Theoretical Economics Letters, 2023, 13, 627-649
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Do Fictitiously High Asset Growth Rates Drive the Asset Growth Anomaly?

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How to cite this paper: Artikis, P., Asopoulos, G. P., Sfakianakis, E., & Diamantopoulou, L. (2023). Do Fictitiously High Asset Growth Rates Drive the Asset Growth Anomaly? *Theoretical Economics Letters, 13,* 627-649.
https://doi.org/10.4236/tel.2023.133038

Received: April 19, 2023
Accepted: June 27, 2023
Published: June 30, 2023

Abstract

Purpose: This paper investigates whether the well-documented asset growth anomaly can be related to information uncertainty due to earnings management. **Design/Methodology/Approach:** We perform both portfolio-based and regression-based analyses. We employ the 5 Variable Version of the Beneish model (Beneish, 1999) as an earnings management proxy and Piotroski's (2000) FSCORE as a proxy for firms' fundamental strength. **Findings:** Overall, our evidence suggests that the asset growth anomaly can be driven by high asset growth firms, manipulating their accounting figures. **Originality:** Given the implicit inferences that attribute the phenomenon to earnings management mainly by employing country-level proxies, we provide new insights by employing variables measured at the firm level.

Keywords

Asset Growth, Stock Returns, Earnings Manipulation, Mispricing

1. Introduction

One of the most pervasive and robust asset pricing puzzles is the well-documented asset growth anomaly[1]. While both rational[2] and mispricing explanations[3] of the asset growth anomaly have been proposed, given the mixed evidence to date, the

[1]See Chan et al., 2006; Fama and French, 2008; Lam and Wei, 2011; Lipson et al., 2011; Cooper and Maio, 2019a, 2019b for U.S. stock market evidence and Titman et al., 2013; Watanabe et al., 2013; Wang et al., 2015; Artikis et al., 2021, 2022 for international stock markets as well.

[2]Rational models employ either the q-theory of investment (Xing, 2008; Li et al., 2009; Liu et al., 2009; Li & Zhang, 2010; Wu et al., 2010) or the real options theory (Berk et al., 1999; Carlson et al., 2004, 2006).

[3]On the mispricing camp researchers mainly attribute the phenomenon to a misunderstanding of agency-related overinvestment, managers' empire building tendencies and earnings management (Titman et al., 2004; Cooper et al., 2008; Teoh et al., 1998a, 1998b; Dai et al., 2017, Cai et al., 2019; Goto et al., 2020; Lambertides, 2022).

purpose of this paper is to extend our understanding of the drivers of this phenomenon by focusing on information uncertainty due to earnings management.

Our motivation draws from the notion that balance sheet records all past accounting choices, so the level of assets can reflect prior earnings management strategies (Barton & Simko, 2002). Although the total asset growth measure proposed by Cooper et al. (2008) captures the synergic effect of a company's investment and financing activities, some aspects of total asset growth could be subject to managerial accounting discretion. To the best of our knowledge, there are only some implicit inferences that attribute the phenomenon to earnings management (Watanabe et al., 2013; Artikis et al., 2022) mainly by employing country-level proxies to assess whether the asset growth effect is indeed more pronounced in countries exhibiting greater managerial discretion over earnings.

Given the limited systematic attempt to examine whether earnings management serves as a driving force behind the occurrence and magnitude of the asset growth effect, the present paper aims to fill this gap by providing a holistic investigation of the asset growth anomaly under information uncertainty due to earnings management. We argue that, on a mispricing camp, high asset growth firms are probably overvalued and their managers have high incentives to manipulate earnings to sustain their firms' overvaluation. If this is the case, then the largest asset growth effect on subsequent stock returns will occur when high asset growth manipulator firms with weak fundamentals are considered.

Although existing literature on earnings management proxies mainly uses discretionary accruals[4], we differentiate by employing the 5 Variable Version of the Beneish model (Beneish, 1999), a measure used to uncover potential financial statement frauds[5]. We also employ a well-cited indicator of firms' fundamental strength, namely Piotroski's (2000) FSCORE. Besides its popularity as a stock screening tool among US investors (Novy-Marx, 2014), Piotroski's (2000) FSCORE has been widely used for various purposes in the academic literature[6]. To perform our analysis, we employ listed firms domiciled in 15 European Union countries, plus Switzerland. These countries are homogeneous in terms of their economic status (i.e. they are all classified as advanced economies, with the possible excep-

[4]Collins et al. (2012) provide evidence that there is a severe problem of falsely rejecting the null hypothesis of no earnings management in samples over-represented by high growth or low growth firms when using performance-adjusted discretionary accruals.

[5]Grove and Cook (2004), Dechow et al. (2011) among others.

[6]In the U.S., Fama and French (2006) apply FSCORE for predicting future firm profitability, Choi and Sias (2012) for predicting institutional investor demand, Turtle and Wang (2017) for testing how public fundamental information is incorporated into prices. In an international setting, Ng and Shen (2016) reveal that FSCORE helps to ex ante separate subsequent winners from losers among Asian value and growth firms. Walkshäusl (2017, 2019) finds supportive evidence that the FSCORE also adds to our understanding of the value and momentum effects in European stock returns that can be traced back to investors' expectation errors concerning firm fundamentals. Tikkanen and Äijö (2018) show that incorporating the information contained in FSCORE improves the performance of various long-only value investing strategies in Europe that are formed on valuation ratios other than book-to-market. Finally, Hyde (2018) and Ng and Shen (2019) provide evidence on the market-wide FSCORE-return relation in Australia and five Asian equity markets.

tion of Greece), legal tradition (i.e. most are classified as code law countries), and accounting regimes (i.e. they have applied IFRS since 2005).

Tabulated cross-sectional regression results reveal a positive and highly statistically significant relation between asset growth rates and earnings management, which is stronger when high asset growth firms are considered. This validates the notion that high asset growth firms have greater incentives to exercise discretion over accounting figures. Portfolio analysis shows that investment strategies taking a short position in high asset growth firms that engage in earnings management earn larger monthly size-adjusted returns than the original low-high asset growth investment strategy. In addition, the predictive ability of asset growth for future returns might be at least partially attributed to earnings manipulation, since asset growth's explanatory power on subsequent stock returns is augmented with the inclusion of an earnings management variable.

