Stockholm School of Economics
Department of Accounting
Master Thesis
Spring 2019

Are Earnings- and Revenue Response Coefficients Time Varying?

Evidence from the S&P 500

Olof Matto* Erik Björk**

Abstract

We test the time variance of the market's reaction to earnings- and revenue surprises, i.e. the earnings- and revenue response coefficients, on S&P 500 constituents during the period 2001 – 2017, split into three different subperiods based on US GDP growth rates. We find that the earnings response coefficient is time varying, and lower during the 2010 – 2017 period than in the ones before. We do not find that the revenue response coefficient is time varying, and the evidence on the relationship between market returns and revenue surprises during the 2008 – 2009 period is inconclusive. Furthermore, we find that the studied accounting figures, primarily earnings, better explain abnormal stock returns surrounding financial announcements during the 2008 – 2009 period of economic contraction than during the 2001 – 2007 and 2010 – 2017 periods of economic expansion. Finally, the model's ability to explain abnormal returns is lower for the 2010 – 2017 period than for the ones before, which may signify that the market has shifted its focus to financial or non-financial factors not included in this study.

Keywords: Earnings Response Coefficient, Revenue Response Coefficient, Capital Markets, S&P 500, Time Variance

Tutor: Håkan Thorsell

Date: 13 May 2019

Acknowledgements: We would like to thank our tutor Håkan Thorsell for guidance and feedback throughout the work with this paper

* 23207@student.hhs.se
** 23079@student.hhs.se

Table of Contents

1. Introduction

1.1 Background

“The investor who says, ‘this time is different’, when in fact it’s virtually a repeat of an earlier situation, has uttered among the four most costly words in the annals of investing.”

- Sir John Templeton

In March 2008, the American jeweller Tiffany & Co. announced its results for the fiscal year of 2007. Compared to the expectations expressed in the analyst consensus forecast, its earnings had beaten the forecast, but the revenues had come up short. What happened to the stock? At the end of the trading day, it had surged over 10%. Four years later, in March 2012, Tiffany & Co. announced its results for the fiscal year of 2011. This time, the results were reverse: Tiffany’s earnings were lower than the forecast, but its revenues were surprisingly high. However instead of focusing on earnings (as it had done in 2008), the market now seemed to prioritize revenues, and the stock surged almost 7%. Similar types of changes in the market’s focal point can be observed throughout stock market history, and while we cannot put all the credit for stock price surges on earnings or revenues, the lack of a clear pattern raises an important four-word question: *are the times different?*

Logically, market reactions should be driven by changes in the factors that determine a company’s value, which in corporate finance literature usually means future earnings or cash flows. However, few economists would claim that one figure can fully capture the fundamental value of a company, as many components in- or outside financial reports are normally considered relevant. With the Tiffany’s example in mind, it seems like the market’s view of what determines value is not constant over time. Barton, Hansen and Pownall (2010) argue that individual performance measures’ usefulness in equity valuation vary as economic circumstances and accounting regimes change. Signs of over-time variation in accounting figures’ value relevance and market reactions to surprises have been observed during the latter half of the 20th century (see **Table II** for a summary), warranting further research in the field.

This study investigates earnings- and revenue response coefficients, which are empirical measures of the stock market’s reaction to surprises in announced earnings- and revenue figures. More specifically, we test whether the sizes of the two response coefficients have changed over time, to examine how abnormal stock returns surrounding financial announcements can be predicted in different periods.

1.2 Purpose of the Study and Contribution

With this study, we intend to fill a void in existing research on earnings- and revenue response coefficients. Previous research has focused primarily on studying the earnings response coefficient's cross-sectional variation. There is a lack of 1) research contrasting the development of earnings- and revenue response coefficients over time, 2) research contrasting response coefficients between different economic climates, 3) general research on the *revenue* response coefficient, and 4) response coefficient studies conducted on the US market during or after the 2008 – 2009 financial crisis.

By studying S&P 500 constituents between 2001 – 2017, we intend to answer the following research question:

Have Earnings Response Coefficients (ERCs) and Revenue Response Coefficients (RRCs) been time varying?

1.3 Scope and Delimitations

The study is based on the S&P 500 constituent companies over the period 2001 – 2017. Based on economic characteristics, three subperiods are used to investigate the development of the response coefficients: subperiod 1 (2001 – 2007), subperiod 2 (2008 – 2009) and subperiod 3 (2010 – 2017). As shown in **Table I**, the first and third periods are periods of economic expansion, with the US economy exhibiting a GDP growth of between one and four percent each year. The second period is one of economic contraction, with the US economy exhibiting negative GDP growth. The period selection enables both contrasting of two periods of economic expansion at different points in time and contrasting of two periods of economic expansion with a period of economic contraction.

Table I. US Annual Real GDP Growth Rates

Subperiod	GDP CAGR	Comment
2001 – 2007	2.77%	Period of economic expansion
2008 – 2009	-2.54%	Period of economic contraction incl. a year of global recession in 2009 (IMF)
2010 – 2017	2.11%	Period of economic expansion

Table I shows the compounded US annual real GDP growth rate of the three subperiods, adjusted for inflation using 2012 dollars
Source: National Income and Product Accounts: Table 3B, Bureau of Economic Analysis, US Department of Commerce

The focus of the study is to investigate *whether* response coefficients have changed over time. *Why* response coefficients change (or do not change) over time is not empirically tested. However potential reasons are discussed in the analysis.

The remainder of this study is organized as follows: Chapter 2 reviews previous research within the field, providing the theoretical background to our study and motivating our research question. Chapter 3 formulates the hypotheses. Chapter 4 details the methodological framework that is used in the paper and discusses method choices. Chapter 5 presents and analyses the empirical findings. Chapter 6 evaluates the study and its rigidity. Lastly, Chapter 7 presents our concluding remarks, limitations of the study and suggestions for future research.

2. Previous Research and Theoretical Framework

In this section, we first introduce the earnings- and revenue response coefficients through presenting the papers which set the foundation for response coefficient research. Next, we outline indications of historical time variance in response coefficients and the value relevance of accounting figures found in previous research, elaborating on the factors which may affect the over-time development. Finally, we discuss relevant issues associated with the design of response coefficient studies and how they have been handled in previous research.

2.1 The Earnings Response Coefficient

Ball and Brown (1968) laid the foundation for research on the relationship between accounting figures and stock returns, finding that the financial information in a company's annual report is useful as it has an empirical relationship with the company's stock price. Following these findings, numerous studies have attempted to explain and predict the market's reactions to changes and surprises in such figures. Collins and Kothari (1989) demonstrate the relationship between earnings surprises and abnormal stock returns through defining the *Earnings Response Coefficient* (or ERC for short) as the slope coefficient of a linear regression between stock returns and earnings surprises. **Equation I** shows how the ERC is operationalized in Collins and Kothari (1989).

Equation I. The Earnings Response Coefficient

$$\mathrm{CAR}_{i,t} = \hat{\alpha} + \beta_1 * \mathrm{SUE}_{i,t} + \varepsilon_{i,t}$$

$\mathrm{CAR}_{i,t}$	The cumulative abnormal return for company i in period t
$\hat{\alpha}$	The intercept
β_1	The *earnings response coefficient, ERC*
$\mathrm{SUE}_{i,t}$	The earnings surprise variable for company i in period t
$\varepsilon_{i,t}$	The error term for company i in period t

Equation I shows the relationship between the cumulative abnormal return and earnings surprises as illustrated by Collins and Kothari (1989)

2.2 The Revenue Response Coefficient

Extant research has expanded the scope of explaining stock returns by going beyond earnings. Swaminathan and Weintrop (1991) find 1) a positive relation between stock returns and revenue surprises, 2) a negative relation between stock returns and expense surprises, and 3) that the information content of revenues and expenses together is higher than that of earnings alone. In a similar vein, Ertimur, Livnat and Martikainen (2003) show that investors value a dollar of revenue surprise more than a dollar of expense surprise. Rees and Sivaramakrishnan (2007) find that the market's reaction to an earnings surprise is accentuated if combined with a revenue surprise in the same direction.

Derived from the same logic as the ERC, the *Revenue Response Coefficient* (or RRC for short) is an observed relationship between revenue surprises and abnormal stock returns. Jegadeesh and Livnat (2006) find that in addition to earnings surprises, stock price reactions surrounding financial announcements are significantly related to revenue surprises. **Equation II** shows Jegadeesh and Livnat's operationalization of the relationship between earnings- and revenue surprises and abnormal return. Although not as frequently studied as the ERC, the relationship between revenue surprises and abnormal stock returns is well-documented in previous research (for example Ertimur et al., 2003; Rees & Sivaramakrishnan, 2007).

Equation II. The Revenue Response Coefficient

$$\mathrm{AR}_{i,t} = \hat{\alpha} + \beta_1 * \mathrm{SUE}_{i,t} + \beta_2 * \mathrm{SUR}_{i,t} + \varepsilon_{i,t}$$

$\mathrm{AR}_{i,t}$	The abnormal return for company i in period t
$\hat{\alpha}$	The intercept
β_1	The *earnings response coefficient, ERC*
$\mathrm{SUE}_{i,t}$	The earnings surprise variable for company i in period t
β_2	The *revenue response coefficient, RRC*
$\mathrm{SUR}_{i,t}$	The revenue surprise variable for company i in period t
$\varepsilon_{i,t}$	The error term for company i in period t

Equation II shows the relationship between the abnormal return and earnings- and revenue surprises as illustrated by Jegadeesh and Livnat (2006)

Consistent with Ertimur et al. (2003) and Ghosh, Gu and Jain (2005), Jegadeesh and Livnat (2006) argue that the economic intuition behind the revenue response coefficient lies in the ability of revenues to predict future earnings persistence and earnings growth. They support this theory by showing that positive revenue surprises for a quarter are related to positive earnings surprises for the quarter thereafter. Similarly, Ghosh et al. (2005) find that the persistence of earnings is higher when earnings surprises are driven by revenue surprises rather than by expense surprises.

Kama (2009) extends the RRC research by empirically highlighting revenue surprises' larger influence on stock returns compared to earnings surprises for R&D intensive companies, showing that revenue surprises are sometimes more important determinants of stock returns than earnings surprises. To explain the logic behind the relationship, Kama (2009) points to revenue as a more important indicator of earnings persistence and future cash flows *"in contexts in which current earnings are a weak indicator of future earnings"*. Bagnoli, Kallapur and Watts (2001) show that for firms reporting losses, stock prices respond to revenue-, but not earnings surprises. Taken together, evidence in Kama (2009) and Bagnoli et al. (2001) show that as opposed to always prioritizing earnings, the market sometimes favours revenues, indicating that the relative importance of revenue- and earnings surprises is not static.

2.3 Response Coefficients' Time Variance

Linderholm (2001) shows that the ERC in Sweden was higher during the period 1989 – 1991 than during 1999 – 2001. Jegadeesh and Livnat (2006) separate their sample period into two subperiods (1987 – 1995 and 1996 – 2003), and although the ERC is consistently larger than the RRC in both subperiods, the observed ERC has *decreased* between the two periods, while the observed RRC has *increased* – indicating that the relative importance of the response coefficients has shifted over time. In a similar vein, Chandra and Ro (2008) find that when valuing firms, the information conveyed in earnings surprises has declined over time, while the incremental information conveyed in revenue surprises has remained stable. Collins, Maydew and Weiss (1997) and Francis and Schipper (1999) find that the value relevance of earnings information decreased during the latter half of the 20th century, with stock markets instead increasingly favouring the value relevance of balance sheet- and book value information. Further evidence on the decreasing value relevance of earnings and ERCs during the second half of the 20th century can be found in Lev and Zarowin (1999) and Brown, Lo and Lys (1999). To conclude, existing research suggests that the ERC and the value relevance of earnings decreased during the second half of the 20th century, and although there is less evidence on the RRC and the value relevance of revenues, there are indications of an increased RRC (see **Table II** for a summary). Since most of the studies do not prioritize the development of the response coefficients/value relevance, none of the studies statistically test the change, and the indicated development is simply based on the size of the values observed.

Table II. Time Variance in Response Coefficients and Value Relevance

Article	Research type	Sample period(s)	Indicated development	
			Earnings	Revenues
Collins et al. (1997)	Value relevance	1953-1993	Decrease	-
Brown et al. (1999)	Value relevance	1958-1996	Decrease	-
Lev & Zarowin (1999)	Relevance + coefficients	1977-1996	Decrease	-
Linderholm (2001)	Response coefficients	1989-1991, 1999-2001	Decrease	-
Francis & Schipper (1999)	Value relevance	1952-1994	Decrease	-
Jegadeesh & Livnat (2006)	Response coefficients	1987-1995, 1996-2003	Decrease	Increase
Chandra & Ro (2008)	Relevance + coefficients	1988-2001	Decrease	Stable

Table II summarizes extant research on accounting measures' response coefficients/value relevance and their development over time. Note that none of the studies statistically test the time variance, the indicated development is based on the sizes of the coefficients/the value relevance metric.

