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Investments in Fallen Angel Stocks
An empirical analysis of quality indicators of disgraced growth companies

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LIST OF ABBREVIATIONS

AQ	Angel quality
BFA	Bad fallen angel
B/M	Book-to-market
bp	Basis point
CAGR	Compound annual growth rate
CAPEX	Capital expenditure
CAPM	Capital asset pricing model
CAR	Cumulative abnormal return
CEO	Chief Executive Officer
CFF	Cash flow from financing activities
CFI	Cash flow from investing activities
CFO	Cash flow from operating activities
COGS	Cost of goods sold
EBIT	Earnings before interest and taxes
EPS	Earnings per share
EU	European Union
FCF	Free cash flow
GARP	Growth-at-a-reasonable-price
GDP	Gross domestic product
GFA	Good fallen angel
GPM	Gross profit margin
I/B/E/S	Institutional Brokers' Estimate System Database by Thomson Reuters
ICB	Industry Classification Benchmark
IFRS	International Financial Reporting Standards
IT	Information technology
M&A	Mergers and acquisitions

M/B	Market-to-book
MSCI	Morgan Stanley Capital International
NASDAQ	National Association of Securities Dealers Automated Quotations
NES	Negative earnings surprise
NI	Net income
NYSE	New York Stock Exchange
P/B	Price-to-book
PEAD	Post-earnings announcement drift
P/E	Price-to-earnings
PEG	Price-to-earnings growth
P/CF	Price-to-cash flow
P/S	Price-to-sales
R&D	Research & development
REIT	Real estate investment trust
ROA	Return on assets
ROE	Return on equity
SG&A	Selling, general & administrative expenses
S&P	Standard & Poor's
SPS	Sales per share
SUE	Standardized unexpected earnings
TR	Total return
TSR	Total shareholder return
U.S.	United States of America
US\$	United States dollar
WS	Worldscope Fundamentals Database by Thomson Reuters

1 Introduction

1.1 Relevance of Topic

“Most analysts feel they must choose between two approaches customarily thought to be in opposition; ‘value’ and ‘growth’. [...] In our opinion the two approaches are joined at the hip;”

*Warren Buffett*¹

Regardless of Buffet’s statement, which is fundamental to his investment philosophy² that so far made him the most successful investor ever³, the distinction between value and growth investment styles is still a very prominent way to separate the investment approach of different investors.⁴ Academics write papers on the performance of value versus growth stocks⁵, stock market indices are split into growth- and value-types⁶, and investors label themselves as applying either growth or value investment principles.⁷ Sometimes it appears as if this divide within the investors’ universe bears dogmatic traits. While growth investors frown upon “boring” value stocks, value investors often ignore fast-growing companies, because they believe that those are overvalued.⁸

From the viewpoint of an investment universe that is strictly separated between growth and value stocks, this behavior might be understandable. Nevertheless, investors might forgive good chances to earn better returns by doing so. Ignoring the attractive returns that growth stocks offer, particularly when you buy into them at early stages of their company development, is not advisable for an equity investor who is striving for high abnormal returns. However, following the thinking of Graham that “[T]here is no such thing as a sound investment regardless of the price paid,”⁹ it is often difficult to find

¹ Arnold (2002), p. xviii.

² See Buffett (2003), p. 113 et. seq.

³ See, for example, Cunningham (1998), p. 13, or Greenwald et al. (2001), p. 161.

Furthermore, as an interesting side note, the Wikipedia entry on the person Warren Buffett (en.wikipedia.org/wiki/Warren_Buffett) shows up as top of the list when entering the search phrase “most successful investor” in Google (as of November 14, 2011).

⁴ See, for example, Sharpe (1992), Kaye (2006), p. 41 et seq., or Postert (2007), pp. 44-63.

⁵ See Chan/Lakonishok (2004) for a good overview.

⁶ See, for example, Morgan Stanley Capital International (2005) or Standard & Poor’s (2011b).

⁷ See, for example, Siegel (1999), Neff (2001), p. 62, or Wyatt (2009), p. 44.

⁸ See Athanassakos (2011) or Haugen (2011), pp. 46 et seq.

⁹ Zweig/Sullivan (2010), p. 15.

growth companies at reasonable values. To increase the chances of finding a company with good long-term growth potential at an attractive price, an investor should look for market conditions when the share price of such companies is particularly depressed and thus a desirable opportunity arises.¹⁰

Although this sounds logical, the key question still remains: How can an investor systematically detect such investment opportunities? Neither looking towards academia nor investment practice helps in answering this question. While academic research has been analyzing the stock returns of different investment styles for several decades¹¹, it did not yet address the subject of fallen angel stocks.¹² In contrast, investment practitioners have touched upon the topic, but only in a qualitative and unsystematic matter.¹³ Boyar, an experienced value investor with a special interest in finding undervalued companies that have suffered from a significant drop in their share price, raises the question: “Is there a black box that spits out fallen angels?”¹⁴ And in answering himself, he underlines the desire of the investment practice for a more systematic approach: “Unfortunately not. We can only rely on decades of experience to sift through a barrel full of fallen angels to find appropriate investments.”¹⁵ Only recently, fund manager and investment advisor Wisdom has addressed the topic of fallen angel investing comprehensively in his book subtitled “How to Profit on Fallen Angels”.¹⁶ However, while he provides investors with some measurable criteria that a promising fallen angel investment opportunity should fulfill, he does not provide statistically backed evidence for them.¹⁷ An investor seeking clear guidance can therefore only either believe in the proposed quantitative thresholds or not. Furthermore, Wisdom mentions several different situations in which investors should look for fallen angels. Since these situations are only qualitatively described and thus not clearly defined, statistical tests of the proposed measurable criteria of

¹⁰ See Fisher (2003), pp. 275-277, and Wisdom (2009), pp. 15-20.

¹¹ See, for example, Chan/Lakonishok (2004) for an overview of published academic research on growth and value investment styles.

¹² The focus of academic research so far has been on fallen angel bonds. See, for example, Blume/Keim (1987), p. 26, Altman/Kao (1992), p. 15, Fridson (1993), p.12, Buffett (2003), pp. 134 et seq., or Fabozzi (2008), p. 265.

¹³ See, for example, Kuhn/Neumeier (1993).

¹⁴ Boyar (2000), p. 5.

¹⁵ Boyar (2000), p. 5.

¹⁶ See Wisdom (2009).

¹⁷ See Wisdom (2009), pp. 95-105.

fallen angel selection cannot be undertaken.¹⁸ In a nutshell, there appears to be a research gap with regard to investments in fallen angel stocks and a demand by the investment practice to gain more solidly backed insights on this topic.

To improve this rather unsatisfying situation for both academics and investors and devise a systematic framework, a good starting point could be negative earnings announcements of growth companies: As growth (or “glamour” as several scholars call them¹⁹) stocks tend to perform significantly worse than value stocks around earnings announcements, it appears that growth investors hold too high expectations concerning the companies’ earnings growth and then sell the stock on disappointing news.²⁰ Fisher, a pioneer in investing in growth companies, highlighted this phenomenon very well: “When a stock has been selling too high because of unrealistic expectations, sooner or later a growing number of stockholders grow tired of waiting. Their selling soon more than exhausts the buying power of the small number of additional buyers who still have faith in the old appraisal. The stock then comes tumbling down. Sometimes, the new appraisal that follows is quite realistic. Frequently, however, as this re-examination evolves under the emotional pressure of falling prices, the negative is overemphasized, resulting in a new financial-community appraisal that is significantly less favorable than the facts warrant and that may then prevail for some time.”²¹ Graham, too, recognized the tendency of financial markets to overshoot: “The market is always making mountains out of molehills and exaggerating ordinary vicissitudes into major setbacks.”²²

This overreaction of the market tends to happen faster in case of negative earnings surprises as compared to positive earnings surprises. Whereas in the latter case one can observe a longer post-earnings announcement drift, negative news are quicker incorporated in stock prices.²³ Consequently, stock prices are depressed soon after the negative news has been conveyed to the market, which opens a window of opportunity for an investor. Fisher compares such drop in the share price of a fallen angel with the previous rise and claims that both phenomena are an expression of market

¹⁸ See Wisdom (2009), pp. 15-55.

¹⁹ See Lakonishok/Shleifer/Vishny (1994), La Porta et al. (1997), Guay (2000), Chan/Lakonishok (2004), Jegadeesh et al. (2004), or Yan/Zhao (2011).

²⁰ See La Porta et al. (1997), pp. 863-866.

²¹ Fisher (2003), p. 209 et seq.

²² Graham (1959), p. 110.

²³ See Berens (2010).

overreaction.²⁴ An investor that picks up shares at such depressed levels has a good chance to benefit from both a continued improvement in the earnings of the company and a future recovery of the price-to-earnings ratio.²⁵ De Bondt and Thaler delivered empirical evidence for this statement by demonstrating that stocks with recently weak share price development outperform those with strong share price performance.²⁶

Nevertheless, knowing which event to watch out for when searching for potential share purchase opportunities is only one part of the desired systematic approach. The other is a set of indicators that help investors in selecting the right stocks from the pool of companies that have negatively surprised with their earnings and afterwards have experienced an abnormal drop in share price. Furthermore, the time horizon in which to check into these potential investment opportunities is also of importance. Providing systematic and empirically backed insights on investments in fallen angel stocks would contribute to narrowing the existing research gap. The academic community would further benefit, since the findings might bring value and growth investment styles closer to each other, thereby supporting the development of new, less dogmatic perspectives in stock return analysis and portfolio management. With regard to the investment practice, a systematic approach including a set of tested indicators that enables investors to identify promising fallen angel stocks would be advantageous. Additionally, supplying the investment community with such insights would allow value investors to earlier invest in companies that have just been shunned by growth investors, thereby narrowing the gap between value and growth investment styles also among investment practitioners.

1.2 Objectives of Research

The main aim of this thesis is to close the existing research gap concerning fallen angel stocks. This shall be achieved by identifying and statistically testing possible indicators that make it possible to better distinguish fallen angel stocks that will generate positive abnormal returns after the negative earnings surprise from those that continue to underperform after such an event. Additionally, the investment practice shall benefit from the findings of this thesis. The resulting set of suitable indicators for the quality of fallen angel stocks would assist investors in their investment analysis and thus improve the quality of their investment decisions. Finally, this thesis strives

²⁴ See Fisher (2003), p. 210.

²⁵ See Fisher (2003), p. 210, and Wisdom (2009), p. 114.

²⁶ See De Bondt/Thaler (1985).

for building a bridge between value and growth investment styles by enabling investments in disgraced growth stocks at an earlier point in time than traditional value investment criteria would suggest.

1.3 Structure of Thesis

Following this introduction, the thesis proceeds along the following structure: Firstly, concepts and theories relevant for investments in fallen angel stocks are described. Chapter 2 defines the terms investment and investor, and describes the characteristics of fallen angels as used in this thesis. Chapter 3 provides some basic information about the underlying philosophies of science that were guiding this research. Moreover, this chapter touches on two fundamental concepts of how financial markets function: the efficient market hypothesis and behavioral finance. Understanding the basics of these concepts as well as their benefits and shortcomings is of great value to put this research and its results in a bigger investment perspective. Chapter 4 addresses the topic of investment styles with a focus on value and growth investing.

Secondly, the design and results of the empirical part as the core of this thesis are presented. Chapter 5 designs a framework of possible indicators for angel quality and derives and explains hypotheses around these indicators. Chapter 6 highlights and discusses the empirical results of the undertaken statistical tests. This also includes a summary of the key results and an analysis of selective variations of the base dataset in order to test for the robustness of the results.

Chapter 7 concludes the thesis with recommendations for the investment practice and an outlook providing potential links for future research.

2 Investment and Fallen Angels

Before elaborating further on the specifics of the approach to investing in fallen angel stocks as proposed by this thesis, the key notions of this activity shall be explained. A clear understanding of the definition of an investment and an investor as used in this thesis, as well as an exact characterization of fallen angels as the research object is key to fully understand and grasp the logic behind and benefits of the undertaken empirical analysis.

2.1 Characteristics of an Investment

With regard to the notion investment or investing, a rather broad variety of definitions used by both academia and investment practice exists. Frequently the term investing is loosely “used to mask what amounts to dice throwing”²⁷, but this is surely not what the underlying understanding of investing is in this thesis.²⁸ The prevalent, more scientific, and fact-based definition of investment revolves around the activities of consuming and saving money and the difference between these two over time. The reason why an investor would defer consume today is that he²⁹ can expect to reap a larger stream of cash flows in the future than what he laid out today.³⁰ Before committing to an investment, an investor will set for himself a required rate of expected return, which compensates him for the time his funds are tied up, for the expected inflation during the investment time, and for the uncertainty involved with the future cash flows.³¹ The expectation of such a return on an investment is the constituting feature under this investment definition.

While this expectation of a return on investment remains a key element of investment activities, Maginn et al. emphasize the importance of risk as the second and equivalent feature of an investment.³² Their definition of investment highlights the strong interdependence between risk and return objectives, which are inseparable from each

²⁷ Buffett (2009), p. ix.

²⁸ See Haviland (2011) for a comprehensive overview on the use of language by financial market participants, including the term “investment“ on a prominent position.

²⁹ In case the use of both genders would have been suitable when using pronouns, for simplicity’s sake the male form was used.

³⁰ See for example, Ellis (1998), Reilly/Brown (2000), pp. 4-6, Kaptan (2001), Ranganatham/Madhumathi (2005), p. 15, or Chandra (2008), p.3.

³¹ See Reilly/Brown (2000), pp. 5 et seq.

³² See Maginn et al. (2007), pp. 11-17.

other and therefore must be considered simultaneously. Besides, any investor has to pay attention to possible constraints, such as liquidity, time horizon, taxation, legal and regulatory factors, or other internal considerations, under which he has to perform his investment activities. Litterman also advocates this balanced understanding of investment and highlights the importance of such a risk-return balance not only for a single investment but particularly so for the overall investment portfolio.³³

The investment definition used in this thesis is specifying an investment further by distinguishing it from speculation. Graham and Dodd went down that route already in 1934 and gained support by others until today.³⁴ They defined an investment as follows: "An investment operation is one which, upon thorough analysis promises safety of principal and an adequate return. Operations not meeting these requirements are speculative."³⁵ Thus, their definition of an investment contains three main elements: Firstly, it is necessary for an investor to spend sufficient time and effort on analyzing the investment object, so that he is in a position to judge the company not only by a couple of numbers, but also in terms of the soundness of its underlying business model. Secondly, an investor has to take precautions to protect him against a sizable loss of principal. Thirdly, he should aim at a reasonable return rather than aspire to achieve an exceptional performance. It is important to keep these qualifying elements of an investment in the sense of Graham and Dodd³⁶ in mind when studying the results of this research and even more so, when one plans to take investment action based on them. The concluding chapter 7 elaborates more on this topic and puts it in context of the results of the statistical tests.

2.2 Definition of an Investor

In general, an investor is someone who employs money with the intention of gaining interest or profit from his action.³⁷ Further specifying this definition with regard to

³³ See Litterman (2003), pp. 7-23.

³⁴ See Graham/Dodd (1934), pp. 50-56, and Graham (2003), pp. 18-22, for the original source of this definition. For other sources building on the difference between investment and speculation when defining what an investment is see, for example, Cunningham (1998), p. 15, Cunningham (2002), p. 12, Buffett (2003), p. 85, Ranganatham/Madhumathi (2005), p. 19, Arnold (2010), pp. 19 et seq., or Klarman/Zweig (2010), p. 23.

³⁵ Graham/Dodd (1934), p. 54.

³⁶ See also Hagstrom (2005), p. 13.

³⁷ See Fisher et al. (2003), p. 5.

timing, an investor is “someone who seeks to make, is making or has made an investment.”³⁸

In the context of this thesis, it is furthermore important to point out that the term investor is always referring to an active investor. This type of investor is characterized as somebody who is looking for ways to improve his investment performance by investing in asset classes or individual securities that he believes are underpriced rather than trying to stick to the composition of the respective benchmark as passive managers do.³⁹

2.3 Characteristics of Fallen Angels

Like investment and investor, the exact meaning of fallen angels as the research object of this thesis requires clarification. In the opening to their groundbreaking work on security analysis, Graham and Dodd quote Horace from *Ars Poetica*: “Many shall be restored that now are fallen and many shall fall that now are in honor.”⁴⁰ This sentence almost perfectly describes the main idea behind fallen angel stocks as the object of this thesis. It is the expectation that stocks that have dropped sharply will eventually return to previous successful times, thus earning decent returns to investors who were able to buy them at depressed valuation levels.

Before proceeding further, however, it is important to mention that the term fallen angels has two different meanings when used by researchers or investors.⁴¹ First and foremost, fallen angels are synonymous for former investment grade corporate bonds that have been downgraded to below investment grade status.⁴² Secondly, the term fallen angels denominates former high-flying stocks which – for whatever reason – have become disgraced and might now be undervalued.⁴³

³⁸ Lauterpacht/Greenwood (2004), p. 135.

³⁹ See Ben Dor/Jagannathan (2003), p. 9 et. seq. The notion “active investor” as used in this thesis is not to be confused with the definition of an active investor as an equity holder who tries to exercise influence on the composition of the board or on strategic or operating issues of the company. See for the use of the notion “active investor” in that sense, for example, Jensen (1989), p. 36, or Milstein et al. (1998), pp. 55-58.

⁴⁰ See Graham/Dodd (1951).

⁴¹ See Wisdom (2009), pp. 4 and 15.

⁴² See Blume/Keim (1987), p. 26, Altman/Kao (1992), p. 15, Fridson (1993), p.12, Buffett (2003), pp. 134 et seq., or Fabozzi (2008), p. 265.

⁴³ See Scott/Stumpp/Xu (1999), Tengler (2003), p. x, Rosenberg (1999), p. 20, Boyar (2000), or AMM (2010). Wisdom (2009), p. 15, uses the stricter definition that a stock is only a fallen angel

As this thesis deals with equity investing, the latter understanding of a fallen angel is the relevant one here. The sudden depression in stock price may not necessarily be related to severe problems in the underlying business fundamentals of the respective companies or – if there are difficulties – could be exaggerated by negative market sentiment. Either case might offer attractive opportunities for investors to purchase the stock of these fallen angels at extraordinarily depressed levels.⁴⁴ However, searching for potential fallen angels without a concrete specification of neither the reasons for the previously abundant nor for the suddenly waning acceptance of these stocks by financial markets is difficult. Rather imprecise terms such as “experiencing temporary difficulties”⁴⁵, “recoverable calamities”⁴⁶, “extremes in prices”⁴⁷, or “the company is forced to make an announcement that the perfect environment is no longer”⁴⁸ do not provide clear guidance on how an investor might systematically proceed in his quest for finding such companies.

Hence, a framework of clearly measurable criteria is needed to enable investors to systematically search for fallen angels. Focusing on companies that have experienced above-average growth until a negative earnings surprise (NES) has caused a sharp unfavorable swing in financial market’s sentiment would establish such a framework. Consequently, a fallen angel in the context of this thesis is defined as a common stock of a growth company that has experienced an abnormal drop in its share price caused by a negative earnings surprise. More specific, for a stock to qualify as a fallen angel under the terms of this thesis it has to show all of the following three characteristics (see also **Figure 1**):

- Negative earnings surprise
- Abnormal negative shareholder return around the time of the negative earnings surprise
- Above-average growth before the negative earnings surprise that caused the abnormal drop in share price

if its value has actually dropped below its intrinsic value and its fundamentals indicate future revenue and earnings growth.

⁴⁴ See Buffett (2003), Graham (2003), p. 205, or Lynch/Rothchild (2004), p. 306.

⁴⁵ Tengler (2003), p. x.

⁴⁶ AMM (2010), pp. 1 et seq.

⁴⁷ Wisdom (2009), p.18.

⁴⁸ Boyar (2000), p. 2.

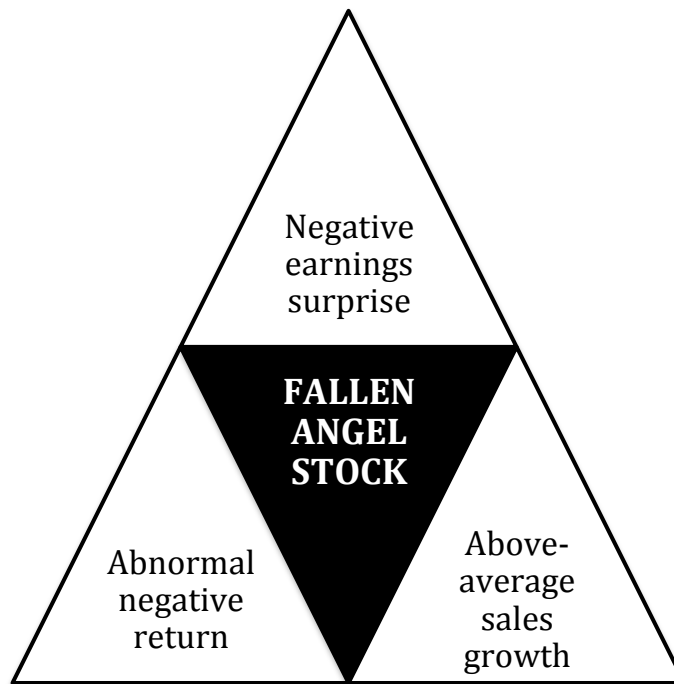


Figure 1: Constituting characteristics of a fallen angel stock

Source: Author

The last two criteria, a sizeable abnormal drop in share price and above-average sales growth before this abnormal drop, also constitute the link between growth and value investing. Whereas growth investors focus on companies with high actual or expected sales and earnings growth rates, value investors are concentrating on buying stocks at low valuations.⁴⁹ Since fallen angels combine both growth and depressed valuation levels, they are a suitable vehicle to bridge the divide between the investment styles of growth and value.

In the following three sections the constituting characteristics of fallen angel stocks are discussed in more detail.

⁴⁹ See section 4.2 for a more detailed description of growth and value investment styles.

2.3.1 Negative Earnings Surprise

Information about a company's earnings constitutes very important input for making investment decisions.⁵⁰ Earnings announcements that deliver actual earnings below analysts' expectations usually lead to a disappointment with financial market participants and a consequent underperformance of the stock of the company.⁵¹ As previous research has shown, stock markets tend to overreact to unexpected events, particularly if they carry negative news.⁵² As Dreman and Berry as well as Skinner and Sloan demonstrate, in particular stocks with high growth expectations suffer from a declining share price after a negative earnings surprise.⁵³ These stocks are the fallen angels as covered by this thesis. The observation from Skinner and Sloan can be explained by the behavior of investors who revise their too optimistic expectations downward in response to lower than expected actual earnings.

Given the importance of earnings announcements on share price, it is not surprising that managers try to manage the earnings of their companies. Degeorge et al. analyze such attempts to manage earnings in order to achieve a positive effect on the companies' share prices. As a result, Degeorge et. al. establish three thresholds which management tries to surpass or at least meet in order to accomplish a positive or at least avoid a negative earnings surprise: (1) report a positive profit, i.e. avoid reporting a loss, (2) sustain recent performance, i.e. avoid a drop in comparison to the last period, and (3) meet analysts' expectations.⁵⁴ However, such aspirations by management face significant headwind in the form of an optimism bias in analysts' forecast, i.e. financial analyst on average tend to make higher earnings per share (EPS) prognoses than what companies can deliver in reality.⁵⁵ As a consequence, the likelihood of earnings surprises increases. Building on this research, Brown and Caylor as well as Dechow et al. demonstrate, that meeting or missing analysts' earnings guidance is the most important driver of investor reaction around an earnings

⁵⁰ See Easton/Harris/Ohlson (1992) and Kothari/Sloan (1992).

⁵¹ See Liodakis et al. (2005), pp. 7 et seq. for Europe, and Ball/Brown (1968), pp. 159-178, Latané/Jones (1979), pp. 717-724, Jones/Rendleman/Latané (1985), pp. 28-32, or Abarbanell/Bernard (1992), pp. 1181-1207, for the U.S. The phenomenon of the earnings surprise anomaly has also been researched and confirmed for emerging market stocks, e.g. see Sen (2008) for the Indian stock market.

⁵² See De Bondt/Thaler (1985) and De Bondt/Thaler (1987).

⁵³ See Dreman/Berry (1995) and Skinner/Sloan (2002). The findings of Skinner and Sloan even indicate that almost all of the return advantage of value versus growth stocks can be attributed to the significantly more negative abnormal return caused by a negative earnings surprise.

⁵⁴ See Degeorge/Patel/Zeckhauser (1999).

⁵⁵ See Liu/Thomas (2000), p. 80.

announcement.⁵⁶ Thus, looking at negative earnings surprises appears to be a suitable way of identifying fallen angels.

In establishing a clear and measurable definition of an earnings surprise, this thesis follows previous authors from both academia and investment practice.⁵⁷ Thus, an earnings surprise is defined as the difference between the actual reported quarterly earnings and the most current quarterly mean consensus estimate made by analysts before the announcement period as provided by the I/B/E/S database.⁵⁸ This database was selected for both actual and estimate data in order to avoid inconsistencies.⁵⁹ Analysts' consensus earnings estimates are a good reference point for measuring earnings surprises, since they are a direct measure of expectations and are timely available.⁶⁰ They can be viewed "as a sufficient summary statistic that incorporate[s] general market information, as well as the numbers in the financial statements of the firm, including past reported earnings, to predict the future earnings of the firm."⁶¹ The difference between actual and estimated earnings is referred to as "unexpected earnings"⁶² in the further course of this thesis.

Looking at the direction of the deviation from the estimate, a positive earnings surprise is a situation in which the number for unexpected earnings is positive. In case unexpected earnings are negative, this state is referred to as a negative earnings surprise. For a summary of the various possible effects of earnings announcements on financial market participants see **Table 1**.

⁵⁶ See Brown/Caylor (2005) and Dechow/Richardson/Tuna (2003).

⁵⁷ See, for example, Lerman/Livnat/Mendenhall (2007), p. 65, or Williams/Goodfellow/Yacoub (2009), p. 2.

⁵⁸ The Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S) database provides detailed and consensus estimates featuring up to 28 forecast measures including estimated EPS for more than 20,000 companies in 76 countries. See Thomson Reuters (2008) for general information on the I/B/E/S database and Beaver et al. (2008), pp. 710, 724, and 729 et seq. for the improvement of I/B/E/S data availability and consistency over time, and p. 738 for the benefit of using I/B/E/S data for both figures.

⁵⁹ See also Morgan Stanley Capital International (2005), p. 20. MSCI constructs its value and growth indices using data from Thomson I/B/E/S for both actual and estimate data as well.

⁶⁰ See Chan/Jegadeesh/Lakonishok (1996), p. 1683.

⁶¹ Anderson et al. (2009), p. 9.

⁶² See Latané/Jones (1977), p. 1457, who used this term as well.

Table 1: Effects of earnings announcements on financial market participants

Result of earnings announcement	Effect on financial market participants
$EPS_{\text{actual}} > EPS_{\text{Analysts' consensus estimate}}$	Positive surprise
$EPS_{\text{actual}} = EPS_{\text{Analysts' consensus estimate}}$	No surprise
$EPS_{\text{actual}} < EPS_{\text{Analysts' consensus estimate}}$	Negative surprise

Source: Author

In order to account for the dispersion in analysts' forecasts as measured by their standard deviation, the Standardized Unexpected Earnings (SUE) score is used to measure the extent of the earnings deviation from the estimate. It is defined as follows⁶³:

$$SUE = \frac{\text{Reported earnings per share} - \text{Estimated earnings per share}}{\text{Standard deviation of estimated earnings per share}}$$

A positive SUE reflects a positive earnings surprise, while a negative SUE is an expression of a negative earnings surprise. Thus, the more negative the SUE score, the stronger the negative surprise effect.

While the negative earnings surprise acts as a trigger for the likely fall in share price, the next section discusses the extent of such negative stock price performance that is required for a company to qualify as a fallen angel.

⁶³ See, for example, Latané/Jones (1977), p. 1457, Bernard/Thomas (1989), pp. 7 et seq., Bartov (1992), p. 613, Chan/Jegadeesh/Lakonishok (1996), pp. 1684 et seq., Liodakis et al. (2005), p. 5, or Lerman/Livnat/Mendenhall (2007), p. 65. This definition of SUE is the one predominantly used in the literature. Whether estimated earnings per share are based on a model or on analysts' consensus estimates does not alter the use of the standard deviation of the estimate values in the denominator. For other definitions using a different denominator see Berens (2010), pp. 2 et seq., who uses the share price at the end of the quarter instead of the standard deviation of analysts' consensus estimates, or Mohanram (2005), p. 159, who does not use a standardizing denominator at all.

2.3.2 Subsequent Negative Abnormal Shareholder Return

Although positive (negative) earnings surprises are usually followed by an increase (decrease) in the stock price of the underlying company, the absolute share price reaction does not contain information about the extent of such a stock price movement relative to the overall stock market. In order to judge whether a stock suffered disproportionately from a negative earnings surprise, its return needs to be compared with a suitable benchmark.⁶⁴ This benchmark could be an index or a portfolio of other companies. The resulting difference between the return on the stock and the benchmark return is called abnormal return.

When making this calculation it is important that both the shareholder return on the sample firm and on the reference portfolio are calculated in the same way. This thesis defines shareholder return in a holistic sense, i.e. it consists not only of capital appreciation, but also includes dividends paid to shareholders who can then reinvest in the stock. Consequently, if an index is chosen as a reference portfolio this index has to be calculated as a performance index and not as a price index.

2.3.3 Above-average Growth before Negative Earnings Surprise

As previously stated, this thesis strives for establishing a system that helps to identify good growth stocks that are temporarily depressed and thus might be undervalued by the market. Therefore, the predominant approach of using market-based ratios like price-to-book (P/B), price-to-cash flow or price-to-earnings (P/E) to identify growth stocks (see section 4.2) does not appear suitable.⁶⁵ An identifier that is independent from the current verdict of financial markets, but is instead rooted in the fundamental performance of the company is far more appropriate for the purpose of this thesis. Hence, choosing the past growth rate of a company-specific statistic, such as sales, earnings or cash flow, appears more suitable. Following Lakonishok et al. the past growth in sales is chosen as an indicator for growth companies, because it is less volatile than earnings or cash flow growth rates.⁶⁶ This is also consistent with Scott who defined fallen angels as companies that showed above-average historical sales

⁶⁴ See Barber/Lyon (1997), p. 342.

⁶⁵ Ahmed and Nanda, for example, note that identifying growth stocks on the basis of earnings yield does not always label companies correctly as growth stocks. See Ahmed/Nanda (2001).

⁶⁶ See Lakonishok/Shleifer/Vishny (1994), p. 1550.

growth and are now expected to deliver below-average long-term growth in earnings per share.⁶⁷

However, defining any company with positive absolute sales growth as a growth company is too simplistic. Since each company acts within a larger economic environment and only very rarely is in a position to enjoy sales growth that is completely disconnected from overall economic activity, a growth company can be defined as one that succeeds in growing considerably faster than the industry average.⁶⁸ However, there are several problems related to the idea of calculating certain industry growth rates and comparing them to the growth of a single company. Firstly, data availability is fairly bad. In particular, since companies rather frequently change the nature of their activities, it is likely not the case that a company's industry classification always remains the same over time. Hence, such time-series data on industry classification are not easily obtainable via financial databases.⁶⁹ Secondly, if industry groups are defined too broadly, comparing their growth rates with a single specific company becomes less meaningful. On the contrary, defining industry groups too narrowly results in a lack of a sufficient number of peers. Thirdly, assigning an industry classification to specific companies always involves a certain amount of subjective judgment by the classifier. Lastly, and probably most important, specific industry growth rates do not matter for an investor who has the choice to invest in all companies listed on the stock market. He would therefore pick his fallen angels from the overall stock market pool of listed companies. Simulating a situation where an investor is artificially limiting himself to a certain set of industries is not a sensible approach for the purpose of this thesis. Therefore, it makes more sense to compare a company's sales growth with the average growth of overall economic activity in the jurisdiction under which the company is active. The utmost average of economic activity is a country's gross domestic product (GDP). Hence, for the purpose of this thesis abnormal sales growth is defined as the compound annual growth rate (CAGR) of sales over the past two years before the earnings surprise minus the average GDP growth rate of the respective company's domicile country during the time horizon of the analysis.⁷⁰ The use of overall GDP growth as a yardstick for individual company

⁶⁷ See Scott/Stumpp/Xu (1999), p. 51.

⁶⁸ See Zweig/Sullivan (2010), p. 52.

⁶⁹ ICBSSC codes, for example, are not available as time series data on Thomson Reuters financial databases.

⁷⁰ The GDP growth data is taken from the Worldbank database and includes the period 1996-2008. 2009 was excluded, since a NES that occurred in 2009 would not make it into the sample due to the minimum time period of one year after the NES.

growth is also supported by Koller and Williams, who show that the average earnings growth rate of S&P 500 companies is almost equal to the growth rate of U.S. GDP during 1980 till 1999.⁷¹

The reasoning behind selecting two years for the above-average growth period is the following: On the one hand, the proof that a company shows above-average growth is the stronger the longer the above-average growth period lasts. A longer period also eliminates the problem that revenue numbers of one specific short time period, such as one year or less, are more susceptible to arbitrary developments. For example, companies might not realize revenues in one period, but then account for them in the following period due to reasons that have little to do with their mid- to long-term growth prospects. On the other hand, it is highly advisable for investors to identify growth companies when they are still emerging and in that process deliver superior returns to investors.⁷² Since it is impossible for a company to deliver above-average growth ad infinitum⁷³, an investor trying to benefit from a company's above-average growth is better off finding such firms sooner than later. Consequently, the period in which the targeted company already delivered above-average growth should be as short as possible. To solve this apparent conflict in choosing a suitable time period, a period of two years was selected, which is also the interval that Ahmed and Nanda use in their study.⁷⁴ This time period allows an investor to still find a growth company early on in its growth process, while avoiding the above-mentioned problem of short-term time horizons.

⁷¹ See Koller/Williams (2001), pp. 114 and 117.

⁷² See Lynch/Rothchild (2004), p. 64.

⁷³ See Harvard Business School Press/Society for Human Resource Management (2005), pp. 136 et seq.

⁷⁴ See Ahmed/Nanda (2001).

2.4 Good versus Bad Fallen Angels

So far, the group of fallen angels consists of all fallen angel stocks as defined above, irrespective of which fallen angels return to a superior share price performance after certain periods of time, i.e. the good fallen angels, or which continue to underperform the market, i.e. the bad fallen angels.⁷⁵ For an investor, however, it is of great importance which stocks he invests in. In order to maximize his investment performance, an investor has to go long in the future winners among the fallen angels and forgive an investment or even short the future losers.

The following two sections provide more information on how to separate the good fallen angels from the bad ones. A discussion of the suitable time frame for measuring the abnormal return for the shareholder after the negative earnings surprise is followed by a description of the exact criteria for dividing the group of fallen angels into good and bad ones.

2.4.1 Time Horizons for Abnormal Return

A key element in defining outperformance of stock prices is the length of the holding period. This thesis examines three time periods and measures the cumulative abnormal return of fallen angel stocks over these intervals: one year (250 trading days), two years (500 trading days) and three years (750 trading years) after a common starting point. This common starting point lies 60 trading days after the relevant earnings announcement.

The reason why the starting point is placed not immediately after the earnings announcement lies in the tendency of investors to underreact to new information over the short-term, whereas investor overreaction can be observed for longer periods.⁷⁶ Investor underreaction leads to a post-earnings announcement share price drift, which means that stock prices do not correct immediately to their full extent, but tend to move into the same direction for some time after the earnings surprise.⁷⁷ In case of a

⁷⁵ Wisdom (2009), pp. 15-27, distinguishes between fallen and falling angels, which is similar to the concept of separating good from bad fallen angels. However, Wisdom's separation approach is not so much based on clear steps involving measurable criteria, but leaves more room for interpretation and subjectivity by the investor. Consequently, Wisdom's recommendations were not subject to statistical analysis.

⁷⁶ See sections 3.3.2 and 3.3.3 for a more detailed description of the overreaction and underreaction theories.

⁷⁷ See, for example, Ball/Brown (1968), Ball (1978), Foster/Olsen/Shevlin (1984), Jones/Rendleman/Latané (1985) Bernard/Thomas (1989), Ball (1992), Livnat/Mendenhall (2006), or Tomcany (2010).

positive earnings surprise share prices would drift upward, in case of a negative earnings surprise they would show a downward momentum for some time. It appears that investors need some time to fully digest the new earnings information and incorporate it in their investment decisions. Several studies show that although the post-earnings announcement drift might last up to one year after the announcement, most of the drift occurs until the next quarter's earnings announcement, i.e. during approximately 60 trading days or three months after the announcement.⁷⁸ By waiting this time with an investment, an investor buying or shorting a fallen angel stock can feel reasonably safe that he is only marginally affected from the post-earnings-announcement drift related to the previous negative earnings announcement. Given that earnings announcements take place on a quarterly basis and thus new earnings information usually reaches the market after at most 62 or 63 trading days (depending on the calendar quarter and possible public holidays), this also makes intuitive sense. A recent study by Alwathainani supports this research design, since his findings show that the downward trend in share prices after a negative earnings announcement is reversed in case the subsequent earnings announcement does not confirm the negative news of the prior announcement.⁷⁹ In other words, if a fallen angel investor waits with the share purchase until the next quarterly earnings announcement, he might miss the opportunity to buy into the fallen angel company at a reasonable price.

The rather longer-term horizon for measuring the abnormal holding period return for the fallen angel stocks is chosen because of three reasons. Firstly, common stocks are long-term assets according to Shleifer and Vishny. Therefore, a mispricing for them might persist for a considerable amount of time.⁸⁰ Secondly, an undervaluation resulting from a negative overreaction of the market – like is the case with fallen angels – might take some time to correct.⁸¹ Thirdly, most possible indicators that this thesis tests with regard to their aptitude to separate good fallen angels from bad ones are rooted in the philosophy of value investing. Value investors like Graham, Buffett, Klarman, or Rogers advocate patience when it comes to waiting for the assumed undervaluation to correct.⁸² Therefore, it would not make sense to look at the shorter time frames applied by growth or momentum investors. Concretely, Graham mentions

⁷⁸ See, for example, Abarbanell/Bernard (1992), Dreman/Berry (1995), Jegadeesh/Livnat (2006), p. 23.

⁷⁹ See Alwathainani (2010).

⁸⁰ See Shleifer/Vishny (1990), p. 148.

⁸¹ See De Long et al. (1990), pp. 713, 727, and 731-733.

⁸² See Buffett (2003), p. 49, Graham (2003), p. 223, Klarman/Zweig (2010), pp. 18 et seq., or Speece/Rogers Jr. (2010), p. 4.

that it takes on average one-and-a-half to two-and-a-half years for a substantial undervaluation to correct.⁸³ Following this logic, De Bondt and Thaler chose a three-year period after portfolio formation to measure returns in their seminal paper on overreaction.⁸⁴ In line with these considerations the selected time frame for tracking abnormal returns after investing in a fallen angel stock spans from one to three years in this thesis. To gauge share price performance in regular intervals over the selected time frame, three measurement dates were established at one, two, and three years after the investment date. The reasoning for recording abnormal returns at three different points in time will be explained in the following section on the separation between good and bad fallen angels.

2.4.2 Separation into Good and Bad Fallen Angels according to Share Price Performance

As previously discussed, it is key for an investor to be able to distinguish between good and bad fallen angels prior to making his investment. Therefore, the definition of angel quality (AQ) is very important. On the one hand, a good fallen angel (GFA) is one that outperforms the benchmark index over the specified time period after the investment date as specified in section 2.4.1. On the other hand, a bad fallen angel (BFA) is defined as a fallen angel stock that underperforms the benchmark over the specified time period after the investment.

Given that this thesis measures abnormal returns on three different dates, combining the various observation dates leads to more than three different measures of angel quality. The main difference between them lies in the consistency of the abnormal share price performance over time. **Table 2** provides an overview of the seven different measures of angel quality that are possible and also mentions what role they play in the statistical analyses of the thesis.

⁸³ See Graham (2005), p. 39.

⁸⁴ See De Bondt/Thaler (1985), p. 799. Other authors like Lakonishok/Shleifer/Vishny (1994), pp. 1544-1546 and 1576, chose even longer time horizons of 3 to 5 years when testing the success of value strategies.

Table 2: Measures of angel quality and their use in the thesis

Angel quality	Description & Requirements	Role in Thesis
AQ13	Strictest measure – consistent out- or underperformance required at all three measurement points	Standard measure for angel quality as used for statistical tests
AQ23	Consistent out- or underperformance required at two and three years after investment	Input for robustness testing
AQ12	Consistent out- or underperformance required at one and two years after investment	Input for robustness testing
AQ1+3	Consistent out- or underperformance required at one and three years after investment	Not taken into consideration
AQ1yr	Out- or underperformance required only at one year after investment	Not taken into consideration
AQ2yrs	Out- or underperformance required only at two years after investment	Not taken into consideration
AQ3yrs	Out- or underperformance required only at three years after investment	Not taken into consideration

Source: Author

AQ13 is chosen as the standard measure of angel quality because of its high rigidity. As a fallen angel stock has to consistently out- or underperform at all three measurement points in order to be classified as either of good or bad quality, the danger of erroneously classifying a stock is minimized. This is not the case particularly for the three angel quality types that only measure abnormal performance once. For example, if a fallen angel stock underperforms the benchmark at most of the points in time after the reference date, but has gotten a boost for whatever speculative or short-lived reasons around the one-year measuring point, it would still show up as a good fallen angel according to AQ1yr. This shortcoming of potential misclassifications due to short-term reasons, which might not even be connected with the company itself, is

inherent in all angel quality classes that are based on only one measuring point. Therefore, they are not taken into consideration in this thesis at all. Using angel quality classes based on multiple return measuring points mitigates the problem of fallen angel misclassification. In that sense AQ12 and AQ23 can be seen as the second most rigid measures of angel quality, with the former having a shorter-term and the latter a more mid- to long-term focus. Both angel quality measures are included in robustness tests (see section 6.6). Although AQ1+3 also covers two measurement dates, it was not taken into consideration. The reason is that this measure would let a stock pass as a good fallen angel if it outperforms the benchmark one and three years after the negative earnings surprise, irrespective of whether it has experienced an almost two year long negative abnormal performance in between. In order to maximize his return when investing in such a stock, an investor would have to rely on getting the market timing right rather than on picking a good instead of a bad fallen angel stock. As market timing is not the focus of this thesis, AQ1+3 has been left out in statistical analyses.

Summing up, AQ13 remains the key measure for angel quality, because it is the most rigid. It shuts fallen angel stocks with changing algebraic signs in terms of abnormal performance out of the sample and thus best separates good from bad fallen angels. Therefore the statistical tests described in chapter 6 are based on it. Before moving on to chapter 4, which describes popular investment styles and their relationship with the fallen angel investing approach as proposed by this thesis, the following chapter takes a look at the philosophies of science underlying this thesis as well as core concepts from financial theory that are relevant to it.

3 Underlying Philosophies of Science and Relevant Frameworks from Financial Theory

3.1 Underlying Philosophies of Science

The main goal of this thesis is to contribute to closing the research gap concerning fallen angel stocks by developing and empirically testing an investment approach for such companies. In order to achieve this, already existing findings from investment theory and practice have to be reviewed, synthesized and tested, and then applied to fallen angels. The outcome of this process shall also provide relevant new information for the investment practice that helps investors to improve the results of their daily activities.

Therefore, the underlying philosophy of science is clearly action-oriented.⁸⁵ The view of management science as a pluralistic and action-oriented academic discipline includes the systematic development of recommendations for investment managers.⁸⁶ Consequently, the generation of purely theoretical findings without a close link to the investment practice would not be sufficient for the proposed fallen angel investment approach.

Furthermore, this thesis proceeds in accordance with critical rationalism as put forward by Karl Popper.⁸⁷ According to Popper's Searchlight Theory of Science, scientific advances are achieved by the development and following empirical testing of theories or hypotheses.⁸⁸ Theories in this context can be defined as consistent systems of hypotheses.⁸⁹ In contrast to induction, which implies deriving hypotheses as a result of empirical data observation, deduction requires the researcher to first develop expectations in the forms of hypotheses and then empirically test them.⁹⁰ In Popper's terminology, the researcher deliberately puts his searchlight on certain aspects and is guided in doing so by the content of his hypotheses. Aspects not covered by them are not tested and thus remain in the dark. However, this does not mean that the researcher

⁸⁵ For the differentiation between applied and fundamental research see Fülbier (2004), p. 267, or Saunders/Lewis/Thornhill (2009), pp. 5-9.

⁸⁶ For a deeper discussion of the pluralistic and action-oriented character of management science see Kirsch/Seidl/van Aaken (2007), pp. 147-172.

