ 1,475,936
Incentive Fees	142,876	104,489
Investment Income (Loss)		
Performance Allocations		
Realized	646,894	1,766,386
Unrealized	(759,212)	1,293,050
Principal Investments		
Realized	108,058	285,104
Unrealized	(491,417)	73,961
Total Investment Income (Loss)	(495,677)	3,418,501
Interest and Dividend Revenue	90,485	54,485
Other	(14,154)	72,869
Total Revenues	**1,381,845**	**5,126,280**
Expenses		
Compensation and Benefits		
Compensation	716,285	656,505
Incentive Fee Compensation	63,281	41,019
Performance Allocations Compensation		
Realized	296,794	717,601
Unrealized	(313,249)	472,284
Total Compensation and Benefits	763,111	1,887,409
General, Administrative and Other	273,394	240,674
Interest Expense	104,441	66,747
Fund Expenses	48,399	2,192
Total Expenses	**1,189,345**	**2,197,022**
Other Income		
Change in Tax Receivable Agreement Liability	(5,208)	761
Net Gains from Fund Investment Activities	71,064	50,876
Total Other Income	**65,856**	**51,637**
Income Before Provision for Taxes	258,356	2,980,895
Provision for Taxes	47,675	483,281
Net Income	**210,681**	**2,497,614**
Net Income (Loss) Attributable to Redeemable		
Non-Controlling		
Interests in Consolidated Entities	(6,700)	5,052
Net Income Attributable to		
Non-Controlling		
Interests in Consolidated Entities	74,869	216,375
Net Income Attributable to		
Non-Controlling		
Interests in Blackstone Holdings	56,700	1,059,313
Net Income Attributable to Blackstone Inc.	$ 85,812	$ 1,216,874
Net Income Per Share of Common Stock		
Basic	**$ 0.12**	**$ 1.66**
Diluted	**$ 0.11**	**$ 1.66**

Figure 11.3. Blackstone Inc. Consolidated Income Statement (Dollars in Thousands, Except Share and Per Share Data) Q1-2023. Source: 10-Q Quarterly Report https://ir.blackstone.com/sec-filings/default.aspx

	Three Months Ended	
	31-Mar-23	31-Mar-22
Operating Activities		
Net Income	$ 210,681	$ 2,497,614
Adjustments to Reconcile Net Income to Net Cash		
Provided by Operating Activities		
Blackstone Funds Related		
Net Realized Gains on Investments	(924,643)	(2,164,499)
Changes in Unrealized (Gains) Losses on Investments	508,398	(101,802)
Non-Cash		
Performance Allocations	753,212	(1,233,050)
Non-Cash		
Performance Allocations and Incentive Fee Compensation	46,827	1,230,904
Equity-Based Compensation Expense	277,431	219,083
Amortization of Intangibles	12,996	18,698
Other		
Non-Cash		
Amounts Included in Net Income	(348,203)	(215,753)
Cash Flows Due to Changes in Operating Assets and		
Liabilities		
Cash Relinquished with Deconsolidation of Fund Entities	(113,588)	-
Accounts Receivable	(470,691)	169,644
Due from Affiliates	151,635	722,779
Other Assets	12,284	118,945
Accrued Compensation and Benefits	(483,939)	(1,079,703)
Securities Sold, Not Yet Purchased	(3)	16
Accounts Payable, Accrued Expenses and Other		
Liabilities	233,965	52,257
Repurchase Agreements	(70,381)	19,310
Due to Affiliates	(65,276)	22,831
Investments Purchased	(1,130,045)	(773,867)
Cash Proceeds from Sale of Investments	1,746,068	3,295,094
Net Cash Provided by Operating Activities	**352,728**	**2,748,501**
Investing Activities		
Purchase of Furniture, Equipment and Leasehold		
Improvements	(69,557)	(56,152)
Net Cash Paid for Acquisitions, Net of Cash Acquired	(5,413)	-
Net Cash Used in Investing Activities	**(74,970)**	**(56,152)**
Financing Activities		
Distributions to		
Non-Controlling		
Interest Holders in Consolidated Entities	(215,124)	(284,496)
Contributions from		
Non-Controlling		
Interest Holders in Consolidated Entities	173,657	181,824
Payments Under Tax Receivable Agreement	(64,634)	(46,880)
Net Settlement of Vested Common Stock and Repurchase of		
Common Stock and Blackstone Holdings Partnership Units	(108,101)	(32,061)
Proceeds from Loans Payable	78	1,481,644

Figure 11.4. Blackstone Inc. Consolidated Cash Flows Statement (Dollars in Thousands) Q1-2023. Source: 10-Q Quarterly Report https://ir.blackstone.com/sec-filings/default.aspx

