Bachelor thesis Economie en Bedrijfseconomie

ASSET GROWTH AND MOMENTUM

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Abstract.

In this paper the long-term effect of asset growth on momentum profits will be discussed. First, firms of the NYSE are grouped based on their past 10 year asset growth, and then each group follows a momentum strategy for 10 years. The results show that especially going short in losing stocks from the low asset growth group is profitable. Results for the winning stocks in the high asset growth group are biased and show no significant results. Secondly a panel regression is made with yearly stock return as dependent variable. The regression shows that asset growth has a significant effect on stock prices four to five years later. Other tested variables such as book-to-market, trading volume and previous stock return do not show significant results.

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1. Introduction

An easy way to gain profits on the stock market would be to know what will happen in the future. Unfortunately, we do not know what will happen, but we do know what has happened. So, investors will instead use this information to attempt to gain profits. A common strategy for this is the momentum strategy, where previous winners are bought, and previous losers are sold (Chan, Jegadeesh, & Lakonishok, 1996).

In essence, the value of a stock is equal to its expected future's dividends discounted. The value of a stock is reflected in its trading price on the market. Fluctuation in this price is caused by the uncertainty of these dividends. Nevertheless investment firms attempt to forecast these dividends, and thus the value of a stock price. Different market and firm specific variables are used for this (Howe & Yang-pin, 1998).

Stock prices fluctuate every day and even every minute. Large fluctuations are often caused by new information about the firm or about the market. Smaller fluctuations are caused by changes in supply and demand of the stock. Supply and demand constantly seek an equilibrium, causing these small fluctuations (Lee & Swaminathan, 2000). The large fluctuations, caused by new information, ensure that all information is incorporated in stock prices, at least in theory.

The theory that all information about stocks is incorporated in their prices, is called the efficient market theory (Keane, 1983). According to the efficient market theory stocks always represent their fair value. Therefore it is impossible to make profits on the stock market by purchasing undervalued stocks or selling overvalued stocks (not taking insider information into account). However, there is still the profit generating momentum strategy. This strategy uses solemnly past stock prices to determine what stocks to buy and sell.

Assuming that the efficient market theory is correct, the gains that investors make when following a momentum strategy should be explainable using market or firm-specific information. This explanation however has not been found yet. Momentum is recognized in the academic world, empirical evidence can be found in many different studies. However, momentum profits without a proper explanation brings consequences to the efficient market theory.

To not have to dismantle the efficient market theory scientists have been trying to explain momentum strategies for several years. Some studies look at investor behavior, Chan, Jegadeesh and Titman (1999) for example say that momentum profits are caused by slow incorporation of information. While other studies focus more on firm-specific variables such as book-to-market, trading volumes and credit rating. Unfortunately none of these variables have shown to be a very convincing driver of momentum.

Except Nyberg and Pöyry (2014), they show very promising results when forecasting momentum profits using aggregated asset growth. In their study they find a strong suggestion that momentum profits are only large for firms that have experienced a large asset expansion or contraction.

Nyberg and Pöyry (2014) show that asset growth has a short-term effect on momentum profits. Meaning that momentum profits are only large shortly after a large asset expansion or contraction. They argue that a change in assets for a firm is caused by its specific investment choices. The lifespan of a firm's investments however is often several years (Berk, Green, & Naik, 1999).

Berk, Green and Naik (1999) show that investments are the cause of asset growth. These investments have a lifespan of several years, and consequently change a firm's expected returns and systematic risk for this period. Therefore investments should have an effect on stock prices for the entire duration of the investment.

Nyberg and Pöyry (2014) do not take this into account in their study. Thereby leaving a gap in available literature. This study will attempt to explain what the effect of asset growth is on momentum, in the long-term.

The necessity of this study originates from the fact that momentum profits go against the well-accepted efficient market theory. If stock prices represent the firm's future dividends, there should be an explanatory variable. By investigating the long-term effect of asset growth on momentum,

In section 2 of this paper related literature of momentum, asset growth and stock prices and asset growth and momentum will be discussed. In section 3 the data and methodology used for studying the relationship between asset growth and momentum. The relationship will be studied in two ways. Firstly momentum results of stocks will studied after the stocks have been split up in groups based on their past asset growth. Secondly a panel regression is made to determine the drivers of stock returns. In section 4 the results of this will be discussed, and section 5 concludes.

2. Related Literature

Before investigating how asset growth effects momentum, it is important to know what is, and what causes momentum, but also how asset growth affects stock prices. Firstly a short history of momentum will be discussed, continued with discussing different articles trying to assign momentum profits to different causes. Then there will be a brief discussion about the effect of asset growth on stock prices. Lastly some earlier research on the effect of asset growth on momentum will be discussed.

Momentum

Overreaction on the stock market in the long term.

De Bondt and Thaler (1985) study the transparency and efficiency of the stock market, and how stock market responds to unexpected and dramatic events. They showed that stocks with the highest price decrease in the previous three years, experienced a price growth of 25% more than the stocks that experienced a price increase over the past three years. This was quite surprising, because the stocks that experienced the price increase in the first period had a significantly higher volatility, and were thus more risky. De Bondt and Thaler contribute this gain to the overreaction on dramatic news events (Chan, Jegadeesh, & Lakonishok, 1996). The results of De Bondt and Thaler's studie gave cause to investigate this effect further.