When we incorporate firms' fundamental strength, the coefficient of the asset growth variable takes larger negative values when high asset growth manipulator firms are considered. Thus, our findings reveal that investors do not assess properly the information captured by asset growth rate conditional on firms' fundamental strength and that this misvaluation is more pronounced under the presence of high asset growth firms manipulating their accounting figure. This evidence is consistent with existing literature suggesting a mispriced-based explanation behind the asset growth anomaly associated with investors' errors in expectations (Lakonishok et al., 1994; Cooper et al., 2008).

The remainder of the paper is structured as follows: Section 2 provides our research design and formulated hypotheses. Section 3 describes the sample selection and reviews the data. Section 4 presents and discusses our empirical findings. Finally, Section 5 concludes and discusses implications for financial decision-makers.

2. Theoretical Framework and Hypothesis Development

Barton and Simko (2002) highlight the effect of upwards earnings management on assets and note that an optimistic bias in earnings implies net assets measured and recorded temporarily at values exceeding those based on a neutral application of GAAP. Dechow et al. (2011) find that misstating firms boost their accruals in years prior to the manipulation, by applying within GAAP tactics such as relaxing credit policies, and building up inventory and fixed asset capacity in anticipation of future growth.

Furthermore, existing studies argue that growth firms often are simultaneously associated with more investment activities and accounting distortion (e.g. Chu, 2019; Zhang, 2007; Doukakis & Papanastasopoulos, 2014). Wei and Xie (2008) report that the investment-based anomaly comes from the abnormal component of capital expenditures, and they suggest that firms ranked the highest in both discretionary current accruals and abnormal capital expenditures earn substantially lower abnormal returns than do firms ranked lowest by these two measures. McNichols and Stubben (2008) find that firms manipulating their earnings, over-invest substantially during the misreporting period. Kedia and Philippon (2009) argue that firms that are subsequently required to restate their financial statements by the SEC, due to GAAP violations, overinvest as a means of providing the appearance of financial soundness. Liu (2019) also notes that asset growth is expected to explain a significant amount of variation in accruals, and vice versa.

Therefore, managers who currently manage high-expected-growth firms have high incentives to manipulate earnings (Beneish, 1999), with a primary motive being the exertion of influence on investor perceptions of firm value (Dechow et al., 1996). All of the above being said, one could conclude that firms that engage in earnings manipulation techniques in order to sustain their firms' overvaluation, will most likely be high asset growth firms. If this is the case, then

*H*1: *We expect asset growth rate to be positively associated with earnings manipulation and this positive relation should be stronger in case of high asset growth rates*.

A stream of papers attributes the asset growth anomaly on mispricing. Under the mispricing hypothesis, it's possible that investors are unduly optimistic about the future prospects of companies that have recently increased capital expenditures or were effective in communicating high-growth-option potential, leading to higher prices and thus lower subsequent returns (Doukas et al., 2002; Lakonishok et al., 1994). In addition, investors underreact to over-investment pursued by managers with a tendency towards empire-building (Titman et al., 2004; Cooper et al., 2008; Chan et al., 2008).

Chan et al. (2006) provide evidence that when existing capital is used inefficiently, the firm's executives may face mounting pressures to inflate earnings in order to meet analyst forecasts, leading to higher growth in assets. Moreover, Watanabe et al. (2013) hypothesize that the asset growth anomaly should be stronger across firms with greater managerial discretion over earnings. Artikis et al. (2022) provide evidence that the asset growth anomaly can be also attributed to an accounting distortion and/or an efficiency component (in line with a mispricing-based explanation).

Thus, existing literature suggests that under the mispricing camp, high asset growth firms are probably overvalued firms whose executives should have higher incentives towards earnings management to sustain this overvaluation (leading to further lower subsequent stock returns). When earnings management reverses, the market is disappointed and revises valuations for high growth firms downward. That being said, we expect that

*H*2: *If earnings management contributes to the asset growth anomaly, on a mispricing basis the asset growth effect on subsequent stock returns will be more pronounced when high asset growth manipulator firms are considered*.

It is often suggested that high-growth firms with lower asset values and more future discretionary investment expenditure by managers are difficult to observe and oversee; as a result, managers are more prone to participate in opportunistic reporting (Skinner, 1993; Skinner & Sloan, 2002). Managers of high asset growth firms, with deteriorating fundamentals, have greater incentives to engage in earnings management to cover up private bad news and sustain their firms' overvaluation. However, the bad news can only be covered up, until a tipping point, when it is released to investors.

Thus, it is only natural to ask how one can distinguish between high asset growth firms with sustainable growth rate (i.e. that is actual well-performing high asset growth firms) and firms with fictitious high asset growth rate engaging in earnings management to conceal their possible bad performance. Put it another way, are all high asset growth firms manipulating their accounting figures to sustain their firms' overvaluation?

Our last hypothesis comes to complement Hypothesis H2. Specifically, we argue that high asset growth firms with deteriorating fundamentals engage in earnings manipulation to sustain their evaluation and their asset growth rate is fictitiously high and not sustainable. Thus, we formulate our last hypothesis as follows:

H3: *The largest asset growth effect on subsequent stock returns should take place when high asset growth manipulator firms with weak fundamentals are considered, under the assumption that they aim to sustain firms' overvaluation.*

3. Data, Sample Formation, and Variable Measurement

We use an integrated European sample of non-financial listed firms from 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. In line with Titman et al. (2013), we require each country to have at least 30 stocks in any year of participation in the sample to ensure a reasonable number of firms for our portfolio tests and cross-sectional regression tests.

We collect accounting data and monthly returns from Worldscope and Datastream International files. We include common stocks listed on the major stock exchange in each country from both active and defunct data files to avoid survivorship bias. Accounting data is obtained for the period 1988-2016, while monthly returns are obtained for the period of 1988-2018 (forward looking returns). The starting year for the inclusion of each country in the sample varies according to the availability of data.