⁸⁷ See Popper (2005).

⁸⁸ For a more comprehensive description of the Searchlight Theory of Science see Popper (1949).

⁸⁹ See Fülbier (2004), p. 270.p

⁹⁰ See Saunders/Lewis/Thornhill (2009), pp. 128 et seq.

cannot adapt his searchlight on the basis of his findings. On the contrary, developed hypotheses are revocable, can be empirically challenged or adapted for further research. Consequently, the process of gaining new insights is a continuous one.⁹¹

The searchlight approach also allows for the application of multiple theories when analyzing an object or issue. This can be compared to positioning the searchlight in different places. Such an integrative approach appears particularly adequate if multiple approaches provide a better, more comprehensive explanation of the researched phenomena than a single theory by shedding more light on the object of analysis due to the different angles the searchlight is coming from.⁹² Analyzing and trying to explain the stock price development of fallen angels is a complex topic that needs to draw upon various theories to come to satisfactory results. As a result, various theories and findings from capital market research, particularly behavioral finance, and from the value investing practice are taken into account. Therefore, the searchlight approach appears to be an adequate way to examine fallen angels as the research object of this thesis.

3.2 The Efficient Market Hypothesis and its Shortcomings

Before moving on to behavioral finance research and the value investing practice, both providing relevant theoretical input and findings for this thesis, the efficient market hypothesis and its implications for this thesis shall be discussed briefly. If it held true, it would be a moot effort to purchase or sell any security at the current market price, because it would not be possible to generate any abnormal return from such a transaction.⁹³ In other words, trying to identify a set of indicators that helps to ex-ante distinguish good fallen angels from bad ones would be in vain. Although the support of the efficient market hypothesis among both academics and investment practitioners has significantly eroded since the late 1970s and particularly so in the light of the market downturn of 2007-2009⁹⁴, the efficient market hypothesis still serves as “an unrealistic but convenient working assumption”⁹⁵ for most market participants. This

⁹¹ Popper contrasts the Searchlight Theory of Science, which is based on deduction, with the induction-based Bucket Theory of Science. The latter tries to gain new insights by gathering independent observations in an uncoordinated manner, and is therefore inferior to the Searchlight Theory of Science. For a more comprehensive explanation see Popper (1979).

⁹² See Nathusius (2005), p. 42, and Picot/Dietl/Franck (2005), p. 29.

⁹³ See Brealey/Myers (1996), p. 323.

⁹⁴ See, for example, Keane (1986), p. 58, Bruns/Meyer-Bullerdiek (2003), pp. 91-94, Malkiel (2003), p.60, Shiller (2003), pp. 83 et seq., or Siegel (2010), pp. 6 et seq.

⁹⁵ Siegel (2010), p. 7.

importance together with the above-mentioned fundamental implication for the topic of this thesis justifies taking a closer look at the efficient market hypothesis and its shortcomings in the light of fallen angel investing.

3.2.1 Key Elements

The initial premise of the efficient market hypothesis assumes that a large number of rationally acting and competing participants independently from each other analyze and value securities in financial markets in order to maximize their profits. Furthermore, new information concerning securities, such as earnings announcements, reaches the market in a random fashion. Finally, such information is rapidly processed by investors, thus leading to an almost instant adjustment in security prices to the new information. Therefore, at any time security prices should reflect all available information.⁹⁶

As a consequence, stock prices follow a “random walk”, which means that all subsequent price changes are random departures from previous prices. Since all information of today is already incorporated in current share prices, any future price changes will only depend on future news and will be completely independent from today’s share price changes. As the information flow to the market is by definition unpredictable, share price changes also have to be unpredictable and random.⁹⁷

The set of information available to investors is very comprehensive and includes all current and past values of any relevant variables. It contains, for example, company-specific information on earnings or macroeconomic information like interest rates or inflation. Moreover, market participants do not only possess this information in isolated form, but are also aware of all relevant relationships among the various pieces of information. Since it cannot be assumed that this most comprehensive set of information possible is available to investors anytime, Fama divided the overall efficient market hypothesis into three subhypotheses according to the extent of information available to investors: Firstly, the efficient market hypothesis in its weak form asserts that current share prices fully reflect all information related to the security market itself, i.e. historical prices, rates of return, trading volume data, etc. As a result, future returns on securities should be independent from past rates of return. Secondly, the semi-strong form of the efficient market hypothesis claims that security prices adjust rapidly to the release of all public information. Since the semi-strong form of

⁹⁶ See Reilly/Brown (2000), pp. 213 et seq.

⁹⁷ See Malkiel (2003), p. 59.

the efficient market hypothesis includes the weak form, public information includes security-market related information and all public nonmarket information. The latter contains company-specific information, such as earnings, dividends, price-to-earnings or price-to-book ratios, as well as macroeconomic or political news. This implies for investors that no above-average returns can be achieved when trading on public information, because such information is already reflected in current share prices. Consequently, positive abnormal returns would only be possible if an investor is trading on stock price-relevant nonpublic information. Thirdly, the efficient market hypothesis in its strong form assumes that stock prices fully reflect all information from public and private sources, thus encompassing the other two forms of the efficient market hypothesis as well. Therefore, no investor should be able to consistently earn abnormal returns if the efficient market hypothesis in its strong form holds true.⁹⁸

As a consequence, it is a vain exercise in the eyes of the supporters of the efficient market hypothesis to try to outperform the overall stock market by spending time analyzing and subsequently picking individual stocks. Any monkey throwing darts and thereby selecting its investments could do as good as an alpha-seeking expert investor.⁹⁹ The fact that there are several investors who were able to beat the market even over very long periods of time could still be attributed to randomness. There only has to be a sufficient number of people flipping coins, so that a few of them will flip the same side of the coin over and over again.¹⁰⁰ Following that logic would make the quest to find good fallen angel investments and avoid bad ones a useless endeavor, since it relies on financial markets that are not only driven by pure rationality, but by other forces as well.

3.2.2 Criticism of the Efficient Market Hypothesis

In contrast to the above-mentioned belief, however, numerous scholars and the empirical evidence they found have been questioning the validity of the efficient market hypothesis.

While even its resolute proponents like Fama no longer support the strong form of the efficient market hypothesis¹⁰¹, the semi-strong form came under attack as well.

⁹⁸ See Fama (1970), Fama (1991), or Reilly/Brown (2000), pp. 214-216.

⁹⁹ See Malkiel (1999), p. 24.

¹⁰⁰ See Malkiel (1999), p. 185.

¹⁰¹ See Fama (1991), pp. 1603-1607.

Already in 1980 Grossman and Stiglitz argued that if market prices reflect all information obtained and processed by “informed individuals (arbitrageurs)”, there has to be an incentive for market participants to undergo the effort of gathering and analyzing such information.¹⁰² In a completely efficient market, on the contrary, investors could not earn any compensation for their effort. As a consequence, they would not engage in any assessment of whether current market prices correctly reflect the available set of information, which would actually stop market prices to do so. Therefore, excess returns earned by informed traders can be viewed as a necessary compensation for gathering and analyzing information, thereby making markets more efficient, but by definition never completely efficient.¹⁰³ This would also explain why rational investors, unlike predicted by the semi-strong form of the efficient market hypothesis, not always choose passive management over active management.¹⁰⁴ Shiller also recognizes the importance of rational investors or “smart money” to counterbalance for the actions of irrational investors, particularly since he believes that “theoretical models of efficient financial markets that represent everyone as rational optimizers can be no more than metaphors for the world around us.”¹⁰⁵ However, he challenges the view of efficient market hypothesis supporters that “smart money” is always sufficiently strong to fully eliminate the impact of irrational – Shiller remarkably calls them “ordinary” – investors on security prices. On the contrary, depending on the underlying assumption of the respective market models, it can well be that smart money investors fail to equalize the effect of ordinary investors, and might even amplify them. As a result, frequently prices of certain securities or segments of the market are temporarily not in line with their underlying risk, and speculative bubbles appear.¹⁰⁶ This is also consistent with the view of various authors who find that investment professionals are far from being completely rational and instead suffer from the same behavioral biases as ordinary investors.¹⁰⁷ For example, mutual fund managers were found to herd in their buying and selling behavior of stocks during a particular quarter¹⁰⁸, or futures and options traders display loss aversion and are willing to take more risk in the afternoon if they suffered from losses

¹⁰² See Grossman/Stiglitz (1980) and Grossman/Stiglitz (1982).

¹⁰³ For another account of the various limits to arbitrage see Barberis/Thaler (2003).

¹⁰⁴ See Jones/Wermers (2011), p. 31.

¹⁰⁵ Shiller (2003), p. 96.

¹⁰⁶ See Shiller (2003).

¹⁰⁷ See, for example, Barberis/Thaler (2003) or Shefrin (2007).

¹⁰⁸ See Hong/Kubik/Stein (2005).

in the morning¹⁰⁹. Even groups of professional investors, such as investment committees, are subject to behavioral biases that significantly affect their decision-making.¹¹⁰

Furthermore, a couple of anomalies were detected that also pose a serious challenge to the semi-strong form of market efficiency. Particularly strong anomalies, which are also fairly persistent over time and geography, are the value anomaly and the size effect. Whereas the value anomaly characterizes the phenomenon that value style investing generates superior returns over mid- to long-term investment horizons¹¹¹, the size effect describes the observation that stocks of firms with smaller market capitalization in general achieve higher returns than larger companies.¹¹² In a semi-strong form efficient market current share prices contain all publicly available information, including share prices, market capitalization, or financial statement information such as book value of equity or earnings. As a consequence, it should not be possible to generate above-average returns by investing based on low price-to-book or price-to-earnings ratios (value anomaly) or in companies with a lower market capitalization (size effect). The existence of both phenomena therefore poses a very serious threat to the efficient market hypothesis. Supporters of the efficient market hypothesis tried to explain the higher returns with the higher risk associated with these stocks.¹¹³ The small size of a company or its low price-to-book ratio could be seen as a proxy for the likelihood of distress. A company in distress would be more vulnerable to adverse changes in the business environment, thus representing more risk to an investor.¹¹⁴ Analyzed data, however, mostly failed to support this stance, particularly since value stocks displayed even lower risk measures than the corresponding growth stocks.¹¹⁵ Not least because of this empirical evidence, behavioral finance theory takes a different approach in explaining these anomalies. Section 3.3 will provide more

¹⁰⁹ See Coval/Shumway (2005).

¹¹⁰ See Hodgson et al. (2000) or Wood (2006).

¹¹¹ For more information on the value anomaly including various sources see chapter 4.2.

¹¹² See, for example, Banz (1981), Reinganum (1981), Keim (1983), Carleton/Lakonishok (1986), Fama/French (1992), or Nguyen/Fetherston/Batten (2004), p. 49.

¹¹³ See, for example, Fama/French (1992), Fama/French (1993), Fama/French (1996), or Malkiel (2003), pp. 67-70.

¹¹⁴ See Fama/French (1993), p. 50.

¹¹⁵ See, for example, Daniel/Titman (1997) and Bauman/Conover/Miller (1998). Additionally, for the value anomaly see Chan/Lakonishok (2004), p. 71, Montier (2009), pp. 60-62, Haugen (2010), pp. 7 et seq., and also chapter 4.2. On the contrary, Avramov/Chordia (2006) claim that asset pricing models incorporating varying betas can largely explain the value and size anomalies.

information on behavioral finance, particularly with regard to the most important elements for this thesis.

Whereas the arguments against the efficient market hypothesis mentioned so far tackled the semi-strong and therefore also the strong form of the efficient market hypotheses, there are also various observations that attack the weak form of the efficient market hypothesis. The most important of them is the so-called momentum effect that describes the positive relationship between a stock's return and its recent relative price history.¹¹⁶ If at least the weak form held true, it would be absolutely irrelevant for future share price development how stock prices moved in the past. As a result, it would be impossible for investors to earn above-average returns by analyzing the price history of stocks. This conclusion, however, was first disproved by Jegadeesh, who discovered that over short-term periods of up to one year, stocks that had been performing exceptionally well continued to do so and vice versa.¹¹⁷ In the article describing his initial findings, he boldly stated that the results of his analysis "reliably reject the hypothesis that the stock prices follow random walks"¹¹⁸, thus attacking one of the cornerstones of the efficient market theory. Since then there have been numerous further studies confirming the existence of the momentum effect not only in the U.S. equity market, but also for other asset classes and in other geographies.¹¹⁹ Beside the momentum effect, there are several other stock price-based anomalies like the January effect¹²⁰ or the weekend effect.¹²¹ However, none of them has received the extent of empirical backing like the momentum effect, which therefore represents the most serious challenge of the weak form of the efficient market hypothesis.¹²²

Summing up the considerations so far, although the efficient market hypothesis still has numerous supporters, behavioral explanatory approaches for stock market

¹¹⁶ See Asness/Moskowitz/Pedersen (2009), p. 2. For a recent review of the momentum literature see Jegadeesh/Titman (2011).

¹¹⁷ See Jegadeesh (1990) and Jegadeesh/Titman (1993).

¹¹⁸ Jegadeesh (1990), p. 897.

¹¹⁹ See, for example, Asness (1994), Rouwenhorst (1998), Rouwenhorst (1999), Griffin/Ji/Martin (2003), Naughton/Truong/Veeraraghavan (2008), Asness/Moskowitz/Pedersen (2009), or Berger/Israel/Moskowitz (2009).

¹²⁰ See Keim (1983), Reinganum (1983), Haugen/Jorion (1996), and Schwert (2003), pp. 943 et seq.

¹²¹ See French (1980) and Schwert (2003), pp. 944 et seq.

¹²² See also Avramov/Chordia (2006) who demonstrated that the momentum effect persists even when varying betas are built into the asset pricing models.

behavior have been gaining a lot of recognition already for many years.¹²³ Their increased popularity is fostered by the inability of the efficient market hypothesis to explain the wild swings in certain parts of the economy, including financial markets, which take place from time to time.¹²⁴ Periods of manias are followed by panics. The objects of these exuberant movements are highly diverse and range from tulips, high-tech stocks, or real estate to precious metals, commodities, or government bonds. The history of these booms and busts has been lasting for centuries and is probably as old as economic activity of mankind.¹²⁵ The largely debt-fueled boom of the real estate prices in several industrialized countries like the U.S., the UK or Spain in the first decade of the 21st century followed by the bust of these bubbles led to the most serious financial crisis and deepest recession after the Great Crash of 1929 followed by the Great Depression. These fairly recent events underpin the necessity for developing a more holistic view of economic events and their causes. The question seems not if, but when and where the next boom and bust scenario will unfold.

Before getting into more detail on these alternative explanatory approaches from the field of behavioral finance, some attention shall be dedicated to the notion of risk and its differing definitions as used by efficient market hypothesis supporters on the one hand and the representatives of behavioral finance and the value investing approach on the other hand.

3.2.3 Differences in Risk Definitions

As already mentioned above, in an efficient stock market current share prices reflect all publicly available information. Therefore, the expected return of a stock should accurately reflect its risk. As a consequence, it is not possible for an investor to earn a return in excess of the expected return as expressed by the current market price.¹²⁶ In such an environment, rational and risk-averse investors will – according to modern portfolio theory – strive for their optimal portfolios in a way that it provides them with

¹²³ Ebering and Wood independently from each other associate the breakthrough for behavioral economics and finance with the award of the Nobel prize for Kahneman and Smith in 2002. See Ebering (2005), pp. 1 et seq., and Wood (2010), pp. vi et seq.

¹²⁴ See Akerlof/Shiller (2009b), p. 129.

¹²⁵ See Kindelberger/Aliber (2005) for an extensive account of past manias and panics in various markets.

¹²⁶ See Fama (1970), pp. 384 et seq., and Reilly/Brown (2000), pp. 214 et seq.

the maximum return at the level of risk they are individually willing to assume.¹²⁷ The capital asset pricing model (CAPM)¹²⁸, which can be seen as one of the building blocks of modern portfolio theory and is thus closely connected with the efficient market hypothesis, links the expected return of a stock purely to its risk that is measured by beta.¹²⁹ Beta represents the extent to which the return of a stock varies with the return of the overall market.¹³⁰ In other words, a stock that is more volatile than the market, i.e. has a beta larger than one, is considered to be more risky than a stock with a low beta and vice versa. An abnormally high decline in share price, as is the case with fallen angels, leads to an increase in beta. The so-defined risk of holding this particular stock has increased, making ownership of it less desirable.

In contrast, an investor who sees himself mainly as the (partial) owner of a company has a different perspective on risk. If he, on the basis of his own thorough analysis, has made the decision to become an owner of the company, i.e. acquire shares of the company, he would be delighted to find out that the stock price in the past weeks has dropped stronger than the market. Unless this drop had been caused by a change in the fundamental basis of his analysis, this would give the investor the chance to purchase the desired stock at a lower price, thereby decreasing his risk of loss from this investment. Therefore, such an investor would see volatility as a positive thing, because it leads to chances of buying good-quality shares at a reasonably low price from time to time.¹³¹ Consequently, equating volatility with risk is not the right thing to do for investors following the value investing approach.¹³² While volatility measures the extent of price fluctuations, risk, as Wisdom defines it, is “the chance of experiencing a permanent loss of capital”¹³³. This is fundamentally different from volatility. From this perspective, risk cannot be captured by a single number like beta, but has to be managed by developing a good understanding of the many risk elements that lie in the valuation, the business, and the financial state of a company. In the analysis of a company’s stock value investors try to figure out whether the share price

¹²⁷ For a more extensive description and explanation of modern portfolio theory and the underlying theory of choice see Markowitz (1952), Markowitz (1991), Copeland/Weston/Shastri (2005), chapter 5.

¹²⁸ For a more extensive description and explanation of the CAPM see Sharpe (1964) or Copeland/Weston/Shastri (2005), chapter 6.

¹²⁹ See Byrne/Brooks (2008), p. 1.

¹³⁰ See Malkiel (2003), p. 68.

¹³¹ See Buffett (2003), p. 103.

¹³² See Cunningham (1998), p. 12.

¹³³ Wisdom (2009), p. 9.

already includes a lot of potential future growth. If this is the case, the stock will be prone to future disappointments. On the contrary, a company with enough headroom between the calculated intrinsic value and the current market valuation would likely offer more safety of principal. Additionally, value investors include factors affecting the underlying business of a company and their consequences on its earnings power in their risk assessment. Last but not least, the financial strength is gauged by analyzing the financial statements of the company under scrutiny. Particularly the balance sheet should demonstrate sufficient financial strength to prevent the risk of financial distress in case business conditions deteriorate.¹³⁴ As said, the purpose of all these efforts is to minimize the risk of losing all or a substantial part of the investment. To further ensure that this goal is reached, investors following the value investment approach are well aware that they might be wrong in their assessment despite their diligent analysis. Therefore, they demand a so-called margin of safety, which develops when the intrinsic value of a company exceeds its current market value for whatever reason.¹³⁵ The higher the margin of safety, the more room for error in the investor's analysis, and consequently the less risky the investment. Adherence to the concept of margin of safety forms the central building block of risk management within the value investing process. In addition, this approach to risk management calls for limited diversification and patience, as it sometimes takes time until the detected undervaluation corrects itself.¹³⁶ Beta, however, does not play a role at all.

Similar to value investors, behavioral finance theorists do not purely focus on volatility as a risk measure, but include an array of factors influencing the risk and return of a potential investment. Behavioral asset pricing models like the one proposed by Shefrin and Statman contain a large number of factors in addition to the three factors (risk as measured by beta, book-to-market ratio, market capitalization as a proxy for size) as used by traditional asset pricing models.¹³⁷ Not all of these factors are exactly measurable, but nevertheless exercise an influence on stock prices, which constitutes another parallel to the investment analysis process conducted by value investors. All this puts both value investment practitioners and behavioral finance theorists in contrast to the CAPM and other traditional finance models like the three-factor model.¹³⁸ The fact that supporters of the efficient market hypothesis have been

¹³⁴ See Montier (2009), pp. 105-111.

¹³⁵ See Hagstrom (2005), p. 13.

¹³⁶ See Greenwald (2009a), pp. 3, 6 and 24.

¹³⁷ See Shefrin/Statman (1994) and Statman (1999a).

¹³⁸ See Byrne/Brooks (2008), pp. 5-7.

increasingly moving away from the CAPM to multi-factor models like the three-factor model by Fama and French¹³⁹ does not change the fundamental difference in their perspective on risk between the efficient market hypothesis and behavioral finance: the interpretation of factors like share price volatility, company size, or book-to-market ratios as measures of risk versus the interpretation of them as a reflection of investors' emotions and cognitive biases.¹⁴⁰

In summary, it depends on the perspective of the investor whether a disproportional drop in share price is regarded as a beneficial risk-decreasing or a disadvantageous risk-increasing event. Nevertheless, simply taking for granted the rather simple definition of risk of the efficient market hypothesis and the associated asset pricing models would not do justice to the investment reality. Particularly, empirical studies have demonstrated that stocks with the highest expected returns are in fact less risky than the stocks with the lowest expected returns.¹⁴¹ The still existing popularity of the efficient market hypothesis in financial circles might be explained by its clarity and simplicity¹⁴²: “The beauty of the efficient market hypothesis is in its simplicity: risk-reward, risk-return.”¹⁴³ Furthermore, it cannot be negated that the efficient market hypothesis describes fundamental mechanisms of financial markets and markets indeed tend to be more efficient when looking at longer investment periods.¹⁴⁴ However, unlike assumed by the efficient market hypothesis, financial markets are not driven by purely rational traders, but by normal human beings who appear to act systematically irrational.¹⁴⁵ Their investment decisions are not only based on rational calculations, but are affected by fear, greed, and other irrational beliefs. Graham recognized this already in the first half of the last century and stated: “Evidently the processes by which the securities market arrives at its appraisals are frequently illogic and erroneous. These processes [...] are not automatic or mechanical, but psychological for they go on in the minds of people who buy and sell.”¹⁴⁶ Thus, it is advisable to obtain a complete picture of the factors that influence investor behavior and their consequences on share prices. The – in the light of Graham's words –

¹³⁹ See Fama/French (1992).

¹⁴⁰ See Byrne/Brooks (2008), pp. 5-7.

¹⁴¹ See, for example, Haugen/Baker (1996).

¹⁴² See Barberis/Thaler (2003), p. 1055.

¹⁴³ Malloy (2011), p.8.

¹⁴⁴ See Malkiel (2003), p. 80.

¹⁴⁵ See Malloy (2011), p.1.

¹⁴⁶ Graham/Dodd (1934), p. 585.

surprisingly new academic discipline of behavioral economics and its sub-discipline behavioral finance attempt to explain these phenomena.¹⁴⁷ Therefore, in the next section more light shall be shed on key behavioral finance concepts and several investor biases that are most relevant for this thesis.

3.3 Behavioral Finance

The recognition that mathematical methods cannot always fully explain the movements in a world where human beings interact with each other dates back a very long time. Sir Isaac Newton, for example, stated pointedly: “I can calculate the motions of heavenly bodies, but not the madness of crowds.”¹⁴⁸ Financial markets are places where such crowds, large numbers of investors, gather and interact with each other. In the end, you always need a buyer and a seller to make a trade happen. The investors will likely differ a lot in terms of their character, investment philosophies, and knowledge, but it can be surely assumed that they are all human beings. Therefore, getting a better understanding of human behavior in financial markets is essential for gaining deeper insights into the movements of stock prices.¹⁴⁹ Even in the case of purely quantitative trading models executed by computers, there are still human beings behind the design and the programming of these models. Human beings make investment decisions on the one hand based on their individual character and knowledge, but on the other hand also under the influence of other investors’ actions. Contemporary behavioral economists like Akerlof and Shiller follow this path of thinking and try to explain why human beings act as they do by broadening the purely rational view of neoclassical economists and also taking non-rational motivations of people into account: “To understand how economies work and how we can manage them and prosper, we must pay attention to the thought patterns that animate people’s ideas and feelings, their animal spirits.”¹⁵⁰ This is clearly a call for a more interdisciplinary approach to financial market research.

¹⁴⁷ Although ideas and concepts containing behavioral finance ideas were already introduced several decades earlier, behavioral finance as a distinct research area within economics and finance emerged only in the early 1980s, gathered momentum during 1990s, and received widespread recognition only after the turn of the millennium. See Campbell (2000), p. 1551, Ebering (2005), pp. 1 et seq., Byrne/Brooks (2008), pp. 9 et seq., and Wood (2010), pp. vi et seq.

¹⁴⁸ See Greenwald/Bellissimo/Otte (2008), p. 10.

¹⁴⁹ See Neill (2007), p. 3.

¹⁵⁰ Akerlof/Shiller (2009a), p. 1

To explain the complex procedures in the process of investment decision-making in financial markets, behavioral finance therefore draws upon insights from psychology, sociopsychology, and neurology and combines them with economics and finance.¹⁵¹ The following section will highlight the key building blocks of behavioral finance theory and how they differ from the assumptions underlying modern portfolio theory.

3.3.1 Key Elements

Behavioral finance differs from modern portfolio theory in four key assumptions: Firstly, investors as the actors in financial markets are seen as “normal” human beings who sometimes act rational, but oftentimes also let their emotions and cognitive biases influence their decisions. In other words, the rationality of investors is bounded.¹⁵² The theory of bounded rationality is in stark contrast to the concept of the fully rational homo oeconomicus that underpins modern portfolio theory.¹⁵³ While Simon recognized the shortcomings of the traditional rational choice theory already in 1955¹⁵⁴, it took more than two decades until Kahneman and Tversky developed prospect theory as an alternative theory of human decision-making under risk.¹⁵⁵ One of its cornerstones is an activity by human beings called coding. Kahneman and Tversky observed that investors tend to evaluate the outcome of investment decisions not in absolute terms, but relative against a subjective reference point.¹⁵⁶ Often this is the purchase price of a stock, but it could also be the sales or earnings growth rate of a company to which investors have gotten used to and which they also expect for the future. As a consequence, growth companies face the difficult task to beat the ambitious expectations of investors every quarter in order not to disappoint investors. However, when they fail to do so and become fallen angels, this does not mean that they are fundamentally doing badly. On the contrary, they might still grow their sales or earnings or improve their position in the market. Nevertheless, as investors do not see the most recently announced earnings in absolute terms, but compare them to the reference point of their expectations, these aspects tend to be pushed to the background. Investors acting in accordance with the prospect theory could therefore be instigated to sell their holdings in a fallen angel company and thus cause an abnormal

¹⁵¹ See Wood (2010), pp. v et seq.

¹⁵² See, for example, Simon (1955), Gigerenzer/Selten (2002), and Kahneman (2003).

¹⁵³ See, for example, Miller/Modigliani (1961), p. 412.

¹⁵⁴ See Simon (1955).

¹⁵⁵ See Kahneman/Tversky (1979).

¹⁵⁶ See Kahneman/Tversky (1979), p. 274.

drop in share price, regardless whether the overall fundamentals or more difficult to evaluate qualitative aspects of the company actually look good. The observation that people perceive losses stronger than profits of the same amount¹⁵⁷ further strengthens the reception of a negative earnings surprise by investors. The successful reception of the prospect theory¹⁵⁸ led to growing popularity of the idea of bounded rationality in human decision-making not only among investment practitioners and psychologists, but also among finance researchers.¹⁵⁹ Still, until today the view of investors taking into account in their investment decision-making reasons beyond the pure maximization of their own utility is by far not a commonplace in business science.¹⁶⁰

Secondly, behavioral finance researchers believe that although financial markets are difficult to beat, this does not mean that they are efficient.¹⁶¹ The various empirical challenges of the efficient market hypothesis have already been discussed in section 3.2.2 above.

Thirdly, behavioral portfolio theory as introduced by Shefrin and Statman¹⁶² is markedly distinctive from the construction of a mean-variance portfolio underlying modern portfolio theory as introduced by Markowitz.¹⁶³ Whereas investors under the mean-variance portfolio theory view their portfolios as a whole and are therefore trying to find the optimal risk-return combination for their complete portfolios, under the behavioral portfolio theory they slice their portfolio into multiple layers. To each of these layers, they assign specific goals and risk attitudes and fill them with securities corresponding to that goal. For example, most investors have a layer that serves their need for safety and downside protection. This layer would likely contain cash or money market funds. Another layer would serve the possible need for ongoing steady income and therefore contain high-rated bonds. Additionally, there is likely a

¹⁵⁷ See Kahneman/Tversky (1979), pp. 277-280, and Kahneman/Tversky (1984).

¹⁵⁸ In 2002, Daniel Kahneman was awarded the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel, better known as the Nobel Prize in Economics, “for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty“, alongside Vernon L. Smith, who received the award for his pioneering usage of laboratory experiments as a new tool in empirical economic analysis. See Nobel Media (2002).

¹⁵⁹ See Nofsinger (2002), p. 1, and Ebering (2005), pp. 1 et seq.

¹⁶⁰ See Achleitner (2011), p. 64.

¹⁶¹ See Statman (2010), pp. 1 and 7 et seq. Thaler has pointedly summarized this issue by stating that “the important intellectual debate is about whether stock prices are right as opposed to whether you can beat the market.“ See Fox (2009), p. 298.

¹⁶² See Statman (1999b) and Shefrin/Statman (2000).

¹⁶³ See Markowitz (1952).

layer that addresses the wish for having an upside potential and thus contains high-risk equities or even lottery tickets. The human tendency to avoid and seek risk at the same time was discovered by Friedman and Savage many years ago.¹⁶⁴ They observed that people simultaneously bought both insurance, which protects them from downside-risk, and lottery tickets, which provides them with the chance to become rich. Despite knowing that the expectation value of any standard lottery is below zero, i.e. they could expect to lose money by “investing” in a lottery ticket, people still consciously sought risk and took part in the lottery. This finding is in contrast to mean-variance portfolio theory, where people are always risk averse and therefore never buy lottery tickets. The problem is that in the process of forming behavioral portfolios, investors tend to overlook covariances between the single layers, as they view each layer as a separate sub-portfolio without connecting it to the other layers. Investors like the idea of diversification, but they do not diversify as suggested by mean-variance portfolio theory.¹⁶⁵ **Figure 2** compares the different structures of a traditional mean-variance portfolio and a behavioral portfolio.

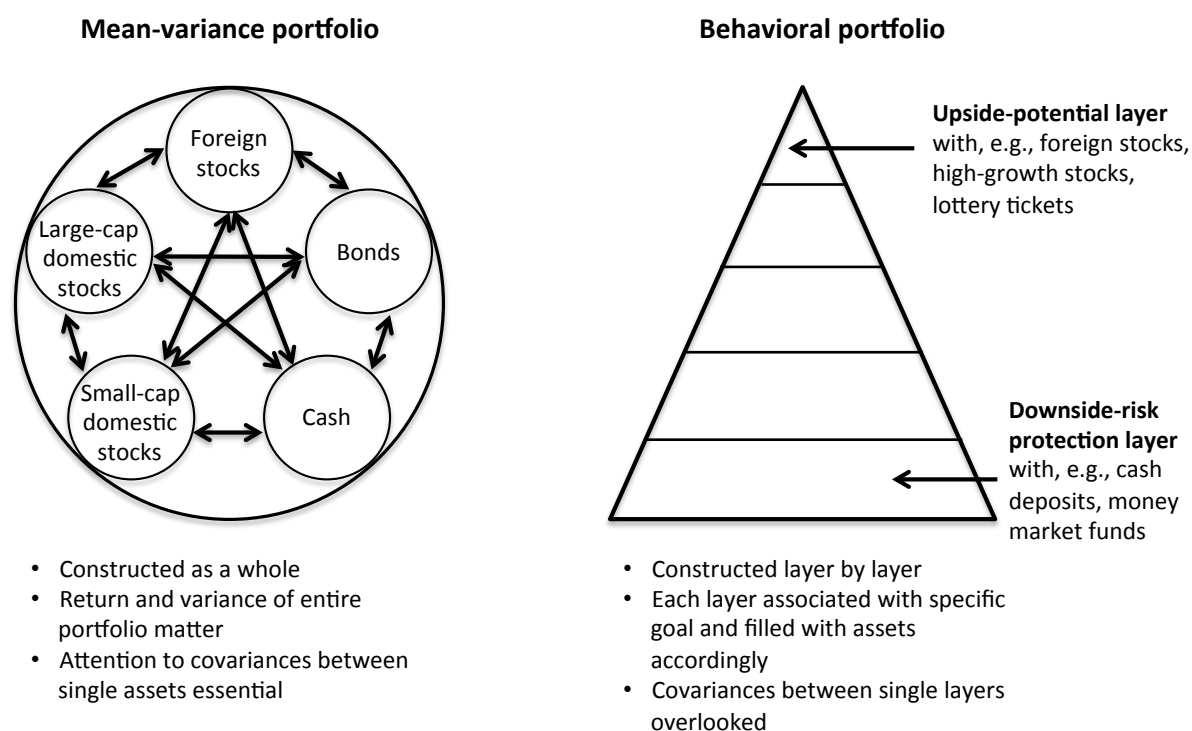


Figure 2: Comparison of structures of mean-variance and behavioral portfolios

Source: Author taking into consideration Statman (1999b)¹⁶⁶

¹⁶⁴ See Friedman/Savage (1948).

¹⁶⁵ See Clarke/Krase/Statman (1994), Nofsinger (2002), pp. 51-60.

¹⁶⁶ See Statman (1999b), p. 14.

The construction of behavioral portfolio layers leads most investors to form inefficient portfolios, as they take too much risk compared to the level of expected return they are getting.¹⁶⁷ The explanation behind this apparently irrational investor behavior is a phenomenon called mental accounting.¹⁶⁸ Instead of having a holistic view on all financial issues in their lives, human beings separate certain situations and goals in life together with the costs and benefits associated with them. They create mental accounts and then ignore the existing interdependencies between them. This behavior can be the result of either differing preferences concerning the various situations, or it could be a neurological reaction to preserve scarce cognitive capacity by simply ignoring the existing interdependencies.¹⁶⁹ In any case, mental accounting incites investors to make suboptimal decisions that are in contradiction to the utility maximizing behavior of modern portfolio theory. For example, investors shy away from realizing losses and thereby reaping beneficial tax deductions, although they could have reinvested the money in a similar if not even the same stock straightaway. Selling the loser stock closes the related mental account, and this causes the investor regret. Although he could have maximized his wealth by lowering his taxes, he acts to avoid regret instead.¹⁷⁰

However, all these differences between mean-variance and behavioral portfolio theory do not mean that both theories are irreconcilable. Only recently an effort has been made to combine them under collaboration of the main protagonists of either theory.¹⁷¹ Under the resulting mental accounting portfolio theory, and likewise under the behavioral portfolio theory, investors start constructing their portfolios by allocating their funds according to their goals into several mental account layers. Then they specify the probability with which they desire to completely reach each goal. For example, an investor with the goal to be wealthy enough to afford an expensive classic sports car after retirement could aspire to reach this goal with a probability of 20 percent. After that step, in each mental account the combination of assets is optimized according to mean-variance theory. Given the aspired probability of reaching the required threshold for buying the car, the investor would likely lean towards a fairly aggressive sub-portfolio containing a substantial part of equity and other riskier assets.

¹⁶⁷ See Nofsinger (2002), p. 58.

¹⁶⁸ See, for example, Thaler (1985), Prelec/Loewenstein (1998), or Nofsinger (2002), pp. 43-50.

¹⁶⁹ See von Nitzsch (2002), p. 21.

¹⁷⁰ See Shefrin/Statman (1984), pp. 779-781.

¹⁷¹ See Das et al. (2010) and Das et al. (2011).

All mental account sub-portfolios together constitute the investor's overall portfolio, which, like all sub-portfolios, lies on the mean-variance efficient frontier.¹⁷²

For fallen angel investing, mental accounting and behavioral portfolio theory are of great importance. They explain why investors construct different sub-portfolios, for example, for less risky value stocks and riskier growth stocks. In case a growth stock now disappoints with a negative earnings surprise, investors might be tempted to remove it from the growth stock portfolio layer, while they, or other investors who have not been invested in the stock yet, do not consider it for inclusion in the lower risk equity portfolio layer. As mentioned at the beginning of this thesis, the resulting increased supply of the particular fallen angel stock paired with the absence of a corresponding growth in demand might lead to a buying opportunity for value-oriented investors who are aware of mental accounting and thus can better avoid the related shortcomings.

Finally, the behavioral finance framework differs from modern portfolio theory as expected returns follow behavioral asset pricing theory rather than being a mere function of risk alone.¹⁷³ The various factors that determinate return and particularly the different understanding of risk have already been discussed in section 3.2.3 above. Concluding this section, **Table 3** summarizes the fundamental differences between modern portfolio theory and behavioral finance.

Table 3: Fundamental differences between modern portfolio theory and behavioral finance

Character of	Modern portfolio theory	Behavioral finance
Investors	Homo oeconomicus, i.e. fully rational	"Normal", i.e. boundedly rational
Financial markets	Efficient	Not efficient
Portfolio construction	According to mean-variance portfolio theory	According to behavioral portfolio theory
Expected return	Determined by risk only	Determined by numerous influence factors

Source: Author taking into consideration Statman (2010)¹⁷⁴

¹⁷² See Statman (2010), p. 4.

¹⁷³ See Shefrin/Statman (1994), Hirshleifer (2001) and Statman (2010), pp. 1 and 5-7.

¹⁷⁴ See Statman (2010), pp. 1-8.

3.3.2 Overreaction Theory and Mean Reversion

The overreaction theory is grounded in the behavioral heuristic of representativeness. This heuristic leads to one of the core biases within behavioral finance and has been widely researched and confirmed.¹⁷⁵ It describes the tendency of people to simplify decision-making under uncertainty by looking for familiar patterns and then assuming that future patterns will resemble the familiar past ones. Thereby individuals neglect the underlying objective probabilities of outcomes as well as the impact of sample size, although the level of confidence for an investment decision should be higher when backed by a larger sample size.¹⁷⁶ As a consequence, investors systematically overweigh the most recent information leading to overreaction compared to when they would process new information in a fully rational Bayesian way¹⁷⁷, a phenomenon the behavioral finance literature categorizes into the availability or saliency bias.¹⁷⁸ This overreaction also takes place when bad news are published, which led Graham to the following colorful statement: “The market is fond of making mountains out of molehills and exaggerating ordinary vicissitudes into major setbacks.”¹⁷⁹

De Bondt and Thaler empirically confirmed the overreaction hypothesis for the stock market¹⁸⁰ by finding out that most people indeed overreact to unexpected news.¹⁸¹ Due to this overreaction and the subsequent mean reversion such fallen angel stocks promise to be abnormally attractive investments over the period of a couple of years.¹⁸² Later other authors supported them by also observing that stock prices tend to overreact particularly over the long run and therefore stocks that previously performed worse are able to beat the prior better performing stocks in the future.¹⁸³ In their

¹⁷⁵ See, for example, Kahneman/Slovic/Tversky (1982), pp. 3-99, Shleifer (2000), pp. 127-133, Coval/Shumway (2005), Montier (2008), pp. 84 et seq., or Malloy (2011), p. 1.

¹⁷⁶ See Tversky/Kahneman (1974), pp. 1124-1127, and Shiller (2000), p. 144.

¹⁷⁷ See De Bondt/Thaler (1987), p. 557, and Malloy (2011), pp. 1 et seq.

¹⁷⁸ See Massa/Simonov (2006), pp. 639 et seq., or Byrne/Brooks (2008), p. 1.

¹⁷⁹ Graham (2005), p. 167.

¹⁸⁰ For insights into the phenomena of over- and underreaction in foreign exchange markets see Fastrich/Hepp (1991), pp. 65 et seq., or Larson/Madura (2001).

¹⁸¹ See De Bondt/Thaler (1985). Zarowin (1990) contested De Bondt and Thaler’s findings and attributed them to the size effect rather than overreaction by investors, but Albert/Henderson (1995) identified a bias in Zarowin’s methodology and – like De Bondt and Thaler – found empirical evidence supporting the overreaction hypothesis.

¹⁸² See De Bondt/Thaler (1985), who found an outperformance of about 25 percent of prior “loser” stock portfolios versus prior “winner” stock portfolios over a period of three years, or Haugen (2011), pp. 18-20.

¹⁸³ See Chopra/Lakonishok/Ritter (1992), Fama/French (1992), Lakonishok/Shleifer/Vishny (1994), or La Porta (1996).

international study on the value anomaly, Bauman et al. also attribute the outperformance of value stocks to the overreaction of investors and analysts who tend to extrapolate past earnings growth trends too far into the future, thus causing an overvaluation for growth respectively an undervaluation for value stocks.¹⁸⁴

In the context of fallen angels, the representativeness bias means that investors prefer to invest in what they see as “good companies”. They regard a company as a good company when it demonstrates strong earnings, high sales growth, high-quality management, etc.¹⁸⁵ Thereby investors make the fallacy to equate good companies with good investments. Shefrin and Statman prove this point by showing that investors believe that companies doing well in the annual Fortune magazine survey of corporate reputation are also good investments.¹⁸⁶ The empirical evidence, however, does not support this assumption. On the contrary, stocks that were rated highly in the surveys delivered inferior returns in comparison to the low-rated, spurned stocks.¹⁸⁷ This surprising relationship can be explained by the concept of subjective risk of a stock. The level of subjective risk of a stock is tied to whether the particular stock commands positive or negative affect. In the eyes of investors, stocks with negative affect carry a higher subjective risk and therefore required returns are higher, while positive affect lowers the subjective risk of investing in a stock.¹⁸⁸ In other words, popular “angel” stocks are low subjective risk and consequently also low return investments. Therefore, they appear to be good purchase opportunities only after they have come out of favor.

When this happens, for example because of investor disappointment due to a negative earnings surprise, investors become worried in processing the latest unfavorable earnings news and consequently rush to sell their shares, thus causing an abnormal drop in share price.¹⁸⁹ La Porta’s findings, that specifically companies with high expected growth rates in earnings are prone to fall out of favor, and analysts are particularly likely to revise their earnings estimates downward for such firms, strengthens the case for fallen angel investing.¹⁹⁰ Buying into growing companies

¹⁸⁴ See Bauman/Conover/Miller (1998), p. 88.

¹⁸⁵ See Nofsinger (2002), p. 62.

¹⁸⁶ See Shefrin/Statman (1995).

¹⁸⁷ See also Statman/Fisher/Anginer (2008).

¹⁸⁸ See Statman/Fisher/Anginer (2008), pp. 25-27.

¹⁸⁹ See Malloy (2011), p. 2.

¹⁹⁰ See La Porta (1996), p. 1739.

before they become fallen angels is on average not a promising strategy to achieve positive abnormal returns, but doing so when the high expectations have already been corrected and price levels have come down accordingly might well be the case. Kaestner backs this view, since he provides evidence that investors show long-term overreaction specifically to earnings surprises.¹⁹¹ His findings demonstrate that investors tend to overestimate respectively underestimate future earnings after extreme positive respectively negative earnings surprises. It appears as if investors are highly impressed by the surprising earnings news, which then affects the formation of their future expectations. However, as, on average, these extreme past surprises are not confirmed by subsequent earnings figures, the initial overreaction tends to correct at the date of the next earnings announcement in case there is no new earnings surprise or one of the opposite direction. If, however, there is a series of earnings surprises of the same type, i.e. several negative earnings surprises in a row, the overreaction effect is magnified, which is consistent with the representativeness bias. Particularly the latter finding highlights the necessity to distinguish the good fallen angels from the bad ones, if an investor engages in fallen angel investing.

Lakonishok et al. present an agency theory-based explanation for overreaction caused by mutual fund managers, who tend to prefer growth to value stocks. Due to the generally higher popularity of growth companies, holding their stock is easier for managers to justify to fund investors. Consequently, share prices of growth companies are driven up by higher demand.¹⁹² However, as soon as a negative earnings surprise makes it publicly known that the glamorous growth story of these companies might come to an end, the agency theory-based effect is reversed. Since fund managers do not want to justify holding such stock in their portfolio, they sell them and thereby create fallen angels.

Akerlof and Shiller add another interesting twist to the explanation of overreaction with their theory of animal spirits.¹⁹³ It claims that not rational behavior, but animal spirits drive human decision-making and thus affect the economy and financial market prices. Some of the five aspects of these animal spirits – confidence and the related feedback mechanisms, fairness, corruption and bad faith, money illusion, and stories – can be related to overreaction.¹⁹⁴ Once disappointing news, such as a negative earnings

¹⁹¹ See Kaestner (2006).

¹⁹² See Lakonishok et al. (1992), pp. 341-344 and 376.

¹⁹³ See Akerlof/Shiller (2009a).