Overreaction on the stock market in the short term.

Where De Bondt and Thaler (1985) focuses on the long term, Lehmann (1990) focuses on the short term. He discovered that stocks that increased in price in one week, showed significant negative results in the next week. Whereas stocks that decreased in price in one week, showed significant positive results in the next week. Because of this he created a portfolio of going short on the previous week's winning stocks, and buying the previous week's losing stocks. He kept these stocks for one week, and then sold all his positions. A strategy of creating this portfolio week in and week out gained him positive results in roughly 90 percent of all weeks investigated.

These results remained significant even after accounting for mismeasurement of security returns due to bid-ask spreads and transaction costs. Identically to De Bondt and Thaler, Lehmann also rejects the theory of an efficient market theory. This return reversal where previous week's winning (losing) stocks show negative (positive) results in the next week is expected by him to be caused by the imbalances in the market for short-run liquidity (Lehmann, 1990).

After the discoveries of Debondt and Thaler (1985) and Lehmann (1990), studies trying to form a portfolio based on past results did not find a return reversal. Instead, the strategy of buying losers and selling winners, changed to buying winners and selling losers.

Buying past winners and selling past losers is the new momentum strategy.

Jegadeesh and Titman (1993) were the first to show that buying winning stocks and selling losing stocks was a good strategy. The goal of their research was to create a strategy with maximum gains based on previous stock prices. The strategy they came up with was selecting stocks based on their past 6-month returns, and hold them for 6 months. The stocks that gained the most (least) in the first 6 months were bought (sold). This strategy generated a compound excess return of 12.01% per year.

The first obvious explanation for the abnormal gain of Jegadeesh and Titman's (1993) strategy is that these stocks have an higher systematic risk, since higher risk leads to higher profits. However, their strategy is only beneficial in a short-term hold period, three to twelve months. The price increase of the first year holding the stocks, dissipates in the two years after that. Since these price increases are only temporary and not systematic, the theory that these increases are caused by systematic risk is debunked. An alternative explanation for these price increases is not found by Jegadeesh and Titman (1993).

Momentum strategy when controlling for market risk, size and book-to-market.

Jegadeesh, Chan and Lakonishok (1999) investigate the momentum anomaly. They split the momentum effect up into a price momentum strategy and an earnings momentum strategy. With price momentum the stocks to buy (sell) are determined by the change in stock prices of the previous period, as described by Jegadeesh and Titman (1993). The stocks to buy (sell) with earnings momentum are determined by the relative highest (lowest) earnings in the previous period. Both strategies show returns which are significantly higher than the market. These returns remain even significantly high when trying to explain them by size and book-to-market effect by using a three-factor model (Chan, Jegadeesh, & Lakonishok, 1996).

The most probable cause for the momentum anomaly given by Jegadeesh, Chan and Lakonishok (1999) is that the market only gradually responds to new information. They argue that earnings provide an ongoing source of information about a firm. The momentum effect is concentrated around the subsequent earnings announcements. For example, when the market is surprised by good (bad) news, stock prices go up (down). During the next two announcements the stock price reacts in the same positive (negative) direction, thus going up (down).

Secondly, they argue that this slow incorporation of news is caused by prolonged forecasts by analysts. Reluctance among management could cause relatively late published information for investors, this is however not backed by any evidence (Chan, Jegadeesh, & Lakonishok, 1999).

Explaining momentum with default probabilities.

Default probability is the likelihood of a company's unability to meet its dept obligations. It is

calculated from a complex formula containing the market value of assets, the debt value, the time to maturity of the debt, the risk-free interest rate and the volatility of the asset returns. From that a normal distribution is created and thus the probability of default.
Lee Liu and Lin (2014) attempt to explain Momentum by creating three DP (default probability) groups, low (30%), medium (40%) and high (30%). They conclude that the best momentum strategy exists of buying winners in the high DP group, and selling losers in the low DP group. Interesting enough this is better than buying winners and selling losers from the same DP group (Lee, Liu, & Lin, 2014). A flaw of this study is that the firms per group have not been tested for market risk. Stocks from the high DP group are bought, where you would expect more market risk. Nevertheless this paper gives good clarification on how to improve the returns of a momentum strategy, but lacks an explanation.

A portfolio of only low-grade firms gains the best momentum profits.

Avramov, Chordia, Jostova and Philipov (2007) study the momentum anomaly by grouping firms by their credit rating. Since firms with a high default probability probably have a low credit rating and vice versa you would expect their results to be similar to those of Lee, Liu and Lin. However, this is not the case. Avramov et al. (2007) conclude that momentum profitability is statistically significant and economically large among firms with a low credit-rating, and momentum profits are non-existent among high-grade firms. This is different from Lee, Liu and Lin's results, where they find that a portfolio of buying winners from low-grade firms and buying losers from high-grade firms (under the assumption that low-grade firms have a high DP, and high-grade firms a low DP).

The first possible explanation of this difference is that the assumption that low-grade (high-grade) firms have a high (low) DP is false. The credit ratings used in their research is from Standard & Poor's. Standard and Poor call credit ratings opinions and thus not an absolute measure of default probability (McGraw Hill Financial, 2014).

