THE PREDICTION OF FUTURE EARNINGS USING FUNDAMENTAL SIGNALS

THE ASYMMETRIC IMPACT OF FUNDAMENTALS ON OPERATING PROFITABILITY

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Abstract

According to fundamental analysis theory, various sources of accounting and economic information may be used to determine the fundamental value of a firm. One such source is information included in the financial statements. Forecasting future earnings has been an objective of various previous studies within the fundamental analysis research field, due to its usefulness in the firm valuation process. Past research has shown that information found in financial statements can be used to predict future earnings. In our paper, we test whether results found in such previous studies hold true under more recent market conditions. Additionally, we test whether the effect of negative signals is stronger than the effect of positive signals. Our results show that the fundamental signals Inventory, Accounts Receivable and CAPEX are significantly related to future earnings, whereas no significant result was found for Gross Margin. We find that a positive signal change in Inventory has a larger effect on future earnings than a negative signal change. However, this asymmetrical effect was not observed for the remaining variables.

Keywords: Earnings prediction, Fundamental signals, Asymmetric impact

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1. Introduction

The ability of financial statement based signals to predict future earnings has been examined thoroughly by prior literature. Numerous studies found a relation between fundamental signals and future earnings (Baruch and Sougiannis, 2009; Ou & Penman, 1989). Despite a large number of studies in the area, there is a lack of clarity regarding the fundamental signals analyzed, as the results of these studies are not always aligned.

Past studies have chosen different approaches to fundamental signals selection, such as statistical methods or observing which fundamental signals are considered important according to financial analysts. In our study, we have decided to replicate the study of Abarbanell and Bushee (1997) who based their variable selection on the study of Lev and Thiagarajan (1993). These studies use variables based on the judgement of financial analysts. The number of variables used in our paper was reduced to four; Inventory, Accounts Receivable, CAPEX, and Gross Margin. This alteration is based on the suggestion expressed by the authors of our benchmark paper to reduce the number of fundamental signals and consequently select ones with a robust relationship to future earnings.

Additionally, we select a short-term period of one-year ahead future earnings. The short-term standpoint has been chosen due to the level of difficulty of forecasting earnings in the current highly competitive market environment, comprising of growth companies and other external factors affecting the ability to forecast earnings.

Furthermore, we modify the model with a more suitable proxy for the measurement of earnings. Both Lev and Thiagarajan (1993) and our benchmark paper have used Earnings per share as their dependent variable for measuring future earnings. Even though using a different variable will deem our results less comparable to our benchmark study, we believe that there is a strong argument supporting this measurement. Earnings per share include a bottom-line earnings measurement, Net Income. Net income is affected also by the financing of the firms. As our variables are connected to the operational side of the company, which is not affected by the financing, we believe that we can get a more accurate association with EBIT which is directly affected by the operations but neither by the effect of financing the company nor company taxes.

We have identified one aspect that has not been investigated in any of the previous studies investigating the relationship between fundamental signals and future earnings, specifically, the impact of the positive versus negative signals. In the past, asymmetrical distribution of stock market returns has been observed as it was shown that stock prices' reaction to negative earnings surprises is larger than their reaction to positive earnings surprises (Lim, 2009). The existence of this asymmetry can be reasoned for in various ways. Firstly, the largest movements in the stock market prices are usually decreases, as opposed to increases. Secondly, market returns indicate "asymmetric volatility" which is a tendency for volatility to increase with negative returns. (Duffee, 1995) (Bekaert & Wu, 2000) Thirdly, since the crash in 1987, the prices of stock index options exhibit negative asymmetry in return, as the volatilities of out-of-the-money puts are much higher than of out-of-the-money calls. This lastly mentioned pattern is known under the term “smirk”, which is a part of the index-implied volatilities. (Bakshi et al., 1997) Even though generally the negative asymmetries in the market are not disputed, the underlying economic mechanism that is reflected by these asymmetries is unsettled (Chen et al., 2001).

As we could not find other studies that would study this phenomenon in the operational setting of the company, our results could be beneficial in order to observe this phenomenon in company operations context. The underlying argument that we used for a suggested company setting implication is the empirical observation indicating that an increase in earnings in the company takes a considerably larger time, e.g., due to competitive market conditions, in comparison to a decrease in earnings. The earning decrease can happen at a more escalated pace due to both external and internal factors.

The scope of this study is limited to firms located in the United States in the Energy, Materials, and Industrial sectors. We have selected these industries due to their stability, implying stable levels for our independent variables, in comparison to values for companies in growth sectors. Additionally, having companies from the sector with stable growth and profitability are aligned with the purposes of our study to obtain a steady next year's estimate of EBIT that can be used in fundamental valuation and forward-looking multiples.

We find a significant relationship between future earnings and fundamental signals Inventory, Accounts Receivable, and CAPEX. Whereas our results do not show a significant result for Gross Margin. Additionally, our results for CAPEX and Gross Margin, show an opposite relationship to future earnings than expected priorly.
The relationship of CAPEX to future earnings is the opposite, suggesting that with the increased CAPEX expenditure, the one-year ahead earnings decrease. Whereas the relationship of GM to future earnings is the opposite as well, which goes against economical intuition. Furthermore, investigating the impact of negative and positive signals shows a significant result for one of our variables, specifically, Inventory. Our findings show that the decrease in Inventory has a positive effect on future earnings, whereas the increase in Inventory has no impact on future earnings. As decrease is Inventory is a positive signal, our initial assumption regarding a larger impact of negative signals was not confirmed. No other fundamental signals have shown a significant result when the asymmetry between positive and negative signals was tested.

2. Literature review

In this section, we summarize relevant literature related to our study. We structure this section beginning from a broader perspective to a narrow one addressing the questions researched in this paper.

2.1. Valuation

Valuation is an important economic activity as it determines how finite resources are allocated to firms and individuals (Hayek, 1945). This implies that efficient valuation increases welfare and has a significant role in our economy. There is a strong link between accounting information and corporate valuation and to fully understand its role in our economy, one must understand its role in valuation (Monahan, 2018).
To value a company, multiples are commonly utilized. Empirical evidence shows that forward-looking multiples, such as those using projected EBIT, are better for valuation purposes compared to trailing multiples (Liu et al.,2002; Schreiner et al., 2007). Forward-looking multiples are in line with the principles of valuations as the company value equals future cash flows, while sunk costs are not incorporated. According to Monahan (2018), based on analytical and empirical evidence, accrual-accounting earnings are a central part of the valuation.

2.2. Fundamental analysis

Penman (2010) defines fundamental analysis as "the analysis of information that focuses on valuation". Identifying mispriced securities with respect to their intrinsic value is of interest to researchers and practitioners, while the latter can use it for investment purposes. Consequently, coming up with improved forecasts of earnings is the focal point of the majority of the fundamental analysis research in accounting, as it assists in the valuation of securities. (Kothari, 2001)
Part of the foundation for fundamental analysis in relation to forecasting earnings based on fundamental signals was created by the early work of Ou and Penman (1989), Lev and Thiagarajan (1993), and Holthausen and Larcker (1992).

Richardson et al. (2010) analyzed the current research in accounting animalities and fundamental analysis, using forecasting of future earnings and stock returns as their framework and organizing concept. They concluded that the fundamental analysis literature demonstrates the usefulness of accounting information to forecast future earnings and stock returns.

2.3. Earnings forecast

Lev and Thiagarajan (1993) examined the relations between the fundamental signals and two indicators of persistence: the earnings response coefficient and future earnings growth. Instead of applying a statistical search procedure used in previous research, such as Ou and Penman (1989), authors identify candidate fundamentals from the written announcements of financial analysts. Lev and Thiagarajan (1993) first conducted OLS estimates of the 1974-1988 year-by-year cross-section regression and an across-years significance test of annual excess stock returns on EPS change and 12 selected accounting-related fundamental signals: Inventory, Accounts Receivable, Capital Expenditure, R&D, Gross Margin, Selling and Administrative Expenses, Provision for Doubtful Receivables, Effective Tax, Order Backlog, Labor Force, LIFO Earnings, and Audit Qualification. For their dependent variable, they have selected a pre-tax earnings proxy.

The result shows Inventory, CAPEX, Gross Margin, S&A, and Labor Force signals are statistically significant at 5% significance level, whereas the Effective Tax and Receivables are significant at the level of 10%. Compared to their benchmark model (regression simply between EPS change and return), the model including fundamental signals has a higher R squared almost every year, which means the examined signals contributed significantly to the "explanation" of excess return variance, beyond reported earnings. Additionally, Lev and Thiagarajan (1993) investigated if their results hold true under various macroeconomic contexts. Their results show that several fundamental signals are value-relevant only under specific economic conditions. Their results showed that Accounts Receivable and provisions for doubtful receivables were more strongly associated with returns during the period of high inflation compared to the results of the unconditional analysis.

