The predictive content of one-time accounting items

Part 1: Analysis of one-time items and possible implications in light of COVID-19

Part 2: One-time items: Impact of firm life cycle

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Master Thesis

Università Commerciale Luigi Bocconi & Stockholm School of Economics

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Abstract:

My research investigates how past core earnings and past one-time items are associated with future earnings over increasing time windows from one to five years. One-time items – hereafter referred to as special items or one-time items – are, by definition, supposed to be transitory, which is why investors usually exclude those items in their earnings forecast models. This approach is only valid if there is no significant association between past one-time items and future earnings. Otherwise, the exclusion of special items implies a loss of information and can cause overvaluations. Given that one-time items peak during economic downturns, my paper is highly relevant in light of the COVID-19 pandemic. My results suggest that one-time expenses are relevant for future earnings in the short-term as well as in the long-term with a persistence that is approximately 1/3 compared to the one of core earnings. Positive special items are also significant over longer time horizons, but my robustness check indicates that my results may overvalue the importance of one-time revenues. Furthermore, my descriptive analysis of one-time items indicates that there is no "one size fits all"-approach for special items, which is why I investigate the relevance of those items across a number of sub-sets, trying to identify patterns. These analyses show that high / low special items frequency and magnitude in a certain sub-set does not necessarily imply high / low special items relevance. Nevertheless, my results suggest that one-time expenses are more relevant for earnings forecasts in Europe, during economic downturns, for high profitability firms (in the short-term) as well as in the Consumer durables, Energy, Utilities, and Healthcare industry portfolios. One-time revenues are associated with future performances when smoothed over longer time horizons for forecasts in North America, in the Consumer non-durables and in the Other industry portfolios, and for medium profitability firms. The one-time sub-items with the highest predictive content are in-process R&D expenses, restructuring charges and M&A related gains / losses.

Keywords: Special items, One-time items, Earnings forecasts, Earnings persistence, Profit margins

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1 Introduction

In February 2020, the S&P 500 index reached a record closing high of 3,386. One month later, it has experienced the third largest one-day percentage crash (-11.98%) in US history, showing interim losses of almost 1,000 points. This drop was caused by global fears about the COVID-19 pandemic, a looming recession and oil price drops. Only half a year later, in August 2020, the S&P 500 rebounded to a new all-time high, marking the quickest recovery from bear-market territory in its history (Wursthorn, 2020). Other major world stock market indices show similar patterns. Despite of the fact that the stock markets appear to have recovered in record time, economic outlook projections expect significant declines for 2020 – IMF's World Economic Outlook forecasts a 5.8% decrease for advanced economies compared to 2019 (IMF, 2020). Temporary lockdowns and changed customer behaviours as a consequence of the pandemic confronted businesses all over the world with issues never faced before. Many companies still face bottlenecks, some players even had to file for bankruptcy, such as the US-based car rental company The Hertz Corporation to name only one well-known example. While this development and the strong volatility is worrying for all investors, it provides at the same time chances. Warren Buffet once famously recommended to “be greedy when others are fearful” (Clifford, 2020). In order to be able to use these chances, it is crucial to get the maximum possible information out of the financial statements of companies, helping to understand which companies will recover from the current downturn. This, however, is not only difficult due to the current uncertainties, which significantly affect companies’ operations and financials, but also because financial statements do not always tell the truth. Several researchers raise concerns over the accuracy of accounting information, finding a deteriorating earnings quality (e.g. Dechow and Schrand, 2004; Dichev & Tang, 2008). One major cause for the observed deterioration is the proliferation of special items. Special items – hereafter referred to as special items or one-time items – are, according to Accounting Principles Board (APB) Opinion No. 30, items that are unusual or infrequent but not both (FASB, 1973). Given that special items contain sub-items such as restructuring charges and asset-write offs, it is sound that Donelson et al. (2011) find that one-time items are mainly triggered by economic changes. In line with this, special items literature finds increasing frequency and magnitude of special items during economic downturns (e.g. Johnson et al., 2011). Therefore, it is reasonable to expect that one-time items will become even more prevalent in coming years as a direct consequence of the COVID-19 pandemic, possibly reducing the usefulness of GAAP earnings even further. Analysts and investors usually address this problem by excluding one-time items and computing core earnings, non-GAAP figures and pro-forma financials (e.g. Bradshaw & Sloan, 2002), as one-time items are supposed to be transitory by definition. In fact, research shows that the most significant pro-forma adjustments include special items, amortization and stock-based compensation (e.g. Ciesielski & Henry, 2017). However, given that prior literature indicates that one-time items gain significance, is it reasonable to categorically exclude those items? “Special items are so prevalent now that they're not special anymore” (Fowler, 2006), indicating that not considering one-time items may imply a loss of information. Indeed, Burgstahler et al. (2002) find that investors underestimate the effect of one-time items on future earnings, on average, by 27%, indicating that we require further clarity on how we should treat those items. Therefore, I investigate the relevance of one-time items for future performance in this paper. This topic is mainly relevant for investors. In particular, since special items are in most cases negative, adjusting for them will lead to a core earnings figure exceeding the actual GAAP figure. Hence, excluding negative one-time charges may cause overvaluations, i.e. investors face the risk of seizing investment opportunities they should not. Furthermore, my paper is of interest for accounting regulators, such as for instance the FASB, whose mission is “to establish and improve financial accounting and reporting standards to provide useful information to investors and other users of financial reports” (FASB, 2020). In order to examine whether one-time items are relevant or whether investors should solely focus on core earnings for their forecasts, I regress lagged core profit margin, lagged negative and positive special profit margin on future profit margin over increasing time windows from one to five years (section