Secondly, the methodologies could cause the difference in results. These are fairly similar, however, the grouping systems are not fully comparable. Lee, Liu and Lin created three groups, with low (30%), medium (40%) and high (30%) default probabilities. Whilst Avramov et al. (2007) state that the significant momentum profits come from only 4% of the rated firms, namely the firms with the low ratings of D, C, CC, CCC-, CCC, CCC+, B-, B, B+ and BB-. Thus the difference might be caused by comparing a group of 30% of all firms with 4% of all firms.

Thirdly, this difference could be caused by the different data used in these researches. Avramov, et al. (2007) use at the NYSE, AMEX and NASDAQ and Lee, Liu and Lin (2014) look at the Taiwan Stock Exchange (TWSE).

Past high trading volumes predict the magnitude and persistence of price momentum.

Lee and Swaminathan (2000) connect trading volumes to price momentum. They argue that on the stock market, price and volume are determined simultaneously to create an equilibrium. In this equilibrium a change in volume (price) will disturb this equilibrium, and to obtain a new equilibrium price (volume) adjusts. Therefore trading volumes should be useful for explaining price changes. They argue that recent trading volumes can predict momentum effects, buying high volume winning stocks and selling low volume losing stocks show significant higher results than an ordinary momentum strategy as from Jegadeesh and Titman (1993). Moreover, by analyzing volume growth they can optimize the best holding period for their portfolio. Lee and Swaminathan (2000) show very interesting results, and trading volume is certainly something to take into account when studying momentum strategies

Asset growth and stock returns

The Five factor model of Fama and French explaining stock price returns.

In the academic world, one of the most widely accepted models to explain stock returns is the five-factor model of Fama and French (2015). This models attempts to explain stock returns using market volatility, firm specific size, market value, profitability and investments. According to their calculations this model explains about 71 to 94 percent of the expected stock returns. For this study, the most interesting factor added here is the investment factor. This investment variable is in fact asset growth, it is the growth percentage of total assets of a firm in one year. With this model they have proven that asset growth is a useful variable for predicting stock price returns.

Using asset growth to predict stock returns.

Cooper, Gulen and Schill (2008) study how to use asset growth to predict stock returns.They discovered that stocks of firms with a low asset growth rate have an annualized risk adjusted growth rate of 9.1% on average. Stocks of firms with a high asset growth rate have an annualized risk adjusted growth rate of 19.5% lower. They speculate that this difference is caused by the fact that asset growth captures complex linkages among returns, size groups and financing types (Cooper, Gulen, & Schill, 2008). These results also suggest that investors overextrapolate past gains of growth. This suggests a negative relationship between asset growth and momentum.

Berk, Green and Naik (1999) look at it in a slightly different way. They argue that investors analyze the specific investments a firm chooses. Furthermore, optimal investment choices change a firm’s assets and growth options in a predictable way. Due to this change in a firm’s assets and growth options, its systematic risk changes. This also affects the firm’s expected returns.

They also argue that a gain in stock prices is caused by higher expected returns. Expected returns are based on the profitability of projects that are started by a firm. So the expected returns for this firm is higher for the lifespan of this particular project, and after that the expected returns and systematic risk go back to its previous height (Berk, Green, & Naik, 1999).

Asset Growth and Momentum

Berk, Green and Naik (1999) have found a strong suggestion that momentum profits are caused by firm specific investments. They underline this by stating that the investment profits are temporary, which is caused by the lifespan of these specific investments. However, the suggestion that momentum profits are caused by firm's investments, is played down by the time-series relationship they discovered between book-to-market and asset growth. Book-to-market is closely related to asset growth, and they were unable to completely distinguish the momentum profits caused by asset growth or book-to-market (Berk, Green, & Naik, 1999).

Aggregate asset growth is one of the main drivers of price momentum profits

Motivated by the fact that the momentum anomaly was still an intellectual curiosity Nyberg and Pöyry (2014) decided to try and link momentum to asset growth. This, because of the growing literature that models the relation between firm-level investment decisions and expected returns. They study the effect aggregated AG has on momentum gains during different business cycles, during up and down markets and periods of low and high sentiment. They conclude that the connection between firm-level asset changes and stock price momentum is robust under all these different market states.

Besides different market states, they have also controlled for previously documented drivers of momentum, such as smaller firms that exhibit larger momentum effects than larger firms, firms that have a low book-to-market ratio, firms with higher trading volumes, firms with high volatility and firms with a higher credit risk. They controlled for these variables with a panel regression with stock return as dependent variable.

They conclude there is positive time-series relationship between aggregate AG and momentum, showing that average momentum returns increase almost monotonically with aggregate AG.

A way to distinguish different momentum strategies is called J/K/L. J is the 'look-back' period, this period the change in stock prices is observed and based on this stocks are bought or sold. K is the length of the holding period. L is the lag period, it is in between the J and K period. Its purpose is to avoid short-horizon negative return autocorrelation. Nyberg and Pöyry (2014) mostly use the J/K/L strategy 11/1/1. In some of their tests they extend the lag period to 3 or 6, however a longer lag period shows less robust results.