Our benchmark paper written by Abarbanell and Bushee (1997), investigated whether current changes in the fundamental signals are informative about subsequent earning changes. Their approach is in line with Penman (1992) and others who consider accounting earnings as a central task of fundamental analysis. Abarbanell and Bushee (1997) based their research variables on the study of Lev and Thiagarajan (1993). They have selected 9 accounting-related fundamental signals: Inventory, Accounts Receivable, Capital Expenditure, Gross Margin, Selling and Administrative Expenses, Effective Tax rate, Earnings Quality, Audit Qualification, and Labor Force. As their dependent variable, they have selected an after-tax earnings proxy, which they motivated by the ability to compare their results with previous. For the one-year-ahead regression 4180 observations were used, between 1983 to 1990. For the subsequent five-year regression 1619 observations were included between 1983 to 1987.

Their results showed that Inventory, Gross Margin, Effective Tax rate, LIFO Earnings, and Labor Force are significant at 5% significance level for one-year ahead earnings. Gross Margin is positively related to future earnings according to their results. CAPEX was negatively related to one-year ahead earnings, implying that CAPEX investments above the industry average affect the one-year ahead earnings negatively. Additionally, the result for Accounts Receivable shows a positive relation.

Results of the five-year regression, Effective tax rate signal, and Labor force signal showed significant relationships to long-term growth. These signals might, according to the authors, capture unidentified risk factors or structural changes. Lev and Thiagarajan (1993) hypothesized that the Effective tax rate signal captures more than just transitory effects, the result obtained by Abarbanell and Bushee (1997) supports this.

Abarbanell and Bushee (1997) have also looked at these fundamental relationships under macroeconomic contexts. They split their data sample into high and low inflation years and GDP years. The results show that macroeconomic trends have little effect on the relations acquired using the unconditioned data.

Luchs et al. (2012) followed the methodology developed by Lev and Thiagarajan (1993) in order to examine the ability of the fundamental signals to explain both future earnings and stock returns. However, to complement the current research that studied firms in the US, they chose an international setting and studied the firms located in India. Future earnings and returns are regressed on five of the original 12 signals (due to data limitation and accounting rules): Inventory, Receivable, R&D, auditor qualification, and effective tax rate. The sample consists of 291 firms and 398 firm years. The results show that the audit opinion and effective tax rate signals are statically associated with future earnings, while the coefficient for the audit opinion is negative, suggesting opinions are associated with lower future earnings. The coefficient of the effective tax r variable is positive, indicating increases in the effective tax rate are correlated with increases in future earnings. These findings differ substantially from the relationship identified by previous studies.

Lev et al. (2010) studied the usefulness of accounting information in order to forecast cash flows and earnings. Their highlight that the quality of financial information is compromised by the high difficulty of making estimates and forecasts, as well as frequent managerial misuse of those estimates. They claim that due to the move to fair value accounting, there is an increasing prevalence of estimates. The number of their data sample was 73,324 observations in the years between 1988-2005. In their study, they also included Capital expenditure and Inventory, Deferred taxes, and aggregated the remaining working capital such as Accounts Receivable.
The result shows that accounting accruals disaggregated to working capital items improve the prediction of earnings. The model that performed best for the out-of-sample data included working capital excluding Inventory and two variables specified by them, EST (all other accruals) and CFO (defined as net cash flow from operating activities adjusted).

2.4. Variables

In this section, we will present the variables used in our benchmark paper by including results from other studies researching the ability of these signals to predict future earnings.

2.4.1. Dependent variable

EBIT

Ebit is a profit obtained from the company's core business activities. As it does not include taxes or interest expenses, it reflects the ability of the company to generate earnings directly from operations. This implies that it is not affected by the capital structure of the company or the tax environment. Even though some studies that included EBIT as a proxy for future earnings were conducted (Basu and Wang, 2011), the majority have used Net Income as the proxy for earnings. This can be put a question, as the majority of independent variables used in the previous studies were operating in their nature. Therefore, including EBIT would be beneficial in order to establish a close relationship between the independent variables and the dependent variable.

2.4.2. Independent variables

2.4.2.1. Variables included in our study

In this section we discuss all independent variables that we decided to include in our study. This selection was based on an observed robust relationship between the variable and future earnings. We also include the expected relationship between the variable and future earnings.

Inventory

Basu and Wang (2011) investigated the relationship between changes in inventories and future earnings performance measured by changes in EPS, changes in ROA, and changes in the market-to-book ratio. The formula for ROA was not specified in their paper but based on the term 'a measure of operating performance', EBIT can be assumed. They followed the methodology used by Abarbanell and Bushee (1997) and Lev and Thiagarajan (1993) but examined a larger sample period covering 56 years (from 1950 to 2005) and including firm-year observations from the primary products, manufacturing, and wholesale and retail sectors to see if the negative correlation holds for all time periods. Instead of year-by-year regression, they also ran the regression over 10-year periods (1950-59, 60-69, 70-79, 80-89, 90-99, 2000-05). The results show that an unexpected increase (decrease) in Inventory is followed by a fall (rise) in short-term earnings during the 1970s and 2000s. However, this conclusion does not hold for other periods as there is no significant relation during the 1950s -1960s and a weaker one in the years after 2000. One possible explanation for a weaker trend seen in the later years raised by Basu and Wang (2011) is the improvement of inventory management. Their results show that Accounts Receivables, CAPEX, Gross Margin, and S&A are significant in most of the time periods.

In addition, Basu and Wang (2011) took the different nature between the manufacturing industry and wholesale/retail industry into consideration: unlike manufacturers, wholesalers/retailers don't produce goods and have more flexibility to adjust the inventories level, so they further tested if the negative relation between Inventory and one-year ahead earnings is smaller in wholesale/retail industries. The result shows that there is a slightly weaker relation for wholesalers and retailers and the relation does not hold for companies with a low Inventory level.

Accounts Receivable

The study by Stober (1993) investigated the relationship of Accounts Receivable and Inventory to future sales, earnings, and profit margins. The study builds on the model built by Bernard and Noel (1991) who investigated a relationship between Inventory and future earnings. His data sample consists of 7 manufacturing industries and one retail department store industry, resulting in 168 firms in the United States, in the time range of 1978-1987. He finds that there is a positive relationship between Accounts Receivable and future sales, earnings, and profit margins.

Barth et al. (2001) studied the prediction of future cash flows based on accruals included in financial statements. The tested accruals were grouped into 6 components: Accounts Receivable, Inventory, Accounts payable, Depreciation, Amortization, and other accruals. Based on the weight of each component, they estimated a different relation to future cash flows. They predicted that an increase in Accounts Receivable will be associated positively with future cash flows. This relation is confirmed by their results as well as a significant relationship between Accounts Receivable and future cashflows.

Capex

Curtis et al. (2020) investigated the association between current-year R&D expenses and future earnings (Y+1/Y+5 net income) in a modern context due to the increasing importance of R&D and spending on it (R&D/other investments ratio increased from 10% to 29%). They examined US companies with positive R&D expenses over the period 1980-2016. With 51,563 firm-year observations, they drew the conclusion that the profitability of R&D dropped significantly from 1980-1990 and then stabilized at a lower level. They reasoned the contributors as firstly, the decreasing interest rates resulting in positive NPV intensifying companies to invest more broadly, and secondly, the nature of R&D shifts from profit generation to keeping current market share.

Gross Margin

Kesavan et al. (2010) have found that firms' sales forecasts can be improved using historical Inventory and Gross Margin at a firm-year level. Their test sample consisted of 230 observations, US retail securities, in the time range between 1993-2007. According to the authors, the negative Gross Margin signal may stem from the differences in firms' ability to resist input price increases or pass them on takes on bigger importance.

2.4.2.2. Variables not included in our study

In this section, we discuss independent variables that we excluded from our study. These variables were included in our benchmark paper Abarbanell and Bushee (1997).

Labor force

According to analysts, there is a relation between corporate restructuring, particularly reductions in labour force and earnings. In this way, analysts estimate the persistence of earnings, as during the year with a high labour reduction wage-related expenses increase (for example due to severance pay). The future benefits are therefore not reflected in the current reported earnings (Lev and Thiagarajan, 1993). Even though (Lev and Thiagarajan, 1993) found a significant relation for this variable, Abarbanell and Bushee (1997) did not find any relation for their one-year-ahead forecast.