	Shares of Blackstone Inc. (a)	Blackstone Inc. (a)							
	Common Stock	Common Stock	Additional Paid-in-Capital	Retained Earnings (Deficit)	Accumulated Other Comprehensive Income (Loss)	Total Stockholders' Equity	Non-Controlling Interests in Consolidated Entities	Non-Controlling Interests in Blackstone Holdings	Total Equity
Balance at December 31, 2022	718,276,923	$7	$ 6,935,273	$ 1,748,106	$ (27,475)	$ 7,666,911	$ 5,856,480	$ 6,253,670	$ 17,966
Transfer Out Due to Deconsolidation of Fund Entities	-	-	-	-	-	-	-	-	-
Net Income (Loss)	-	-	-	85,812	-	85,812	74,809	56,700	217
Currency Translation Adjustment	-	-	-	-	5,142	5,142	-	3,548	8
Capital Contributions	-	-	-	-	-	-	123,952	2,447	126
Capital Distributions	-	-	-	(677,809)	-	(677,809)	(194,866)	(451,978)	(1,334
Transfer of Non-Controlling Interests in Consolidated Entities	-	-	-	-	-	-	(2,345)	-	(2
Deferred Tax Effects Resulting from Acquisition of Ownership Interests from Non-Controlling Interest Holders	-	-	2,001	-	-	2,001	-	-	2
Equity-Based Compensation	-	-	117,227	-	-	117,227	-	76,468	193
Net Delivery of Vested Blackstone Holdings Partnership Units and Shares of Common Stock	2,143,256	-	(18,004)	-	-	(18,004)	-	-	(18
Repurchase of Shares of Common Stock and Blackstone Holdings Partnership Units	(1,000,000)	-	(90,097)	-	-	(90,097)	-	-	(90
Change in Blackstone Inc.'s Ownership Interest	-	-	(4,927)	-	-	(4,927)	-	4,927	
Conversion of Blackstone Holdings Partnership Units to Shares of Common Stock	1,374,788	-	15,581	-	-	15,581	-	(15,581)	
Balance at March 31, 2023	712,794,968	$7	$ 5,957,054	$ 1,156,109	$ (22,333)	$ 7,090,837	$ 5,858,090	$ 4,928,201	$ 17,060

Figure 11.5. Blackstone Inc. Consolidated Stockholders Equity Statement (Dollars in Thousands, Except Share and Per Share Data) Q1-2023. Source: 10-Q Quarterly Report https://ir.blackstone.com/sec-filings/default.aspx

They are complemented by the Management discussion and analysis (MD&A) that the management uses to add more qualitative information not captured in the financial statements. It has to give a narrative explanation and comment on liquidity, capital requirements, unusual or infrequent events, known trends or uncertainties, and material changes (item 303 (b) of Regulation S-K, ("Regulation S-K," 2022)).

11.2 Financial Analysis for Investors

Analyzing a company's financial documents should help investors evaluate its investment prospects. For instance, the famed value investor Benjamin Graham (Graham et al., 2006) recommended analyzing financial statements to value a company's intrinsic value and calculate a margin of safety, the difference between intrinsic value and market value. Warren Buffet, a disciple of Graham, in its 1987 shareholder letter (Buffett, 1987), described companies he was interested in investing in:

We hope to buy more businesses that are similar to the ones we have, and we can use some help. If you have a business that fits the following criteria, call me or, preferably, write.

Here's what we're looking for:

(1) large purchases (at least $10 million of after-tax earnings),

(2) demonstrated consistent earning power (future projections are of little interest to us, nor are "turnaround" situations),

(3) businesses earning good returns on equity while employing little or no debt,

(4) management in place (we can't supply it),

(5) simple businesses (if there's lots of technology, we won't understand it),

(6) an offering price (we don't want to waste our time or that of the seller by talking, even preliminarily, about a transaction when price is unknown).

Warren Buffet emphasizes consistent earning power, good return on equity, and low leverage, all data originating from the financial statements.

If a company is listed and markets are efficient (Chapter 3), it is not obvious that such information would give a clear edge to investors. Nowadays, machines automatically read and analyze financials at a much faster speed than a human can ever hope to do. Even before the era of algorithmic trading machines, researchers investigated whether accounting information such as earnings was useful.

11.2.1 The Role of Earnings

A stock price can be seen as the present value of future earnings; therefore, earnings are essential for the valuation of a company. Everything else being equal, higher earnings should give a higher stock price. Thus, earnings and stock returns are intimately linked (Dechow et al., 2014). Earnings from financial statements are accounting earnings that might differ from true economic earnings because they contain imperfect accounting adjustments such as accruals, historical inventory costs, and accounting conventions.

(Beaver, 1968) studies the information content of annual earnings announcements by looking at the abnormal trading volume and price volatility (Beaver variables) in the week around earnings announcements and found that they both increase; therefore, earnings seem informative to investors. (Landsman and Maydew, 2001) reproduce similar results with data of 1000 US firms from 1972 to 1998 and find the Beaver variables are higher for companies in high intangible industries, larger firms, lower for utilities, financial services, and service firms, and firms with negative earnings.

