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Good Will or Risky Business?

- The required risk premium for stocks with goodwill

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Abstract

This paper studies the empirical relationship between goodwill and the cross-sectional variation in US stock returns during different market conditions. In order to better understand how goodwill is priced in the market, the correlation with both absolute and risk-adjusted future stock returns are investigated using a Fama-MacBeth regression setting. When controlling for other variables known to affect stock returns, the results indicate a positive relationship between goodwill and future absolute stock returns. This result provides evidence for the hypothesis that investors perceive goodwill as risky and requires a risk premium as compensation for holding stocks with large goodwill. Furthermore, our findings show that firms with goodwill have higher market betas, earn lower returns during market downturns and higher return during market upturns.

Keywords: Goodwill, risk premium, stock returns, market downturns, market upturns
JEL Classifications: G32 (Financial risk and management, Value of firms, Goodwill)

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1. Table of contents

1. TABLE OF CONTENT 1
2. INTRODUCTION 2
3. THEORETICAL FRAMEWORK 4
3. 1 THEORY 4
3.1.1 THE PRINCIPAL-AGENT PROBLEM AND ASYMMETRIC INFORMATION 4
3.1.2 INFORMATION RISK 5
3.1.3 VALUATION OF GOODWILL 6
3.1.4 THE RELATIONSHIP BETWEEN RISK AND RETURN 7
3.2 PREVIOUS LITERATURE 8
3.2.1 ACCOUNTING QUALITY AND RISK PREMIUM 8
3.2.2 FINDINGS FROM USING WEAK - FORM AND SEMI - STRONG TESTS 9
4. DATA AND VARIABLES 10
4.1 SOURCES 10
4.2 DATASET AND ADJUSTMENTS MADE 10
4.3 VARIABLES 11
4.3.1 OPERATIONALIZATION OF KEY VARIABLES 11
4.3.2 MARKET INDEX 12
4.3.3 ESTIMATING MARKET BETAS 12
4.3.4 CONTROL VARIABLES 14
5. METHODOLOGY 15
5.1 GOODWILL AND FIRM CHARACTERISTICS 15
5.2 STYLE PORTFOLIO CONSTRUCTION 16
5.3 REGRESSION SETTING 18
5.3.1 MATCHING OF DATA 18
5.3.2 TWO-STAGE FAMA-MACBETH REGRESSION 19
5.4 OTHER RISK-FACTOR ASSET PRICING MODELS 20
6. RESULTS 21
7. ANALYSIS 26
8. ROBUSTNESS TEST 28
9. PROBLEMATIZATION 29
10. CONCLUSION 30
11. FUTURE RESEARCH 30
12. REFERENCES 31
13. APPENDIX 33

2. Introduction

Performing company valuation based on accounting data is common practice for investors. It is therefore interesting to investigate how specific firm characteristics in the company accounts affect the valuation and thus the stock returns. The goodwill item is one of them. Large amounts of this item are frequently found in financial reports and it is considered to be surrounded by uncertainty of what it is and how much it is worth. This uncertainty might be reflected in the stock price of a security with goodwill, which is what distinguish this item from other firm characteristics. White et al (2003) describe how goodwill appears as an asset in the balance sheet when the paying price for the target company in an acquisition exceeds the fair value of its net assets. The residual is called goodwill and is classified as an intangible asset shown in the consolidated accounts. Conceptually, goodwill can be seen as a compensation for the abnormal returns that the acquirer expects to obtain from the acquisition. For example, this item might include brand value or research and development resources. Hence, incorporated in large goodwill items are characteristics that are supposed to generate higher performance and profitability in the future.

Companies with a mergers and acquisitions growth strategy may differ from companies that grow organically in several ways. For instance, a faster growing pace can be obtained through mergers and acquisitions with the cost of a more extensive adaption period compared to the slower organic growth option with gradual adaption to new businesses. Furthermore, conglomerates have the tendency of being present in more business areas. These economical differences are most likely to affect the performance of the firm. However, in this paper, the effects of the underlying economical events are not examined. Instead, it is the potential extra risk that exists in the valuation of a company with large goodwill that is of interest. This extra risk factor is proxied by a factor called *goodwillintensity*. Goodwillintensity is defined as goodwill divided by shareholder´s equity of common stocks. This paper tests if goodwillintensity can be used as a proxy for one dimension of risk in explaining stock returns. To use proxies for one dimension of risk, regardless of the unnamed underlying sources of risk, is not an uncommon practise. Several acknowledged publications have tested for other factors used as proxies for risk dimensions, which might correlate with absolute future stock returns. More specifically, this study is conducted by examining the empirical relationship between goodwillintensity and the cross-sectional variation of absolute future stock returns (both unadjusted and risk-adjusted returns are used in the empirical tests).

Furthermore, the stock returns for firms with goodwill are investigated during different market states.

Previous literature on goodwill has focused on short-term effects, such as stock price reaction to goodwill impairments. Another intensive research area includes the effects from different goodwill accounting methods on company valuation (purchase method, pooling method etc.). A few papers have touched upon the subject "goodwill´s effect on the market value of the firm". Our first contribution to the literature is therefore the long-term examination of the performance of goodwill stocks, both compared to stocks without goodwill and conditional on the size of goodwillintensity. Consistent with theories regarding the role of information risk in asset pricing, we demonstrate that goodwill has a positive relationship with future returns indicating a required risk premium for holding stocks with goodwill. This result is consistent with the idea that information risk surrounding the goodwill item is priced in the market.

The possibility of realizing the incorporated expected value of goodwill increases in times of market expansion. When the market state turns down, on the other hand, expected earnings will decrease along with the expected future abnormal return earned from the goodwill item. It is therefore natural to expect that in times of market slowdown, firms with goodwill will present lower stock performance than those firms without goodwill. Our second contribution is thus the finding that the goodwill stocks underperform in market downturns and outperform in market upturns. Taken together, having controlled for other factors known to correlate with stock returns, the results in this paper suggest that goodwillintensity can be viewed as a proxy for exposures to sources of risk.

Our main hypothesis and the three sub-hypotheses (contingent on the main hypothesis being true) are defined as follows:

Main hypothesis

H_0: $\beta_1 = 0$	Goodwillintensity does not correlate with absolute future stock returns
H_1: $\beta_1 \neq 0$	Goodwillintensity correlate with absolute future stock returns

The logic behind this hypothesis is as follows. Since goodwill is surrounded by uncertainty regarding what it is and how much it is worth, this uncertainty is expected to be reflected in absolute future stock returns.

Sub-hypotheses

(1) $H_0: \beta_1 < 0$ There is a negative relationship between goodwillintensity and absolute future stock returns

$H_1: \beta_1 > 0$ There is a positive relationship between goodwillintensity and absolute future stock returns

The first sub-hypothesis is in line with previous studies, which show that investors require a risk premium when investing in risky stocks. Therefore, we expect a higher excess return for stocks when the amount of goodwill in the company´s balance sheet is larger.

(2) H_0: Firms with goodwill does not underperform in market downturns

H_1: Firms with goodwill underperform in market downturns

(3) H_0: Firms with goodwill does not outperform in market upturns

H_1: Firms with goodwill outperform in market upturns

The risk incorporated in the goodwill item is expected to be reflected differently in stock returns during different market conditions. In an optimistic market, investors can be expected to be willing to take on more risk than in a pessimistic market, thus effecting the valuation of the goodwill stocks.

3. Theory

This section will first present relevant theories and models followed by previous literature within the relevant research area of this paper.

3.1 Theoretical framework

3.1.1 The Principal-Agent problem and asymmetric information

The Principal-Agent theory is a well-known economical theory describing the relationship between a principal and an agent. A principal-agency relationship is created when an arrangement between two parties exists, where one party´s welfare is dependent upon the other party´s actions. The acting party is called the agent and the party that is affected by the agent´s actions is called the principal. This principal-agent relationship can be applied on

investors, the owners of the company stocks, and the corporate management in the company. The corporate management act as the agent and the stockholders act as principals. The principal-agent theory assumes that agents do not necessarily act in the best interest of the principals. Instead, they are driven by their own goals and interests (apart from monetary achievements) such as perks and power (Pindyck and Rubinfeld, 2009). Considering the separation of ownership and control in a company, there is thus a risk that the agent takes advantage of the situation and does not maximize the principal´s utility, creating agency costs. This line of reasoning can be applied to the goodwill item. There is a risk that this item is not fairly valued, but instead a result of management´s utility maximisation. Moeller (2010) argues that this principal-agency problem is particularly common in mergers and acquisitions. He describes how most acquisitions fail and that managerial hubris and chief executive ego are main reasons for the failure. Additionally, boards and management are infected by exuberance, resulting in an overestimation of their own ability. The overestimation of their abilities leads to overpayment of targets, with large premiums. The winners are often target shareholders, managers receiving larger responsibility and corporate advising companies. Left behind are clients, most employees and the acquiring company thus hurting the stockholders. To conclude, there is an uncertainty from a principal´s perspective of what the goodwill item includes and how much it is worth. Due to the principal-agent problem, the expected future economical value from the goodwill item might not be realized.