To detect suspicious returns, we exclude from our sample stocks with price returns above 300% or less than 50% that is reversed within one month (Ince & Porter, 2006). All firm-level variables are winsorized at the 1% and 99% level to mitigate the impact of outliers. Finally, we restrict our sample to firm-year observations without missing data to compute the primary variables of interest (i.e. total asset growth, Beneish's (1999) earnings management M-score, size and book-to market ratio) as well as nonnegative book values of equity. These criteria yield a final sample size of 55,731 firm-year observations.

Total Asset Growth (AG) is the asset growth measure proposed by Cooper et al. (2008) and is estimated as the annual percentage change in total assets. The 5 Variable Version of the Beneish's Model excludes Sales, General and Administrative expenses Index (SGAI), Total Accruals to Total Assets (TATA) and Leverage Index (LEVI) which were found to be insignificant in Beneish's original model. Thus, the following mathematical formula, gives us the 5 Variable Beneish's MSCORE:

$$\begin{aligned} \text{MSCORE} = & -6.065 + 0.823 * \text{DSRI} + 0.906 * \text{GMI} + 0.593 * \text{AQI} \\ & + 0.717 * \text{SGI} + 0.107 * \text{DEPI} \end{aligned}$$

where DSRI is the Days' Sales in Receivables Index measured as the ratio of days' sales in receivables in year t to year $t - 1$; GMI is the Gross Margin Index measured as the ratio of gross margin in year $t - 1$ to gross margin in year t; AQI is the Asset Quality Index measured as the ratio of non-current assets other than plant, property and equipment to total assets, in year t to year $t - 1$; SGI is the Sales Growth Index is the ratio of sales in year t to sales in year $t - 1$ and DEPI is the Depreciation Index measured as the ratio of the rate of depreciation in year $t - 1$ to the corresponding rate in year t.

A MSCORE higher than −2.22 means that a firm has been manipulating on corporate earnings. According to Beneish (1999), a "typical earnings manipulator," is a firm that is 1) growing extremely quickly, 2) exhibiting deteriorating fundamentals (e.g. a decline in asset quality, eroding profit margins, and increasing leverage), and 3) engaging in aggressive accounting practices (e.g. receivables growing much faster than sales, large income-inflating accruals, decreasing depreciation expense). Notably, the five financial rations in the Beneish's model are designed to capture both financial statement distortions that result from earnings manipulation (DSRI, AQI and DEPI,) and a predisposition to engage in earnings manipulation owing to economic conditions (GMI and SGI).

FSCORE (Piotroski, 2000) is a score that gauges a company's fundamental strength (or weakness). FSCORE is a discrete score between zero and nine that applies nine criteria to determine the strength of a firm's financial position. Low FSCORE values, which are between 0 and 4, indicate deteriorating fundamentals, whereas high FSCORE values, which are between 5 and 9, indicate improving fundamentals. The FSCORE is expressed as follows:

$$\begin{aligned} \text{FSCORE} = & \text{ROA} + \text{CFO} + \Delta\text{ROA} + \text{ACCRUAL} + \Delta\text{LEVER} \\ & + \Delta\text{LIQUID} + \text{ISSUANCE} + \Delta\text{MARGIN} + \Delta\text{TURN} \end{aligned}$$

where, Return on Assets (ROA) is calculated as net income scaled by lagged total assets and should be positive; Cash Flow from Operations (CFO) is measured as cash flow from operations scaled by lagged total assets and should be positive; Change in Return on Assets (ΔROA) is measured as the annual change in return on assets and should be positive; Accruals (ACCRUAL) is measured as net income less cash flow from operations, scaled by average total assets and should be negative;

Change in Leverage (ΔLEVER) is measured as the change in the ratio of long-term debt to total assets and should be negative; Change in Liquidity (ΔLIQUID) is measured as the annual change in the ratio of current assets to current liabilities and should be positive; The firm did not Issue Common Equity (ISSUANCE); Change in gross Margin Ratio (ΔMARGIN) measured as the annual change in gross Margin Ratio (MARGIN) and should be positive; and Change in asset Turnover (ΔTURN) is measured as the annual change in asset turnover ratio and should be positive.

The Size of the firm (SZ) is measured by its market equity (Fama & French, 1992, 1993). Book-to-Market (BM) is the ratio of the financial year-end book value of equity to the market capitalization (Fama & French, 1992, 1993).

Stock returns are calculated using the return index provided by Datastream (item RI), which is defined as the theoretical growth in the value of a share-holding unit of equity at the closing price applicable on the ex-dividend date. The raw equity return for a firm at month j is calculated as: $r_j = \mathrm{RI}_{j+1}/\mathrm{RI}_j - 1$. To calculate size-adjusted returns, each year we form size benchmark portfolios by sorting stocks into quintiles (five equally weighted portfolios by market equity) on firm size. Then, the size-adjusted return for a firm is the difference between its monthly raw return and the matching monthly return of the benchmark size portfolio to which the firm belongs. For cross-sectional regressions, we also calculate one-year-ahead annual size-adjusted stock returns.

Table 1 provides details about the final sample and basic statistics of the primary firm-level variables within each country. The statistics of the variables are comparable to those documented in prior international studies on the asset growth anomaly (e.g. Titman et al., 2013; Watanabe et al., 2013).

As we can observe in **Table 1**, AG ranges from 0.10 (Portugal, Norway and Italy) to 0.25 (Belgium). MSCORE varies from −4.95 (Belgium) to 3.74 (Portugal). Based on the −2.22 threshold (less negative or positive values of MSCORE indicate earnings manipulation), ten countries exhibit high MSCORE values: Portugal, Norway, Italy, France, Sweden, Denmark, Austria, The U.K., Germany and Ireland.