¹⁹⁴ See Akerlof/Shiller (2009a), p. 5 et seq., and Akerlof/Shiller (2009b), p. 128.

surprise, reaches the market, investors' confidence in the affected company and its future prospects starts to be shaken. Consequently, investors begin selling the company's stock, thereby driving share prices down. This in return might ignite a self-perpetuating feedback mechanism, as media or prominent investment experts increasingly start to talk negatively about the company, its disappointing earnings, and deteriorating share price. As a result, a downward momentum gains force and pushes the share price further down. Since the existence of good and intact stories plays an important role in Akerlof and Shiller's theory¹⁹⁵, growth companies might particularly suffer in such a situation. The fact that their growth story suddenly appears to be not intact anymore, or at least is much less appealing than the investment community had thought before, amplifies the negative sentiment among investors. This could lead to the fact that growth-style investors (see section 4.2.2) drop the company from their investment list, because they believe that the promise of strong future growth, which was their fundamental reason for investing in the stock, has ceased to exist. Value investors, however, will very likely not have these stocks on their radar screen, as growth stocks usually come along with certain characteristics that value investors do not like (see section 4.2.1). As a result of both, the drop in confidence and the severe damage to the growth story, the share prices of these companies fall more in reaction to the negative earnings announcement than would be rationally justified.¹⁹⁶

An argument often brought forward against the overreaction hypothesis by proponents of the efficient market hypothesis claims that while normal investors might overreact, this effect will be balanced by professional investors who are not endangered to overreact. De Bondt and Thaler, however, refute this argument by proving that professional analysts – like “normal” investors – suffer from overreaction, too.¹⁹⁷

Closely related to overreaction theory is the concept of mean reversion. It is based on the empirical observation that economic data in general and stock prices in particular have a tendency to move towards their long-term averages respectively fundamentally justified values. The cause for this mean reversion lies in the correction of overreactions as described above.¹⁹⁸ Mean reversion has been detected with regard to a variety of variables, most prominently for stock prices, but also for valuation ratios or

¹⁹⁵ See Akerlof/Shiller (2009a), pp. 51-56.

¹⁹⁶ See Skinner/Sloan (2002).

¹⁹⁷ See De Bondt/Thaler (1990).

¹⁹⁸ See Bruns/Meyer-Bullerdiek (2003), pp. 97 et seq.

for fundamental economic variables such as revenue or earnings growth rates.¹⁹⁹ For stock prices, the tendency to revert back to their mean is particularly strong when looking at longer time periods or when stocks have experienced significant price movements.²⁰⁰ The latter event is exactly the situation in which fallen angels usually find themselves after they negatively surprised with their earnings announcement.

In concluding this section, the importance of overreaction theory and mean reversion for this thesis shall be emphasized. Both are fundamental to the logic behind fallen angel investment as addressed here. Without an abnormal drop in share price caused by an overreaction triggered by a negative earnings surprise and the subsequent reclassification of the stock as a fallen angel, it would not make sense to investigate whether such a company constitutes a good investment opportunity or not. And without mean reversion as the promise for the fallen angel investor to benefit from the resulting correction of this overreaction over time, there would be no basis for generating positive abnormal returns.

Since the overreaction phenomenon is particularly strong over longer periods of time, the rather long-time horizon for measuring angel quality as described in section 2.4.1 makes sense as well. With regard to shorter time horizons of up to one year, however, empirical evidence poses a challenge to overreaction theory. These findings and the related underreaction theory shall be shortly described in the next section.

3.3.3 Underreaction Theory

The phenomenon of the post-earnings announcement drift as mentioned in section 2.4.1 contrasts the overreaction theory. It denotes the tendency of share prices to not immediately correct in the light of new earnings information, but gradually move into the direction indicated by the earnings announcement. In attempting to explain this drift, academics refer to a delayed response by investors.²⁰¹

This delayed response, or underreaction, to new information is rooted in the behavioral bias of conservatism, which conflicts with the representativeness bias. While the representativeness bias – as has been discussed in the previous section – prevails in the

¹⁹⁹ For stock price mean reversion see Poterba/Summers (1988) or De Bondt/Thaler (1989), for price-earnings-ratio mean reversion see Goedhart/Koller (2003) and Goedhart/Koller/Wessels (2005), for revenue growth rate mean reversion see Cao/Jiang/Koller (2011), and for earnings growth rate mean reversion see Fuller/Huberts/Levinson (1993).

²⁰⁰ See De Bondt/Thaler (1989), p. 190, who mention a “long-term perspective“ of three to seven years.

²⁰¹ See Bernard/Thomas (1989), Jegadeesh/Titman (1993), or Chan/Jegadeesh/Lakonishok (1996).

long run, causing investors to overreact, in the short-term people tend to only slowly change their beliefs in the face of new evidence.²⁰² The phenomenon of anchoring causes this initially slow reaction, which means that investors start their decision-making process from an initial value which is then adjusted accordingly to come to the final answer.²⁰³ Empirical evidence suggests that although investor underreaction might exist up to one year after the news arrived, it is largely disappearing over a much shorter time of three months or less.²⁰⁴

In the context of fallen angel investing, it appears that investors holding popular high-growth stocks require some time to digest the bad news of a negative earnings surprise. Stock prices do not adjust immediately to the new information, but investors also do not ignore it long-term. Therefore, it appears sensible for a fallen angel investor not to rush into a fallen angel stock right after the earnings announcement, but allow himself up to three months to make his investment decision and then implement it. This is also fully consistent with the design of this thesis as discussed above in section 2.4.1.

3.3.4 Reconciliation between Overreaction and Underreaction Theories

With factual evidence present for representativeness and overreaction on the one hand and conservatism and underreaction on the other hand, the main challenge for both academics and investors lies in reconciling both theories. Whether investors initially underreact and then slowly move towards the state of overreaction, or whether the underreaction effect hardly occurs and overreaction is very soon the dominating influence factor, seems to depend on how strong the opinions formed by investors about a particular stock are. Malloy argues that if investors do not have a strong opinion about a stock they tend to overreact quicker, while anchoring in deeply rooted beliefs causes investors to stick to them longer and thus underreact to new information.²⁰⁵ This could favor an overreaction for growth stocks with a rather short growth history so far and delay the negative price response for stocks with a long and consistent history of growth. Fallen angel investor might pay attention to this finding when assessing how much time they have after a negative earnings surprise before reaching an investment decision.

²⁰² See Ritter (2003).

²⁰³ See Tversky/Kahneman (1974), p. 1128.

²⁰⁴ See Foster/Olsen/Shevlin (1984), Bernard/Thomas (1989), Abarbanell/Bernard (1992), Dreman/Berry (1995), or Jegadeesh/Livnat (2006), p. 23.

²⁰⁵ See Malloy (2011), p. 3.

Support for this conclusion can be found in findings by Hirshleifer who – following Griffin and Tversky²⁰⁶ – attributes the extent of investor reaction on how much investors rely on the strength of a new information signal rather than on its weight.²⁰⁷ If investors assign more importance to the strength of the signal, e.g. the size of a negative earnings surprise, and less to the weight, e.g. the frequency of negative earnings surprises in the past or the number of analysts making up the consensus estimate, they will likely overreact to the news and vice versa. As a consequence, growth stocks with a long history of positive earnings surprises and broad analyst coverage, i.e. more weight, would suffer less than stocks with a shorter growth history and low analyst coverage. Moreover, Hirshleifer argues that a higher negative earnings surprise, i.e. more size, should also lead to a stronger reaction by investors. For fallen angel investing, it would mean that investors would have a particularly gloomy view and consequently overreact in case of a strongly negative earnings surprise, a short growth history of the company, and a thin analyst coverage. Since this overreaction will be reversed over time, the argument would be – *ceteris paribus* – to prefer such fallen angels to fallen angels that only mildly disappointed with their earnings announcement, have a long history of sales growth, and are covered by many analysts.

Particularly interesting for the reasoning behind fallen angel investing is another contribution to the discussion about when to expect over- and when underreaction to news made by Dreman and Barry. They shed more light on what they called the mispricing-correction hypothesis by finding out that there is a difference between event triggers and reinforcing events.²⁰⁸ While event triggers contain unexpected news opposite the expected direction, reinforcing events are surprises that reinforce investors' current perceptions of a stock. A negative earnings surprise for a growth stock would therefore be classified as an event trigger, while a negative earnings surprise of a company that is already badly rated by investors is seen as a reinforcing event. Dreman and Berry found out that the abnormal stock price reaction is significantly larger for event triggers than for reinforcing events. Furthermore, there is an asymmetric effect of surprising news on stocks that are highly favored by investors versus those with less good standing. While positive surprises have significantly stronger effects on the less-favored stocks with low price-to-earnings ratios, negative earnings surprises have a much stronger downward impact on the favored stocks with a high price-to-earnings ratio. These findings are very relevant for fallen angel

²⁰⁶ See Griffin/Tversky (1992).

²⁰⁷ See Hirshleifer (2001), p. 1547.

²⁰⁸ See Dreman/Berry (1995).

investing. As already their name indicates, angel stocks are held highly by investors because of their promising growth perspective. Therefore, investors will more likely overreact in the case of negative earnings surprises for angel stocks as compared to other stocks. Consequently, investors could take advantage of this effect by engaging in fallen angel investing. However, they have to be aware that the extent of underreaction and the related earnings announcement drift is likely less prominent and occurs over a shorter amount of time for angel stocks than for “normal” stocks.

In trying to reconcile over- and underreaction by investors, academics have also developed various asset pricing models that offer an explanation for both phenomena.²⁰⁹ In the model of Barberis, Shleifer, and Vishny actual earnings for a risky asset like a stock follow a random walk, but it is assumed that investors fail to recognize this.²¹⁰ They erroneously believe that earnings are guided by two regimes, a regime with mean-reverting earnings and an expected earnings growth regime. Once a company reverses its past earnings trend by delivering an earnings surprise, investors erroneously believe that this firm entered the mean-reversion regime, and thus initially underreact to the earnings news. This is consistent with conservatism and the post-earnings announcement drift. However, when investors notice a sequence of growing earnings, they falsely infer that the respective company is in the growth regime. This causes them to overextrapolate the growth trend, which leads to overreaction and is consistent with the representativeness bias.²¹¹ However, a recent study by Alwathainani, tested the conservatism effect contained in the model of Barberis, Shleifer, and Vishny, and failed to find proof of it.²¹² On the contrary, earnings surprises appear to lead to strong stock price momentum already in the three months following the announcement. If the subsequent earnings announcement contradicts the initial earnings surprise, stocks exhibit significant price reversals. These findings indicate that financial markets tend to overreact to surprising information also in the short-term.

In Hong and Stein’s model, two groups of boundedly rational investors act in financial markets: “newswatchers” and “momentum traders”.²¹³ Since information picked up by the newswatchers only gradually diffuses across the investor population, an initial

²⁰⁹ See Barberis/Thaler (2003), pp. 1092-1095, for a good overview.

²¹⁰ See Barberis/Shleifer/Vishny (1998).

²¹¹ See Hirshleifer (2001), p. 1569.

²¹² See Alwathainani (2010).

²¹³ See Hong/Stein (1999).

underreaction of share prices to news occurs. Momentum traders can profit from this by chasing the short-term trend established by initial investor underreaction. Over time, however, their actions push prices too far, thus leading to overreaction.²¹⁴

Daniel, Hirshleifer, and Subrahmanyam argue that investors tend to be more overconfident with regard to information they have uncovered through hard work during their own stock analysis.²¹⁵ If public news arrives disconfirming this information, investors are giving less attention to it because of their high confidence level in their own information. A slower than rationally expected change in opinion and a resulting underreaction would be the consequence. For fallen angels, investors will probably have formed some positive opinions about the angel stocks, causing them to purchase the growth stock on its way up. The disturbing public news of a negative earnings surprise might therefore at first be not strong enough to shatter the confidence in the stock, thus resulting in an initial underreaction of the fallen angel stock. In contrast to that, if public news confirms the view of the investor's own information, his already high confidence in it further increases. As a consequence, share prices will even more trend in the already existing direction, finally leading to overreaction.

Veronesi draws upon rational expectations theory in developing his dynamic equilibrium model of asset prices.²¹⁶ In his model stock prices overreact to bad news in good times and underreact to good news in bad times. At least for market situations that are generally seen as positive by investors this is consistent with the idea of fallen angel investing as applied in this thesis.

Summing up, although conceptual explanations and empirical evidence are not fully unambiguous, there appears to be a general tendency for stock prices to initially underreact to adverse news like a negative earnings surprise before mid- and long-term overreaction sets in. This is consistent with the longer-term investment horizon of a fallen angel investor under this thesis. Furthermore, the presented findings suggest that an initial underreaction to an earnings surprise is less evident than the long-term overreaction and might even be less distinct for angel stocks. Therefore, fallen angel investors should keep in mind that although share prices of fallen angels might remain

²¹⁴ The hypotheses of the gradual-information-diffusion model by Hong and Stein were later largely confirmed by Hong/Lim/Stein (2000), particularly with regard to the slow diffusion of negative news.

²¹⁵ See Daniel/Hirshleifer/Subrahmanyam (1998).

²¹⁶ See Veronesi (1999).

abnormally weak for some time after the earnings surprise, there is no guarantee for this and they should not take too much time before making an investment decision. As mentioned before in section 2.4.1, this thesis assumes an investment within the rather short time of 60 trading days after the negative earnings announcement, i.e. still before the next earnings announcement.

3.3.5 Other Cognitive Biases

Apart from the broadly discussed biases of representativeness and conservatism, which are particularly relevant for fallen angel share price development, there are several other cognitive biases of investors that also play a role for fallen angel investing. One fundamental trait of investors that supports the development of other biases is overconfidence.²¹⁷ Multiple studies have so far demonstrated that human beings tend to assign an overly high probability of success to their own forecasts.²¹⁸ For investors, overconfidence can lead them to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events.²¹⁹ Overconfidence also seems to be the reason for the surprising finding that despite Warren Buffett's outstanding track record and the fact that all of his trades have to be published on a quarterly basis, analysts tend to downgrade and institutional investors tend to sell stocks recently purchased by Buffett.²²⁰ In the context of fallen angel investing, overconfidence on behalf of investors might initially lead to a delayed price response to the negative earnings surprise, because overconfident investors only slowly update their opinion (see also the model of Daniel, Hirshleifer, and Subrahmanyam described in section 3.3.4 above). However, once they have done so, overconfidence will likely lead to a bleak outlook for the fallen angel stock, since investors now strongly believe that the growth story is over, thereby neglecting other available information that might support a more optimistic view about the company.

Akin to overconfidence is the so-called belief bias. In general, human beings tend to rely more on their beliefs than on their logic when drawing conclusions on different issues.²²¹ This belief bias is the tendency to evaluate an argument or information more

²¹⁷ For a more comprehensive account of overconfidence see Nofsinger (2002), pp. 9-20, or Montier (2008), pp. 109-114.

²¹⁸ See, for example, Kahneman/Tversky (1973), Fischhoff/Slovic/Lichtenstein (1977), or Shefrin (2007), pp. 18 et seq.

²¹⁹ See Nofsinger (2002), p. 9.

²²⁰ See Hughes/Liu/Zhang (2010).

²²¹ See Evans/Barston/Pollard (1983).

on the basis of whether or not one agrees with the conclusion, rather than on whether or not the conclusion makes sense from a logical point of view.²²² The strength of a belief is connected with the pattern-recognition bias of storytelling. People have the tendency to more strongly believe in a set of facts when they are presented as part of a coherent story.²²³ If investors believe that the growth story of an angel company is intact, they therefore tend to underestimate information inconsistent with this growth story. In case investors' beliefs, however, have shifted to the negative, because the new information is too strong to be neglected, like a negative earnings surprise, their attitude towards the former angel company tends to swing in the opposite direction and a fallen angel is created.

Another bias observed by Kahneman and Tversky is the tendency of human beings to attach more significance to these observations about an object that they made earlier than to those they made later.²²⁴ This tendency to be irrationally fixed on early trends in data is absolutely not compatible with the assumption of a rationally acting investor who follows the rules of statistical inference.²²⁵ With regard to fallen angels, this bias could cause investors to too early condemn a company as a fallen angel, because a few pieces of negative information, such as missing the earnings forecast, a delay in introducing a new product, or other disappointing qualitative information, have reached the market. Even if other pieces of information paint a different picture, investors' minds might have been preset to the negative image of the fallen angel company, thus putting selling pressure on its stock.

Before moving on to the summary of this chapter, the next section provides a selection of what influential investment practitioners think about the drivers of market movements. After all, this thesis is also geared towards helping investment managers to make better investment decisions, and it is investors in their daily work who are closest to the market and its movements.

²²² See Montier (2009).

²²³ See Lovallo/Sibony (2010), p. 45.

²²⁴ See Tversky/Kahneman (1971).

²²⁵ See Fox (2009), pp. 177 et seq.

3.4 Perspective of the Investment Practice

Although there are supporters of both the efficient market hypothesis and the behavioral perspective of looking at financial markets among investment practitioners, it seems noteworthy that several seasoned investors with a long successful track record take a clear stance against the conclusions of the efficient market hypothesis.

Already in 1934, i.e. many years before the appearance of the efficient market hypothesis, Graham – interestingly both an investment professional and an academic – expressed his view that irrational human sentiment has a decisive influence on financial markets: “[...] the price of common stocks are not carefully thought out computations, but the resultants of a welter of human reactions. The stock market is a voting machine rather than a weighing machine.”²²⁶ Although Graham made this statement after he had experienced four very bad years as an investor in the aftermath of the Black Friday 1929 and later modified this statement in the light of the then more stable stock markets²²⁷, he never distanced himself from his view of financial markets that are sometimes driven by rational considerations and at other times by pure emotion. In his parable about the price movements in financial markets, he introduces “Mr. Market”, a manically depressive character who comes to investors every day and offers them to buy or sell shares at a certain price: “Sometimes his idea of value appears plausible and justified by business development and prospects as you know them. Often, on the other hand, Mr. Market lets his enthusiasm or his fears run away with him, and the value he proposes seems to you a little short of silly.”²²⁸

Buffett, one of the, if not the most successful equity investor of the past decades, shares the view of his former professor and employer. In a seminar held at Columbia University in 1984 he, sitting on a panel together with Jensen²²⁹, contested the view of markets being always efficient. At first, he conceded that the random-walk theory would be backed in case the identified alpha-generating investors would themselves be fully randomly distributed without any interconnections between themselves at all. However, as Buffett moved on, this is not the case, as a significant number of these successful investors emerged from the intellectual school of Graham and Dodd. He

²²⁶ Graham/Dodd (1934), p. 452.

²²⁷ See Graham (1963), pp. 66 and 68, and Fox (2010), pp. 1 et seq.

²²⁸ Graham (2003), pp. 204 et seq.

²²⁹ Jensen, who is mainly known for his groundbreaking research in the field of principal-agent theory, strongly supported the efficient market theory in both writings and statements. See, for example, Jensen (1978).

prevailed against Jensen by adding factual evidence of the strong outperformance of these investors of Graham-and-Doddsville, as Buffett called them.²³⁰ On another occasion, he pointedly stated that it would be a dangerous fallacy to assume from the fact that markets are efficient oftentimes, they are efficient all the time.²³¹ And in an interview with Fortune Magazine on April 3, 1995, he remarked colorfully: “I’d be a bum on the street with a tin cup if the market were efficient.”

In the same edition of Fortune Magazine, Lynch also voiced his disagreement with the efficient market hypothesis: “Efficient markets? That’s a bunch of junk, crazy stuff.”²³² Less catchy, but nonetheless convincing Fisher also makes a case against the efficient market hypothesis.²³³ His argument focuses on the observable large variations of stock returns. Would all available information be always correctly incorporated in the current share prices, like the efficient market hypothesis claims, share prices should not display such tremendous movements from day to day.

Soros and his Theory of Reflexivity serve as another example of a high-profile investor who does not believe in efficient market theory. In a famous speech Soros delivered at the MIT Department of Economics World Economy Laboratory Conference in Washington in 1994, he stated: “financial markets cannot possibly discount the future correctly because they do not merely discount the future [as the efficient market hypothesis claims]; they help to shape it.”²³⁴ Soros further elaborated that while the methodology of natural sciences with its clear separation between events and observed facts has great value, this approach provides a distorted picture of reality when applied to an environment that is driven by human beings. In such a surrounding, there is no clear relationship between cause and effect anymore. Facts and thoughts cannot be separated like they are in natural sciences. The thinking of people, and thus also of investors, is inherently biased and cannot only be based on pure rational knowledge, as the efficient market hypothesis assumes. The thoughts of investors can actually exercise influence on objectively observable data, such as share prices or fundamental company data. As a consequence, there is not only a passive relationship between fundamental data in financial markets and investor reaction, but also an active

²³⁰ See Buffett (1984), or Schroeder (2008), p. 529 et. seq.

²³¹ See Buffett (2003), p. 99.

²³² See Friedman (2003), p. 89.

²³³ See Fisher (2003), pp. 267-270.

²³⁴ Soros (1994), p. 1.

one. Neglecting this fundamental extension of the efficient market model is, in Soros's eyes, very dangerous for any investor.²³⁵

It would not be a problem to continue this list by adding numerous other investment practitioners to it, but that would not change the main point of it. Noteworthy, though, is that this list does not contain the names of mediocre investment professionals, who might claim that financial markets are inefficient and sometimes irrational in order to divert from their bad performance. Instead, it is highly successful investors, who have managed to consistently beat the market over many years, sometimes even many decades, who articulate their misbelief in the efficient market hypothesis. Neglecting their opinion on financial markets, which is grounded in extensive experience of working in them, does not seem to be a wise decision for anyone concerned with investment management.

3.5 Summary

In summarizing the relevance of both the efficient market hypothesis and behavioral finance for fallen angel investing as presented in this thesis, their differing explanations of the cause of market bubbles illustrate why behavioral finance plays the more important role. Whereas the cohesive theoretical construct of efficient market hypothesis and its related asset pricing theories argue that market bubbles occur because prices are right and such high-priced stocks are less risky or have superior cash flow prospects, behavioral economists argue that bubbles are caused by certain swings in investor sentiment.²³⁶ When looking at historical bursts of bubbles like the Dutch tulip bubble in the 17th century, the Japanese real estate and stock price bubble in 1989, the new economy bubble in 2000, or the real estate bubble in the U.S. and other countries in 2008²³⁷, it becomes difficult to argue that any of these inflated assets were less risky or had better cash flow prospects than other asset classes at the time of their peak. On the contrary, Japanese stocks never reached their peak valuations until the date of this research leading to the “lost decade” – in the meantime it would be even more correct to use the plural – for investors in the Japanese stock market.²³⁸ Many internet companies did not only see a sharp drop in their share prices from March 2000 on, but often had to close shop entirely. And in May 2011 the S&P/Cash-

²³⁵ See Soros (1994) and Soros (2003), pp. 49-84.

²³⁶ See Malloy (2011), p. 5.

²³⁷ For a good account of stock market bubbles and crashes see Komáromi (2006) or Kaplan (2011).

²³⁸ See Kaplan (2011), p. 203.

Shiller Home Price Index was still approximately 32 percent down from its peak reached about five years ago.²³⁹ These admittedly drastic examples document that there must be other forces beyond rational information processing and decision-making that drive financial markets. Behavioral finance has started to provide answers to why asset prices do behave irrationally from time to time. Fallen angel investing is trying to profit from such irrational market behavior, as it is based on the assumption that stock prices overreact and afterwards revert to their mean. This share price behavior provides an opportunity to earn abnormal returns for fallen angel investors. Such opportunity would not exist, if financial markets were efficient. Consequently, this thesis has its theoretical basis more in behavioral economics than in efficient market theory.

Nevertheless, it would be a misconception to conclude that because financial markets do not appear to be efficient that it is easy to exploit these inefficiencies and by doing so earn abnormal returns. Numerous studies have demonstrated that active investors such as mutual fund managers on average fail to beat the market and if they manage it fail to do so on a continuous basis.²⁴⁰ This fact can also be seen as a key driver behind the strongly increased importance and broadened offering of exchange traded funds in recent years.²⁴¹ However, as mentioned by Buffett in his above-mentioned speech at Columbia University, there is the striking fact that numerous investors have consistently managed to beat the general market and often still do so until today. The investment philosophy of these investors is often grounded in a traditional value investing approach as introduced by Graham. To expand this traditional value investing approach by adding an easily identifiable and measurable growth element to it is a key goal of this thesis. Fallen angel investing in this sense can therefore be seen as providing a bridge between value and growth investing. The next chapter will more thoroughly address the topic of investment styles in general and value and growth investment styles in particular.

²³⁹ The non-seasonally adjusted S&P/Case-Shiller Composite-10 index (CSXR) was down 32.1% from its peak reached in June 2006. The broader non-seasonally adjusted S&P/Case-Shiller Composite-20 index (SPCS20R) was quoted 32.3% lower than its peak in July 2006. The picture does not change when looking at seasonally adjusted index data with 31.8% off from the peak in April 2006. See Standard&Poor's (2011a).

²⁴⁰ See, for example, Malkiel (1995) or Carhart (1997).

²⁴¹ See Gastineau (2010), pp. 19-42.

4 Investment Styles

4.1 Overview on Investment Styles

4.1.1 Function and Definition of Investment Styles

During the past several decades both practitioners' and academics' interest in investment styles has grown strongly.²⁴² This is likely due to the fact that investment style analysis promises to increase the understanding of an investment manager's active return. With both investment consultants and investors themselves having a strong need to understand an investment manager's performance and specialization, investment style analysis offers helpful and sought-after orientation.²⁴³ Particularly the styles value and growth have – apart from small-cap and large-cap – received strong attention.²⁴⁴ However, before moving on directly to these two seemingly opposing investment styles, which are also the relevant styles for this thesis, some general information about investment styles shall be provided.

The fundamental idea behind style investing is that an investor's performance is driven by his exposure to one or several different parts of the economy.²⁴⁵ According to Schwob such exposure is based on recognizing “that only a few things matter, or, more sensibly, that there are only a few things that really matter most.”²⁴⁶ The origins of investment style analysis go back to Sharpe.²⁴⁷ His goal was to develop a tool with which institutional investors could better assess and measure the performance of investment managers.²⁴⁸

²⁴² See Postert (2007), pp. 44-63.

²⁴³ See Michaud (1999), pp. 3 et seq., Brentani (2004), pp. 170 et seq., and Lhabitant (2004), pp. 213 et seq.

²⁴⁴ See Michaud (1999), p. 1, and Postert (2007), pp. 40 et seq.

²⁴⁵ See Jones (2008), p. 21.

²⁴⁶ Schwob (2000), p. 39.

²⁴⁷ See Sharpe (1988) and Sharpe (1992).

²⁴⁸ See Jones (2008), pp. 20 et. seq.

Following the definition of Brown and Goetzmann²⁴⁹, an investment style can be seen “as a natural grouping of investment disciplines that has some predictive power in explaining the future dispersion in returns across portfolios”²⁵⁰. In further specifying this definition, this thesis is geared to investment style in its narrow sense according to Postert.²⁵¹ Thus, investment style focuses on microeconomic issues and does not encompass a selection along asset classes, countries, currencies, or industries. In this sense it is purely focused on stock selection.²⁵²

4.1.2 Classification of Investment Styles

Figure 3 provides a systematic overview of the most common investment styles:

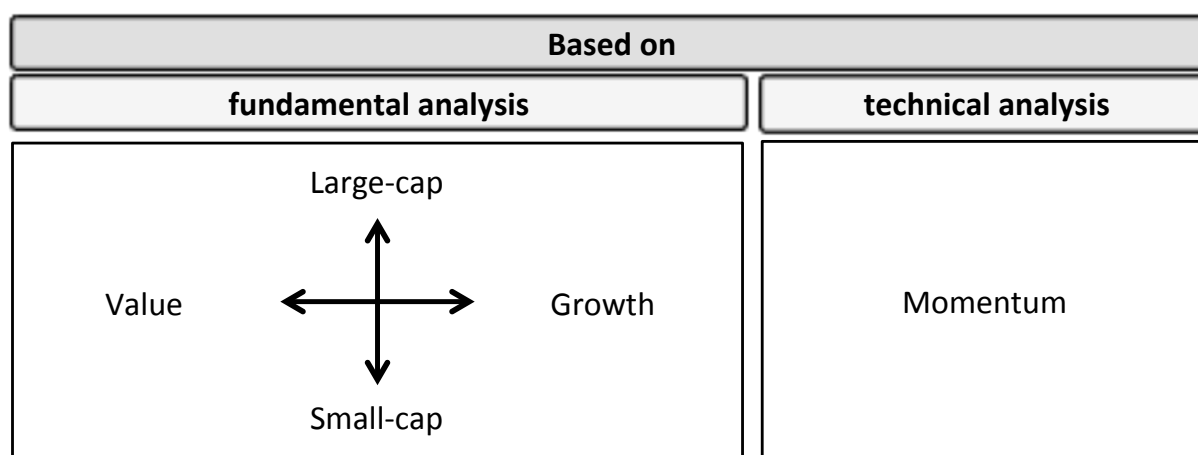


Figure 3: Overview of equity investment styles

Source: Author taking into consideration Sharpe (1992), Gorodess (1997), Hardy (1997), and Otte/Castner (2007)²⁵³

²⁴⁹ See Brown/Goetzmann (1997).

²⁵⁰ Maginn et al. (2007), p. 8.

²⁵¹ See Postert (2007), pp. 66 et seq.

²⁵² See Brown/Bentley (2002), p. 31.

²⁵³ See Sharpe (1992), Gorodess (1997), pp. 277 et seq., Hardy (1997), p. 58, and Otte/Castner (2007), p. 41.

Small-cap and large-cap relates to the size of the market capitalization of the underlying company. The exact definition of what constitutes a small-cap and what a large-cap company varies. In the U.S., a small-cap stock usually has a market capitalization between 300 million and 2 billion US\$, whereas a company has to show a market capitalization of 10 billion US\$ or more to classify as a large-cap stock. Stocks with a market capitalization between two and 10 billion US\$ are usually referred to as mid-cap stocks. Stocks below 300 million US\$ in market cap classify as micro cap.²⁵⁴ However, it should be noted that these market cap thresholds are not uniform over time and particularly not across countries. Generally, U.S. stock markets use higher market cap figures, which also reflects the larger size of U.S. financial markets.²⁵⁵ All market capitalization-based investment styles can be combined with either value or growth investing. For example, an investment manager can pursue a large-cap value investment style, or he can be a small-cap growth investor.

Momentum, however, is predominantly associated with growth investing and regarded as incompatible with value investing. Investors following a momentum style invest their funds based on the assumption that existing trends will continue. They attempt to detect these trends by various metrics or technical stock chart analysis²⁵⁶, thus “investing in shares with positive relative price strength without regard to fair value”²⁵⁷. Often such trends persist when an industry or company is experiencing above-average sales or earnings growth, and analysts’ growth expectations are at least met if not beaten.²⁵⁸ Fallen angel companies before announcing their negative earnings surprise are typical stocks on the buy lists of momentum growth investors. And momentum investors also play a role for such stocks after the negative earnings surprise, since they now regard the previous upward trend as broken and thus start to sell their shares. The consequent downward post-earnings announcement drift can be viewed as an expression of the novel negative trend in stock price that is amplified by the behavior of momentum investors. Since Jegadeesh and Titman have found evidence supporting the momentum strategy over a three to twelve month holding period, the momentum strategy also has received backing from the academic side.²⁵⁹ Several other studies have confirmed the findings of Jegadeesh and Titman for both

²⁵⁴ See Switzer (2010), pp. 341 et seq.

²⁵⁵ See Petrella (2005) for European stocks, and Switzer (2010), p. 342, for Canadian stocks.

²⁵⁶ See Otte/Castner (2007), p. 41.

²⁵⁷ Wisdom (2009), p. 150.

²⁵⁸ See Ferri (2008), pp. 318-320.

²⁵⁹ See Jegadeesh/Titman (1993).

the U.S. and other countries as well.²⁶⁰ Nevertheless, there is plenty of evidence that contrarian investment behavior, which is in essence the opposite to momentum investing, leads to superior returns over longer periods of time.²⁶¹

In contrast to momentum investors, value investors do not buy or sell stocks based on trend analysis, but rather act as a contrarian investor focused on the intrinsic value of a company and the possibly resulting undervaluation of its stock.²⁶² Therefore, value and momentum are very difficult to reconcile, although O'Shaughnessy or Henning have come up with investment strategies and models that try to combine the advantages of both investment styles.²⁶³ A recent study by Asness et al. highlights that the returns of value and momentum strategies are indeed negatively correlated both within and across asset classes, particularly during extreme return events. However, their findings also advocate a combination of both investment strategies within a broader portfolio approach, since such combination delivers superior results for investors.²⁶⁴ Bernhard and Verhoven also recommend a combined value-momentum strategy, but like Asness et al. do so on a portfolio level and not by creating a new blended investment style.²⁶⁵ However, as it is not the goal of this thesis to bring value and momentum investment styles closer together, but rather build a bridge between value and growth investing, the focus shall be placed more on the investment styles of value and growth and their relationship towards one another.

²⁶⁰ See, for example, Oehler (2002).

²⁶¹ See, for example, De Bondt/Thaler (1985), De Bondt/Thaler (1987), Poterba/Summers (1988), or De Bondt/Thaler (1989).

²⁶² See Greenwald et al. (2002), pp. 3 et seq.

²⁶³ See O'Shaughnessy (2005) and Henning (2010).

²⁶⁴ See Asness/Moskowitz/Pedersen (2009).

²⁶⁵ See Bernhard/Verhofen (2011).

4.2 Value versus Growth Investing

4.2.1 Value Investment Style

Both academics and investment practitioners view value and growth as among the most important, if not even the most important investment styles. There has been an extensive amount of academic empirical research on value and growth investing, and many financial market participants use these two styles as reference points in the investment universe.²⁶⁶ Together with this frequent use of value and growth often goes the – erroneous – view that value and growth are diametrically opposing investment styles.²⁶⁷ Following this view, major index providers like MSCI or S&P construct value and growth indices by splitting the underlying investment universe along certain dimensions into value and growth stocks.²⁶⁸

Value investors, on the one hand, are looking to buy stocks of companies that they believe are undervalued in their current state.²⁶⁹ Plainly spoken, they are trying to “buy a dollar for 60 cents”²⁷⁰. Therefore, they are looking for low valuation ratios, such as price-to-book, price-to-earnings, or price-to-cash flow.²⁷¹ A high dividend yield is also often a feature of a stock that is preferred by value investors.²⁷² Although value investors do not completely neglect potential future growth when evaluating investment opportunities, they do not focus on it as the key element for a stock’s current valuation.²⁷³ Value investors also do not see stocks purely as vehicles to participate in the ups and downs of the stock market, but refer to investing in a stock as “buying a fractional interest in a business”²⁷⁴. Consequently, they spend a lot of their analysis effort on trying to understand the business of a company, its current and long-term competitive position, and the quality of its management.²⁷⁵ Based on this deep

²⁶⁶ See Chan/Lakonishok (2004) for an overview on academic research published until 2003. See Brown/Bentley (2002), pp. 31-48, for information on the use of investment styles by investment practitioners.

²⁶⁷ See, for example, Bernstein (1995), pp. 3 et seq., Arnott/Luck (2003), pp. 47-60, Speidell/Graves (2003), pp. 171 et seq., or Chan/Lakonishok (2004).

²⁶⁸ See Morgan Stanley Capital International (2005) and Russell Investments (2011a).

²⁶⁹ See Greenwald et al. (2002), p. 4.

²⁷⁰ Browne (2007), p. 145.

²⁷¹ See Brush (2007) or Postert (2007), p. 71.

²⁷² See Greenwald et al. (2002), pp. 160 and 222, or Postert (2007), p. 71.

²⁷³ See Greenwald et al. (2002), pp. 101 et seq.

²⁷⁴ See Klarman/Zweig (2010), p. 20.

²⁷⁵ See Buffett (1998), p. 152, Whitman (2000), p. 4, Graham (2003), pp. 206 et seq. and 293, or Zweig (2003), pp. 399 et seq.

understanding of a company's business value investors estimate the intrinsic value of a company's stock and compare it with the current market price. However, it is not enough that the intrinsic value of a company exceeds the prevailing market valuation. Value investors acknowledge the fact that they might be wrong in their calculations despite the generally extensive effort they put into the fundamental analysis of a stock. To protect themselves against such risk they demand a certain percentage that the current market price has to be below the intrinsic value of a stock before investing in it. This difference between intrinsic value and market price is called the margin of safety and is one of the key concepts of value investing.²⁷⁶ Although the size of the demanded margin of safety varies from value investor to value investor, the usual range lies between 10 and 50 percent.²⁷⁷

The popularity of the value investment approach is mainly due to two reasons: first, the documented superior returns that can be earned by investors in following a value investment strategy, and second, the existence of a systematic process of valuing a company based on value investment principles.²⁷⁸

Concerning the superior performance of value investment strategies, both the investment results of value investment practitioners and a large body of academic research lend support to it. Often relating to the tradition of value investing as established by Graham in the first half of the twentieth century, there are numerous investment professionals who have been achieving superior returns by applying value investment strategies. As previously mentioned, Buffett elaborates vividly on this fact in a speech in front of students of Columbia University on the occasion of the fiftieth anniversary of the publication of Graham's and Dodd's book titled "Security Analysis".²⁷⁹ He points out that the outstanding investment results of these investors are rooted in their exposure to the principles of value investing during their time with Graham. They achieved their superior performance independently from each other and consistently over several decades. Thus, this accumulation of well above-average investment performance cannot be purely accidental. Until today, investors who follow value investment criteria in their decision-making process have been able to beat the market over longer time periods.²⁸⁰ To verify these observations in a systematic and

²⁷⁶ See Klarman (1991) or Graham (2003), pp. 512-524.

²⁷⁷ See Yee (2008).

²⁷⁸ See Rehder (2006), pp. 3-6.

²⁷⁹ See Buffett (1984).

²⁸⁰ See Rehder (2006), p. 6.

statistically firm way, scholars have conducted numerous studies demonstrating the significantly superior return of value style investing over mid- to long-term investment horizons and across countries.²⁸¹ The academic world refers to this phenomenon as value anomaly.²⁸² Since these findings are contradictory to efficient market theory, they were initially received with surprise. Later on, two main explanations for the value anomaly emerged.²⁸³ On the one hand, supporters of the efficient market theory attributed the anomaly to the higher risk of value stocks on some dimension not yet identified by academics, but already priced by investors.²⁸⁴ This argument was weakened by the observation that the beta of value portfolios did not reflect such higher risk, but was even lower than overall market betas.²⁸⁵ On the other hand, behavioral finance theory explained the value anomaly with the systematic mistakes market participants make due to numerous biases that influence their investment decisions.²⁸⁶ The so-called expectational errors hypothesis states that investors initially have overly optimistic expectations about the future earnings' prospects of growth stocks. These are later corrected and thus lead to the underperformance of growth stocks.²⁸⁷ Skinner and Sloan supported the expectational errors hypothesis by studying the share price performance of growth stocks relative to value stocks. According to their findings the underperformance of growth stocks is predominantly due to the significantly worse stock price reaction of growth stocks to negative earnings announcements, thus strengthening the case for the quest for good fallen angel stocks.²⁸⁸ A third explanation of the value anomaly ascribed the underperformance of growth investing style to methodological issues of data-selection bias, but this

²⁸¹ See, for example, Basu (1977), Rosenberg/Reid/Lanstein (1985), Jaffe/Keim/Westerfield (1989), Chan/Hamao/Lakonishok (1991), Fama/French (1992), Capaul/Rowley/Sharpe (1993), Lakonishok/Shleifer/Vishny (1994), Arshanapalli/Coggin/Doukas (1998), Fama/French (1998), Chan/Lakonishok (2004), Hahn/O'Neill/Swisher (2007), or Brandes Institute (2010).

²⁸² See, for example, Kang/Ding (2006), pp. 114-116.

²⁸³ See Chan/Lakonishok (2004), p. 71.

²⁸⁴ See Fama/French (1992).

²⁸⁵ See Greenwald et al. (2002), p. 7.

²⁸⁶ For a deeper discussion of efficient market theory and behavioral finance see chapter 3.

²⁸⁷ See Lakonishok/Shleifer/Vishny (1994).

²⁸⁸ See Skinner/Sloan (2002). Their finding that a large part of the negative abnormal returns occurs during the 31 days leading up to the earnings announcement and only a smaller part during the three days surrounding the announcement does not substantially hurt this thesis, because fallen angels are defined as stocks showing, among other features, a negative abnormal return in a five-day window around the earnings announcement. Therefore, a slightly negative abnormal return is already sufficient to pass this criterion for a fallen angel.

approach was materially challenged by a subsequent study shortly after it was made public.²⁸⁹

Regarding the process of value investing, the fact that a systematic process of valuing a company on the basis of value investment principles exists, thereby making value investing more practical, also supports the popularity of the value investment style. Developed by Graham and Dodd during their time at Columbia University, this process was and still is further refined at Columbia University's Heilbrunn Center for Graham & Dodd Investing.²⁹⁰ Starting from an in-depth analysis of the company's book value, which represents the most reliable information, value investors continue with estimating the earnings power of a company. This is done on the basis of conservative assumptions on the durable amount of earnings under average conditions and without making any assumptions about possible future growth. Only after that step, growth potential is taken into consideration, which prevents the fairly safe assumptions on book value and earnings power to be diluted by the speculative element of potential future growth.²⁹¹ Furthermore, there is not only a systematic company valuation process based on value investing criteria. Moreover, true value investing encompasses a complete structured investment process as proposed by Greenwald.²⁹² This process covers four phases: The search for an appropriate investment target as the point of origin is followed by the valuation of the target stocks as described above. In their search for investment opportunities, value investors focus on stocks that Greenwald calls "cheap, ugly, obscure, otherwise ignored"²⁹³. The outcome of the two initial phases is then thoroughly reviewed in light of the key issues discovered, the collected information for or against the investment hypothesis, and existing personal biases. Lastly, the investment risk has to be managed by paying attention to the demanded margin of safety, by being patient, and by diversifying to a limited extent.

²⁸⁹ See Kothari/Shanken/Sloan (1995), Chan/Jegadeesh/Lakonishok (1995), and Chan/Lakonishok (2004), p. 71. See also Davis (1994), who confirmed the book-to-market effect in a sample that was less susceptible to biases affecting early observations in the Compustat files, which were used in many studies.

²⁹⁰ See Rehder (2006), pp. 5 et seq.

²⁹¹ See Greenwald et al. (2002), pp. 40-44.

²⁹² See Greenwald/Bellissimo/Otte (2008), p. 24, and Greenwald (2009a), p. 3.

²⁹³ Greenwald/Bellissimo/Otte (2008), p. 3.

4.2.2 Growth Investment Style

Growth investors, on the other hand, are looking for above-average and continued growth in sales, earnings, and cash flows. Consequently, this group of investors is looking more at the future potential of a company and not at the value that is already reflected in financial statements today. Growth investors are generally not afraid to buy stocks with high price-to-book or price-to-earnings ratios, since they believe that the expected future growth of the company makes price-to-book, price-to-earnings, or other market value-focused ratios based on current financial statement data less relevant.²⁹⁴ When separating growth from value stocks, researchers often use the price-to-book (P/B) ratio, which is defined as the market value of the company's stock divided by the book value of its equity. In academic research, this relationship is frequently used in its rearranged form as the book-to-market (B/M) ratio. Growth stocks are those with high P/B ratios (low B/M ratios) while value stocks command a low P/B ratio (high B/M ratio).²⁹⁵ Besides, there are other criteria such as cash-flow-to-price, price-to-earnings (P/E) or past growth in sales that are used to distinguish growth from value stocks, but P/B respectively B/M appears to be the most widely used ratio.²⁹⁶ As previously mentioned, some academic studies use the term glamour stocks as a synonym to growth stocks²⁹⁷, which represents the widely held belief that value investing concerns itself with boring and stagnant investment targets, while growth investing deals with attractive and growing companies.²⁹⁸ As Jegadeesh et al. demonstrate, even professional analysts appear to suffer from a bias towards growth stocks. They prefer growth above value stocks in their recommendations, but this is by no means a reliable predictor of future stock returns.²⁹⁹ On the contrary, Dreman and Berry show that stocks with a high P/E ratio, i.e. growth stocks, react particularly unfavorably to a negative earnings surprise compared to stocks with a low P/E ratio. This is also consistent with the overreaction hypothesis and the negative price response is by far strongest for the quintile containing the stocks with the highest P/E ratio. Furthermore, the impact of a negative earnings surprise on the price of a growth stock

²⁹⁴ See Bruns/Meyer-Bullerdiel (2003), p. 149, or Au (2004), pp. 27 et seq.

²⁹⁵ See, for example, Lakonishok/Shleifer/Vishny (1994), p. 1546, Rosenberg/Reid/Lanstein (1985), La Porta et al. (1997), p. 861, Fama/French (2007), p. 44, or Jiang/Koller (2007), p. 12.