The principal-agent problem seems to persist regarding goodwill, and asymmetric information can therefore be expected to exist between the corporate management and investors whether or not goodwill has the potential to generate future excess returns. Companies´ goodwill can thus be viewed as a case of adverse selection. Adverse selection results in what is called *the lemon principle.* Berk and DeMarzo (2007) describes the principle as follows:

> *"When a seller has private information about the value of a good, buyers will discount the price they are willing to pay due to adverse selection." (p. 535)*

3.1.2 Information risk

When investors trade securities in a market, Easley and O'Hara (2004) has developed a model in which asymmetric information transforms idiosyncratic risk into systematic risk. In the model, there are two types of rational investors, informed and uninformed. The informed

investor can weight his or her portfolio, spread the risk and obtain full diversification of the idiosyncratic risk. The uninformed investor, on the other hand, is assumed to rationally diversify him or herself to the best of his or her ability given the information he or she has at hand. However, due to lack of private information, the uninformed investor is unable to fully diversify his or her portfolio. This implies that the uninformed investor will unavoidably hold some unwanted idiosyncratic risk. Furthermore, given that the uninformed investor has rational expectations, he or she will expect the portfolio to include idiosyncratic risk and will therefore require a risk premium for his or her investment as compensation for the extra risk. Due to the asymmetric information that exists between investors and the corporate management regarding the future prospects of the goodwill item as described above, investors can be expected to require a risk premium for holding stocks with goodwill.

3.1.3 Valuation of goodwill

White et al (2003) describes the valuation considerations regarding the goodwill item as follows:

> *"To sum up, the existence of economic goodwill is largely independent of the existence of accounting goodwill. The former is a function of economic performance; the latter is a function of accounting standards. Investors and financial analysts are primarily interested in economic goodwill, yet accounting goodwill exist in abundant quality in the financial statements of many companies. For purposes of analysis, therefore, the analyst should remove goodwill from reported balance sheets. When a company clearly earns excess returns, this factor will enter into the valuation of the company´s share." (p. 526)*

This implies that in ordinary DCF - models, the goodwill item is excluded. Instead the goodwill item can be expected to be included in the overall valuation of the firm, potentially as a risk factor.

During periods of market stability and expansion, investors are generally more willing to take on more risk, risk premiums shrink and stock prices increase even further. In the end, the bubble is reversed in which investors are willing to take on less risk (Bodie et al., 2011). Loss aversion is a linked theory that presents how investors are more sensitive to losses than to gains, which further strengthen the previous statement (Bodie et al., 2011). In market downturns, the risk of goodwill can therefore be expected to be to high to bear, which would result in lower returns for companies with goodwill compared to companies without.

Malmqvist (2010) further argues that there is a higher risk that companies with high goodwillintensity needs to make large goodwill impairments in market downturns. These companies might be forced by credit holders to issue new shares, in order to obtain a acceptable level of equity. Issuing new shares during market slowdowns are generally negatively perceived by investors and the stock price is likely to fall. This effect will have a further risk factor incorporated in the goodwill item.

3.1.4 The relationship between risk and return

If looking back a few decades, the capital asset pricing model of Sharpe (1964), Lintner (1965), and Black (1972) shaped the way financial academics and practitioners viewed the relationship between risk and return. The Capital Asset Pricing Model (CAPM) determines the appropriate required rate of return of an asset by creating a relationship between an asset´s expected return and it´s non-diversifiable (systematic) risk called market beta. The model specification is as shown below.

$$r_i = \alpha_i + r_f + \beta_i(r_m - r_f) + \epsilon_i$$

where:

r_i = expected return of security/portfolio i

α_i = alpha for security/portfolio i

r_f = risk-free rate

β_i = market beta of security/portfolio i, $= \frac{Cov(r_i, r_m)}{var(r_m)}$

r_m = expected market return

ϵ_i = error term

The formula consists of two parts based on the idea that investors need to be compensated for two things: the time value of money and risk. The first factor of the model, the risk free rate (r_f), compensates investors for choosing any investment other than the risk-free one over a period of time. The other factor, the risk premium $\beta_i(r_m - r_f)$, compensates investors for additional risk incurred in security i. Hence, combining the two factors, the expected return on a security/portfolio i equals the rate of a risk-free security plus the risk premium. If the expected return does not meet or exceed the required rate of return, the investment should not be undertaken.

In the CAPM model, the efficient market hypothesis is assumed to hold. This hypothesis states that stock prices will be updated directly based on new information. The prices will therefore follow a random walk since new information cannot be foreseen. Based on this hypothesis, a theory has developed to include three forms of market efficiency, weak, semi-strong and strong (Bodie et al., 2011). In the weak form, stock prices includes information that can be obtained by observing market trading data such as past historical prices and trading volume. Semi-strong market efficiency states that all public information is reflected in the stock price. Finally, in the strong market efficiency, prices include both private and public information regarding the future prospect of the company.

Empirical tests of the CAPM assuming strong market efficiency have failed to confirm the theoretical approach. Several eminent and well-known academics have therefore argued for the misspecification of the CAPM model. A new approach to asset pricing models has evolved with weak and semi-strong market efficiency tests. The weak-form tests examine trends in stock market returns. The semi-strong market efficiency tests are called multifactor models and can be used to test multiple risk sources and their corresponding risk premiums and thus extend the research surrounding the relationship between risk and return (Bodie et al, 2011). A semi-strong test is used in this paper, using some implications of the weak-form tests further presented in the next section.

3.2 Previous literature

The literature presented below has been extracted based on the theoretical framework above in order to highlight previous finding in this area.

3.2.1 Accounting quality and risk premium

Previous literature has examined the effect of accounting quality on stock returns. One conclusion is that poor accounting quality and uncertain information incurred in stock valuation parameters are related to higher expected returns (Callen et al., 2011). Moreover, these results are confirmed by another result in which investors demand a higher return to hold stocks with greater private information (Easly and O´Hara, 2004). Combining the facts that investors only have access to public information about the value of the goodwill and the accounting quality cannot be expected to be reliable, there are reasons to believe that investors require compensation for holding this extra risk. Informed investors are better able to shift their portfolio weights to incorporate new information. Lack of information thus

constitutes a form of systematic risk. In equilibrium, investors require compensation for bearing that risk.

3.2.2 Findings from using weak - form and semi - strong tests

From the weak-form testing literature, the main findings include the tendency for a stock price to continue in the same direction as in the past, the so called *momentum effect*. This effect implies serial correlation between stock returns resulting in mispricing. Another discovery from this type of tests that is linked to the momentum effect is the *reversal effect* in which previous high performers fade back and previous low performers recover after a certain time of the momentum effect (Bodie et al., 2011).

Regarding the findings in the semi-strong tests, Banz (1981) documents a *small-firm-in-January effect*, demonstrating that small firms earn higher annual return compared to large firms. Arbel and Strebel (1983) developed the small-firm-in-January effect to what has been named the *neglected-firm effect*. They argued that information about smaller firms is less available. The lack of information makes smaller firms a riskier investment requiring higher returns. Merton (1987) strengthens Arbel and Strebel´s finding by showing that neglected firms expect higher equilibrium returns as compensation for the information risk. Another paper by Amihud and Mendelson (1986) combines the small-firm-in-January effect with the neglected firm effect. They find that investors demand a higher rate of return for less liquid stocks incurring higher trading costs. This could be linked to the previous mentioned authors' findings, since small- and lack of information-stocks are less liquid. In addition, Basu (1982) find that E/P ratio can help explain the variation in the return of a stock listed on the NYSE.

Fama and French (1993) are the most eminent authors and have argued for the semi-strong tests. They claim that if stocks are priced rationally, a stock´s accumulated risk is multidimensional. This implies that several factors except beta can help in explaining the variation of stock returns. They find that an overall market factor, size, measured as market value of equity, and book-to-market equity constitutes three dimensions of risk impacting stock returns. They explain their findings with a risk premium associated with the factors earning higher average returns. Another result is the discovery that the return to their style portfolios (based on book-to-market or size) can predict GDP growth in many countries.

Although the factors described above are not natural risk factors, they might act as proxies for mode fundamental risk determinants. These previous findings in the literature provide evidence of several factors other than the market beta, which can explain stock

returns. It is therefore reasonable to expect that goodwillintensity is reflected in absolute future stock returns and a proxy for one dimension of risk.