4. Results

4.1. Is Earnings Manipulation a Determinant of Total Asset Growth?

We begin our analysis by examining whether Beneish's (1999) MSCORE variable is a determinant of total asset growth rates. **Table 2** tabulates average coefficient estimates derived from panel analysis using OLS regressions with clustered s.e., of yearly total Asset Growth (AG) rates on Beneish's (1999) earnings manipulation score (MSCORE) expressed as a dummy variable, and two control variables namely, Size (SZ) and Book-to-Market (BM). The MSCORE dummy takes the value of one if a firm is classified as a manipulator and zero otherwise. The cross-sectional regressions are estimated for the full sample and the two extreme

Table 1. Summary statistics on asset growth and earnings management score across countries.

Country	Obs.	% Participation	Mean (MSCORE)	Mean (AG)
Austria	1042	1.87%	−1.28	0.14
Belgium	1422	2.55%	−4.95	0.25
Denmark	1561	2.80%	−1.23	0.12
Finland	1711	3.07%	−3.13	0.19
France	11,012	19.76%	0.59	0.11
Germany	9048	16.24%	−1.80	0.15
Greece	2592	4.65%	−2.45	0.17
Ireland	590	1.06%	−1.80	0.17
Italy	3259	5.85%	1.79	0.10
Netherlands	1860	3.34%	−2.55	0.18
Norway	1781	3.20%	2.99	0.10
Portugal	772	1.39%	3.74	0.10
Spain	1907	3.42%	−2.33	0.17
Sweden	3846	6.90%	−0.30	0.12
Switzerland	3130	5.62%	−3.57	0.21
The U.K.	10,198	18.30%	−1.50	0.14
N. Obs	**55,731**	**100.00%**		
Country Average (Equally - Weighted)			**−1.11**	**0.15**
Country Average (Participation - Weighted)			**−0.10**	**0.14**

Table 1 presents the basic statistics of AG and MSCORE variables by country. N. Obs. is the number of firm-year observations. We also report the percentage participation of each country in the overall sample. AG is total asset growth. MSCORE is Beneish's (1999) earnings management score. Mean AG and Mean MSCORE are the time-series average of the annual means over the sample period. The country-average characteristics are formed in two ways: (a) equally weighted country-specific characteristics (country average, equally weighted) and (b) weights based on the percentage participation of each country in the overall sample (country average, participation weighted).

quintiles "D1" and "D5" based on the magnitude of total asset growth, that is low asset growth firms and high asset growth firms respectively.

Table 2 documents a positive (negative) relation between high (low) asset growth rates and earnings manipulation, statistically significant at the 1% level. MSCORE's high positive coefficient loading of 0.84 suggests that high asset growth rates can actually be attributed to earnings manipulation. In the full sample, the relation between earnings manipulation and total asset growth rates remains positive (its coefficient loading is 0.40) and highly statistically significant, after controlling for firm size and book-to market.

Table 2. Regressions of total asset growth on earnings management.

$AG_{i,t} = a_{i,t} + MSCORE_{i,t} + SZ_{i,t} + BM_{i,t} + u_{i,t}$			
	All	**D1**	**D5**
MSCORE	0.40***	−0.06***	0.84***
	(4.63)	(−5.15)	(8.20)
ln(SZ)	0.01***	−0.02***	0.06***
	(4.39)	(−2.59)	(3.45)
ln(BM)	0.01	0.00	0.12**
	(0.76)	(0.17)	(2.39)

Table 2 reports the results from cross-sectional regressions of yearly total Asset Growth (AG) rates on Beneish's (1999) earnings Management Score (MSCORE) after controlling for Size (SZ) and Book-to-Market (BM) ratio. MSCORE is expressed as a dummy variable, taking the value of 1 if a firm is classified as a manipulator and zero otherwise. The "All" sample consists of all stocks included in our sample. The "D1" and "D5" subsamples consist of firms of extreme quintiles 1 and 5 based on total asset growth; that is low asset growth firms and high asset growth firms, respectively. The annual cross-sectional regressions are estimated using OLS with clustered standard errors and the relevant t-statistics are given in parentheses (two-tailed). The t-statistics are adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level, respectively.

Thus, tabulated results suggest that firms' total asset growth rates are positively related to accounting figures' manipulation (validation of H1 Hypothesis).

4.2. Returns of Asset Growth Strategies

Having established that the earnings manipulation is a determinant of total asset growth rates, we move forward to examine the occurrence of the well-documented asset growth phenomenon conditional to the probability of firm's engaging in earnings manipulation.

4.2.1. Baseline Results

First, at the end of June of each year t stocks are allocated into quintiles (five equally-weighted portfolios) based on their annual asset growth rates, and equal-weighted monthly size-adjusted returns are calculated for the subsequent twelve months, from July of year t to June of year $t + 1$. The same procedure is followed for the next year, thus, resulting in annual rebalancing of the portfolios. A firm is classified as a low (high) total asset growth firm if its total asset growth falls into the lowest (highest)-ranked quintile portfolio.

Then, at the end of June of each year, t stocks are independently allocated into manipulators and non-manipulators based on the value of their corresponding MSCORE. A firm is classified as a manipulator if its MSCORE is greater than −2.22 (less negative or positive) and as a non-manipulator if its MSCORE is less than −2.22 (more negative). To form the interacted portfolios, we split each of the five asset growth portfolios into two MSCORE portfolios. One portfolio is formed for high values of MSCORE (manipulators) and another for low values of MSCORE (non-manipulators).

Table 3 below presents average monthly size-adjusted returns[7] for the univariate and bivariate portfolios that are sorted on total asset growth and Beneish's M-score.

The results from the univariate sorts (Panel A) are consistent with a statistically significant asset growth effect. Low asset growth firms outperform high asset growth firms by 0.59% on a monthly size-adjusted basis. Firms characterized as manipulators exhibit low positive returns, whereas firms characterized as non-manipulators exhibit high negative returns, leading in a statistically significant size-adjusted return difference of 0.32% per month. Our results contradict the findings in Beneish et al. (2013) that firms flagged as possible manipulators exhibit lower future returns than non-flagged firms at an aggregated European level.