Selling and administrative expenses

This fundamental signal was used both in Abarbanell and Bushee (1997) and Lev & Thiagarajan (1993). A disproportional increase in S&A compared to the changes in sales is considered a negative signal, as these costs are usually fixed cost. Their increase might suggest a loss of managerial cost control. Furthermore, it might suggest an unusual sales effort. (Bernstein et al., 1988)

Effective tax rate

Accor to the analyst, an increase in the effective tax rate in relation to the change of statutory tax rate is transitory and does not reflect less persistent earnings (Lev and Thiagarajan, 1993). Therefore, in their research, Lev and Thiagarajan (1993), considered this signal as negative. (We keep a question mark here and consider this indicator more related to a statutory tax change, so we want to exclude this one in our thesis.)

LIFO Earnings

This variable measures which Inventory method the company is using. Since LIFO earnings are regarded as better at reflecting the economic value than FIFO earnings, LIFO Inventory methods is considered a positive signal. (Lev and Thiagarajan, 1993) Even though the study of Abarbanell and Bushee (1997) shows a significant result for this variable, the study of Lev and Thiagarajan (1993) did not obtain a significant result.

Audit qualification

In previous studies (Abarbanell and Bushee (1997), Lev and Thiagarajan (1993), the Audit qualification variable is included, dividing firms according to the audit qualification criteria into qualified and unqualified firms. Unqualified companies have their finances completely in order and aligned with the auditors' requirements, while the financial statements of qualified companies lack a complete alignment and auditors can not conclude an unqualified opinion (Cipriano, 2017). The number of qualified companies is close to zero for US SEC registrants from 2000–2015, (Cipriano, 2017), therefore we do not consider this variable useful as the number of qualified firms is too small.

2.5. The effect of positive versus negative signals

Findings of numerous studies performed in the field of sociology indicate a phenomenon called negativity bias (Rozin and Royzman, 2001). Baumeister et al. (2001) suggested that negative information generally has a stronger pull on attention than positive information does. Previous literature shows that people are more sensitive to negative than to neutral or even positive events of equal intensity, which is known as Negative Bias and is frequently mentioned by humanists. In Accounting and Finance fields, we see a limited number of studies related to this phenomenon.

Chang and Hao (2022) extend their research on Negativity Bias when examining the analyst's forecast behavior. They found that negative local income growth on analysts' forecast bias is 1.5 times that of positive income growth, which is supportive of their hypothesis of the existence of Negativity Bias. The methodology Chang and Hao (2022) applied to measure the negative effect is separating observations into 2 groups with positive and negative local income growth respectively and running regression for each of the two groups. Before separating, the coefficient of local income growth is 0.02 and not significant while the coefficients become -0.05 and 0.08 for the positive and negative groups, and both are significant at the 1% level.

Lim (2009) investigated how positive versus negative earnings surprises affect the stock price using the data sample based on US companies. His findings showed that the negative surprises had a larger impact on stock price behavior than the positive earnings surprises.

2.6. Hypothesis

H1: Fundamental signals derived from the financial statements are related to future earnings

H2: Negative signals have a larger impact on future earnings than positive signals

3. Methodology

In this section, we explain our choice of method, define our variables and present our prediction models.

3.1. Choice of Model

To investigate the relationship between fundamental signals to future earnings we have decided to do a quantitative study. We use panel data including historical numbers as we want to predict future earnings based on the operational variables in the previous period. To control for the industry effect, we have created a categorical variable showing the affiliation to the specific industry: Energy, Industrials, and Material industry.

Fundamental signals Inventory, Accounts Receivable, Capital Expenditure, and Gross Margin are included in our model to examine their relationship to future earnings. Compared to previous research where Net Income or EPS served as an earnings indicator, in this paper we chose Earnings before Interest and Tax (EBIT) as the dependent variable given our considerations. At first, the effective tax rate is not included as one of the signals. Secondly, EBIT is the key input to calculate Free Cash Flow for DCF valuation. Thirdly, according to the order of items in the income statement, there is naturally a closer relationship between these independent variables (Inv, AR, Capex, GM) and EBIT compared to EPS.

In addition, the net change of EBIT, Inventory, Accounts Receivable, and Capital Expenditure is not comparable among companies of different sizes, while the Gross Margin stands comparable, all variables but Gross Margin are divided by the Total assets of the firm to ensure that all signals are allocated in the same dimension. (Gross Margin is scaled by 100 for the consistency of coefficients in later regression.) The selection of Total Assets instead of Total Revenues as the denominators is due to Gross Margin equal to Gross Profit over *Total Revenues.* If all signals have Total Revenues as the denominators, the regressors will be simplified to a net change of Inv, AR, Capex, and Gross Profit, which creates discrepancies in the research aim.

3.2. Variable Definitions

Signal	*Measured as:*	*Description:*	*Relation**
EBIT	$\frac{EBIT_{t+1} - EBIT_t}{Total\ Assets_t}$	ΔEBIT in year t+1, scaled by Total Assets in year t	
INV	$\frac{Inventory_t - Inventory_{t-1}}{Total\ Assets_t}$	ΔInventory in year t, scaled by Total Assets in year t	−
AR	$\frac{Accounts\ Receivable_t - Accounts\ Receivable_{t-1}}{Total\ Assets_t}$	ΔAccounts Receivable in year t, scaled by Total Assets in year t	+
CAPEX	$\frac{Capital\ Expenditure_t - Capital\ Expenditure_{t-1}}{Total\ Assets_t}$	ΔCapital Expenditure in year t, scaled by Total Assets in year t	+
GM	$\frac{Gross\ Margin_t - Gross\ Margin_{t-1}}{100}$	ΔGross Margin in year t, scaled by 100	+

Table 1. Variables included in our study, their measurement description, and expected relation to future earnings

Note: Signal GM is scaled by 100 to ensure the consistency of coefficients in later regression
This column expresses the expected relationship between the variable and future earnings; + denotes a positive relation; - denotes a negative relation

In the following parts, tested signals will be simplified to *EBIT*, *INV*, *AR*, *CAPEX*, and *GM* respectively.

3.3. Earnings Prediction Model based on fundamental signals

$$EBIT_{i,t+1} = \alpha_{i,t} + \beta_1 INV_{i,t} + \beta_2 AR_{i,t} + \beta_3 CAPEX_{i,t} + \beta_4 GM_{i,t} + \varepsilon_{i,t}$$

3.4. Earnings Prediction Model incorporating the negative signal effect

After testing the relation between fundamental signals and future earnings, we will further test the presence of negative signal effect. For each signal with a significant coefficient, a dummy variable will be generated to obtain the positivity (+/-). For the new model, a new variable will be added which equals Dummy*Signal. The coefficient μ indicates the change of slope at different sides of the x-axis.

$$EBIT_{i,t+1} = \alpha_{i,t} + \beta_1 INV_{i,t} + \beta_2 AR_{i,t} + \beta_3 CAPEX_{i,t} + \beta_4 GM_{i,t} \\ + \mu Dummy * Signal_{\ i,t} + \varepsilon_{i,t}$$

Where Dummy = 1 when Signal >0

4. Data Analysis

In this section, we describe our Sample Selection, Raw Data, Data Process and Descriptive Statistics.

4.1. Sample Selection

Geographically, we focus on the US market, on one hand, it is consistent with the previous studies and on the other hand, there are more listed companies under the same accounting rules on a yearly basis that can be included in our data sample. We consider it beneficial to use only one accounting system, US GAAP, due to the consistency in reporting rules. Based on the GICS (The Global Industry Classification Standard), out of the nine total, the *Energy*, *Materials*, and *Industrials industries* were selected as these three industries have a more stable Inventory and Accounts Receivable level. On contrary to this, some retail businesses have a relatively low-level Inventory, and Health Care or the Financials industry does not necessarily have inventories. Through the screening process in Capital IQ, 2029 common stocks listed in the United States from Energy, Materials, and Industrials were selected out of 113206 among the whole security universe. Additionally, these industries have more stable growth compared to others, leading to less volatile earnings.

For time series selection, we want to focus on the modern context. FY 2019 onwards was excluded given the pandemic influence, so subscript t ranges from 2006 to 2017.

To create our panel data set, Total Assets, Earnings Before Interest and Taxes (EBIT), Accounts Receivable, Capital Expenditure (Capex), and Gross Margin were extracted from annual reports FY 2005 - FY 2018, and 2029 companies were selected as they fulfilled our screening criteria (*Table 2.*). Period FY 2006 - FY 2014 served as the test data set for our model and FY 2015 - FY 2017 was separated as the out-of-sample test data period.