2.4 Factors Potentially Causing Time Variance in Response Coefficients

In addition to introducing the ERC, Collins and Kothari (1989) find that the coefficient varies based on firm-specific factors such as interest rates, riskiness, growth, size, and earnings persistence – to which subsequent studies have later contributed. For example, Ertimur et al. (2003) find that the market reacts differently based on whether the firm is a value- or growth firm, and Ng, Rusticus and Verdi (2008) find that the ERC is lower for firms with high transaction costs. Given that the factors causing cross-sectional variation may themselves change over time, it follows that the estimated response coefficients could change. In this section, we elaborate on the factors that we believe have affected the time variance of the response coefficients during the observed period.

2.4.1 Management of Accounting Figures and Reporting Quality

Burgstahler and Eames (2006) find that managers tend to engage in earnings management, while simultaneously trying to manage analyst expectations downward, to achieve zero or small positive earnings surprises. The connection between earnings management and response coefficients has been explored in Hackenbrack and Hogan (2002), who find that the perceived precision of the earnings report affects the ERC, and Teoh and Wong (1993), who find that a high-credibility earnings report is associated with high ERCs. Kama (2009) argues that more frequent occurrence of earnings management and larger write-offs lead to lower earnings persistence and precision, which lowers the ERC.

Since the reliability of earnings figures has been shown to affect the ERC, the reliability of revenue figures may affect the RRC. However, compared to earnings management, revenue management is a less prevalent subject in response coefficient literature. Although Ertimur et al. (2003) argue against the prevalence of revenue management since accounting manipulation of expenses may be easier to carry out and harder to detect than manipulation of revenue figures, Edmonds, Leece and Maher (2013) find that CEOs receive lower bonuses when they miss the analysts' revenue forecast, which could represent a clear incentive for CEOs to manage revenues. Additionally, Caylor (2010) finds that managers use both accrued revenue and deferred revenue to avoid negative earnings surprises.

The occurrence of accounting figures management is to a large degree affected by the prevailing accounting regimes. For example, Cohen, Dey and Lys (2008) show that firms' management of accounting earnings declined significantly after the passage of the Sarbanes-Oxley Act. Accounting regulations change continuously in efforts from the governing authorities to ascertain reliability and materiality in the figures. As an example, FASB issued 29 changes to U.S. GAAP in 2010 alone, and recently, IFRS 15 and ASC 606 changed revenue reporting for many firms. Given the relationship between earnings management and the ERC, a continuously changing regulatory landscape and recent major reporting changes may have caused time variance in both of the response coefficients.

2.4.2 Information Availability

Collins and Kothari (1989) show that the ERC is affected by differences in information environment. Logically, a higher availability of more value-relevant information should facilitate the market's assessment of a company's intrinsic value, diminishing the importance of the information conveyed through financial announcements. Francis, Nanda and Olsson (2008) find that firms which provide more voluntary disclosure are rewarded with lower cost of capital, providing a clear incentive for firms to contribute to increased information availability.

Definition: Collins and Kothari (1989) define information environment broadly, including all sources of information relevant to assess firm value. For example macroeconomic reports, industry reports, analyst reports, firm-specific news in the financial press etc.

Drake, Roulstone and Thornock (2012) find that the market's reaction to earnings news is smaller when the volume of related internet searches prior to the announcements is larger, a relationship which may be explained by information availability. As information availability is affected by the introduction of new or improved information technology, response coefficients may in turn be affected

2.4.3 Growth Opportunities

Based on corporate valuation theory, Collins and Kothari (1989) show that there is a positive association between companies' earnings growth opportunities and the ERC. The valuation impact of an earnings surprise is higher for these firms since a change in earnings is associated with a larger change in cash flow expectations (Martikainen, 1997). Ertimur et al. (2003) expand this discussion to revenue- and expense surprises, arguing that investors are more concerned about the existence and growth of customer demand for growth firms, while investors care more about management's ability to control expenses for value firms. Ultimately, Ertimur et al. (2003) show that the positive association that exists between growth opportunities and ERCs also holds for RRCs.

Response coefficient studies typically approximate growth opportunities using company market-to-book ratios (for example Collins & Kothari, 1989; Jegadeesh & Livnat, 2006). **Figure 1** shows that the average market-to-book ratio of the S&P 500 constituents has varied considerably during the observed period, which in turn may have impacted the response coefficients.

Figure 1. S&P 500 Market-to-Book Value (2001-2017)

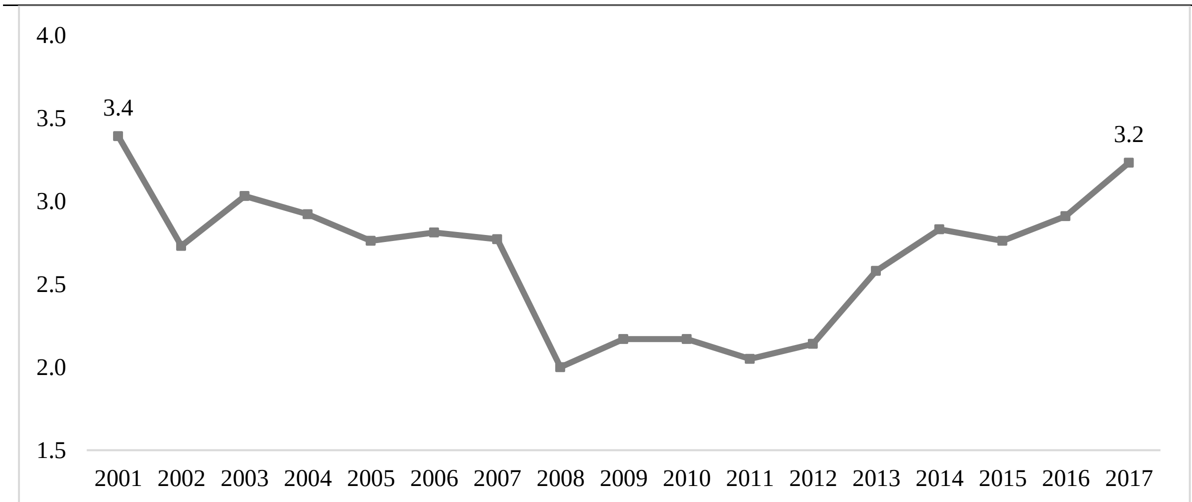


Figure 1 shows the total market-to-book value for S&P 500 constituents as of 31st December each year. Source: Standard & Poor's

2.5 Expected Returns and the Capital Asset Pricing Model

An important component of the response coefficient regression is the abnormal stock return – the difference between actual and expected returns. Response coefficient studies portray expected return in several different ways: Kama (2009) and Jegadeesh and Livnat (2006) use observed size- or book-to-market matched portfolio returns to determine expected returns, Swaminathan and Weintrop (1991) use a market index, and Collins and Kothari (1989) the CAPM. The CAPM uses the risk-free rate and the market risk premium adjusted for some measure of systematic risk (Beta) to arrive at the expected return of a security or portfolio (Sharpe, 1964; Lintner, 1965). Using the CAPM, an estimation of the expected return for a security or portfolio over a specified period can be made.

Fama and French (1996) find that certain "anomalies" in the returns estimated by the CAPM could be explained by additional firm-specific factors. Based on the CAPM, they construct the Fama-French three-factor model. The model extends the CAPM and incorporates firm size, based on market capitalization, and the book-to-market equity ratio, finding that the "anomalies" to a large extent can be explained by the additional variables. They ultimately also find that small companies (low market capitalization) and value companies (high book-to-market ratio) tend to outperform large- and growth companies.

2.6 Announcement Drift

Ball and Brown (1968) did not only find that information in financial reports is related to stock prices on the announcement date, but also that prices continue to drift during periods *after* the earnings announcement. Bernard and Thomas (1989) describe this concept as *post-earnings announcement drift*, and it is shown in for example Joy, Litzenberger and McEnally (1977), Rendleman, Jones and Latané (1982), and Zhang (2012). Bernard and Thomas (1989) argue that post-earnings announcement drift may arise because transaction costs inhibit immediate responses, and because market participants *"fail to appreciate the full implications of earnings information"*. Jegadeesh and Livnat (2006) test the drift over longer periods of time, finding that there is a market underreaction to the information that is conveyed by revenue surprises at the time when the figures are announced, and that it may take up to six months for analysts to incorporate the revenue surprise information in their forecasts.

Price drift occurring *before* the announcement date is referred to as *pre-earnings announcement drift,* usually explained either by changes in expectations stemming from related firms' earnings announcements (Foster, 1981; Ramnath, 2002), or by information leakage causing some market participants to receive the information early (Brunnermeier 2005). To account for both pre- and post-earnings announcement drift, response coefficient studies typically measure returns over multiple days surrounding an announcement.

3. Hypotheses

Market participants and researchers have over the course of half a century attempted to predict stock price movements by studying surprises in accounting figures. As a result of this, the earnings response coefficient has evolved as an important predictor in the estimation of abnormal stock returns. By studying accounting figures beyond earnings, researchers have also found a positive relationship between revenue surprises and the abnormal stock return, and that the relative importance of the RRC and ERC depends on firm-specific factors such as R&D intensity and profitability (see **Section 2.2**). Cross-sectional variation in response coefficients has been shown in previous research, with factors such as reporting quality, information availability and growth opportunities affecting market reactions (see **Section 2.4**).

The ERC and the perceived value relevance of earnings seem to have decreased over time, while the RRC has shown tendencies to increase (see **Table II**). Stricter regulations on earnings management and revenue recognition, adoption of new accounting regimes, and changes in information availability and growth opportunities may have affected the relationship between accounting figures and stock returns. With all this in mind, we hypothesize that earnings- and revenue response coefficients have not been static – rather, they have varied over time. Consequently, this study will investigate the two following hypotheses:

H1: The market's reaction to an earnings surprise (the earnings response coefficient) varied over time during the period 2001 – 2017

H2: The market's reaction to a revenue surprise (the revenue response coefficient) varied over time during the period 2001 – 2017

4. Method

In this section, we first present how the sample has been selected and subdivided. Then, the regression model is shown, followed by the operationalization of the variables. Finally, we show observation shortfall relating to methodological choices.

4.1 Sample Selection

The dataset is based on S&P 500 constituents over the period 2001 – 2017. The use of S&P 500 constituents over any other sample is based on two factors: 1) it is arguably the most commonly used gauge of US large cap equities, capturing around 80% of the total US market capitalization (Standard & Poor's) and 2) data availability for the constituent companies is high, particularly with regards to analyst forecasts. The sample period 2001 – 2017 is chosen both to contribute to the research body with more recent evidence than prior studies, and since it encompasses multiple stages of the business cycle.

We separate the sample into three different subperiods, each starting on the 1st of January of the first year, and ending on the 31st of December of the final year: subperiod 1 (Jan 1st 2001 – Dec 31st 2007), subperiod 2 (Jan 1st 2008 – Dec 31st 2009) and subperiod 3 (Jan 1st 2010 – Dec 31st 2017). The observations are separated based on the fiscal year ends: a financial announcement in February 2010 belongs to subperiod 2 if the financial results pertain to a fiscal year ending in December 2009.

Since the constituents of the S&P 500 change over time as companies are excluded and included based on for example market capitalization and trading activity, the sample does not contain the same companies throughout the whole period. Observations from periods where a company was not a part of the S&P 500 are removed, and all observations pertain to companies that *at the time of the announcement* were constituents of the S&P 500.

4.2 The Regression Model

We use a linear regression model similar to the one used by Jegadeesh and Livnat (2006), including a total of five variables (not counting industry dummy variables) shown in **Equation III**. The abnormal return variable (AR) serves as the dependent variable, and the earnings- and revenue surprise variables (SUE and SUR) serve as the main independent variables. The size variable (SIZE) controls whether the firm is large or small, and the value/growth variable (VG) whether the firm is a value- or growth firm. Industry-specific dummy variables are included in the regression based on the 11 industry categories shown in **Table III**. To facilitate reading the tables, these are not shown in **Equation III**, nor are their coefficients presented in **Table XII – Table XV**.

Equation III. The Regression Model

$$\mathrm{AR}_{i,t} = \hat{\alpha} + \beta_1 * \mathrm{SUE}_{i,t} + \beta_2 * \mathrm{SUR}_{i,t} + \beta_3 * \mathrm{SIZE}_{i,t} + \beta_4 * \mathrm{VG}_{i,t} + \varepsilon_{i,t}$$

$\mathrm{AR}_{i,t}$	The abnormal return for company i in period t (CAPM or Index)
$\hat{\alpha}$	The intercept
β_1	The *earnings response coefficient, ERC*
$\mathrm{SUE}_{i,t}$	The earnings surprise variable for company i in period t
β_2	The *revenue response coefficient, RRC*
$\mathrm{SUR}_{i,t}$	The revenue surprise variable for company i in period t
β_3	The coefficient associated with the size variable
$\mathrm{SIZE}_{i,t}$	The size variable, determining whether the company is a small or a large firm
β_4	The coefficient associated with the value/growth variable
$\mathrm{VG}_{i,t}$	The value/growth variable, determining whether the company is a value or a growth firm
$\varepsilon_{i,t}$	The error term for company i in period t

Equation III shows the OLS regression model used in this paper. The size variable can assume either the value 1 (small) or 0 (large), and the value/growth variable can assume either the value 1 (growth) or 0 (value). Dummy variables for SIC codes, classifying each company into a specific industry, are included in the regression but omitted in the illustration of the model. Time fixed effects have not been used.