²⁹⁶ See, for example, Chan/Hamao/Lakonishok (1991), p. 1746 et seq., Lakonishok/Shleifer/Vishny (1994), p. 1543, Fama/French (1998), p. 1975, or Chahine/Choudry (2008), p. 2.

²⁹⁷ See Lakonishok/Shleifer/Vishny (1994), La Porta et al. (1997), Guay (2000), Chan/Lakonishok (2004), Jegadeesh et al. (2004), or Yan/Zhao (2011).

²⁹⁸ See, for example, Greenwald (2009b), p. xxviii, or Marks (2011), pp. 19 and 21.

²⁹⁹ See Jegadeesh et al. (2004), pp. 1083 et seq.

is much more pronounced compared to the positive effect of an earnings surprise reaffirming the high growth expectations.³⁰⁰ These findings clearly strengthen the case for fallen angel investing. It appears that investors assume that growth companies are still able to beat or at least meet the high growth expectations and are thus not significantly more bullish when companies do so. However, if a company fails to overcome the high earnings growth hurdle, then investors are heavily disappointed and dump the stock. Exactly the opposite is true for stocks with a low P/E ratio, i.e. companies with unambitious or even negative earnings growth expectations. Their share prices are not hurt a lot by negative surprises, but benefit substantially from a positive earnings surprise. This is also consistent with prospect theory and the activity of coding as explained in section 3.3.1.

The simplifying – and unjustified – treatment of growth investing as the direct antagonist to value investing is stressed by the frequent association of growth investing with momentum investing. Although there are similarities between growth and momentum, equalizing growth with momentum would be incorrect. Since a seemingly positive growth perspective of a company is often the cause of the relative outperformance of its stock, sales growth frequently is the driver of the momentum, thus making the growth stock also a momentum stock. Nevertheless, there can be other reasons than growth for a positive (or negative) stock price momentum, such as overall economic, demographic, political, or industry trends. Such circumstances can generate positive perspectives for certain companies and thus initiate a positive momentum for their stocks without substantial actual above-average sales growth. Examples are the sharp stock price gains of many freshly listed New Economy firms during 1999 and early 2000, which were very often caused by mere growth phantasies rather than actual revenue or earnings growth.

Moreover, not only are there momentum drivers besides sales or earnings growth, but also limiting growth investors to risk-seeking people who are only interested in riding on a company's positive growth trend regardless of the price they have to pay would be misleading.³⁰¹ Successful growth investing requires a deep understanding about the current and future products of an investment target and about how well they will be accepted by customers. As a consequence, growth investing is often more demanding on investors than value or momentum investing.³⁰² Therefore, a much more accurate

³⁰⁰ See Dreman/Berry (1995).

³⁰¹ See Damodaran (2003), pp. 269 et seq.

³⁰² See Lifson/Geist (1999), p. 64.

description of growth investors is that they “buy companies whose growth potential is being undervalued by the market.”³⁰³

An approach within growth investing that tries to place more emphasis on this aspect is Growth-at-a-reasonable-price (GARP). GARP investors can be seen as conservative growth investors who try to purchase stocks of companies with above-average growth potential while at the same time watching out that share price levels are still reasonable.³⁰⁴ Like growth investors, they look for companies with rising sales and earnings. Like value investors, they are conscious about not overpaying on an investment.³⁰⁵ To find suitable stocks GARP investors often either select companies with a P/E ratio that is lower than their earnings growth rate or they look for a low price-earnings-growth (PEG) ratio.³⁰⁶ In either case they take both the earnings growth and the valuation component into consideration. The PEG ratio is calculated by dividing the current or estimated future P/E ratio by the current or estimated future earnings growth rate. Sometimes investors use an average earnings growth rate over more than one year as the denominator and eventually adjust it further to filter out cyclical companies that have just happened to had one good growth year.³⁰⁷ The lower the PEG ratio of a stock, the more the stock would appear like an attractively valued opportunity to buy into a growing company and vice versa. As a result, a company with a very high earnings growth rate could still be deemed an attractive investment despite its seemingly high price, while a low price-earnings ratio of an only slowly growing company might not be low enough to justify an investment. Overall, GARP investing can be seen as one attempt to overcome the existing divide between value and growth investment styles and is therefore akin to the spirit of this thesis, which strives for combining elements of value and growth investing in its fallen angel investment approach.

³⁰³ Damodaran (2003), p. 269.

³⁰⁴ See Fabozzi (1998), p. 59, and Postert (2007), p. 72.

³⁰⁵ See Kaye (2006), p. 72.

³⁰⁶ See Damodaran (2004), pp. 208-212.

³⁰⁷ See Bruner (1998), p. 9.

4.2.3 Comparison of Value and Growth Investment Styles

Summarizing, **Table 4** highlights the main differing characteristics of value and growth investment styles including related indices and investors.

Table 4: Overview on value and growth investment styles

	Value investing	Growth investing
Common ideas	<ul style="list-style-type: none"> • Quest for “cheap” stocks • Margin-of-safety • Focus on established sectors • Actual growth and growth expectations of minor importance • Based on fundamental analysis 	<ul style="list-style-type: none"> • Quest for high growth companies • Focus on dynamic sectors • Price of secondary importance • Based on fundamental analysis
Frequently used investment criteria	<ul style="list-style-type: none"> • Low P/B ratio • Low P/E ratio • Low P/CF ratio • High dividend yield • Low P/S ratio 	<ul style="list-style-type: none"> • High earnings growth (historic and future, e.g. measured as EPS growth) • High sales growth (historic and future, e.g. measured as SPS growth) • High P/B ratio • High P/E ratio • High P/CF ratio • High ROE
Important indices	<ul style="list-style-type: none"> • MSCI Global Value Index Series • S&P U.S. Value Indices • S&P U.S. Pure Value Indices • Russell Global Value Indices • Russell U.S. Value Indices 	<ul style="list-style-type: none"> • MSCI Global Growth Index Series • S&P U.S. Growth Indices • S&P U.S. Pure Growth Indices • Russell Global Growth Indices • Russell U.S. Growth Indices
Prominent investors	<ul style="list-style-type: none"> • Benjamin Graham • Warren Buffett • Seth Klarman • Walter and Edwin Schloss • Howard Marks 	<ul style="list-style-type: none"> • T. Rowe Price • Phil Fisher • Peter Lynch • Martin Zweig

Source: Author taking into consideration Williams, Ellie (2001), Greenwald, Bruce C. et al. (2002), Damodaran (2003), Morgan Stanley Capital International (2005), Otte/Castner (2007), Postert (2007), Greenwald, Bruce C./Bellissimo/Otte (2008), Reese/Forehand (2009), Montier (2010), Russell Investments (2011a), Russell Investments (2011b), and Standard & Poor’s (2011b)³⁰⁸

³⁰⁸ See Williams (2001), Greenwald et al. (2002), Damodaran (2003), pp. 219-311, Morgan Stanley Capital International (2005), p. 2, Otte/Castner (2007), p. 41, Postert (2007), pp.

4.3 Investment Styles and Fallen Angels

4.3.1 Previous Attempts to Reconcile Value and Growth Investment Styles

In contrast to the mainstream opinion of value and growth as diametrically opposing investment styles, several well-respected investors or authors on investment topics have voiced disagreement with this view. Buffett, for example, notes that “market commentators and investment managers who glibly refer to ‘growth’ and ‘value’ styles as contrasting approaches to investment are displaying their ignorance, not their sophistication. Growth is simply a component [...] in the value equation.”³⁰⁹ He clearly articulates that the widely held belief of growth and value as being diametrically opposite investment styles in his view does not appear sensible.³¹⁰ As for himself, he claims to be “15 percent Fisher and 85 percent Benjamin Graham.”³¹¹ Buffett made this statement already in 1969 and appears to have migrated more towards a balance between value (Graham) and growth (Fisher) since then.³¹² His claim that he tries to “find an outstanding business at a sensible price, not a mediocre business at a bargain price”³¹³ is a clear expression that he fully internalized the combination of value and growth elements in his investment philosophy.

Buffett’s business partner Munger also highlights the faultiness of the value-growth confrontation, since it would not be sensible to pay more for a stock than it is worth for. As a consequence, “all intelligent investing is value investing”³¹⁴ and that is true for the purchase of growth stocks like it is for any other investment operation.

Vinall, a Swiss-based hedge fund manager and speaker on value investment-related topics, also negates the wrongfully assumed contradiction between value and growth. For him, growth is one of the two most important components in valuing a company, with cash being returned to the owners as the other. While it would certainly be foolish to not consider the value of an asset when making an investment decision, neglecting the aspect of growth would likewise lead to disappointing results. Consequently, a

47 et seq. and 69-72, Greenwald/Bellissimo/Otte (2008), p. 6, Reese/Forehand (2009), pp. 31-54 and 95-196, Montier (2010), pp. 69-71, Russell Investments (2011a), pp. 12-16, Russell Investments (2011b), pp. 15-20, and Standard & Poor’s (2011b), p. 7.

³⁰⁹ See Buffett (2001), p. 13.

³¹⁰ See Altucher (2005).

³¹¹ Buffett (1969), p. 82.

³¹² See Hagstrom (2005), p. 27.

³¹³ Buffett (1988), p. 15.

³¹⁴ See Baer (2009), p. 2.

company's earnings should always be adjusted for the investments it is undertaking in making it grow. As a result, valuations that looked high for certain stocks might do less so after adjusting for growth investments.³¹⁵

While one would classify Buffett, Munger, and Vinall as value investors who adapted certain aspects of growth investing in their investment philosophies, there are also representatives of the group of growth investors who believe in the inseparability of value and growth. One of them is Fisher, the “doyen of growth investors.”³¹⁶ Although Fisher was first and foremost looking for companies with sufficient potential to significantly grow sales and earnings for at least several years ahead, he did never fail to look at the price that he had to pay for obtaining a share in such companies. The fact that he was particularly emphasizing the long-term aspect of his growth investing philosophy demonstrates that the equation of growth and momentum investing is faulty. Fisher deliberately checked whether a company's management did enough to foster the long-term growth prospects of a company in his investment analysis. This was much more important to him than showing rising sales or earnings in each year, since even the most outstanding growth companies failed to do so from time to time.³¹⁷

Lynch, another pronounced representative of the group of growth investors, would also fiercely oppose the view that sensible growth investing can be separated from a company's valuation.³¹⁸ With his approach of blending investment criteria from both growth- and value-style investors, he is regarded as one of the early and the most popular representative of the GARP investment style.³¹⁹ During the thirteen years from 1977 until 1990, when he managed Fidelity Investment's Magellan Fund, he achieved a phenomenal track record of an annualized performance of 29.2 percent.³²⁰

Besides the fact that prominent and successful representatives of the growth investing style disagree with the alleged contradiction between value and growth, it is also noteworthy that Graham as the “father of value investing”³²¹ himself was not alien to the value of growth for value investing at all. Although practitioners have used the notion of Graham-and-Dodd-style investing as the opposite to growth investing,

³¹⁵ See Vinall (2008).

³¹⁶ Arnold (2002), p. 111.

³¹⁷ See Arnold (2002), pp. 109-146, and Fisher (2003), pp. 47-78.

³¹⁸ See Arnold (2002), pp. 3-30, and Lynch/Rothchild (2004).

³¹⁹ See Kimmel/Hirsch (2009), p. 118, and Reese/Forehand (2009), p. 137.

³²⁰ See Arnold (2002), p. 5.

³²¹ Graham/Klein/Darst (2009), subtitle on book's title page.

Graham and Dodd never made that distinction.³²² On the contrary, in their view sound investment valuation required an assessment of favorable possibilities for future growth.³²³ In the last edition of “The Intelligent Investor” Graham even specifically noted that the “philosophy of investment in growth stocks parallels in part and in part contravenes the margin-of-safety principle. [...] [T]he growth-stock approach may supply as dependable a margin of safety as is found in the ordinary investment.”³²⁴ In order to achieve this a growth investor must carefully and conservatively estimate future earnings, which substitute the past earnings record as the orientation mark for company valuation. Additionally, he has to make sure that he includes a satisfactory margin of safety in his calculations. However, Graham sees particular difficulty in achieving the latter, since most growth stocks show high market valuation levels that do not leave sufficient room for the required margin of safety. Nevertheless, he does not rule out that investors can successfully pick growth stocks.³²⁵ They only need a “special degree of foresight and judgement [...] in order that wise individual selections may overcome the hazards inherent in the customary market level of such issues as a whole.”³²⁶ Although Graham never unconditionally endorsed growth investing, he got to appreciate the power of this approach over the course of his investment career.³²⁷

With even Graham as the most pronounced representative of the value investment style acknowledging that value and growth investment styles are closer to each other as the common view suggests, it does not come as a surprise that support for this opinion can not only be found among investment practitioners, but also among academic writers.

Cunningham, for example, puts forward the view that despite a differing emphasis with regard to what drives the intrinsic value of a company, value and growth investors both share the view that there is a difference between value and price of a stock. Whereas value investors focus on known values and compare them to the current price of a company, growth investors emphasize expected values arising from future growth.³²⁸ From this perspective, “growth investing is a cousin of value

³²² See Speidell/Graves (2003), p. 172.

³²³ See Graham/Dodd (1940), pp. 11-14.

³²⁴ Graham (2003), p. 517.

³²⁵ See Graham (2003), p.517.

³²⁶ Graham (2003), p. 517.

³²⁷ See Martin et al. (2011), pp. 4-8.

³²⁸ See Cunningham (2004), pp. 1-4.

investing.”³²⁹ This is also not materially challenged by the fact that value fund managers tend to be more style-consistent than their growth counterparts.³³⁰ This might be attributable to the fact that value investors more strongly base their decisions on clearly measurable criteria, while growth investors more heavily rely on future growth perspectives, which are by definition more difficult to grasp, thus introducing an element of subjectivity. According to Cunningham, however, value investors will – although to a lesser extent – also have to deal with this issue, as potential future growth is always an element in valuing any company, no matter if it suffices standard value investing criteria or not.³³¹ Again, value and growth investors share important common ground in coming up with investment decisions.

Another author stressing the commonalities between value and growth investment styles is the German scholar and value investor Otte. Together with Castner he derives the proximity between value and growth investing from the fact that both investment styles apply long-term fundamental analysis in their investment decision-making.³³² This clearly distinguishes growth investing from the short-term, technical analysis-based momentum investing, thus refuting the frequently assumed close link between growth and momentum styles.

Ahmed and Nanda provide empirical evidence for the superiority of a combination between value and growth investing. While confirming the earlier, more general finding that stocks with low P/E ratios deliver better returns than those with high P/E ratios, their analysis also demonstrates that portfolios of stocks combining high growth rates with low P/E ratios dominate pure low P/E portfolios in terms of return.³³³ A study of stock returns in Euro zone financial markets confirms these findings and attributes the highest return to a value investment strategy that is focused on growth stocks.³³⁴

Arnold takes a comprehensive approach to the topic of combining value and growth investment styles.³³⁵ Besides his research on traditional value investment topics³³⁶, he

³²⁹ Cunningham (2004), p. 4.

³³⁰ See Lawton/Jankowski (2009), p. 322.

³³¹ See Cunningham (1998), pp. 15 et seq.

³³² See Otte/Castner (2007).

³³³ See Ahmed/Nanda (2001).

³³⁴ See Chahine (2008).

³³⁵ See Arnold (2002).

³³⁶ See Arnold/Xiao (2008) or Arnold (2009).

has developed an investment approach that he calls Valuegrowth Investing after having extensively studied the approaches used by several highly successful investors. In the center of his investment process stands the figure of owner earnings. The calculation of this figure starts with net income to which depreciation, depletion, amortization and other non-cash charges are added. Then the annual expenditures for plant, machinery, and other fixed assets that are required to maintain the company's long-term competitive position, unit volume, and pursuit of all new value creating projects are subtracted. Finally, Arnold also subtracts the annual expenditure for working capital that is required for the same purposes as above. The resulting owner earnings figure resembles the free cash flow that is available to equity holders after all investments to keep the company as a long-term going concern are made.³³⁷ Since estimating these expenditures in fixed assets and working capital requires a deep understanding of the company, its industry, and the long-term dynamics of the business model, long-term fundamental analysis is necessary. On the basis of the calculated owner earnings, Arnold derives an intrinsic value of the company and compares this to the current market price. In order to be considered as an investment the difference between intrinsic value and current market price must be large enough to constitute a satisfactory margin of safety. Since Arnold combines elements of traditional value investing, such as financial strength as the required sound basis for the future development of a company or the concept of margin of safety, with elements of growth investing, such as estimating the required expenditures in fixed assets and working capital in the light of long-term growth, he indeed has developed an investment framework that justifiably bears the name value-growth.³³⁸

4.3.2 Fallen Angel Investing as a New Attempt to Reconcile Value and Growth Investment Styles

However, neither Arnold nor other approaches that combine value and growth investing elements provide investors with an easily and regularly observable means of finding possible promising value-growth investments. All more or less rely on a broad-based observation of a very large number of companies. Fallen angel investing as put forward in this thesis can close this gap and equip investors with a value investment style-based tool set for identifying promising growth stock investment opportunities.

³³⁷ See Arnold (2002), pp. 253-256, for the calculation of owner earnings under Arnold's Valuegrowth Investing framework.

³³⁸ See Arnold (2002), pp. 235-334.

In that sense fallen angel investing can also be seen as an easily operational subset of growth investing at a reasonable price. When looking at the characteristics of fallen angels, it becomes clear why. Fallen angels are growth companies that have experienced an abnormal drop in their share price due to a negative earnings surprise, thus valuation levels are currently depressed. Plainly spoken, fallen angels are growth companies that you can now purchase at lower, i.e. more reasonable, valuations than before. Consequently, the fallen angel investment approach can be seen as akin to the GARP investment style. However, there are two main differences, since firstly fallen angel investment is more limited than GARP investing with regard to the universe of available investment opportunities. Fallen angel investing by definition is limited to fallen angel stocks, whereas GARP investors search for opportunities among growth companies in general. Secondly, and much to its advantage, the fallen angel investment approach provides an investor with a very concrete trigger when to look at a specific stock. This makes the fallen angel investment approach easy to implement for the investment practice. Its set of measurable criteria helps investors to distinguish the good, i.e. undervalued, fallen angels from the bad, i.e. overvalued, fallen angels. In that sense, fallen angel investing serves as a vehicle to overcome the artificial divide between value and growth investing styles.

5 Development of Possible Indicators for Angel Quality

This chapter will introduce a framework of potential influence factors on the quality of a fallen angel stock, the set of possible indicators for angel quality derived from this framework, and the hypotheses that have been formulated with regard to the single independent variables. Before introducing the overall framework of influence factors as used in this thesis and describing the individual indicators in more detail, the influence of value investment principles on the design of the framework shall be reviewed.

5.1 Input from Value Investing Practice

As this thesis also aims at bringing value and growth investment styles closer together, turning to principles of value investment when analyzing growth stocks that delivered disappointing earnings (aka fallen angel stocks) seems like a logical move. Additionally, the previously mentioned overall superior investment performance of value investors provides further reason why looking at value investment criteria appears promising when making individual stock selection decisions. Investing in fallen angel stocks is such a situation.

A main concern for value investors is to strictly limit the risk of losing their investment. With regard to that concern, Buffett has coined a vivid phrase: “Rule number one, don’t lose money. Rule number two, don’t forget rule number one.”³³⁹ As a consequence, value investors in general are looking for healthy and financially stable companies with high and sustainable profits and free cash flows.³⁴⁰ It is seen as advantageous if management focuses on efficiency and cost control, rather than pursuing empire building via overpriced acquisitions.³⁴¹

However, value investors are not only concerned with the business fundamentals, but equally so with the valuation of a stock. They consider investing in a good company at a cheap or at least a good price³⁴², but would not do so if they can only purchase its stock at a high price. Value investors invest only if the calculated intrinsic value of a

³³⁹ Schroeder (2008), p. 543.

³⁴⁰ See, for example, Arnold (2002), pp. 244-246, Greenwald et al. (2002), p. 3, Damodaran (2003), pp. 225 et seq., or Whitman/Shubik (2005), pp. xvii et seq.

³⁴¹ See, for example, Arnold (2002), pp. 251 et seq., Whitman/Shubik (2005), pp. 135 et seq., McNiven (2008), or Jain (2009), p. 18.

³⁴² See, for example, Greenblatt (2006), pp. xviii and 48-57, or Tavakoli (2009), p. 17.

company's share is sufficiently above the current market price, i.e. the previously described margin of safety is large enough.³⁴³

Although value investing focuses on both quantitative and qualitative aspects of a company and its business, it has its roots in fundamental analysis.³⁴⁴ From that perspective, the statistical testing of financial ratios as conducted in this thesis suggests itself. However, the use of financial statement information as a potential predictor of future share price performance also gains support from academic studies. For example, Piotroski demonstrates that the selection of financially strong companies out of a broad sample of high book-to-market (aka value) firms leads to superior investment results.³⁴⁵ And Shapovalova and Subbotin found evidence that fundamental company characteristics, like contemporary accounting figures, are more important for predicting future stock returns than sensitivities to Fama and French risk factors.³⁴⁶

5.2 Framework of Possible Influence Factors on Angel Quality

Largely drawing on the above-mentioned input from the value investment practice, the framework of possible influence factors on fallen angel quality as applied in this thesis contains seven possible factors: 1) financial stability, 2) profitability, 3) cash flow, 4) cost structure, 5) mergers and acquisitions activities, 6) valuation, and 7) the extent of the negative earnings surprise itself.

Whereas the first six influence factors are all rooted in value investment philosophy, the last considered factor has no apparent connection to value investors. It is included in this thesis because of the constitutive importance of a negative earnings surprise for fallen angel stocks, and the findings of behavioral finance research on investor over- and underreaction, which tend to be corrected in the future, when stock prices revert to their mean. Therefore, it appears promising to analyze whether the strength of the negative earnings surprise and of the related negative abnormal share price reaction has an influence on the quality of a fallen angel stock.

³⁴³ See, for example, Klarman (1991), Greenwald et al. (2001), pp. 3 et seq., Arnold (2002), p. 251, or Graham (2003), pp. 512-524.

³⁴⁴ See Whitman (2000), pp. 69 et seq.

³⁴⁵ See Piotroski (2000).

³⁴⁶ See Shapovalova/Subbotin (2009).

Figure 4 gives an overview of the possible influence factors on angel quality as included in this thesis:

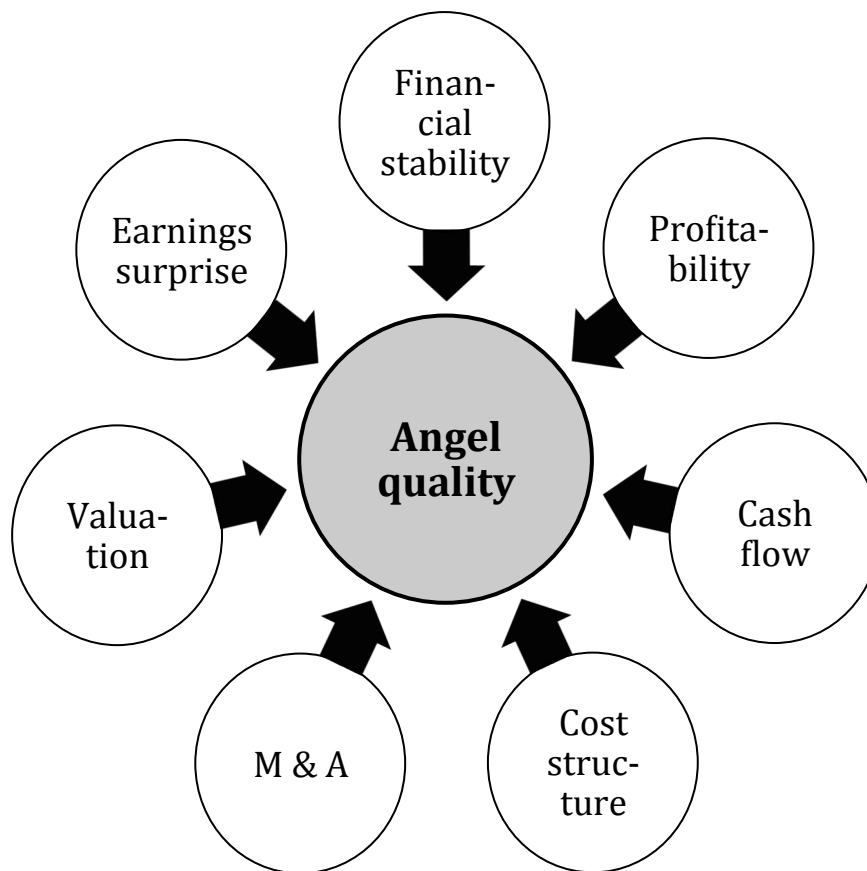


Figure 4: Possible influence factors on angel quality

Source: Author

For each of these influence factors one or more measurable variables are established in order to test them as indicators for angel quality.

5.3 Financial Stability

The first two ratios address the financial stability of a company. They cover both short-term financial stability measured by short-term liquidity and long-term financial stability as expressed by the capital structure. The underlying assumption is that – all other factors equal – the more financially stable a company is, the more successful it will be over time. Thus, the more likely the fallen angel will be of good quality. The reasons behind this argument are twofold: Firstly, financially stronger companies are more likely to stay afloat than their weaker counterparts. Secondly, they should be

better able to take advantage of growth opportunities.³⁴⁷ Both arguments should particularly hold for growing companies that experience problems. This is exactly the case with fallen angels.

5.3.1 Current Ratio as Measure of Short-Term Liquidity

The first ratio concerning the financial stability of a fallen angel is the current ratio. It reveals information about the short-term solvency of a company and is defined as the relationship between all current assets and liabilities³⁴⁸:

$$\text{Current ratio} = \frac{\text{Current assets}}{\text{Current liabilities}} \quad 349$$

The definition of current assets and liabilities follows prevailing international accounting standards as adopted by the EU commission. Therein current means all assets or liabilities expected to be realized or to be settled within twelve months after the balance sheet day, i.e. within a short-term horizon.³⁵⁰ In case a company's current assets are not sufficient to cover short-term liabilities, i.e. the current ratio is below one, it might be a sign of potential problems.³⁵¹ This might particularly be the case for fallen angel companies, which, due to their good past corporate development, enjoyed favorable trade terms with suppliers and ample short-term credit facilities with banks. A reassessment of these terms triggered by the negative news of the earnings surprise could lead to short-term solvency problems for companies that do not possess a sufficient short-term liquidity cushion.³⁵² At worst such firms might become insolvent, at best they have to take cash-preserving measures that might hurt their growth perspectives, like cutting back on capital expenditures.

³⁴⁷ See Kaye (2006), p. 30.

³⁴⁸ See Glautier/Underdown (2000), pp. 247 et seq., and Gramlich/McAnally/Thomas (2001), p. 290.

³⁴⁹ For the purpose of this thesis, both numerator (abbreviation: WC02201) and denominator (abbreviation: WC03101) were extracted from the Worldscope database.

³⁵⁰ See European Commission (2008), p. 11 et seq. The commission provides further criteria for classification of an asset or liability as current. In addition to the one-year period after the balance sheet date, classification as current is also required if the asset or liability is likely to be realized or settled in the company's normal operating cycle or is held primarily for trading purposes. Furthermore, cash or cash equivalents are always counted as current assets unless their use is restricted for at least 12 months after the balance sheet date.

³⁵¹ See Kaye (2006), p. 30.

³⁵² See Glautier/Underdown (2000), pp. 247 et seq.

Following the presented line of argument, a higher current ratio should be an indicator for better angel quality and the corresponding hypothesis therefore is:

$$H_1 = \textit{The higher the current ratio} \\ \textit{the more likely the fallen angel is of good quality.}$$

However, particularly successful companies with a strong business model and durable competitive advantage frequently show a current ratio of below one.³⁵³ This observation puts the assumed direction of hypothesis H₁ into perspective.

5.3.2 Equity Ratio as Measure of Capital Structure Stability

The second financial stability ratio is the equity ratio. It represents the capital structure of a company and thus addresses the long-term aspect of financial stability. Investors use it frequently in their investment decision-making models and processes.³⁵⁴ It states how many percent of a company's assets are funded with equity³⁵⁵:

$$\textit{Equity ratio} = \frac{\textit{Total shareholders' equity}}{\textit{Total assets}} \quad ^{356}$$

Most firms carry a substantial portion of debt on their balance sheets. Although this makes absolute sense from an economic standpoint, because debt financing puts the leverage effect to work³⁵⁷, in general investors prefer companies with low debt levels³⁵⁸. A low debt level is analogous to a high equity ratio. Particularly for fallen angels a sufficiently high level of equity funding should be important. Whereas dividends to shareholders can be lowered or even put off due to the disappointing earnings situation, debt holders usually have a contractual right to receive their interest payments independent of the economic situation of the company. Furthermore, creditors are entitled to receive their principal back at maturity date of the debt, putting further strain on a fallen angel's liquidity. As equity funding becomes more difficult and more expensive after a steep drop in share price, particularly highly indebted

³⁵³ See Buffett/Clark (2008), pp. 88 et seq.

³⁵⁴ See, for example, Levermann (2011), pp. 42 and 154.

³⁵⁵ See Thommen/Achleitner (2009), p. 587.

³⁵⁶ For the purpose of this thesis, both numerator (abbreviation: WC03995) and denominator (abbreviation: WC02999) were extracted from the Worldscope database.

³⁵⁷ For an explanation of the leverage effect see Thommen/Achleitner (2009), pp. 661-663.

³⁵⁸ See, for example, Kaye (2006), p. 30.

fallen angels could run into financial difficulties. Consequently, the less debt a company has, the more financially stable it should be.³⁵⁹ Another argument put forward by Fisher focuses on a growth company's ability to finance its growth without tapping into further equity funding.³⁶⁰ A company with a high equity ratio and therefore a stronger borrowing power more probably will be able to take on further debt to fund its growth. Consequently, no new equity will have to be issued and current investors in the company will not be diluted.

Therefore, the corresponding hypothesis for the equity ratio is:

*H₂ = The higher the equity ratio
the more likely the fallen angel is of good quality.*

However, Jensen put forward the argument that since debt reduces the cash flow that is at the free disposal by management, a higher debt level has a disciplining effect and therefore helps to mitigate agency problems.³⁶¹ Thus, the expected direction of hypothesis H₂ remains ambiguous.

5.4 Profitability

Profitability is the second possible influence factor on angel quality that is addressed. Although growth companies are mainly characterized by the growth in their topline, being able to develop and maintain a profitable business is the key to success for any enterprise. Additionally, a company with a higher profit margin also offers more safety for an investor, especially during an economic downturn. If overall profit margins narrow due to worsening economic conditions, the company commanding a higher profit margin may still remain profitable, while the lower profit margin company might already suffer from losses and resulting financial distress.³⁶² Therefore, the underlying assumption here is that the higher the level of profitability is the more likely a company will belong to the group of good fallen angels.

³⁵⁹ See Kaye (2006), p. 30 et seq., or Wisdom (2009), p. 21.

³⁶⁰ See Fisher (2003), p. 74 et seq.

³⁶¹ See Jensen (1986) and Jensen (1989), pp. 41-44, regarding the benefits of debt in reducing agency costs, and Jensen/Meckling (1976) regarding agency theory in general.

³⁶² See Fisher (2003), p. 199 et seq.

5.4.1 Gross Profit Margin

The first measure of profitability chosen is the gross profit margin. It is defined as gross profit divided by net sales with gross profit being the difference between net sales and cost of goods sold (COGS)³⁶³:

$$\text{Gross profit margin} = 1 - \frac{\text{COGS}}{\text{Net sales}} \quad ^{364}$$

Many investors see a high gross profit margin as an indication of a good business model. It cannot be easily manipulated and is therefore regarded as a fairly reliable indicator of a decent enterprise.³⁶⁵ Companies who command a durable competitive advantage with their offering are in a position to charge higher prices resulting in a higher gross profit margin. On the contrary if a company lacks a durable competitive advantage it has to compete mainly on price, thus lowering the gross profit margin.³⁶⁶ A fallen angel that possesses a durable competitive advantage that is reflected by a high gross profit margin should have better chances to get back on its former growth track than a company with a low gross profit margin.

The corresponding hypothesis therefore is:

$$H_3 = \textit{The higher the gross margin} \\ \textit{the more likely the fallen angel is of good quality.}$$

³⁶³ See Buffett/Clark (2008), p. 32 et seq.

³⁶⁴ For the purpose of this thesis, both numerator (abbreviation: WC01051) and denominator (abbreviation: WC01001) were extracted from the Worldscope database.

³⁶⁵ See Kaye (2006), p. 82.

³⁶⁶ See Buffett/Clark (2008), p. 33 et. seq.

5.4.2 Return on Assets

The second profitability ratio is return on assets (ROA), which is widely used by financial analysts as a performance measure.³⁶⁷ It addresses the key deficiency of other return ratios, such as return on sales or return on equity, which is that they neglect the asset base a company needs to generate its profits. Since funding for this asset base has to come from investors, it matters to them how much capital is required to produce a certain amount of profit. ROA accounts for this issue by relating the net income of a company to its total asset base:³⁶⁸

$$\text{Return on assets} = \frac{\text{Net income}}{\text{Total assets}} \quad 369$$

ROA indicates the efficiency with which management employs the resources of the company to earn a profit.³⁷⁰ Particularly during the turbulent times in which fallen angels often find themselves in, a more efficient management constitutes an advantage. With potentially narrowing profit margins and less availability of capital for investments, the ability of management to efficiently use the assets of a company is even more important than under normal circumstances. Therefore, the corresponding hypothesis reflects the preference of investors for a company with higher ROA:

$$H_4 = \textit{The higher the return on assets} \\ \textit{the more likely the fallen angel is of good quality.}$$

³⁶⁷ See Kieso/Weygandt/Warfield (2010), p. 586.

³⁶⁸ See Helfert (2008), p. 133.

³⁶⁹ For the purpose of this thesis, both numerator (abbreviation: WC01551) and denominator (abbreviation: WC02999) were extracted from the Worldscope database.

³⁷⁰ See Glautier/Underdown (2000), p. 253.

5.5 Cash Flow

The third possible influence factor on fallen angel quality included in this thesis deals with cash flow. The importance of cash flow cannot be underestimated, since “in business, cash is what pays the bills.”³⁷¹ To an investor, cash flow matters, because the ability of a company to generate cash for its owners is a key driver of shareholder value. In the end, it is the expected amount and timing of cash flows to the shareholders that are essential to a potential investor.³⁷² This is reflected by the widely held belief that the intrinsic value of a stock is the sum of all discounted expected future cash flows to the shareholders.³⁷³ Furthermore, cash flow-related information is highly valued by investors, because the cash flow statement is not based on accrual accounting, and therefore less subject to management discretion than earnings.³⁷⁴ In addition, not only investment practitioners, but also academics look at cash flow numbers when analyzing drivers for stock returns.³⁷⁵

Similar to profitability, the underlying assumption here is that the higher the level of positive cash flow a fallen angel company can produce, the more likely it will belong to the group of good fallen angels. However, the analysis of cash flows needs to provide a more differentiated picture, as it is important from which sources the company’s liquid funds are coming from and what they are used for. The three main cash flow streams are cash flow from operating activities (CFO), cash flow from investing activities (CFI), and cash flow from financing activities (CFF).³⁷⁶ Each stream has a different quality for an investor and it might also be worthwhile to look at the relationships among the main cash flow streams. The following two ratios will address these different aspects of the cash flow generation power of a company.

³⁷¹ Gallagher/Andrew (2007), p. 7.

³⁷² See Hawawini/Viallet (2010), p. 6.

³⁷³ See Richardson/Sloan/You (2011), p. 2.

³⁷⁴ See Glautier/Underdown (2000), pp. 33-35 and 229 et seq.

³⁷⁵ See, for example, Vuolteenaho (2002), who attributes the largest part of an individual firm’s stock return to changes in cash flow expectations.

³⁷⁶ See Hawawini/Viallet (2010), pp. 108-120.

5.5.1 Free Cash Flow Margin

The first cash flow measure is free cash flow. It reflects the power of a company to sustainably generate cash out of its operational activities. The calculation is the difference between cash flow from operating activities less capital expenditure:

$$\text{Free cash flow} = \text{CFO} - \text{CAPEX}$$

The logic behind this definition of free cash flow is that a company needs to continuously make investments to sustain its business. Consequently, the free cash flow figure should represent the cash generated from operations minus such investments.³⁷⁷ Other parts of the cash flow from investing activities, such as cash outflows for acquisitions, are not taken into consideration, since they are usually infrequent in- or outflows and therefore are not closely associated with the ordinary, sustainable course of business. Including other items of the cash flow from investing activities than capital expenditure would therefore introduce an element of chance, thus hurting the free cash flow figure as an expression for a company's sustainable cash generating ability.³⁷⁸ Cash flow from financing is not included in the free cash flow definition used in this thesis, because the financing structure and its associated cash flows can be changed irrespective of the underlying business. Thus, the sustainable cash generating ability of a company's operations has to be evaluated independent from its financing structure.

To put this ability in relation to the size of a company's business, the free cash flow margin is used as a possible indicator for angel quality. It is defined as follows:

$$\text{Free cash flow margin} = \frac{\text{Free cash flow}}{\text{Net sales}} \quad 379$$

³⁷⁷ See Wisdom (2009), p. 23.

³⁷⁸ See Mulford/Comiskey (2005), p. 361.

³⁷⁹ For the purpose of this thesis, all variables were extracted from the Worldscope database. Free cash flow was calculated as the difference between CFO (abbreviation: WC04860) and CAPEX (abbreviation: WC04601). Net sales (abbreviation: WC01001) was directly extracted from Worldscope.

Since investors could benefit from a high free cash flow in the form of higher dividend payments or stock repurchases, they *ceteris paribus* prefer companies with higher free cash flow margins. Particularly for fallen angel companies, which might experience problems in obtaining further equity financing after the drop in share price, a sustainable and strong ability to generate cash from operations is important. Otherwise they might not be able to take advantage of all their growth opportunities due to lack of funds, thus hurting their future cash generation power. This, in turn, would make it more likely that they become part of the group of bad fallen angels. Therefore, the corresponding hypothesis is:

*H₅ = The higher the free cash flow margin
the more likely the fallen angel is of good quality.*

5.5.2 Cash Flow from Operating Activities-to-Net Income Ratio

The second measure of cash flow strength of a company used in this thesis is the ratio between cash flow from operating activities (CFO) and net income:

$$CFO - to - net\ income\ ratio = \frac{CFO}{Net\ income} \quad ^{380}$$

Since net income is an accrual-based accounting measure and cash flow from operating activities is not, this ratio can be seen as an indication of earnings quality. It expresses to what extent management has boosted earnings by aggressive assumptions regarding accruals and other profit adjustments.³⁸¹ Earnings that are backed up by cash generated from operations are believed to be of higher quality, since they can be used to make investments, pay back debt, or distribute cash to shareholders.³⁸² This is also backed up by empirical research undertaken by Sloan, who shows that earnings driven by positive accrual adjustments, i.e. a low CFO-to-net income ratio, are a negative sign for future profitability and returns.³⁸³

³⁸⁰ For the purpose of this thesis, both the numerator (abbreviation: WC04860) and the denominator (abbreviation: WC01551), were extracted from the Worldscope database.

³⁸¹ See Albrecht et al. (2007), pp. 687 et seq.

³⁸² See Siegel/Shim (2006), p. 358.

³⁸³ See Sloan (1996).

As a consequence, it is seen as a positive sign if cash flow from operating activities as a pure reflection of operating performance is high relative to accrual accounting-based net income. This is particularly the case for fallen angels, since a low CFO-to-net income ratio paired with the negative earnings surprise might be an indication that the growth of the past periods was based on aggressive accounting and therefore might not be sustained in the future. In other words, a low CFO-to-net income ratio could be a sign that the growth story of the fallen angel is fundamentally flawed rather than only temporarily interrupted. This would make it more likely that such a fallen angel will become part of the group of bad fallen angels. Therefore, the corresponding hypothesis is:

*H₆ = The higher the CFO-to-net income ratio
the more likely the fallen angel is of good quality.*

5.6 Cost Structure

The fourth possible influence factor on fallen angel quality addresses the cost structure of a company. Thereby, particular emphasis shall be placed on whether a fallen angel company commands a lean cost structure or not. Selling, general & administrative (SG&A) expense is a substantial cost position across all industries. It is generally seen as an indicator of efficiently and effectively run operations.³⁸⁴ The resulting SG&A ratio represents a company's overhead costs as contained in the SG&A cost categories in comparison to its overall sales activity³⁸⁵:

$$SG\&A\ ratio = \frac{SG\&A\ expenses}{Net\ sales} \quad 386$$

Since SG&A consists of both expenses related to sales activities and expenses related to general & administrative activities, a low SG&A ratio could be due to several reasons. First, it could be an indication of an effective and efficient sales approach. Second, it might reflect superior product or service quality that allows the company to keep marketing and selling expenses to a minimum. Third, a favorable company

³⁸⁴ See Gildersleeve (1999), p. 114.

³⁸⁵ See Bragg (2002).

³⁸⁶ For the purpose of this thesis, both numerator (abbreviation: WC01101) and denominator (abbreviation: WC01001) were extracted from the Worldscope database.

structure with lean overhead would lead to lower general & administration expenses. And fourth, it could be a combination of these reasons. In any case, it would be a good sign to see a low SG&A ratio. This is also the opinion of investment professionals like Buffett.³⁸⁷ Furthermore, Fisher argues that a high degree of sales effectiveness and efficiency is particularly important for the continued success of growth companies.³⁸⁸ Additionally, a fallen angel with a high SG&A ratio might come under further pressure, since SG&A expenses suffer from stickiness.³⁸⁹ This might make it difficult to swiftly adjust such a fallen angel's cost structure to the now less optimistic growth pace. The corresponding hypothesis therefore is:

*H₇ = The lower the SG&A ratio
the more likely the fallen angel is of good quality.*

A word of caution has to be added, though. A low SG&A ratio might not be the reflection of a lean cost structure, but could also be caused by short-term cost cutting measures.³⁹⁰ The latter could hurt the growth potential of the company, particularly mid- to long-term. For example, if a fallen angel cuts its investment in brand building, sales organization, or distribution system in the aftermath of a negative earnings surprise, it likely endangers its long-term success. Spending too little on advertising might mean sacrificing the company's durable competitive advantage for short-term savings.³⁹¹ Thus, the SG&A ratio requires critical evaluation with regard to the specific situation of a fallen angel company.

5.7 Mergers & Acquisitions

The fifth possible influence factor on angel quality concerns the mergers & acquisitions (M&A) activities of a fallen angel. To measure these, goodwill as the reflection of excess costs over equity of net assets acquired by the fallen angel company has been selected.³⁹² Dividing the goodwill as recorded in the balance sheet by total assets puts the amount of acquired goodwill in relation to the overall balance sheet size.

³⁸⁷ See, for example, Buffett/Clark (2008), pp. 39 et seq.

³⁸⁸ See Fisher (2003), p. 59.

³⁸⁹ See Anderson/Banker/Janakiraman (2003)

³⁹⁰ See Gildersleeve (1999), p. 114.

³⁹¹ See Shah/Akbar (2008).

³⁹² See Poitras (2010), p. 299.

The result is the goodwill ratio:

$$\text{Goodwill ratio} = \frac{\text{Goodwill}}{\text{Total assets}} \quad ^{393}$$

The goodwill ratio is a reflection of the acquisition history of the fallen angel company. A high goodwill ratio shows that a fallen angel company has paid a higher price for an acquisition object than the fair value of its net tangible and identifiable intangible assets.³⁹⁴ This does not necessarily mean that the fallen angel company has overpaid or the acquisitions have been harmful to it. For example, there could be synergies from the acquisition or unidentifiable intangible assets acquired that justify the purchase price. Nevertheless, the assumptions that have led to paying an excess purchase price might become outdated, thus causing the goodwill to decrease in the course of regular impairment tests. Therefore, a high amount of goodwill contains a possible future burden on earnings, if the annual impairment test signals that an impairment charge is necessary.³⁹⁵ Hence, successful investors like Graham or Buffett have taken a cautious stance when it comes to including accounting goodwill figures in a company's valuation.³⁹⁶ As previously mentioned, particularly value investors prefer when a company's management is more concerned with improving operational efficiency and enabling the company to grow internally than with aggressively pursuing external growth via acquisitions.³⁹⁷ The corresponding hypothesis reflects this logic:

$$H_8 = \textit{The lower the goodwill ratio} \\ \textit{the more likely the fallen angel is of good quality.}$$

³⁹³ For the purpose of this thesis, both numerator (abbreviation: WC018280) and denominator (abbreviation: WC02999) were extracted from the Worldscope database.

³⁹⁴ See Stern (2006), p. 82.

³⁹⁵ See Castedello/Klingbeil (2009), p. 4.

³⁹⁶ See Cottle/Murray/Block (1987), p. 235.