The 11/1/1 strategy of Nyberg and Pöyry (2014) showed significantly high results. The short holding period makes this strategy quite trade intensively. Even though some stocks will return in their portfolio several months in a row, the high volume of trading brings high transaction costs. Unfortunately they do not discuss transaction costs in their paper. To improve the economic relevance of a momentum strategy based on AG, it is necessary to test the effect of AG on momentum with a strategy with lower the transaction costs by less intensive trading. Because of this, in this paper the momentum strategy based on AG will use an 11/6/1 and an 11/12/1 strategy. This strategy is also supported by Jegadeesh and Titman (1993) who discovered that the optimal holding period of a momentum strategy is three to twelve months.

The existence of the price momentum anomaly has been known for quite some time. It has been studied by many and been assigned to several possible drivers. Even though it is probably driven by several different factors. In this paper the effect of AG on price momentum will be further investigated with a grouping on AG. Also to be able to exclude the effect of other drivers on momentum results, a panel regression will be made to test for this.

3. Data and Methodology

Firstly, the data and methodoly used to test the effect of AG on momentum will be discussed. Secondly, the data and methodology of the panel regression, which is used to test for other variables that might influence momentum, will be discussed.

The effect of AG on Momentum

The data on asset growth used in this paper is collected from Compustat Capital IQ, and contains North American companies listed on the New York Stock Exchange from 1995 – 2015. To minimize potential backfilling and survival biases all firms have to be listed at least two years before their AG is calculated, as suggested by earlier studies such as Nyberg and Pöyry (2014). Furthermore, financial companies are excluded because they have an unusual high leverage compared to non-financial firms, where this more likely indicates distress (Fama & French, The Cross-Section of Expected Stock Returns, 1992).

The data taken from this database is the company specific 9-digit CUSIP code and the variable AT; "The total assets/liabilities of a company at a point in time". Variable AT is annually given and used to create the variable AG, which is defined as the yearly percentage change in total balance sheets assets. For a given firm i, the AG variable that is given for t=0 is calculated by:

$$AG_{i,t} = 100 * \frac{AT_{i,t} - AT_{i,t-1}}{AT_{i,t-1}}$$

Where $AG_{i,t}$ is the asset growth for firm i, in year t. This is calculated for each year. This is in line with the methodology used by Nyberg and Pöyry to be certain of unbiased and comparable results.

CRSP is used to find the connecting stock price data to these firms for the period 2005 - 2015. To make sure that tiny and illiquid stocks do not influence the results, stocks below the 20th percentile of the New York Stock Exchange are excluded. This is recommended by Fama and French (2008), and the excluded stocks are by them defined as microcaps.

To answer the question whether long-term AG is able to forecast price momentum profits, the firms have been divided into three groups based on their AG in the period 1995-2005. The first group has the lowest 30% AG, middle has the firms with AG 30%-70%, and high is the group with the highest 30% AG. Table 1 shows the descriptive statistics of these groups.

Table 1.

In this table all firms investigated in this paper are ranked according to their average aggregate AG from 1995-2005 and divided into three groups, 0-30%, 30-70% and 70-100%, these are the descriptive statistics of these groups.

	N	Mean	Std. Deviation	Percentage with negative AG
Low AG	305	3.37	3.79	16.07%
Medium AG	408	12.98	3.51	0.00%
High AG	305	44.70	95.97	0.00%
All	1018	19.61	55.21	4.81%

Table 2.

In this table the N, mean and standard deviation is given of the monthly equal weighted returns per group of the period January 2005 to December 2015, where the groups are based on the AG of these firms over the period 1995-2005. It also shows the correlation with the other AG groups and the market cap, where 1 asterisk indicates significance on the 5 percent level, and two asterisks on the 1 percent level, two-tailed.

	N	Mean	Std. Deviation	Correlation with Low	Correlation with Medium	Correlation with High	Market
Low AG	131	-0,41	5,16	1	0,511**	0,948**	0,875**
Medium AG	131	0,37	5,74	0,511**	1	0,533**	0,850**
High AG	131	1,63	10,60	0,948**	0,533**	1	0,893**
Market	131	0,51	6,11	0,875**	0,850**	0,893**	1

Table 3.

In this table the means of the average stock price return per month of each AG group is tested in a One-sample t-test for difference in means.

	t-statistic	df	Significance (2-tailed)	Mean Difference
Low AG	-0,91	130	0,366	-0,41
Medium AG	0,73	130	0,468	0,37
High AG	1,75	130	0,082	1,63

The relatively high standard deviation of the high AG group is caused by a series of extremes, however when only looking at the different groups it seems unnecessary to remove them since the actual value is not used in these calculations. The standard deviations of the low and medium AG group are very similar and a lot smaller. The standard deviation of the low AG group is slightly higher due to a few companies with quite negative AG's. Whilst the medium AG group covers the middle ground, which includes relatively average firms.

Table 2 shows the equally weighted monthly average stock return of each group over the period 2005 - 2015. The difference in monthly gains per group is economically large, the difference on annual basis between the low and high AG group is 24,41 percent. But, as can be seen in table 3, on a five percent significance level these means all do not differ from zero.