The paper by (Ball and Brown, 1968) was the first event study that documented that stock prices anticipate change in earnings many months before the annual earnings release dates and that there was price drift after release. The study used monthly data and an event period twelve months before the end of the earnings release month and six months afterward. Stock returns were calculated as abnormal returns after controlling for a market factor. Three types of earnings variables were tested. (Kothari and Wasley, 2019) provide a good overview of this field of research.

(Ball and Kothari, 1991) examine the risk and return of stocks around earnings announcements and find that abnormal returns are higher for the smaller firms after controlling for increased risk. They reject the hypothesis that a risk premium causes abnormal returns due to uncertainty resolution and also reject the information hypothesis that states the timing of earnings release is informative because management wants to release good news early and bad news late.

11.2.2 Post-Earnings Announcement Drift

(Bernard and Thomas, 1989) investigate the post-earnings announcement drift (PEAD), the tendency for prices to continue to drift (for a quarter or more) in the direction of the earnings surprise. If earnings are unexpectedly higher (lower), prices continue to increase (decrease). Investors' underreaction could explain the PEAD returns to the earnings news or a risk premium to compensate for some risk factors. (Fink, 2021) summarizes the findings of the extensive literature around PEAD:

- *The PEAD is a global phenomenon.*
- *The abnormal return of the PEAD was around 4% per quarter in the past but may be disappearing.*
- *The PEAD used to persist for multiple quarters, but research now typically focuses on the quarter directly following the announcement.*
- *The strength of the PEAD is inversely related to firm size.*
- *Earnings surprises used to detect PEAD can be defined via earnings time series, analyst forecasts, and returns.*
- *PEAD is a separate anomaly, not subsumed by others.*

- *Insufficient risk adjustment typically does not explain abnormal returns.*
- *Information uncertainty leads to an underreaction to earnings news, and the delayed reaction results in PEAD.*
- *Trading frictions (transaction costs, liquidity) are positively related to PEAD and partly explain it.*
- *Information processing costs cannot explain the PEAD.*
- *Active institutional ownership weakens PEAD.*
- *Investors fail to incorporate or underestimate earnings autocorrelation.*
- *Naive expectations are more prevalent in unsophisticated investors.*
- *Underestimation of earnings autocorrelation depends on the level of autocorrelation.*
- *Analysts (and managers) exhibit biases that are similar to those found in the market.*
- *SUE ("Standardized Unexpected Earnings," the difference between realized and expected earnings, normalized by earnings volatility) autocorrelation and drift are stronger when earnings surprises are driven by cash flow (as opposed to accruals) or revenue (as opposed to expense) surprises.*
- *PEAD returns can be affected by firm characteristics such as past PEAD, reputation, and celebrity status.*
- *Accounting practices and earnings management lead to variations in PEAD returns.*
- *Sensitivity of earnings to inflation can partly explain the PEAD.*
- *Limited investor attention contributes to the PEAD.*
- *Overconfidence bias and cultural dimensions contribute to the PEAD.*
- *The disposition effect affects the PEAD.*
- *Anchoring and recency bias affect PEAD.*

The study concludes that not a single explanation is the source of PEAD but that underreaction to news, limits to arbitrage (PEAD does not exist for liquid stocks), and information uncertainty are good candidates.

11.2.3 Accruals

Accruals play an essential role in financial accounting. They reconcile earnings and cash flows so that revenues and expenses are recorded when they occur and match more closely in the same period. A business could sell goods to customers today but invoice them and be paid later. Accruals will book the revenue today even though the money has not been received. Accruals depend on projections and might not be realized, for instance, if the customer never pays or the good is returned.

Accruals are calculated as working capital accruals from the balance sheet and the income statement (Dechow et al., 1995):

Accruals = (change in current assets - change in cash/cash equivalents) - (change in current liabilities - change in debt included in short-term liabilities - change in income tax payables) - depreciation and amortization expenses

Earnings, accruals, and cash flows are then simply related by:

Earnings = Income from Continuing Operations/Average Total Assets

Accrual Component = Accruals/Average Total Assets

Cash Flow Component = (Income from Continuing Operations-Accruals)/Average Total Assets

(Dechow, 1994; Dechow and Dichev, 2002) look at the quality of accruals. Good accruals improve earnings quality by better matching revenues and expenses, while poor accruals introduce estimation errors. They find that the quality of accruals improves with firm size but worsens for firms with volatile sales, cash flows, earnings, larger accruals, and longer operating cycles.

An important issue related to accruals is the possibility of earnings management by firms. Company management can be tempted to make favorable accrual assumptions to smooth or beat some quarterly earnings numbers. (Dechow et al., 1995) and (Dechow et al., 2012) propose some methods to detect such earnings management. An essential data source is the SEC Accounting and Auditing Enforcement Release

(AAER), which contains companies accused of overestimating their earnings. Using such a list, they can test their models.

In the same line of research, earnings can also be managed downward, though it is less common. For instance, (Jones, 1991) documents that firms that could benefit from import relief managed their earnings downward with smaller accruals to appear weaker and more exposed to foreign competition during the investigation phase that would recommend imposing import tariffs or quotas.