4. Data and variables

This section describes the dataset, the adjustments made and the variables generated for the purpose of our research.

4.1 Sources

Considering the risk of *selection bias* when using a limited dataset, we decided to use the widest and largest sample of historical data available to us. The data used in this paper has therefore been obtained from *WRDS (Wharton Research Data Services) Compustat, CRSP* and *Fama-French & Liquidity Factors*. WRDS was chosen due to its position as a leading data research platform, and the availability of strong historical company data. Our data includes listed US companies on NYSE, NASDAQ and AMEX (and other listed companies) for the years 1990-2013. The time period was decided upon considering the history of the economic climate. The intention was to capture both the IT-bubble in 2001 and the global financial crisis in 2008, their pre-and post crisis periods.

Fiscal year-end accounting items, share data items and sic-codes have been retrieved from Compustat *fundamentals annual*, daily and monthly closing prices (adjusted for dividends and splits) from Compustat *securities monthly and daily* and value-weighted and equally-weighted market indexes from CRSP *stock market indexes*. Finally, Fama-French factors have been obtained from *Fama-French & Liquidity Factors* (monthly and daily frequencies). Due to higher accurateness in annual compared to quarterly reports, we chose annual accounting data over quarterly. For comparability purposes, all variables used are measured in million US dollars (excluding CA dollars). The Compustat id item *gvkey* has been used as company identifier when merging the datasets. Compared to other firm identifiers such as *isin* or *ticker*, *gvkey* has the advantage of being constant over time, thus allowing for analysis of companies over time. Moreover, monthly date format (%tm) has been used creating time-series data on a monthly basis. For full list of data sources and variables, see appendix.

4.2 Dataset and adjustments made

To make the data more applicable to our research question, adjustments have been made to the initial dataset. To start with, our dataset includes only companies in the US, excluding

ADRs to avoid across country differences. Only common stocks are kept and financial firms (sic code: 6XXX) have been excluded. These companies are excluded because the high level of leverage that is normal for financial firms normally translate into financial distress for nonfinancial firms. Furthermore, we have dropped companies that have observations less than three years. This limitation could potentially cause *survivorship bias* but increases the robustness in regressions. Another related drawback of this type of dataset is the presence of *biasing attrition*. It is amiable to follow the same companies over time. However, due to bankruptcy, delistings and IPOs, the composition of companies will vary over time. If the companies that leave/join the listed companies have similar attributes such as financial distress or rapid growth, a bias will occur.

Approximately 18% of all observations have missing values for goodwill, which makes it worthwhile to fill in the data. If a company had missing values in between observations with values on goodwill, the missing values were approximated to the previous value before the missing observations. If a company had zero goodwill and missing values in the beginning or the end of the studied period, the missing values were replaced with zero. For companies with goodwill, missing values in the beginning or the end of the studied period were dropped. Random checks in financial statements have been made and this extension of the dataset seems to be representative. The dataset has also been checked and adjusted for duplicates and outliers. Together, these adjustments and restrictions result in an effective dataset of 3259 companies, where 1306 are companies with goodwill and 1953 are companies without. It is worth mentioning that the goodwill and the non-goodwill group are almost equal in size making both groups large enough for comparative analysis.

4.3 Variables

In the section below, key variables used in this paper are defined and discussed.

4.3.1 Operationalization of key variables

The aim of this paper is to examine the relationship between stock returns and goodwill. It is logical to analyse the relationship from a shareholder´s perspective since it is the market that determines the prices of stocks. Therefore, when operationalizing the main independent variable goodwill, the absolute value is related to the book value of common stock shareholder´s equity (goodwill/equity). In addition, this measure ought to be appropriate due to the fact that impairments of goodwill are directly impaired against equity. This is the

reason why large values of this measure have the potential of capturing the riskiness of goodwill. We call this measure *goodwillintensity*.

As a next step, a dummy variable for goodwill is generated that takes on the value of zero if the company has no goodwill and one if the company has goodwill. The purpose of the separation is to be able to compare the two groups. This variable will be frequently used throughout the paper. The dependent variable is absolute monthly percentage returns (with the appropriate adjustments for capital changes such as stock splits and dividends) for all common stocks. The calculation of stock returns is as follows:

$$r_{i,t} = \log(1 + r_{i,t+1}) = \log\left(\frac{P_{i,t+1}}{P_{i,t}}\right) = \log(P_{i,t+1}) - \log(P_{i,t})$$

where:

$r_{i,t}$ = absolute return for stock *i* in month *t*

$P_{i,t}$ = price for stock *i* in month *t*

4.3.2 Market Index

The market index used is the CRSP value-weighted index, calculated based on NASDAQ, NYSE and AMEX stocks. The value-weighted index is calculated as follows.

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t}$$

where

$w_{i,t}$ = weight for stock *i* in month *t* based on market capitalization

$r_{i,t}$ = absolute return for stock *i* in month *t*

$r_{m,t}$ = absolute market return in month *t*

This index is considered to be representative for the sample used, since the dataset contains companies of different size with stocks traded on NYSE, NASDAQ and AMEX.

4.3.3 Estimating market betas

When estimating a variable later used in a main regression, it is important that the estimate includes as little bias as possible. If the right-hand side variable of a regression is measured with error, the slop coefficient will have a downward bias and the intercept an upward bias in the main regression (Bodie et al. 2011). In order to avoid biased beta estimations, the beta in

this study is calculated using market model regressions, which is an empirical version of the CAPM. More specifically, *the Dimson (1979) aggregated coefficients (AC) method* is used to estimate stock betas. This method has been developed to overcome biased estimations of systematic risk (beta) due to infrequently traded shares in the dataset. The major bias occurs when prices recorded at the end of a time period represent the outcome of a transaction, which took place earlier in, or prior to, the period in question. This results in serial correlation and downward biased beta estimates. The sample in this study covers listed companies in the US (NASDAQ, NYSE and AMEX and other listed companies) and it is therefore probable that our price share data is subject to infrequent trading and thin markets. In this method, yearly stock betas are estimated as the sum of coefficients from regressing daily absolute excess stock return for stock i in year τ on daily absolute excess market return in year τ. The four preceding (lagged), the synchronous (matching) and the subsequent (leading) market returns are used as the explanatory variables. According to Dimson (1979), at least one leading term and four lagging terms are required and his advice is thus followed in this study. The multiple regressions model can be written as follows:

$$R_{i,t} = \alpha_i + \sum_{k=-L}^{L} \hat{\beta}_{i,k} R_{M,t+k} + \upsilon_{i,t}$$

$$\hat{\beta}_i = \sum_{k=-L}^{L} \hat{\beta}_{i,k}$$

where:

$R_{i,t}$ = excess return for stock *i* in day *t*

α_i = alpha of stock *i*

$\hat{\beta}_{i,k}$ = coefficient from factor *k*

$R_{M,t+k}$ = market excess return for factor/explanatory variable *k*

$\upsilon_{i,t}$ = error term

Dimson´s method is more generally applicable compared to alternative methods available and a consistent estimate of beta is obtained by aggregating the slope coefficients on a yearly basis for each security from the regression above.

4.3.4 Control variables

The control variables are chosen from previous findings of variables that correlate with future stock returns. In addition, relevant financial statement measures which potentially could help in explaining stock returns are used.

Three-factor risk controls:

1. Book-to-Market Equity

$$BM = \frac{Book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}{Market\ common\ equity\ for\ the\ end\ of\ December\ of\ calender\ year\ t-1}$$

BE = Book value of shareholder´s equity plus deferred taxes and investment tax credit minus the book value of preferred stock.

2. A factor related to firm size

Size = market capitalization

3. An overall market factor

Beta = as defined above

Balance sheet based controls:

$$Intangibles = \frac{Intangible\ assets\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}{Book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}$$

$$Debt = \frac{Long-term\ debt\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}{Book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}$$

$$Cash = \frac{Cash\ and\ cash\ equivalents\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}{Book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}$$

Profitability and growth controls:

$$ROE^{1} = \frac{Net\ income\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1}{Average\ book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t}$$

$$Growth = \frac{Book\ common\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t}{Book\ commin\ equity\ for\ the\ fiscal\ year\ ending\ in\ calender\ year\ t-1} - 1$$

[1] Due to the difficulty of interpreting negative values of ROE, all negative values have been excluded

Given the definitions of the control variables above, and assuming that $r_{i,t}$ is the absolute return for stock *i* in time *t* and GWI is the company´s goodwillintensity, the main regression specification in this paper can be written as follows:

$$r_{i,t} = \beta_0 + \beta_1 GWI + \beta_2 Beta + \beta_3 Size + \beta_4 BM + \beta_5 Intangibles + \beta_6 Debt$$
$$+\beta_7 Cash + \beta_8 ROE + \beta_9 Growth$$

The methodology used to perform this regression is described in the following section.