5.1). This approach is a replication of the one used by Fairfield et. al (2009) and is very intuitive, as it can be interpreted as the predictive content past core earnings and past one-time items provide for future earnings.

Prior literature as well as my descriptive analysis of one-time items in chapter 4 indicate that the relevance of one-time items depends on a number of parameters, meaning there is no “one size fits all”-approach for those items. As previously mentioned, one-time expenses peak in frequency and magnitude during economic downturns and crises (e.g. Johnson et al., 2011). Hence, I examine whether investors should adapt their approach with respect to special items, depending on the current economic environment. Thereby, I analyse how the association between past core earnings, past one-time items and future earnings changes between 2001 and 2018 (section 5.5). This is particularly interesting in light of the current COVID-19 pandemic, even though it needs to be emphasized that every crisis is unique, meaning special item patterns observed during previous downturns are not necessarily representative for the current one. Besides of my analysis by time, I investigate four additional dimensions – namely, I examine whether the predictive content of one-time items varies across profitability (section 5.2), geography (5.3), industry (5.4) and one-time sub-items (5.6). As “special items reported by low and high profitability firms are likely to be triggered by different economic circumstances and incentives, they may also have different implications for future profit margins” (Fairfield et al., 2009, p. 216). Cutillas-Gomariz et al. (2016) find that earnings relevance increased for publicly listed Spanish companies after an IFRS reformation forced these companies to include non-recurring items into operating income. This might potentially indicate that one-time items have a higher predictive ability in Europe compared to North America, as US-focused literature suggests that earnings quality declines as a result of special items (e.g. Dichev & Tang, 2008). Johnson et al. (2011) finds evidence suggesting that industries that report the fewest one-time charges also report the fewest one-time revenues, while the industries with the most one-time expenses are not the ones with the most one-time revenues. Consequently, the usefulness of special items may vary by industry. Finally, some sub-items may capture more useful information for future performance than others. For instance, restructuring charges should ideally lead to improved future performances, while goodwill impairments can be a sign that a company overpaid when acquiring another company and, hence, do not necessarily affect future performance. In short, investors require additional clarity on how one-time items should be treated across those five dimensions. My research provides analysts and investors with frameworks for different circumstances, hopefully improving their investment decisions. It needs to be emphasized, however, that my results may not be representative for all conditions, meaning investors should not trust blindly my results without questioning whether they are applicable to their specific investment decisions.