The values for Total Assets, Inventories, Accounts Receivable, and Capex were directly extracted from Financial Reports; whereas EBIT, and Gross Margin values were calculated by Capital IQ, where:

$$Gross\ Margin = \frac{Gross\ Profit}{Total\ Revenues}$$

$$EBIT = Total\ Revenues - Total\ Operating\ Expenses$$

Step	Screening Criteria	Observations:
1	Country/Region of Incorporation: United States	113206
2	Industry Classifications: Energy OR Materials OR Industrials	19161
3	Equity Security Features: Primary Listing	10488
4	Equity Security Features: Active	2071
5	Equity Security type: Common Stock	2029

Table 2. Screening process in Capital IQ

4.2. Raw Data Description

In FY 2006, there are 244 US-listed firms in the Energy industry, 557 in the Industrials industry, and 243 in the Materials industry. As of 2022, the numbers increased to 335, 849, and 339 for Energy, Industrials, and Materials respectively.
The mean EBIT from FY 2006-2018 ranged from $189mn (2009) to $361mn (2008). Except for FY2015-FY2017, the Energy industry has the highest operating income and the Materials industry has the lowest operating income among all the years with standard deviation following the same trend. Before the crude oil price plunge started in mid-2014, the mean EBIT of the Energy Industry is three times the mean EBIT of Materials. Afterward, the EBIT difference became smaller among the three industries. FY2006-2017, Energy Industry has the highest average total assets, followed by Industrials then Materials.
From FY 2005-2017, the mean Inventory ranged from $161mn (2005) to $335mn (2017). The Inventory levels are similar for the three industries but there’s a continued growth trend in Inventory over time. In terms of Accounts Receivable, the growth trend is less significant, and the average Capex varies over time, while the Energy industry has the highest value of both fundamentals.
The average Gross Margin of Energy, Materials and Industrials in the States from FY 2005-2017 ranged from 30% to 40%, whereas in most years it was stabilized at 32% with a median of 28%. Aligned with the EBIT statistic, the Energy sector with the

highest mean EBIT is supported by a highest Gross Margin of around 45%, and the Materials industry with the lowest mean EBIT has around 27% margin.

For some extreme values, we examined the data with company annual reports to ensure accuracy.
Devon Energy Corporation (DVN) reported a -$18 billion loss, the lowest EBIT among all years in FY 2015. An $18 billion U.S. oil and gas assets impairment occurred in 2015, resulting from the crude oil price plunge between mid-2014 and early 2016(the biggest oil price drop in modern history). General Electric Company keeps owning the largest total assets in all the years from 2006-2007. The Boeing Company has the highest Inventory level among the panel data: $61 billion in FY2017, which includes $1.8 billion in long-term contracts in progress, $52.8 billion in commercial aircraft programs related to 737 and 787, and $6.8 billion in commercial spare parts, used aircraft, general stock materials and other. The high Inventory backed up with orders was in line with its 87% stock rise as well as outstanding performance in 2017. In FY2009, Avis Budget Group, Inc. has a negative CAPEX of $330mn (net cash inflow). The reason is Avis had $7.1 billion "Proceeds received on the disposition of vehicles" and they reported this item under Investing activities in Statement of Cash Flow to offset Investment in vehicles.

4.3. Data Process

We detected some data points have abnormal values which would cause problems in statistical procedures. Therefore, we conducted an analysis to identify the possible causes.

Firstly, some raw data exported directly from Capital IQ had a value of zero or NAN. When listed companies are not reporting accounting items like Inventory or Accounts Receivable, it would automatically show NAN as a result. The 0 value, however, means that for some of the years, companies disclosed certain accounting items while in some other years they did not. To be more specific, Allied Resources, Inc (OTCPK:ALOD) reported a $0.835 million Capital Expenditure in FY2007 but no Capex spending in other years. Under such a situation, we dropped the firms with a 0 or NAN value which shows inconsistency in reporting. Secondly, for some company years, Gross Margin is bigger than 1. The reason is companies reported negative COGS in their P&L. For example, Providence Resources, Inc. recorded a $5,000 total revenue and a (-$30,000) Cost of Sales in FY2006, making the Gross Margin hike to 7,365%. As a result, years with a Gross Margin greater than 1 were also dropped.

As visible from the boxplot graphs in Appendix 2, there are many data points that have extremely high or low values. Signal *EBIT* has many extremely high values while signal *INV* and *AR* have many extremely small values. These kinds of outliers could make the R-Squared statistic exaggerated (Initially we got an insane R-Squared of 92% for the cross-year model). On the other side, these extreme values are event-driven and relevant to the macro economy (as mentioned in section 4.2 Raw Data Description; for example, the oil price hike). To avoid the effect of outliers, Z-score is calculated for each independent variable based on yearly data, consequently, observations that contain any independent variable with a z-score bigger than 3 or smaller than -3 were dropped.

$$z\_score = \frac{x - \mu}{sd}$$

4.4. Descriptive statistics

There are 395 US-listed firms in Energy, Industrials, and Material industry continuously report the four fundamental data during 2005-2017. After excluding the outliers and other abnormal values, we get 3242 observations as cross-year data. The average and median values of both the dependent variable and independent variable are positive. Signal *GM* has the highest standard deviation, followed by Signal *Inv*, and Signal *Capex* has the smallest standard deviation. From a year-by-year perspective, each year contributes 354 (FY 2010) to 367 (FY 2014) observations.

Descriptive statistics

SIGNAL	(1) N	(2) mean	(3) sd	(4) min	(5) max
EBIT	3,242	0.00596	0.0557	-0.285	0.241
INV	3,242	0.00733	0.0317	-0.186	0.148
AR	3,242	0.00704	0.0348	-0.185	0.172
CAPEX	3,242	0.00439	0.0272	-0.134	0.130
GM	3,242	0.00143	0.0361	-0.235	0.186

Table 3. Descriptive statistics of variables used in the study.

5. Results

In this section, we describe the results of our regression models.

5.1. Hypothesis 1: Fundamental Signals

Table 4. shows the regression results for OLS with and without industry and Year fixed effects over the cross-year panel data. Signals *INV*, *AR*, and *CAPEX* all have significant coefficients at a 99% level in all models we tested. *GM* shows a significant result only in the models with the Year fixed effects model, with a 95% significance level. Our results show that *INV* has a negative coefficient, *AR* has a positive coefficient, *CAPEX* has a negative coefficient, and *GM* has a negative coefficient. With fixed effects added in, the R squared will be increased while the coefficients will become smaller.

VARIABLES	(1) OLS	(2) Fixed Effect Industrials	(3) Fixed Effect Year	(4) Fixed Effect Industry & Year
INV	-0.191***	-0.196***	-0.126***	-0.130***
	(-5.76)	(-5.92)	(-3.83)	(-3.99)
AR	0.299***	0.300***	0.268***	0.268***
	(9.91)	(9.95)	(9.06)	(9.11)
CAPEX	-0.153***	-0.133***	-0.124***	-0.103***
	(-4.25)	(-3.65)	(-3.54)	(-2.92)
GM	-0.024	-0.028	-0.055**	-0.058**
	(-0.90)	(-1.02)	(-2.12)	(-2.26)
_IIndustrials		0.013***		0.013***
		(4.02)		(4.24)
_IMaterials		0.010***		0.010***
		(2.85)		(3.00)
Year Fixed Effects	No	No	Yes	Yes
Constant	0.006***	-0.005	0.017***	0.007*
	(5.96)	(-1.58)	(6.01)	(1.73)
Observations	3,242	3,242	3,242	3,242
R-squared	0.035	0.040	0.126	0.131

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Results of regression analysis for OLS and Fixed effects models

Regression (1) is the basic regression model without industry and year fixed effect, Regression (2) includes Industry fixed effects, Regression (3) includes Year fixed affects and Regression (3) includes both Industry and Year fixed effects.

The *INV* signal has a negative coefficient ranging from -0.13 to -0.19, indicating the increase in Inventory will have a negative influence on next year's operating income. This is aligned with the results of Basu and Wang (2011) and our prior expectation.

For *AR*, it has a positive coefficient ranging from 0.27 to 0.3, which means the increase in Accounts Receivable has a positive effect on future earnings. These findings are aligned with Stober (1993) who found this relation for his data sample of firms within the manufacturing industry as well as our prior expectations.

CAPEX signal has a negative coefficient ranging from –0.153 to –0.103, suggesting an increase in capital expenditure is actually bad news for the one–year ahead earnings. This result is consistent with Abarbanell and Bushee (1997)'s when they looked at the one-year forecast. However, it is not aligned with our expectation as we expected a positive sign.

GM signal has a negative coefficient, with a very small value ranging from –0.058 to –0.024. This result is also in line with the results of our benchmark paper Abarbanell and Bushee (1997) which also found a negative coefficient for this variable. However, neither this variable coefficient aligned with our expectations as we expected a positive sign.