Next, we further investigate the return predictability using bivariate sorts (Panel B). Specifically, we examine the relationship between total asset growth and future stock returns, by taking into account whether the firm engages or not

Table 3. Univariate and bivariate portfolios sorts based on total asset growth & earnings management score.

	Size-adjusted Returns		Characteristics			
Portfolio	Mean	(t-statistic)	Firms	AG	MSCORE	SZ
***Panel A**: Univariate Portfolios*						
Low AG.	0.23%***	(3.08)	461	−0.17	−0.99	11.62
High AG.	−0.36%***	(−3.87)	461	0.82	3.56	12.03
L - H AG.	0.59%***	(4.15)				
Low MSCORE	−0.26%***	(−3.46)	1,920	0.12	−3.86	12.38
High MSCORE	0.06%***	(3.54)	385	0.47	14.39	11.74
H - L MSCORE	0.32%***	(3.51)				
***Panel B**: Bivariate Portfolios*						
L. AG. H. MSCORE	0.08%	(0.50)	78	−0.21	19.52	11.22
L. AG. L. MSCORE	0.26%***	(3.34)	376	−0.16	−5.11	11.70
H. AG. H. MSCORE	−0.54%***	(−4.42)	142	1.19	26.47	11.71
H. AG. L. MSCORE	−0.24%***	(−2.59)	311	0.64	−4.60	12.17
L. AG. H. MSCORE - H. AG. L. MSCORE	0.32%	(1.71)				
L. AG. L. MSCORE - H. AG. H. MSCORE	0.80%***	(5.10)				

Table 3 presents average monthly size-adjusted returns for univariate sorts based on total asset growth and Beneish's (1999) earnings management score, as well as bivariate sorts based on both variables. Table 3 also reports various characteristics (the number of observations, mean values of total asset growth rate, Beneish's (1999) earnings management score and firm size within each portfolio). The t-statistic for the average monthly returns is given in parentheses. The t-statistics are adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level, respectively.

[7]For time-averaging newly introduced literature see among others (Cherstvy et al., 2017, 2021).

in earnings manipulation. In particular, we report the return differences of two portfolio formations namely: 1) L. AG. H. MSCORE - H. AG. L. MSCORE, and 2) L. AG. L. MSCORE - H. AG. H. MSCORE.

L. AG. H. MSCORE - H. AG. L. MSCORE is the return difference between low asset growth firms that are manipulators and high asset growth firms that are non-manipulators. L. AG. L. MSCORE - H. AG. H. MSCORE is the return difference between low asset growth firms that are non-manipulators and high asset growth firms that are manipulators.

The results presented in the bivariate sorts validate that the return difference between low-high asset growth firms varies conditional upon their classification as manipulators or non-manipulators. An investment strategy taking a long position in low asset growth firms that do not engage in earnings manipulation and a short position in high asset growth manipulator firms is awarded with a large and highly statistically significant positive return difference of 0.80% per month in size-adjusted returns. In contrast, an investment strategy taking a long position in low asset growth manipulator firms and a short position in high asset growth firms that are non-manipulators provides results that are statistically insignificant.

As we can observe from Panel B of **Table 3**, the superior returns of low asset growth relative to high asset growth firms are magnified only when high asset growth manipulators are considered. Given that, the return difference between manipulators and non-manipulators is more consistent with rationality (i.e. in the sense that investors require higher returns as a compensation for the higher risk resulting from manipulating accounting figures), a possible interpretation would be that investors fail to interpret and/or react correctly to the combined information of total asset growth conditional on the probability of earnings manipulation. Put it another way, investors may overreact to past firm high-growth rates and myopically ignore the possibility of earnings manipulation[8]. Thus, the enhancement of the total asset growth ratio with the information captured by earnings manipulation seems to strongly influence the observed return differences.

According to the portfolio characteristics, low asset growth firms are slightly smaller, in terms of market equity, than high asset growth firms (Fama & French, 1992). Furthermore, manipulators are slightly smaller, in terms of market equity, than non-manipulators (Lee & Choi, 2002). In the bivariate sorting, we can observe that firms belonging to the L.AG.H.MSCORE or L.AG.L.MSCORE portfolios have on average very similar negative total asset growth ratios, whereas firms belonging to the H.AG.H.MSCORE or H.AG.L.MSCORE portfolios exhibit large differences in total asset growth ratios. Thus, the high returns to the L. AG. L. MSCORE - H. AG. H. MSCORE strategy may be attributed to a wider spread in the total asset growth characteristic. Furthermore, we observe that high asset growth firms are on average manipulators, whereas low asset growth firms also manipu-

[8]This finding implicitly favors a mispricing-based interpretation of the asset growth anomaly. From the mispricing perspective, the asset growth anomaly arises from naïve investors who inefficiently incorporate information associated with asset growth into stock prices.

late earnings but not as excessively as high asset growth firms. This finding is also validated since firms flagged as possible manipulators exhibit higher mean AG values than non-flagged firms[9].

4.2.2. Cross-Sectional Regressions

Mimicking bivariate-type portfolios, as an aggregation method, could not capture the individual information of stocks. Furthermore, it might also be subject to concerns that such predictability is attributable to omitted firm characteristics. To mitigate these concerns, we investigate the predictive power in terms of returns of total asset growth and earnings manipulation at a panel level employing the OLS regression with clustered standard errors to account for the residual dependence created by the time effect and the firm effect[10]. The regressions are estimated first for the full stock sample and then separately for the lowest and highest quintiles (low asset growth and high asset growth firms, respectively).

We estimate yearly panel data regressions, using OLS with clustered standard errors, of annualized size-adjusted returns on total Asset Growth (AG), earnings Manipulation (MSCORE), firm Size (SZ) and Book-to-Market (BM) ratio, as common control variables. The independent variables in the regressions are updated annually at the end of each June to predict yearly stock returns from July of the current year to June of the subsequent year (forward-looking returns). **Table 4** documents the average coefficient estimates.