³⁹⁷ See, for example, Arnold (2002), pp. 251 et seq., Whitman/Shubik (2005), pp. 135 et seq., McNiven (2008), or Jain (2009), p. 18.

5.8 Valuation

Whereas the previous possible influence factors on angel quality dealt with company-internal performance only, the sixth factor introduces the financial market perspective. The general idea behind using valuation ratios reflects the above-mentioned importance of the price of an investment for value investors.³⁹⁸

5.8.1 Price-to-Book Ratio

The first valuation measure is the price-to-book ratio. Often it is also called market-to-book ratio, or, in its reciprocal form, book-to-market ratio.³⁹⁹ The price-to-book ratio is defined as follows:

$$\text{Price – to – book ratio} = \frac{\text{Market value of equity}}{\text{Total shareholders' equity}} \quad 400$$

Both academics and practitioners frequently use it when deciding whether a stock should be classified as a value or a growth stock. Already in 1934, Graham elaborated extensively on the values of investing in stocks that an investor can buy at a significant discount to their book value of equity, the proverbial dollar for fifty cents.⁴⁰¹ By this statement he was referring exclusively to the relationship between the book value of equity on a company's balance sheet to the market value of all his outstanding shares. Later, Fama and French mentioned this ratio in first place when separating their universe of stocks into value and growth stocks in their studies.⁴⁰² For the investment practice, the importance of the price-to-book ratio is well illustrated by the fact that all key value indices are constructed by using this ratio. S&P Barra, for example, groups the stock universe into value and growth categories by determining the median price-to-book ratio so that the market capitalization above and below this median is equal. The stocks belonging to the value index are the ones below the median. The stocks with an above-median price-to-book ratio constitute the growth index. Russell, another

³⁹⁸ See, for example, Greenblatt (2006), pp. xviii and 48-57, or Tavakoli (2009), p. 17.

³⁹⁹ See, for example, Lakonishok/Shleifer/Vishny (1994), p. 1546, or Chan/Lakonishok (2004), p. 71.

⁴⁰⁰ For the purpose of this thesis, the numerator was extracted from Datastream (abbreviation: MV) and the denominator from Worldscope (abbreviation: WC03995) databases.

⁴⁰¹ See Greenwald et al. (2002), p. XI.

⁴⁰² See Fama/French (1998), p. 1978.

important index provider, enlists stocks in its Russell Value Indexes based on both low price-to-book ratios and low forecasted growth rates.⁴⁰³

It is therefore not surprising, that already several decades ago academics started to test the hypothesis that a value strategy based on buying stocks with a low book-to-market ratio leads to superior investment performance.⁴⁰⁴ For example, Rosenberg, Reid and Lanstein's findings show that a strategy of buying stocks with a high book-to-price ratio, i.e. a low price-to-book ratio, and selling stocks with a low book-to-price ratio yields superior returns.⁴⁰⁵ The logical reasoning behind using a low price-to-book ratio as an indicator for a good buying opportunity and vice versa is the assumption that companies will take advantage of overvaluations that are expressed by a high price-to-book ratio and issue additional equity at favorable conditions.⁴⁰⁶ Therefore, it appears sensible to test whether a low price-to-book ratio is a statistically significant indicator for angel quality.

Following the line of thought of the school of value investment in the tradition of Benjamin Graham, a lower price-to-book ratio should indicate a more favorable investment opportunity and thus a better angel quality. Therefore, the corresponding hypothesis is:

*H₀ = The lower the price-to-book ratio
the more likely the fallen angel is of good quality.*

⁴⁰³ See Kaye (2006), p. 58.

⁴⁰⁴ See, for example, Rosenberg/Reid/Lanstein (1985), Fama/French (1992), or Lakonishok/Shleifer/Vishny (1994).

⁴⁰⁵ See Rosenberg/Reid/Lanstein (1985), p. 12 et seq.

⁴⁰⁶ See Parsons/Titman (2009), p. 20.

5.8.2 Price-to-Earnings Ratio

Like the price-to-book ratio, the second valuation ratio to be tested is frequently used as an indicator for the valuation level by both academics and investment practice.⁴⁰⁷ Already in 1977, Basu tested the efficient market hypothesis by relating the share price performance of common stocks to its price-to-earnings (P/E) ratio.⁴⁰⁸ Later, Ahmed and Nanda used earnings yield, which is the reciprocal of the P/E ratio, as one of two dimensions to form stock portfolios.⁴⁰⁹ The P/E ratio is defined as follows:

$$\text{Price – to – earnings ratio} = \frac{\text{Market value of equity}}{\text{Net income}} \quad 410$$

It is a very intuitive measure, since it states how many Euros an investor would have to pay for one Euro of current or projected next year's earnings. Likewise, it represents the number of years it takes to earn the investment back in case the annual profit remains the same in the future. As investors tend to think in pay-back periods, the popularity of the P/E ratio is understandable.

However, caution should be exercised regarding the type of net income figure to be used in the denominator of the P/E ratio. Logically, this ratio is most meaningful when there is little uncertainty around the earnings figure. Unlike with sales or book value of equity, swings in net income are larger and more frequent. Therefore, it is essential to use a reliable earnings figure. Since future earnings matter to investors, current fiscal year's forecast net income is often used in calculating the P/E ratio. However, forecasted earnings figures are only reliable when there is little doubt about the accuracy of the earnings forecast. By definition, this is not true for fallen angels, since they have become fallen angels precisely because of falling short of the earnings forecast. The visibility on fallen angels' future earnings will therefore be rather cloudy, which points towards using past fiscal year's net income for calculating the P/E ratio.

⁴⁰⁷ See Kaye (2006), p. 32.

⁴⁰⁸ See Basu (1977).

⁴⁰⁹ See Ahmed/Nanda (2001).

⁴¹⁰ For the purpose of this thesis, the numerator was extracted from Datastream (abbreviation: MV) and the denominator from Worldscope (abbreviation: WC01551) databases.

Similarly to the price-to-book ratio, an investor would seek to buy the company that is cheaper in his eyes, i.e. has a lower P/E ratio. Thus, the corresponding hypothesis is:

*H₁₀ = The lower the price-to-earnings ratio
the more likely the fallen angel is of good quality.*

5.9 Negative Earnings Surprise

Whereas all possible influence factors and ratios described so far had a connection with the financial statements of the respective company, the seventh possible influence factor on angel quality is related to the strength of and the share price reaction caused by the negative earnings surprise.

5.9.1 Standardized Unexpected Earnings

The first earnings surprise-related measure analyzed in this thesis is standardized unexpected earnings (SUE). It is an expression of the extent of the negative earnings surprise. As previously mentioned, the SUE is defined as the absolute figure of the earnings shortfall divided by the dispersion in analysts' forecasts:

$$\text{SUE} = \frac{\text{Reported earnings per share} - \text{Estimated earnings per share}}{\text{Standard deviation of estimated earnings per share}} \quad 411$$

Although there is substantial research available on the short-term effects of earnings surprises⁴¹², little can be said about the effect of SUE on mid- to long-term share price performance. This is particularly the case when looking at fallen angel stocks.

The underlying rationale behind including SUE as a possible indicator for angel quality is that the magnitude of the earnings surprise might matter, because financial market participants might particularly overreact to strong negative surprises. If a company misses the consensus earnings forecast by far, it will also lead to a decrease in confidence in the management's ability to deliver accurate forecasts in the future.⁴¹³ This might lead to a more severe overshooting of the stock price, and thus a better

⁴¹¹ For the purpose of this thesis, all variables were extracted from the I/B/E/S database.

⁴¹² See Brown (1997) for a good overview on the so-called SUE effect, which is also known as the post-earnings announcement drift. It describes the tendency of share prices to continue to move into the direction of the earnings surprise for some time after the earnings announcement.

⁴¹³ See Kasznik/Lev (1995), pp. 121 et seq., or Bartov/Givoly/Hayn (2002).

opportunity to buy the shares at a low price. Although the direction of the relationship between SUE and angel quality ex-ante is not clear, it is assumed that in line with the overreaction theory a particularly strong negative surprise also leads to a relatively stronger abnormal share price reaction, thereby creating more upside potential once this overreaction corrects. Since SUE is always negative, the hypothesis is as follows:

$$H_{11} = \textit{The lower the SUE} \\ \textit{the more likely the fallen angel is of good quality.}$$

5.9.2 Cumulative Abnormal Return

The second earnings surprise-related measure is cumulative abnormal return (CAR). It measures the extent of the share price reaction around a negative earnings surprise. For that purpose, total shareholder return (TSR) is calculated for both the fallen angel stock and the benchmark index. The calculation of CAR is then as follows:

$$\textit{Cumulative abnormal return} = \textit{TSR}_{\textit{Fallen Angel Stock}} - \textit{TSR}_{\textit{Benchmark Index}} \quad ^{414}$$

The reasoning behind using CAR lies in the overreaction hypothesis.⁴¹⁵ If the share price decline caused by a negative earnings surprise is particularly steep, the fallen angel stock might be a particularly good bargain. Since CAR as used in this thesis is by definition always has a negative value, a low CAR means that the market has strongly reacted to the negative earnings surprise by pushing down the share price. Thus, the corresponding hypothesis is:

$$H_{12} = \textit{The lower the CAR} \\ \textit{the more likely the fallen angel is of good quality.}$$

⁴¹⁴ For the purpose of this thesis, all data required to calculate TSR for both fallen angel stocks and the benchmark index were extracted from the Datastream database.

⁴¹⁵ See chapter 3.3.2.

5.9.3 Cumulative Abnormal Return-to-Standardized Unexpected Earnings Ratio

The third earnings surprise-related measure is the cumulative abnormal return-to-standardized unexpected earnings ratio (CAR-SUE ratio). It combines the magnitude of both the negative share price reaction and the negative earnings surprise in one ratio:

$$CAR - SUE \text{ ratio} = \frac{CAR}{SUE}$$

The CAR-SUE ratio puts the extent of the abnormal share price drop in relation to the size of the negative earnings surprise as measured by standardized unexpected earnings. The assumption is that the stock of a company that suffers disproportionately strong relative to the size of its earnings surprise should constitute a good bargain opportunity. In such an instance, the market appears to have overreacted by punishing the stock more than the size of the earnings surprise justifies. With both CAR and SUE being negative as used in this thesis, the CAR-SUE ratio always shows a positive value. Consequently, the higher the CAR-SUE ratio the more the share price has suffered in relative terms. Therefore, the corresponding hypothesis is:

*H₁₃ = The higher the CAR-SUE ratio
the more likely the fallen angel is of good quality.*

5.10 Overview of Hypotheses

As a synopsis of the sections above, **Table 5** provides an overview of the mentioned hypotheses and the assumed effect on angel quality as the dependent variable:

Table 5: Overview of hypotheses and related independent variables

Hypo-thesis	Classification of ratio	Independent variable	Description	Assumed effect on AQ
The more financially stable a fallen angel is the more likely it will be a good fallen angel and vice versa.				
H ₁	Financial stability (short-term liquidity)	curratio	Current ratio	The higher the better.
H ₂	Financial stability (capital structure)	eqratio	Equity ratio	The higher the better.
The more profitable a fallen angel is the more likely it will be a good fallen angel and vice versa.				
H ₃	Profitability	gpm	Gross profit margin	The higher the better.
H ₄	Profitability	roa	Return on assets	The higher the better.
The stronger the cash flow of a fallen angel is the more likely it will be a good fallen angel and vice versa.				
H ₅	Cash flow	fcfmrg	Free cash flow margin	The higher the better.
H ₆	Cash flow	cfoni	Cash flow fr. operating activities-to-net income ratio	The higher the better.
The more optimized the cost structure of a fallen angel is the more likely it will be a good fallen angel and vice versa.				
H ₇	Cost structure	sgaratio	Selling, general & administrative expenses ratio	The lower the better.

The less aggressive a fallen angel's mergers & acquisitions activities are the more likely it will be a good fallen angel and vice versa.

H ₈	Mergers & acquisitions	goodwill	Goodwill ratio	The lower the better.
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The lower the valuation of a fallen angel is the more likely it will be a good fallen angel and vice versa.

H ₉	Valuation	pb	Price-to-book ratio	The lower the better.
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H ₁₀	Valuation	pe	Price-to-earnings ratio	The lower the better.
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The stronger the overreaction by financial markets to a negative earnings surprise of a fallen angel is the more likely it will be a good fallen angel and vice versa.

H ₁₁	NES	sue	Standardized unexpected earnings	The lower (= more negative) the better.
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H ₁₂	NES	car	Cumulative abnormal return	The lower (= more negative) the better.
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H ₁₃	NES	carsue	CAR-SUE ratio	The higher the better.
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Text highlighted in grey refers to the underlying assumptions leading to the assumed effect of each tested independent variable on angel quality.

Source: Author

In the following chapter these hypotheses are empirically tested in order to assess their prognostic power with regard to distinguishing good fallen angels from bad ones.

6 Empirical Tests of Angel Quality Indicators

6.1 Introductory Remarks

The main objective of this thesis is to contribute to closing the research gap regarding fallen angel stocks and thereby assisting an investor in making good purchase decisions concerning fallen angel stocks. This shall be achieved by providing him with information about what distinguishes fallen angels of good quality from those of bad quality and also what does not.

Therefore, the core of this thesis consists of statistically testing the possible indicators for angel quality mentioned in the previous chapter. Before the results of the statistical tests are presented later in this chapter, the generation of the raw dataset, the processing of the raw dataset into the base dataset, and the creation of industry subsets out of the base dataset are described. Several robustness tests conclude the chapter.

6.2 Raw Dataset Description

6.2.1 Selection of Geography

In terms of geography, this thesis covers the U.S. stock market. This stock market was selected, because it is the most developed equity market: As of December 31, 2009, the two leading U.S. stock exchanges NYSE and NASDAQ accounted for approximately 32 percent of the regulated stock market capitalization world-wide⁴¹⁶, and for 11.5 percent of all listed companies on those exchanges⁴¹⁷. Additionally, the U.S. is leading in terms of advancement of equity culture as measured by the percentage of households who participate in the stock market.⁴¹⁸ Furthermore, data availability and data quality concerning analysts' estimates⁴¹⁹ and the selected possible

⁴¹⁶ See World Federation of Exchanges (2009a), p. 1.

⁴¹⁷ See World Federation of Exchanges (2009b), p. 1.

⁴¹⁸ See Guiso et al. (2003), pp. 125 et seq. and p. 138.

⁴¹⁹ I/B/E/S analysts' estimates were often not available in good quality for other countries' stock markets, particularly for the earlier years of the research period. For example, quarterly earnings estimates and actuals started to become available for German companies from the fourth quarter of 1998 only. Data availability increased to reach a reasonable level of coverage in terms of companies with quarterly data from 2000 on. This finding of sparse data availability for European analysts' estimates in earlier years of the research period is also consistent with Liodakis et al. (2005), p. 5. For many companies in smaller countries, however, a lack of sufficient analysts making an EPS estimate on a quarterly basis remained a problem throughout the full research period.

indicators⁴²⁰ for angel quality have been the best for U.S. stocks.⁴²¹ Finally, the U.S. stock market is regarded as the world's most efficient one with the strongest arbitrage mechanisms.⁴²² As a consequence, testing the aforementioned hypotheses in such an environment increases the likelihood to deliver meaningful results.

6.2.2 Selection of Benchmark

Following the selection of the geography, the construction of a suitable sample of companies requires the selection of an appropriate index that serves as the benchmark for identifying over- and underperformance of individual stocks. The criteria for selecting an index were threefold: Firstly, the index should be a broad market index. Given the characteristics of fallen angel stocks mentioned above, it is fairly unlikely that the most prominent stock market indices such as the Dow Jones Industrial, which contains established large-cap stocks that are extensively covered by many analysts, will be the best reservoir for finding fallen angel stocks. Therefore, it is necessary to use an index that covers broader parts of the market. Secondly, the index has to have a history going back to the starting point of the research, i.e. until 1996. Thirdly, the index should be available as a performance index in order to make it easier to compare the total return to shareholders from individual stocks to the total return from holding the index.

In considering these three requirements, the S&P Composite 1500 (TR) index was selected as a benchmark. This index combines the S&P 500, the S&P MidCap 400 and the S&P SmallCap 600 and was designed to form “an investable benchmark of the U.S. equity market”⁴²³. The S&P Composite 1500 accounts for approximately 85% of the U.S. market capitalization.⁴²⁴ It has been calculated since the end of 1994 and – like all S&P U.S. equity indices – is available both as a price and a performance index, with the latter including both ordinary cash dividends and special dividends.⁴²⁵ For the purpose of this thesis, the performance index variant representing total return to

⁴²⁰ Financial statement data availability and quality for listed European companies has improved since 2005, when application of IFRS became mandatory for financial market-oriented companies. See Weißenberger (2007), pp. 38f.. Nevertheless, this does not solve the problem of data availability and quality before 2005.

⁴²¹ For problems with the usage of accounting and financial databases in Europe see also García Lara/García Osma/Gil de Albornoz Noguera (2006).

⁴²² See Malloy (2011), p. 7.

⁴²³ Standard&Poor's (2009), p. 1.

⁴²⁴ See Standard&Poor's (2009), p. 1.

⁴²⁵ See Russell Investments (2011a), p. 17.

shareholders has been selected. Other broad U.S. stock market indices such as the Russell 3000⁴²⁶ or the Wilshire 5000 Total Market Index⁴²⁷ have not been selected, as the S&P 1500 is more widely regarded than those other broad market indices⁴²⁸.

The chosen dataset is free of survivorship bias, as all historical constituents of the S&P 1500 index during the research period were included and not only the stocks that were in the index at the end of the research period.⁴²⁹

6.2.3 Selection of Time Horizon

Data was gathered for all stocks in the selected index for the time period from 1996 until 2009. There were several reasons for choosing this particular time horizon: Firstly, the time horizon had to be long enough to generate a large number of negative earnings surprise events in order to make the research statistically meaningful. Secondly, the time horizon should be chosen such that it covers various stock market phases. When looking at **Figures 5 and 6** it becomes clear that the selected research period is indeed one that contains periods of strongly increasing share prices as well as phases of sideward movement or sharply dropping prices. Before, the U.S. stock market as measured by the Dow Jones Industrial Index has shown an over 20-year long period of fairly flat share price development followed by the extended bull market of the nineteen-eighties and -nineties. Thirdly, studies by Brown and Caylor as well as Dechow et. al. indicate that the importance of meeting or missing analysts' earnings expectations has grown since the mid-1990s which corresponds with the beginning of the chosen time frame for this thesis.⁴³⁰

⁴²⁶ See Russell Investments (2010), p. 1.

⁴²⁷ See Wilshire Associates (2010).

⁴²⁸ An indication for the wide recognition of the S&P 1500 is the fact that futures on its three components S&P 500, S&P MidCap 400 and the S&P SmallCap 600 are available for trading on the Chicago Mercantile Exchange, whereas this is not the case for the other two indices (see CME Group (2008), p. 1et seq.).

⁴²⁹ See Liodakis et al. (2005), p. 4.

⁴³⁰ See Brown/Caylor (2005) and Dechow/Richardson/Tuna (2003).

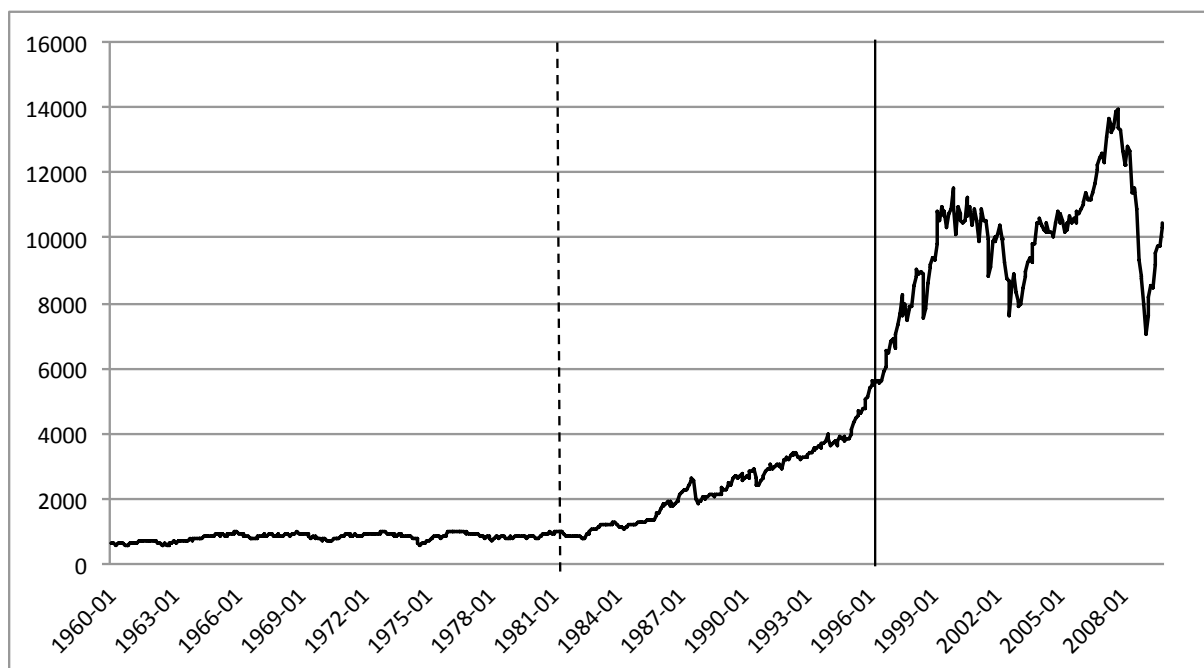


Figure 5: Chart of Dow Jones Industrial index 1960-2009

Source: Author based on data extracted from Yahoo! Finance (<http://finance.yahoo.com>)



Figure 6: Chart of S&P Composite 1500 index 1996-2009

Source: Author based on data extracted from Yahoo! Finance (<http://finance.yahoo.com>)

6.2.4 Calculation of Abnormal Returns

In order to measure cumulative abnormal returns, total shareholder returns (TSR) were calculated. These figures comprise both capital appreciation gains and dividends received under the assumption that all dividends are reinvested immediately after shareholders have received them. The reinvestment price is the price close on the day the dividend is paid. Therefore, TSR represents the “capital appreciation rate investors achieve if they purchase shares at the start date, reinvest all dividends to buy additional shares, and hold all shares to the terminal date.”⁴³¹ Gross values were used for both dividends and capital gains, because the S&P 1500 total return benchmark index is calculated without consideration of taxes as well.⁴³²

The abnormal return is calculated as the TSR on a single company stock less the TSR on the S&P 1500 benchmark. The required input data for TSR and abnormal return calculation – price close and dividend payment data for equity issues and price close data for the benchmark index – were extracted from Datastream.⁴³³

In order for a stock to qualify as a fallen angel it has to show a worse performance than the benchmark, i.e. any abnormal return of less than zero suffices. This minimal threshold has been selected, because it avoids any randomness in setting the required performance benchmark. Furthermore, Skinner and Sloan have found out that the relative underperformance of growth stocks versus value stocks is largely due to their asymmetric reaction to earnings surprises. Interestingly, a large part of their disproportionately strong negative share price reaction to a negative earnings surprise occurs during the 31 days leading up to the earnings announcement and only a smaller part during the three days surrounding the announcement.⁴³⁴ This phenomenon might be “driven by preemptive earnings disclosures, and in particular [by] the tendency for managers of growth firms to preannounce adverse earnings news.”⁴³⁵ Using the above-mentioned minimal threshold of an abnormal return of less than zero mitigates the

⁴³¹ Rappaport (2006), p. 119.

⁴³² See Russell Investments (2011a), p. 16.

⁴³³ As share price close variable `ds.p#t` was chosen, because this variable removes all data after the day the company’s stock exchange listing became inactive, whereas the standard Datastream variable `ds.p` continues to list the final share price close value even after the company had stopped its stock exchange listing due to merger, liquidation or other reasons. Another potentially suitable variable, `ds.p#s`, was not selected, because it not only removes all data after the inactive day, but also on public holidays, which is not compatible with a uniform database and data analysis design.

⁴³⁴ See Skinner/Sloan (2002), pp. 300-307.

⁴³⁵ Skinner/Sloan (2002), p. 307.

danger of erroneously missing to include fallen angel stocks due to an artificially set higher negative abnormal return threshold.

6.2.5 Time Frame Around Earnings Surprise

As demonstrated by numerous studies, share prices do not fully react immediately to the positive and negative surprises conveyed by earnings announcements. Moreover, substantial adjustments already occur shortly before the announcement day of earnings and – though smaller, but still significant – the same is true for the time period after the announcement.⁴³⁶ It is therefore important for an investor to be aware of these share price adjustment processes before and after an earnings surprise, because the failure to identify an early significant share price drop related to a negative earnings surprise hurts performance. The same is true for buying a fallen angel stock too early, i.e. before the full effect of the negative earnings surprise has been incorporated in its share price.

Previous research has either focused on short-term share price reactions covering a time frame of only few days around the announcement, or longer-term time spans that lasted up to one quarter until the next quarterly earnings announcement, or both. Using a longer-term perspective, Bernard and Thomas in one of their earlier studies contemplate a time frame of 60 trading days subsequent to the earnings announcement day.⁴³⁷ Jones et al. use an even longer time frame that is starting the day following the prior earnings announcement up to and including the day of the following one.⁴³⁸ Staying within the larger time frame, but extending the observation period to trading days prior to the earnings announcement, Liodakis et al. start their analysis 25 days before the earnings announcement date and end 25 days thereafter.⁴³⁹ Foster et al. take a broader view by looking at both short two-day intervals (including the trading day preceding and the trading day of the earnings announcement) and longer time frames (61 respectively 60 trading days before and after the announcement) at the same time.⁴⁴⁰ Other researchers concentrate on shorter intervals around the earnings announcement date: Kama uses a four-day window starting two days before and ending one day after the announcement⁴⁴¹ and Bernard et al. in a later study look at an

⁴³⁶ See Jones/Rendleman/Latané (1985), pp. 29-31.

⁴³⁷ See Bernard/Thomas (1989), p. 9.

⁴³⁸ See Jones/Rendleman/Latané (1985), p. 29.

⁴³⁹ See Liodakis et al. (2005), p. 7.

⁴⁴⁰ See Foster/Olsen/Shevlin (1984), p. 586.

⁴⁴¹ See Kama (2009), p. 36.

announcement window of three days starting two days before and including the day of the earnings announcement.⁴⁴² Taylor starts to measure performance two days after the earnings announcement.⁴⁴³ Akin to the shorter time frame, several other studies use a three-day window around the date of the earnings announcement, i.e. they analyze the share price change in the period starting one day before the announcement and ending one day after.⁴⁴⁴ Among the scholars analyzing a shorter window around earnings announcement day, Berens not only uses the short time frame to gauge abnormal returns around earnings announcements, but also defines a longer period spanning from the second trading day after the earnings announcement to the first day after the next quarterly earnings announcement in order to measure long-term abnormal returns. In his study, he finds that market prices adjust asymmetrically to positive and negative earnings surprises. Whereas positive earnings surprises show both a short-term and long-term positive effect on the respective stock's abnormal return as measured in above-mentioned time frames, negative earnings surprises – like in the case of fallen angels – predominantly have a short-term dampening effect on returns.⁴⁴⁵

Taking the findings of the mentioned previous studies into account, analyzing longer time periods around an earnings surprise does not seem to be particularly rewarding when looking at negative earnings surprises. Moreover, the likelihood that other news regarding the business activities of the fallen angel reach the market is increasing with a longer time span after the earnings announcement, thereby possibly blurring the causal relationship between the negative earnings surprise and the share price development. Thus, a rather short time frame after the earnings announcement appears more suited for this thesis from a methodological standpoint. Furthermore, from a more practical point of view, an investor is in danger of missing the window of opportunity during which he could buy into a company at a reasonable price. Since he likely requires time for conducting an investment analysis after having identified the negative earnings announcement as the trigger, it is advisable not to let too much time pass after the earnings announcement. Until the investment analysis is completed and an informed investment decision can be made, often several days or weeks will have passed. Sticking to a shorter time frame around the earnings announcement for the purpose of this thesis means that the investor would still have sufficient time to buy the stock within the longer-lasting post-earnings announcement drift period as

⁴⁴² See Bernard/Thomas/Wahlen (1997), p. 103.

⁴⁴³ See Taylor (2009), p. 13.

⁴⁴⁴ See La Porta et al. (1997), p. 862; Mohanram (2005), p. 161, and Berens (2010), p.3.

⁴⁴⁵ See Berens (2010), p. 2 et seq.

indicated by studies prior to the one conducted by Berens.⁴⁴⁶ That time is of essence here is also underpinned by Kaestner who demonstrates that a negative price reaction caused by a negative earnings surprise is on average followed by positive abnormal returns and vice versa at the time of the subsequent earnings announcement.⁴⁴⁷ In other words, investors should make an investment decision before the next quarterly earnings announcement occurs in order to avoid the danger of missing the opportunity to purchase the fallen angel stock at depressed price levels.

As a consequence of all the points mentioned above, a research design incorporating a shorter time frame around the earnings announcement seems appropriate. A five-day window starting two trading days before the negative earnings announcement and ending two trading days after it was chosen. Like in the above-mentioned studies by Kama and Berens, two days prior to the announcement date were selected to allow enough time for traders to act on information that might have leaked prior to the official earnings announcement. Following the same logic, two days after the announcement should be enough time to digest and react to the news. However, the used earnings announcement data do not specify whether the announcement took place before or after the close of the stock market. Providing only one trading day after the announcement date would leave investors with only that one day if the announcement was after the market-close on the day before. To cope with this possible problem, one trading day was added to form a five-day window with two days before and after the recorded announcement date. By doing so it is guaranteed that investors have at least two trading days to digest and act on the news irrespective of the exact timing of the announcement.

⁴⁴⁶ These studies demonstrate empirical evidence that most of the post-earnings announcement drift occurs within 60 trading days after the actual announcement. Afterwards the effect is significantly fading away. See, for example, Foster/Olsen/Shevlin (1984) or Bernard/Thomas (1989). For further information on the post-earnings announcement drift see section 2.4.1.

⁴⁴⁷ See Kaestner (2006), pp. 13-17.

6.2.6 Descriptive Statistics of Raw Dataset

The resulting raw dataset contains a total of 2,846 companies that were at least for some time part of the selected benchmark index during the chosen time period from 1996 until 2009. For all these companies, EPS actuals, the date of the earnings announcement, analysts' EPS estimates and their standard deviation were extracted on a quarterly basis from the I/B/E/S database for all companies in the sample.⁴⁴⁸ As a result, SUE values could be calculated for each earnings announcement, thus allowing the identification of negative earnings surprises.

All annual financial statement data necessary to calculate the possible indicators of angel quality were collected for all companies from the Worldscope database.⁴⁴⁹ Afterwards, they were matched with the respective earnings announcement dates, so that the most current financial statement information was properly linked to each earnings announcement. On a daily basis, share prices and index values were gathered at market close. The same was done for dividends. Additionally, general information such as company name, various unique identifiers, and industry classification were collected.

To assign companies to certain industries, industry classification benchmark (ICB) codes were used.⁴⁵⁰ The ICB system allows for analyzing data along four levels of industry classification: industry, supersector, sector, and subsector. This flexibility to analyze aggregate industry groups while being able to drill deep if necessary is one key advantage of the ICB system. Another one is the wide availability of ICB data via Datastream.⁴⁵¹

As expected for a large and broad-based economy such as the U.S., the 2,846 companies in the raw dataset are distributed across a wide variety of industries. Nevertheless, there are spikes with regard to consumer goods and services, industrials, financials, technology, and healthcare (see **Figure 7**).

⁴⁴⁸ Variable IBH.EPSActualValue (qtrly) for actual earnings, variable IBH.EPSMean (qtrly) for mean consensus estimates, and variable IBH.EPSStdDeviation (qtrly) for the standard deviation of analysts' earnings estimates. See Beaver et al. (2008), p. 738, for the advantages of having both actual data and estimates from one source.

⁴⁴⁹ See footnotes in chapter 5 for exact specifications of the single Worldscope variables.

⁴⁵⁰ ICB is a widely regarded industry classification system jointly owned by FTSE International Ltd. and Dow Jones & Company, Inc. See **Table 42** and **Table 43** for a detailed depiction of the ICB industry classification system.

⁴⁵¹ Five-letter variable: ds.IndustryGroupCode. This variable is also available for listed companies outside the U.S., which allows for potential future research on an international scope.

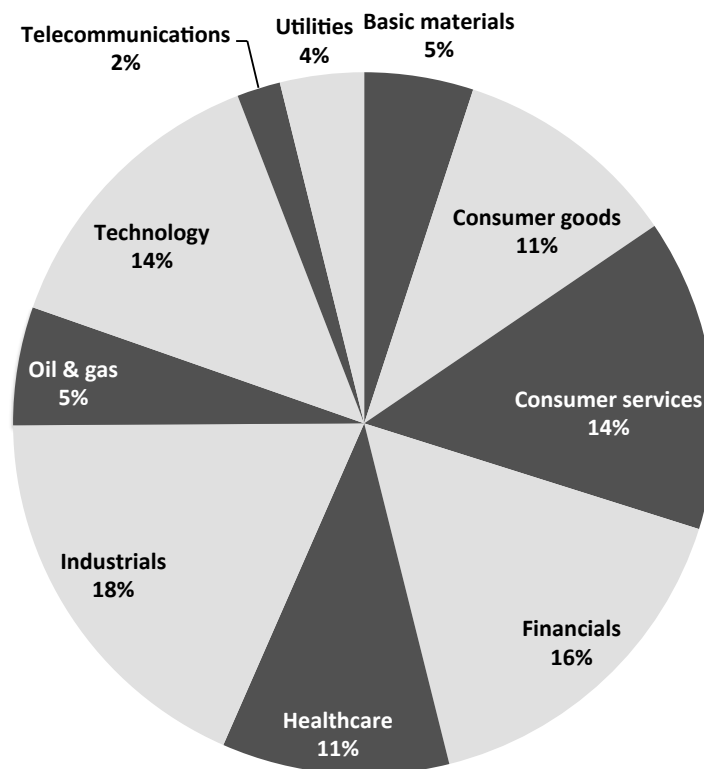


Figure 7: Industry distribution in the raw dataset

Source: Author

When using the more granular segmentation along industry sectors, health care equipment & services, technology hardware & equipment, software & computer services, banks, general retailers, and support services constitute the most prominent sectors. However, the fact that these six most important sectors only account for 39 percent of all companies in the raw dataset demonstrates its broad industry base (see **Table 6**).

Table 6: Sector distribution in the raw dataset

Sector	Number of companies	Percentage of total
Health Care Equipment & Services	205	7,2%
Technology Hardware & Equipment	203	7,1%
Software & Computer Services	189	6,6%
Banks	185	6,5%
General Retailers	180	6,3%
Support Services	148	5,2%
Travel & Leisure	108	3,8%
Financial Services	100	3,5%
Electronic & Electrical Equipment	96	3,4%
Pharmaceuticals & Biotechnology	93	3,3%
Oil & Gas Producers	91	3,2%
Industrial Engineering	85	3,0%
Media	82	2,9%
Real Estate Investment Trusts	77	2,7%
Chemicals	75	2,6%
Electricity	70	2,5%
Personal Goods	68	2,4%
Food Producers	67	2,4%
Household Goods & Home Construct.	66	2,3%
Nonlife Insurance	64	2,2%
Oil Equipm., Services & Distribution	63	2,2%
Construction & Materials	56	2,0%
Industrial Transportation	50	1,8%
Aerospace & Defense	46	1,6%
General Industrials	41	1,4%
Gas, Water & Multiutilities	40	1,4%
Food & Drug Retailers	39	1,4%
Leisure Goods	38	1,3%
Automobiles & Parts	37	1,3%
Fixed Line Telecommunications	33	1,2%
Industrial Metals & Mining	31	1,1%
Life Insurance	25	0,9%
Mobile Telecommunications	24	0,8%
Forestry & Paper	19	0,7%
Mining	18	0,6%
Beverages	14	0,5%
Tobacco	8	0,3%
Real Estate Investment & Services	7	0,2%
Equity Investment Instruments	4	0,1%
Alternative Energy	1	0,0%

Source: Author

6.3 Processing of Raw Dataset into Base Dataset and Subsets

The raw dataset described above is processed in two main steps. In the first step, some stocks are excluded from the raw dataset in order to maintain consistency and validity of the dataset in the light of the research design. The resulting dataset is called the base dataset. In the second step, this base dataset is split along industries into six data subsets that are then used for statistical tests.

6.3.1 Exclusion of Stocks

To safeguard the quality and consistency of the base dataset, a negative earnings surprise event was excluded once it failed to overcome at least one of the four hurdles: (i) meeting the criteria for fallen angel stocks, (ii) suitable industry, (iii) sufficient analyst coverage, and (iv) sufficiently long time period between negative earnings surprises.

6.3.1.1 Criteria for Fallen Angel Stocks

To begin with, the wide variety of companies from the raw dataset described above was filtered by applying the three criteria for fallen angel stocks as defined in chapter 2: (i) negative earnings surprise, (ii) subsequent negative abnormal shareholder return, and (iii) above-average growth before negative earnings surprise. Firstly, 2,551 companies, i.e. almost 90 percent of all companies in the raw dataset, delivered at least one negative earnings surprise during the research period from 1996 till 2009. Secondly, 2,465 companies with 15,041 negative earnings surprise events were still left after checking for negative abnormal share price performance in the five trading day-window around the negative earnings surprise. Allowing for at least one year of share price development after the negative earnings surprise, which is the minimum time required to sensibly identify good and bad fallen angels, reduces these numbers to 2,343 companies with 13,405 negative earnings surprise events. Of these 2,343 companies, just about 10 percent manage to disappoint only once with their earnings. Most companies deliver a negative earnings surprise between two and five times during the research period. About one third disappoints up to nine times. The remaining twelve percent are frequently disappointing companies with 10 negative earnings surprises or more during the research period (see **Figure 8**). One company holds the doubtful record of 22 negative earnings surprises delivered during the 56 quarters of the research period.

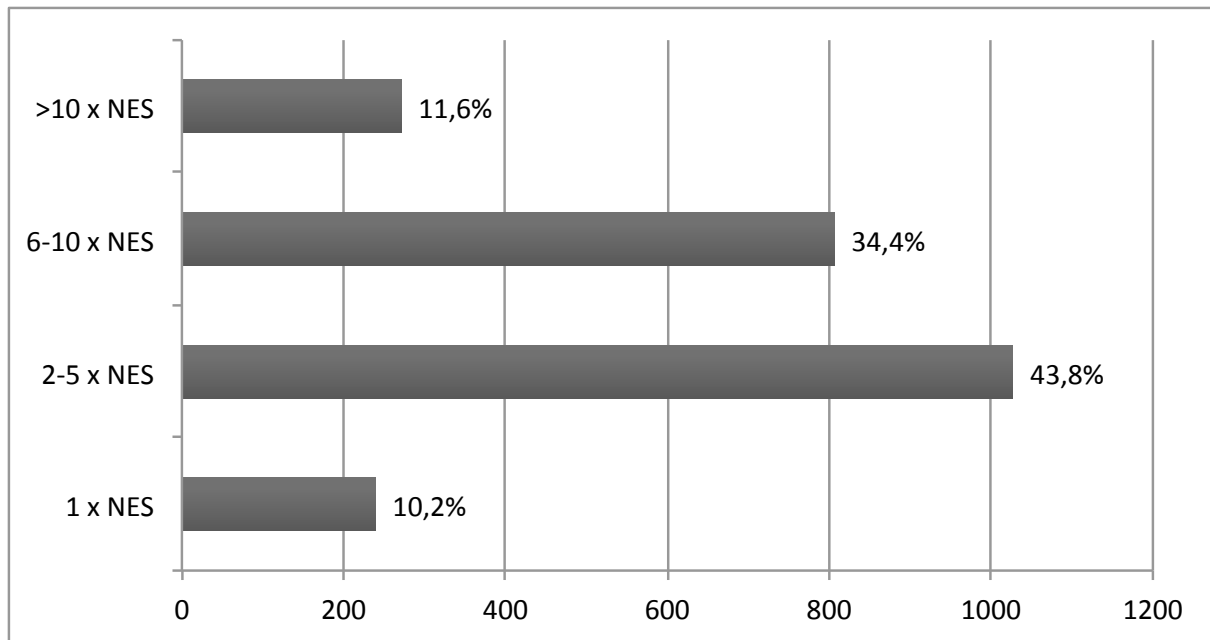


Figure 8: Negative earnings surprise frequency distribution in the raw dataset

Source: Author

Thirdly, a company had to demonstrate abnormal sales growth before the negative earnings surprise. Abnormal sales growth was chosen as an identifier for growth companies, which is independent from financial market sentiment. It is defined as the sales CAGR over the past two years before the earnings surprise minus the average real GDP growth rate of the respective company's domicile country, i.e. the U.S. for this thesis, during the time horizon of the research. In other words, if a company demonstrated sales growth above the U.S. average real GDP growth, the abnormal sales growth figure was positive and the company was included in the sample. Consequently, a company's stock was not included if the abnormal sales growth figure was negative. Such a company would not count as a growing company under the definition used in this thesis. After this step 2,231 companies with 11,392 negative earnings surprise events still remained in the dataset. The benchmark data for GDP growth were extracted from the Worldbank database.⁴⁵² Since an earnings surprise that happened in 2009 is not taken into account in the research due to the minimum required time period after the earnings surprise of one year (see section 2.4.1), the period for the GDP benchmark calculation was limited to 1996-2008. The respective CAGR value for the U.S. economy is 2.87 percent.

⁴⁵² See Worldbank (2010), variable "GDP growth (annual %)".

6.3.1.2 Industry Characteristics

With regard to industry classification, financial companies and utilities were excluded. The reason for taking these companies out of the sample lies in the fundamentally different structure of their financial statements.⁴⁵³ According to the ICB classification system, financial companies include banks, insurance companies, financial services providers, and real estate investment trusts (REITs). Banks, for example, have a much lower equity ratio than ordinary companies from other industries. The same is true for many financial services companies, such as leasing firms, which additionally tend to have a much larger asset base than companies from other industries with comparable revenues. Judging the financial performance of insurance companies also requires a different approach with specific performance indicators. REITs have to obey specific legal regulations, such as to pay out at least 90 percent of their taxable income as dividends to its shareholders.⁴⁵⁴ Finally, utilities tend to have much higher capital expenditures and higher debt levels. Given their rather stable operating cash flows and their fixed asset base that serves as collateral, they have fewer problems in obtaining and servicing this debt than companies from other industries. To sum it up, these peculiarities would either require a focus on different ratios and performance indicators, which would not be consistent with the overall research design, or would cause the designed statistical tests to become less meaningful, if not even meaningless. These problems could only be avoided by excluding financials and utilities from the sample.

6.3.1.3 Strength of Analyst Coverage

In terms of analyst coverage, stocks with less than three quarterly earnings forecasts by analysts were eliminated from the sample. Since the standard deviation of earnings forecasts is used as a measure of the degree of analysts' uncertainty contained in their estimates, basing the consensus estimate on only one or two analysts' opinions would be too little to establish a reasonably sound basis for classifying a company's earnings announcement as a surprise, no matter whether it is positive or negative. A sample including stocks that are covered by only one or two analysts is by definition more prone to earnings surprises, which could introduce a bias in the sample. In other words, the more analysts provide an earnings estimate, the lower the danger that an earnings surprise is only recorded because one analyst is significantly off. Setting a

⁴⁵³ See Fama/French (1992), p. 429, or Kama (2009), p. 35, who excluded all companies carrying a SIC-code of 6000-6999 (financial institutions) or 4900-4999 (public utilities).

⁴⁵⁴ See Block (2011), p. 34.

higher threshold than three analysts' estimates, however, would bear the danger of excluding smaller fallen angel companies, which usually are only covered by a handful of specialized analysts and investment banks. In addition, the increase in quality of the analysts' consensus earnings estimate would likely be only marginal, given the tendency of analysts to look at their colleagues' forecasts and consequently engage in herding behavior.⁴⁵⁵ Therefore, choosing a minimum coverage of three analysts appears like a sensible compromise, which is also consistent with several prior studies.⁴⁵⁶ Like the earnings surprise data, the number of analysts providing an earnings estimate was extracted from I/B/E/S.⁴⁵⁷

6.3.1.4 Time Period Between Negative Earnings Surprises

The last criterion for excluding companies in constructing the base dataset deals with the issue of repeated negative earnings surprises and the length of time between them. In case a company misses analysts' earnings expectations several times in a row or at least produces disappointments more often than once in a rather short period of time, data quality would suffer. The reason for this problem is the following: Firstly, analysts do not always update their estimates for all companies on a quarterly basis. Consequently, the repeated negative earnings surprise might not really be a disappointment, since it could rather be due to outdated analysts' forecasts and not to the company's repeated bad performance. In this case, the company and its data would enter the sample erroneously for a second time, thus distorting the data. Secondly, an investor would be alerted to focus his attention on a fallen angel already by the first negative earnings surprise. In case he made an investment based on his analysis following this first surprise, he would wait – as explained above in section 2.4.1 – for one to three years to see whether his investment hypothesis plays out. Therefore, he would very likely not consider investing again if a second or third negative earnings surprise occurred during this time horizon. Therefore, it makes little sense to look at multiple negative earnings surprises occurring during a short period of time within the scope of this thesis. To prevent that such multiple consecutive surprises harm data quality, a “quiet period” of three years after a recorded negative earnings surprise has been selected during which negative earnings surprises are not taken into the sample database. Only after the end of this period it is possible that another negative earnings

⁴⁵⁵ For findings on herding behavior among analysts see Scharfstein/Stein (1990), Trueman (1994), Hong/Kubik/Solomon (2000), and Clement/Tse (2005).