Appendix 3 presents OLS estimates of 2006-2014 year-by-year cross-sectional regression and one cross-year regression. Each year has observations ranging from 354-367, with Adjusted R-squared ranges from 0% in 2014 to 12% in 2009. In 2014, the R-squared dropped from 1.2% to 0% after adjustment, which could be due to an over-fitting problem. Note that in 2008 and 2009, *INV* has a significant coefficient compared to all the other years. During the great recession, the higher level of inventories might indicate a weak demand in the market and would further indicate a negative change for the next year's operating income. This result is interesting as according to Basu and Wang (2011), there is only a weak relation between inventories and future earnings after 2000. However, their data set only reached 2005. They have proposed that the weaker relation is due to improved Inventory management systems. Our results suggest that the great recession has influenced this relationship. Except years 2013 and 2014, all the yearly coefficients of *AR* are positive and these years with negative coefficients show a significant result. Even though Lev and Thiagarajan (1993) suggest that increased Accounts Receivable might suggest credit extension, we believe that our results suggest a larger sales momentum. To obtain a credit extension is not a commonality, as usually the contracts between the supplier and customer are specified for longer periods. Furthermore, we can not see any deviations around the great recession where more credit extensions were expected to occur. *CAPEX* is significant in 4 years (out of 9) - 2006, 2009, 2010, 2013. Except for the year 2012, all the coefficients are negative. As there is no longer a period where the effect could be identified, it questions the reliability of this signal. As discussed in previous literature (Abarbanell and Bushee, 1997), increasing *CAPEX* benefits the company in the longer term, but the earnings effect of the new project is usually not immediate, however, the depreciation cost increase is instant. *GM* is significant only in the years 2009 and 2011. *GM* is significant only in the years 2009 and 2011. *GM* is significant only in the years 2009 and 2011. For 3 years its coefficient is negative; in 2008, 2009, and 2011; and it is positive in the rest of the 6 years. As all years with significant results are located around the great recession, this might be caused by fixed cost staying constant in the short term for the firms (e.g. due to long-term labor contracts). At the same time, the total number of units sold has decreased due to the lower purchasing capacity of their customers during the recession.

Appendix 4. shows the result of LSDV (Least Square Dummy Variable Model) based on the year-fixed effect which presents the estimates of the heterogeneous effect for each year. The base year was set as the year 2006. The coefficients range from -0.051 in 2018 to 0.01 in 2009. As stated above, the results obtained by the year-fixed effect model show a higher R squared but the coefficients are smaller compared to OLS for all of the observed variables except *GM*, for which the coefficient increases from -0.024 to -0.058. Furthermore, even though the result for *GM* was insignificant in the OLS model, in the LSDV model it is significant with 95% significance level. This result is more aligned with the economic intuition and the results of previous studies that have found a relationship between Gross Margin and future earnings.

5.2. Hypothesis 2: Asymmetric Impact of Negative Signal

We further test if negative signals have an asymmetric impact on future earnings.

VARIABLES	(1) OLS	(2) INV	(3) AR	(4) CAPEX
INV	-0.191***	-0.454***	-0.191***	-0.189***
	(-5.76)	(-8.06)	(-5.76)	(-5.69)
AR	0.299***	0.305***	0.317***	0.301***
	(9.91)	(10.13)	(6.20)	(9.96)
CAPEX	-0.153***	-0.142***	-0.154***	-0.241***
	(-4.25)	(-3.94)	(-4.26)	(-3.52)
GM	-0.024	-0.023	-0.025	-0.021
	(-0.90)	(-0.87)	(-0.91)	(-0.77)
INV_Dummy		0.451***		
		(5.76)		
AR_Dummy			-0.032	
			(-0.43)	
CAPEX_Dummy				0.141
				(1.50)
Constant	0.006***	0.001	0.006***	0.005***
	(5.96)	(1.12)	(4.74)	(3.76)
Observations	3,242	3,242	3,242	3,242
R-squared	0.035	0.045	0.035	0.036

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Results of regression incorporating negative signal effect

Table 5. shows the results of tests investigating the impact of negative and positive signals on future earnings. One of the selected variables, *INV*, shows a significant result at 99% significance levels. For this variable, the coefficient β equals -0.454 and coefficient μ equals 0.451. As the Dummy equals 1 for values larger than 0, this result shows that when the Inventory levels increase, there is almost no effect on future EBIT. However, we can observe an effect when Inventory levels decrease, as this results in increased future EBIT. Therefore, we observe an asymmetry, as the positive signal has an effect on future earnings (β = -0.454) whereas the negative signal does not show this result (-0.454+0.451= -0.003).

6. Robustness Tests

In this section, we describe the results of selected validity checks.

6.1. Multicollinearity

As we use multiple linear regression models in our analysis, we chose to test if the problem of multicollinearity does not affect our results. This phenomenon refers to an instance when 2 or more independent variables are highly correlated. Some authors also call this phenomenon ill conditioning or collinearity (Read & Belsley, 1994), (Puntanen, 2013). Due to multicollinearity, the coefficients can become significant or nonsignificant falsely, as well as the sign of the coefficient can be false (Tsagris & Pandis, 2021).

To test multicollinearity within our independent variables, we have used a variance inflation factor analysis (VIF). Besley (1982) stated in his paper that VIF in the range of 0-10 indicates weak dependencies. As our results indicate a VIF close to the value 1, we do not consider our regression coefficients affected by this phenomenon.

Variance inflation factor

	VIF	1/VIF
AR	1.198	.835
INV	1.193	.838
CAPEX	1.045	.957
GM	1.03	.971
Mean VIF	1.116	.

Table 6. Result of collinearity diagnostics

6.2. Model Variation Test

We also conducted an additional robustness test by removing one regressor at a time. *Table 7.* shows that we obtained the same variable significance results as in our complete OLS regression analysis. The only deviation occurs when *AR* is removed, as the significance level of *Inventory decreases from 99% significance level to 95%*

significance level. The coefficient signs are as well identical, except for the test where *AR* is removed, and the coefficient of *GM* becomes slightly positive contrary to the negative one in our OLS result. The R squared of the conducted tests is comparable. However, even in this case, the regression model with the deducted *AR* stands out, as the R squared decreased to only 0.6% in this model variation. This result in not surprising as the *AR* signal is the one with the largest coefficient and strongly significant results.

VARIABLES	(1) OLS	(2) Drop_INV	(3) Drop_AR	(4) Drop_CAPEX	(5) Drop_GM	(6) 2015-2017
INV	-0.191***		-0.072**	-0.206***	-0.192***	-0.046
	(-5.76)		(-2.31)	(-6.25)	(-5.81)	(-0.85)
AR	0.299***	0.237***		0.287***	0.297***	0.215***
	(9.91)	(8.36)		(9.52)	(9.87)	(4.90)
CAPEX	-0.153***	-0.176***	-0.119***		-0.156***	-0.208***
	(-4.25)	(-4.89)	(-3.26)		(-4.33)	(-3.92)
GM	-0.024	-0.033	0.002	-0.033		-0.074**
	(-0.90)	(-1.21)	(0.08)	(-1.21)		(-2.12)
Constant	0.006***	0.005***	0.007***	0.005***	0.006***	0.007***
	(5.96)	(5.14)	(6.95)	(5.51)	(5.96)	(5.39)
Observations	3,242	3,242	3,242	3,242	3,242	1,087
R-squared	0.035	0.025	0.006	0.030	0.035	0.036

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Result of regressions with change in set of regressors and change in sample

6.3. Heteroskedasticity

Homoscedasticity, an assumption that the variance of the regression errors is constant, is an important presumption in OLS models. If this assumption is violated, the errors in the regression model are called heteroskedastic, and this situation is called heteroskedasticity. (Hayes & Cai, 2007)

We conducted a Breusch-Pagan Test for Heteroskedasticity and obtained a nonsignificant result (chi2(1) = 1.93, Prob > chi2 = 0.1651). As the test did not show heteroskedasticity occurring in our data, we do not conduct additional testing with control for this phenomenon.

6.4. The Returns - Fundamentals Specification

To examine empirically the incremental value-relevance and validity over predicted earnings based on our four fundamentals and negative shock impact, we ran the two cross-sectional regressions with signal *EBIT* as an independent variable, the one-year forward stock total return (same period as signal *EBIT*) as the dependent variable for each industry respectively. The *EBIT* signal stands for a net change of EBIT/ Total Assets, which could be considered as a Proxy for the ROA indicator.