Moreover, we build the model gradually. Panel A reports average coefficient estimates derived from panel analysis of yearly size-adjusted returns on total Asset Growth (AG), Size (SZ) and Book-to-Market (BM). Panel B reports average coefficient estimates derived from panel analysis of yearly size-adjusted returns on Beneish's earning Manipulation Score (MSCORE), Size (SZ) and Book-to-Market (BM). Finally, Panel C reports average coefficient estimates for the full model.

As is evidenced from **Table 4** (Panel A), AG carries a large negative coefficient. This finding reveals that the asset growth anomaly exists in European stock markets. However, MSCORE's explanatory power for the cross-section of stock returns is statistically not existent. Tabulated results contradict the findings in Beneish et al. (2013). In line with earlier portfolio analysis, when we include both variables in our cross-sectional regressions (Panel C), AG's coefficient is augmented under the presence of MSCORE. Furthermore, MSCORE turns to be statistically significant and positively related to subsequent stock returns at 10% level. Results in **Table 4** suggest that the predictive ability of asset growth for future returns might be (at least partially) attributed to earnings manipulation. Overall, both portfolio and regression analysis validate our H2 Hypothesis.

[9]Untabulated results using size segments verify the robustness of baseline portfolio analysis hold for both large and small firms.

[10]According to Petersen (2009), both OLS and the Fama-MacBeth standard errors are biased downward. Petersen (2009) reports evidence that only clustered standard errors are unbiased as they account for the residual dependence created by the firm effect. Thus, we estimate the OLS regression with clustered s.e. on one-dimensional clustering, i.e. separately for a time effect and a firm effect, as well as on two-dimensional clustering accounting for both a firm and a time effect. The results in all cases are qualitatively the same.

Table 4. Panel regressions using OLS with clustered S.E.

Panel A: Cross-sectional regressions of yearly size-adjusted returns ($SRET_{t+1}$) on AG, formally the regressions equation is as follows:

$$SRET_{i,t+1} = AG_{i,t} + \ln(SZ)_{i,t} + \ln(BM)_{i,t} + u_{i,t}$$

	AG	ln(SZ)	ln(BM)
$SRET_{t+1}$	−0.07***	0.01***	0.02***
	(−4.13)	(3.51)	(2.54)

Panel B: Cross-sectional regressions of yearly size-adjusted returns ($SRET_{t+1}$) on MSCORE, formally the regressions equation is as follows:

$$SRET_{i,t+1} = MSCORE_{i,t} + \ln(SZ)_{i,t} + \ln(BM)_{i,t} + u_{i,t}$$

	MSCORE	ln(SZ)	ln(BM)
$SRET_{t+1}$	−0.01	0.01***	0.02**
	(−0.13)	(3.28)	(2.48)

Panel C: Cross-sectional regressions of yearly size-adjusted returns ($SRET_{t+1}$) on AG and MSCORE, formally the regressions equation is as follows:

$$SRET_{i,t+1} = AG_{i,t} + MSCORE_{i,t} + \ln(SZ)_{i,t} + \ln(BM)_{i,t} + u_{i,t}$$

	AG	MSCORE	ln(SZ)	ln(BM)
$SRET_{t+1}$	−0.09***	0.01*	0.01***	0.02***
	(−4.38)	(1.98)	(3.53)	(2.53)

Table 4 presents average coefficient estimates derived from panel analysis of yearly size-adjusted returns on total Asset Growth (AG), Beneish's (1999) earnings Management Score (MSCORE), Size (SZ) and Book-to-Market (BM). Panel A reports average coefficient estimates derived from panel analysis of yearly size-adjusted returns on total Asset Growth (AG), Size (SZ) and Book-to-Market (BM). Panel B reports average coefficient estimates derived from panel analysis of yearly size-adjusted returns on Beneish's (1999) earnings Management Score (MSCORE), Size (SZ) and Book-to-Market (BM), while Panel C reports average coefficient estimates for the full model. Cross-sectional regressions are estimated by using OLS regressions with clustered s.e., and the relevant t-statistics (two-tailed) are given in parentheses. The t-statistics are adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level, respectively.

4.2.3. Accounting for Firms' Fundamental Strength

Up to this point, we have established that the asset growth effect on subsequent stock returns is stronger when high asset growth manipulators are incorporated. In this subsection, we examine whether the asset growth anomaly is even more pronounced when high asset growth manipulator firms with weak fundamentals are considered.

Well-performing high asset growth firms are expected to show improving fundamentals and to not participate in opportunistic reporting whereas high asset growth firms with deteriorating fundamentals are expected to manipulate accounting figures to cover up their possible bad future prospects in order to sustain their overvaluation. Using an indicator variable for firms' fundamental strength, namely, Piotroski's (2000) FSCORE[11], we argue that high asset growth firms with sustainable growth rates should exhibit strong fundamental strength (congruent signals). On the other hand, high asset growth firms with fictitious asset growth rate should exhibit weak fundamental strength (incongruent signals).

Thus, under the assumption that high asset growth firms with deteriorating fundamentals are engaging in earnings manipulation to sustain their overvaluation, then the asset growth effect on subsequent stock returns should be the largest when high asset growth manipulator firms with deteriorating fundamentals are considered (incongruent signals in terms of total asset growth rates, indicated by AG, and firms' fundamental strength, indicated by FSCORE).

Each June, we form portfolios by sorting stocks based on total asset growth and FSCORE from the fiscal year ending in the previous calendar year. Within each total asset growth quintile, firms are further classified as either with weak fundamentals (i.e. if they have a FSCORE between zero and four), or as with strong fundamentals (i.e. if they have a FSCORE between five and nine). We use size-adjusted monthly returns of the portfolios for the subsequent twelve months, and the portfolios are rebalanced each year. Then, each year we separate firms into manipulators and non-manipulators using Beneish's −2.22 MSCORE threshold and replicate the above-mentioned portfolio formation separately for manipulator and non-manipulator firms.

Table 5 tabulates average monthly size-adjusted returns for bivariate portfolios, sorted on total asset growth and Piotroski's FSCORE (Panel A), as well as sorted on total asset growth and Piotroski's FSCORE conditional on firms being manipulators and non-manipulators (Panels B and C respectively). The column L. AG. - H. AG. presents the return difference between low asset growth firms and high asset growth firms. The line S-W presents the return difference between strong and weak firms in each case, conditional upon the second sorting variable.