(Sloan, 1996) (Richardson et al., 2010, 2005) have tested investment strategies using accruals. High accruals are temporary and tend to reverse, while cash flows are more permanent. Investors are fixated on earnings and ignore the accrual component. The strategy to have a portfolio of long low accrual companies and short high accrual companies is profitable.

11.2.4 Prediction of Earnings and Stock Returns

(Ou and Penman, 1989) test whether financial statement analysis can be used to predict stock returns. Using a logistic regression, they start with a list of 68 predictors and test if they can predict the direction of future earnings (earnings up or down and controlling for a long-term drift in earnings). Using univariate estimates, they select 16 predictors for the period 1965-1972 and 18 for the period 1973-1977:

The combined list of predictors is as follows:

- Percentage change in the current ratio
- Percentage change in quick ratio
- Percentage change in inventory turnover
- Inventory/total assets
- Percentage change in inventory/total assets
- Percentage change in inventory
- Percentage change in sales
- Percentage change in depreciation
- Change in dividend per share
- Percentage change in (depreciation/plant assets)
- Return on opening equity

- Change in return on opening equity
- Percentage change in (capital expenditures/total assets)
- One-year lag of percentage change in (capital expenditures/total assets)
- Debt-equity ratio
- Percentage change in debt-equity ratio
- Percentage change in (sales/total assets)
- Return on total assets
- Return on closing equity
- Gross margin ratio
- Percentage in (pretax income/sales)
- Sales to total cash
- Percentage change in total assets
- Cash flow to debt
- Working capital/total assets
- Operating income/total assets
- Repayment of LT debt as a percentage of total LT debt
- Cash dividend/cash flows

They then test a long-short investment strategy from 1973–1983 based on the probability of earnings going up (long) or down (short). The positions are taken three months after the publication of the annual financials and held for 24 months. They find the strategy profitable with an average two-year return of around 12.5% (without transaction costs) and suggest that fundamental information contains information not reflected in prices.

(Abarbanell and Bushee, 1998) also explore the effectiveness of applying fundamental analysis concepts to achieve abnormal returns in the stock market. They also use various signals related to fundamental analysis, including changes in inventories, accounts receivables, gross margins, etc. They find that portfolios constructed based on these signals yielded an average 12-month cumulative abnormal return of 13.2

percent and, therefore, suggest that fundamental analysis can generate abnormal returns in the stock market, particularly in the context of short to medium-term investment horizons and for specific types of companies.

(Azevedo et al., 2021) To improve forecast accuracy, introduce a combined model (CM) that integrates analysts' earnings forecasts, gross profits, and past stock performance. This CM outperforms other popular models, including raw analysts' forecasts and various regression-based models, regarding bias, accuracy, and Earnings Response Coefficients (ERC). The model is also applied to estimating the Implied Cost of Capital (ICC). The ICC calculated using the CM yields a more meaningful relationship with gross profitability and stronger associations with ex-post realized returns, making it a valuable tool for investment decisions.

11.3 AI and Financial Analysis

11.3.1 Data Collection and Preprocessing

Financial reports include relevant non-financial data, such as in the letter to shareholders or management discussion and analysis (Figure 11.6). Using sentiment analysis (Chapter 10), an AI could update the financial data based on these text reports and the context of these data. More hedging comments could, for instance, signal more uncertainty in some financial forecasts. AI could understand discussions around market competition, innovation, corporate governance, and geopolitics and relate them to broader studies and research findings.

Microsoft Annual Report 2022

Discussion & Analysis

MANAGEMENT'S DISCUSSION AND ANALYSIS OF FINANCIAL CONDITION AND RESULTS OF OPERATIONS

The following Management's Discussion and Analysis of Financial Condition and Results of Operations ("MD&A") is intended to help the reader understand the results of operations and financial condition of Microsoft Corporation. MD&A is provided as a supplement to, and should be read in conjunction with, our consolidated financial statements and the accompanying Notes to Financial Statements in our fiscal year 2022 Form 10-K. This section generally discusses the results of our operations for the year ended June 30, 2022 compared to the year ended June 30, 2021. For a discussion of the year ended June 30, 2021 compared to the year ended June 30, 2020, please refer to in our fiscal year 2022 Form 10-K, "Management's Discussion and Analysis of Financial Condition and Results of Operations" in our Annual Report on Form 10-K for the year ended June 30, 2021.

OVERVIEW

Microsoft is a technology company whose mission is to empower every person and every organization on the planet to achieve more. We strive to create local opportunity, growth, and impact in every country around the world. Our platforms and tools help drive small business productivity, large business competitiveness, and public-sector efficiency. They also support new startups, improve educational and health outcomes, and empower human ingenuity.

We generate revenue by offering a wide range of cloud-based and other services to people and businesses; licensing and supporting an array of software products; designing, manufacturing, and selling devices; and delivering relevant online advertising to a global audience. Our most significant expenses are related to compensating employees; designing, manufacturing, marketing, and selling our products and services; datacenter costs in support of our cloud-based services; and income taxes.