Appendix 6 shows the mean yearly stock return for the Materials, Energy, and Industrials sector from 2006 to 2015. The dots present the standard deviation of each industry. Note that there's a strong rebound after the great recession in 2019, and the US Materials sector was the best performer back then. Starting from the year 2012, the Industrials sector kept outperforming the other two sectors. In most years, the Energy sector has the lowest standard deviation.
In regression (1) we test the correlation between signal *EBIT* and stock return as a comparison group. *Table 8.* shows that it has a positive and significant coefficient within each sector. Note that a higher EBIT increment can indicate a higher current-year stock return. The *EBIT* signal presents the strongest effect in the Materials industry, followed by Industrials and Energy.

$$Returns_{i,t+1} = \alpha + \beta EBIT_{i,Actual,t+1} + \varepsilon \qquad (1)$$

Where:
$Returns = the\ stock\ return\ for\ firm\ i\ from\ Jan1 - Dec31\ the\ same\ year\ EBIT\ covers$

VARIABLES	(1) Industrials	(2) Materials	(3) Energy
EBIT	1.592***	1.709***	0.719*
	(8.05)	(5.90)	(1.75)
Constant	0.079***	0.099***	0.074***
	(8.31)	(6.01)	(2.60)
Observations	1,796	711	277
R-squared	0.035	0.047	0.011

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Result of regression analysis for EBIT and stock return

Then we use the four fundamentals *INV*, *AR*, *CAPEX*, and *GM*, together with the negative shock variable of *AR*: Negative_AR in year t to predict Signal *EBIT* in year t+1.

In regression (2) we test the correlation between our predictor and same-year stock return. The results in *Table* 9. indicate our prediction based on the four fundamental signals cannot explain the contemporary stock return given that R-squared is close to zero and the coefficient is not significant, let alone the coefficient is also negative.

In general, the result is opposite to our expectations and rejects the hypothesis that our predicted earnings based on accounting fundamentals and negative shock signal is incremental value-relevance in the capital market.

$$Returns_{i,t+1} = \alpha + \beta EBIT_{i,Predict,t+1} + \varepsilon \qquad (2)$$

VARIABLES	(1) Industrials	(2) Materials	(3) Energy
Predictor	-0.308	-1.619	-2.338
	(-0.36)	(-1.01)	(-1.02)
Constant	0.092***	0.114***	0.079***
	(8.67)	(6.14)	(2.63)
Observations	1,796	711	277
R-squared	0.000	0.001	0.004

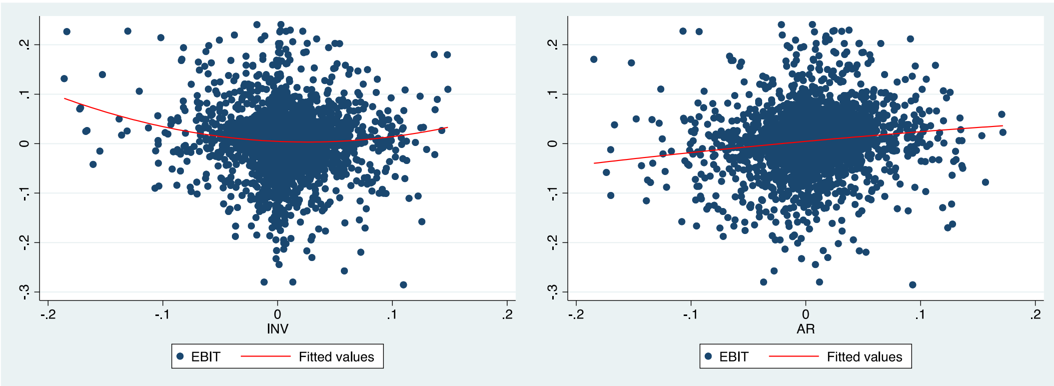
t-statistics in parentheses

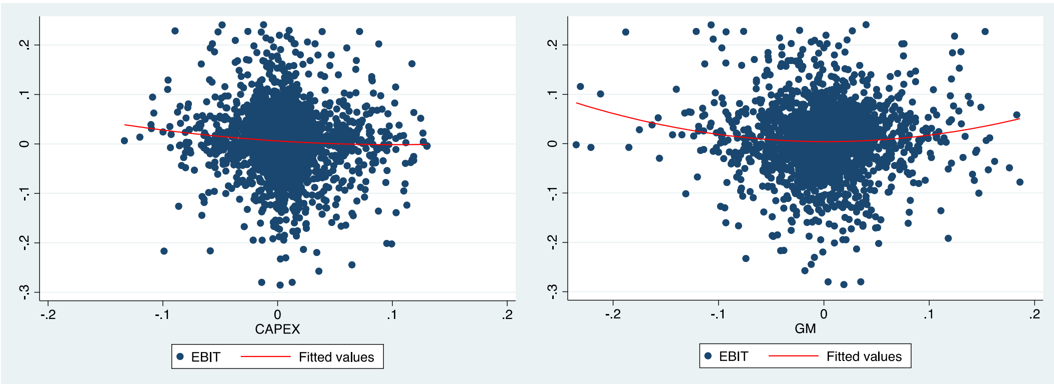
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Result of regression analysis for EBIT predictor and stock return

6.5. Quadratic Regression – Nonlinear regression

Two-way quadratic prediction plots





Given the low R-squared, the variables cannot perfectly explain or predict the future net change of operating income. In order to investigate if there are any non-linear relationships between independent variables and EBIT, two-way quadratic prediction plots were drawn for each signal. The figures for *INV* and *GM* show “U” shape trend, and the *AR* figure continues with a linear trend. To further test our hypothesis, we run quadratic regressions for each fundamental signal. The model is built as follows:

$$EBIT_{t+1} = \alpha + \beta_1 Signal_t + \beta_2 Signal^2{}_t + \varepsilon$$

Once differentiate the formula with respect to Signal:

$$dEBIT_{t+1} = \beta_1 + 2\beta_2 Signal_t$$

Where $Signal$ stands for the primary term of *INV*, *AR*, *CAPEX*, and *GM* respectively and $Signal^2$ stands for INV^2, AR^2, $CAPEX^2$, and GM^2.

The result shows the primary term follows the previous significance. The squared term of signal *INV* and *GM* are positive and significant. β_2 of *GM* tells the curvature is upwards, showing the huge Gross Margin net change (regardless up or down) would have a positive effect on firms' one-year forward operating earnings. One postulate is the huge Gross Margin loss, if not from market competitiveness or bad operating, might be from a more aggressive pricing strategy based on lower margin to boost the top-line sales, leading the operating income to increase.

VARIABLES	(1) INV	(2) AR	(3) CAPEX	(4) GM
β_1	-0.102***	0.211***	-0.148***	-0.008
	(-3.31)	(7.56)	(-3.94)	(-0.28)
β_2	1.972***	-0.159	0.729	1.389***
	(5.40)	(-0.48)	(1.35)	(5.08)
Constant	0.005***	0.005***	0.006***	0.004***
	(4.33)	(4.36)	(5.75)	(4.01)
Observations	3,242	3,242	3,242	3,242
R-squared	0.011	0.017	0.005	0.008

Table 10. Result of Quadratic Regression

7. Discussion

In this section, we will discuss the results presented in section 6 by connecting our findings to previous literature. Section 7.2. present the limitations associated with our study and in section 7.3 we propose our suggestions for future research.

7.1. Results analysis

Our findings confirm the findings of previous papers indicating a relationship between fundamental signals and future earnings. However, while our findings reinforce the informative value of most of the signals involved in our study, it raises questions with respect to others.

The results for Inventory are aligned with previous research. Aligned with other numerous papers, we obtained a significant result, and the negative relation to future earnings was confirmed. Our results were aligned in all the models that were tested. Lev and Thiagarajan (1993) suggested various signals for the negative relation. For instance, increased inventories might signal problems in generating sales or indicate slow-moving or obsolete items Inventory buildups. On the other hand, decreased inventories might indicate sales above expectations. Accounts Receivable also showed results aligned with previous expectations. Accounts Receivable show a significant result in all of the models tested and positive relation to future earnings was found. Moreover, this variable had a significantly larger number of years with a significant result identified in the year-by-year regression compared to other variables included in the model. (Appendix 3) Even though there are conflicting opinions regarding the relation of Accounts Receivable to future earnings, the findings of several papers indicate a positive relation. One explanation might be that Accounts Receivable might signal a trend of sales increase in the company. The Gross Margin signal shows a significant result in all of the models tested, however, the relation to future earnings is surprisingly negative in all of them. This result supports the result of our benchmark paper, which also found a negative relationship for one-year ahead earnings, however a positive one for the five-year ahead one. The reason why we initially expected a positive relationship is due to the economical intuition and findings in other studies. The authors of our benchmark paper argue that this short-term effect might be due to the fact that the immediate earnings are usually not affected by CAPEX immediately, however, depreciation charges are put in the place directly. Normally, companies would raise CAPEX when their operating situation is good and they want to invest in new projects and expand their capacity, which should result in an increase in earnings in a long term. On the contrary, companies would cut CAPEX when the growth rate is achieving their expectation, or they need the capital to cover losses. For example, in 2022 Q3, Taiwan Semiconductor Company announced cutting their estimated 2022 CAPEX by 10%, flagging challenges from rising inflationary costs, and predicting a chip downturn next year. The Gross Margin did not show a significant result in our OLS regression model; however, it showed a slightly weaker significance of 95% significance level in two models, the year fixed model and the year and industry fixed model. Additionally, our results show a negative relationship of this variable to future earnings. Our benchmark paper and various other papers found a significant result with a positive relationship to future earnings. Observing the year-by-year regression analysis we can observe that years with significant results for this result variable occur in the period around the great recession, which might have influenced our findings, but we would need further information to draw further association.