4.3 Operationalization of the Dependent Variable (AR)

The abnormal return (AR) is defined as the *actual* stock return observed during the event window less an estimate of the *expected* stock return over the same period. We use two models for estimating the expected return: Index and CAPM.

Equation IV. Abnormal Return

$$\mathrm{AR}_{i,t} = \mathrm{R}_{i,t} - \mathrm{E}(\mathrm{R}_{i,t})$$

$\mathrm{AR}_{i,t}$	The abnormal return for company i surrounding the announcement date t
$\mathrm{R}_{i,t}$	The actual return for company i surrounding the announcement date t
$\mathrm{E}(\mathrm{R}_{i,t})$	The expected return for company i surrounding the announcement date t

Equation IV shows how the abnormal stock return in the event window surrounding an announcement date t is calculated for company i using the observed return and some model of expected return (CAPM or Index)

4.3.1 Event Window

To account for the concepts of pre- and post-earnings announcement drift, response coefficients are normally studied using event windows, during which companies' returns are measured. Long event windows spanning for example six months have the advantage of capturing stock price drifts stemming from slow market reactions to accounting figures (Jegadeesh & Livnat 2006). However, long event windows may also include effects from information other than what is presented in the observed announcement (Lee & Park 2000).

The event window size and shape vary between studies. For example, Ertimur et al. (2003) use an event window of three days centered around the announcement date, whereas Jegadeesh and Livnat (2006) use an event window starting two trading days before the announcement day and ending one trading day thereafter. This study uses the same event window as Jegadeesh and Livnat (2006). Since there are trade-offs between long and short event windows, and no established best practice, we carry out tests with longer event windows in the sensitivity analysis.

4.3.2 Actual Stock Return

The actual stock return is calculated as the percentage change in the company's stock price observed during the event window. Stock price data is retrieved from The Center for Research in Security Prices (CRSP).

Equation V. Actual Stock Return

$$R_{i,t} = \frac{p_{i,t+1} - p_{i,t-2}}{p_{i,t-2}}$$

$R_{i,t}$	The actual return for company i surrounding the announcement date t
$p_{i,t+1}$	The observed closing price of the company one trading day after t
$p_{i,t-2}$	The observed closing price of the company two trading days before t

Equation V shows how the actual stock return in the event window surrounding an announcement date t is calculated for company i. Stock prices have not been adjusted for corporate actions such as new issues, dividends, or stock repurchases.

4.3.3 Expected Stock Return (Index)

The first model for estimating expected stock returns uses the percentage change in the observed index level of the NYSE/AMEX/NASDAQ Composite Value Weighted Index during the event window.

Equation VI. Expected Stock Return (Index)

$$E(R_{i,t})_{IND} = r_{m,t} = \frac{p_{IND_{t+1}} - p_{IND_{t-2}}}{p_{IND_{t-2}}}$$

$E(R_{i,t})_{IND}$	The expected return for company i surrounding the announcement date t
$p_{IND_{t+1}}$	The observed closing price of the index one trading day after t
$p_{IND_{t-2}}$	The observed closing price of the index two trading days before t

Equation VI shows how the expected stock return in the event window surrounding an announcement date t for company i is estimated using the observed return of the NYSE/AMEX/NASDAQ Composite Value Weighted Index (with reinvested dividends)

4.3.4 Expected Stock Return (CAPM)

The second model for estimating expected stock returns uses the CAPM. Unlike the simpler Index model, the CAPM incorporates companies' difference in exposure to the market's systematic risk. By using proxies for the risk-free rate, the market return and individual company betas, an expected return over the event window is calculated. The risk free rate is approximated using the US 10-year constant maturity treasury bill rate at the end of the announcement month, and the market return is approximated using the NYSE/AMEX/NASDAQ Composite Value Weighted Index. Betas are retrieved from WRDS Betasuite where they are calculated based on the same index as the one used for market return. Primarily, 60 month rolling betas are used, but to limit the amount of data shortfall caused by for example recent listings or company mergers, down to 30 month rolling betas are allowed.

Equation VII. Expected Stock Return (CAPM)

$$E(R_{i,t})_{CAPM} = r_{f,t} + \beta_{i,t} * (r_{m,t} - r_{f,t})$$

$E(R_{i,t})_{CAPM}$	The expected return for company i surrounding the announcement date t
$r_{f,t}$	The accumulated risk-free rate surrounding the announcement date t
$\beta_{i,t}$	The observed Beta for company i on the last trading day of the month of the announcement date t
$r_{m,t}$	The observed return of the index during the period surrounding the announcement date t

Equation VII shows how the expected stock return in the event window surrounding an announcement date t for company i is estimated using the CAPM. $r_{f,t}$ is approximated by the US 10-year constant maturity treasury bill rate at the end of the month of the announcement date t, divided by 360 and multiplied by 4 to approximate a 4-day return. $\beta_{i,t}$ is represented using 30-60 month rolling Betas retrieved from WRDS Betasuite. $r_{m,t}$ is approximated by the observed return of the NYSE/AMEX/NASDAQ Composite Value Weighted Index (with reinvested dividends).

To limit the effect from extreme values, we winsorize the abnormal return at the 0.5- and 99.5% levels, similar to Jegadeesh and Livnat (2006b), although they choose to remove these observations rather than keeping them in the sample.

4.4 Operationalization of the Independent Variables

4.4.1 The Earnings Surprise Variable (SUE)

The earnings surprise variable (SUE) is calculated as the forecast error scaled by an appropriate denominator. The forecast error is calculated as the actual earnings (net income) less the expected earnings, measured on a per-share basis (EPS), as done in Jegadeesh and Livnat (2006) and Ertimur et al. (2003).

Definition: The forecast error is defined as actual earnings less expected earnings

The first part of the forecast error, i.e. the actual EPS, can be obtained in companies' financial reports, and is available in databases. The second part of the forecast error, the expected EPS, is a less clear-cut component as it is impossible to exactly pinpoint the market's expectations. The most commonly used methods are time series models which base the forecast on historical data, and analyst consensus forecasts. Brown, Hagerman, Griffin and Zmijewski (1987) and O'Brien (1988) find that analysts' forecasts are superior to time series models in forecasting earnings, and Kothari (2001) argues that it has in recent years become common practice to assume that analysts' estimates function as better forecasts than time series models. Hence, we operationalize expected EPS using the analyst consensus forecast.

The actual- and expected results are collected from I/B/E/S, as done in previous studies such as Ertimur et al. (2003) and Rees and Sivaramakrishnan (2007). The actual results used are those that are announced on the announcement date. Although figures may have been restated in the time since, it is deemed safe to assume that the market did not have information about these restatements during the relatively narrow event window.

Although the dataset could be expanded by including interim financial announcements, we study only figures for the full fiscal year. Lee and Park (2000) argue that fourth fiscal quarters are better to use because 1) interim reports are often not audited and subject to more approximation of annual costs and 2) the year end-information settles the whole fiscal year, acting as a better indicator of future performance. While the figures are presented on an annual basis, it can be assumed that the surprise stems from the forecast error for the fourth fiscal quarter, since the information pertaining to earnings for the first three fiscal quarters is already known to the market following prior announcements.

To ensure comparability between firms, the forecast error needs to be scaled to arrive at the earnings surprise variable. Collins and Kothari (1989) separately use the last year's earnings and the price of the stock to scale the forecast error, Ertimur et al. (2003), Ghosh et al. (2005), and Rees and Sivaramakrishnan (2007) scale using stock prices, Jegadeesh and Livnat (2006) use the standard deviation of earnings growth, and Imhoff and Lobo (1992) use the standard deviation of the analyst consensus forecast.

Lipe (1990) and Imhoff and Lobo (1992) find that high uncertainty (or low predictability) in earnings forecasts has an inverse relationship with the earnings response coefficient. Imhoff and Lobo (1992) defines this as the uncertainty effect, showing that when there is a lot of uncertainty in the expected earnings measure, the market's reaction to an earnings surprise is small. It could be argued that this effect arises because market participants expect that the actual results will most likely differ from the forecast in advance. Additionally, Zhang (2006) finds that uncertainty prior to the announcement of new information delays stock price reactions, causing stock price drifts in the months following the announcement which usually are not captured by response coefficient studies' event windows.

To adjust for the uncertainty effect, Imhoff and Lobo (1992) scale the forecast error using the standard deviation of the analyst consensus forecast and find that this effectively controls for it. Similarly, Jegadeesh and Livnat (2006) scale the forecast error using the standard deviation of historical earnings/revenue growth, making surprises of a firm with large variations in historical growth smaller. In the sense that variation in historical growth is also a proxy for uncertainty, Imhoff and Lobo (1992) and Jegadeesh and Livnat (2006) use two different methods to control for the uncertainty effect. In our view, the reason for the divergence lies in that the two papers operationalize the market's expectations in different ways (Jegadeesh and Livnat 2006 use a random walk model and Imhoff and Lobo 1992 use analyst forecasts). Since we use analyst forecasts to estimate expected earnings and revenues, we use the approach of Imhoff and Lobo (1992) and scale the forecast error using the standard deviation of the analyst consensus forecast, adjusting for the uncertainty effect which could otherwise create bias in the estimated response coefficients.

We enhance the accuracy of the analyst consensus forecast by requiring it to be based on a minimum of five analysts' forecasts. By only using forecasts based on multiple opinions, the consensus forecast arguably better approximates the market's expectation as it limits the impact of a single analyst's potentially biased view. Imhoff and Lobo (1992) also require at least five analyst forecasts, arguing that it *"permits a reasonable statistical estimate of the standard deviation of analysts' forecasts"*. Since our sample is based on the S&P 500, multiple analysts tend to follow each company, and this requirement does not generate a substantial downfall. We test the impact of this decision in the sensitivity analysis. The information regarding the number of analysts participating in the consensus is obtained directly from I/B/E/S.

For each observation, we include only the most recent consensus forecast, since it should reflect the best approximation for market expectations on the announcement date (O'Brien, 1988). To ensure that the forecast portrays a relevant picture of the market's expectation, we exclude all observations where the most recent forecast is more than 50 days before the announcement date. This decision is tested in the sensitivity analysis in Chapter 6.

Equation VIII. The Earnings Surprise Variable (SUE)

$$\mathrm{SUE}_{i,t} = \frac{\mathrm{EPS}_{i,t} - \mathrm{E(EPS)}_{i,t}}{\sigma_{\mathrm{E(EPS)}_{i,t}}}$$

$\mathrm{SUE}_{i,t}$	The earnings surprise variable for company i in period t
$\mathrm{EPS}_{i,t}$	The actual EPS for company i in period t
$\mathrm{E(EPS)}_{i,t}$	The consensus forecast for EPS for company i in period t
$\sigma_{\mathrm{E(EPS)}_{i,t}}$	The standard deviation of the consensus forecast for EPS for company i in period t

Equation VIII shows the earnings surprise variable (SUE), calculated as the forecast error, i.e. actual EPS less forecasted EPS, scaled by the standard deviation of the consensus forecast

Like Jegadeesh and Livnat (2006), we adjust for outliers by winsorizing the earning surprise variable at the 5- and 95% levels. The consequences of this decision are tested in the sensitivity analysis.

4.4.2 The Revenue Surprise Variable (SUR)

To maintain consistency between the two surprise variables, the figures are retrieved from the same source, and the same methodological steps are used for both variables in order to ascertain comparability. To summarize, we 1) use analyst consensus forecasts for expected figures, 2) use non-restated figures, 3) use the full year figures in the fourth fiscal quarter reports, 4) scale with the standard deviation of the analyst consensus forecasts, 5) put a requirement of five estimates for each analyst consensus forecast, 6) use the most recent analyst consensus forecasts, 7) exclude observations where the most recent forecast is more than 50 days before the announcement date, and 8) winsorize the variable at the 5- and 95% levels.