In the next chapter, I discuss background literature on earnings quality, special items, and pro-forma adjustments. Subsequently, section 3 provides a discussion of the regression model and sample used for my empirical analysis. Section 4 includes a descriptive analysis of one-time items with regards to frequency, persistence, magnitude and sub-items for my consolidated sample as well as by geography and by industry. Section 5 reports my regression results, while section 6 discusses potential robustness issues. Finally, section 7 concludes.

2 Literature review

The research on pro-forma adjustments and special items is vast. The connecting dot of both topics is the prevalent opinion that earnings quality has been declining over time (e.g. Dichev & Tang, 2008). While one-time effects are among the primary reasons for the observed deterioration of earnings quality (e.g. Donelson et al., 2011), pro-forma adjustments and non-GAAP figures provide a possible attempt for solving this issue (e.g. Ciesielski & Henry, 2017).

2.1 Earnings quality

Dechow & Schrand (2004) define earnings quality based on three pillars – high quality earnings are persistent, predictable and annuitize the intrinsic value of a firm. In other words, earnings are supposed to be a useful indicator for assessing and predicting current and future performance as well as for determining firm value. Prevalent research documents a deteriorating earnings quality, as there is a declining trend in all three pillars. Literature on earnings relevance finds that the correlation between earnings and stock returns is decreasing, implying that earnings nowadays are a less suitable figure for assessing firm value than they have been in the past (e.g. Dechow & Schrand, 2004). Fama & French (2004) show that there is an increase in the left skewness of the overall earnings distribution in the US. Dichev & Tang (2008) provide evidence, supporting a declining correlation between current period revenues and expenses, causing an increasing earnings volatility and a decreasing persistence and predictability. According to Dichev & Tang (2008), the poor revenue-expense matching – and thus also the deteriorating earnings quality – can primarily be traced back to the increasing importance of one-time items, but they are unable to explain what causes this development. Consistent with that, Alford & Berger (1999) find that earnings forecast accuracy is declining and that it is negatively correlated with lagged special items. Donelson et al. (2011) shed light on the question whether the increasing importance of special items is triggered by economic changes or by new accounting standards. They show that special items are strongly correlated to economic events. Consequently, it is reasonable to postulate the hypothesis that the current economic events in light of the COVID-19 pandemic might worsen the situation even further. Summarizing the literature on earnings relevance, we can conclude that earnings quality is declining. This decline is mainly triggered by the increasing importance of one-time items, which, in turn, is primarily a consequence of economic changes.

2.2 Transitory one-time items and non-GAAP earnings

According to Accounting Principles Board (APB) *Opinion No. 30 Reporting the Results of Operations—Reporting the Effects of Disposal of a Segment of a Business, and Extraordinary, Unusual and Infrequently Occurring Events and Transactions*, special items are items that are unusual or infrequent but not both. Consistently with that, research which dates back in time – usually before the turn of the century – finds evidence supporting the transitory character of special items. Fairfield et al. (1996) find that one-time items are not informative about one-year ahead earnings. Moreover, they find that the persistence of items on the income statement declines, the further one moves down the income statement. This becomes evident based on their finding that the persistence of special items is five times lower than the one of core earnings. Burgstahler et al. (2002) provide evidence supporting that special items are more transitory than non-special item earnings components. Consequently, it is common practice for analysts and investors to exclude one-time items when computing core earnings, non-GAAP figures and pro-forma financials (e.g. Bradshaw & Sloan, 2002).