Incongruent signals are measured by taking a long position in low asset growth firms with strong fundamentals and a short position in high asset growth firms with weak fundamentals. Congruent signals are measured by taking a long position in low asset growth firms with weak fundamentals and a short position in high asset growth firms with strong fundamentals.

First, all panels suggest that the asset growth effect remains robust after controlling for firms' fundamental strength. However, the asset growth effect in realized returns is strongest among firm with ex-ante incongruence between firms' fundamental strength and asset growth expectations embedded in price. The incongruent high/low asset growth strategy generates one-year-ahead ahead buy-and-hold size-adjusted returns that are both economically and statistically significant (0.87% in Panel A, 1.69% in Panel B and 0.68% in Panel C). Conversely, the congruent

[11]The FSCORE (Piotroski, 2000) has grown in popularity among US investors as a stock screening tool (Novy-Marx, 2014), but it has also been utilized in academic literature in the United States for a variety of objectives. For instance, it has been applied to predict future firm profitability (Fama & French, 2006), institutional investor demand (Choi & Sias, 2012), and as an instrumental variable to test how public fundamental information is incorporated into prices (Turtle & Wang, 2017).

Table 5. Accounting for firms' fundamental strength.

Panel A: Bivariate portfolios sorted on AG and FSCORE			
	H. AG	L. AG	LAG-HAG
Weak	−0.61%***	0.01%	0.61%***
	(−4.26)	(0.03)	(3.32)
Strong	−0.24%***	0.27%***	0.51%***
	(−2.81)	(4.12)	(4.09)
S-W	0.36%***	0.26%**	
	(2.57)	(2.06)	
Incongruent Signals			**0.87%*** **
L. AG. Strong - H. AG. Weak			(5.40)
Congruent Signals			**0.25%**
L. AG. Weak - H. AG. Strong			(1.38)
Panel B: Bivariate portfolios sorted on AG and FSCORE for manipulator firms			
	H. AG	L. AG	LAG-HAG
Weak	−1.49%***	0.11%	1.61%***
	(−5.40)	(0.35)	(3.71)
Strong	−0.74%***	0.20%	0.94%***
	(−4.03)	(0.97)	(3.72)
S-W	0.75%***	0.08%	
	(2.57)	(0.23)	
Incongruent Signals			**1.69%*** **
L. AG.Strong - H. AG. Weak			(5.11)
Congruent Signals			**0.28%**
L. AG. Weak - H. AG. Strong			(1.89)
Panel C: Bivariate portfolios sorted on AG and FSCORE for non-manipulator firms			
	H. AG	L. AG	LAG-HAG
Weak	−0.41%***	−0.04%	0.37%**
	(−3.27)	(−0.33)	(2.24)
Strong	−0.10%	0.27%***	0.38%***
	(−1.24)	(4.12)	(3.00)
S-W	0.31%**	0.32%***	
	(2.15)	(2.50)	
Incongruent Signals			**0.68%*** **
L. AG. Strong - H. AG. Weak			(4.53)
Congruent Signals			**0.06%**
L. AG. Weak - H. AG. Strong			(0.36)

Table 5 presents average monthly size-adjusted returns for bivariate portfolios sorted on total asset growth and Piotroski's FSCORE (Panel A), as well as sorted on total asset growth and Piotroski's FSCORE conditional on firms being manipulators and non-manipulators (Panels B and C respectively). The t-statistics are given in parentheses and they are adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level, respectively.

high/low asset growth strategy yields no excess returns at conventional levels of significance. The lack of an asset growth effect across these congruent high/low asset growth portfolios is consistent with the unconditional high/low asset growth effect being driven by investors' systematic misinterpretation of the information captured in firms' total asset growth rate.

The most intriguing findings come from Panels B and C. The asset growth effect on subsequent stock return (the return difference LAG-HAG) is the largest, after controlling for firms' fundamental strength, in the subgroup of manipulator firms. In addition, the incongruent high/low asset growth strategy also yields the largest one-year-ahead ahead buy-and-hold size-adjusted returns statistically significant at 1% level. The fact that, Piotroski's FSCORE fails to distinguish winners from losers in low asset growth firms reinforces the notion that: 1) the asset growth effect on stock returns derives from overvalued high asset growth firms and 2) this overvaluation is even more pronounced when asset growth rates are fictitiously high due to earnings manipulation. On the other hand, in the subgroup of non-manipulators (Panel C) both the asset growth effect and the incongruent high/low asset growth strategy are mitigated downwards, although highly statistically significant.

Overall, the results in **Table 5** suggest that the asset growth effect captures price corrections that arise from the reversal of investors' misvaluation, downwards, of high asset growth firms and this reversal is stronger in case of high asset growth manipulator firms probably due to investors' disappointment.

Since portfolio analysis initially investigates how meaningful regression analyses would be, we further investigate our results in terms of cross-sectional regressions. **Table 6** presents average coefficient estimates derived from panel

Table 6. Panel regressions accounting for congruence/incongruence between firms' fundamental strength and asset growth, conditional on high asset growth manipulator firms.

	Incongruence FSCORE		Congruence FSCORE	
	H.AG Manipulators	H.AG Non-Manipulators	H.AG Manipulators	H.AG Non-Manipulators
AG	−0.10***	−0.05**	−0.03	0.02
	(−5.44)	(−2.26)	(−1.48)	(0.37)
ln(SZ)	0.01***	0.01*	0.01**	0.01*
	(2.96)	(1.97)	(2.40)	(1.99)
ln(BM)	0.02	0.02	0.01	0.02
	(1.59)	(1.00)	(1.11)	(1.79)

Table 6 presents average coefficient estimates derived from panel analysis of yearly size-adjusted returns on total Asset Growth (AG), Size (SZ) and Book-to-Market (BM). Cross-sectional regressions are estimated by using OLS regressions with clustered s.e., and the relevant t-statistics (two-tailed) are given in parentheses. The t-statistics are adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level, respectively.

analysis of yearly size-adjusted returns on total Asset Growth (AG), Size (SZ) and Book-to-Market (BM).