Equation IX. The Revenue Surprise Variable (SUR)

$$\mathrm{SUR}_{i,t} = \frac{\mathrm{REVENUE}_{i,t} - \mathrm{E(REVENUE)}_{i,t}}{\sigma_{\mathrm{E(REVENUE)}_{i,t}}}$$

$\mathrm{SUR}_{i,t}$	The revenue surprise variable for company i in period t
$\mathrm{REVENUE}_{i,t}$	The actual total revenue for company i in period t
$\mathrm{E(REVENUE)}_{i,t}$	The consensus forecast for total revenue for company i in period t
$\sigma_{\mathrm{E(REVENUE)}_{i,t}}$	The standard deviation of the consensus forecast for total revenue for company i in period t

Equation IX shows the Revenue Surprise Variable (SUR), calculated as the forecast error, i.e. actual revenues less forecasted revenues, scaled by the standard deviation of the consensus forecast

4.4.3 The Value/Growth Variable (VG)

To control for the differences in stock returns between value- and growth companies (Fama & French, 1996), a firm is classified as a value firm if it has a market-to-book figure that is lower than that of the S&P 500 weighted average on the final day of the calendar quarter preceding the fiscal year end date, and as a growth firm if the market-to-book is higher. Given that both an individual firm's market-to-book and the S&P 500's may vary over time, a single firm may be classified as a value firm in one firm-year observation, and as a growth firm in another. The individual market-to-book components are retrieved from Compustat, and the S&P 500 weighted averages from Standard & Poor's.

4.4.4 The Size Variable (SIZE)

To control for the differences in stock returns between large- and small companies (Fama & French, 1996), a firm is classified as small if it has a market capitalization smaller than that of the S&P 500 weighted average on the final day of the calendar quarter preceding the fiscal year end date, and large if its market capitalization is greater. Just as for the value/growth variable, a single firm may be classified as a small firm in one firm-year observation, and as a large in another, due to variation in both the firm's market capitalization and the S&P 500 average. The individual market capitalization figures are retrieved from Compustat, and the S&P 500 weighted average is retrieved from CRSP.

4.4.5 Industry (SIC-codes)

Biddle and Seow (1991) find that response coefficients differ substantially across industries. We assign each firm-year observation an industry using dummy variables based on four-digit SIC codes retrieved from Compustat. We exclude banks, insurance firms, investment firms and other financial firms (SIC codes 6000-6499 and 6700-6799), since these firms' revenues are not comparable to those of other firms (Jegadeesh & Livnat 2006).

Table III. SIC Classification

Range of codes	Division
0100 – 0999	Agriculture, Forestry and Fishing
1000 – 1499	Mining
1500 – 1799	Construction
2000 – 3999	Manufacturing
4000 – 4999	Transportation, Communications, Electric, Gas and Sanitary Service
5000 – 5199	Wholesale Trade
5200 – 5999	Retail Trade
6000 – 6799	Finance, Insurance and Real Estate
7000 – 8999	Services
9100 – 9729	Public Administration
9900 – 9999	Non-classifiable

Table III shows the division structure of SIC codes, retrieved from the United States Department of Labor

4.5 Data Shortfall

The initial dataset contains 6,410 firm-year observations from the period 2001 – 2017. This corresponds to an average of 377 observations per year, which is reasonable considering the S&P 500 includes 500 constituent companies, and many firm-year observations lack data in the I/B/E/S database.

Table IV shows the sources of data shortfall in the sample. The first shortfall arises because of missing SIC classification, which is required to assign an industry classification to the observation. The next shortfall – which is the largest one – pertains to the removal of banks, insurance firms, investment firms and other financial firms. This decision entails a shortfall of 1,170 observations, or approximately 18% of the initial sample. A shortfall of 278 observations pertains to a missing (or a value of zero) standard deviation of the earnings- or revenue consensus forecasts from I/B/E/S. Although a value of zero may simply imply completely homogenous analyst forecasts, the observations are removed as scaling the surprise variables with a standard deviation of zero would require dividing by zero. The requirement of at least five estimates per consensus forecast generates a total shortfall of 355 observations, with the majority stemming from a too low number of revenue forecasts. The removal of observations with forecast data from more than 50 days before the announcement date generates a shortfall of 125 observations. An additional 53 observations are lost due to missing stock prices from the CRSP database, and 62 more are lost due to missing Beta values in WRDS Beta Suite. The final shortfall of 126 relates to negative or missing market- or book values.

The final sample consists of 4,214 observations, an average of 248 observations per year. Thus, on average, half of the S&P 500 constituents each year are included in the final sample.

Table IV. Data Shortfall

	Number of observations
Initial sample	6,410
SIC unavailable	-27
Classified as banks, insurance firms, investment firms and other financial firms	-1,170
Missing or zero standard deviation (EPS)	-219
Missing or zero standard deviation (Revenue)	-59
Four or fewer estimates (EPS)	-75
Four or fewer estimates (Revenue)	-280
More than 50 days between estimate and results	-125
Missing stock price data	-53
Missing beta values	-62
Negative or missing market- or book values	-126
Final number of observations	**4,214**

Table IV shows the size of the initial sample, all the data shortfall as well as the final number of observations

5. Results and Analysis

In this section, we first present the descriptives of the final sample and the correlations between variables. Next, we show the regression results for each of the subperiods and the full period, followed by the results of the hypotheses tests. Finally, we analyse the results.

5.1 Descriptive Statistics and Correlations

As shown in **Table V**, more than half of the observations belong to the 2010 – 2017 period. This is explained in part by the period being longer than the others, and in part by less data shortfall in the period.

Table V. Sample Distribution by Subperiod

Period	Number of observations	Percent
2001 – 2007	1,388	33%
2008 – 2009	508	12%
2010 – 2017	2,318	55%
2001 – 2017	**4,214**	**100%**

Table V shows the period distribution for the observations included in the final sample

Table VI shows the mean values and standard deviations for the independent variables Earnings Surprise (SUE) and Revenue Surprise (SUR). As can be seen in the table, the mean of SUE is fairly constant over the period, with a slightly lower value in 2008 – 2009. The mean of SUR varies more but shows a similar pattern with its lowest mean value in the 2008 – 2009 period, and its values are consistently lower than for SUE. The standard deviations are relatively stable over the three periods for both variables.

Table VI. Statistics for Independent Variables

	SUE		SUR	
Period	μ	σ	μ	σ
2001 – 2007	0.98	1.67	0.61	1.52
2008 – 2009	0.86	1.81	0.17	1.54
2010 – 2017	0.97	1.81	0.36	1.47
2001 – 2017	**0.96**	**1.76**	**0.42**	**1.51**

Table VI shows the mean values and standard deviations for the independent variables SUE and SUR

Table VII shows the mean value and standard deviations for the dependent abnormal return variable AR (adjusted for CAPM or Index). The means are positive in the first and third periods, and slightly negative in the second period. The differences between the two return models are negligible.

Table VII. Statistics for Dependent Variables

	CAPM		Index	
Period	μ	σ	μ	σ
2001 – 2007	0.0060	0.0591	0.0061	0.0585
2008 – 2009	-0.0001	0.0691	-0.0005	0.0696
2010 – 2017	0.0037	0.0542	0.0036	0.0544
2001 – 2017	**0.0040**	**0.0578**	**0.0039**	**0.0578**

Table VII shows the mean values and standard deviations for the dependent variable Abnormal Return (AR) for both return models

Table VIII shows how the sample is distributed between the two variables SIZE and VG. The sample contains considerably more firms classified as small than as large, and more firms classified as growth than as value.

Table VIII. Statistics for the Variables SIZE and VG

	SIZE n = 4,214		VG n = 4,214	
Period	Large	Small	Value	Growth
2001 – 2007	360	1,028	603	785
2008 – 2009	139	369	221	287
2010 – 2017	606	1,712	875	1,443
2001 – 2017	**1,105**	**3,109**	**1,699**	**2,515**
% of Sample	*27%*	*73%*	*40%*	*60%*

Table VIII shows how the observations are distributed between the two dummy variables SIZE and VG. SIZE classifies the companies as either large or small, and VG classifies the companies as either value or growth.

Table IX shows the sample's industry distribution based on SIC codes. A majority of the observations pertain to companies classified as part of the 'Manufacturing' division, while few observations belong to the 'Agriculture, Forestry and Fishing', 'Construction' and 'Nonclassifiable' divisions. The 'Finance, Insurance and Real Estate' and 'Public Administration' divisions are not displayed as they contain no observations in the final sample.

Table IX. Sample Separation per SIC Codes and Subperiod

Division / Subperiod	2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
Agriculture, Forestry and Fishing	0%	0%	0%	**0%**
Construction	1%	2%	2%	**1%**
Manufacturing	57%	51%	48%	**51%**
Mining	5%	6%	7%	**6%**
Nonclassifiable	0%	0%	1%	**0%**
Retail Trade	10%	11%	10%	**10%**
Services	14%	14%	14%	**14%**
Transport, Communication, Electric	11%	12%	14%	**13%**
Wholesale Trade	3%	3%	3%	**3%**
Total (n)	**1,388**	**508**	**2,318**	**4,214**

Table IX shows how the observations are classified based on SIC/industry classification on a percentage basis. Transport, Communication, Electric also includes Gas and Sanitary Services.

Table X shows the correlations between the independent variables for the full period 2001 – 2017. The earnings- and revenue surprise variables exhibit the highest correlation, amounting to 0.2825 significant at the 1%-level. SUE is correlated with VG, significant at the 1%-level, but not significantly correlated with SIZE. SUR is positively correlated with VG at the 1%-level, and negatively correlated with SIZE, significant at the 5%-level. Finally, SIZE is negatively correlated with VG at the 1% level.

Table X. Correlation Between Independent Variables

	SUE	SUR	SIZE	VG
SUE				
SUR	0.2825***			
SIZE	0.0145	-0.0355**		
VG	0.0423***	0.0737***	-0.1600***	

Table X shows the Pearson correlation between the independent variables. SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = p < 0.01, ** = p < 0.05, * = p < 0.10

Table XI shows the correlation between the earnings surprise variable (SUE) and revenue surprise variable (SUR) for each subperiod. The correlations are statistically significant in each subperiod, with a relatively lower value in the 2001 – 2007 period.

Table XI. Correlation Between Earnings Surprise (SUE) and Revenue Surprise (SUR)

Period	2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
Correlation	0.2335***	0.3062***	0.3058***	**0.2825*** **

Table XI shows the Pearson correlation between the SUE and SUR variables. SUE is the earnings surprise variable. SUR is the revenue surprise variable. SUE and SUR have been winsorized at the 5- and 95% levels.
*** = p < 0.01, ** = p < 0.05, * = p < 0.10

5.2 Regression Results

5.2.1 2001 – 2007 (Period 1)

Table XII shows the regression results for the first period, 2001 – 2007. SUE has a coefficient of 0.0099 and 0.0100 in the CAPM- and Index-adjusted models, respectively, significant at the 1% level, and SUR has a coefficient of 0.0043 and 0.0042, also significant at the 1% level. Neither SIZE nor VG have significant coefficients. The R^2 value is slightly higher for the Index model.

Table XII. Regression Results, Period 2001 – 2007

Model	CAPM		Index	
Variable	Coefficient	Robust std. Error	Coefficient	Robust std. Error
SUE	0.0099***	0.0010	0.0100***	0.0009
SUR	0.0043***	0.0011	0.0042***	0.0010
SIZE	0.0031	0.0032	0.0036	0.0031
VG	-0.0043	0.0035	-0.0033	0.0034
R^2	0.1158		0.1167	

Table XII shows the coefficients and the robust standard errors for the four independent- and dummy variables, as well as the R^2 for the two regressions (abnormal return adjusted for either Index or CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = p < 0.01, ** = p < 0.05, * = p < 0.10

5.2.2 2008 – 2009 (Period 2)

Table XIII shows the regression results for the second period, 2008 – 2009. SUE has a coefficient of 0.0119 and 0.0111 in the two models, significant at the 1% level, and SUR has a coefficient of 0.0038 and 0.0037, significant at the 10% level. SIZE has a coefficient of -0.0119 and -0.0125, significant at the 5% level. VG is negative, and not significant. The R^2 value is one percentage point higher for the CAPM model.

Table XIII. Regression Results, Period 2008 – 2009

Model	CAPM		Index	
Variable	Coefficient	Robust std. Error	Coefficient	Robust std. Error
SUE	0.0119***	0.0018	0.0111***	0.0018
SUR	0.0038*	0.0022	0.0037*	0.0021
SIZE	-0.0119**	0.0058	-0.0125**	0.0059
VG	-0.0005	0.0062	-0.0003	0.0064
R^2	0.1586		0.1486	

Table XIII shows the coefficients and the robust standard errors for the four independent- and dummy variables, as well as the R^2 for the two regressions (abnormal return adjusted for either Index or CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

5.2.3 2010 – 2017 (Period 3)

Table XIV shows the regression results for the third and final period, 2010 – 2017. SUE has a coefficient of 0.0068 in the two models, significant at the 1% level, and SUR has a coefficient of 0.0045 and 0.0046, significant at the 1% level. Neither SIZE nor VG are significant. The R^2 value is slightly higher for the Index model.