Highlights from fiscal year 2022 compared with fiscal year 2021 included:

- Microsoft Cloud (formerly commercial cloud) revenue increased 32% to $91.2 billion.
- Office Commercial products and cloud services revenue increased 13% driven by Office 365 Commercial growth of 18%.
- Office Consumer products and cloud services revenue increased 11% and Microsoft 365 Consumer subscribers grew to 59.7 million.
- LinkedIn revenue increased 34%.
- Dynamics products and cloud services revenue increased 25% driven by Dynamics 365 growth of 39%.
- Server products and cloud services revenue increased 28% driven by Azure and other cloud services growth of 45%.
- Windows original equipment manufacturer licensing ("Windows OEM") revenue increased 11%.
- Windows Commercial products and cloud services revenue increased 11%.

Figure 11.6. Management Discussion & Analysis from Microsoft Annual Report 2022. Source: https://www.microsoft.com/en-us/corporate-responsibility/reports-hub

(Bryzgalova et al., 2022) address the issue of missing data in firm characteristics, which are essential for academic research in finance. They highlight that the standard source of fundamental firm-level data, the Compustat database, often lacks information on various variables, including R&D data, current assets and liabilities, physical assets, investment, profits, and taxes. Missing data is a significant issue, both historically and in recent data. It affects more than 75% of all stocks during the 2000s. This missing data has implications for empirical tests in asset pricing and corporate finance.

A statistical model for imputing missing values in firm characteristics is introduced. This model efficiently leverages available information from time series and cross-section data, making it applicable to various missing data patterns. The authors demonstrate that missing data can impact asset pricing research. Using a subset of stocks with fully observed characteristics can lead to selection bias in asset pricing metrics. Moreover, imputing missing data using less accurate methods, such as median imputation, can distort parameter estimates in asset pricing models.

11.3.2 Forecasting and Predictive Analytics

An important for an AI analyst is to forecast stock returns and risk based on financial statements, reporting, and disclosure analysis. This task can involve predicting revenues, earnings, cash flows, and capital expenditures based on all kinds of data, including alternative data (Chapter 12). For instance, ad spending or consumer purchasing power could be correlated with future revenues. An AI analyst could update all the financial data and produce an updated stock price forecast in real-time and even a distribution of price forecasts, which human analysts do not provide quantitatively. Furthermore, with a layer of explainability focused on the important data features and removing noise, AI could improve financial data quality, transparency, and interpretability.

Even though financial reporting aims to provide all the helpful information for investors to follow and understand financial performance, it is still limited by accounting convention, infrequent and lagged reporting, and emphasis on historical accounting data instead of market data. It, therefore, can introduce biases in the financial data. An AI system could find the optimal trade-off between historical and market data, between the accuracy and volatility of financial data. Intangible assets are another case where the accounting value might significantly diverge from the true value, and AI could provide a better estimate between the historical value measured at acquisition time if it was part of an M&A and zero. AI could automatically make the relevant accounting and market adjustments to make the financial data more informative.

(Huang et al., 2022) evaluate machine learning methods for long-term stock prediction based on fundamental analysis. They compare the prediction performance of three advanced machine learning methods using fundamental features, using data extracted from quarterly financial reports of 70 stocks in the S&P 100 between 1996 and 2017. They explore feed-forward neural networks (FNN), random forests (RF), and adaptive neural fuzzy inference systems (ANFIS), which are the machine learning techniques used in the research. Their methodology includes data preparation, local learning, evaluation metrics, feature selection, and model aggregation. They find that all "Buy" portfolios outperform the market, while "Sell" portfolios underperform. RF performs best in constructing portfolios, followed by FNN and ANFIS. Feature selection improves the prediction performance of FNN but not ANFIS or RF. Model aggregation, particularly "agg3," outperforms individual models in constructing portfolios.

(Ding et al., 2020) use machine learning to improve accounting estimates, mainly focusing on data from insurance companies. Accounting estimates are crucial in financial reporting but are prone to errors and manipulation. Their study demonstrates that machine learning-generated loss estimates using input variables related to business operations, company characteristics, and external environment outperform managerial estimates in the context of insurance claims. This suggests that machine learning can enhance the reliability of financial reports and assist auditors in evaluating accounting estimates. While the study focuses on insurance data, it highlights the potential for machine learning to improve accounting estimates more broadly.

(Chen et al., 2022) use machine learning techniques to analyze comprehensive financial data, including financial statements and footnote disclosures, to predict corporate performance and stock returns. They address two key challenges in this analysis: the high dimensionality of financial data and the need to arrange detailed information in a machine-readable format.

To tackle the first challenge, they employ machine learning methods such as random forests and stochastic gradient boosting, which can handle complex relationships and many predictors. These methods predict the direction of one-year-ahead earnings changes as a measure of corporate performance. The authors leverage eXtensible Business Reporting Language (XBRL) for the second challenge. They collected over 8,000 XBRL filings from 2012 to 2018, resulting in more than 4,000 unique financial items.