However, when performing a t-test to compare the means of the High and Low AG groups, the hypotheses that they are equal is rejected on a 5 percent level. So, buying a portfolio of stocks containing the top 30% performers based on their AG of the past ten years, will give significantly higher returns than buying the 30% worst performers. Even though this seems quite obvious, the difference is economically large.

Nyberg and Pöyry conclude that momentum profits are largest for firms that have experienced a large asset expansion or contraction. Their study shows that the optimal momentum strategy would be to buy winners and sell losers from the high AG group. This result is quite counterintuitive. The data on which they base their AG groups is roughly the same period as used to determine what stocks to buy/sell in the momentum strategy. Apparently a growth in assets can result in two different things for a firm, stock prices going up in that year and the year after, or stock prices going down in that year and the year after.

The cause of this effect is not investigated, however, they do conclude that firm level investment has great influence on momentum strategy, but in a way described by Berk, Green and Naik, where investors look at the firm-specific investment choices made and respond to how well these choices are (Berk, Green, & Naik, 1999).

Differently from Nyberg and Pöyry in this research the long term effect of AG will be investigated by looking at a firm's AG over a ten year period, because of this long term period, only three AG groups have been created, differently from Nyberg and Pöyry, who created ten. The reason this has been chosen is to keep these groups bigger, whereas with Nyberg and Pöyry the firms within each AG group might change each period, when looking at the firm's long term AG and only looking at their stock prices afterwards this is not possible.

However, to keep the momentum strategy clean, instead of the best (worst) 20 percent performers, only the best (worst) 10 percent performing stocks are bought (sold) each period. This should still give enough firms to not let extremes bias the results, because the AG groups are relatively large. Also this is different from the methodology used by Nyberg and Pöyry who split the momentum strategy into five groups based on the firm's performance of the previous eleven months and one lag month in between.

The panel regression

For the panel regression, data is also collected from Compustat Capital IQ. The data is annually and from 2004 – 2015, for the same 1018 companies that were used earlier in this study. This means that financial companies and microcaps are excluded. The variables taken from this database are: Total assets, earnings per share, common shares traded, Stock price close and total market value.

The following variables are created from this data, and will be used in the regression:

- ST_RET: This is the dependent variable annual stock return, it is calculated by subtracting the closing stock price of year t-1 from the closing stock price of year t, divided by the closing stock price of year t-1, multiplied with 100.
- AG: Total assets is used to create the variable AG, by the formula earlier discussed in the data and methodology part of this paper.
- BM: The second variable, book-to-market is created by dividing the total assets of year t by the total market value of year t.
- EAR_MAR: The variable EAR_MAR is earnings as percentage of the market value. It is calculated by dividing earnings per share of year t by closing stock price of year t.
- RET_11: This is the return of eleven months of the year t-1, December is excluded to avoid short-horizon negative return auto-correlation.
- TRAD: This is the variable change in volume traded, it is calculated by subtracting the volume traded of year t-1 from volume traded in year t, divided by volume traded t-1, multiplied with 100.

These variables are computed for each firm individually over the period 2004 – 2015. The goal of this panel regression is to observe the effect of AG on stock returns and specifically momentum. By making a panel regression the possible causality of AG on momentum is tested against possible third variables over a longer period with many different firms. This is necessary since there is a lot of literature about momentum, which describe many other drivers besides AG.

Hou and McKnight (2004) argue that book-to-market is negatively related with momentum profits. Lee and Swaminathan (2000) connected momentum profits to trading volumes, therefore book-to-market ratio and change in trading volume have to be taken into the panel regression.

Jegadeesh, Chan and Lakonishok (1999) investigate momentum by looking at both price momentum and earnings momentum. Their finding was that price momentum has a stronger effect than earnings momentum. However, to be certain any momentum profits are caused by AG and price momentum, it has to be controlled for earnings momentum as well.

A panel regression has been chosen to investigate the different possible drivers of momentum because it is a relatively easy way to investigate a time-series relationship of a large number of entities. The time-series chosen in the study is relatively short, however it is done over a large number of firms. Unfortunately the number of firms is only 768 instead of 1018, this is caused by unavailability of data.

Differently from the first part of this paper the variable AG is now calculated for each year. Whilst in the first part for every firm one average AG was calculated over a ten-year period, in the panel regression the variable AG is calculated for each year. AG will be used to estimate stock returns for the next year. However, to be able to understand the long term estimation effect of AG on stock returns and specifically momentum, different lags of AG will be tested as well.

To prevent multicollinearity among the predictor variables the correlations of all variables have been tested against each other in table 4. The highest correlation in absolute terms is only 0,146, and thus there should be no problems with multicollinearity.

Table 4.

This table shows the correlations between the variables, asset growth (AG), book-to-market (BM), earnings as percentage of market value (EAR_MAR), first difference of stock trading volumes (TRAD) and the stock price returns of the months Jan-Nov of year t-1. The period is 2004 – 2014.

	AG	BM	EAR_MAR	TRAD	RET_11
AG	1	0,020	0,004	0,004	-0,005
BM		1	-0,146	0,005	-0,002
EAR_MAR			1	-0,023	0,018
TRAD				1	0,060
RET_11					1

4. Results

First the results of the momentum strategy based on AG will be discussed, where it will also be compared to the results of Nyberg and Pöyry. Secondly the results of the panel regression will be discussed and also the complications this brings to the conclusions made.