Additionally, we find that the impact of positive signal on future earnings is larger than the impact of negative signal for Inventory, which contradicts our initial hypothesis. However, there was no significance found during our test for the remaining variables. One possible explanation why we were able to find this asymmetric relationship for Inventory, where only the decrease of Inventory had an effect on future earnings, is the attribute of the industries included in our study, *Energy*, *Materials,* and *Industrials.* It might be that due to their operations with large fixed costs, and higher production limits than other industries, in the case of higher demand they can not upscale quickly and inventory levels go down. However, if the demand goes down, they can instead decrease the production levels. Even though this explanation is one of many possible, finding a significant result showing asymmetric impact within the fundamental analysis is valuable. The idea for our hypothesis originated in the field of sociology and it shows that asymmetries can be found in connection to prediction models based on accounting numbers.

7.2. Limitations

Our findings have various limitations. Firstly, the variables included in our study are based on the judgement of financial analyst and not statistical methods. This implies that there might be fundamental signals based on financial statement with a stronger relation to future earnings. Secondly, we only included firms listed in the US market, where all publicly listed companies are required to prepare their financial statements under GAAP. As other countries commonly apply IFRS, our findings might not hold true under different reporting environments. Thirdly, the data sample used in our study is limited to the time range from the year 2006 to 2014, which was beneficial for the purpose to study the recent market conditions, however, our result might not be applicable during other time periods.

Furthermore, The Return-Fundamental robustness test invalidated the significant result obtained for Hypothesis 2. However, we believe that this can be put into question. SEC requires US-listed companies to disclose their annual report (so-called 10-K file) no more than 60 days after fiscal year-end. With the fact that different companies could have different fiscal year end, the cutoff date for 10-K disclosure also varies, which means the fundamental data is exposed to investors at different time points. Theoretically, the stock price only reflects the market sentiment after relevant information is disclosed. During the Returns-Fundamentals part, we didn't take this into consideration. We selected stock return in year t+1 as dependent variables, and use the *EBIT* signal (net change of EBIT/ total assets) we predicted via fundamental data in year t. Since fundamental data are exposed to investors on different dates depending on company announcement, so the stock return should be calculated with starting date as the 10-K disclosure date of the firm.

7.3. Conclusion & Future research suggestions

This paper helps to identify a relation between fundamental signals included in financial statements and future earnings. Various research papers have investigated this association and sought to identify which fundamental signals should be used in earnings prediction models. While there is a large overlap in the current findings, there are also discrepancies. Our results, even though mainly overlapping with previous observations, show some divergence in relation to which fundamental signals are significant and their impact on future earnings. As we considered our most novel finding to be the significant result for the asymmetric impact of Inventory signal, we would suggest further research connected to this phenomenon. For instance, investigating the asymmetric impact of other fundamental signals included in the financial statements. Furthermore, we would suggest testing the validity of our results in settings where IFRS is a required reporting regulatory standard. Additionally, our results should be investigated under different industry, and macroeconomic contexts, for instance, higher inflationary environment. We tested our models in periods with low rates of inflation, however, results of Abarbanell and Bushee (1997) indicate that Accounts Receivable show more significant results under a high inflationary environment.

To conclude, our findings support the use of fundamental analysis in earnings prediction models, however further research including various circumstances is required, which would also enable the understanding of the mechanism behind these relations.

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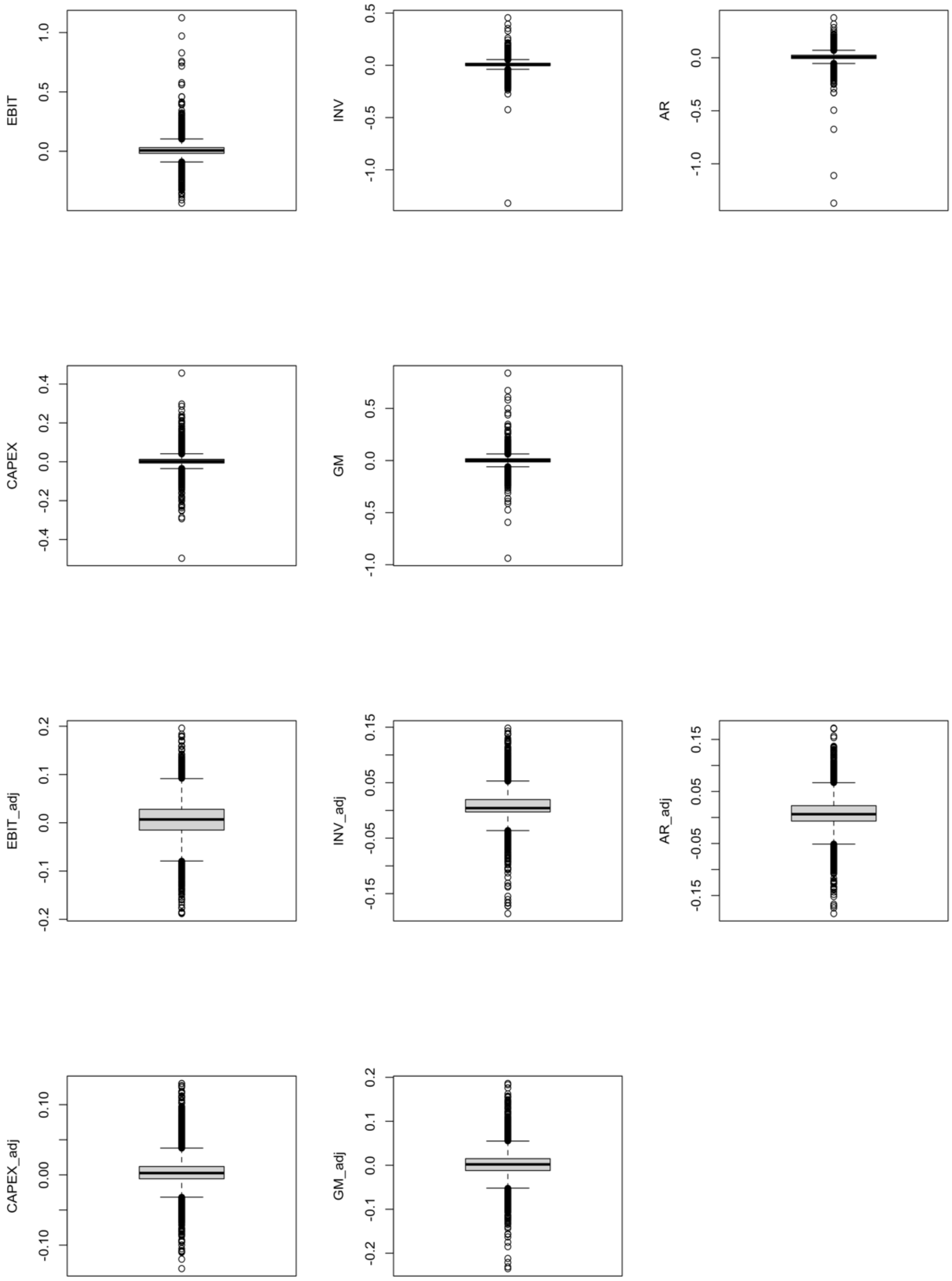
9. Appendix