Table XIV. Regression Results, Period 2010 – 2017

Model	CAPM		Index	
Variable	Coefficient	Robust std. Error	Coefficient	Robust std. Error
SUE	0.0068***	0.0007	0.0068***	0.0007
SUR	0.0045***	0.0008	0.0046***	0.0008
SIZE	0.0011	0.0022	0.0016	0.0022
VG	0.0001	0.0024	-0.0004	0.0024
R^2	0.0864		0.0878	

Table XIV shows the coefficients and the robust standard errors for the four independent- and dummy variables, as well as the R^2 for the two regressions (abnormal return adjusted for either Index or CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

5.2.4 2001 – 2017 (Full Period)

Table XV shows the regression results for the full period (all subperiods taken together), 2001 – 2017. SUE has a coefficient of 0.0083 in both models, significant at the 1% level and SUR has a coefficient of 0.0044 in both models, significant at the 1% level. Neither SIZE nor VG are significant. When the full period is studied, the R^2 value is slightly higher for the CAPM model.

Table XV. Regression Results, Period 2001 – 2017

Model	CAPM		Index	
Variable	Coefficient	Robust std. Error	Coefficient	Robust std. Error
SUE	0.0083***	0.0005	0.0083***	0.0005
SUR	0.0044***	0.0006	0.0044***	0.0006
SIZE	0.0003	0.0017	0.0006	0.0017
VG	-0.0014	0.0019	-0.0014	0.0019
R^2	0.0968		0.0962	

Table XV shows the coefficients and the robust standard errors for the four independent- and dummy variables, as well as the R^2 for the two regressions (abnormal return adjusted for either Index or CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

5.2.5 Regression Summary

The estimated earnings response coefficients differ considerably between the periods, with the highest value in the 2008 – 2009 period, and the lowest value in the 2010 – 2017 period. The revenue response coefficient is more stable, with the lowest value in the 2008 – 2009 period, and the highest value in the 2010 – 2017 period. The SIZE coefficient shifts markedly between the periods, yielding its only significant values in the 2008 – 2009 period. The VG coefficient is not statistically significant in any observed period. The highest explanatory power can be observed during the 2008 – 2009 period. There are no substantial differences between the CAPM and Index models (see **Appendix A** and **Appendix B** for a summary of the regression results).

5.3 Hypothesis Testing

In chapter three, two hypotheses were presented:

H1: The market's reaction to an earnings surprise (the earnings response coefficient) varied over time during the period 2001 – 2017, and

H2: The market's reaction to a revenue surprise (the revenue response coefficient) varied over time during the period 2001 – 2017

The regression results show that the ERC and RRC are statistically different from zero in all periods. To test the hypotheses, the coefficients' differences between periods need to be statistically tested as well.

The results of these tests are presented in **Table XVI**, where the null hypothesis for both H1 and H2 is that the coefficient (either ERC or RRC) is the same in the two tested periods. In total, we carry out twelve tests (six for each variable), where we compare the coefficients between all the periods. The tests yield a Chi^2 value representing a probability to reject H0, and these probabilities are shown in **Table XVI**.

Table XVI. Hypothesis Testing

$$\text{H0: } \beta_{\text{periodx}} = \beta_{\text{periody}}$$
$$\text{Reject H0 if } p < 0.10$$

CAPM

SUR: βperiodx \ βperiody	1	2	3	SUE: βperiodx \ βperiody	1	2	3
1				1			
2	0.8321			2	0.3222		
3	0.9204	0.7812		3	<u>**0.0071**</u>	<u>**0.0069**</u>	

Index

SUR: βperiodx \ βperiody	1	2	3	SUE: βperiodx \ βperiody	1	2	3
1				1			
2	0.8347			2	0.5583		
3	0.7778	0.7028		3	<u>**0.0063**</u>	<u>**0.0217**</u>	

Table XVI shows the results from the Wald test of the difference between the estimated coefficients between subperiods for the two variables SUE and SUR. SUE is the earnings surprise variable. SUR is the revenue surprise variable. Bold and underlined results have probabilities that entail rejection of H0.

A significant result is obtained only for the SUE's coefficients, which together with the regression results indicates that the ERC is lower in period 3 than in period 1, and lower in period 3 than in period 2. For the SUR coefficient, no significant results are obtained. The results are consistent across both the Index and CAPM models.

Table XVII. Hypothesis Summary

H1	*The market's reaction to an earnings surprise (the earnings response coefficient) has varied over time during the period 2001 – 2017*	**Supported**
H2	*The market's reaction to a revenue surprise (the revenue response coefficient) has varied over time during the period 2001 – 2017*	**Not Supported**

Table XVII shows the two hypotheses and whether the statistical tests support them

5.4 Analysis

5.4.1 The Time Variance of Response Coefficients

Both SUE and SUR have significant relationships with abnormal returns, regardless of which period or expected return model that is studied. In line with the previous research earlier presented, this shows that stock returns are affected both by earnings surprises and information beyond earnings surprises, in this case revenue surprises. The regressions and hypotheses tests show that the ERC has varied over time, with a lower observed ERC for the 2010 – 2017 period than for the 2001 – 2007 and 2008 – 2009 periods, while the RRC cannot be shown to have changed significantly. This implies that the market's reaction to earnings surprises was smaller in the most recent period than the ones before, and although previous research argues that investors may shift focus from earnings to revenue (Jegadeesh & Livnat, 2006; Chandra & Ro, 2008; Kama, 2009), we do not observe that the market's reaction to revenue surprises has increased between the periods.

Previous research has found that the ERC decreased over the latter half of the 20th century, while the RRC has increased or remained stable, and our results show a continuance of the former trend. Our results also show that the ERC not only varies between periods with significantly different macroeconomic circumstances, but also between periods during which the macroeconomic circumstances are more similar. It seems like macroeconomics do not fully explain differences in ERCs.

Instead, the lower R^2 values obtained in the latter period compared to the two earlier periods may indicate that the market has shifted focus onto other financial or non-financial factors which are not included in the model. With the same logic, the substantially higher R^2 in the 2008 – 2009 subperiod shows that accounting figures better explain abnormal returns for the period of economic contraction. This could imply that when the economy goes south, investors increasingly turn to the figures that determine company value according to corporate finance literature. **Appendix C** shows that when not adjusting for outperformance tendencies, the model's R^2 (and its variation) is lower. Although a similar pattern of decreasing R^2 over time can be observed in both models, the largest value is no longer observed in the 2008 – 2009 period in the Index model. Furthermore, this shows that the difference in performance tendencies between small/large and value/growth companies has a substantial impact on the model if not adjusted for.

5.4.2 Potential Reasons for the Time Variance

Since response coefficients are associated with information availability and growth opportunities (see **Section 2.4**), a potential source for the decrease in the ERC could be an overall increase in information availability caused by information technology or fewer growth opportunities. Given the relationship between growth opportunities and market-to-book ratios, the increase from 2.0 to 3.2 shown between 2008 – 2017 in **Figure 1** should have had an incrementally positive effect on the response coefficients. However, as the results show that the ERC has decreased between subperiods 2 and 3, and that the RRC has not changed, this effect could have been offset by for example increased information availability caused by information technology.

Kama (2009) argues that earnings management and ERCs are negatively related, and Cohen, Dey and Lys (2004) show that accruals earnings management has decreased, implying an incrementally positive effect on the ERC. However, Cohen et al. (2008) showed that rather than decreasing, earnings management may have shifted from accruals earnings management to real earnings management. Although not tested for in this study, a potential reason for the decrease in the earnings response coefficient could be an increase in real earnings management.

We do not find any evidence supporting the theory that a supposed increase in revenue recognition- and earnings management regulation in recent years has led to a rise in response coefficients. An explanation could lie in that the latest revenue recognition principles stipulated by IASB and FASB have not yet come into effect, as the early adoption of these principles was voluntary.

Considering the financial relationship between revenues, expenses and earnings, the correlation of 0.28 (**Table XI**) between the revenue- and earnings surprise variables is not surprising. However, the comparatively lower correlation between the two surprise variables in the 2001 – 2007 period may indicate that earnings surprises were caused by a reduction in expenses rather than by an increase in revenues. Ghosh et al. (2005) show that the persistence of earnings is higher when earnings surprises are driven by revenue surprises rather than by expense surprises, and Collins and Kothari (1989) find a positive association between the ERC and earnings persistence. Hence, the comparatively lower correlation between SUE and SUR in the 2001 – 2007 subperiod should entail a lower ERC compared to the other subperiods. However, the observed results show that the ERC was in fact lower in the 2010 – 2017 subperiod, which further emphasizes the fact that earnings response coefficients are affected by a multitude of factors.

Barton et al. (2010) study the value relevance of different financial measures and find that *"no single measure dominates around the world"*. Instead, a measure is of more relevance when it directly and quickly measures a firm's cash flows (Barton et al., 2010). They also find that out of eight different performance measures, sales and total comprehensive income are the least relevant to investors – instead, investors seem to focus on numbers like operating profit or EBITDA. An explanation to our results indicating a decrease in the ERC could be that earnings have become less relevant over time as more investors shift their focus towards cash flow surrogates found in the income statement. Another reason could be that earnings today are less representative of cash flows compared to before, providing reason for investors to look at other metrics, lowering the ERC.

5.4.3 The Accuracy of Analysts' Forecasts and Sample Outperformance

The relatively stable positive mean values of the SUE variable imply that companies, throughout the three periods, tend to outperform analysts' earnings forecasts. For the SUR variable, the mean varies considerably between the periods, and they are lower than those for the SUE variable. Even though companies on average also tended to beat revenue expectations, either the forecast error was smaller, or the analysts' forecasts were less unanimous (yielding higher standard deviations and thus lower values). The positive correlation between VG and SUR/SUE shows that growth companies' revenues and earnings tend to have more positive surprises than value companies', implying that analysts on average underestimate the potential of growth companies. The negative correlation between SIZE and SUR shows that large companies’ revenues tend to come in higher than the market expects, implying that analysts on average underestimate the revenue potential of large companies.

As indicated by the mean values of the abnormal return, the sample companies on average performed above the expected return during the event windows in both the first and third period, and below the expected return during the event windows in the second period. It should be noted that the standard deviations are large, signifying high variation in abnormal returns in connection to financial announcements.

6. Discussion

6.1 Sensitivity Test

To test the robustness of the methodological choices, we conduct a sensitivity analysis by altering certain parameters. In the interest of maintaining readability, the sensitivity tests are presented using only the CAPM model as the two return models show highly similar results. The results, including number of observations, R^2, ERC and RRC are presented in **Table XVIII**, for a total of six sensitivity tests, side by side with the original results from **Section 5**:

1) ***The event window is changed from [-2, +1] days to [-30, +30] days,*** yielding lower R^2 values for the three time periods and slightly higher ERCs in all periods. The RRC in the 2001 – 2007 period is no longer significant. The RRC in the 2008 – 2009 period is significant and considerably higher, and the RRC in the 2010 – 2017 period is significant and slightly higher.

2) ***The event window is changed from [-2, +1] days to [-5, +5] days,*** yielding lower R^2 values for the three time periods, with similar, somewhat higher, ERCs and RRCs for most periods. The RRC in 2008 – 2009 is smaller and no longer significant.

3) ***The number of analyst estimates required for each observation is increased to at least 10 for both the SUE and SUR variables.*** We observe a slightly lower R^2 for the 2001 – 2007 period, higher R^2 for the other two periods, and a lower number of observations in all periods. The results are similar to the original test, but once again, the RRC in 2008 – 2009 is smaller and no longer significant.

4) ***The SUE and SUR variables are winsorized at the 2.5- and 97.5% levels instead of at the 5- and 95% levels.*** The impact on R^2 is small, and the coefficients are slightly smaller for all periods.

5) ***The SUE and SUR variables are winsorized at the 10- and 90% levels instead of at the 5- and 95% levels.*** The impact on R^2 is small, the coefficients are larger across all periods, and once again the RRC in the 2008 – 2009 period is not significant.

6) ***All forecasts where the days between the estimation period and the announcement date is longer than 30 days are removed,*** yielding a small observation shortfall and results similar to the original regression.

To conclude, the sensitivity analysis shows that there are some variations in the results that depend on the methodological approach that has been chosen for this study. Most interesting is the fact that the RRC in the 2008 – 2009 period varies heavily in the sensitivity tests, and the result is often not significant, putting the existence of the RRC in the 2008 – 2009 period into question. Thus, the evidence of the connection between revenue surprises and abnormal returns is inconclusive during the economic downturn. In the other periods, the initial model's rigidity is supported by the sensitivity analysis.