5. Methodology

The aim of this paper is to investigate the relationship between goodwill and stock returns during different economic conditions. This section will explain how the study is conducted. As main sources of inspiration for the methodology applied in this paper, we have used Simuntin (2009) "*Excess Cash and Stock Returns*" and Fama, French (1992) *"The cross-section of Expected Stock Returns"*. Firstly, the correlation between goodwillintensity and selected firm characteristics is explored. Secondly, we create style portfolios based on goodwillintensity by dividing the sample in a two-step procedure. Thirdly, we present the main regression setting of the two-step Fama-MacBeth regression method and how it is used to analyse the relationship between goodwill and stock returns. Finally, other asset pricing models that are used in the robustness test are presented.

5.1 Goodwill and firm characteristics

When analysing the effect of our main independent variable, goodwillintensity, on stock returns we must distinguish between the effect of this variable and the effects from other potential explanatory variables. Therefore, we test for multicolliniarity between goodwillintensity and other variables discovered by previous literature to explain, or variables that we think potentially can explain, the variation in stock returns. If strong correlation between our main independent variable and another variable exists, using these variables in the regression setting is essential. As can be seen in *Table 1*, goodwillintensity has the highest correlation with leverage (debt/equity), 48.5%, which seems reasonable considering that many firms use debt as financing for acquisitions. In addition, it is especially important to control for debt in regressions since it is most likely to be another source of risk in a

company. Furthermore, intangible assets (intangibles/equity) is another variable that has relatively high correlation with goodwillintensity and needs to be controlled for.

Table 1 – Correlation matrix between the independent variables for companies with goodwill

	GWI	β	*BM*	*Marketcap*	*Debt*	*Cash*	*Intangibles*	*ROE*	*Growth*
GWI	100								
β	-2.16	100							
BM	-8.98	-3.81	100						
Marketcap	1.10	0.47	-2.44	100					
Debt	48.54	1.15	-3.38	-0.11	100				
Cash	2.08	8.22	-10.34	-0.87	15.52	100			
Intangibles	23.54	-2.63	-7.41	2.14	22.78	4.84	100		
ROE	16.72	4.44	-13.75	0.06	20.26	26.32	9.63	100	
Growth	2.47	11.30	-4.93	1.28	2.97	4.97	-0.61	26.78	100

Notes: Numbers in percent.

5.2 Style portfolio construction

When using a random sample of individual stocks in asset pricing models, it is most likely that these stocks are representative for the market as a whole and that the market portfolio will be the only factor to significantly explain the stock returns. Hence, it would be preferable to find another method that can highlight risk factors other than the market portfolio. Previous literature has argued that forming portfolios is one solution that would solve this issue. Grouping stocks avoid random sampling and increase the chances of emphasizing other explanatory factors. There are other advantages as well. Firstly, when stocks are grouped into portfolios, noise in individual stock returns is reduced (Chen et al, 1986). Secondly, stocks may not have constant loadings on factors across time but portfolio construction allows stocks to shift between groups when their factors change.

As early indicators of how to form goodwillintensity portfolios, *Table 2* and *Table 3* below are used. *Table 2* shows the characteristics of the goodwillintensity. Based on the information in the table, the companies were formed into ten goodwillintensity groups at the end of each calendar year t. Decile one includes companies with goodwillintensity over zero and up to 10%, and decile two includes companies with goodwill between 10-20% and so on up to decile 10, which includes companies with goodwillintensity larger than 90%. This method was chosen in order to create portfolios with an appropriate scale of the continuous variable goodwillintensity.

Table 2 – Summary statistics for main independent variable goodwillintensity for companies with goodwill

Min	0.004		
10 pct	1.986		
20 pct	4.840	*Observations*	176,270
30 pct	8.641	*Mean*	31.367
40 pct	13.229	*Std*	37.937
50 pct	18.886		
60 pct	26.213	*Variance*	14.392
70 pct	36.734	*Skewness*	3.224
80 pct	50.898	*Kurtosis*	21.971
90 pct	75.880		
Max	494.165		

Notes: Numbers in percent, except for observations, skewness and kurtosis.

Before deciding on using the ten created goodwillintensity groups, it is fruitful to initially shed light on the firm characteristics within each decile. If there is a strong trend from decile one to decile ten, it is fruitful to first divide the sample based on that firm characteristic in order to allow for variation in that variable that is unrelated to goodwillintensity Then, within the created subgroups goodwillintensity deciles can be formed (Fama and French, 1992).

Table 3 shows the mean of selected characteristics for the goodwillintensity deciles. As seen in this table, debt has the strongest (increasing) trend from decile one to decile ten, from approximately 32.4% to 153.5%. It is natural to expect debt to increase as goodwillintensity increases due to debt financed acquisitions. The second strongest (negative) trend of a firm characteristic between the deciles is book-to-market (BM) with a total decrease of approximately 30.1%. The result that BM decreases with more goodwill can also be expected considering that growth stocks have lower book-to-market values and an M&A growth strategy can be expected to occur more frequently among growth stocks. Worth mentioning is also the variable intangible assets (intangibles/equity), with an increase from decile one to ten of approximately 14.1%. The return on equity (ROE) also shows a positive trend from the lowest to the highest decile. However, the rest of the variables show an unsystematic and weak trend.

Based on the results in *Table 3*, it seems natural to first divide the sample based on debt due to the strong trend from decile one to decile ten. However, since debt strongly covariate with goodwillintensity, it is hard to extract variation in debt that is unrelated to goodwillintensity. This is something that is covered further in the problematization and robustness section. Instead, the first division into groups is based on the firm characteristic

showing the second strongest trend, book-to-market. The sample was thus divided into equally-sized book-to-market quintiles. This subdivision allows for variation in the book-to-market value that is unrelated to goodwillintensity. Then, within each book-to market quintile, a second division into ten deciles was made based on the same cut-off levels of goodwillintensity used above.

Table 3 - Mean firm characteristics for goodwillintensity deciles

GWI	β	*BM*	*Marketcap*	*Debt*	*Cash*	*Intangibles*	*ROE*	*Growth*
Low	1.08	102.46	5,244	32.40	25.14	4.08	14.30	20.22
D2	1.04	95.58	9,554	39.43	21.19	5.40	14.52	15.94
D3	0.99	90.96	7,641	48.26	21.30	7.37	15.27	16.91
D4	1.03	86.36	8,228	52.06	20.47	9.92	15.47	19.07
D5	1.09	81.73	65,780	51.88	18.09	11.31	14.76	19.83
D6	1.03	74.82	48,918	60.74	18.38	13.90	14.94	20.33
D7	1.04	74.36	11,233	70.30	17.02	14.83	15.11	21.31
D8	1.03	70.33	12,703	72.56	15.62	14.61	15.68	20.83
D9	1.02	70.40	13,046	90.42	18.05	16.50	16.93	27.18
High	1.01	72.41	11,729	153.50	25.66	18.18	23.80	21.58
High-Low	-0.075	-30.057	6,486	121.101	0.517	14.100	9.503	1.360
	[10.41]	[24.41]	[16.62]	[160.00]	[1.67]	[66.78]	[52.38]	[2.55]

Notes: Numbers in percent (except for market cap and beta). Marketcap is calculated as common shares outstanding multiplied with the stock price (adjusted for stock splits and dividends)

Portfolio construction method is also used when studying the performance of companies with goodwill and companies without goodwill during different market states. The data is divided into equally-sized quintiles based on the CRSP value-weighted index. Quintile one represents the lowest market returns and quintile five the highest. When analysing levels of goodwill during different market states, the goodwill companies will be divided into quintiles (cut-off levels being 20%, 40%, 60% and 80%).

5.3 Regression setting

5.3.1 Matching of data

When trying to explain stock returns with accounting data it is essential to consider the structure of the data and how it should be matched. The accounting data consists of fiscal year-end data in (any month of) calendar year t while stock returns are recorded at the end of each month for calendar year t. However, it is not eligible to perform an arbitrary match between the two for each month since the accounting numbers cannot be assumed to be available to investors at fiscal year-end. In the US, companies are required to file the so called 10-K reports including accounting numbers within 90 days of their fiscal year-ends. However,

on average, 19.8% do not submit their reports on time. A common practise in earlier work has been to assume that the accounting data is available within three months of fiscal year-ends. Fama, French (1992) use a more conservative approach with a six months lag. Considering the above, a four months lag is implemented in this study. The 4-month gap is structured as follows: the accounting data for all fiscal yearends in calendar year $t-1$ (1990-2013) is matched with stock returns for April of year t to Mars of $t+1$. This match together with the declaration of time-series data is a prerequisite for a successful Fama-MacBeth regression, which is described in the following section.