The study finds significant predictive power in the machine learning models when forecasting the direction of earnings changes. The models outperform traditional regression models, particularly in capturing nonlinear interactions among variables. The results also show that footnote disclosures contribute the most to the predictive power of the models.

(Green and Zhao, 2022) provide a review of recent developments in forecasting earnings and returns in the financial markets. They emphasize the challenges forecasters face, including the unpredictability of earnings and returns, noisy variables, and model uncertainty. They categorize recent research efforts in addressing these challenges and offer several important insights:

Finding new meaningful predictors remains a crucial task, even with recent advancements in data and methodologies. While new methods may hold promise, their usefulness can be limited. However, applying thoughtful estimation methods and constraints can offer promising opportunities. Despite efforts, finding earnings predictors that outperform lagged earnings as a forecasting tool remains challenging. The process of sorting through and understanding various models and methods is complex, and achieving recommended best practices in forecasting has room for improvement.

11.3.3 Forensic Accounting

(Kondo et al., 2019) discuss the issue of accounting fraud and its economic implications. Accounting fraud, which involves misreporting financial statements, can distort decision-making in financial transactions and result in inefficient resource allocation. It can also affect policy interventions and lead to errors in policy evaluation. The study highlights that theoretical research has explored the reasons behind accounting fraud and identified correlated financial information, particularly discretionary accounting accruals, that may indicate fraud.

The study emphasizes two critical issues in existing research on accounting fraud detection. First, current efforts are limited regarding the number of variables considered, which can affect the accuracy of fraud detection models. Second, most research focuses on detecting fraud in current financial statements (nowcasting) rather than forecasting future fraud events.

To address these issues, the authors propose using machine learning methods to build a fraud detection model that can incorporate many explanatory variables. The expanded set of variables includes financial indicators, corporate governance-related variables, and bank transaction variables. The study aims to improve the detection performance of fraud models.

Additionally, they introduce the concept of forecasting accounting fraud, which involves predicting fraud events occurring one year after the assessment. The results suggest that machine learning models with high-dimensional data can effectively forecast future accounting fraud.

They also identify variables, such as the average length of employee service and the percentage of outstanding shares held by company executives, as essential contributors to fraud detection and forecasting. These findings suggest that additional variables beyond those considered in existing research may significantly impact fraud detection and prediction.

(Bao et al., 2020) focus on the development of a new model for predicting accounting fraud in publicly traded U.S. firms using readily available financial statement data. Accounting fraud poses significant risks to stakeholders, and detecting it is challenging. By leveraging machine learning techniques, they create a predictive model that can identify accounting fraud beyond existing models.

They use detected material accounting misstatements from the SEC's Accounting and Auditing Enforcement Releases (AAERs) as the sample for accounting fraud. They focus on financial data as a readily available and cost-effective predictor.

Two benchmark models are used: a logistic regression model based on financial ratios and a model using machine learning techniques (Support Vector Machines) to create financial kernels for prediction. The study evaluates model performance using two metrics: the area under the Receiver Operating Characteristics (ROC) curve (AUC) and Normalized Discounted Cumulative Gain at the position k (NDCG@k). Results indicate that the ensemble learning model outperforms both benchmark models in predicting accounting fraud, with higher AUC and NDCG@k scores.

11.4 Case Studies

11.4.1 Fundamental Analysis Via Machine Learning

Expectations about future earnings are essential in determining the value of securities and the challenges investors face when forming these expectations using historical financial statements. However, despite incorporating various financial statement items, traditional accounting models often fail to consistently outperform a simple random walk model in forecasting future earnings.

(Cao and You, 2020) look at forecasting of corporate earnings with fundamental financial data and machine learning models. They compare the performance of six machine learning models and several existing models in forecasting earnings using 56 input variables, including financial statement line items.

They use US fundamental data of publicly listed companies from Compustat and the Center for Research in Security Prices (CRSP) from 1965 to 2019.

They train different machine learning models, three linear models and three nonlinear models:

- Linear models:
    - Linear regression (OLS)

  - LASSO regression
  - Ridge regression
- Nonlinear models:
  - Random Forest (RF)
  - Gradient Boosting Regression (GBR)
  - Artificial Neural Network (ANN)

The variable definitions are as follows:

Earnings to be forecasted

$Et+1$ Earnings in year t + 1

$EPSt+1$ Earnings in year t + 1 scaled by shares outstanding

The input features for machine learning models are:

- Income statement items:
  - Sales
  - Cost of goods sold
  - Selling, general, and administrative expenses
  - Advertising expense
  - Research and development (R&D) expense
  - Depreciation and amortization
  - Interest and related expense
  - Non-operating income (expense) – Other
  - Income taxes
  - Extraordinary items and discontinued operations
  - Earnings
  - Common dividend
- Balance sheet items:
  - Cash and short-term investments
  - Inventories