Table XVIII. Sensitivity Analysis

Period	Comp.	**Original**	1	2	3	4	5	6
2001 – 2007	n	**1,388**	1,388	1,388	872	1,388	1,388	1,323
	R^2	**0.1158**	0.0403	0.0931	0.1074	0.1159	0.1134	0.1150
	ERC	**0.0099*** **	0.0129***	0.0107***	0.0103***	0.0086***	0.0120***	0.0099***
	RRC	**0.0043*** **	0.0046	0.0042***	0.0045***	0.0039***	0.0053***	0.0043***
2008 – 2009	n	**508**	508	508	347	508	508	486
	R^2	**0.1586**	0.0924	0.1135	0.1812	0.1607	0.1529	0.1575
	ERC	**0.0119*** **	0.0138***	0.0134***	0.0140***	0.0100***	0.0150***	0.0119***
	RRC	**0.0038* **	0.0116**	0.0027	0.0029	0.0037*	0.0041	0.0039*
2010 – 2017	n	**2,318**	2,318	2,318	2,048	2,318	2,318	2,188
	R^2	**0.0864**	0.0386	0.0633	0.0904	0.0883	0.0807	0.0888
	ERC	**0.0068*** **	0.0099***	0.0072***	0.0067***	0.0060***	0.0083***	0.0070***
	RRC	**0.0045*** **	0.0060***	0.0057***	0.0051***	0.0039***	0.0052***	0.0046***

Table XVIII shows the number of observations, the R^2, the ERC and the RRC, for the different time periods when performing the sensitivity tests. The original results pertain to the results generated from the CAPM adjusted model.
*** = p < 0.01, ** = p < 0.05, * = p < 0.10

6.2 Evaluation of Test Design and Variable Selection

6.2.1 Subperiod Division

As previously mentioned, the reason for the specific sample period separation points lies in the economic characteristics of each period. The likeness between subperiods 1 and 3, and their difference from subperiod 2 could be put into question, as the effectiveness of using GDP growth as the divisor rather than any other measure is not given. However, determining exact start and end dates for the period of economic contraction is difficult, and the decision to use the calendar year as the divisor is made for simplicity and consistency.

To further test the subperiod division, we show the estimated coefficients for SUE and SUR in a year-by-year regression in **Table XIX** (plotted in **Appendix D**). The ERC is statistically significant in each year and shows variation over time, and the RRC varies but loses significance in almost half of the years. The year-by-year separation does not contradict our previous findings, and while some tendencies of variation can be observed also in the RRC, inferences are difficult to make because of the problems with significance. The primary advantages of using subperiods consisting of multiple years is that each subperiod consists of enough observations for the inferences to be significant, and the consistency with previous research (Jegadeesh & Livnat 2006).

Table XIX. Regression Results, Period 2001 – 2017 (Year-by-Year)

Year	SUE		SUR		n	R^2
	Coefficient	Robust std. error	Coefficient	Robust std. error		
2001	0.0091*	0.0055	0.0075	0.0074	125	0.1126
2002	0.0168***	0.0038	0.0023	0.0037	159	0.1949
2003	0.0090***	0.0024	0.0042	0.0029	202	0.1106
2004	0.0081***	0.0018	0.0006	0.0024	215	0.1134
2005	0.0103***	0.0021	0.0063**	0.0025	218	0.1975
2006	0.0058***	0.0019	0.0095***	0.0023	235	0.1889
2007	0.0132***	0.0026	0.0022	0.0027	234	0.1990
2008	0.0094***	0.0032	0.0028	0.0041	252	0.1457
2009	0.0127***	0.0019	0.0062***	0.0023	256	0.3185
2010	0.0072***	0.0020	0.0038*	0.0023	280	0.1038
2011	0.0062***	0.0021	0.0107***	0.0028	275	0.1553
2012	0.0058**	0.0023	0.0085**	0.0033	278	0.1127
2013	0.0050***	0.0016	0.0069***	0.0024	292	0.1170
2014	0.0094***	0.0016	-0.0007	0.0020	294	0.1638
2015	0.0062***	0.0017	0.0072***	0.0023	298	0.1478
2016	0.0086***	0.0019	0.0040*	0.0023	298	0.1708
2017	0.0054***	0.0019	-0.0014	0.0020	303	0.0777

Table XIX shows the coefficients and the robust standard errors for SUE and SUR, as well as the R^2 for the regression (abnormal return adjusted for CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. SIZE and VG have been omitted from the table to facilitate reading. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

6.2.2 The Expected Return Component of the Abnormal Returns Variable

As previously explained, response coefficient studies use different ways of estimating expected returns, through for example weighted portfolios, Index models, and the CAPM. The CAPM is based on several strong assumptions and its usefulness and connection to real-world economics has been critiqued in various papers over the years (see for example Roll, 1977). However, it remains one of the most widely used models of risk and return, and while not perfect, it is regarded as a useful approximation to estimate a security's expected return (Berk & DeMarzo 2009, p.386). We use the CAPM and Index models to estimate expected returns and find that both models yield similar results.

Both the CAPM and Index models use the NYSE/AMEX/NASDAQ Composite Value Weighted Index with reinvested dividends, while the share prices have not been adjusted for dividends or other corporate actions. Although this could create a discrepancy between the actual and expected returns, a lack of available data for adjustments motivates the decision to use unadjusted stock prices, and we argue that it is rare for firms to engage in corporate actions in immediate connection with its own financial announcements. The dividend-adjusted index is used to mitigate the potential effect from other firms' corporate actions.

6.2.3 The Earnings- and Revenue Surprise Variables

Since an exact approximation of the market's expectation is virtually non-existent, the operationalization of the surprise variables is not a clear-cut process. For example, the objectivity of analyst estimates could be criticized because of analyst bias. Since many analysts are employed by financial institutions with multiple revenue streams, analysts may have incentives to provide biased forecasts to impact the market to the benefit of the employer's other divisions (see for example Michaely & Womack, 1999 and Lin & McNichols, 1998). On the other hand, Kothari (2001) argues that *"superior forecasters survive, but poor performers are possibly weeded out in the marketplace"*, and analysts thus have incentives to provide accurate and unbiased forecasts to maintain credibility.

Time series models, common in earlier response coefficient studies, are not subject to individual analysts' bias, but the effectiveness of using the past to predict the future is not given. Recent studies do use analyst consensus forecasts (for example Ertimur et al., 2003; Rees & Sivaramakrishnan, 2007; Ng et al., 2008), and while no model is perfect, the use of multiple analysts' forecasts to operationalize the market's expectation mitigates the effect of a single analyst's potential bias. Moreover, Kothari (2001) argues that the use of analyst consensus forecasts has become commonplace in response coefficient research, and the consistent use of analyst forecasts across all regressions should ensure relevant inferences.

Prior studies have used different denominators in their earnings- and revenue surprise variables, including for example expected figures, stock prices and standard deviations of expected figures. **Appendix E** shows the regression results when the surprise variables instead have been scaled with the market's expectation, using the mean estimate of the analyst consensus forecast rather than its standard deviation (see for example Collins & Kothari, 1989). Although the resulting inferences do not fully agree with the ones from the original operationalization, the significance levels are lower and the R2 values are considerably lower at around 1-5%. This shows that the operationalization of the surprise variables has a large impact on the magnitude of the response coefficients and the effectiveness of the model. As previously explained, there is no best practice for scaling the forecast error, and the standard deviation of the consensus forecast is used since it controls for uncertainty in the consensus forecast which could otherwise cause bias in the estimated response coefficients.

6.2.4 The Size- and Value/Growth Variables

The reason behind the sample containing roughly twice as many small as large firms is likely the use of the dynamic point-in-time *average* S&P 500 constituent size to determine the cut-off point between large and small. Data retrieved from Thomson Reuters shows that the 50 largest constituents of the S&P 500 today make up roughly 50% of the market capitalization, which means that most of the constituents would be classified as small. Jegadeesh and Livnat (2006) use the median value as the cut-off point between large and small firm size, and in this aspect, our study differs. The lack of reliable data on quarterly median market capitalization of the S&P 500 constituents is the main motivation for this decision. Other alternatives, such as using the *sample's* median or a *static* median, would introduce additional unwanted effects, as the sample could be biased and market capitalizations change considerably over time.

The proportion of value-/growth firms is also imbalanced, yet the values are arguably in line with what should be expected. Ertimur et al. (2003) argue that a higher prevalence of growth firms compared to value firms may be explained by a self-selection bias caused by analysts being more inclined to provide revenue forecasts for growth companies, for which revenues may be a more important factor of the valuation. Another reason could be that the relative interest from investors and the media is higher for growth companies, giving grounds for an increased analyst following, and in turn generating a larger presence in consensus forecast databases. While Jegadeesh and Livnat (2006) use the median to determine the cut-off point between value and growth firms, data availability motivates our use of market-to-book ratio means. Data retrieved from Compustat shows that today, the market-to-book ratios for the S&P 500 constituents are not disproportionately distributed (as is the case with market capitalization), and the mean is significantly closer to the median.

6.2.5 The Linear Regression Model

The use of the linear regression model in ERC and RRC studies is well documented in for example Collins and Kothari (1989), Teoh and Wong (1993), Swaminathan and Weintrop (1991) and Ertimur et al. (2003), and it typically generates significant results. However Freeman and Tse (1992) and Lipe, Bryant and Widener (1998) found that the relationship between earnings surprises and abnormal returns is not necessarily linear as the relationship between financial market reactions and extreme earnings surprises are typically not of the same magnitude as the relationship observed during smaller earnings surprises. To limit the diminishing impact on the coefficients caused by extreme observations, we winsorize SUE, SUR, and AR – allowing the linear regression model to handle the extreme values.

6.3 Discussion of Sample Bias

The sample from which the observed results are based on may be biased because of sample selection and model specifications. As shown in **Table IX**, the sample is quite heavily biased towards manufacturing firms which make up around 50% of the sample, while other categories such as agriculture, forestry and fishing, construction, and financials are nearly or fully left out. Since firms followed by few analysts are excluded, the sample is also biased in the sense that it only contains companies deemed ‘interesting’ enough to have a considerable analyst following. Finally, companies engaged in large mergers or with short listing periods have a lower weight in the sample as the minimum of 30-month beta values puts a lower limit on the companies’ trading periods.

6.4 Robustness Test

6.4.1 Multicollinearity

Multicollinearity is present when one independent variable can be linearly predicted by the other ones, which could reduce the model's effectiveness, since it makes discerning an individual dependent variable's effect on the dependent variable difficult. As shown in **Appendix F**, the observed Variance Inflation Factor (VIF) values are far below both the critical value of 10 (Hair, Black, Babin & Anderson, 1995, p.200), signifying that multicollinearity is not a problem in the model.

6.4.2 Heteroscedasticity

A common source of inaccuracy in statistical testing is that the error terms exhibit heteroscedastic traits. To test this, we apply White's test for heteroscedasticity to the eight different regressions (two for each period including the full period) to see if the standard errors need to be adjusted. The results from the White tests are shown in **Appendix G**.

As shown, H0 can be rejected for every scenario on a 5% significance level or better, implying that the error terms are of heteroskedastic nature. Although visual inspection of **Appendix H** does not provide definitive evidence of heteroscedasticity, robust standard errors have been used in all the regressions presented in **Table XII – Table XV** to adjust for the heteroscedasticity detected in the White's tests.

6.4.3 Serial Correlation / Autocorrelation

Serial correlation (autocorrelation) occurs when the dependent variable correlates with itself across observations for a specific firm and is usually adjusted for using firm-fixed effects in the regressions. We use the Wooldridge test to detect autocorrelation in the abnormal returns variable. As shown in **Appendix I**, the null hypothesis cannot be rejected for any of the tests, implying that there is no problem with autocorrelation between the observations' abnormal returns. The p-values for the full period (2001 – 2017) come close to the cut-off point, but H0 cannot be rejected. Furthermore, our main inferences are drawn from the three subperiods, and firm-fixed effects have thus *not* been included in the regressions in **Table XII – Table XV**.

7. Conclusions and Avenues for Future Research

7.1 Concluding Remarks

We find that earnings- and revenue surprises have a significant relationship with abnormal returns for all subperiods, and that the earnings response coefficient has decreased over time, but do not find evidence of a change in the revenue response coefficient. After sensitivity testing the results, we find that the evidence of the connection between revenue surprises and abnormal returns is inconclusive for the 2008 – 2009 period of economic contraction. We also find that the explanatory power of the response coefficient regression was substantially higher during the same period, signifying the importance of accounting fundamentals, primarily earnings, during an economic downturn. Additionally, the model's decreasing explanatory power indicates that investors have over time shifted more attention to figures beyond the ones studied in this paper.

We contribute to previous research in several ways. First, we fill a void in response coefficient research by explicitly contrasting and statistically testing the over-time development of the response coefficients. Second, we affirm the trend indicated in previous research by showing that the earnings response coefficient has continued to decrease over time. Third, we provide evidence on earnings- and revenue response coefficients during time periods which have previously not been studied. Finally, we show that the ability of accounting figure surprises to predict abnormal stock returns may be different depending on the characteristics of the economy.

7.2 Limitations

Research on response coefficients sets out to measure the relationship between stock returns and accounting data, and as with other studies concerning financial markets and stock prices, a lot of noise should be expected. As shown by the relatively low R^2-values observed in ERC-studies, there is a myriad of factors affecting stock returns. However, the study's methodological consistency and the alignment with previous research should ensure that the model is measuring what is intended. Moreover, through the use of consistent and well-motivated variable operationalizations, well-established statistical tests to evaluate similarities and differences, and sensitivity tests of the methodological approaches, the validity of the inferences should be ensured.