As research shows, the common practice to exclude one-time items for non-GAAP numbers has not changed over time. With 27.4% of all adjustments, the most significant adjustment in 2014 have been impairments followed by amortization (19.7%), acquisition activity related items (19.3%) and restructuring charges (17.1%) (Ciesielski & Henry, 2017). Consequently, the only significant non-GAAP adjustment, which is not a special item, is amortization, while the other three items are one-time items. Somewhat surprisingly, non-GAAP literature does not really question whether the exclusion of special items is valid. Instead, the vast majority of research papers focus solely on whether the exclusion of core items (such as amortization) is justified (e.g. Whipple, 2016). This is particularly puzzling, since special items literature finds that one-time items become increasingly important.

2.3 The increasing importance of one-time items

The discussed importance of one-time items is mainly reflected in an increasing frequency, but also in a stable, slightly increasing magnitude of special items. Frequency is defined as the percentage of firms which report one-time items in a given year. Research suggests that this percentage is growing and that the growth can mainly be traced back to negative special items (e.g. Riedl & Srinivasan, 2010; Johnson et al., 2011). For instance, Johnson et al. (2011) show that, while in 1980 only 21.1% of the publicly listed US companies reported special items, in 2009 this number grew almost threefold to 59.2%. This increase is primarily driven by negative special items, as the frequency of one-time expenses grew from 7.8% in 1980 to 44.4% in 2009, implying that they contribute for ¾ of special items in 2009. Furthermore, the analysis of Johnson et al. (2011) suggests that the frequency of negative special items peaks during economic downturns. Therefore, it is reasonable to believe that one-time items might have a different predictive content during recessions and crises, making my research highly relevant. While one-time expenses became more significant over the past decades, the frequency of one-time revenues remained fairly constant between 9% and 15% over the entire observation period from 1980 to 2009. Despite of the fact that the overall trend shows a growing / constant frequency for negative / positive special items, Johnson et al. (2011) find evidence supporting that this trend appears to reverse between 2002 and 2007. My research adds to this by extending the observation period to 2018, which enables to analyse whether this pattern change continues. As previously mentioned, the augmentation of special items is not only reflected in an increasing frequency, but also in an increasing magnitude. Research defines magnitude as the relative size of one-time items in relation to revenues (e.g. Fairfield et al., 2009), total assets (e.g. Johnson et al., 2011) or operating expenses (e.g. Bradshaw & Sloan, 2002). Depending on which denominator has been chosen, the results on the development of the magnitude of one-time items vary slightly. Relating one-time items to total assets, Riedl & Srinivasan (2010) find an increasing magnitude from approximately 4% in 1980 to 8% in 2002, whereby positive special items remained constant and negative special items grew (Johnson et al., 2011). In line with their results of the frequency analysis, Johnson et al. (2011) find that this pattern changes after 2002. Their evidence shows that the size of both positive and negative special items slightly decreases between 2002 and 2009. In contrast to this analysis, Fairfield et al. (2009) relates positive and negative special items to revenues and finds that the magnitude has not changed noteworthy between 1984 and 2003. Summarizing the literature on the importance of one-time items, we can conclude that their frequency increased significantly, while their magnitude remained constant or increased slightly, depending on the selected denominator and observation period.

Considering the overall increasing importance of special items, it is necessary to scrutinize whether the common practice by analysts and investors to exclude them categorically is justified. Research casts doubts on this approach, as there is evidence indicating that investors are not able to accurately interpret special items. Dechow & Ge (2006) suggest that investor undervalue firms with low accruals that report special items in the present, causing higher future stock returns. Excluding special items when compounding core earnings would only be a correct approach, if they do not provide any useful information at all for any company. However, Burgstahler et al. (2002) find that investors underestimate the effect of one-time items on future earnings, on average, by 27%. Furthermore, it should be questioned whether a "one size fits all"-approach for one-time items exists. Elliot & Hanna (1996) as well as Johnson et al. (2011) provide evidence, showing that prior reporting frequency of special items is correlated with future reporting frequency, i.e. firms that reported one-time items in the past are more likely to do so again in the future. Besides of that, Johnson et al. (2011) find that industry effects may drive the recognition of one-time items. These observations indicate that we might have to adapt different approaches for special items depending on the circumstances. Hence, my research paper tries to identify special item patterns across a number of different dimensions (profitability, geography, industry, time and sub-items), providing different frameworks for investors.