The long term effect of AG on momentum

The results of the momentum strategies of the different AG groups can be seen in table 5. Panel A shows the results of buying the 10 percent worst and best performers for the holding periods of six and twelve months. The first important observation is the negative results for buying the worst 10% performers of the low AG group, -6,94% and -6,25%. This is in accordance with the momentum strategy results of Chan et al. (1993), since selling losers gives significant profits.

Nyberg and Pöyry (2014) state that momentum profits are only large for firms that have experienced a big asset expansion or contraction. The results in panel A do not fully underline this conclusion. Even though a strategy of buying winners and selling losers is profitable in the low AG group, it is not optimal within the high AG group. Regarding the high AG group, the worst performing stocks in the look-back period still give a positive average monthly return of 1,80% or 1,26% depending on the holding period. Because of this, a full momentum strategy of buying winners and selling losers is less profitable than only buying the winning stocks of the High AG group.

Based on the results of table 5 panel A, the optimal momentum strategy would be to sell the worst stocks in the look-back period from the low AG group and buy the best stocks in the look-back period from the high AG group. This seems unquestionable from these results based on an equal-weighted portfolio. However, even though this result is equal-weighted and financial companies and microcaps are excluded, it still has a bias. The high AG group contains a firm with an extremely high volatility. It reached its lowest point in November 2011, with a stock price of 0,0322 dollar. A month later, however it climbed to 9,97 dollar. This is a growth of 30.862,73%. This has an enormous effect on the best performers of the AG group. Excluding this stock from this study results in 8,83% monthly gain with best stocks in an 11/1/6 strategy dropping to only 0,30%. Similarly the 9,04% gain per month on the best performing stocks with an 11/1/12 strategy drops to 0,53%. This gives reason for cautious interpretation.

The last interesting part about panel A is the medium AG group. The worst performing stocks in the look-back period show better results in the holding period than the best performing stocks from the holding period do in the holding period. The difference with the 11/1/12 strategy is with 2,66% per month economically large and gives reason for further investigation. It is not surprising that the medium AG group does not show any momentum profits, since Nyberg and Pöyry (2014) also concluded this already. However this is so far off from earlier studies about momentum, it is even in line with the return reversal of DeBondt and Thaler (1985).

Nyberg and Pöyry created ten AG groups, and after that sorted to the returns of five past return groups. Thus when looking at the best (worst) performers in their look-back period, they looked at the best (worst) twenty percent. Panel A and B differ significantly in monthly percentages, where the results in panel B are up to 50 percent lower than panel A. This difference is caused by the group of 10 to 20 percent worst or best performers in the look-back period that are in panel B also taken into the portfolio. Apparently these stocks show significantly less momentum effect, negative and positively. This indicates that Nyberg and Pöyry might have underestimated the effect of AG on momentum.

Table 5.

This table shows the results of a momentum strategy over the period 2005 – 2015. The firms have first been divided into three groups based on their asset growth in the period 1995 – 2005. Then, in panel A each year the performance of the worst 10% performers (Low) and the best 10% performers (High) over a period of eleven months. In panel B, the worst 20% performers (low) and best 20% (high) performers are used for the portfolio. The last month is the lag period and is excluded. The table shows the average monthly returns in percentages for holding these stocks for a period of 6 or 12 months.

Panel A	**11/6/1**		**11/12/1**	
10%	**Low**	**High**	**Low**	**High**
Low AG	-6,94	1,12	-6,25	0,92
Medium AG	2,17	0,56	2,56	-0,10
High AG	1,80	8,83	1,26	9,04

Panel B	**11/6/1**		**11/12/1**	
20%	**Low**	**High**	**Low**	**High**
Low AG	-3,40	0,67	-2,78	0,38
Medium AG	1,52	0,30	1,85	-0,02
High AG	1,28	4,69	1,00	4,76

The results of the panel regression

The grouping in table 2 has shown how strong the effect of AG on stock return is. Differences in stock returns between AG groups are economically significant. However, to which extent can AG be credited for these differences?

Table 6 shows the different panel regressions that have been made to find the optimal coefficient estimates of the earlier discussed variables on yearly stock returns. The first regression was created similarly to the regression made by Nyberg and Pöyry (2014). In the second regression all insignificant variables are excluded, except AG(-1). AG(-1) is left in the regression to await the full results of all AG variables. In the third regression the other lags of AG are added to get a complete picture of the long-term effect of AG on stock prices. In the fourth regression the insignificant variables are excluded, except BM(-1). BM(-1) is left in the regression to be able to further investigate why it suddenly became insignificant. In regression 5 all insignificant variables are excluded.

In regression 1, the variable TRAD is insignificant. Thus no evidence is found to support the findings of Lee and Swaminathan (2000) that volume influences stock prices and drives momentum. Therefore it is removed from regression 2 onwards

Also RET_11 is insignificant in regression 1. This seems to have some consequences for the assumption on the existence of momentum. When following a momentum strategy of buying winners and selling losers, the expectation is that past returns have some predictive power over future returns. The reason to not completely dismantle the strategy of momentum is that it only uses the biggest losing stocks and the highest winning stocks. Therefore 60 to 80 percent of all stock price changes are not accounted for in a momentum strategy. Since RET_11 is insignificant it is taken out of the next regressions.