9.1.Appendix 1: Descriptive statistics by Industries

INDUSTRY		EBIT	INV	AR	CAPEX	GM
Energy	mean	-.0051586	.0051044	.0080059	.0149441	.000097
	sd	.0716186	.0280561	.0348832	.043285	.0434137
	min	-.2444625	-.1859358	-.1519398	-.133502	-.221
	max	.2286074	.1483516	.1334742	.1269615	.156
Industrials	mean	.0082042	.0072126	.0069906	.0029376	.0022556
	sd	.0507379	.0328395	.0367285	.0237434	.0311009
	min	-.279902	-.1836461	-.1737452	-.1200295	-.235
	max	.2407006	.1478788	.1717172	.1302191	.186
Materials	mean	.0052301	.0086649	.0067354	.0032982	-.0001254
	sd	.0590279	.0303312	.0293355	.0251158	.0435824
	min	-.2854203	-.1724138	-.1846626	-.1099874	-.231
	max	.2410297	.1430192	.1192513	.1246377	.183
Total	mean	.0059581	.0073294	.0070433	.0043889	.0014267
	sd	.055699	.0317329	.0348377	.0272478	.0360577
	min	-.2854203	-.1859358	-.1846626	-.133502	-.235
	max	.2410297	.1483516	.1717172	.1302191	.186

9.2.Appendix 2: Boxplot before and after excluding outliers



9.3.Appendix 3: Year-by-year regression

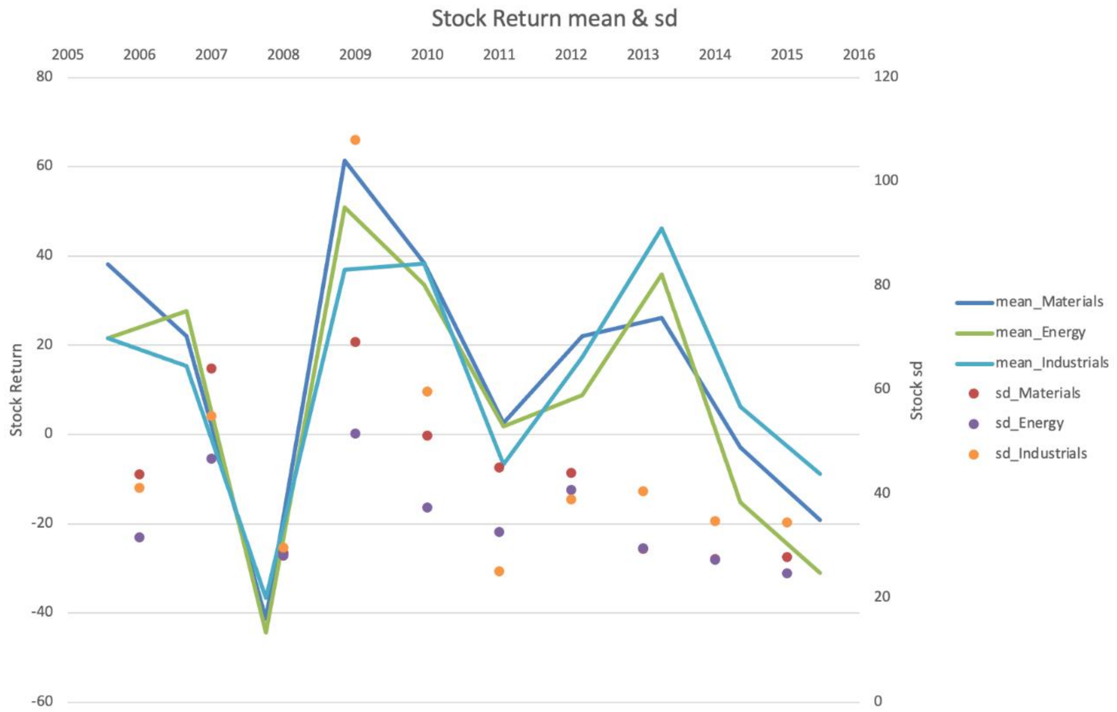
Results: Year-by-year regression &Cross-year Regression

	Dependent variable:									
	EBIT									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	Cross-year
INV	0.156*	0.008	-0.403***	-0.350***	-0.075	-0.121	-0.181*	0.214**	0.046	-0.191***
	(0.084)	(0.127)	(0.123)	(0.075)	(0.091)	(0.091)	(0.095)	(0.097)	(0.107)	(0.033)
AR	0.343***	0.441***	0.339***	0.311***	0.441***	0.276***	0.253***	-0.061	-0.055	0.299***
	(0.086)	(0.103)	(0.096)	(0.078)	(0.085)	(0.080)	(0.092)	(0.069)	(0.094)	(0.030)
CAPEX	-0.197**	-0.043	-0.081	-0.227**	-0.176*	-0.057	0.055	-0.194**	-0.148	-0.153***
	(0.092)	(0.100)	(0.136)	(0.104)	(0.095)	(0.088)	(0.100)	(0.089)	(0.122)	(0.036)
GM	0.033	0.037	-0.044	-0.221***	0.076	-0.216***	0.111	0.094	0.153	-0.024
	(0.079)	(0.109)	(0.108)	(0.054)	(0.064)	(0.065)	(0.077)	(0.071)	(0.098)	(0.027)
Constant	0.010***	-0.00001	-0.031***	0.021***	0.019***	0.004	0.003	0.008***	-0.003	0.006***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)
Observations	358	357	365	357	354	361	364	359	367	3,242
R^2	0.089	0.056	0.052	0.126	0.080	0.062	0.037	0.029	0.012	0.035
Adjusted R^2	0.079	0.045	0.041	0.116	0.070	0.051	0.026	0.018	0.001	0.034
Residual Std. Error	0.050 (df = 353)	0.058 (df = 352)	0.073 (df = 360)	0.055 (df = 352)	0.045 (df = 349)	0.042 (df = 356)	0.042 (df = 359)	0.037 (df = 354)	0.052 (df = 362)	0.055 (df = 3237)
Note:										*p**p***p<0.01

9.4.Appendix 4: OLS with FE

	(1)	(2)	(3)	(4)
VARIABLES	OLS	Fixed Effect_Industrials	Fixed Effect_Year	Fixed Year Effect Industry Dummies
INV	-0.191***	-0.196***	-0.126***	-0.130***
	(-5.76)	(-5.92)	(-3.83)	(-3.99)
AR	0.299***	0.300***	0.268***	0.268***
	(9.91)	(9.95)	(9.06)	(9.11)
CAPEX	-0.153***	-0.133***	-0.124***	-0.103***
	(-4.25)	(-3.65)	(-3.54)	(-2.92)
GM	-0.024	-0.028	-0.055**	-0.058**
	(-0.90)	(-1.02)	(-2.12)	(-2.26)
_Iyear_2007			-0.013***	-0.012***
			(-3.24)	(-3.19)
_Iyear_2008			-0.051***	-0.051***
			(-12.83)	(-12.85)
_Iyear_2009			0.010**	0.010**
			(2.38)	(2.41)
_Iyear_2010			0.007*	0.007*
			(1.75)	(1.77)
_Iyear_2011			-0.013***	-0.013***
			(-3.21)	(-3.24)
_Iyear_2012			-0.013***	-0.013***
			(-3.43)	(-3.43)
_Iyear_2013			-0.011***	-0.011***
			(-2.77)	(-2.75)
_Iyear_2014			-0.021***	-0.021***
			(-5.39)	(-5.40)
_IIndustrials		0.013***		0.013***
		(4.02)		(4.24)
_IMaterials		0.010***		0.010***
		(2.85)		(3.00)
Constant	0.006***	-0.005	0.017***	0.007*
	(5.96)	(-1.58)	(6.01)	(1.73)
Observations	3,242	3,242	3,242	3,242
R-squared	0.035	0.040	0.126	0.131

9.5. Appendix 5: Yearly Stock Return



Stock Yearly Return (Jan1-Dec31) from 2005-2015

	Materials		Energy		Industrials	
year	Total Return	sd	Total Return	sd	Total Return	sd
2006	38.0966667	43.770432	21.5319211	31.5864921	21.5291927	41.1807313
2007	22.0863678	64.0115594	27.7341579	46.6854683	15.3018028	54.9498685
2008	-41.386437	28.6842363	-44.384211	28.0427042	-36.620523	29.6354358
2009	61.4630345	69.1189907	50.9174737	51.5715131	36.9549037	107.971465
2010	38.4721609	51.2227423	33.6165263	37.410555	38.2382569	59.6768452
2011	2.6307931	45.0822035	1.88886842	32.6089797	-6.6548716	25.1569567
2012	22.1015862	43.9888409	8.86621053	40.7164621	17.3568532	38.9059184
2013	26.1727586	29.3406497	35.9118421	29.5129378	46.2725321	40.4207917
2014	-2.9327471	27.4107885	-15.140526	27.3532872	6.29512385	34.7007451
2015	-19.180069	27.7791013	-31.024737	24.6522382	-8.8436376	34.4624007