2.4 Why are one-time items not transitory nowadays?

The increasing importance of one-time items in combination with investors' inability to accurately interpret those items made many researchers wonder whether special items are truly transitory. Researchers who believe that one-time items capture useful information for future performance postulate two possible theories: i) special items could be relevant for future performance, because they are core expenses or expenses from other periods misclassified as current special items (earnings management hypothesis), or ii) one-time items affect future earnings, because they signal future performance improvement or decline (real performance hypothesis). In the following, I will discuss the prevalent research for both hypotheses.

2.4.1 Earnings management hypothesis

Healy & Wahlen (1999, p. 368) define earnings management as following:

> “when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers.”

This behaviour is not rare as a survey with 169 CFOs of public companies by Dichev et al. (2013) shows – participants admit that, on average, 20% of earnings are managed to misrepresent economic performance. One-time items provide management as a useful tool for managing earnings, as investors pay less attention to special items (e.g. Bradshaw & Sloan, 2002). Cain et al. (2020) suggest that 30% to 60% of reported special items are indeed opportunistic. They do so by predicting an economically driven special item component and allocating the residual to opportunistic actions. While there are in theory several ways how a company can manage its earnings, special items literature focuses primarily on two techniques. Firstly, accrual management, also referred to as inter-period transfer (e.g. Pierk, 2020). When applying this technique, managers are transferring expenses or revenues from other periods into current period special items. Hence, there will be a one-to-one earnings change from the opposite sign in a future period. One common application of accrual management is big bath accounting. Thereby, managers are recording future expenses as current one-time expenses, leading to lower current earnings and a one-to-one increase in future earnings (e.g. McVay, 2006). Regulatory bodies are well aware of companies opportunistically exploiting big bath accounting - Arthur Levitt, former president of the Security Exchange Commission (SEC), claimed in a New York Times article “that the commission was frustrated with companies that used a factory closing or a work force reduction as an opportunity to take millions of dollars of one-time charges for ''restructuring.'' By inflating those write-offs, companies get the bad news out of the way at once and can clear their balance sheets of expensive assets that would otherwise reduce the bottom line for years to come” (Petersen, 1998). Pierk (2020) suggests that overconfident CEOs are 6.3% to 10.6% more likely to pursue big bath accounting. Consistent with that, Frankel & Roychowdhury (2009) show that negative special items are more transitory for firms with conservative accounting policies. Consequently, understanding a firm's accounting policy can be helpful in assessing earnings management attempts as well as the usefulness of one-time items. Besides of accrual management, special items literature suggests that companies may engage in classification shifting to manage their earnings. McVay (2006) defines classification shifting as a misclassification of current core expenses or revenues as one-time revenues or expenses. This does not affect GAAP earnings, but only non-GAAP earnings, as analysts usually exclude one-time items when compounding non-GAAP figures (e.g. Bradshaw & Sloan, 2002). Hence, classification shifting is difficult to detect, as there is no reversal. McVay (2006) suggests that, on average, 2.2% of reported special items are misclassified core expenses. Classification shifting appears more frequent in the fourth quarter (Fan et al., 2010), to beat analyst forecasts (Fan et al., 2010), when a firm is in a declining life cycle stage (Nagar & Sen, 2017) as well as to boost valuations before events such as seasoned equity offerings (Siu & Faff, 2013).