5.3.2 Two-stage Fama-MacBeth regression

As mentioned above, the data is declared to be time-series data. The alternative to time-series data is to use a panel data setting. Although panel data setting is generally considered to be a solid structure of the data, it is not applicable in this study. The main issue with using panel data in this case is that fixed effects regressions will automatically drop variables that are constant over time. The dataset in this study includes accounting data that is constant over year t and stock returns that change on a monthly basis. If a panel data setting together with fixed effects regression had been applied, the results would have omitted the accounting data, thus eliminating the main independent variable goodwillintensity. In addition, it is worth mentioning that none of the other panel data regressions are fruitful to use considering the aim of this study. Time-series data methods, on the other hand, can run multi-cross-sectional regressions for each time unit including an alternative way of performing analysis over time without dropping the variable of interest. Therefore, a time-series data regression method called *the two-stage Fama - MacBeth regression* is used.

The two-stage Fama - MacBeth regression is an implementation of the two-step procedure used in Fama, MacBeth (1973). In the first step, a cross-sectional regression is performed for each single time period, and in the second, the final coefficient estimates are calculated as the average of the first step cross-sectional coefficient estimates. The idea is to run cross-sectional regressions at different points in time and the model is intended to capture across-portfolio characteristics by minimizing within-portfolio variance and thereby testing the CAPM. Thus, the Fama-MacBeth regression tolerates the use of panel data and cross-sectional analysis combined, which is the primary reason for choosing this method. Furthermore, it is built to estimate parameters for asset pricing models, more precisely estimate beta and risk premium for any risk factors that are expected to determine asset prices. However, it is important to note how this regression setting provides standard errors, which

are corrected for cross-sectional correlation but not for time-series autocorrelation. For daily or weekly stock trading analysis this error is not considered to be an extensive one, since stocks have weak time-series autocorrelation. In this study, however, monthly returns are used that might have higher autocorrelation due to the longer horizon. The risk of a potential bias thus needs to be taken into consideration when evaluating the robustness of the results.

The model specification is as follows. Assume that $r_{i,t}$ is the return for stock *i* in time *t.* Let $F_{1,t}$, $F_{2,t}$,…,$F_{m,t}$ be factors which explanatory power of stock returns is tested.

First stage regression:

$$r_{i,t} = \alpha_i + \beta_{i,F1}F_{1,t} + \beta_{i,F2}F_{2,t} + \cdots + \beta_{i,F_x}F_{x,t} + \epsilon_{i,t}$$

where:

$r_{i,t}$ = stock return for stock *i* in month *t*
α_i = intercept for stock *i*
β_{i,F_x}= coefficient for stock *i* and risk factor *x*
$F_{x,t}$ = Risk factor *x* in month *t*
$\epsilon_{i,t}$ = error term for stock *i* in month *t*

Second stage regression:

$$r_i = a + \gamma_1\beta_{i,F_1} + \gamma_2\beta_{i,F_2} + \cdots + \gamma_x\beta_{i,F_x}$$

The second stage regression calculates the average of the first step cross-sectional coefficient estimates. Thus, all parameters in the second regression are averages of the first regression for stock *i* over the specified time period.

5.4 Other risk-factor asset pricing models

As presented in the theory section above, the CAPM is the most well known asset-pricing model from which many alterations have been made resulting in alternative asset-pricing models. Fama-MacBeth that is used in the main regression setting is one of them. In this section, two other relatively newly developed methods are described: *The Fama-French three-factor model* and *the Cahart four-factor model.* The Fama-French three-factor model is an extension of the Capital Asset Pricing Model (CAPM) and is constructed in order to better explain the cross-sectional variation in stock returns. Compared to the traditional asset pricing model CAPM that only uses one explanatory variable, the *market beta*, this model uses two additional explanatory variables: the *size* and the *value* factor. The Cahart four-factor model

extends this model further by adding a fourth variable called *momentum*. The specification is shown below:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,m}(r_{m,t} - r_{f,t}) + \beta_{i,s}SMB_t + \beta_{i,h}HML_t + \beta_{i,mom}MOM_t + \epsilon_{i,t}$$

where:

$r_{i,t} - r_{f,t}$ = excess return (risk-adjusted return) calculated as return for security i at time t minus the risk-free rate at time t

α_i = The intercept, an investment´s return over it´s benchmark

$\beta_{i,m}$ = The exposure to market risk

$r_{m,t} - r_{f,t}$ = The excess return on the market at time t

$\beta_{i,s}$ = The exposure to size risk

SMB_t = *Small minus big:* This factor is called the size premium[2]

$\beta_{i,h}$ = *Value loading factor:* The exposure to value risk

HML_t = *High Minus Low:* This factor is called the value premium[3]

$\beta_{i,mom}$ = The exposure to momentum risk

MOM_t = *Momentum:* The tendency of a stock price to continue in the same direction as previously

$\epsilon_{i,t}$ = Error term (firm-specific risk)

These models are commonly used in methods to adjust for risk. The factors described above are supposed to be controls for market-wide risk factors. These methods are therefore considered to be natural complements to Fama-MacBeth regressions used in this paper and useful in a robustness test of the results.

6. Results

In this section, results are presented in the following order. An initial examination of the performance of ten goodwillintensity decile portfolios is presented followed by the results from regressing future, absolute stock returns on goodwillintensity in a Fama-MacBeth regression setting. Thereafter, the mean returns for companies with goodwill and companies

[2] The size premium is calculated as the average return on the three smallest portfolios minus the average return on the three largest portfolios

[3] The value premium is calculated as the average return on the two highest book-to-market portfolios minus the average return on two lowest book-to-market portfolios

without goodwill during different market states, both during periods of slowdowns and expansions are shown. Finally, corresponding market condition results for five goodwillintensity portfolios are disclosed.

An initial study of the stock returns and the two groups, companies with goodwill and companies without, reveal some intriguing outcomes. *Graph 1* below shows the equally-weighted mean of monthly returns for companies with goodwill and companies without. A distinct difference between the two groups can be observed. Companies with goodwill clearly show a more volatile trend in stock returns. These firms seem to earn lower returns in market slowdowns and higher returns in market upturns. In addition, as can be observed in *Table 4*, the estimated mean of yearly stock beta values are generally higher for companies with goodwill (1.05 compared to 0.96). These figures indicate differences in stock valuation between the two groups. This difference will be further examined below.

Graph 1 - Monthly Equally-Weighted Absolute Mean Return (%) for companies with and without goodwill (1990-2013)

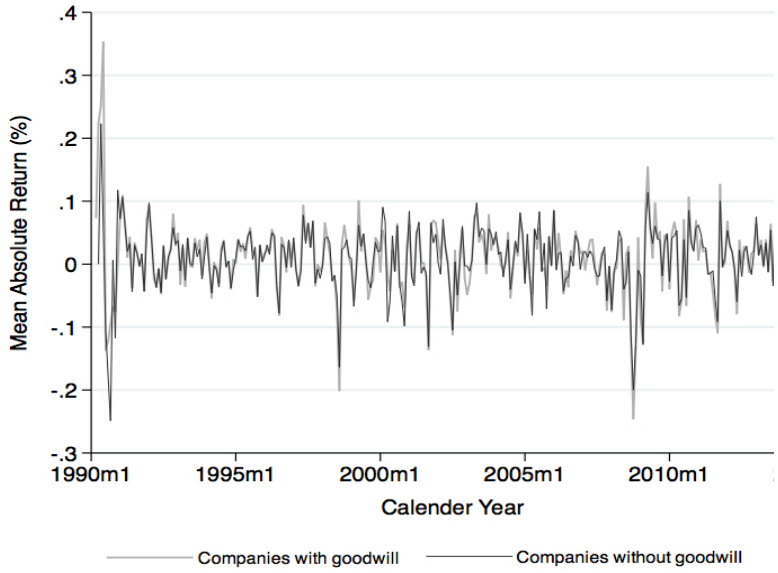


Table 4 – Mean firm characteristics for companies with goodwill and companies without goodwill (1990-2013)