In regression 3, several lags of AG have been added to discover the long-term effect of AG on stock prices. Surprisingly lag 4 and 5 are significant, whilst the first three lags of AG are not. This supports the hypotheses that AG has a long term effect on stock prices and also price momentum.

Variable BM is significant in the second regression, with even a high t-statistic of 14,053 and a coefficient estimate of 13,825. This effect disappears when the lags 2 up to 5 of AG are added to the model. Even with lags -1 to -3 are removed, BM is still insignificant. This gives reason to suspect multicollinearity. Therefore after regression 4 another set of correlations calculated. Table 7 shows the correlations between BM and the significant lags of AG. The high correlation between AG(-5) and BM(-1) of 0,730 gives reason to exclude one of them from the model. Since AG(-5) is before BM(-1) timeline wise, BM(-1) is probably affected by AG(-5). This is not surprisingly since total assets is used to calculate BM, however there are still three years in between. Since BM is also insignificant it is removed from the regression, and thus the final regression is regression 5.

This regression shows evidence of a long-term effect of AG on stock prices, as expected by the results from the momentum strategy. In contrary to the results of Nyberg and Pöyry (2014) this data does not show evidence of a short-term effect of AG on stock prices. The similarity it does have is the negative relationship.

Both AG(-4) and AG(-5) have a negative coefficient estimate. This suggests that a growth in assets, results in a loss of stock price value four to five years later. This is strongly opposing the results of the grouping in table 2 that shows that firms with a higher long term AG have better stock price returns than stocks with a lower long term AG.

The negative relationship between AG and stock returns is not new. Cooper Gulen and Schill (2008) have documented similar results, where firms with a low AG have an annualized risk-adjusted return of 19,5% higher than firms with high AG's. They conclude that this is caused by investors overextrapolating past growth of assets

The only other variable left in the regression besides the AG lags is earnings as percentage of market value. Its relationship with stock price change in the following year is negative, but highly significant with a t-statistic of -35,958. Past earnings have a strong effect on stock prices, whilst past stock prices do not. This might suggest that earnings momentum is still relevant, even though the latest literature mostly focuses on price momentum.

The negative coefficient of earnings as percentage of market is quite peculiar. In other similar regressions with stock returns as dependent variable, earnings has a positive coefficient. This includes studies from Fama and French (2015), Nyberg and Pöyry (2014) and Da (2009). A possible explanation could be that past returns have been overextrapolated. Meaning that high returns in year t, increases the stock price in year t, but not in year t+1. Even though there is no empirical evidence to back this up.

Even though short-term asset growth does not show significant effect on stock prices, longer term asset growth does. Other variables that have shown to be drivers of momentum or stock prices in the past, such as trade volumes and book-to-market ratios also did not show any significance. One of the probable causes of the lack of results is the short period of observations. Another cause could be the misuse of data, this study used trade volume as percentage increase with the year before. Whilst Lee and Swaminathan (2000) used change as percentage of total outstanding stocks. Nevertheless, the lack of evidence on drivers of stock prices demands further investigation.

Table 6.

Table 5 shows the outputs of different panel regressions on the dependent variable ST_RET. The variables are; asset growth (AG), book-to-market (BM), earnings as percentage of market value (EAR_MAR), first difference of stock trading volumes (TRAD) and stock price returns from Jan-Nov of year t-1 (RET_11). The period of these regressions is 2006 – 2015. 768 firms are included

	1	2	3	4	5
Intercept	10,861 (3,470)	-43,263 (-2,785)	14,810 (3,681)	13,306 (3,452)	13,069 (3,420)
AG(-1)	-0,014 (0,4548)	-0,027 (-0,279)	-0,174 (-1,050)		
AG(-2)			-0,021 (-1,118)		
AG(-3)			0,016 (-0,844)		
AG(-4)			-0,055 (-2,744)	-0,055 (-2,734)	-0,058 (-3,050)
AG(-5)			-0,119 (-4,166)	-0,119 (-4,162)	-0,129 (-6,732)
BM(-1)	1,041 (5,477)	13,825 (14,053)	-0,156 (-0,479)	-0,154 (-0,475)	
EAR_MAR(-1)	-0,309 (-23,358)	-3,251 (-90,985)	-1,476 (-34,387)	-1,475 (-34,374)	-1,469 (-35,958)
TRAD(-1)	-0,039 (-1,138)				
RET_11	0,001 (0,561)				

Table 7.

This table shows the correlation between lag 4 and 5 of asset growth and the first lag of Book-to-market over the period 2005 - 2015

	BM(-1)	AG(-1)	AG(-2)	AG(-3)	AG(-4)	AG(-5)
BM(-1)	1	-0,044	0,019	0,016	0,222	0,723
AG(-1)		1	0,002	-0,006	-0,016	-0,011
AG(-2)			1	-0,003	0,006	-0,005
AG(-3)				1	-0,002	0,006
AG(-4)					1	-0,002
AG(-5)						1

5. Conclusion

This paper has sought to explore the relationship between AG and momentum. In the first part of this study a grouping on AG was used to predict momentum profits, and in the second part a panel regression was used to find the driver of stock returns.