2.4.2 Real performance hypothesis

Some research papers suggest that special items may capture relevant information for future earnings, not only because companies use them as an earnings management tool, but also because special items may signal future performance improvement or decline. This contradicts with the initial definition that special items are transitory and would imply that it is wrong to exclude them when computing non-GAAP figures. Cready et al. (2012) find that CEOs use one-time items for accrual management, but, given that they find an earnings reversal of > 130% (i.e. greater than 100%), they conclude that special items also capture useful information for future performance. Moreover, there evidence suggests that the real performance effect is stronger for restructuring expenses than for other one-time items. Literature that exclusively focuses on restructuring charges is mostly supporting the real performance hypothesis (e.g. Bens & Johnston, 2007). However, Atiase et al. (2004) as well as Khurana & Lippincott (2000) find that restructuring charges are only associated with improved future performance for low profitability companies with fundamental operational problems. Consequently, the real performance hypothesis differs across various dimensions. Fairfield et al. (2009) regress lagged core earnings, lagged negative special items, and lagged positive special items on earnings over time windows from one to five years. They conclude that for high profitability firms, negative special items provide predictive content for future profits and this association becomes stronger over long horizons. Riedl & Srinivasan (2010) claim that only the special items that receive footnote presentation are persistent. Cutillas-Gomariz et al. (2016) show that earnings relevance significantly increased for publicly listed Spanish companies after an IFRS reformation forced these companies to include non-recurring items into operating income. This suggests that the real performance effect of special items might also differ across geographic regions.

3 Research design and descriptive statistics

Most research approaches in this field test the persistence of special items by regressing a lagged core earnings figure and one or multiple lagged one-time items on earnings (e.g. Burgstahler et al., 2002; Fairfield et al., 2009; Skinner & Soltes, 2011). This approach is very intuitive, because the regression result can be interpreted as the predictive content past core earnings and past one-time items provide for future earnings. While the underlying methodology of the empirical models used in these papers is identical, most papers include some additional specifications in their models. For instance, breaking up special items into one-time charges and revenues (e.g. Fairfield et al., 2009) or into special items receiving income statement or footnote presentation (Riedl & Srinivasan, 2010). Furthermore, existing research differs in the sense that they deflate the variables in their models by different denominators to normalize their numbers. Some papers are taking a return on assets perspective by dividing their variables through total assets (e.g. Dechow & Ge, 2006; Skinner & Soltes; 2011). Other papers deflate all variables with market value of equity, meaning they are taking a return on equity perspective (e.g. Frankel & Roychowdhury, 2009; Riedl &

Srinivasan, 2010). Finally, Fairfield et al. (2009) uses sales as denominator, analysing the persistence of core earnings and special items from a profit margin perspective.

Since my research aims to provide a useful framework for analysts and investors, I decided to adopt the profit margin perspective. This does by no means imply that return on assets and return on equity are less relevant than profit margin for analysts and investors. However, when projecting future earnings, most analysts would start by forecasting sales and derive earnings through assumptions with respect to profitability margins. Therefore, I decided to replicate the model used by Fairfield et al. (2009) to ensure consistency and comparability.

3.1 Research model and variable definition

Fairfield et al. (2009) regress lagged decomposed profit margin (consisting of core profit margin, positive and negative special profit margin) on future profit margin over increasing time windows from one to five years. They perform their regression over increasing windows because one-time items tend to be irregular and by averaging their variables over several years those irregular items are smoothed. There is no overlap between the time windows of the dependent and independent variables. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. Extending the time window to its maximum of w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Consequently, we require at least 10 years of consecutive data for w = 5 (**Table 20** in the Appendix shows a list of the years included in the one- and five-year windows).