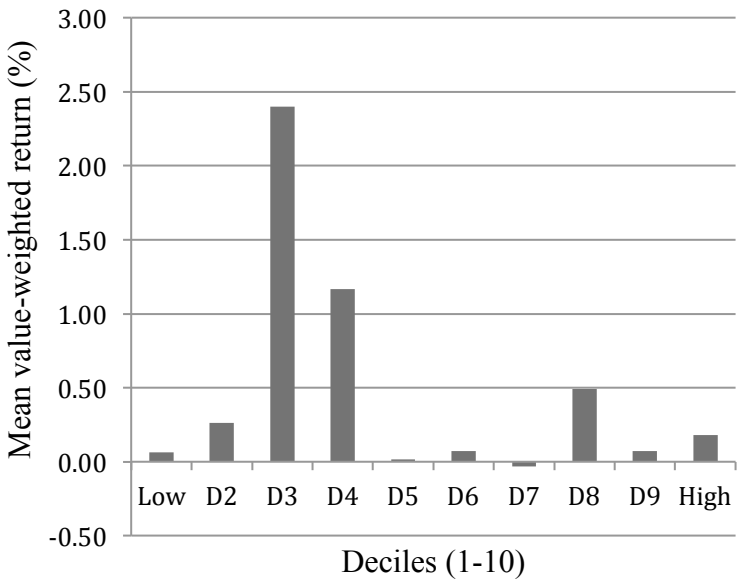
Goodwillintensity	β	*BM*	*Marketcap*	*Debt*	*Cash*	*Intangibles*	*ROE*	*Growth*
Companies with goodwill	1.05	90.90	14,054	52.01	22.02	8.13	15.38	19.06
Companies without goodwill	0.96	122.23	4,928	44.24	24.35	3.82	15.12	19.06

To further examine the stock returns for companies with goodwill, the next table, *Table 5*, reports average value-weighted return, over the whole studied period (1990-2013), in percent per month, for each decile and corresponding t-statistics for rejecting the mean value. Moreover, *Table 5* shows the difference between the mean return values in the highest and the lowest decile (high-low). As can be observed in table 5, there is a higher mean return for decile ten compared to decile one (difference of 0.18%). Thus, companies with higher goodwillintensity seem to have higher performance. For the deciles in the middle, the returns fluctuate quite substantially with no particular trend. Therefore, the higher performance for the top decile compared to the lowest decile is only an indication of a result which must be investigated more thoroughly.

Table 5 - Portfolio mean value-weighted monthly returns for goodwillintensity deciles (1990-2013)

Decile	*Return*	t-value
Low	0.07	0.0000
D2	0.26	0.0001
D3	2.40	0.0000
D4	1.17	0.0000
D5	0.02	0.0000
D6	0.07	0.0000
D7	-0.03	0.0000
D8	0.49	0.0000
D9	0.07	0.0000
High	0.18	0.0000
High-Low	0.11 [1.86]	

Notes: The numbers are in percent per month. The t-statistics shown is the t-value for rejecting the mean value.



The possible, positive trend between stock returns and goodwillintensity, is tested in a series of Fama-MacBeth regressions presented in *Table 6* below. Firstly, a regression is run between absolute future stock returns and goodwillintensity. Thereafter, the control variables are added one at a time resulting in nine regressions. In *Table 6,* the following variables are significant in regression (9): goodwillintensity (GWI), beta (β), book-to-market (BM) and growth. Non-significant variables include: debt, cash, intangibles, size and ROE. A significant positive correlation, with t-value 2.67, can be observed between goodwillintensity and absolute future

stock return after controlling for all relevant variables. The positive relationship amounts to approximately 0.4% implying that 1% increase in goodwillintensity leads to 0.4% increase in the stock return. The correlation (and the significance) increases when more control variables are added to the regression, augmenting the strength of the result. Goodwillintensity shows the third most significant coefficient value. BM presents the strongest significance and highest correlation with a t-value of 5.79 and beta coefficient of 0.53%. Growth shows the second strongest result with a beta coefficient of -0.42% and a t-value of 3.22.

Table 6 – Regressing future, absolute stock return on goodwillintensity for companies with goodwill (1990-2013)

	GWI	β	*Size*	*BM*	*Intangibles*	*Debt*	*Cash*	*ROE*	*Growth*
(1)	0.188								
	[1.3]								
(2)	0.232	0.285							
	[1.61]	[1.43]							
(3)	0.357	0.340	-0.154						
	[2.66]	[1.66]	[3.82]						
(4)	0.372	0.386	-0.038	0.498					
	[2.80]	[1.89]	[0.73]	[5.67]					
(5)	0.395	0.387	-0.041	0.500	0.496				
	[2.92]	[1.81]	[0.78]	[5.69]	[2.27]				
(6)	0.334	0.381	-0.034	0.511	0.428	0.048			
	[2.28]	[1.77]	[0.65]	[5.84]	[1.93]	[0.59]			
(7)	0.373	0.378	-0.031	0.521	0.445	-0.018	0.204		
	[2.52]	[1.76]	[0.59]	[5.99]	[1.99]	[0.22]	[1.02]		
(8)	0.386	0.377	-0.031	0.512	0.431	0.010	0.240	-0.300	
	[2.59]	[1.75]	[0.59]	[5.74]	[1.95]	[0.12]	[0.15]	[0.77]	
(9)	0.397	0.411	-0.030	0.531	0.471	-0.004	0.272	0.200	-0.424
	[2.67]	[1.89]	[0.58]	[5.79]	[2.11]	[0.04]	[1.3]	[0.49]	[3.22]
R2	0.1629	0.1732	0.1823	0.1876	0.1897	0.1926	0.1955	0.1900	0.2009
Prob > F	0.0295	0.0313	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs	125,421	125,421	125,421	125,421	125,421	125,421	125,421	125,421	125,421

Notes: The numbers are in percent and t-statistics are shown in brackets. Regressions are controlled for industry fixed effects.

The positive relationship established above occurs when running regressions for the whole studied period. Thus, the next step is to study the effects during different economical market conditions. *Table 7* reports mean value-weighted portfolio returns for companies with and without goodwill during five different market states. Quintile one (called low) represents the lowest market state and quintile five (called high) represents the highest. Looking at the results in the table, all values and differences are significant, that is the mean values can not be rejected. In market downturns, the mean value-weighted return for companies with goodwill is lower (-5.33%) than the mean value-weighted return for companies without

goodwill (-4.70%) with a difference of -0.63%. In market upturns, on the other hand, mean value-weighted return for companies with goodwill is higher (5.38%) than the mean value-weighted return for companies without goodwill (approximately 4.25%) with a difference of approximately 1.12%. The difference between the groups is thus greater during market slowdowns. In addition, a wider range of returns (high-low of 10.71%) for companies with goodwill over different market states can be observed, compared to companies without goodwill (high-low of 8.95%). *Table 7* also shows that unconditional on market state the mean value-weighted return is higher for companies with goodwill than the mean value-weighted return for companies without goodwill (0.522% compared to 0.08%).

Table 7 - Goodwill portfolio mean value-weighted returns during different market states (1990-2013)

Market state	*Low*	*2*	*3*	*4*	*High*	*High-Low*	*Unconditional on market state*
Companies with goodwill	-5.330	-0.441	0.032	2.910	5.377	10.707	0.522
t-value	0.0000	0.0000	0.0000	0.0002	0.0001	[220]	0.0001
Companies without goodwill	-4.701	-1.770	0.566	1.665	4.253	8.954	0.077
t-value	0.0002	0.0001	0.0001	0.0002	0.0002	[240]	0.0001
Difference between the groups	-0.629	1.329	-0.534	1.245	1.124		
	[15.22]	[25.05]	[6.97]	[28.81]	[23.45]		

Notes: The numbers are in percent per month. Market states are calculated based on a weighted index (CRSP). The t-statistics shown is the t-value for rejecting the mean value.

Having compared the return for companies with goodwill and companies without, the return for goodwillintensity quintiles are investigated conditional on market state in *Table 8.* This table shows the mean value-weighted portfolio returns for the goodwillintensity quintiles during five different market states. As can be observed in the table, companies with the highest goodwillintensity have lower return in market downturns (-7.42%) compared to companies with the lowest goodwillintensity (-5.29%). On the contrary, in market expansions, a higher return can be observed for companies with the highest goodwillintensity (5.05%) compared to companies with the lowest goodwillintensity (4.4%). Taken these results together, the difference between goodwillintensity quintiles is greater in market slowdowns compared to market expansions (high-low of -2.13% compared to high-low of 0.65%). In addition, the t-value for high-low is stronger for the lowest market state quintile, which further supports the previous statement. Finally, it is worth noting that the range for the lowest goodwillintensity quintile is lower compared to the range for the highest goodwill intensity decile. The lowest goodwillintensity quintile has a range of 9.69% and the highest goodwillintensity quintile has a range of 12.47%.