The evidence of the grouping on AG is not overwhelming. It has shown that selling losers in a low AG group gives significantly more returns than selling losers in higher AG groups. The evidence on buying winners in the high AG group however, has a strong bias. The high equal weighted return is driven by only one stock that had a tremendous relative growth in one month. Excluding that stock diminishes the return on buying winners in the high AG group to an insignificant low return.

The lack of evidence on abnormal returns could be caused by several factors. The first is data, the data is of a relatively short period, only ten years. Secondly within these ten year the financial crisis of 2007-2008 is incorporated. Even though financial companies are excluded, other firms were also influenced by this crisis. In 2007 and 2008 of all stocks, 85,65% and 55,22% respectively had a loss in stock price. As this crisis was unpredicted, so were the results of the stock prices as its result. Therefore the lack of results could be caused by unpredictability caused by for example the financial crisis. And since the observation period is only ten years, this has a large effect. To prevent this in future studies, longer data samples should be used.

Also the panel regression did not show the expected results. Not surprisingly the factors mentioned above could also have caused the lack of results in the panel regression. Only lag 4 and 5 of AG and earnings as percentage of market value showed to be significant predictors of stock prices. Other variables like book-to-market, previous stock returns and trade volumes, that were proven to be drivers of momentum in previous studies, did not show significant results.

The effect of lag 4 and 5 of AG on stock prices however is very interesting. It shows that investment decisions now, have a strong effect on stock prices four to five years from now. This effect is also supported by the results of table 2. Table 2 shows the average monthly returns of stocks from 2005-2015, after they have been divided over three groups based on their asset growth in 1995-2005. Where firms with low asset growth have significantly lower stock returns than firms with high asset growth.

How AG interacts with stock prices 4 to 5 years later has not been studied in this paper. The answer however can most probably be found by looking at investor responses to specific investment choices. Berk, Green and Naik (1999) argue that investors respond to specific investment choices, because it affects the firm's expected returns and systematic risk. This direct link, is not studied in this paper.

However, the lagged response in stock prices after asset growth could be caused by the investors not immediately responding to an investment, but waiting for its results. Another cause could be that the investments' lifespan ends after this time, and the systematic risk and expected return of the stock go back to its original values. This would also explain why both lag 4 and 5 have a negative coefficient. This paper gives no empirical evidence to back this up, however it would be interesting for further studies to examine the precise effect of lagged asset growth on stock prices and momentum.

Other suggestions for further studies are to combine the long and short term effect of asset growth on momentum. Another interesting subject to study is the negative coefficient of earnings as percentage of market value, from the panel regression. Lastly, the combination of these two subjects, where not only price momentum is investigated with asset growth as explanatory variable, but also earnings momentum.

Bibliography

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2007). Momentum and Credit Rating. *The Journal of Finance*, 2503-2520.

Berk, J. B., Green, R. C., & Naik, V. (1999). Optimal Investment, Growth Options, and Security Returns. *The Journal of Finance*, 1553-1607.

Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1999). The Profitability of Momentum Strategies. *Financial Analysts Journal*, 80-90.

Chan, L., Jegadeesh, N., & Lakonishok, J. (1996). Momentum Strategies. *The journal of Finance*, 1681-1713.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset Growth and the Cross-Section of Stock Returns. *The Journal of Finance*, 1609-1651.

Da, Z. (2009). Cash Flow, Consumption Risk, and the Cross-Section of Stock Returns. *The Journal of Finance*, 923-956.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 3-56.

Fama, E. F., & French, K. R. (2008). Dissecting Anomalies. *Jounal of Finance*, 1653.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 1-22.

Hou, T. C., & McKnight, P. J. (2004). An Explanation of Momentum in Canadian Stocks. *Canadian Journal of Administative Sciences*, 334-343.

Howe, J. S., & Yang-pin, S. (1998). Information associated with dividend initiations: Firm-specific or industry-wide? *Financial Management*, 17-26.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 65-91.

Keane, S. M. (1983). *Stock market efficiency: theory, evidence and implications.*

Kent, D., & Titman, S. (1999). Market efficiency in an irrational world. *Financial Analysts Journal*, 28-40.

Koijen, S., Rodríguez, J., & Sbuelz, A. (2009). Momentum and Mean Reversion in Strategic Asset Allocation. *Management Science*, 1199-1213.

Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *The Journal of Finance*, 2017-2069.

Lee, N., Liu, J.-F., & Lin, W.-Y. (2014). Default probability anomalies in the momentum strategies. *Applied Economics Letters*, 1206-1209.

Lehmann, B. (1990). Fads, Martingales, and Market Efficiency. *The Quarterly journal of Economics*, 1-28.

McGraw Hill Financial. (2014). *298e606f-ce5b-5ece-9076-66810cd9b6aa.* Retrieved from spratings: http://www.spratings.com/documents/20184/760102/SPRS_Understanding-Ratings_GRE.pdf/298e606f-ce5b-4ece-9076-66810cd9b6aa

Nyberg, P., & Pöyry, S. (2014). Firm Expansion and Stock Price Momentum. *Review of Finance*, 1465-1505.