⁴⁵⁶ See also Scott/Stumpp/Xu (1999), p. 52, Kim/Kim (2003), p. 386, Liodakis et al. (2005), p. 5, or Kaye (2006), p.76.

⁴⁵⁷ Variable IBH.EPSNbrEst (qrtly) for the available number of analyst estimates.

surprise of the same company is allowed into the sample. The three years is also consistent with the length of the chosen angel quality AQ13. In robustness testing, a data sample with a waiting period of only one year is tested as well (see section 6.6.2.).

6.3.2 Development of Base Dataset Subsets According To Industry Classifications

The resulting base dataset consists of 1,641 non-financial and non-utility fallen angel companies with at least three analysts covering them. These companies caused 2,982 negative earnings surprises under the limitations discussed above. However, their values for possible indicators for angel quality vary widely across industry, which is documented in **Table 7**.

Table 7: Mean and median values across different industries for angel quality AQ13

Potential indicator for angel quality		All industries*	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Technology & Telco
Current ratio	Mean	2.801	1.842	2.618	1.802	3.908	2.280	4.753
	Median	1.954	1.544	2.245	1.547	2.832	1.843	2.876
Equity ratio	Mean	0.514	0.391	0.499	0.510	0.593	0.470	0.642
	Median	0.499	0.390	0.487	0.521	0.577	0.460	0.668
GPM	Mean	0.404	0.362	0.373	0.334	0.526	0.335	0.552
	Median	0.392	0.335	0.359	0.385	0.583	0.319	0.543
ROA	Mean	0.061	0.052	0.075	0.066	0.044	0.061	0.063
	Median	0.064	0.052	0.072	0.067	0.069	0.059	0.070
FCF margin	Mean	0.016	0.018	0.010	0.031	-0.086	0.038	0.044
	Median	0.037	0.027	0.034	0.023	0.047	0.042	0.055
CFO/NI	Mean	1.100	1.768	1.120	1.453	1.139	0.602	0.821
	Median	1.409	1.607	1.249	1.635	1.159	1.443	1.227
SG&A ratio	Mean	0.239	0.095	0.218	0.211	0.352	0.173	0.374
	Median	0.204	0.071	0.198	0.214	0.331	0.147	0.332
Goodwill	Mean	0.111	0.065	0.107	0.095	0.152	0.154	0.085
	Median	0.041	0.015	0.041	0.012	0.096	0.101	0.006
P/B	Mean	4.400	2.841	3.291	6.300	5.788	3.105	5.309
	Median	2.434	2.001	2.226	2.419	3.104	2.288	3.125
P/E	Mean	28.47	19.43	18.09	27.03	25.51	28.09	48.24
	Median	18.17	14.63	14.79	18.33	22.08	17.54	24.48
SUE	Mean	-45.67	-8.647	-53.27	-62.14	-56.90	-34.80	-59.06
	Median	-3.094	-2.062	-2.660	-4.052	-3.784	-2.795	-3.390
CAR	Mean	-0.075	-0.054	-0.061	-0.065	-0.080	-0.076	-0.103
	Median	-0.053	-0.039	-0.051	-0.048	-0.061	-0.050	-0.079
CAR/SUE	Mean	0.087	0.068	0.034	0.035	0.100	0.056	0.219
	Median	0.015	0.017	0.014	0.009	0.014	0.016	0.019

* *except financials and utilities*

Source: Author

Mixing together such inhomogeneous groups would distort the results of statistical analyses and therefore conflict with the attempt of deriving meaningful conclusions from the data. For example, the healthcare industry displays high gross profit margins in comparison to other industries. Therefore, a healthcare company with a relatively low gross profit margin compared to its peers would likely appear as a company with a high gross profit margin when compared to industrials or basic materials companies. In case this exemplary company is a bad fallen angel, as would be expected according to the assumed direction of hypothesis H_3 , it would turn up in the upper ranks in the total base dataset in terms of gross profit margin, while a good fallen angel industrial company would likely be ranked in the lower percentiles due to the comparatively low gross profit margins in that industry. As a consequence, potential statistical relationships between the magnitude of the possible indicators and angel quality would rather be influenced by industry affiliation than by the quality of the single company. To mitigate this problem and account for the peculiarities of different industries, the base dataset is split into six subsets according to industry classification. Therefore, several data subsets are constructed according to ICB groups.⁴⁵⁸ With financials and utilities excluded before, the following six main groups remain:

- Basic materials (incl. oil & gas)
- Consumer goods
- Consumer services
- Healthcare
- Industrials
- Technology & Telecommunications

Table 8 shows the number of companies and negative earnings surprise events for each industry in total as well as the number of good and bad fallen angels for the angel qualities considered in this thesis. The strictest measure of angel quality, AQ13, is highlighted.

⁴⁵⁸ See FTSE International Limited/Dow Jones & Co Inc. (2008).

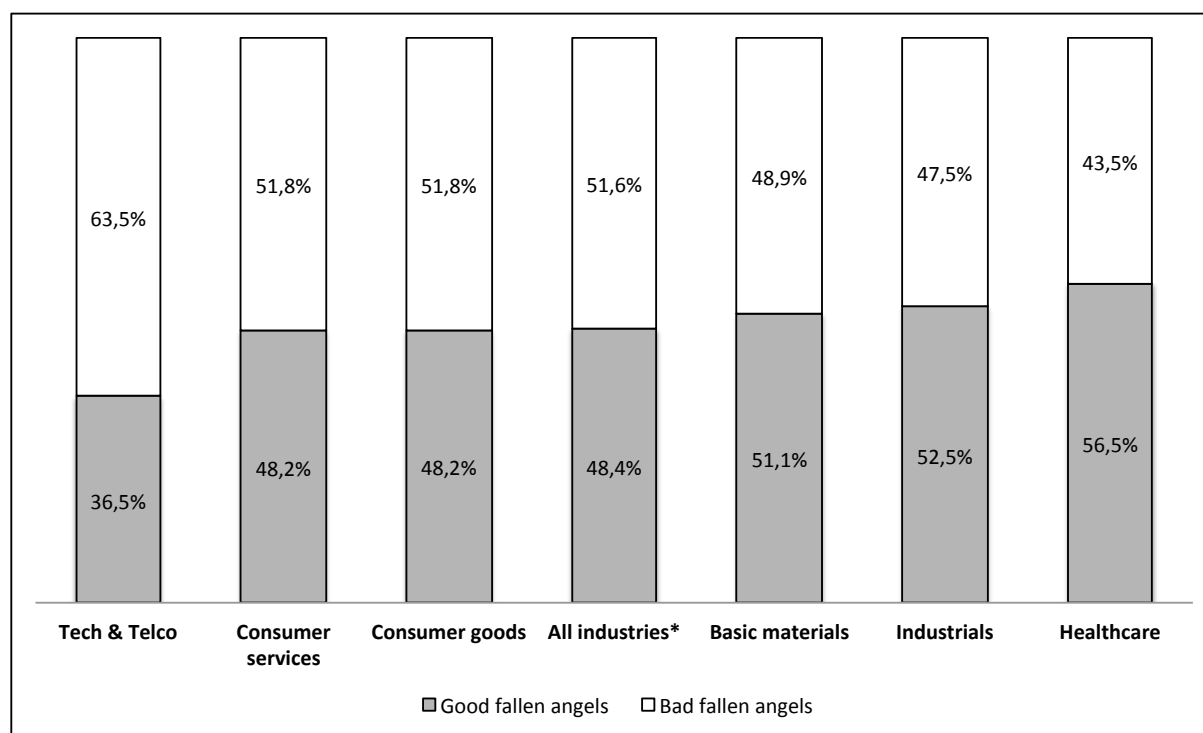
Table 8: Number of fallen angels according to angel quality and industry

Number of	All industries*	Basic materials	Consumer goods	Consumer services	Healthcare	Industrials	Technology & Telco
companies	1,641	219	200	299	210	378	335
NES	2,982	432	330	593	373	688	566
GFA ^o for	871	134	96	173	121	224	123
BFA ^{oo} AQ13	927	128	103	186	93	203	214
GFA ^o for	1,105	162	131	225	153	278	156
BFA ^{oo} AQ12	1,057	146	123	204	117	226	241
GFA ^o for	1,076	184	112	216	149	250	165
BFA ^{oo} AQ23	1,334	185	141	261	146	304	297

* *except financials and utilities* ^{o/oo} *Good/bad fallen angels*

Source: Author

The fact that the relative distribution of good and bad fallen angels differs significantly across industries (see **Figure 9**) further strengthens the case for conducting the statistical tests at an industry level rather than at the aggregate level.



* *except financials and utilities*

Figure 9: Share of good and bad fallen angels across industries for AQ13

Source: Author

6.4 Methods of Testing of Angel Quality Indicators

In general, the selection of statistical analysis methods depends on the underlying research questions and the scale of the dependent variables. With the above-mentioned goal and the binary character of the dependent variable angel quality (0 for bad and 1 for good AQ), the initial focus of the empirical analysis is placed on univariate testing of the difference-in-means of the aforementioned possible indicators for angel quality. The univariate t- and Wilcoxon rank-sum tests are then followed by a multivariate LOGIT regression analysis that also controls for company size and timing effects and a calculation of average marginal effects for each tested potential angel quality indicator.

With regard to the selection of univariate testing methods, the skewed distribution of most variables due to a relatively large number of outliers recommends the use of a non-parametric test such as the Wilcoxon rank-sum test⁴⁵⁹, which is also referred to as the Mann-Whitney U-test⁴⁶⁰. Goal of the test is to find out whether two populations are identically distributed or not. The null hypothesis assumes an identical distribution. In order to determine whether the null hypothesis can be rejected or not, the test compares one sample of size n_1 from population 1 with another sample of size n_2 from population 2. The samples can be both of equal or arbitrary size. All observations are expressed as ordinal or continuous measurements and are supposed to be independent of each other. As a first step, the Wilcoxon rank-sum test sorts all observations of both samples, i.e. in total n_1+n_2 , from the smallest to the largest value. Secondly, each observation is assigned a rank starting with 1 for the smallest to n_1+n_2 for the largest value. In case there is a tie between two or more observations, the average of the ranks for those observations is assigned as the rank to all of those observations. Thirdly, the expected value for each sample under the assumption that the two samples display identical distributions is calculated as follows: $n_1/(n_1+n_2)$ respectively $n_2/(n_1+n_2)$ times the total sum of all ranks. As a fourth step, the actual sum of all rank numbers is computed for each of the two samples. The fifth and final step is comparing the actual and expected rank sums for each sample. If actual and expected values are not statistically different from each other the null hypothesis cannot be rejected. This means that the distribution of the sum of the ranks only depends on the number of the observations in the respective sample and not on the shape of the population distribution. If there are significant differences between actual and expected values of

⁴⁵⁹ See Wilcoxon (1945).

⁴⁶⁰ See Mann/Whitney (1947).

each sample the populations are not equally distributed and the null hypothesis can be rejected.⁴⁶¹

In addition to the Wilcoxon rank-sum test, a standard two-tiered t-test on the equality of means was performed to test the null hypothesis that the means of tested variables for the groups of good and bad fallen angels are equal.⁴⁶² In order to take care of outliers, data was winsorized at a 1 percent level.⁴⁶³

With regard to multivariate analysis, a LOGIT regression was performed for each possible angel quality indicator for each selected industry in order to test all hypotheses more rigorously.⁴⁶⁴ The model for the logistic regression is as follows:

$$y_{it} = \beta_0 + \beta_1 VAR + \beta_2 \log SALES_{it} + \beta_n YEAR_n + \varepsilon_{it}$$

The dependent variable y_{it} is the angel quality of firm i at the time of the NES t . It is dichotomous and can either have the value 0 for a bad fallen angel or 1 for a good fallen angel. VAR represents the tested independent variable, i.e. the possible indicator for angel quality. The first control variable is company size, which is measured by the log of sales of company i at time t . The second factor the model controls for is time. This is measured by the variable $YEAR_n$, with n representing each year between 1996 and 2009.

Apart from the statistical significance that is measured by the respective t- or z- statistics, average marginal effects were calculated to gauge the economic importance of variations of the respective independent variables.⁴⁶⁵ Marginal effects for LOGIT models can be interpreted as the change of the predicted probability of a positive outcome of the dependent variable in reaction to a change in the underlying

⁴⁶¹ See Wilcoxon (1945) and Mann/Whitney (1947) .

⁴⁶² See Park (2003) for further information on the t-test on the equality of means.

⁴⁶³ See, for example, Chernobai/Rachev (2006), for a discussion of the advantages of winsorizing over trimming of data.

⁴⁶⁴ A Logit regression is very similar to a Probit regression. Although both models differ in terms of their underlying distribution functions, they both arrive at very similar results. See Stock/Watson (2007), pp. 394-396. Therefore, this thesis used only one of these two methods for statistical testing.

⁴⁶⁵ See Bartus (2005) and Williams (2011) for a discussion of the advantages of average marginal effects in comparison to marginal effects of the mean. In terms of STATA commands, `margeff` was used, which reports partial changes caused by unit changes, while the `margins` command reports the effects of marginal changes. Differences in coefficient and standard error values between the two commands are minimal. See Bartus (2005) for a more detailed discussion of the advantages of the `margeff` command.

independent variable, holding all other independent variables constant at the respective reference points.⁴⁶⁶ While marginal effects at the mean calculate the change only at the sample mean, average marginal effects do so at all observations, and the reported marginal effects are sample averages of these effects.⁴⁶⁷ In the case of continuous independent variables, which is the case for all angel quality indicators tested in this thesis, the marginal effects can be interpreted as the percentage change in the predicted probability that a fallen angel stock will be part of the group of good fallen angels in reaction to a one unit change in the tested independent variable.⁴⁶⁸ Nevertheless, this useful and intuitive interpretation will not always be accurate, given the non-linear trend of LOGIT regression graphs. Although the calculation of average marginal effects is supposed to mitigate the problem that marginal effects at a specific point of the regression function will likely differ from the reported marginal effects, there is still no guarantee that this will be so in any specific case.⁴⁶⁹ Therefore, marginal effects for LOGIT regression functions should always be interpreted with caution. While marginal effects are helpful in evaluating the probability that a certain fallen angel stock will become a good fallen angel, they should not be the sole basis of an investment decision.

6.5 Test Results for Angel Quality Indicators

The structure of the following depiction of the results of the aforementioned statistical tests follows the one provided in the previous chapter. Firstly, the influence of financial stability on angel quality is analyzed, followed by profitability, cash flow, cost structure, mergers and acquisitions activity, valuation, and negative earnings surprise-related information.

6.5.1 Financial Stability Ratios

6.5.1.1 Current Ratio

The first hypothesis concerning financial stability addresses the short-term financial stability of a company. H_1 claims that a higher current ratio represents a higher degree of short-term financial stability and is thus an indicator for good angel quality.

⁴⁶⁶ See Park (2010), pp. 7 et seq.

⁴⁶⁷ See Bartus (2005), pp. 320 et seq.

⁴⁶⁸ See Bartus (2005), p. 321, and Park (2010), p. 8.

⁴⁶⁹ See Williams (2011), p. 8.

Univariate test results, however, point towards the opposite direction. For all industries except consumer services, test statistics are significant at a 99 percent level, but demonstrate that a lower current ratio is associated with a higher probability of becoming a good fallen angel (see **Table 9**).

Table 9: Short-term liquidity as measured by current ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	127	119	1.624	2.074	1.404	1.685	3.311***	3.340***
Consumer goods	90	96	2.177	3.031	1.973	2.667	3.123***	3.466***
Consumer services	161	175	1.669	1.925	1.573	1.542	0.863	1.910*
Health-care	112	81	3.300	4.750	2.286	3.454	3.575***	3.461***
Industrials	213	192	1.878	2.724	1.736	1.970	4.280***	5.431***
Tech & Telco	107	202	2.748	5.815	2.671	2.995	2.785***	3.635***
^{°/°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				† winsorized at 1% level	

Source: Author

These results are confirmed by the LOGIT regression (see **Table 10**), though at slightly lower significance levels for most industries. Again except for consumer services, a low current ratio appears to be a statistically significant indicator for good angel quality.

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case the current ratio goes up by one. They are strongest for industrials with a change of -8.7 percent, followed by technology & telecommunication companies with -7.3 percent. Consumer goods and basic materials follow closely with -7.0 respectively -6.7 percent. For healthcare companies, marginal effects are markedly lower at -3.7 percent. Consumer services trail the other industries with -1.6 percent (see **Table 10**).

Table 10: Short-term liquidity as measured by current ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Indus-trials	Tech & Telco
Current ratio	-0.482** (-2.25) [-0.067]	-0.396** (-2.14) [-0.070]	-0.100 (-0.73) [-0.016]	-0.183** (-2.18) [-0.037]	-0.483*** (-3.60) [-0.087]	-0.359*** (-3.87) [-0.073]
Control size	-0.064 (-0.49)	-0.156 (-1.07)	-0.23 (-0.24)	0.105 (0.88)	0.078 (0.77)	-0.211** (-2.37)
Control time	YES	YES	YES	YES	YES	YES
Constant	2.213 (1.13)	2.631 (1.10)	-17.717*** (< -10) [†]	1.026 (0.54)	-1.120 (-0.73)	5.815*** (3.59)
Observations	224	162	317	169	375	285
McFadden's Pseudo-R ²	0.362	0.237	0.298	0.142	0.214	0.108

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of these seemingly counterintuitive results leads to the importance of operational efficiency. Having a high current ratio could not only be seen as a safety cushion, but also as an indication for operational inefficiency and bad working capital management. If a company has an unnecessarily high amount of cash, inventory, or accounts receivables on its balance sheet, while at the same time having negotiated payment terms with suppliers too leniently or paying its accounts receivables too quickly, its operational management would simply be worse compared to the one of a company with a lower current ratio. Additionally, a high current ratio could also point towards a structurally worse business model, which requires a high amount of net working capital. These effects appear to more than offset the increased short-term financial stability that was assumed to go along with a higher current ratio. Furthermore, sufficient short-term financial stability does not necessarily require a higher amount of current assets that allegedly can be liquidated short-term, but can also be achieved by having large enough credit lines or other asset-based financing instruments in place.

This explanatory approach is also consistent with the differences between industries. Particularly for industrial, consumer goods, and basic materials companies efficient

production processes that swiftly turn raw materials into semi-finished and finished goods and thus keep working capital needs low are of great importance. The same holds true for a significant part of the technology & telecommunications industry subset, where companies such as computer equipment manufacturers additionally face the risk of write-offs if their inventories are oversized and have to be written down once technological progress has made them obsolete. All these issues are of less concern for healthcare and consumer service companies, thus explaining their lower marginal effects. With regard to the consumer services industry, weak results might also be attributable to the significant influence of media and travel & leisure companies within that industry class. Net working capital is generally not a key topic in these industries, as the focus lies on fixed assets or fixed costs. For example, it is much more important for a hotel or restaurant company to get its beds or tables filled than to excel in working capital management. The same is true for a newspaper or television company with its high fixed cost base in terms of personnel and infrastructure. The other sub-group making up the consumer service industry class is retail, in which excellence in working capital management should play a role. This could also explain why the results for consumer service companies lean towards the general tendency for other industries as well, but only with significance in the t-test and comparatively low marginal effects.

6.5.1.2 Equity Ratio

The second hypothesis concerning financial stability ratios, H_2 , states that a higher equity ratio indicates long-term financial stability and is thus an indicator for good angel quality.

Like with H_1 regarding the current ratio, univariate tests do not support this statement. Instead, they point towards a lower equity ratio as an indicator for good angel quality, though generally not with statistical significance. The only exception is industrials for which both univariate tests are significant at a 95 (Wilcoxon rank-sum test) respectively 99 (t-test) percent level pointing against the hypothesized direction. Consequently, test results indicate that industrial companies with a lower equity ratio are more likely to become good fallen angels than fallen angels with a higher equity ratio. The same is true for basic materials and technology & telecommunications companies, although for these two industry groups only the t-tests are significant at a 90 percent level, whereas the Wilcoxon rank-sum tests are insignificant (see **Table 11**).

Table 11: Capital structure as reflected by equity ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	120	107	0.360	0.425	0.383	0.416	1.126	1.779*
Consumer goods	78	87	0.491	0.506	0.506	0.464	0.026	0.374
Consumer services	123	138	0.500	0.520	0.505	0.533	0.384	0.814
Health-care	98	75	0.583	0.604	0.561	0.591	0.646	0.695
Industrials	180	169	0.441	0.501	0.451	0.471	2.477**	3.279***
Tech & Telco	91	172	0.612	0.659	0.654	0.676	1.498	1.849*
^{°/°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

The LOGIT regression results show a slightly different picture. Firstly, the significant result for industrials is repeated, though at a significance level of only 90 percent, thereby confirming the direction indicated by univariate tests. Secondly, technology & telecommunications receives a significant result at a 95 percent level, stating that a low equity ratio is an indicator for good angel quality within that industry, thereby strengthening the results of the univariate tests. Thirdly, results for all other industries, including basic materials, are insignificant (see **Table 12**).

With regard to economic importance, marginal effects show the percentage change in probability that a fallen angel stock is part of the group of good fallen angels in case the equity ratio goes up by one. To put these percentages in perspective, an increase of the equity ratio by one is practically not possible, as the equity ratio can only reach a maximum value of one. Therefore, real marginal effects will be lower depending on the change of the equity ratio as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Nevertheless, the values for the marginal effects demonstrate the difference of economic importance across the various industries. They are strongest for technology & telecommunication companies with a change of -43.3 percent, followed by industrials with -32.3 percent. Healthcare companies come next in terms of absolute value, though with marginal effects in the opposite direction of 23.9 percent. Markedly lower are the values for consumer services with 8.3 percent, basic materials with -3.6 percent, and consumer goods with 0.5 percent (see **Table 12**).

Table 12: Capital structure as reflected by equity ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Equity ratio	-0.251 (-0.42) [-0.036]	0.027 (0.02) [0.005]	0.521 (0.56) [0.083]	1.158 (0.92) [0.239]	-1.778* (-1.95) [-0.323]	-2.035** (-2.49) [-0.433]
Control size	0.027 (0.21)	-0.018 (-0.09)	0.011 (0.09)	0.310** (2.42)	0.147 (1.25)	-0.100 (-1.07)
Control time	YES	YES	YES	YES	YES	YES
Constant	-0.284 (-0.16)	2.027 (0.60)	-18.683*** (< -10) [†]	-4.851** (-2.11)	-2.513 (-1.30)	2.943* (1.76)
Observations	210	143	245	152	322	241
McFadden's Pseudo-R ²	0.347	0.234	0.294	0.120	0.210	0.073

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

When interpreting the results for technology & telecommunication as well as industrial companies, which point towards a lower equity ratio as an indicator for good angel quality, referring to the disciplining effect of debt theory offers help.⁴⁷⁰ It states that the management of a company with higher debt levels focuses much more on keeping its operations lean and refrain from pursuing costly “nice-to-have” projects or “empire building” via aggressive acquisitions. Therefore, such companies are much more concentrated on activities that really matter for the business and do not waste resources on non-value creating issues. Applying this theory to fallen angels, it would mean that fallen angels abstain from acquisitions to externally stimulate the slowed-down growth. Particularly for the technology & telecommunications industry, where M&A activities take place frequently, this explanation appears plausible. Furthermore, fallen angels that were more efficient as a result of disciplining higher debt levels when the negative earnings surprise had to be announced, are better prepared to react and correct the negative developments having caused the earnings shortfall. It is more likely that such companies will quickly take action even if this encompasses drastic measures. The reason why they are more likely to do so than companies with a more comfortable

⁴⁷⁰ See Jensen (1986) and Jensen (1989), pp. 41-44.

equity cushion is firstly that they simply do not have an alternative. Given their tighter financial situation, they have to rely more on their own inherent strength to generate sufficient capital for their operations. Secondly, it could also be that taking swift action and being thrifty has already been instilled in their culture given their past as a company with rather tight financial resources. On the contrary, companies with a higher equity ratio might be more complacent and therefore less willing to take action against the negative earnings development. A slower reaction on the negative earnings surprise would likely cause further negative news in the future and disappoint the investment community again. Additionally, they might also have less experience with alternative funding sources outside external equity funding, which can put them under severe funding pressure leading to a further decline in their stock price. Such a negative downward spiral would likely earmark these companies as bad fallen angels.

As the disciplining effect of debt theory can indeed explain why a more debt-financed fallen angel is more likely to turn into a good fallen angel, this still leaves the question unanswered why this is not the case for the majority of industries. According to the theory, the disciplining effect of debt is working across any company. So why do only technology & telecommunication and industrials companies show this relationship? With regard to industrials, many sectors in this industry, for example construction & materials, electronic & electrical equipment, or industrial transportation are of a cyclical nature and therefore experience relatively strong fluctuations in demand. In comparison to other more stable industries such as healthcare or consumer-oriented segments, a negative earnings surprise will more likely be caused by a general drop in demand rather than by a company-specific event. Companies that are more agile and command more efficient operations will be quicker in reacting to such fluctuating demand levels and thus be faster in emerging out of the trough. Logically, such companies are more likely to be rewarded by the stock market and become good fallen angels. For technology and telecommunication companies, the same argument holds. Technology hardware and software companies as well as office and telecommunications or semiconductor companies, which generate a sizeable part of their revenues with other businesses and make up for almost 80 percent of the companies in this industry sample, do suffer from economic downturns caused by IT budget cuts and the consequent delay of IT investments. Furthermore, the dynamic force of technological change might play a role. A more efficient company should be better prepared for the imponderabilities of technology shifts. A formerly well-performing technology company can very quickly find itself in a difficult condition if it misses one or more important technological trends. The changing fortunes of

companies like Apple or Nokia serve as good examples here. In this case it is surely helpful if the company is able to react quickly and is clearly focused on rebuilding the core of its business. The fact that the industry group technology & telecommunication has the relatively highest share of bad fallen angel highlights the risk of becoming a victim of such disadvantageous shifts in technology, which often can only be countered by fairly radical changes.

Lastly, the comparatively high result with regard to marginal effects for healthcare companies needs some explanation. Though insignificant, it points towards confirmation of the hypothesis, i.e. that a higher equity ratio is an indicator for good angel quality. The indication that a higher equity cushion is beneficial for the angel quality of healthcare companies could lie in the long and expensive research & development cycles for its products. Particularly for pharmaceutical or biotechnology companies, it takes several years until a new drug has been developed, tested, and approved by regulatory authorities. Furthermore, this process is an “all-or-nothing game”, in which the drug is either successfully brought to market or the process has to be stopped at same stage without reaping any benefits for the company. Given the low probability of success and the high investments involved, a strong equity base is advantageous, if not essential for the long-term success of a company active in this industry.

6.5.2 Profitability Ratios

6.5.2.1 Gross Profit Margin

The first hypothesis concerning profitability ratios, H_3 , presumes that companies with a higher gross profit margin should more likely become good fallen angels than fallen angels with a lower gross profit margin.

Overall, univariate tests underpin this assumption. For consumer goods, technology & telecommunication, and basic materials companies, both Wilcoxon rank-sum and t-tests are significant at a 99 percent level. Results for healthcare companies are also significant at a 99 percent level for the t-test and at a 95 percent level for the Wilcoxon rank-sum test. While industrials show significant results for the t-test at a 95 percent level, but are insignificant for the Wilcoxon rank-sum test, neither of the univariate tests shows significance for consumer services companies (see **Table 13**).

Table 13: Gross profit margin and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	Z	t-statistic
Basic materials	126	119	0.411	0.310	0.364	0.316	-3.333***	-4.417***
Consumer goods	90	96	0.422	0.327	0.422	0.318	-4.145***	-4.679***
Consumer services	160	171	0.415	0.258	0.385	0.383	-1.067	-1.342
Health-care	108	75	0.588	0.436	0.609	0.520	-2.301**	-2.735***
Industrials	209	190	0.350	0.318	0.323	0.306	-1.573	-2.247**
Tech & Telco	106	200	0.620	0.516	0.619	0.524	-4.022***	-4.814***
^{°/°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

Univariate test results are confirmed by LOGIT regression tests. For all industries, the direction points towards confirmation of the hypothesis. Results are significant at a 99 percent level for technology & telecommunication, consumer goods, and basic materials companies, at a 95 percent level for industrials, and at a 90 percent level for healthcare. Only for consumer services, test results again show no significance (see **Table 14**).

With regard to economic importance, marginal effects show the percentage increase in probability that a fallen angel stock is part of the group of good fallen angels in case the gross profit margin goes up by one. Since an increase of the gross profit margin by one is only theoretically possible, the real marginal effects will be lower depending on the change of the gross profit margin as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Nevertheless, marginal effects appear relatively strong. Their value is highest for consumer goods with 107.6 percent, followed by technology & telecommunication companies with 68.1 percent, and basic materials with 60.8 percent. Industrials and healthcare are trailing with 35.7 percent respectively 28.5 percent. Weakest marginal effects are found for consumer services companies with 20.0 percent (see **Table 14**).

Table 14: Gross profit margin and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Gross profit margin	4.531*** (3.48) [0.608]	6.839*** (3.97) [1.076]	1.265 (1.27) [0.200]	1.377* (1.73) [0.285]	1.863** (2.04) [0.357]	3.395*** (4.23) [0.681]
Control size	0.164 (1.23)	0.029 (0.19)	-0.085 (-0.90)	0.119 (1.23)	0.227 (2.60)	-0.104 (-1.23)
Control time	YES	YES	YES	YES	YES	YES
Constant	-3.497* (-1.77)	-1.756 (-0.71)	-17.510*** (-9.35)	-2.697* (-1.65)	-5.898*** (-3.80)	0.007 (0.01)
Observations	222	165	315	160	368	273
McFadden's Pseudo-R ²	0.393	0.306	0.300	0.110	0.172	0.100

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

In accordance with these results, which are pointing to a higher gross profit margin as an indicator for angel quality, a high gross margin can be interpreted as an indication of a strong competitive position that allows a company to command higher prices for its products or services. As a consequence, a company in such a more favorable position should be able to better overcome a negative earnings surprise and thus become more likely a good fallen angel. This logic appears to hold for all analyzed industries except consumer services. Given that in this industry media companies and retailers play an important role the results appear more reasonable. Firstly, for media companies the metric gross profit margin is generally not important, since media companies usually do neither rely on reselling nor on manufacturing products involving a high input of purchased goods. Secondly, for retailers a significant part of their expenses lies in the costs of the goods sold to the consumer. However, purchase prices of many consumer goods are very competitive, thus leaving little room to make sizeable gross profit margin improvements here. Economies of scale in purchasing could make a difference, but a certain size can be assumed for all companies in the S&P 1500 to make them a good customer for any producer of consumer goods.

6.5.2.2 Return on Assets

The second hypothesis concerning profitability ratios, H_4 , addresses the ability of a company to use its asset base in order to create profits from it. The assumption is that the higher the return on assets for a company, the more likely it will become a good fallen angel.

Univariate tests support this hypothesis for all industries except basic materials. For technology & telecommunication and healthcare companies, both test results are significant at a 99 percent level. For consumer goods and consumer services, this is the case for the t-tests, while the Wilcoxon rank-sum tests are significant at a 95 percent respectively 90 percent level. For industrials, the 99 percent significance level achieved by the t-tests is not accompanied by significant results of the Wilcoxon rank-sum test, although the test statistic falls only slightly short of the 90-percent-significance-level threshold. Only with regard to basic materials, both univariate tests are insignificant (see **Table 15**).

Table 15: Return on assets and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	Z	t-statistic
Basic materials	113	108	0.056	0.048	0.047	0.057	0.324	-0.336
Consumer goods	83	86	0.089	0.062	0.076	0.065	-2.204**	-2.591***
Consumer services	145	160	0.077	0.057	0.071	0.063	-1.876*	-2.722***
Health-care	103	79	0.074	0.004	0.075	0.062	-2.667***	-3.656***
Indus-trials	194	174	0.069	0.052	0.063	0.056	-1.635	-2.867***
Tech & Telco	91	185	0.109	0.040	0.100	0.053	-5.153***	-5.694***

^{°/°°} Good/bad fallen angels *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ [†] winsorized at 1% level

Source: Author

Overall, LOGIT test results confirm the results of the univariate tests, though with slightly differing significance levels regarding the various industries. While results for technology & telecommunication, industrial, and healthcare companies are significant at a 99 percent level, test results for basic materials and consumer services are

significant at a 95 percent level. Only the test statistic for consumer goods does not quite meet the threshold for significance at a 90 percent level (see **Table 16**).

With regard to economic importance, marginal effects show the percentage increase in probability that a fallen angel stock is part of the group of good fallen angels in case ROA goes up by one. Since an increase of the ROA by one is only theoretically possible, because ROA values only very rarely exceed 100 percent, the real marginal effects will be lower depending on the change of the ROA as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Nevertheless, marginal effects appear relatively strong. They are strongest for industrials with a change of 192.5 percent, closely followed by technology & telecommunication companies with 189.1 percent and basic materials with 168.8 percent. Consumer services and healthcare companies come next with 107.3, respectively 100.6 percent. And despite scarcely missing the 90-percent significance level, marginal effects for consumer goods companies are comparatively strong at 95.6 percent (see **Table 16**).

Table 16: Return on assets and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Return on assets	12.052** (2.50) [1.688]	5.426 (1.64) [0.956]	7.008** (2.07) [1.073]	5.091*** (2.69) [1.006]	10.705*** (3.44) [1.925]	9.935*** (4.55) [1.891]
Control size	-0.027 (-0.20)	-0.021 (-0.14)	0.027 (0.25)	0.067 (0.61)	0.353*** (3.69)	0.001 (0.01)
Control time	YES	YES	YES	YES	YES	YES
Constant	-0.662 (-0.37)	1.849 (0.76)	-19.215*** (< -10) [†]	-1.472 (-0.89)	-7.958*** (-4.83)	1.070 (0.69)
Observations	205	148	287	161	340	253
McFadden's Pseudo-R ²	0.364	0.234	0.315	0.151	0.214	0.145

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

In summary, empirical evidence supports the hypothesis that a higher return on assets as an indication of management's efficiency in profitably employing the resources of the company also appears to be a good indicator for future good angel quality. This is particularly the case for industrials, technology & telecommunication, and healthcare companies, but also holds true for basic materials and consumer services. Even for consumer goods as the industry with the lowest z-value of the test statistic and lowest marginal effects, results still tend to suggest that companies which succeed in making better use of their assets to produce profits for their shareholders are also in a better position when faced with the problems that lead to or are caused by a negative earnings surprise. Thus, their likelihood to become a good fallen angel is higher.

6.5.3 Cash Flow

6.5.3.1 Free Cash Flow Margin

H₅, the first cash flow-related hypothesis, examines the free cash flow (FCF) margin of a fallen angel as an indication of the sustainable cash generation power of a company relative to its revenue base. It assumes that fallen angels with a higher free cash flow margin are more likely to turn into good fallen angels and vice versa.

Univariate tests predominantly underpin this assumption. For consumer goods, industrials, and technology & telecommunication companies both Wilcoxon rank-sum and t-tests are significant at a 99 percent level supporting the hypothesis. For healthcare, this is also the case at a 95 percent significance level for the Wilcoxon rank-sum and at a 99 percent significance level for the t-test. For basic materials companies, t-test results indicate significance at a 99 percent level, while the Wilcoxon rank-sum test statistic slightly misses the 90 percent significance threshold. Only for consumer services, results are insignificant with regard to both univariate tests (see **Table 17**).

Table 17: Free cash flow margin and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	119	105	0.043	-.011	0.030	0.026	-1.617	-3.005***
Consumer goods	82	87	0.063	-.041	0.053	0.016	-4.552***	-4.500***
Consumer services	128	140	0.033	0.029	0.020	0.025	0.860	-0.069
Health-care	104	80	0.043	-.254	0.059	0.032	-2.471**	-3.416***
Industrials	190	170	0.060	0.013	0.049	0.034	-3.596***	-4.607***
Tech & Telco	95	178	0.107	0.010	0.074	0.037	-3.288***	-4.469***
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

These univariate test results are fully confirmed by the results of the LOGIT regressions. For all industries, the values of the test statistics indicate that a high free cash flow margin is related to a higher probability of becoming a good fallen angel, although the significance levels differ across industries. While the significance level is at 99 percent for industrials and technology & telecommunication companies, it is at 95 percent for consumer goods, basic materials, and healthcare companies. Only consumer service companies again fail to achieve significant results (see **Table 18**).

With regard to economic importance, marginal effects show the percentage increase in probability that a fallen angel stock is part of the group of good fallen angels in case the free cash flow ratio goes up by one. Since an increase of the FCF margin by one is practically unlikely, because the FCF margin only very rarely will take on extreme values of, for example, minus 50 or plus 50 percent, the real marginal effects will be lower depending on the change of the FCF margin as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Nevertheless, marginal effects appear relatively strong. They are strongest for industrials with a change of 174.5 percent, followed by consumer goods with 148.4 percent. Technology & telecommunication companies come next with 110.3 percent before basic materials companies with 78.2 percent. Only for healthcare and consumer services companies marginal effects are comparatively low at 36.1 and 33.0 percent (see **Table 18**).

Table 18: Free cash flow margin and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Free cash flow margin	5.986** (2.44) [0.782]	9.228** (2.58) [1.484]	2.039 (0.94) [0.330]	1.762** (2.10) [0.361]	10.033*** (4.36) [1.745]	5.490*** (4.22) [1.103]
Control size	-0.068 (-0.51)	-0.055 (-0.36)	-0.023 (-0.21)	0.002 (0.02)	0.229** (2.38)	-0.055 (-0.59)
Control time	YES	YES	YES	YES	YES	YES
Constant	1.865 (0.94)	1.732 (0.73)	-17.957*** (-9.14)	0.167 (0.11)	-4.112*** (-2.83)	-0.183 (-0.13)
Observations	204	149	250	163	332	252
McFadden's Pseudo-R ²	0.391	0.292	0.283	0.130	0.236	0.117

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of these results is similar for all industries except consumer services. The underlying assumption behind the hypothesis that a more cash-generating company should be more able to act against the disadvantageous factors having caused the negative earnings surprise appears to be correct. With regard to consumer services companies, where no such relationship could be found, it is important to note that capital expenditures are included in the free cash flow as a cash drain and the consumer services industry is strongly influenced by retail and leisure companies such as hotels or restaurants. In case a retailer or leisure company is successful, it will be able to grow mainly by expanding its existing network of locations, such as shops, restaurants, or hotels. In order to benefit from its current popularity and to maintain and extend its competitive advantage, such an expansion must take place rather quickly. In any case, increasing the number of locations usually requires a substantial investment in fixed assets and also working capital, thus decreasing free cash flow. Since the connection between sales and the number of locations is not near as close for all other industries, it is comprehensible that the free cash flow margin does not appear to be a good angel quality indicator for consumer service companies.

Furthermore, it is not surprising that marginal effects are strongest for industrial and consumer goods companies. Both industries tend to have large fixed asset bases that have to be replaced in regular intervals, resulting in significant ongoing capital expenditures. Minimizing these expenditures by using existing capacity effectively and replacing outdated assets efficiently is essential for success of these companies, and a sign that they are well managed. This logic also holds for parts of the technology & telecommunication companies, namely for telecom network operators or computer hardware and office equipment producers, but less so for software companies, which explains the slightly weaker marginal effects in comparison to industrials and consumer goods companies. A similar pattern can be detected for the basic materials industry, where all companies command a large asset base, but assets in place such as oil or mining production facilities do not have to be replaced as frequently as in other industries, thus making capital expenditures to sustain operations less important. This is even more so for healthcare companies, where R&D and SG&A expenses are of higher importance compared to capital expenditures.

6.5.3.2 Cash Flow from Operating Activities-to-Net Income Ratio

The second cash flow-related hypothesis, H_6 , analyzes the cash flow from operating activities-to-net income ratio. This ratio is an indication of earnings quality⁴⁷¹ and a low CFO-to-net income ratio is regarded as a negative sign for future profitability and returns.⁴⁷² Consequently, the hypothesis assumes that fallen angels with a higher CFO-to-net income ratio are more likely to turn into good fallen angels and vice versa.

Univariate tests point towards confirmation of this logic. Both Wilcoxon rank-sum and t-tests are significant at a 99 percent level for industrials, consumer goods, and basic materials companies. Results for technology & telecommunications companies show significance at a 95 percent level for the Wilcoxon rank-sum and at a 99 percent level for the t-test. For healthcare companies, both tests are significant at a 95 percent level. Only for consumer services companies, the Wilcoxon rank-sum test shows insignificant results, although the t-test demonstrates significance at a 95 percent level (see **Table 19**).

⁴⁷¹ See Albrecht et al. (2007), pp. 687 et seq.

⁴⁷² See Sloan (1996).

Table 19: Cash flow from operating activities-to-net income ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	119	105	2.235	1.238	1.867	1.427	-2.629***	-2.876***
Consumer goods	80	87	1.861	0.438	1.495	1.092	-3.614***	-3.300***
Consumer services	128	143	1.750	1.188	1.626	1.652	-0.348	-2.439**
Health-care	105	80	1.324	0.900	1.281	1.032	-2.458**	-2.380**
Industrials	191	171	1.865	-0.808	1.645	1.188	-4.930***	-5.266***
Tech & Telco	92	178	1.469	0.486	1.331	1.157	-2.258**	-3.449***
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

LOGIT regressions confirm these findings with significant results for all industries pointing towards confirmation of the hypothesis, i.e. a higher CFO-to-net income ratio as an indicator for good angel quality. Test results are significant at a 99 percent level for all industries except healthcare, where the significance level is 95 percent (see **Table 20**).

With regard to economic importance, marginal effects show the percentage increase in probability that a fallen angel stock is part of the group of good fallen angels in case the CFO-to-net income ratio goes up by one. They are strongest for healthcare companies with a change of 11.1 percent, followed by consumer goods with 9.3 percent. Thereafter, industrials and technology & telecommunication companies show marginal effects of 7.9 percent and 7.7 percent. Basic materials and consumer services companies trail the other industries with 5.0 percent respectively 4.6 percent (see **Table 20**).

Table 20: Cash flow from operating activities-to-net income ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
CFO/NI ratio	0.390*** (2.76) [0.050]	0.609*** (2.65) [0.093]	0.297*** (2.71) [0.046]	0.543** (2.11) [0.111]	0.452*** (3.71) [0.079]	0.382*** (3.44) [0.077]
Control size	-0.162 (-1.23)	-0.125 (-0.83)	-0.071 (-0.70)	0.105 (1.21)	0.204** (2.18)	-0.071 (-0.80)
Control time	YES	YES	YES	YES	YES	YES
Constant	2.589 (1.35)	2.610 (1.11)	-17.772*** (< -10) [†]	-1.752 (-1.36)	-4.116*** (-2.95)	0.703 (0.50)
Observations	205	144	251	162	335	247
McFadden's Pseudo-R ²	0.404	0.325	0.307	0.125	0.234	0.115

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The explanation of these results is rooted in the higher robustness of cash flow figures against management influence as compared to earnings numbers. Since net income is subject to accounting policies and thus to the extent of setting up or dissolving accruals, and cash flow from operations cannot be influenced by management in such a way, it is assumed that a high cash flow from operations relative to net income indicates a higher earnings quality of the company. Consequently, a company with a higher earnings quality should be more likely in a position to become a good fallen angel than a company with a relatively weak cash flow from operations relative to its net income. This reasoning is supported by empirical results across all industries.

6.5.4 Cost Structure: Selling, General & Administrative Expenses Ratio

The general assumption regarding cost structure is that a leaner, more efficient cost structure, particularly in the area of selling, general & administrative (SG&A) expenses, is beneficial for the likelihood of becoming a good fallen angel. Therefore, hypothesis H₇ claims that a lower SG&A ratio is linked to a higher probability of becoming part of the group of good fallen angels and vice versa.