Although the study examines the S&P 500, an index capturing a great deal of the US market's total listed value, the generalizability of the study can be considered somewhat limited. Approximately half of the index is on average included in the sample for each year, companies belonging to for example the financial industry are fully excluded, and manufacturing companies make up more than 50% of the sample. It is also likely that the larger companies that analysts are more inclined to provide estimates for are more prevalent than smaller or less interesting ones. Due to S&P 500 market capitalization requirements, the study's results are most relevant for large cap US equities. However, these companies' share of global listed market capitalization should not be understated.

7.3 Future Research

Although this study aims to examine response coefficients on a wide and general sample, future research could increase the generalizability by also including more companies from other geographies, industries and firm sizes. Future research could study other metrics like surprises in EBIT and EBITDA, and other financial or non-financial figures to test whether the decrease in explanatory power observed in this study can be offset by using other variables. Additionally, as the model specification and variable operationalization used in extant research differ, it is difficult to directly compare response coefficients between studies. Future research could therefore study longer periods using consistent operationalization – shedding more light on the development of the response coefficients. Finally, future research could study the reasons determining time variance in response coefficients, to improve the prediction of stock price movements.

8. References

Bagnoli, M., Kallapur, S., & Watts, S. G. (2001). *Top line and bottom line forecasts: A comparison of internet firms during and after the bubble.* Unpublished manuscript.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research, 6*(2), 159-178.

Barton, J., Hansen, T. B., & Pownall, G. (2010). Which performance measures do investors around the world value the most - and why? *The Accounting Review, 85*(3), 753-789.

Berk, J., & DeMarzo, P. (2016). *Optimal portfolio choice and the capital asset pricing model* (4th ed.). Harlow, United Kingdom: Pearson Education Limited.

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research, 27*(1), 1-36.

Biddle, G. C., & Seow, G. S. (1991). The estimation and determinants of associations between returns and earnings: Evidence from cross-industry comparisons. *Journal of Accounting, Auditing and Finance, 6*(2), 183-232.

Brown, L. D., Hagerman, R. L., Griffin, P. A., & Zmijewski, M. E. (1987). Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting and Economics, 9*(1), 61-87.

Brown, S., Lo, K., & Lys, T. (1999). Use of R2 in accounting research: Measuring changes in value relevance over the last four decades. *Journal of Accounting and Economics, 28*(2), 83-115.

Brunnermeier, M. K. (2005). Information leakage and market efficiency. *The Review of Financial Studies, 18*(2), 417-457.

Bureau of Economic Analysis, US Department of Commerce. (2018). *National income and product accounts: Table 3B.* Retrieved from https://www.bea.gov/system/files/2018-08/gdp2q18_adv_4.pdf

Burgstahler, D., & Eames, M. (2006). Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *Journal of Business Finance & Accounting, 33*(5-6), 633-652.

Caylor, M. L. (2010). Strategic revenue recognition to achieve earnings benchmarks. *Journal of Accounting and Public Policy, 29*(1), 82-95.

Chandra, U., & Ro, B. T. (2008). The role of revenue in firm valuation. *Accounting Horizons, 22*(2), 199-222.

Cohen, D. A., Dey, A., & Lys, T. Z. (2004). *Trends in earnings management and informativeness of earnings announcements in the pre- and post-sarbanes oxley periods.* Unpublished manuscript.

Collins, D. W., & Kothari, S. P. (1989). An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics, 11*(2-3), 143-181.

Collins, D. W., Maydew, E. L., & Weiss, I. S. (1997). Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics, 24*(1), 39-67.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor information demand: Evidence from google searches around earnings announcements. *Journal of Accounting Research, 50*(4), 1001-1040.

Edmonds, C. T., Leece, R. D., & Maher, J. J. (2013). CEO bonus compensation: The effects of missing analysts' revenue forecasts. *Review of Quantitative Finance & Accounting, 41*(1), 149-170.

Ertimur, Y., Livnat, J., & Martikainen, M. (2003). Differential market reactions to revenue and expense surprises. *Review of Accounting Studies, 8*(2-3), 185-211.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance, 51*(1), 55-84.

Financial Accounting Standards Board. (2019). Accounting standards updates issued. Retrieved from https://www.fasb.org/jsp/FASB/Page/SectionPage&cid=1176156316498

Foster, G. (1981). Intra-industry information transfers associated with earnings releases. *Journal of Accounting and Economics, 3*(3), 201-232.

Francis, J., Nanda, D., & Olsson, P. (2008). Voluntary disclosure, earnings quality, and cost of capital. *Journal of Accounting Research, 46*(1), 53-99.

Francis, J., & Schipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research, 37*(2), 319-352.

Freeman, R. N., & Tse, S. Y. (1992). A nonlinear model of security price responses to unexpected earnings. *Journal of Accounting Research, 30*(2), 185-209.

Ghosh, A., Gu, Z., & Jain, P. C. (2005). Sustained earnings and revenue growth, earnings quality, and earnings response coefficients. *Review of Accounting Studies, 10*(1), 33-57.

Hackenbrack, K. E., & Hogan, C. E. (2002). Market response to earnings surprises conditional on reasons for an auditor change. *Contemporary Accounting Research, 19*(2), 195-223.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Essex: Pearson Education Limited.

Imhoff, E. A., & Lobo, G. J. (1992). The effect of ex ante earnings uncertainty on earnings response coefficients. *The Accounting Review, 67*(2), 427-439.

Jegadeesh, N., & Livnat, J. (2006). Post-earnings-announcement drift: The role of revenue surprises. *Financial Analysts Journal, 62*(2), 22-34.

Jegadeesh, N., & Livnat, J. (2006). Revenue surprises and stock returns. *Journal of Accounting and Economics, 41*(1-2), 147-171.

Joy, O., Litzenberger, R., & McEnally, R. (1977). Adjustment of stock-prices to announcements of unanticipated changes in quarterly earnings. *Journal of Accounting Research, 15*(2), 207-225.

Kama, I. (2009). On the market reaction to revenue and earnings surprises. *Journal of Business Finance & Accounting, 36*(1-2), 31-50.

Kothari, S. P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics, 31*(1-3), 105-231.

Lee, J., & Park, C. W. (2000). Intraday stock price reactions to interim-quarter versus fourth-quarter earnings announcements. *Journal of Business Finance & Accounting, 27*(7&8), 1027-1046.

Lev, B., & Zarowin, P. (1999). The boundaries of financial reporting and how to extend them. *Journal of Accounting Research, 37*(2), 353-385.

Lin, H., & McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, *25*(1), 101-127.

Linderholm, H. (2001). *Har marknaden blivit mer "neurotisk"?* Bachelor thesis, Stockholm School of Economics, Stockholm, Sweden

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, 47*(1), 13-37.

Lipe, R. C., Bryant, L., & Widener, S. K. (1998). Do nonlinearity, firm-specific coefficients, and losses represent distinct factors in the relation between stock returns and accounting earnings? *Journal of Accounting and Economics*, *25*(2), 195-214.

Lipe, R. (1990). The relation between stock returns and accounting earnings given alternative information. *The Accounting Review, 65*(1), 49-71.

Lys, T. Z., Cohen, D. A., & Aiyesha, D. (2008). Real and Accrual-Based earnings management in the pre- and Post-Sarbanes-Oxley periods. *The Accounting Review, 83*(3), 757-787.

Martikainen, M. (1997). Accounting losses and earnings response coefficients: The impact of leverage and growth opportunities. *Journal of Business Finance & Accounting, 24*(2), 277-292.

Michaely, R., & Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies, 12*(4), 653-686.

Ng, J., Rusticus, T. O., & Verdi, R. S. (2008). Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research, 46*(3), 661-696.

O'Brien, P. C. (1988). Analysts' forecasts as earnings expectations. *Journal of Accounting and Economics, 10*(1), 53-83.

PwC. (2018). *Revenue from contracts with customers: Figure 1-1.* Retrieved from https://www.pwc.com/us/en/cfodirect/assets/pdf/accounting-guides/pwc-revenue-recognition-global-guide.pdf

Ramnath, S. (2002). Investor and analyst reactions to earnings announcements of related firms: An empirical analysis. *Journal of Accounting Research, 40*(5), 1351-1376.

Rees, L., & Sivaramakrishnan, K. (2007). The effect of meeting or beating revenue forecasts on the association between quarterly returns and earnings forecast errors. *Contemporary Accounting Research, 24*(1), 259-290.

Rendleman, R., Jones, C. P., & Latané, H. A. (1982). Empirical anomalies based on unexpected earnings and the importance of risk adjustments. *Journal of Financial Economics, 10*(3), 269-287.

Roll, R. (1977). A critique of the asset pricing theory's tests part I: On past and potential testability of the theory. *Journal of Financial Economics, 4*(2), 129-176.

S&P Dow Jones Indices LLC. (2019). S&P 500. Retrieved from https://us.spindices.com/indices/equity/sp-500

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.

Swaminathan, S., & Weintrop, J. (1991). The information content of earnings, revenues, and expenses. *Journal of Accounting Research, 29*(2), 418-427.

Teoh, S. H., & Wong, T. J. (1993). Perceived auditor quality and the earnings response coefficient. *The Accounting Review, 68*(2), 346-366.

United States Department of Labor. SIC division structure. Retrieved from https://www.osha.gov/pls/imis/sic_manual.html

Zhang, F. (2006). Information uncertainty and stock returns. *The Journal of Finance, 61*(1), 105-137.

Zhang, L. (2012). The effect of ex ante management forecast accuracy on the post-earnings-announcement drift. *The Accounting Review, 87*(5), 1791-1818.

9. Appendices

Appendix A. Regression Results Comparison, All Subperiods and Total

		2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
SUE	CAPM	0.0099***	0.0119***	0.0068***	**0.0083*** **
	Index	0.0100***	0.0111***	0.0068***	**0.0083*** **
SUR	CAPM	0.0043***	0.0038*	0.0045***	**0.0044*** **
	Index	0.0042***	0.0037*	0.0046***	**0.0044*** **
SIZE	CAPM	0.0031	-0.0119**	0.0011	**0.0003**
	Index	0.0036	-0.0125**	0.0016	**0.0006**
VG	CAPM	-0.0043	-0.0005	0.0001	**-0.0014**
	Index	-0.0033	-0.0003	-0.0004	**-0.0014**

Appendix A shows the coefficients for the four independent- and dummy variables (abnormal return adjusted for either Index or CAPM). SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

Appendix B. Explanatory Power Comparison

		2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
R^2	CAPM	0.1158	0.1586	0.0864	**0.0968**
	Index	0.1167	0.1486	0.0878	**0.0962**

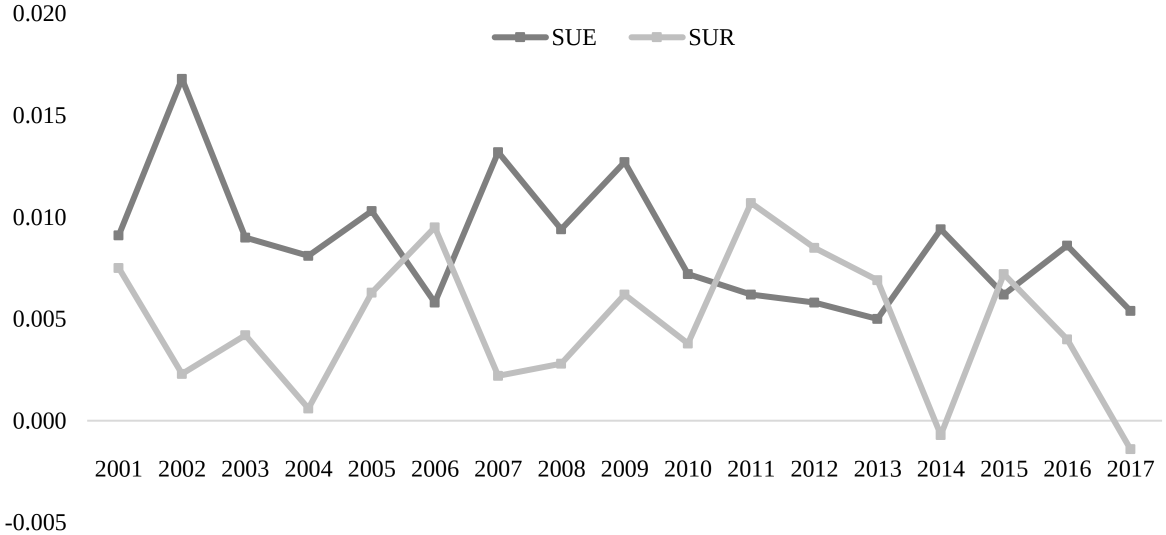
Appendix B shows the explanatory power, R^2, for the four different regressions for each model (adjusted for either CAPM or Index)

Appendix C. Coefficients for the Independent Variables, Including Only SUE and SUR

Model	Component	2001 – 2007	2008 – 2009	2010 – 2017
INDEX	SUE	0.0098***	0.0108***	0.0069***
	SUR	0.0044***	0.0035*	0.0046***
	R^2	0.1050	0.0982	0.0853
CAPM	SUE	0.0097***	0.0115***	0.0069***
	SUR	0.0045***	0.0037*	0.0045***
	R^2	0.1031	0.1130	0.0844

Appendix C shows the results for the coefficients for SUE and SUR when the SIZE and VG are not included in the regression. SUE is the earnings surprise variable. SUR is the revenue surprise variable.