  - Receivables
  - Total current assets
  - Property, plant, and equipment – Net
  - Investments and advances – other
  - Intangible assets
  - Total assets
  - Accounts payable
  - Debt in current liabilities
  - Income taxes payable
  - Total current liabilities
  - Long-term debt
  - Total liabilities
  - Common/Ordinary equity
  - Cash flow from operating activities
- First-order differences of the above 28 items:
  - Computed as the corresponding item in year t less the same item in year t - 1

They compare their models with five linear regression models in the literature:

Random Walk model:

$$E_{i,t+1} = E_{i,t} + \varepsilon_{i,t+1}$$

An auto-regressive model (AR):

$$E_{i,t+1} = \alpha_0 + \alpha_1 E_{i,t} + \varepsilon_{i,t+1}$$

A model by (Hou et al., 2012):

$$EPS_{i,t+1}=\alpha_0+\alpha_1 A_{i,t+}+\alpha_2 D_{i,t}+\alpha_3 DD_{i,t-}+\alpha_4 E_{i,t+}+\alpha_5 NegE_{i,t}+\alpha_6 AC_{i,t}+\varepsilon_{i,t+1}$$

A model by (So, 2013):

$$EPS_{i,t+1}=\alpha_0+\alpha_1 EPS_{i,t+}+\alpha_2 NegE_{i,t}+\alpha_3 AC_{i,t-}+\alpha_4 AC_{i,t+}+\alpha_5 AG_{i,t}+\alpha_6 NDD_{i,t}+\alpha_7 DIV_{i,t}+\alpha_8 BTM_{i,t}+\alpha_9 Price_{i,t}+\varepsilon_{i,t+1}$$

And two models by (Li and Mohanram, 2014), the EP (earnings persistence):

$$E_{i,t+1}=\alpha_0+\alpha_1 NegE_{i,t}+\alpha_2 E_{i,t}+\alpha_3 NegE_{i,t}*E_{i,t}+\varepsilon_{i,t+1}$$

and RI (residual income) models:

$$E_{i,t+1}=\alpha_0+\alpha_1 NegE_{i,t}+\alpha_2 E_{i,t}+\alpha_3 NegE_{i,t}*E_{i,t}+\alpha_4 BVE_{i,t}+\alpha_5 TACC_{i,t}+\varepsilon_{i,t+1}$$

The inputs of these regression models are:

- Et Earnings in year t
- At Total assets
- Dt Dividend payment
- DDt Dummy variable indicating dividend payers
- $NegEt$ Dummy variable indicating negative earnings
- ACt Accruals calculated as the change in non-cash current assets minus the change in current liabilities, excluding short-term debt and taxes payable minus depreciation and amortization
- $EPSt+$ Earnings per share when earnings are positive, and zero otherwise
- $ACt-$ Accruals per share when accruals are negative and zero otherwise

- $ACt+$ Accruals per share when accruals are positive, and zero otherwise
- AGt Percentage change in total assets
- $NDDt$ Dummy variable indicating zero dividend per share
- $DIVt$ Dividend per share
- $BTMt$ Book-to-market ratio, calculated as the book value of equity divided by the market equity as of three months after the end of the last fiscal year
- $Pricet$ Stock price as of three months after the end of fiscal year t
- $BVEt$ Book value of equity
- $TACCt$ Total accruals defined in (Richardson et al., 2005)

Their results show that machine learning models, especially nonlinear ones, generally provide more accurate earnings forecasts than traditional models. Composite forecasts combining predictions from different models are even more accurate, particularly for firms with volatile earnings. The machine learning models also offer new insights by identifying significant predictors and capturing subtle nonlinear relationships in financial statement data.

They find that the machine learning models provide more accurate forecasts than the previous linear models described in the literature. They conclude that the traditional models underestimate the value of fundamental data to forecast earnings.

Furthermore, the study demonstrates that the information from machine learning forecasts has economic significance, as it predicts future stock returns and analyst earnings forecast errors. This implies that investors and analysts often underreact to the valuable information uncovered by machine learning algorithms.

In the same line of research, (Amel-Zadeh et al., 2020) look at whether fundamental statement analysis can predict market reaction to quarterly earnings announcements and whether fundamental data contains information not fully included in stock prices.

They use several models to predict abnormal return reactions to quarterly earnings: a regression model (OLS), LASSO regression, Random Regression Forests, a Deep Neural Network (DNN), and a Recurrent Neural Network (RNN) on fundamental data of US public companies from 1990 to 2017.

The Random Forest model was the most accurate at predicting returns. The model outperforms linear models because there is a non-linear relationship between earnings surprises and stock returns. However, long-short strategies based on the model prediction are only profitable for large earnings surprises. They generate quarterly alphas from 5.3% to 6.7% for predictions of market reactions above 20%.

11.4.2 Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence

(Commerford et al., 2022) study the effect of relying on AI for decision-making. Auditors are accounting professionals who provide independent opinions about a client company's financial statements. They often work for the Big 4 accounting firms, Deloitte, PwC, EY, and KPMG, and are assigned to companies to audit their financial statements. They must also rely on these companies' management for accounting information, projections and assumptions, data inputs, and estimates.