Univariate tests confirm this assumption only for healthcare companies with 95 percent significance for the Wilcoxon rank-sum and 90 percent significance for the t-test. With regard to consumer goods companies, test results point against the direction of the hypothesis with a 99 percent significance level for both Wilcoxon rank-sum and t-tests. For all other industries, univariate tests do not show significance (see **Table 21**).

Table 21: Sales, general and administration ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])	
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic	
Basic materials	52	63	0.098	0.093	0.073	0.068	0.146	-0.274	
Consumer goods	42	40	0.265	0.169	0.287	0.126	-2.876***	-3.238***	
Consumer services	79	75	0.217	0.206	0.214	0.213	-0.540	-0.672	
Health-care	51	48	0.316	0.390	0.292	0.366	2.289**	1.892*	
Industrials	104	96	0.176	0.169	0.140	0.153	0.247	-0.452	
Tech & Telco	60	119	0.380	0.372	0.333	0.332	0.028	-0.200	
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level		

Source: Author

LOGIT regressions confirm these results with regard to consumer goods companies. Test results indicate at a 99 percent significance level that consumer goods companies with a higher SG&A ratio are more likely to become good fallen angels. The same is true for consumer services companies at a 90 percent level. For all other industries, results are insignificant, although mostly pointing towards confirmation of the hypothesis according to the sign of the test statistic (see **Table 22**).

With regard to economic importance, marginal effects show the percentage change in probability that a fallen angel stock is part of the group of good fallen angels in case its SG&A ratio goes up by one. Since an increase of the SG&A ratio by one is only theoretically possible, the real marginal effects will be lower depending on the change of the SG&A ratio as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Marginal effects are strongest for consumer goods companies with a change of 195.7 percent, i.e. against the assumed direction of the hypothesis. The same is true,

although to a lesser extent, for consumer goods companies with 54.0 percent. The one remaining industry, where a higher SG&A ratio points towards a higher probability for becoming a good fallen angel, is industrials, but only with relatively weak marginal effects of 7.8 percent. For healthcare and basic materials companies, marginal effects of -27.3 respectively -21.8 percent show that a lower SG&A ratio is an indicator of good angel quality. For technology & telecommunication companies, the same is true with regard to the direction, but marginal effects are very weak with -1.5 percent (see **Table 22**).

Table 22: Sales, general and administration ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
SGA ratio	-1.182 (-0.31) [-0.218]	14.968*** (2.78) [1.957]	3.545* (1.81) [0.540]	-1.436 (-1.03) [-0.273]	0.389 (0.23) [0.078]	-0.069 (-0.07) [-0.015]
Control size	-0.129 (-0.68)	0.535 (1.24)	-0.005 (-0.04)	0.210 (1.26)	0.188 (1.38)	-0.087 (-0.64)
Control time	YES	YES	YES	YES	YES	YES
Constant	1.726 (0.67)	-8.860 (-1.34)	-19.066*** (< -10) [†]	-3.526 (-1.32)	-3.890* (-1.81)	0.415 (0.20)
Observations	85	59	146	86	171	162
McFadden's Pseudo-R ²	0.180	0.418	0.325	0.186	0.127	0.034

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of results differs strongly from industry to industry. The initial assumption was, that companies with a lean cost structure, and therefore lower SG&A expenses, should be in a better position to overcome the set-backs that have caused the negative earnings surprise. The significant results for consumer goods companies in the opposite direction of the hypothesis are likely connected with the high importance of advertising and marketing activities for such companies. Consumer goods companies rely on their brand recognition with consumers for winning and retaining a sufficient amount of customers. Unless consumers do not know about a company and its brands, they will neither buy its products directly from the company nor, and

usually more important, will they buy it off the shelves of retailers. Furthermore, brands weakened by low advertising spending will also find it hard to be allowed by retailers to occupy scarce shelf space. As a consequence, consumer goods companies rely heavily on sufficient marketing activities to build their brands as an essential element of their long-term success. Cutting SG&A expenses and thereby lowering the SG&A ratio is usually a short-term measure of last resort and therefore more a sign of weakness rather than strength. This explains why good fallen angels in the consumer goods industry are more likely to be found among companies with a higher SG&A ratio. The same logic applies for consumer services companies, thus also explaining the results in opposite direction of the hypothesis for this industry. The strength of this effect, however, is weaker, which is also comprehensible given the relatively lower importance of marketing expenses for consumer services companies like media firms, restaurants, hotels, or retailers with their frequent direct contact to the consumer.

For other industries with comparatively strong marginal effects supporting the hypothesis, i.e. healthcare and basic materials companies, the reasoning is different. For healthcare companies, research and development activities are of high importance. A lean cost structure with regard to SG&A expenses leaves a company more room to step up or at least avoid cutting R&D spending, which is important for the medium- to long-term success particularly of a healthcare company. For basic materials companies, marketing and advertising generally plays a less important role, as products are often standardized and prices are – at least for parts of the product range – fixed on commodity markets. Thus, operational efficiency as indicated by a low SG&A ratio becomes more important.

6.5.5 Mergers & Acquisition Activities: Goodwill Ratio

H₈, the hypothesis concerning mergers & acquisition activities of a fallen angel, claims that a lower goodwill ratio is an indicator for good angel quality.

However, univariate tests do not support this assumption. Only for technology & telecommunication companies, the Wilcoxon rank-sum test indicates significance at a 90 percent level, pointing towards the direction of the hypothesis. T-test results, though, remain insignificant. This is also the case for all other industries, for which both univariate tests show no significance (see **Table 23**).

Table 23: Goodwill ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	120	113	0.061	0.068	0.014	0.017	0.371	0.588
Consumer goods	86	91	0.119	0.096	0.057	0.032	-1.030	-0.974
Consumer services	154	168	0.085	0.104	0.012	0.013	0.818	1.131
Health-care	109	83	0.162	0.138	0.121	0.060	-0.951	-0.944
Industrials	201	183	0.153	0.156	0.112	0.090	-0.086	0.264
Tech & Telco	101	191	0.069	0.094	0.000	0.013	1.725*	1.315
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

LOGIT regression results are also insignificant for most industries, but show a slightly different result. For basic materials companies, results are significant at a 95 percent level, indicating that a lower goodwill ratio is associated with a higher probability for good angel quality, i.e. pointing towards confirmation of the hypothesis. For all other industries, including technology & telecommunication companies, LOGIT regression results are insignificant (see **Table 24**).

With regard to economic importance, marginal effects show the percentage change in probability that a fallen angel stock is part of the group of good fallen angels in case its goodwill ratio goes up by one. To put these percentages in perspective, a change of the goodwill ratio by one is not possible, as the goodwill ratio can only reach a maximum value of one, which itself is only a theoretical value. Therefore, real marginal effects will be lower depending on the change of the goodwill ratio as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. The industry with the strongest marginal effects is basic materials with a change of -65.1 percent. Consumer services, industrial, and technology & telecommunication companies follow with -13.9 percent, -12.2 percent, and -11.3 percent. Marginal effects for consumer goods and healthcare companies show an opposite sign, but are relatively weak with 11.9 percent and 9.2 percent (see **Table 24**).

Table 24: Goodwill ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Goodwill ratio	-4.501** (-2.21) [-0.651]	0.641 (0.47) [0.119]	-0.903 (-0.88) [-0.139]	0.436 (0.39) [0.092]	-0.656 (-0.87) [-0.122]	-0.513 (-0.50) [-0.113]
Control size	0.135 (1.05)	0.026 (0.18)	0.023 (0.22)	0.195** (2.06)	0.310*** (3.44)	-0.018 (-0.23)
Control time	YES	YES	YES	YES	YES	YES
Constant	-0.619 (-0.33)	-1.308 (-0.63)	-18.420*** (-9.53)	-2.743** (-1.99)	-5.261*** (-3.80)	0.438 (0.38)
Observations	216	156	304	170	355	269
McFadden's Pseudo-R ²	0.347	0.205	0.311	0.104	0.190	0.049

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of these results leads to the conclusion that except for basic materials companies, the relative amount of goodwill is not a suitable indicator for angel quality. The underlying assumption that companies with a large amount of goodwill on their balance sheets are probably bad acquirers and thus also bad fallen angels, because the high amount of goodwill might serve as an indication of having overpaid, cannot be confirmed. It seems like that the success of an M&A strategy depends on specific acquisitive qualities of a fallen angel company, and that the goodwill ratio is not a suitable indicator for identifying good and bad acquirers. A possible explanation for the significant LOGIT regression results for basic materials companies is that acquisition values in this industry should be predominantly based on "hard" assets, like proven reserves of oil, gas, or other raw materials, or aluminum or steel manufacturing plants. Thus, if a fallen angel pays a significant amount of goodwill in a basic materials transaction, it appears reasonable to assume that the acquisition price could have been too high. Since this argument does not hold for all other industries, where the motives behind an acquisition and the values inherent in the acquisition target are generally more diverse, it appears to be a suitable reasoning for the significant test results for basic materials companies.

6.5.6 Valuation Ratios

6.5.6.1 Price-to-Book Ratio

The first hypothesis concerning valuation ratios, H_9 , presumes that companies with a low price-to-book ratio should more likely become good fallen angels and vice versa. As described earlier, the price-to-book ratio is a widely used criterion to separate value from growth stocks.⁴⁷³ Therefore, testing the hypothesis that a low price-to-book ratio as a typical attribute of a value stock is a suitable indicator for the good quality of a fallen angel (aka growth) stock almost suggests itself given that this thesis aims at bringing value and growth investment styles closer together.

Univariate test results largely support this hypothesis. For industrials, both univariate tests are significant at a 99 percent level. The same is true for the Wilcoxon rank-sum tests for healthcare and technology & telecommunication companies, whose t-tests indicate significance at a 95 percent level. For basic materials companies, both tests are significant at levels of 99 percent (Wilcoxon rank-sum test) and 90 percent (t-test). For consumer services, the t-test shows significance at a 99 percent level, while the Wilcoxon rank-sum test is insignificant. The latter is also the case for consumer goods, with the t-test indicating significance at a 95 percent level (see **Table 25**).

Table 25: Price-to-book ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test) [†]
	GFA ^{°°}	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	127	113	2.529	3.191	1.821	2.180	2.927***	1.779*
Consumer goods	85	96	2.325	4.147	2.256	2.224	1.586	2.299**
Consumer services	134	148	2.703	9.557	2.340	2.506	1.629	2.585***
Health-care	111	86	3.320	8.974	2.928	3.422	2.467**	2.879***
Industrials	200	186	2.298	3.972	2.102	2.441	2.923***	4.110***
Tech & Telco	102	189	3.463	6.306	2.974	3.231	2.062**	3.056***
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level	

Source: Author

⁴⁷³ See Rosenberg/Reid/Lanstein (1985), Fama/French (1992), or Lakonishok/Shleifer/Vishny (1994).

Significance is confirmed by LOGIT regression tests at a 99 percent level for industrials, technology & telecommunication, and consumer services companies. For the other three industries, test results also point toward confirmation of the hypothesis, but with no statistical significance. For healthcare and basic materials companies, though, test statistics fall only slightly short of meeting the 90-percent significance level thresholds (see **Table 26**).

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case its price-to-book ratio goes up by one. They are strongest for industrials with a change of -5.8 percent, followed by consumer services and technology & telecommunication companies with -3.5 percent respectively -3.2 percent. Healthcare and consumer goods companies ensue with -2.6 percent respectively -2.2 percent. Basic materials companies trail with -1.0 percent (see **Table 26**).

Table 26: Price-to-book ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Indus-trials	Tech & Telco
Price-to-book ratio	-0.073 (-1.53) [-0.010]	-0.131 (-1.10) [-0.022]	-0.229*** (-2.74) [-0.035]	-0.126 (-1.62) [-0.026]	-0.336*** (-3.77) [-0.058]	-0.157*** (-2.93) [-0.032]
Control size	-0.048 (-0.39)	-0.098 (-0.73)	-0.023 (-0.22)	0.147* (1.70)	0.186** (2.06)	-0.090 (-1.05)
Control time	YES	YES	YES	YES	YES	YES
Constant	1.577 (0.84)	3.525 (1.58)	-17.190*** (< -10) [†]	-1.536 (-1.17)	-2.709** (-2.01)	2.427* (1.90)
Observations	221	157	267	171	355	269
McFadden's Pseudo-R ²	0.375	0.254	0.314	0.121	0.241	0.109

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of the results is based on the underlying assumption that investors on average achieve positive returns when they “buy the dollar for 60 cents”⁴⁷⁴, i.e. aim for the lowest price-to-book ratio possible. This assumption is confirmed given the fact that test statistics across all tested industries point in this direction. However, industry-specific differences in significance levels are substantial. One possible explanation for the 99 percent significance level of results for consumer services, industrials, and technology & telecommunication companies could be the differing importance of intangible assets that are not recorded on the balance sheet across the various industries. This position should be particularly important for basic materials companies with regard to their amount of proven reserves⁴⁷⁵, for consumer goods firms in terms of brand equity, and for healthcare companies in terms of their drug patent and research pipeline.⁴⁷⁶ Although the value of these assets is not visible on the balance sheet, it will likely be recognized by financial markets, thus boosting the respective company’s market value without a corresponding increase in book value of equity. Thus, price-to-book ratios are distorted in such instances, making them less usable as angel quality indicators. This problem is less acute for companies with a lower share of assets that are unrecognized in the balance sheet. For consumer services and industrials companies, unrecognized intangible assets should play a less important role relative to their generally high value of recognized tangible assets. With regard to the technology & telecommunication industry, the same is true for telecommunication network operators or electronics equipment manufacturers. And software companies have to capitalize certain software development costs under SFAS 86, which is an exception to the general rule of expensing R&D expenses, thereby decreasing the share of unrecognized intangible assets in their balance sheets and bringing the book

⁴⁷⁴ Browne (2007), p. 145.

⁴⁷⁵ The SEC has recognized this deficiency itself by updating their regulation with regard to accounting of proven reserves in the oil & gas industry, which is included in the industry group basic materials as used by this thesis, effective as of December 1, 2010.

See Securities and Exchange Commission (2009), p. 2158.

Furthermore, Schreiner classifies oil & gas and basic materials (the two industries grouped together as industry group basic materials as used by this thesis) as so called science-based industries that significantly depend on investments in intangible assets and R&D, which are often not properly reflected in financial statements. See Schreiner (2007), pp. 104-106.

⁴⁷⁶ A recent study by KPMG Corporate Finance Advisory of realized goodwill and intangible asset allocation of 342 selected M&A transactions showed that consumer- and life science/healthcare-oriented companies record the highest percentage of intangible assets in relation to the total purchase price. The industry group basic materials was not analyzed separately in this study. See Castedello/Klingbeil (2009), p. 15.

value of equity closer to market valuation.⁴⁷⁷ However, it should be noted that these explanations are not fully researched yet and therefore should be handled with caution.

6.5.6.2 Price-to-Earnings Ratio

The second valuation ratio analyzed is the price-to-earnings ratio. The related hypothesis, H_{10} , presumes that companies with a lower price-to-earnings ratio should more likely become good fallen angels and vice versa.

The results of univariate tests support this hypothesis for most industries. Industrials, technology & telecommunication, and consumer services companies demonstrate significance levels of 99 percent for both the Wilcoxon rank-sum and t-tests. For healthcare and basic materials companies, t-tests are significant at 95 percent respectively 90 percent, while Wilcoxon rank-sum tests are insignificant for both industries. The latter is also the case for consumer goods companies with regard to both univariate tests (see **Table 27**).

Table 27: Price-to-earnings ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])	
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic	
Basic materials	112	105	15.97	23.11	13.48	15.27	0.785	1.883 [*]	
Consumer goods	86	85	15.85	20.36	14.57	14.80	-0.056	1.400	
Consumer services	145	159	18.57	34.74	17.46	19.42	2.933 ^{***}	3.980 ^{***}	
Health-care	93	64	22.78	29.74	22.08	22.35	1.468	2.400 ^{**}	
Industrials	199	173	17.50	40.26	16.73	18.84	3.543 ^{***}	4.220 ^{***}	
Tech & Telco	88	154	23.86	62.17	21.59	28.65	3.900 ^{***}	3.218 ^{***}	
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 1% level		

Source: Author

⁴⁷⁷ See Mohd (2005) or Heinrichs (2009), p. 84.

LOGIT regression results are significant at a 99 percent level confirming the assumed direction of the hypothesis for industrials, technology & telecommunication, consumer services, and basic materials companies. For healthcare and consumer goods companies, however, no significant results are shown, though test statistics for both industries also point towards supporting the hypothesis (see **Table 28**).

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case its price-to-earnings ratio goes up by one. They are strongest for industrials with a change of -1.0 percent, followed by technology & telecommunication and consumer services companies with -0.8 percent respectively -0.7 percent. Basic materials companies ensue with -0.6 percent. Healthcare and consumer goods companies trail with -0.4 percent respectively -0.1 percent (see **Table 28**).

Table 28: Price-to-earnings ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Price-to-earnings ratio	-0.049 ^{***} (-2.87) [-0.006]	-0.006 (-0.39) [-0.001]	-0.047 ^{***} (-3.17) [-0.007]	-0.018 (-1.40) [-0.004]	-0.058 ^{***} (-4.29) [-0.010]	-0.038 ^{***} (-3.52) [-0.008]
Control size	-0.170 (-1.23)	-0.205 (-1.39)	-0.019 (-0.18)	-0.038 (-0.32)	0.159 [*] (1.70)	-0.151 (-1.54)
Control time	YES	YES	YES	YES	YES	YES
Constant	4.480 ^{**} (2.06)	5.060 ^{**} (2.11)	-16.938 ^{***} (-10) [†]	0.006 (0.00)	-3.464 ^{**} (-2.25)	3.521 ^{**} (2.27)
Observations	196	151	287	136	341	220
McFadden's Pseudo-R ²	0.441	0.258	0.367	0.106	0.252	0.155
^{***} $p < 0.01$, ^{**} $p < 0.05$, [*] $p < 0.1$; z-values in parentheses, average marginal effects in brackets. [†] If z-value is smaller than -10.0, STATA displays an empty value “.” instead of the actual z-value.						

Source: Author

The interpretation of the results for the four industries with significance at a 99 percent level pointing towards confirmation of the hypothesis is in line with mean reversion. Companies that already have a high price-to-earnings ratio, i.e. market expectations regarding their future earnings are high, are more endangered to disappoint in the future and thus are more likely to belong to the category of bad fallen angels. However, the question remains why there is no significance for consumer goods and healthcare. With regard to consumer goods, the positive brand recognition a company has with consumers is of essential importance for its current and long-term success. A strong brand helps a company by inducing a buoyant demand for its products. A company in such a position might eventually be able to charge a price premium based on its brand name. Furthermore, a strong brand is neither built up nor destroyed short-term, i.e. results in profits over more than one period. Thus, financial markets will likely assign a relatively high valuation to a successful consumer goods company with a strong brand and vice versa. Since it requires large financial clout to invest in the build-up and support of a brand, a fallen consumer goods angel that does not already possess a strong brand is likely more vulnerable to the difficulties evolving in the wake of the negative earnings surprise. With regard to healthcare companies, the explanation is similar to the one brought forward above in conjunction with the price-to-book ratio. Particularly for pharmaceutical and biotechnology companies, the research and development pipeline is very important for future success. Like a brand for consumer goods companies, a strong R&D pipeline cannot be build up in a short time, but requires continuous investment. Companies with strong R&D activities will therefore likely command a higher valuation by financial markets. At the same time, it is these companies that are more robust against temporary turbulence caused by negative earnings surprises. Therefore, the effect of having a strong brand and a strong R&D pipeline appears to work in opposite direction than the valuation effect of a relatively low share price.

6.5.7 Negative Earnings Surprise-Related Ratios

The three last possible indicators for angel quality tested in this thesis reflect the force of the negative earnings surprise and the related abnormal drop in share price. The underlying assumption builds on overreaction theory, and states that the stronger the negative earnings surprise respectively the related abnormal share price return, the more likely the company will be a good fallen angel and vice versa.

6.5.7.1 Standardized Unexpected Earnings

SUE as defined in section 2.3.1 measures the extent of the negative earnings surprise. The smaller, i.e. more negative, the value of the SUE, the stronger the negative earnings surprise. Following above-mentioned underlying assumption, a fallen angel stock will more likely be a good fallen angel stock in case the SUE is stronger, i.e. the SUE value is smaller.

The results of both univariate tests are pointing towards support of the hypothesis for most industries. For basic materials, the Wilcoxon rank-sum test is significant at a 95 percent level, and the t-test indicates significance at a 99 percent level. For both industrials and healthcare companies, significance levels are at 99 percent for the Wilcoxon rank-sum tests, whereas t-tests show significance levels of 95 percent (industrials) respectively 90 percent (healthcare). For consumer services companies, both univariate tests support the hypothesis at a 95 percent significance level. While the Wilcoxon rank-sum test is significant at a 99 percent level for technology & telecommunication companies, t-test results fail to achieve significance for this industry. The latter is also the case for consumer goods companies with regard to both univariate tests (see **Table 29**).

Table 29: Standardized unexpected earnings ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	134	128	-7.1	-10.3	-2.37	-1.73	2.371**	3.124***
Consumer goods	96	103	-45.9	-60.1	-2.87	-2.42	0.984	0.290
Consumer services	173	186	-88.6	-37.5	-4.97	-3.62	2.220**	1.992**
Health-care	121	93	-82.9	-23.0	-6.19	-2.37	3.371***	1.955*
Industrials	224	203	-46.5	-21.9	-3.45	-2.38	2.599***	2.238**
Tech & Telco	123	214	-74.7	-50.0	-4.87	-2.88	2.906***	0.734
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 5% level	

Source: Author

LOGIT regression results, however, are largely not able to confirm these results. Only for basic materials, test results are significant at a 99 percent level supporting the

direction of the hypothesis. While for all other industries the algebraic sign of the test statistic also points towards the assumed direction, test results are insignificant (see **Table 30**).

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case SUE ratio goes up by one. They are by far strongest for basic materials companies with a change of -1.7 percent. The following industries are consumer goods, healthcare, and industrials, with a change of -0.04 percent for the first two mentioned industries and of -0.02 percent for the latter. Consumer services and technology & telecommunication companies trail the other industries with -0.01 percent for both industries (see **Table 30**).

Table 30: Standardized unexpected earnings ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
SUE ratio	-0.122 ^{***} (-2.63) [-17 x 10 ⁻³]	-0.002 (-1.04) [-0.4 x 10 ⁻³]	-0.001 (-1.03) [-0.1 x 10 ⁻³]	-0.002 (-1.42) [-0.4 x 10 ⁻³]	-0.001 (-1.55) [-0.3 x 10 ⁻³]	-0.000 (-0.98) [-0.1 x 10 ⁻³]
Control size	0.058 (0.49)	-0.050 (-0.40)	-0.010 (-0.11)	0.139 [*] (1.72)	0.226 ^{***} (2.79)	-0.104 (-1.39)
Control time	YES	YES	YES	YES	YES	YES
Constant	-0.765 (-0.43)	2.043 (1.06)	-18.068 ^{***} (< -10) [†]	-1.450 (-1.23)	-5.396 ^{***} (-3.93)	1.888 [*] (1.73)
Observations	236	172	339	186	394	306
McFadden's Pseudo-R ²	0.376	0.225	0.298	0.101	0.177	0.064

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

The interpretation of these results leads to two main conclusions: Firstly, there seems to be a general tendency that stocks affected by a stronger negative earnings surprise are more likely to come back as good fallen angels, but this tendency overall lacks significance. A possible explanation for this tendency is offered by overreaction theory. Particularly in the light of strong negative earnings surprises, investors might adapt a too pessimistic view of the events surrounding the fallen angel company. The

strength of the negative earnings surprises might be due to extraordinary events, such as disruptions in production, the loss of important customers or contracts, or other severe mishaps. Although such instances may appear catastrophic at the first glance and often indeed entail severe negative economic consequences, they are also fairly often short-lived and once a company overcomes the crisis, investors' sentiment towards its stock improves again. Secondly, the significant results for basic materials companies might be attributable to the fact that their earnings often depend more on raw materials' price levels than on company-specific events or activities like marketing or product development. Raw material prices, however, are rather volatile and are strongly related to the overall economic climate, which is largely beyond the control of single companies. Thus, strong negative earnings surprises might be triggered without any company-specific problems. However, once raw material prices recover, the fallen angel's earnings would rebound as well, thus leading to an outperformance of the fallen angel stock. This logic could explain the fact that while LOGIT regression results are significant for basic materials companies, they do not indicate significance for other industries with negative earnings surprises that are more likely rooted in company-specific reasons.

6.5.7.2 Cumulative Abnormal Return

The second earnings surprise-related ratio deals with the extent of the negative cumulative abnormal return (CAR) in the five-day window around the earnings announcement. The hypothesis is based on the assumption that the more a fallen angel stock drops relative to its benchmark, the more likely this market overreaction will correct, turning the stock into a good fallen angel.

Univariate tests, however, do not support this hypothesis. Neither the Wilcoxon rank-sum nor the t-tests show any significant results. This is the case across all industries. Additionally, the algebraic signs of the test statistics indicate changing directions across the various industries (see **Table 31**).

Table 31: Cumulative abnormal return and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	134	128	-.055	-.053	-.038	-.040	-0.732	-0.329
Consumer goods	96	103	-.058	-.064	-.048	-.051	-0.579	-0.780
Consumer services	173	186	-.069	-.062	-.046	-.049	-0.442	0.950
Health-care	121	93	-.084	-.076	-.068	-.054	1.164	0.746
Industrials	224	203	-.077	-.075	-.047	-.053	-0.180	0.247
Tech & Telco	123	214	-.106	-.101	-.084	-.075	0.595	0.475
^{°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 5% level	

Source: Author

The same is true for the results of the LOGIT regression tests. The values of the test statistics remain low and are therefore clearly below the chosen significance levels at 90, 95, and 99 percent (see **Table 32**).

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case CAR goes up by one. To put the seemingly high percentages in perspective, a change of CAR by one is only theoretically possible, as that would translate into a change of 100 percentage points, like the drop of the fallen angel stock to basically zero while the market remains at least stable. Therefore, real marginal effects will be lower depending on the change of the CAR as measured in percentage points, e.g. 0.1 for a 10 percentage point increase. Marginal effects are highest for consumer goods with 62.8 percent, followed by industrial companies with 32.9 percent. For basic materials, healthcare, and consumer services companies marginal effects are negative with -17.5 percent, -15.2 percent, and -11.8 percent. Technology & telecommunication companies show almost no marginal effects with -0.2 percent (see **Table 32**).

Table 32: Cumulative abnormal return and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
Cumulative abnormal return	-1.205 (-0.42) [-0.175]	3.484 (0.95) [0.628]	-0.745 (-0.31) [-0.118]	-0.705 (-0.32) [-0.152]	1.716 (1.13) [0.329]	-0.011 (-0.01) [-0.002]
Control size	0.016 (0.14)	-0.095 (-0.73)	-0.013 (-0.14)	0.139* (1.71)	0.210*** (2.60)	-0.111 (-1.48)
Control time	YES	YES	YES	YES	YES	YES
Constant	0.300 (0.17)	0.622 (0.31)	-18.083*** (< -10) [†]	-1.476 (-1.24)	-5.049*** (-3.66)	1.980* (1.74)
Observations	236	172	339	186	394	306
McFadden's Pseudo-R ²	0.340	0.223	0.296	0.090	0.174	0.061

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

Concluding, it appears that CAR does not have significant influence on the probability of whether the fallen angel stock is of good or bad quality. Therefore, further interpreting these results does not appear to be worthwhile.

6.5.7.3 Cumulative Abnormal Return-to-Standardized Unexpected Earnings Ratio

The third and last earnings surprise-related ratio combines the two other ratios from above by dividing the cumulative abnormal return by the standardized unexpected earnings. The hypothesis states that the more strongly a fallen angel stock has dropped relative to the extent of the negative earnings surprise, the more likely this drop will correct in the future, thus creating a good fallen angel.

Univariate tests cannot find support for the hypothesis. If significant, tests indicate that a high CAR-SUE ratio is linked to a lower probability of becoming a good fallen angel stock. This is the case for healthcare companies, where the Wilcoxon rank-sum test is significant at a 99 percent level, while the t-test is significant at a 90 percent level. For basic materials, both univariate tests are significant as well at significance levels of 95 percent (Wilcoxon rank-sum test) respectively 90 percent (t-test). For consumer

services, industrials, and technology & telecommunication companies, the Wilcoxon rank-sum tests indicate significance at a 95 percent level, but all t-tests remain insignificant. The latter is also true with regard to both univariate tests for consumer goods companies (see **Table 33**).

Table 33: Cumulative abnormal return-to-standardized unexpected earnings ratio and angel quality – results of univariate tests of base dataset (AQ13) split by industries

Industry	Observations		Mean		Median		Diff. test (Wilcoxon)	Diff. test (t-test [†])
	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	GFA [°]	BFA ^{°°}	z	t-statistic
Basic materials	134	128	0.053	0.085	0.016	0.020	1.985**	1.862*
Consumer goods	96	103	0.026	0.041	0.012	0.016	1.047	1.539
Consumer services	173	186	0.031	0.039	0.007	0.011	2.284**	1.056
Health-care	121	93	0.038	0.180	0.010	0.017	2.729***	1.936*
Industrials	224	203	0.050	0.063	0.013	0.018	2.233**	0.455
Tech & Telco	123	214	0.098	0.288	0.015	0.020	2.139**	1.412
^{°/°°} Good/bad fallen angels			*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				[†] winsorized at 5% level	

Source: Author

LOGIT regression test results partially confirm the results of the univariate tests with significance at a 95 percent level pointing against the assumed direction of the hypothesis for consumer services, healthcare, and industrials companies. For the other three industries, however, results are insignificant (see **Table 34**).

With regard to economic importance, marginal effects show the percentage decrease in probability that a fallen angel stock is part of the group of good fallen angels in case the CAR-SUE ratio goes up by one. The seemingly high percentage values are put into perspective when recalling that the CAR-SUE ratio values are generally very small. As the CAR measures the cumulative abnormal return in the five-day window around the negative earnings surprise, it is usually a very small figure in absolute terms. In contrast, the SUE is generally larger in absolute terms, often reaching values of one and above. Therefore, dividing CAR by SUE (both with negative algebraic signs) leads to small absolute results. The resulting marginal effects are strongest for healthcare with -143.2 percent, followed by consumer goods and consumer services with -77.0 percent respectively -53.8 percent. Industrial and basic materials companies

ensue with -32.6 percent and -25.1 percent. Technology & telecommunication companies trail the other industries with -6.5 percent (see **Table 34**).

Table 34: Cumulative-abnormal-return-to-standardized-unexpected-earnings ratio and angel quality – results of LOGIT regression of base dataset (AQ13) split by industries

	Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telco
CAR/SUE ratio	-1.759 (-1.55) [-0.251]	-4.294 (-1.27) [-0.769]	-3.431 ** (-2.12) [-0.538]	-6.872 ** (-2.10) [-1.432]	-1.715 ** (-1.98) [-0.326]	-0.300 (-0.94) [-0.065]
Control size	-0.005 (-0.04)	-0.073 (-0.58)	-0.018 (-0.20)	0.109 (1.32)	0.223 *** (2.75)	-0.115 (-1.55)
Control time	YES	YES	YES	YES	YES	YES
Constant	0.715 (0.41)	0.295 (0.16)	-17.823 *** (< -10) [†]	-1.123 (-0.92)	-5.278 *** (-3.84)	2.193 ** (1.97)
Observations	236	172	339	186	394	306
McFadden's Pseudo-R ²	0.348	0.227	0.305	0.115	0.179	0.067

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; z-values in parentheses, average marginal effects in brackets.
[†] If z-value is smaller than -10.0, STATA displays an empty value "." instead of the actual z-value.

Source: Author

Interpreting these results with regard to possible explanations for them does not appear to be a promising attempt. As the CAR-SUE ratio is both driven by the strength of the reaction of financial markets to and the extent of the negative earnings surprise at the same time, the reasons for a relatively low or high CAR-SUE ratio can be very complex. Therefore, speculating about a possible reason does not appear to be a worthwhile endeavor.

6.5.8 Summary of Results of Empirical Tests

Summing up, statistical tests show differentiated results across the various possible indicators and industries. The following table displays a summary of the findings.

Table 35: Summary of empirical test results of possible indicators for angel quality for the base dataset (AQ13) split by industries

Indicator		Influence on good fallen angel probability (AQ13=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	–**	–**	–	–**	–***	–***
	av. marg. eff.	[-0.067]	[-0.070]	[-0.016]	[-0.037]	[-0.087]	[-0.073]
Equity ratio	stat. signific.	–	+	+	+	–*	–**
	av. marg. eff.	[-0.036]	[0.005]	[0.083]	[0.239]	[-0.323]	[-0.433]
Gross profit margin	stat. signific.	+***	+***	+	+*	+**	+***
	av. marg. eff.	[0.608]	[1.076]	[0.200]	[0.285]	[0.357]	[0.681]
Return on assets	stat. signific.	+**	+	+**	+***	+***	+***
	av. marg. eff.	[1.688]	[0.956]	[1.073]	[1.006]	[1.925]	[1.891]
Free cash flow margin	stat. signific.	+**	+**	+	+**	+***	+***
	av. marg. eff.	[0.782]	[1.484]	[0.330]	[0.361]	[1.745]	[1.103]
Cash flow fr. oper./net inc.	stat. signific.	+***	+***	+***	+**	+***	+***
	av. marg. eff.	[0.050]	[0.093]	[0.046]	[0.111]	[0.079]	[0.077]
SG&A ratio	stat. signific.	–	+***	+*	–	+	–
	av. marg. eff.	[-0.218]	[1.957]	[0.540]	[-0.273]	[0.078]	[-0.015]
Goodwill ratio	stat. signific.	–**	+	–	+	–	–
	av. marg. eff.	[-0.651]	[0.119]	[-0.139]	[0.092]	[-0.122]	[-0.113]
Price-to-book ratio	stat. signific.	–	–	–***	–	–***	–***
	av. marg. eff.	[-0.010]	[-0.022]	[-0.035]	[-0.026]	[-0.058]	[-0.032]
Price-to-earnings ratio	stat. signific.	–***	–	–***	–	–***	–***
	av. marg. eff.	[-0.006]	[-0.001]	[-0.007]	[-0.004]	[-0.010]	[-0.008]
Stand. unexp. earnings	stat. signific.	–***	–	–	–	–	–
	av. marg. eff.	[-17x10 ⁻³]	[-0.4x10 ⁻³]	[-0.1x10 ⁻³]	[-0.4x10 ⁻³]	[-0.3x10 ⁻³]	[-0.1x10 ⁻³]
Cum. abn. return	stat. signific.	–	+	–	–	+	–
	av. marg. eff.	[-0.175]	[0.628]	[-0.118]	[-0.152]	[0.329]	[-0.002]
CAR/SUE ratio	stat. signific.	–	–	–**	–**	–**	–
	av. marg. eff.	[-0.251]	[-0.770]	[-0.538]	[-1.432]	[-0.326]	[-0.065]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Overall, the most suitable indicators for good fallen angel quality appear to be high **cash flow** ratios – particularly the CFO-to-net income ratio with its significance across all industries – and high **profitability** ratios, i.e. gross profit margin and ROA. A low **current ratio** (except for consumer services) and low **valuation** ratios (except for consumer goods and healthcare) also seem to be suitable indicators for good angel quality. A more industry-specific approach has to be taken with regard to equity ratio, SG&A ratio, goodwill, and the earnings surprise-related ratios.

With regard to the specific industries, a fallen angel investor who is looking at **basic materials** companies will more likely find good fallen angels among companies that score high in terms of gross profit margin, return on assets, free cash flow margin, and CFO-to-net income ratio. Furthermore, good fallen angels in this industry tend to have low values with regard to current ratio, goodwill ratio, price-to-earnings ratio, and SUE ratio.

When looking at the **consumer goods** industry, a high gross profit margin, free cash flow margin, CFO-to-net income ratio, and SG&A ratio are indicators for good angel quality. The same is also true for a low current ratio.

Consumer services companies tend to be more likely fallen angels of good quality when their valuation ratios, i.e. price-to-book or price-to-earnings, or their CAR-SUE ratio is low. Furthermore, a high ROA, CFO-to-net income, and SG&A ratio also appear to be indicators of good angel quality.

With regard to **healthcare** companies, a high CFO-to-net income ratio, ROA, free cash flow margin, and gross profit margin tend to be associated with good angel quality. The same is the case for a low CAR-SUE and a low current ratio.

Concerning **industrials**, high values for ROA, free cash flow margin, and CFO-to-net income ratio tend to be particularly strong indicators for good angel quality. The same is true for a low price-to-book and price-to-earnings ratio as well as a low current ratio. Furthermore, a high gross profit margin and a low equity or CAR-SUE ratio also seem to point towards good angel quality.

Finally, a **technology & telecommunication** company that turns into a good fallen angel tends to have a high ROA, gross profit margin, free cash flow margin, CFO-to-net income ratio, as well as a low current, price-to-book and price-to-earnings ratio. Particularly for this industry, a low equity ratio also seems to be a sign for good angel quality.

6.6 Robustness Testing

The results of the statistical tests of the base dataset and its industry subsets were subject of various robustness tests. These tests were conducted by varying the tested samples of fallen angels along several dimensions with leaving all other criteria of creating the base dataset and its industry subsets unchanged. The single factors changed in the various test scenarios were:

- level of sales growth required
- length of time period between negative earnings surprises
- length of post-earnings announcement drift period after the negative earnings surprise
- used measure of angel quality

In the following sections these variations of the base dataset are discussed further and the outcomes of statistically testing them are described.

6.6.1 Level of Sales Growth

Empirical studies demonstrate that the share prices of companies with higher growth rates suffer more strongly from a negative earnings surprise than companies with more moderate growth rates.⁴⁷⁸ In vivid terms, this means that if an angel company is flying exceptionally high, the fall after a negative surprise will be steeper. As the intensity of growth might also have an effect on fallen angel investing as presented in this thesis, it appears reasonable to gauge the extent of this possible effect on the underlying hypotheses.

To do so, three growth scenarios have been designed in order to adjust the base dataset for robustness testing. In the order of increasing sales growth requirements during the two years prior to the negative earnings surprise, these are:

- GROWTH I: Sales growth faster than the overall U.S. economy, which represents the base dataset as empirically tested above.
- GROWTH II: Sales growth faster than the average mid- to large-size U.S. firm
- GROWTH III: Sales growth in the top third of U.S. companies

The GROWTH I sample contains companies that have demonstrated sales CAGR of above 2.87 percent p.a. in the two years prior to the negative earnings surprise. This

⁴⁷⁸ See Dreman/Berry (1995) and Bauman/Miller (1997).

constitutes the base dataset as tested in the sections above. It is the most lenient sales growth condition possible, since it means that the companies in the sample have at least grown one basis point (bp) faster than the economy. In case a company did not grow faster than the overall economy, it is very hard to argue to classify such a stock as a growth stock.

The GROWTH II sample requires the respective CAGR of sales to be at least 5.9 percent annually. This figure corresponds with the median real revenue growth rate of U.S. non-financial companies with revenues of more than US\$ 500 million during 1997 until 2007.⁴⁷⁹ It should be noted that the 5.9 percent average growth rate is the result of both organic growth and growth through mergers and acquisitions. This is one explanation for the significant difference between economy and corporate revenue growth rates. Another reason is the fact that U.S. companies benefitted from globalization with their revenues generated abroad growing at a much faster rate than their revenues at home.⁴⁸⁰

The GROWTH III sample further sharpens the growth requirements by setting the necessary sales CAGR to 10 percent p.a. This means that a company only enters the sample if it belongs to the upper third of aforementioned U.S. non-financial companies in terms of sales growth.⁴⁸¹ The logic behind this more rigid sampling is that separating a sample of companies purely into growth and non-growth on the basis of a median or mean average – like in sample GROWTH II – is somewhat arbitrary. As a consequence, a company with a sales CAGR of one bp above the average could be classified as a growth company and therefore enter the sample, while another with one bp below the sales growth hurdle would be left out. To circumvent this problem, the pool of companies could be broken down into three parts, thus establishing a middle group that would neither be classified as growth or non-growth. This group could be seen as a kind of puffer between the group of growing companies and that of laggards.⁴⁸² It should be noted that Wisdom, although he does not bring forward this argument, also uses the 10 percent annual sales growth threshold in his selection of

⁴⁷⁹ See Cao/Jiang/Koller (2011), pp. 27f., and Koller/Dobbs/Huyett (2010), p. 144.

⁴⁸⁰ See Cao/Jiang/Koller (2011), p. 27.

⁴⁸¹ See Cao/Jiang/Koller (2011), p. 28, and Koller/Dobbs/Huyett (2010), p. 144.

⁴⁸² The idea of breaking up datasets into smaller samples in a way that there is some kind of puffer between the more distinguished subsamples representing the features to be analyzed has been used frequently by other researchers in various contexts before. See among others De Bondt/Thaler (1985), De Bondt/Thaler (1987), p. 559, or Fama/French (1998), p. 1978.

fallen angels.⁴⁸³ However, this rigid selection criterion comes with a severe drawback, because sample sizes in the various industry subsets decrease significantly. Thus, deriving statistically meaningful results from these smaller samples becomes a problem, particularly with regard to the industries with less fallen angel companies. Consequently, more aggressive growth samples, such as a sample containing only companies with sales CAGR of 20 percent p.a. or more, which represents the top ten percent of the aforementioned group of U.S. non-financial companies⁴⁸⁴, were not analyzed.

Test results for the GROWTH II sample confirm the results for the base dataset (GROWTH I). All significant effects point to the same direction and mostly at identical significance levels. Marginal effects are also very similar with slight upward and downward variations as compared to the base dataset (see **Table 36** in the appendix).

For the GROWTH III sample, test results are also largely confirmed, although significance levels for several possible indicators did not reach the significance levels met by the GROWTH I (base dataset) or GROWTH II sample data (see **Table 37** in the appendix). This might also be caused by the markedly lower sample sizes, which – depending on industry and independent variable – dropped below 100 observations in multiple instances. Furthermore, marginal effects are not always smaller or only slightly smaller, when significance levels are lower.

6.6.2 Length of Time Period between Negative Earnings Surprises

As discussed above in section 6.3.1.4 the “quiet period” between repeating negative earnings surprises necessary to enter the base dataset is set at 1050 days. This ensures maximum data integrity such that negative earnings surprises in the sample cannot be erroneously associated with financial statement data from the same date. However, as financial statement data are updated annually and it can be assumed that analysts refresh their earnings estimates at least in the same interval, a “quiet period” of 365 days might be a reasonable time span as well. Thus, statistical tests have been conducted on a sample that contains fallen angels selected in accordance with the same criteria like for the base dataset with the exception of a shorter “quiet period” of one year between recurring negative earnings surprises.

⁴⁸³ See Wisdom (2009), p. 97.

⁴⁸⁴ See Cao/Jiang/Koller (2011), p. 28.

Test results largely confirm the findings for the base dataset with some smaller deviations in terms of significance levels and strength of marginal effects (see **Table 38** in the appendix). Although marginal effects on average are slightly weaker than for the base dataset, there do not appear to be significant differences. In a nutshell, using the shorter “quiet period” data sample with its mix of an advantageous larger sample size and the disadvantageous less “clean” negative earnings surprise data does not appear to have a material effect on test results.

6.6.3 Length of Post-Earnings Announcement Drift

As explained in section 2.4.1, the calculation of the abnormal returns that determine the quality of a fallen angel stock in the base dataset starts 60 trading days after the negative earnings surprise. Assuming that an investor would not wait that long before buying the fallen angel stock, the question arises, whether such a faster investment decision-making behavior would alter the conclusions from the statistical tests of the base dataset. To find an answer, the starting point for measuring abnormal share price performance after the negative earnings surprise has been moved forward to right after the end of the five-trading day window around the negative earnings surprise, i.e. to the beginning of the third trading day after the announcement. Therefore, the resulting sample contains companies as good (bad) fallen angels that have outperformed (underperformed) the benchmark almost exactly one, two, and three years after the negative earnings surprise has happened.

The results of the statistical tests of this sample are not materially different from the base dataset, both with regard to direction and significance levels (see **Table 39** in the appendix). The same is true for the strength of marginal effects, although they appear to be on average slightly weaker than for the base dataset. Only for CAR-SUE ratios, significance levels of the test results are markedly and consistently lower. This, however, does not come as a surprise, because the reason for implementing the above-mentioned period of 60 trading days in the base dataset lies in the empirically confirmed post-earnings announcement drift as described above. Since this phenomenon describes the initial underreaction of investors to earnings surprises, omitting a sufficient time span in which this effect can subside should have consequences on the test results of negative earnings surprise-related variables such as the CAR-SUE ratio.