Appendix D. Regression Coefficient Plot, Period 2001 – 2017 (Year-by-Year)



Appendix D plots the SUE and SUR coefficients for the year-by-year regression results found in **Table XIX**

Appendix E. Regression Results with SUE/SUR Scaled by Consensus Forecast

		2001 - 2007	**2008 - 2009**	**2010 - 2017**	**2001 - 2017**
SUE	*Coefficient*	0.0358**	0.0234	0.0169	0.0216***
	Robust std. Error	0.0143	0.0189	0.0110	0.0097
SUR	*Coefficient*	0.0468*	0.2061***	0.1018***	0.0845***
	Robust std. Error	0.0272	0.0865	0.0321	0.0233
Other	R^2	0.0325	0.0540	0.0153	0.0179
	n	1,323	482	2,264	4,069

Appendix E shows the coefficients and the robust standard errors for SUE and SUR, as well as the R^2 and the number of observations, when the forecast error is scaled using the analyst consensus forecast instead of the standard deviation. SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels, and observations with negative values of expected earnings have been removed. SIZE and VG have been omitted for visual purposes. Industry dummy variables have been omitted for visual purposes.
*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$

Appendix F. Variance Inflation Factor

Variable	VIF	1 / VIF
SUE	1.12	0.89
SUR	1.13	0.88
SIZE	1.03	0.97
VG	1.19	0.84
Mean	**1.12**	

Appendix F shows the Variance Inflation Factor (VIF) and 1 divided by the VIF for each independent variable, as well as the dummy variables VG and SIZE. SUE is the earnings surprise variable. SUR is the revenue surprise variable. SIZE classifies the companies as either large (value 0 in regression) or small (value 1 in regression), based on market capitalization for the calendar quarter preceding the calendar quarter in which the fiscal year ends. VG classifies the companies as either value (value 0 in regression) or growth (value 1 in regression), based on market-to-book ratio for the calendar quarter preceding the calendar quarter in which the fiscal year ends. SUE and SUR have been winsorized at the 5- and 95% levels. Industry dummy variables have been omitted for visual purposes.

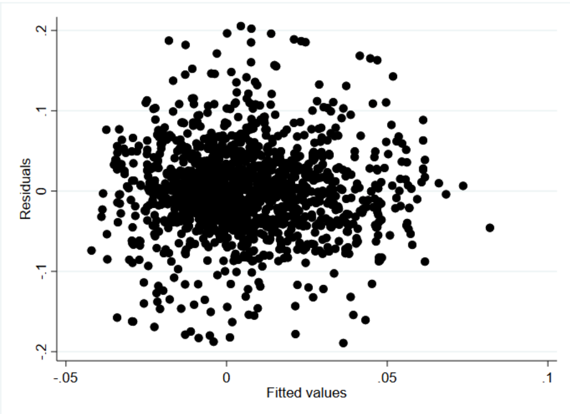
Appendix G. White's Test for Heteroscedasticity

H0: Error terms are of homoscedastic nature Reject H0 if $p < 0.10$					
Model	Value	2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
CAPM	χ^2	88.23	57.67	122.69	**188.13**
	p	0.0000	0.0348	0.0000	**0.0000**
Index	χ^2	88.54	56.65	121.44	**186.09**
	p	0.0000	0.0423	0.0000	**0.0000**

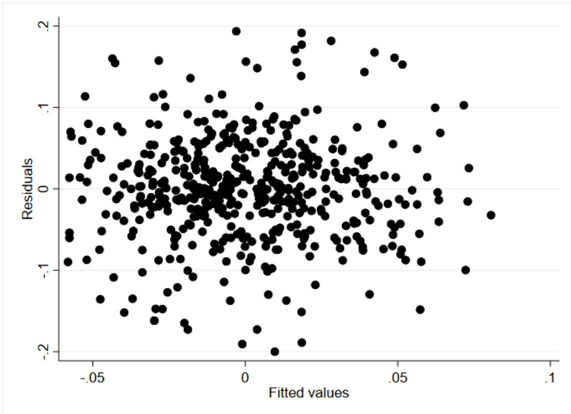
Appendix G shows the results for White's test for heteroscedastic error terms

Appendix H. Heteroscedasticity Visualization (CAPM)

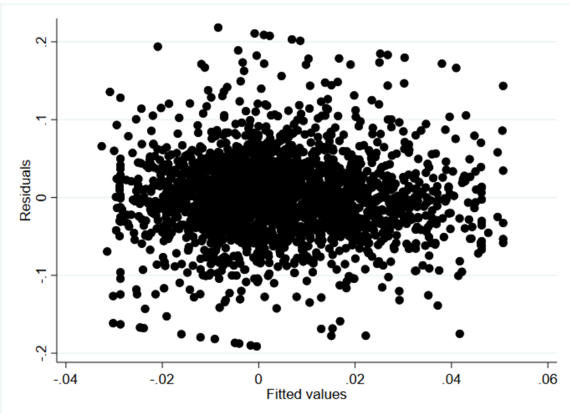
2000 – 2007



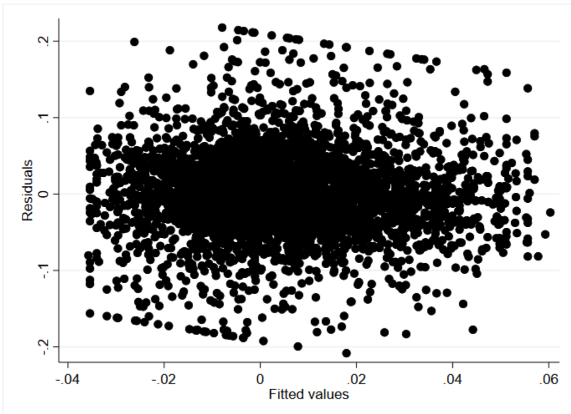
2008 – 2009



2010 – 2017



2000 – 2017



Appendix H shows the heteroscedasticity visualization plotting the residuals against the abnormal returns variable based on the CAPM model of expected return. The dependent variable has been winsorized at the 0.5%- and 99.5%-levels

Appendix I. Wooldridge Test for Autocorrelation

$H0$: No first − order autocorrelation					
Reject H0 if $p < 0.10$					
Model	Value	2001 – 2007	2008 – 2009	2010 – 2017	**2001 – 2017**
CAPM	F	0.688	0.587	0.166	**2.465**
	p	0.4078	0.4445	0.6841	**0.1172**
Index	F	1.188	0.539	0.161	**2.575**
	p	0.2769	0.4637	0.6886	**0.1094**

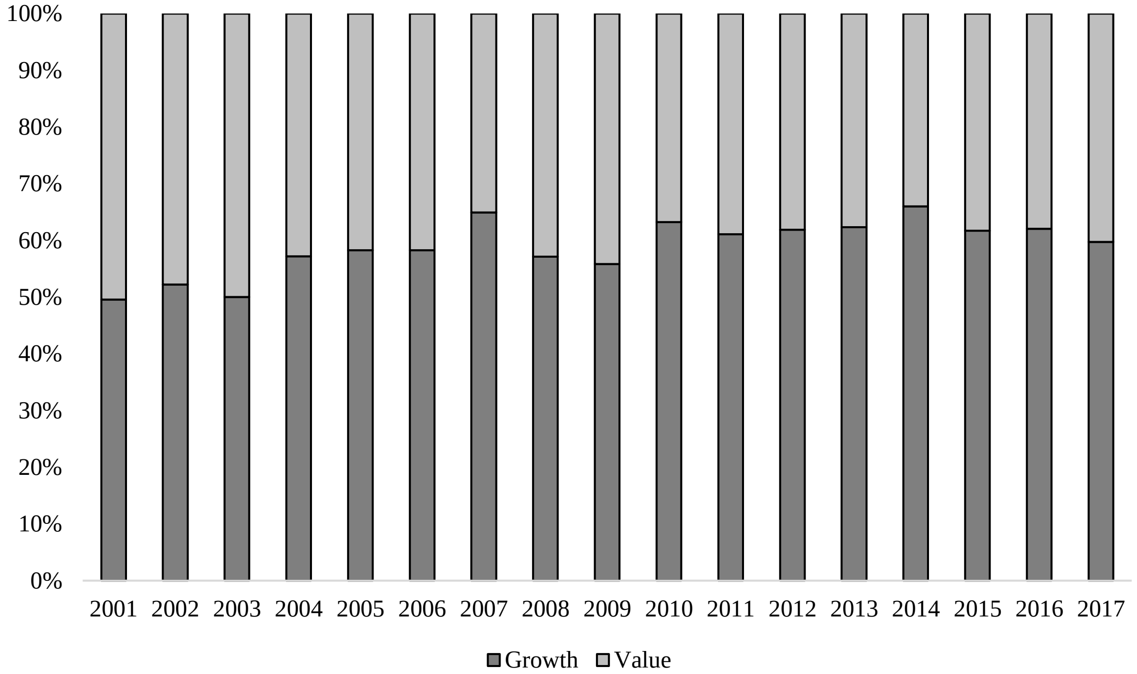
Appendix I shows the results for the Wooldridge test, testing for autocorrelation for the dependent variable abnormal returns

Appendix J. Data Components and Sources

Component	Comment	Source
Earnings surprise	Analyst revenue consensus forecasts and actuals, number of analysts in the consensus, and the standard deviation	I/B/E/S
Revenue surprise	Analyst revenue consensus forecasts and actuals, number of analysts in the consensus, and the standard deviation	I/B/E/S
Stock prices	Daily closing stock prices	CRSP
Index levels	Daily closing index levels of the NYSE/AMEX/NASDAQ Value-Weighted Index (including dividends)	CRSP
Company beta	Rolling 30-60-month company betas	WRDS Betasuite
Risk-free rate	US 10-year Constant Maturity Treasury Bill rate at month end	Federal Reserve
Company value/growth	Book-to-market ratio at fiscal year end	Compustat
Value/growth classification	Average S&P 500 book-to-market ratio,calendar quarter end	S&P
Company size	Company market capitalization at fiscal year end	Compustat
S&P 500 average Size	Avg. S&P 500 constituent market cap, calendar quarter end	CRSP
Company industry	SIC Industry Codes	Compustat

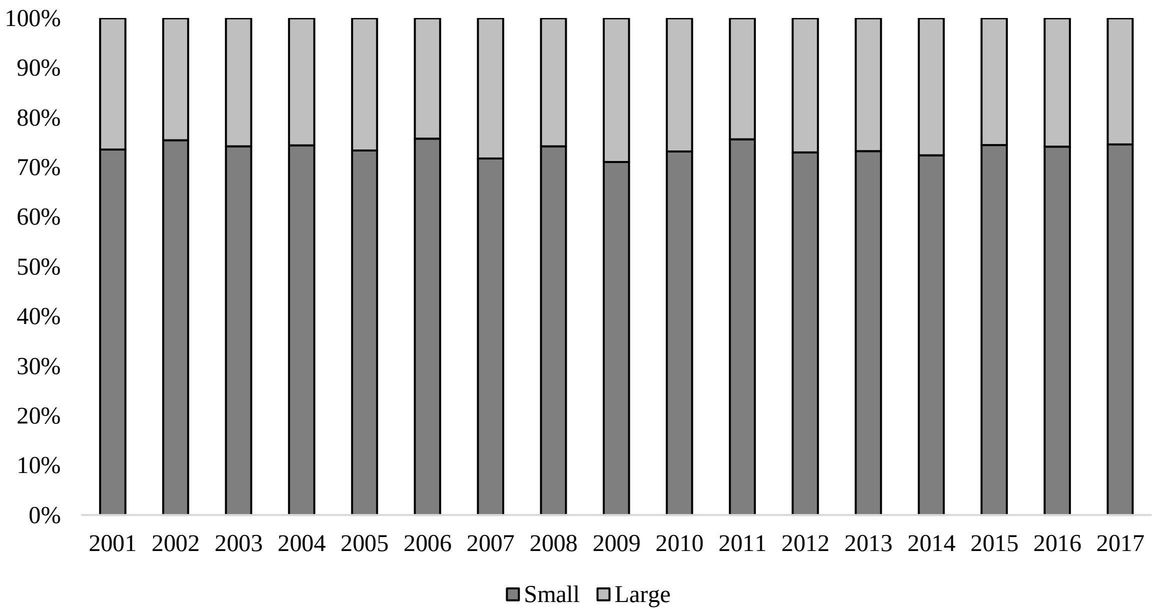
Appendix J shows data components and their respective sources. The bulk of the data has been retrieved via Wharton Research Data Services (WRDS). Data has been retrieved during January and February 2019.

Appendix K. Observation Distribution by Value/Growth Classification



Appendix K shows how the observations are distributed between value and growth classification

Appendix L. Observation Distribution by Size Classification



Appendix L shows how the observations are distributed depending on size classification