Accounting firms are not using fully autonomous AI systems yet. Instead, they are developing AI systems (similar to the firms' human specialists) to assist their auditors in performing specific tasks ("narrow AI"), such as evaluating commercial loan grades.

In the context of auditors making adjustments to company management's estimates and receiving advice from a human expert or an AI system, the researchers want to test if the auditors are averse to AI algorithms (because they think AI does not have the appropriate knowledge and expertise) through two hypotheses:

- Hypothesis 1: Auditors will propose smaller adjustments to management's estimates when evidence contradicting management's preferences is received from a firm AI system instead of a human specialist.
- Hypothesis 2: Receiving contradictory evidence from an AI system instead of a human specialist will reduce proposed adjustments to a greater extent when management's estimates are based on relatively more objective than subjective inputs.

They ran their experiment on 170 audit seniors from two Big 4 firms. They find that auditors adjust their estimate less (more) if they think the source is the AI system (a human expert) and if the management's input seems more subjective (objective).

They report the means of the accounting adjustments (in millions) (Figure 11.7) and their standard errors. The adjustment is most significant when the source is a human expert, and the management's input is subjective. The adjustment is smallest when the source is an AI system expert and the management's input is objective.

They analyze variance (ANOVA) tests and report p-values that confirm the statistical significance and the direction of the nature of inputs and source effects.

Nature of Inputs\Source	Human Specialist	AI System	Overall
Subjective Inputs	22.13 (1.52)	19.94 (1.55)	21.04 (1.09)
Objective Inputs	19.81 (1.58)	11.20 (1.76)	15.51 (1.19)
Overall	20.97 (1.10)	15.57 (1.17)	

Figure 11.7. Descriptive statistics of proposed audit adjustments

Hypotheses 1 and 2 are true in their sample and confirm that auditors tend to discount contradictory evidence from AI systems more heavily than from human specialists. This effect is amplified when management's competing evidence appears more objective and credible. Algorithm aversion could become an impediment to wide AI adoption.

11.4.3 Financial Statement Adequacy and Firms' MD&A Disclosures

(Brown et al., 2021) study the disclosures in MD&A (Management Discussion and Analysis) and how they relate to the financial statements' quality. GAAP accounting can sometimes be inadequate, for instance, when some costs, such as R&D and advertising, have to be incurred immediately before revenues come in the future. This mismatch between cost and revenue creates noisy earning numbers that are less informative.

Hypothesis 1 to be tested states that "firms with less adequate financial statements use the MD&A channel for communication to a larger extent." Because management knows the limitations of GAAP accounting, they are willing to provide more information in the MD&A, particularly about non-GAAP items.

Other tests include:

Hypothesis 1a. Firms with less adequate financial statements provide more non-GAAP discussion in the MD&A.

If the financial statements are inadequate, future economic performance should be more challenging to predict, and management will provide more forward-looking statements (FLS).

Hypothesis 1b. Firms with less adequate financial statements provide more forward-looking statements in the MD&A.

The quality of a financial statement (Value Relevance) is measured as the R^2 (coefficient determination) in the regression of stock price on the book value and earnings per share.

The regression is using the last 20 quarters for each firm.

$$P_q = a_0 + a_1 \, EPS_q + a_2 \, BPS_q + e_q$$

P_q: the firm's stock price at the end of fiscal period q

EPS_q: the diluted EPS reported for period q

BPS_q: the book value of equity divided by the number of common shares outstanding at the end of period q

If the R^2 is very low, it means that financial statements are inadequate to inform about the stock price. Inadequacy is defined as $1\text{-}R^2$.

The dataset contains 36,552 firm-year observations and comes from electronic 10-K reports filed with the SEC available on EDGAR and Compustat from 2003 to 2016.

The authors look at the disclosure of non-GAAP data such as earnings or research and development expenses and how it is related to the quality of the financial statement by using keywords such as "non-GAAP," "non GAAP," and "adjusted earnings."

They use a machine learning library called Spacy, a Convolutional Neural Networks (CNN) model, and train it to recognize forward-looking statements in the MD&A.

In the training set, each sentence is manually labeled as:

(1) a forward-looking statement about the company,

(2) a statement that is future-oriented but could be said about almost any company or

(3) not a forward-looking statement.

They run a linear regression with the count of non-GAAP words as a dependent variable:

$$\text{Log}(1+\textit{NonGAAP Count}) = b_0 + b_1\textit{Inadequacy} + \Sigma\rho_n\text{Control}_n + \text{fixed effects} + \xi$$

They find a negative relationship between the probability of non-GAAP disclosure and Value Relevance (positive with Inadequacy).

They also run a regression of forward-looking statements (the number of forward-looking sentences in the firm's MD&A for the fiscal year) as a dependent variable:

$$\textit{FLS} = c_0 + c_1\textit{Inadequacy} + \Sigma\rho\rho_{nn}\text{Control}_n + \text{fixed effects} + \mu$$

They also find a negative relationship between the number of forward-looking statements (FLS) and Value Relevance. Hypothesis 1a and 1b are confirmed.