Table 8 – Goodwill decile mean value-weighted portfolio returns for goodwillintensity quintiles conditional on market state (1990-2013)

Market state	*Low*	*2*	*3*	*4*	*High*
Low	-5.289	-1.822	0.325	2.166	4.400
	0.000	0.000	0.000	0.000	0.000
Q2	-2.585	5.443	0.277	1.669	10.641
	0.000	0.000	0.000	0.000	0.000
Q3	-5.307	-1.638	0.128	2.029	5.520
	0.000	0.000	0.000	0.000	0.000
Q4	-4.642	-1.485	2.928	2.323	3.022
	0.000	0.000	0.000	0.000	0.000
High	-7.418	-0.925	1.709	2.554	5.054
	0.000	0.000	0.000	0.000	0.000
High-Low	-2.129	0.897	1.383	0.388	0.654
	[13.75]	[X]	[11.44]	[4.01]	[4.21]

Notes: Numbers in percent per month. Goodwillintensity quintiles are shown on the vertical axis and market state quintiles are shown on the horizontal axis. All numbers are significant

7. Analysis

The first conclusion that can be drawn from the results presented is that stocks with goodwill seem to be more volatile over time compared to securities without goodwill. Recognizing the higher mean betas for firms with goodwill further strengthens this argument. In addition, companies with goodwill earn lower return in times of market slowdowns and higher returns in market upturns compared to companies without goodwill. Finally, the dynamics within the style portfolios demonstrate how the described effects during different market states are higher for companies with higher goodwillintensity. Considering that investors are known to be willing to take on more risk in times of a stable and optimistic market, the goodwill stock might tend to rise, due to shrinking required risk premiums. On the contrary, in market downturns, given that investors are loss averse and less willing to take on more risk, investors are more careful and require a higher risk premium for holding the goodwill stock. The greater underperformance in downturns compared to outperformance in upturns indicates stronger effects in times of market slowdowns, which is further evidence of loss aversion and the incorporated risk in these stocks.

One possible concern is that a part of the effects during market downturns might be caused by higher debt in companies with higher goodwill or by forced new issues of stock. As shown in *Table 3*, goodwillintensity can be assumed to covariate with debt and previous literature argue that companies with large goodwill have a higher tendency of issuing new shares in market slowdowns. Therefore, it is hard to extract the effect on return from the

possible effects from these variables. However, even though the results are not filtered for underlying or linked effects, goodwillintensity may act as a proxy for a dimension of risk representing underlying fundamental risk determinants such as acquisition financing.

Table 5 showed a positive increase in the mean value-weighted return from goodwillintensity decile one to decile ten. This result was further explored in FamaMacBeth regressions where a positive relationship between goodwillintensity and future absolute stock returns was found. These results indicate that higher goodwillintensity result in higher stock returns. This result can be interpreted in two ways. The first possible explanation is that high goodwillintensity companies are generally relatively underpriced compared to companies without goodwill and thus earn higher returns. However, the underpricing theory does not conform well to the volatile nature of the goodwill stock, with sharper peaks and declines in the stock returns. Instead, a second possible explanation is that the goodwillintensity is serving as a proxy for a risk factor that effects equilibrium expected returns. This is a more likely explanation to the observed results, implying that investors require a risk premium for investing in companies with higher goodwillintensity.

Even though this study performs a semi-strong test, the patterns observed may not necessarily contradict the efficient market hypothesis (EMH). The CAPM model, which is based on the EMH, includes the systematic risk as the only explanatory variable for stock returns. However, research has shown that idiosyncratic risk can be transformed into systematic risk when information about the security is sparse. It might seem natural to view the risk of goodwillintensity as being a form of idiosyncratic risk. However, due to the information asymmetry and information risk belonging to this balance sheet item, the entailed risk transform into systematic risk. This reasoning implies that the risk of goodwillintensity might explain a part of the true systematic risk used in the CAPM model.

On the contrary, another viewpoint is that the results can be seen as evidence of inefficient markets, thus rejecting the EMH. Investors might overemphasise past performance when forecasting the future prospects of the firm. This results in overpriced firms with higher performance in the past and underpriced firms with lower performance in the past. When market participants discover the systematic errors in the forecasting, prices are reversed towards the intrinsic value of the firm. This reasoning is linked to the momentum and the reversal effect.

8. Robustness test

In order to test the robustness of the findings in the result section, this part further explores whether the higher returns earned by companies with higher goodwillintensity can be explained by other risk factors using a Fama-French regression setting. Each month, a portfolio that takes a long position in stocks with the highest goodwillintensity and a short position in stocks with the lowest goodwillintensity is created. The positions are then hold without rebalancing for the next 12 months. The high-low goodwillintensity portfolio is regressed on risk factors from 3- and 4-factor models. A series of regressions are then conducted and the results are shown in *Table 10* below. As can be seen in the table, none of the regression settings, including the three-factor Fama-French model and the Cahart four-factor model, can explain the superior performance of the top goodwillintensity decile over the lower goodwillintensity decile. In fact, when adding controls in the table below, the intercept only increases. As a result, the interpretation of a risk premium associated with goodwillintensity still holds.

Table 10 – Regressing high-low goodwillintensity portfolio on other high-low risk portfolios (1990-2013)

	Intercept	*MKT*	*SMB*	*HML*	*MOM*	*R2*
(1)	0.000					0.0000
	[0.01]					
(2)	0.055	-8.572				0.0034
	[3.48]	[23.85]				
(3)	0.057	-7.951	-3.191			0.0037
	[3.62]	[21.44]	[6.23]			
(4)	0.070	-8.436	-4.242	-3.356		0.0040
	[4.44]	[22.25]	[8.28]	[6.14]		
(5)	0.159	-11.795	-3.191	-0.625	-10.070	0.0092
	[9.89]	[29.87]	[6.23]	[11.28]	[29.53]	

Numbers are in percent.

Another possible concern is the proxies and assumptions made in this study. One example is the assumption that accounting data is available four months after fiscal year-ends. A sensitivity analysis was therefore performed, using both a three-month lag and a six-month lag. However, changing this assumption had no significant effect on the results.
Another assumption is the definition of goodwill intensity. When changing the definition to goodwill divided by total assets and using total assets as a base in the control ratios instead of

equity, the results still hold. Nonetheless, changing other assumptions made in this study might still generate different results.

9. Problematization

When interpreting the results in this paper, it could be misleading to argue for causality between goodwillintensity and future absolute returns. It is possible that higher goodwillintensity leads to higher future stock returns. However, it might also be the other way around. Higher stock returns might provide firms with more capital, thus enabling more acquisitions. The results should therefore be interpreted with caution.

Perhaps the main weakness in the results is the general difficulty of interpreting semi-strong tests, which usually rejects CAPM and the efficient market hypothesis. The difficulty occurs since these models need to adjust for risk before evaluating portfolio performance. Beta has commonly been used to adjust for risk, which is also the case in this paper. Even if beta theoretically should be able to represent the overall market-risk factor, the estimated beta might differ from the true, theoretical beta and might therefore not be representative. Thus, other proxies in the main Fama-MacBeth regression and in the Fama-French regression have been used to control for risk. However, the chance of inappropriately adjusting for risk due to invalid proxies and data still remains. Our result that the high-low goodwill portfolio can generate superior return might be misleading if the risk adjustment procedure is incorrect.

There is also a risk of data mining. Datamining implies that a factor can appear to predict future stock return by chance. However, there seems to be one to many linked factors significantly affecting stock returns for rejecting the anomalies. One solution to the risk of data mining could be to replicate the research with another dataset and see if the same results are obtained.

10. Conclusion

This paper documents a positive relationship between goodwillintensity and absolute future stock returns. The mean value-weighted return for companies with goodwill is 0.45% higher than for companies without goodwill. Dividing the sample into style portfolios based on goodwillintensity, companies with high goodwillintensity outperform companies with low goodwillintensity by 0.11%. The superior performance of a portfolio that takes a long position in stocks with the highest goodwillintensity and a short position in stocks with the lowest goodwillintensity persists when running three- and four-factor asset pricing models. The positive relationship is likely to be caused by a required risk premium. Due to the extra risk of information imperfections incorporated in the goodwill item, investors require a compensation for investing in companies with higher goodwill.

The empirical evidence also suggests a volatile nature for firms with goodwill generally showing higher market betas than companies without goodwill. Furthermore, companies with goodwill earn lower returns in times of market slowdowns and higher returns in times of market expansions. This result is further supported by the dynamics within the goodwillintensity style portfolios, showing lowest return for the highest goodwillintensity firms in market downturns and the highest return in market upturns. In addition, the range between the lowest market state and the highest market state is greatest for the portfolio with the highest goodwillintensity. These findings can be explained by investors being more willing to take on more risk in market upturns than downturns, which results in lower risk premium in upturns and higher risk premium in downturns. To conclude, goodwillintensity help in explaining cross-sectional variation is future stock returns.