For investors, these findings have the practical implication that there does not seem to be a material difference of whether they invest shortly after the negative earnings surprise or whether they wait until shortly before the next earnings announcement.

6.6.4 Measures of Angel Quality

The last robustness test deals with the strictness of defining good and bad fallen angels. The angel quality measure AQ13, which was used for the construction of the base dataset, requires that fallen angel stocks have to consistently outperform the benchmark on three measurement dates set at one-year intervals from the beginning of the measurement period. Softening the requirements by reducing the necessary outperformance to less measurement dates should lead to less consistent results, because the likelihood that a fallen angel stock passes the required quality criteria by chance, or other factors than the ones analyzed by this thesis, is higher than in the base dataset. The next strictest threshold in terms of required measurement dates is consistent out- or underperformance at two consecutive measurement dates, i.e. at one and two years respectively two and three years after start of the measurement period. The resulting angel qualities are called AQ12 and AQ23.

As expected, although often in line with base dataset test results, results for both the AQ12 and the AQ23 sample are less consistent. Relatively, results for the AQ12 sample are more in line with the findings for the base dataset (see **Table 40** in the appendix). Most of the directions of the influence of tested indicators on angel quality were confirmed, although in fourteen cases sample AQ12 showed significance, when the base dataset results did not or vice versa. Additionally, eleven times there was a variation in the significance level. In comparison, test results for AQ23 recorded nineteen instances, when significance was indicated and the base dataset results did not or vice versa. Furthermore, variations in significance levels occurred six times (see **Table 41** in the appendix). As sample AQ23 focuses on the longer end of the performance measurement period, where the influence of events unrelated to the negative earnings surprise on the share price is likely higher, this finding does not surprise.

Summing up, robustness tests with samples consisting of companies selected on the basis of less strict angel quality requirements produce less consistent results and thus do not add to achieving this thesis's goals. These findings support the chosen focus on the strictest hurdle for angel quality as implemented in the base dataset. Since the negative effects on sample data quality are further magnified when measuring performance at only one date, tests of such samples have not been conducted.

7 Conclusion

7.1 Summary and Recommendations for the Investment Practice

When revisiting the key goals of this thesis and comparing them with the outcome of this thesis, it can be said that they are achieved. Statistical tests have resulted in a set of suitable indicators for distinguishing good from bad fallen angels. Therefore, the existing research gap concerning fallen angel stocks has narrowed, and investors are now in a better position to make profitable investment decisions when considering a purchase of fallen angel stocks. Furthermore, value investors can now systematically consider an investment in growth companies already at the time when they become fallen angels and not only when they meet traditional value investment criteria. Consequently, the time until value investors start to contemplate an investment in such stocks is significantly shortened, thus building a bridge between value and growth investment styles.

However, a general word of caution should be posted before applying the gained statistical insights in daily investment practice. The input for the conducted statistical tests is a vast amount of undisputable factual stock market and financial statement data. Thus, the statistically tested predictive power of certain variables for the future stock price development of fallen angels might appear as a precise reflection of objective relationships that are not subject to historical change. Therefore, it could be tempting to take the tested correlations for granted and mechanically apply them when picking individual stocks. However, movements on financial markets and actions within companies are very often the product of human actions. Hence, the less unpredictable element of psychology enters the field. This makes a purely mechanical application of statistical findings inadequate, like Neill pointedly stated: “You may have all the statistics in the world at your finger tips, but still you do not know how or when people are going to act.”⁴⁸⁵ No economic situation is completely alike, because of the infinite mixture of influences on human behavior.⁴⁸⁶ A thoughtful investor should not forget – in particular against the backdrop of the previous extensive data analysis – that before making an investment decision based on findings from this thesis, he should always thoroughly review the specific investment situation. Buying fallen angel stock is nothing else than obtaining ownership of a part of the related fallen angel companies. It is therefore necessary to understand the underlying business

⁴⁸⁵ Neill (2007), p. 98.

⁴⁸⁶ See McCraw (2007), pp. 504 et seq.

of these companies and not only act on the basis of a couple of numbers. Becoming an owner of something just because a statistically tested model tells you to do so is something an investor in the sense of this thesis would not want to do. A thorough and cautious investor would always check vital issues for a company's success, such as quality and integrity of management, or information about a company's product pipeline, before committing himself to an investment. Only by adding a qualitative element to sound quantitative analysis, it is possible to grasp these pieces of information that do not lend themselves to exact statistical analysis, but could still be a crucial element of the investment decision.⁴⁸⁷ Unfortunately, this often requires a substantial amount of work and judgmental ability from the investor, but there does not seem to be a way around it.⁴⁸⁸

In that sense, the clear recommendation for any investor willing to apply the findings of this thesis in his investment practice is to use them as guidance for, but not as substitution of a well-rounded in-depth investment analysis. Nevertheless, having statistically grounded investment principles as provided by this thesis is surely something of value, since it helps to overcome the unpredictability and instability of human decision-making. A set of such firm rules helps investors in disciplining their emotions in order not to go astray due to mood swings or a currently predominant market opinion exercising persuasive influence on them. In this context, the following statement by Goldman Sachs senior investment strategist Abby Joseph Cohen perfectly summarizes how investors should apply the findings of this thesis: "Investors are urged to use models as tools, often very powerful tools, but not as replacements for sound analysis and common sense."⁴⁸⁹

7.2 Outlook and Potential for Future Research

The insights gained from this thesis can surely be deepened by future research at least along two dimensions. Firstly, the relatively young discipline of behavioral finance will almost surely evolve further. Secondly, there are multiple potential influence factors on angel quality that have not been tested for various reasons in this thesis.

⁴⁸⁷ See Bernstein (1956), pp. 94 and 97, for an early discussion of this issue.

⁴⁸⁸ This is also in line with the opinion held by Buffett, the world's most successful investor over a period of several decades, who claims that neither secret formulae nor computer programs or signals from share or index price charts are key for achieving investment success, but rather good business judgment and the ability to stand firm against mood swings in the market. See Buffett (2003), p. 89.

⁴⁸⁹ See Cohen (2008), p. xiii.

Before giving attention to them, some light shall be shed on the current streams of development in the area of behavioral finance.

Although Thaler already in 1999 called for the “end of behavioral finance” in the sense that its underlying ideas will be seen as completely natural and will thus be fully incorporated in “normal” finance⁴⁹⁰, this development has by far not been concluded. Besides the inertia with which new theories and findings are incorporated into the standard body of knowledge of a science, there are also still many blank spots that need to be addressed and covered by behavioral finance research. Particularly the field of neuroeconomics, which tries to trace human economic decision making back to certain brain functions, is only in its beginning with regard to gaining insights into how investors make decisions.⁴⁹¹ It is therefore very likely that future research will generate new and more advanced theories and insights that might also have implications for the field of investments in fallen angel stocks.

Independent from such future developments in the field of behavioral finance, there are also multiple possible indicators for angel quality that are not covered by this thesis, but still might bear valuable new insights. An area that appears particularly promising with regard to further analysis is the quality of management of a fallen angel company. A more experienced management should be more able to deal with the adversarial situation of a negative earnings surprise and the consequent underperformance of the company’s stock. Although management quality is generally difficult to measure, there are some proxies for it, such as tenure⁴⁹², number of years in the industry, the percentage of internally promoted top management⁴⁹³, or information about the salary structure within a management team⁴⁹⁴. These variables can be obtained, though usually not in an easily automatable way, and might shed light on the strength and depth within a fallen angel’s management team. Related to that is the information whether the fallen angel company experienced a management change right before the earnings announcement or whether the negative surprise was delivered by tenured management. In case the fallen angel has company-specific issues, new

⁴⁹⁰ See Thaler (1999).

⁴⁹¹ For accounts of the relevance of neuroscience for economics see, for example, Camerer/Loewenstein/Prelec (2004), Camerer/Loewenstein/Prelec (2005), or Bernheim (2009) together with the comments by Gul/Pesendorfer (2009) and Sobel (2009).

⁴⁹² Zhang, for example, found a relationship between CEO tenure and earnings announcements in the sense that CEOs with long tenures on average report less aggressive earnings than CEOs with short tenure. See Zhang (2010).

⁴⁹³ See Fisher (2003), p. 188.

⁴⁹⁴ See Fisher (2003), p. 189.

management tends to put as many charges and bad news as possible into their first earnings announcement. This so-called “big bath accounting” shall put the blame for the disappointing performance on the old management, and at the same time make it easier for new management to meet future expectations. In such case, a negative earnings surprise might appear in a different light.

Besides management quality, the quality of a company’s product or service pipeline seems to deserve more attention. Particularly when it comes to the point of assessing whether the problems of a fallen angel stock are temporary or more of a permanent nature, the success of a company’s research and development activities might matter. The share of R&D spending relative to a company’s sales could be a promising variable to be tested, particularly when industry-specific R&D intensity levels are considered.⁴⁹⁵

Related to but not limited to R&D expenditure is a concept that could also be of interest in the context of fallen angel investing. It is based on the assumption that a fallen angel company that offers unique products should be in a better position to overcome the current weakness than one with a fairly standard offering. Titman and Wessels suggest three measurable indicators for the uniqueness of the products a company sells: R&D intensity as defined by R&D expenditure over sales, selling expenses over sales, and quit rates with the latter being defined as the percentage of the company's total work force that voluntarily left their jobs in the sample years.⁴⁹⁶ Although it will likely be difficult to obtain all data necessary to compute these three variables, an analysis of them as possible indicators for fallen angel quality might be a worthwhile endeavor.

Another important field to find suitable indicators of angel quality might be the shareholder structure of a fallen angel company in its various facets. For example, the percentage of institutional ownership could be an expression of whether shareholders will actively push management to solve the problems of the company or whether they remain passive. As professional investment institutions, such as banks, insurance companies, pension funds, mutual funds, or hedge funds, tend to actively manage their portfolio of companies, individual shareholders tend to stay more on the sidelines. Furthermore, it is assumed that institutional owners are smarter investors and have

⁴⁹⁵ See, for example, Hall (1999) or Duqi/Torluccio (2010) for the positive relationship between R&D expenditure and market value.

⁴⁹⁶ See Titman/Wessels (1988), p. 5, and Parsons/Titman (2009), p. 21.

better insights into the companies⁴⁹⁷, thus potentially not only creating pressure for management, but also contributing valuable insights and support. Another interesting aspect of a company's shareholder structure could be the level of fragmentation. While a highly fragmented ownership leads to a greater degree of short-termism in the form of earnings management and underinvestment in order to avoid a short-term decrease in net income, a concentrated shareholder structure tends to mitigate these problems and result in a more long-term view.⁴⁹⁸ Particularly fallen angel companies, which experience a high pressure to improve short-term earnings in order to quickly meet their ambitious earnings targets again, should therefore benefit from a concentrated, more long-term oriented shareholder structure. Additionally, the extent of insider ownership in fallen angel companies could be an interesting independent variable to be tested. In general, corporations with a high percentage of insider ownership tend to be more shareholder-friendly.⁴⁹⁹ Empirical studies support this assumption by providing evidence for a positive correlation between the extent of insider ownership and share price performance.⁵⁰⁰ Testing this relationship might also be worthwhile in the context of fallen angels, particularly since a management incentivized by a significant equity stake is more likely to stay with the company in difficult times and take appropriate measures to overcome the problems that caused the negative earnings surprise.

Akin to insider ownership is trading activity by insiders. This could be particularly interesting with respect to fallen angels, because share purchases by insiders are widely seen as a sign of confidence in the company and vice versa. Insiders are believed to have most knowledge of the inner workings of a company, so if they acquire stock in their own company, the signaling to outsiders, who do not command this degree of knowledge, is clearly positive.⁵⁰¹ This view is backed by academic studies.⁵⁰² Specifically for growth stocks the extent of insider selling was found to be high when they are overvalued and vice versa⁵⁰³, which provides valuable information in the context of fallen angel investing. Therefore, it is highly recommended to look at

⁴⁹⁷ See Kaye (2006), p. 36.

⁴⁹⁸ See, for example, Brunzell/Liljebloom/Vaihekoski (2011).

⁴⁹⁹ Kaye (2006), p. 36.

⁵⁰⁰ See, for example, Ruenzi/Von Lilienfeld-Toal (2010), who demonstrate a positive correlation between CEO ownership and stock market performance.

⁵⁰¹ See Kaye (2006), p. 36.

⁵⁰² See, for example, Lakonishok/Lee (2001) or Jeng/Metrick/Zeckhauser (2003), who found positive abnormal returns for insider transactions in the U.S. stock market, and Gregory/Tharyan/Tonks (2009), who found positive abnormal returns for directors' transactions in the UK stock market.

⁵⁰³ See Knewton/Sias/Whidbee (2010).

the direction and degree of insider trading activities before and after the negative earnings surprise to get a more complete picture of the potential fallen angel investment target. Empirically analyzing whether such activity is also significantly linked to angel quality remains an outstanding task for future research.

Furthermore, it appears promising to extend this research beyond the analysis of absolute values to also include the change in certain fundamental variables, such as inventory, accounts receivables, capital expenditure, or gross margin.⁵⁰⁴ However, changes in financial statement data are much more volatile than the absolute figures used in this study. Therefore, such an analysis should be based on quarterly financial statement data. Only then it seems possible to capture trends in the development of the analyzed variables early enough to sensibly link them to consequent abnormal stock returns. The hope is that with improving quarterly availability of financial data in the future, it should be possible to extend the research horizon long enough to achieve meaningful results for variables representing changes in financial statement data as well.

Summing up, the set of variables examined by this thesis might only be the beginning of further research in the field of fallen angel stocks. There appears to be still a vast set of possible indicators for angel quality to be possibly covered by future research. The key obstacle for undertaking such research will surely be data availability, which was also the reason why these variables were not included in this thesis already. However, there is hope that these hurdles will become lower over time, thus enabling more extensive and deeper analyses on suitable indicators for good investments in fallen angel stocks.

⁵⁰⁴ See Lev/Thiagarajan (1993). This study by Baruch Lev and S. Ramu Thiagarajan has shown the predictive power of several such variables for excess stock returns.

APPENDIX

Table 36: Summary of empirical test results of possible indicators for angel quality of data sample GROWTH II for angel quality AQ13 split by industries

Indicator		Influence on good fallen angel probability (AQ13=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	–**	–*	–	–*	–***	–***
	av. marg. eff.	[-0.078]	[-0.070]	[-0.031]	[-0.031]	[-0.076]	[-0.054]
Equity ratio	stat. signific.	+	+	–	+	–***	–**
	av. marg. eff.	[0.027]	[0.375]	[-0.150]	[0.262]	[-0.508]	[-0.495]
Gross profit margin	stat. signific.	+***	+***	+	+*	+**	+***
	av. marg. eff.	[0.632]	[1.010]	[0.070]	[0.285]	[0.388]	[0.476]
Return on assets	stat. signific.	+**	+*	+	+***	+***	+***
	av. marg. eff.	[1.608]	[1.389]	[0.301]	[1.147]	[1.545]	[1.252]
Free cash flow margin	stat. signific.	+***	+***	+	+**	+***	+***
	av. marg. eff.	[0.982]	[3.648]	[0.403]	[0.371]	[1.598]	[0.967]
Cash flow fr. oper./net inc.	stat. signific.	+**	+***	+**	+	+***	+***
	av. marg. eff.	[0.052]	[0.132]	[0.048]	[0.093]	[0.066]	[0.080]
SG&A ratio	stat. signific.	–	+*	+**	–	–	–
	av. marg. eff.	[-0.252]	[1.096]	[0.731]	[-0.307]	[-0.090]	[-0.041]
Goodwill ratio	stat. signific.	–*	+	–*	–	–	–
	av. marg. eff.	[-0.583]	[0.114]	[-0.316]	[-0.018]	[-0.086]	[-0.149]
Price-to-book ratio	stat. signific.	–***	–	–**	–	–***	–*
	av. marg. eff.	[-0.063]	[-0.034]	[-0.032]	[-0.023]	[-0.059]	[-0.016]
Price-to-earnings ratio	stat. signific.	–**	–	–***	–	–***	–***
	av. marg. eff.	[-0.005]	[-0.004]	[-0.007]	[-0.004]	[-0.006]	[-0.004]
Stand. unexp. earnings	stat. signific.	–**	–	–	–	–	–
	av. marg. eff.	[-15x10 ⁻³]	[-0.1x10 ⁻³]	[-0.0x10 ⁻³]	[-0.3x10 ⁻³]	[-0.0x10 ⁻³]	[-0.0x10 ⁻³]
Cum. abn. return	stat. signific.	+	+	–	–	+	+
	av. marg. eff.	[-0.171]	[1.069]	[-0.158]	[-0.129]	[0.318]	[0.153]
CAR/SUE ratio	stat. signific.	–	–	–	–**	–	–
	av. marg. eff.	[-0.194]	[-0.813]	[-0.333]	[-1.667]	[-0.225]	[-0.047]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 37: Summary of empirical test results of possible indicators for angel quality of data sample GROWTH III for angel quality AQ13 split by industries

Indicator		Influence on good fallen angel probability (AQ13=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	-	-	-	_ **	_ ***	_ ***
	av. marg. eff.	[-0.063]	[-0.062]	[-0.020]	[-0.043]	[-0.089]	[-0.065]
Equity ratio	stat. signific.	+	-	-	-	_ **	_ **
	av. marg. eff.	[0.173]	[-0.168]	[-0.007]	[-0.069]	[-0.585]	[-0.483]
Gross profit margin	stat. signific.	+ **	+	+	+	+	+ ***
	av. marg. eff.	[0.474]	[0.274]	[0.028]	[0.250]	[0.337]	[0.539]
Return on assets	stat. signific.	+	+	+	+ *	+ **	+ ***
	av. marg. eff.	[0.638]	[1.049]	[1.046]	[0.713]	[1.565]	[1.115]
Free cash flow margin	stat. signific.	+ **	+ **	+	+ **	+ ***	+ ***
	av. marg. eff.	[0.922]	[2.177]	[0.369]	[0.325]	[2.466]	[0.875]
Cash flow fr. oper./net inc.	stat. signific.	+	+ **	+	-	+ **	+ **
	av. marg. eff.	[0.021]	[0.140]	[0.028]	[-0.005]	[0.059]	[0.199]
SG&A ratio	stat. signific.	-	+	+	-	-	+
	av. marg. eff.	[-1.300]	[1.278]	[0.200]	[-0.670]	[-0.006]	[-0.015]
Goodwill ratio	stat. signific.	-	+	-	+	-	+
	av. marg. eff.	[-0.624]	[0.276]	[-0.297]	[0.220]	[-0.105]	[0.143]
Price-to-book ratio	stat. signific.	_ **	-	_ **	_ **	_ ***	-
	av. marg. eff.	[-0.076]	[-0.067]	[-0.032]	[-0.048]	[-0.076]	[-0.009]
Price-to-earnings ratio	stat. signific.	-	-	_ ***	_ *	_ ***	_ **
	av. marg. eff.	[-0.004]	[-0.003]	[-0.009]	[-0.006]	[-0.009]	[-0.003]
Stand. unexp. earnings	stat. signific.	_ **	-	-	-	-	-
	av. marg. eff.	[-24x10 ⁻³]	[-0.1x10 ⁻³]	[-0.0x10 ⁻³]	[-0.3x10 ⁻³]	[-0.0x10 ⁻³]	[-0.1x10 ⁻³]
Cum. abn. return	stat. signific.	+	-	+	-	+	+
	av. marg. eff.	[0.142]	[-0.789]	[0.049]	[-0.262]	[0.176]	[0.370]
CAR/SUE ratio	stat. signific.	-	-	_ *	-	-	-
	av. marg. eff.	[-0.227]	[-0.726]	[-0.858]	[-1.115]	[-0.167]	[-0.053]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 38: Summary of empirical test results of possible indicators for angel quality of data sample with “quiet period” between negative earnings surprises of 365 days for angel quality AQ13 split by industries

Indicator		Influence on good fallen angel probability (AQ13=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	_*	_**	-	_**	_***	_***
	av. marg. eff.	[-0.044]	[-0.064]	[-0.007]	[-0.033]	[-0.034]	[-0.063]
Equity ratio	stat. signific.	+	-	+	+	_***	_**
	av. marg. eff.	[0.022]	[-0.078]	[0.124]	[0.005]	[-0.444]	[-0.298]
Gross profit margin	stat. signific.	+***	+***	+	+*	+***	+***
	av. marg. eff.	[0.474]	[0.974]	[0.109]	[0.235]	[0.537]	[0.468]
Return on assets	stat. signific.	+***	+**	+***	+***	+***	+***
	av. marg. eff.	[1.632]	[1.110]	[1.591]	[1.126]	[2.636]	[0.928]
Free cash flow margin	stat. signific.	+**	+***	+*	+***	+***	+***
	av. marg. eff.	[0.429]	[2.842]	[0.607]	[0.338]	[1.872]	[0.813]
Cash flow fr. oper./net inc.	stat. signific.	+**	+***	+***	+	+***	+***
	av. marg. eff.	[0.029]	[0.098]	[0.046]	[0.043]	[0.057]	[0.042]
SG&A ratio	stat. signific.	-	+***	+	-	+	+
	av. marg. eff.	[-0.265]	[1.250]	[0.264]	[-0.325]	[0.005]	[0.130]
Goodwill ratio	stat. signific.	-	+	_*	-	-	-
	av. marg. eff.	[-0.275]	[0.054]	[-0.262]	[-0.001]	[-0.125]	[-0.033]
Price-to-book ratio	stat. signific.	_***	-	_***	-	_***	_***
	av. marg. eff.	[-0.062]	[-0.009]	[-0.036]	[-0.014]	[-0.048]	[-0.021]
Price-to-earnings ratio	stat. signific.	_***	-	_***	_*	_***	_***
	av. marg. eff.	[-0.004]	[-0.001]	[-0.008]	[-0.003]	[-0.011]	[-0.003]
Stand. unexp. earnings	stat. signific.	-	-	-	-	-	-
	av. marg. eff.	[-0.5x10 ⁻³]	[-0.3x10 ⁻³]	[-0.0x10 ⁻³]	[-0.5x10 ⁻³]	[-0.1x10 ⁻³]	[-0.1x10 ⁻³]
Cum. abn. return	stat. signific.	+	+	+	-	+*	+
	av. marg. eff.	[0.056]	[0.122]	[0.378]	[-0.317]	[0.437]	[0.146]
CAR/SUE ratio	stat. signific.	_***	-	_***	-	_**	-
	av. marg. eff.	[-0.646]	[-0.420]	[-0.736]	[-0.504]	[-0.392]	[-0.139]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 39: Summary of empirical test results of possible indicators for angel quality of data sample without post earnings announcement drift period of 60 trading days for angel quality AQ13 split by industries

Indicator		Influence on good fallen angel probability (AQ13=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	–***	–***	–	–***	–***	–***
	av. marg. eff.	[-0.084]	[-0.102]	[-0.027]	[-0.049]	[-0.074]	[-0.050]
Equity ratio	stat. signific.	–	–	–	+	–**	–**
	av. marg. eff.	[-0.025]	[-0.075]	[-0.226]	[0.382]	[-0.332]	[-0.352]
Gross profit margin	stat. signific.	+***	+***	+	+*	+**	+***
	av. marg. eff.	[0.530]	[0.840]	[0.088]	[0.319]	[0.370]	[0.399]
Return on assets	stat. signific.	+***	+*	+	+**	+***	+***
	av. marg. eff.	[2.122]	[1.292]	[0.463]	[0.990]	[1.744]	[1.065]
Free cash flow margin	stat. signific.	+***	+***	+	+**	+***	+***
	av. marg. eff.	[0.821]	[2.586]	[0.484]	[0.531]	[1.620]	[0.605]
Cash flow fr. oper./net inc.	stat. signific.	+	+**	+**	+**	+***	+***
	av. marg. eff.	[0.031]	[0.069]	[0.040]	[0.106]	[0.072]	[0.059]
SG&A ratio	stat. signific.	+	+***	+*	–	–	–
	av. marg. eff.	[0.312]	[1.964]	[0.593]	[-0.325]	[-0.116]	[-0.230]
Goodwill ratio	stat. signific.	–	+	–*	+	–	–
	av. marg. eff.	[-0.341]	[0.480]	[-0.277]	[0.045]	[-0.020]	[-0.101]
Price-to-book ratio	stat. signific.	–**	–	–***	–	–***	–**
	av. marg. eff.	[-0.047]	[-0.007]	[-0.064]	[-0.009]	[-0.054]	[-0.023]
Price-to-earnings ratio	stat. signific.	–***	–	–***	–**	–***	–***
	av. marg. eff.	[-0.002]	[-0.001]	[-0.010]	[-0.005]	[-0.009]	[-0.004]
Stand. unexp. earnings	stat. signific.	–***	–	–	–	–	–
	av. marg. eff.	[-20x10 ⁻³]	[-0.3x10 ⁻³]	[-0.1x10 ⁻³]	[-0.3x10 ⁻³]	[-0.2x10 ⁻³]	[-0.0x10 ⁻³]
Cum. abn. return	stat. signific.	–	+	–	–	+	–
	av. marg. eff.	[-0.096]	[0.784]	[-0.445]	[-0.182]	[0.270]	[-0.405]
CAR/SUE ratio	stat. signific.	–	–	–*	–	–	–
	av. marg. eff.	[-0.233]	[-0.800]	[-0.499]	[-0.332]	[-0.307]	[-0.029]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 40: Summary of empirical test results of possible indicators for angel quality for angel quality AQ12 split by industries

Indicator		Influence on good fallen angel probability (AQ12=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	-	***	+	*	***	***
	av. marg. eff.	[-0.039]	[-0.079]	[0.008]	[-0.023]	[-0.064]	[-0.035]
Equity ratio	stat. signific.	-	-	+	+	*	-
	av. marg. eff.	[-0.000]	[-0.168]	[0.027]	[0.160]	[-0.269]	[-0.252]
Gross profit margin	stat. signific.	***	***	+	**	+	***
	av. marg. eff.	[0.554]	[0.889]	[0.145]	[0.346]	[0.190]	[0.462]
Return on assets	stat. signific.	***	***	+	***	***	***
	av. marg. eff.	[2.179]	[1.430]	[0.425]	[1.070]	[1.419]	[1.519]
Free cash flow margin	stat. signific.	***	+	+	***	***	***
	av. marg. eff.	[0.608]	[0.100]	[0.482]	[0.409]	[1.077]	[1.062]
Cash flow fr. oper./net inc.	stat. signific.	+	-	-	*	***	***
	av. marg. eff.	[0.001]	[-0.002]	[-0.001]	[0.054]	[0.063]	[0.047]
SG&A ratio	stat. signific.	-	***	*	-	+	-
	av. marg. eff.	[-0.327]	[1.415]	[0.0465]	[-0.055]	[0.196]	[-0.077]
Goodwill ratio	stat. signific.	-	+	-	+	-	-
	av. marg. eff.	[-0.439]	[0.309]	[-0.186]	[0.048]	[-0.050]	[-0.055]
Price-to-book ratio	stat. signific.	-	-	***	*	-	***
	av. marg. eff.	[-0.008]	[-0.003]	[-0.033]	[-0.023]	[-0.003]	[-0.029]
Price-to-earnings ratio	stat. signific.	*	-	***	-	*	**
	av. marg. eff.	[-0.002]	[-0.002]	[-0.006]	[-0.003]	[-0.001]	[-0.001]
Stand. unexp. earnings	stat. signific.	-	-	-	-	-	-
	av. marg. eff.	$[-5.1 \times 10^{-3}]$	$[-0.1 \times 10^{-3}]$	$[-0.0 \times 10^{-3}]$	$[-0.3 \times 10^{-3}]$	$[-0.2 \times 10^{-3}]$	$[-0.0 \times 10^{-3}]$
Cum. abn. return	stat. signific.	-	+	-	-	+	+
	av. marg. eff.	[-0.167]	[0.396]	[-0.092]	[-0.271]	[0.182]	[0.030]
CAR/SUE ratio	stat. signific.	-	-	*	-	-	-
	av. marg. eff.	[-0.216]	[-0.109]	[-0.518]	[-0.407]	[-0.254]	[-0.073]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 41: Summary of empirical test results of possible indicators for angel quality for angel quality AQ23 split by industries

Indicator		Influence on good fallen angel probability (AQ23=1)					
		Basic materials	Consumer goods	Consumer services	Health-care	Industrials	Tech & Telecom
Current ratio	stat. signific.	−***	−	+	+	−***	−***
	av. marg. eff.	[-0.061]	[-0.031]	[0.004]	[0.004]	[-0.009]	[-0.053]
Equity ratio	stat. signific.	−	+	+*	+*	−**	−**
	av. marg. eff.	[-0.021]	[0.049]	[0.223]	[0.306]	[-0.328]	[-0.383]
Gross profit margin	stat. signific.	+***	+***	+	+	+**	+***
	av. marg. eff.	[0.303]	[0.567]	[0.076]	[0.198]	[0.377]	[0.440]
Return on assets	stat. signific.	+**	+	+***	+*	+***	+***
	av. marg. eff.	[0.817]	[0.579]	[1.333]	[0.485]	[1.071]	[1.021]
Free cash flow margin	stat. signific.	+	+***	+	+**	+***	+***
	av. marg. eff.	[0.125]	[1.324]	[0.138]	[0.204]	[0.918]	[0.967]
Cash flow fr. oper./net inc.	stat. signific.	+	+***	−	−	+	+
	av. marg. eff.	[0.000]	[0.080]	[-0.002]	[-0.001]	[0.007]	[0.004]
SG&A ratio	stat. signific.	−	+***	+	−	+	+
	av. marg. eff.	[-0.187]	[1.488]	[0.344]	[-0.273]	[0.257]	[0.131]
Goodwill ratio	stat. signific.	−	+	−	+	−	+
	av. marg. eff.	[-0.335]	[0.166]	[-0.117]	[0.027]	[-0.022]	[0.006]
Price-to-book ratio	stat. signific.	+	−	−	−	−	−
	av. marg. eff.	[0.001]	[-0.021]	[-0.013]	[-0.007]	[-0.047]	[-0.003]
Price-to-earnings ratio	stat. signific.	−	+	−***	−	−***	−
	av. marg. eff.	[-0.000]	[0.000]	[-0.005]	[-0.000]	[-0.010]	[-0.000]
Stand. unexp. earnings	stat. signific.	−***	+	−	−*	−*	−
	av. marg. eff.	[-15x10 ⁻³]	[0.0x10 ⁻³]	[-0.2x10 ⁻³]	[-0.4x10 ⁻³]	[-0.3x10 ⁻³]	[-0.0x10 ⁻³]
Cum. abn. return	stat. signific.	+	+	−	−	+	−
	av. marg. eff.	[0.060]	[0.880]	[-0.051]	[-0.109]	[0.375]	[-0.011]
CAR/SUE ratio	stat. signific.	−	−	−**	−*	−**	−
	av. marg. eff.	[-0.200]	[-0.891]	[-0.557]	[-0.690]	[-0.329]	[-0.050]

***/**/* 99/95/90 percent significance level (based on LOGIT regression test results)
Average marginal effects in brackets
Gray shading indicates that a significant result points in the opposite direction than hypothesized

Source: Author

Table 42: ICB industry classification system (part 1)

ICBIC	Industry	ICBSupSec	Supersector Name	ICBSec	Sector Name	ICBSubSec	Textcode	Subsector Name
0001	Oil & Gas	0500	Oil & Gas	0530	Oil & Gas Producers	0533	OILEP	Exploration & Production
0001	Oil & Gas	0500	Oil & Gas	0530	Oil & Gas Producers	0537	OILIN	Integrated Oil & Gas
0001	Oil & Gas	0500	Oil & Gas	0570	Oil Equipment, Services & Distribution	0573	OILSV	Oil Equipment & Services
0001	Oil & Gas	0500	Oil & Gas	0570	Oil Equipment, Services & Distribution	0577	PIPEL	Pipelines
0001	Oil & Gas	0500	Oil & Gas	0580	Alternative Energy	0583	RENEE	Renewable Energy Equipment
0001	Oil & Gas	0500	Oil & Gas	0580	Alternative Energy	0587	ALTFI	Alternative Fuels
1000	Basic Materials	1300	Chemicals	1350	Chemicals	1353	CHEMS	Commodity Chemicals
1000	Basic Materials	1300	Chemicals	1350	Chemicals	1357	CHMSP	Specialty Chemicals
1000	Basic Materials	1700	Basic Resources	1730	Forestry & Paper	1733	FORST	Forestry
1000	Basic Materials	1700	Basic Resources	1730	Forestry & Paper	1737	PAPER	Paper
1000	Basic Materials	1700	Basic Resources	1750	Industrial Metals & Mining	1753	ALUMN	Aluminum
1000	Basic Materials	1700	Basic Resources	1750	Industrial Metals & Mining	1755	NOFMS	Nonferrous Metals
1000	Basic Materials	1700	Basic Resources	1750	Industrial Metals & Mining	1757	STEEL	Iron & Steel
1000	Basic Materials	1700	Basic Resources	1770	Mining	1771	COALM	Coal
1000	Basic Materials	1700	Basic Resources	1770	Mining	1773	DIAMD	Diamonds & Gemstones
1000	Basic Materials	1700	Basic Resources	1770	Mining	1775	MINES	General Mining
1000	Basic Materials	1700	Basic Resources	1770	Mining	1777	GOLDS	Gold Mining
1000	Basic Materials	1700	Basic Resources	1770	Mining	1779	PLTNM	Platinum & Precious Metals
2000	Industrials	2300	Construction & Materials	2350	Construction & Materials	2353	BMATS	Building Materials & Fixtures
2000	Industrials	2300	Construction & Materials	2350	Construction & Materials	2357	HVYCN	Heavy Construction
2000	Industrials	2700	Industrial Goods&Services	2710	Aerospace & Defense	2713	AEROS	Aerospace
2000	Industrials	2700	Industrial Goods&Services	2710	Aerospace & Defense	2717	DEFEN	Defense
2000	Industrials	2700	Industrial Goods&Services	2720	General Industrials	2723	CONPK	Containers & Packaging
2000	Industrials	2700	Industrial Goods&Services	2720	General Industrials	2727	DIVIN	Diversified Industrials
2000	Industrials	2700	Industrial Goods&Services	2730	Electronic & Electrical Equipment	2733	ELEQP	Electrical Components & Equipment
2000	Industrials	2700	Industrial Goods&Services	2730	Electronic & Electrical Equipment	2737	ELETR	Electronic Equipment
2000	Industrials	2700	Industrial Goods&Services	2750	Industrial Engineering	2753	COMMV	Commercial Vehicles & Trucks
2000	Industrials	2700	Industrial Goods&Services	2750	Industrial Engineering	2757	IMACH	Industrial Machinery
2000	Industrials	2700	Industrial Goods&Services	2770	Industrial Transportation	2771	DELSV	Delivery Services
2000	Industrials	2700	Industrial Goods&Services	2770	Industrial Transportation	2773	MARIN	Marine Transportation
2000	Industrials	2700	Industrial Goods&Services	2770	Industrial Transportation	2775	RAILS	Railroads
2000	Industrials	2700	Industrial Goods&Services	2770	Industrial Transportation	2777	TRNSV	Transportation Services
2000	Industrials	2700	Industrial Goods&Services	2770	Industrial Transportation	2779	TRUCK	Trucking
2000	Industrials	2700	Industrial Goods&Services	2790	Support Services	2791	BUSUP	Business Support Services
2000	Industrials	2700	Industrial Goods&Services	2790	Support Services	2793	BUSTE	Business Training & Employment Agencies
2000	Industrials	2700	Industrial Goods&Services	2790	Support Services	2795	FINAD	Financial Administration
2000	Industrials	2700	Industrial Goods&Services	2790	Support Services	2797	INSUP	Industrial Suppliers
2000	Industrials	2700	Industrial Goods&Services	2790	Support Services	2799	WASTE	Waste & Disposal Services
3000	Consumer Goods	3300	Automobiles & Parts	3350	Automobiles & Parts	3353	AUTOS	Automobiles
3000	Consumer Goods	3300	Automobiles & Parts	3350	Automobiles & Parts	3355	AUPRT	Auto Parts
3000	Consumer Goods	3300	Automobiles & Parts	3350	Automobiles & Parts	3357	TYRES	Tires
3000	Consumer Goods	3500	Food & Beverage	3530	Beverages	3533	BREWS	Brewers
3000	Consumer Goods	3500	Food & Beverage	3530	Beverages	3535	DISTV	Distillers & Vintners
3000	Consumer Goods	3500	Food & Beverage	3530	Beverages	3537	SOFTD	Soft Drinks
3000	Consumer Goods	3500	Food & Beverage	3570	Food Producers	3573	FMFSH	Farming & Fishing
3000	Consumer Goods	3500	Food & Beverage	3570	Food Producers	3577	FDPRD	Food Products
3000	Consumer Goods	3700	Personal&Household Goods	3720	Household Goods&Home Construction	3722	DURHP	Durable Household Products
3000	Consumer Goods	3700	Personal&Household Goods	3720	Household Goods&Home Construction	3724	NDRHP	Non-durable Household Products
3000	Consumer Goods	3700	Personal&Household Goods	3720	Household Goods&Home Construction	3726	FURNS	Furnishings
3000	Consumer Goods	3700	Personal&Household Goods	3720	Household Goods&Home Construction	3728	HOMES	Home Construction
3000	Consumer Goods	3700	Personal&Household Goods	3740	Leisure Goods	3743	CNELE	Consumer Electronics
3000	Consumer Goods	3700	Personal&Household Goods	3740	Leisure Goods	3745	RECPR	Recreational Products
3000	Consumer Goods	3700	Personal&Household Goods	3740	Leisure Goods	3747	TOYSG	Toys
3000	Consumer Goods	3700	Personal&Household Goods	3760	Personal Goods	3763	CLTHG	Clothing & Accessories
3000	Consumer Goods	3700	Personal&Household Goods	3760	Personal Goods	3765	FOOTW	Footwear
3000	Consumer Goods	3700	Personal&Household Goods	3760	Personal Goods	3767	PRSNL	Personal Products
3000	Consumer Goods	3700	Personal&Household Goods	3780	Tobacco	3785	TOBAC	Tobacco
4000	Health Care	4500	Health Care	4530	Health Care Equipment & Services	4533	HCPRO	Health Care Providers
4000	Health Care	4500	Health Care	4530	Health Care Equipment & Services	4535	MEDEQ	Medical Equipment
4000	Health Care	4500	Health Care	4530	Health Care Equipment & Services	4537	MEDSP	Medical Supplies
4000	Health Care	4500	Health Care	4570	Pharmaceuticals & Biotechnology	4573	BIOTC	Biotechnology
4000	Health Care	4500	Health Care	4570	Pharmaceuticals & Biotechnology	4577	PHRMC	Pharmaceuticals
5000	Consumer Services	5300	Retail	5330	Food & Drug Retailers	5333	DGRET	Drug Retailers
5000	Consumer Services	5300	Retail	5330	Food & Drug Retailers	5337	FDRET	Food Retailers & Wholesalers
5000	Consumer Services	5300	Retail	5370	General Retailers	5371	APRET	Apparel Retailers
5000	Consumer Services	5300	Retail	5370	General Retailers	5373	BDRET	Broadline Retailers
5000	Consumer Services	5300	Retail	5370	General Retailers	5375	HIMPR	Home Improvement Retailers
5000	Consumer Services	5300	Retail	5370	General Retailers	5377	SPCSV	Specialized Consumer Services
5000	Consumer Services	5300	Retail	5370	General Retailers	5379	SPRET	Specialty Retailers
5000	Consumer Services	5500	Media	5550	Media	5553	BRDEN	Broadcasting & Entertainment
5000	Consumer Services	5500	Media	5550	Media	5555	MEDAG	Media Agencies
5000	Consumer Services	5500	Media	5550	Media	5557	PUBLS	Publishing
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5751	AIRLN	Airlines
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5752	GAMNG	Gambling
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5753	HOTEL	Hotels
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5755	RECSV	Recreational Services
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5757	RESTS	Restaurants & Bars
5000	Consumer Services	5700	Travel & Leisure	5750	Travel & Leisure	5759	TRAVL	Travel & Tourism
6000	Telecommunications	6500	Telecommunications	6530	Fixed Line Telecommunications	6535	TEFLI	Fixed Line Telecommunications
6000	Telecommunications	6500	Telecommunications	6570	Mobile Telecommunications	6575	TELMB	Mobile Telecommunications
7000	Utilities	7500	Utilities	7530	Electricity	7535	CNVEL	Conventional Electricity
7000	Utilities	7500	Utilities	7530	Electricity	7537	ALTEL	Alternative Electricity
7000	Utilities	7500	Utilities	7570	Gas, Water & Multiutilities	7573	GASDS	Gas Distribution
7000	Utilities	7500	Utilities	7570	Gas, Water & Multiutilities	7575	MTUTL	Multiutilities
7000	Utilities	7500	Utilities	7570	Gas, Water & Multiutilities	7577	WATER	Water

Table 43: ICB industry classification system (part 2)

ICBIC	Industry	ICBSupSec	Supersector Name	ICBSec	Sector Name	ICBSubSec	Textcode	Subsector Name
8000	Financials	8300	Banks	8350	Banks	8355	BANKS	Banks
8000	Financials	8500	Insurance	8530	Nonlife Insurance	8532	FLINS	Full Line Insurance
8000	Financials	8500	Insurance	8530	Nonlife Insurance	8534	INSBR	Insurance Brokers
8000	Financials	8500	Insurance	8530	Nonlife Insurance	8536	PCINS	Property & Casualty Insurance
8000	Financials	8500	Insurance	8530	Nonlife Insurance	8538	REINS	Reinsurance
8000	Financials	8500	Insurance	8570	Life Insurance	8575	LFINS	Life Insurance
8000	Financials	8600	RealEstate	8630	Real Estate Investment & Services	8633	RLDEV	Real Estate Holding & Development
8000	Financials	8600	RealEstate	8630	Real Estate Investment & Services	8637	RLSRV	Real Estate Services
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8671	RITIO	Industrial & Office REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8672	RITRT	Retail REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8673	RITRS	Residential REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8674	RITDV	Diversified REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8675	RITSP	Specialty REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8676	RITMG	Mortgage REITs
8000	Financials	8600	RealEstate	8670	Real Estate Investment Trusts	8677	RITHL	Hotel & Lodging REITs
8000	Financials	8700	Financial Services	8770	Financial Services	8771	ASSET	Asset Managers
8000	Financials	8700	Financial Services	8770	Financial Services	8773	CNFIN	Consumer Finance
8000	Financials	8700	Financial Services	8770	Financial Services	8775	SPFIN	Specialty Finance
8000	Financials	8700	Financial Services	8770	Financial Services	8777	INVSV	Investment Services
8000	Financials	8700	Financial Services	8770	Financial Services	8779	MORTF	Mortgage Finance
8000	Financials	8700	Financial Services	8980	Equity Investment Instruments	8985	INVNK	Investment Companies
8000	Financials	8700	Financial Services	8990	Nonequity Investment Instruments	8995	ITINT	Investment Trusts
8000	Financials						ITPEQ	Private Equity
8000	Financials						ITVCT	Venture Capital Trusts
8000	Financials						EXTRF	Exchange Traded Funds
8000	Financials						ITHSI	Housing Income Investment Trusts
8000	Financials						OEINC	Open Ended Investment Companies
8000	Financials						OFFSH	Offshore Funds
8000	Financials						CURFD	Currency Funds
8000	Financials						INVTO	Other Investment Trusts
8000	Financials						ITSPL	Split Capital Investment Trusts
8000	Financials						UNITS	Authorised Unit Trusts
8000	Financials						INSPF	Insurance & Property Funds
8000	Financials						PRPUT	Property Unit Trusts
8000	Financials						COMUT	Commodity Unit Trusts
8000	Financials						MUTFS	Mutual Funds
8000	Financials						MMFDS	Money Market Funds
8000	Financials						PENSF	Pension Funds
8000	Financials						HEDGE	Hedge Funds
9000	Technology	9500	Technology	9530	Software & Computer Services	9533	CMPSV	Computer Services
9000	Technology	9500	Technology	9530	Software & Computer Services	9535	INTNT	Internet
9000	Technology	9500	Technology	9530	Software & Computer Services	9537	SOFTW	Software
9000	Technology	9500	Technology	9570	Technology Hardware & Equipment	9572	COMPH	Computer Hardware
9000	Technology	9500	Technology	9570	Technology Hardware & Equipment	9574	OFFEQ	Electronic Office Equipment
9000	Technology	9500	Technology	9570	Technology Hardware & Equipment	9576	SEMIC	Semiconductors
9000	Technology	9500	Technology	9570	Technology Hardware & Equipment	9578	TELEQ	Telecommunications Equipment

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