The "Incongruence FSCORE" subsample consists of firms in the lowest (highest) quintile based on total asset growth [i.e. low (high) asset growth firm] that reveal incongruence with firms' fundamental strength i.e. strong (weak) fundamental strength and high (low) FSCORE values)]. The "Congruence FSCORE" subsample consists of firms in the lowest (highest) quintile based on total asset growth [(i.e. low (high) asset growth firms)] that reveals congruence with firms' fundamental strength [i.e. weak (strong) fundamental strength and low (high) FSCORE values]). Within each group (Incongruent/Congruent), we further classify firms into manipulators and non-manipulators based on the −2.22 MSCORE threshold. The "H. AG. manipulators" subsample consists of low asset growth non-manipulator firms and high asset growth manipulator firms, whereas the "H. AG. non-manipulators" subsample consists of low asset growth manipulator firms and high asset growth non-manipulator firms.

We aim to examine variations in AG's explanatory power in case of high asset growth manipulators, after taking into account congruent/incongruent signals with firms' fundamental strength. If the asset growth effect is driven by investors' misinterpretation of the combined signals in asset growth rates and firms' fundamental strength, then AG should be statistically significant and negatively correlated to subsequent stock returns, only in case of incongruent signals. Furthermore, if high asset growth manipulator firms drive, at least to a certain extent, the overall asset growth effect, we expect that AG's coefficient will take higher negative values when these firms are considered.

Results in **Table 6** can be interpreted as follows: First, AG is statistically significant only in the case of incongruent signals, validating the fact that investors do not assess properly the information captured by asset growth rate, conditional on firms' fundamental strength. Thus, this evidence is consistent with existing literature suggesting a mispriced-based explanation behind the asset growth anomaly; second, in the case of high asset growth firms with weak fundamentals and a high probability of earnings manipulation, AG's coefficient takes higher negative values and is highly statistically significant. This finding suggests that high asset growth firms are more overvalued when their asset growth rates are fictitious high; finally, with respect to high asset growth firms with strong fundamentals and a high probability of earnings manipulation, AG exhibits no explanatory power over subsequent stock returns. This finding reinforces the notion that investors are more rational in valuing high asset growth firms with sustainable growth rates.

5. Conclusion

The most extensively examined debate is about asset growth anomaly's underlying drivers. Drawing our motivation from the limited systematic attempt to address information uncertainty due to earnings management as an underlying origin behind this market puzzle, we aim to fill this gap by providing further evidence using variables calculated at the firm level. To that end, we employ well-cited scoring tools (namely Beneish's (1999) M-SCORE for fraudulent reporting and Piotroski's (2000) FSCORE for firms' fundamental strength) that are perceived to be easy to implement in order to minimize information gathering and other analysis-related costs, as well as to have a predicting ability on future stock returns as well.

First, cross-sectional regression of total asset growth rates on Beneish's (1999) MSCORE variable reveals that firms' total asset growth rates are indeed related to the manipulation of accounting figures (validating our first hypothesis). Specifically, MSCORE carries a large positive coefficient loading in the full sample, but at the same time, its coefficient is even larger in the high asset growth subsample, suggesting that high asset growth rates might arise from accounting figures' manipulation.

Then, portfolio analysis showed that investment strategies taking a short position in high asset growth firms that engage in earnings manipulation, earn larger monthly size-adjusted returns than the original low-high asset growth investment strategy. An investment strategy taking a long position in low asset growth firms that do not engage in earnings manipulation and a short position in high asset growth firms that manipulate accounting figures is awarded with a return difference of 9.6% per annum in size-adjusted returns.

At an individual level of analysis (i.e. cross-sectional regressions), we find that the predictive ability of asset growth for future returns can be attributed to earnings manipulation, since asset growth's explanatory power on subsequent stock returns is augmented with the inclusion of M-Score. Overall, both portfolio-based and regression-based results validate our hypothesis that the asset growth effect is more pronounced under the presence of earnings manipulation and is probably driven by high asset growth firms that manipulate their accounting figures (validating our second hypothesis).

Finally, we examine whether the largest asset growth effect on subsequent stock returns is realized when high asset growth manipulator firms with weak fundamentals are considered (incongruent signals), under the assumption that they aim to sustain their overvaluation. Portfolio analysis reveals that an "incongruent" high/low asset growth strategy yields the largest difference in size-adjusted returns, when high asset growth manipulator firms are considered.

Cross-sectional regressions reveal two important findings. First, asset growth's explanatory power on the cross-section of stock returns is statistically significant only in the case where the information captured by asset growth rates points in the opposite direction, relative to the information captured by firms' fundamental strength. Thus, this finding is consistent with existing evidence on a mispriced-based explanation of the asset growth anomaly. Then, and more importantly, asset growth's coefficient loads more negatively and is highly statistically significant under the presence of high asset growth firms with weak fundamentals engaging in earnings manipulation. This finding reveals that high asset growth firms are more overvalued when their high asset growth rates are fictitiously high. Overall, our evidence suggests that the asset growth anomaly on subsequent stock returns can actually be driven by high asset growth firms, manipulating their accounting figures (validating our last hypothesis).

Our research makes at least three important contributions. First, our results suggest that the asset growth anomaly in Europe is more likely to be due to mispriced high asset growth firms and, more specifically, due to fictitiously high asset growth firms covering up bad news. Second, our findings imply that it may be more fruitful for academics to take into consideration accounting distortions, when studying whether and why the asset growth anomaly arises and persists. Third, our research may help investment managers, who operate globally, in making the appropriate top-down decisions on international asset allocation.

Overall, our study strongly emphasizes the significance of developing richer hypotheses and additional empirical analyses, in order to obtain a deeper understanding of the asset growth anomaly. However, the empirical analysis adopted may be subject to time-averaging issues. Thus, further research may also consider this aspect as a ground for further analysis.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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