11. Future research

The results of this paper do not contribute to the precise nature of the underlying economical risk factors. Therefore, a further study could examine possible underlying or related economical risk factors that might help in explaining stock returns, such as “number of acquisitions” or “acquisition financing”. In addition, weak-form test theories are to some extent discussed in this paper. However, due to the restrictions of semi-strong tests in this study, statistical weak-form tests have not been included. Therefore, more thorough weak-form tests could be another suggested further study to test for momentum and reversal effects in goodwill stocks. A third suggestion for further research regarding the goodwill item is to loosen *the rational investor assumption* and allow for irrational behaviour.

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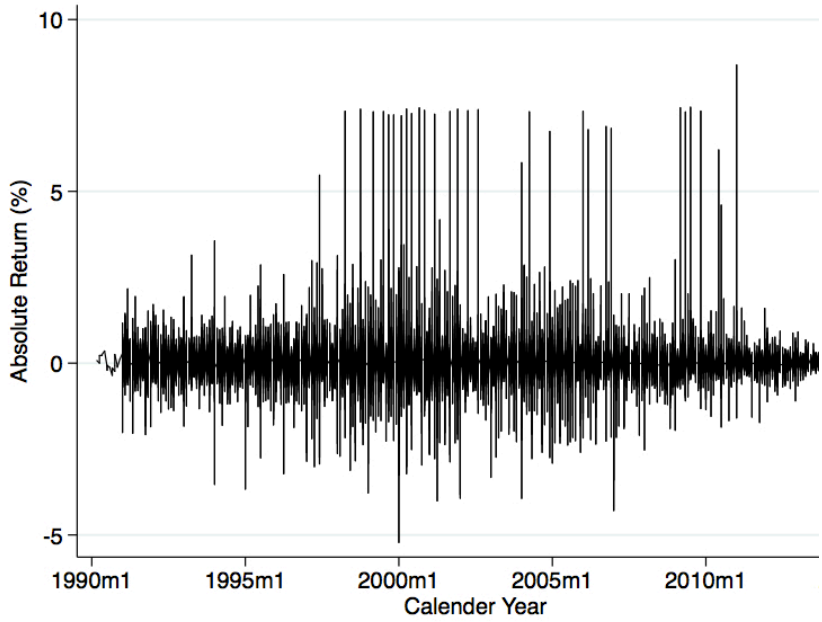
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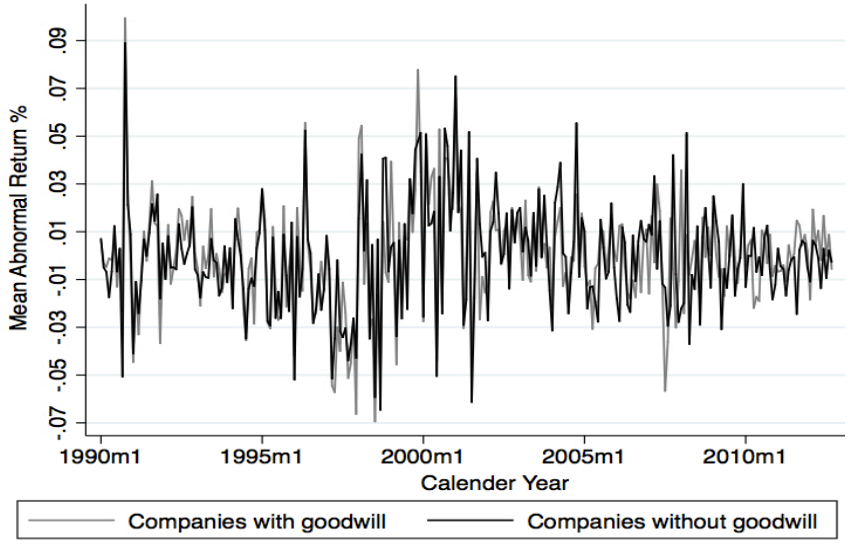
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13. Appendix

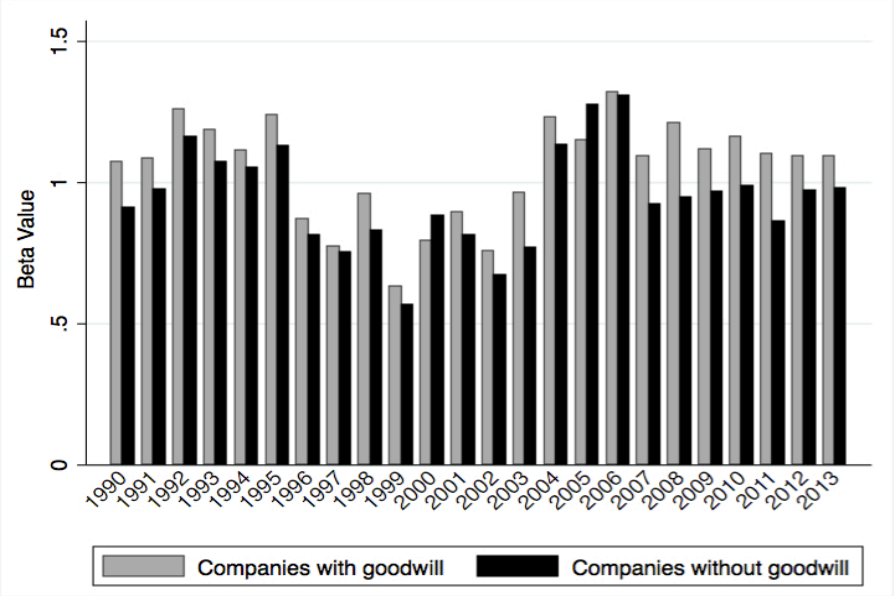
1. Monthly Absolute Returns (%) for all companies (1990-2013)



2. Monthly Abnormal Equally-Weighted Mean Return, in percent per month, for companies with and without goodwill



3. Yearly Beta Values (mean) for companies with and without goodwill



4. Descriptive Statistics for high-low portfolios used in Fama-French regressions

	GHML	*MKT*	*HML*	*SMB*	*MOM*
Mean	0.000	0.634	0.265	0.186	0.608
Std	6.309	4.338	3.096	3.281	4.811
Skewness	-66.240	-70.746	9.155	82.778	-149.725
Kurtosis	12.128	4.314	6.046	11.279	14.015
Min	-37.897	-17.230	-12.680	-16.390	-34.720
Max	23.545	11.340	13.870	22.020	18.390

5. Correlation Matrix for portfolios used in Fama-French regressions

	GHML	*SMB*	*HML*	*MOM*	*MKT*
GHML	100				
SMB	-3.070	100			
HML	0.680	-33.580	100		
MOM	-5.460	5.910	-12.670	100	
MKT	-5.870	24.650	-27.320	-23.330	100

Notes: The numbers are in percent.

6. Data variable list with corresponding WRDS North America identification codes

COMPUSTAT – Fundamentals Annual

A) Daily frequency

[1]	Closing Price	PRCCD
[2]	Cumulative Adjustment Factor by Ex Date	AJEXDI

B) Monthly frequency

[1]	Closing Price	PRCCM
[2]	Cumulative Adjustment Factor by Ex Date	AJEXM
[3]	Issue Security Monthly Descriptor	IID

C) Fiscal annual frequency

[1]	Assets	AT
[2]	Cash and Short Term Investments	CHE
[3]	Long Term Debt	DLTT
[4]	Goodwill	GDWL
[5]	Intangible Assets, including goodwill	INTAN
[6]	Stock Holders Equity	SEQ
[7]	Net Income	NI
[8]	Common Shares Outstanding	CSHO
[9]	Preferred/Preference Stock, Total Capital	PSTK
[10]	Fiscal Year-End	FYR
[11]	SIC codes	SIC
[12]	Company Name	CONM
[13]	Shares Issued For Acquisition	ACQCSHI
[14]	Current Primary Issue Tag	PRIUSA
[15]	Investing Activities, Net Cash Flow	IVNCF
[16]	Deferred Taxes and Investment Tax Credit	TXDITC
[17]	Issue id	

CRSP

A) Monthly frequency

[3]	Value-Weighted Return (excluding dividends)	VWRETX
[4]	Equally-Weighted Return (excluding dividends)	EWRETX

Fama French & Liquidity Factors

A) Monthly frequency

[1]	Small Minus Big	SMB
[2]	High Minus Low	HML
[3]	Excess Return on the Market	MKTRF
[4]	Risk-Free Interest Rate (One Month Tresury Bill Rate)	RF
[5]	Momentum	UMD

B) Daily frequency

[1]	Excess Return on the Market	MKTRF
[2]	Risk-Free Interest Rate (One Month Tresury Bill Rate)	RF

Company identifier: GVKEY
Date variable: DD-MM-YYYY