Consistently with Fairfield et al. (2009), my base model looks as follows:

$$PM_{t+1}^{w} = \alpha_{0,0} + \beta_{0,1}^{w} * core\ PM_{t}^{w} + \beta_{0,2}^{w} * negative\ special\ PM_{t}^{w} + \beta_{0,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{0,4}^{i} * YEAR_{i} + \varepsilon_{t+1} \quad (1)$$

All the variables are derived from the Annual Industrial COMPUSTAT database between 2001 to 2018. Moreover, all variables are summarized and defined in

Table 1 as well as described below. The dependent variable PM^{w}_{t+1} is profit margin in period t+1, which is defined as net operating income (NOI) in t+1 divided by sales in t+1. Net operating income (NOI) is computed back-of-the-envelope as net income (#172) before extraordinary items and discontinued operations (#48), non-controlling interest income (#49), taxes (#16), non-operating income (#61), and interest income (#62) / expense (#15). In line with Fairfield et al. (2009), I exclude taxes, as I do not have any information on the tax deductibility of special items. Interest income and expenses are not considered, because otherwise capital structure changes might distort my analysis. Furthermore, I have chosen to compute NOI back-of-the-envelope, as this was the only way to make sure that my dependent variable reflects operating income including special items. In other words, if I had taken an operating income figure by COMPUSTAT instead, there would be the risk that COMPUSTAT already excluded some / all one-time items. This would be an issue, as my independent variables decompose profit margin into lagged core profit margin (core PM^{w}_{t}), lagged negative special profit margin (negative special PM^{w}_{t}) and lagged positive special profit margin (positive special PM^{w}_{t}). Lagged core profit margin is defined as NOI minus special items in period t deflated with sales. Consequently, if my NOI did not include one-time items, my core profit margin would deduct special items twice. Lagged negative and positive special profit margin are derived by dividing negative / positive special items through sales in period t. Since a company can only report negative or positive net special items (= sum of all one-time items), negative and positive special profit margin can never be ≠ 0 at the same time. As previously discussed, all variables are indexed with a superscripted w, implying the model will be estimated for time windows from one to five years.

As mentioned in chapter 2.3 and 2.4, prior research indicates that there is no “one size fits all”-approach for one-time items. In order to provide analysts and investors with the necessary tools for a variety of different circumstances, I run regressions by profitability (section 5.2), geography (section 5.3), industry (section 5.4), time (section 5.5) and sub-items (section 5.6). In the following, I will explain which model adjustments I pursue for each of the sub-sections.

For the sub-sections by profitability (5.2), geography (5.3), and industry (5.4), I run the base model as postulated above with the only difference that the model is not estimated for the entire sample, but instead for three different profitability classes ranked according to core RNOA, for Europe and North America and for my industry portfolios.

For my regression by time (section 5.5), I run the basic regression model separately for each year of my observation period (i.e. from 2001 to 2018). For instance, I regress lagged decomposed profit margin from year 2001 on profit margin of 2002 and so on.

$$PM_{2002} = \alpha_{2001,0} + \beta_{2001,1} * core\ PM_{2001} + \beta_{2001,2} * negative\ special\ PM_{2001} + \beta_{2001,3} * positive\ special\ PM_{2001} + \varepsilon_{2002} \tag{1a}$$

$$PM_{2003} = \alpha_{2002,0} + \beta_{2002,1} * core\ PM_{2002} + \beta_{2002,2} * negative\ special\ PM_{2002} + \beta_{2002,3} * positive\ special\ PM_{2002} + \varepsilon_{2003} \tag{2a}$$

$$\ldots$$

$$PM_{2018} = \alpha_{2017,0} + \beta_{2017,1} * core\ PM_{2017} + \beta_{2017,2} * negative\ special\ PM_{2017} + \beta_{2017,3} * positive\ special\ PM_{2017} + \varepsilon_{2018} \tag{17a}$$

This leaves me with 17 regressions, as I cannot use year 2001 as a dependent variable, because I would require data from year 2000 for my independent variables to do so. As opposed to my base model, the regression by time analysis does not investigate the correlation between lagged decomposed profit margin and profit margin over increasing time windows, as I specifically try to examine whether there are annual differences. My 17 regressions give me one coefficient per year for all my explanatory variable, which is useful for descriptive analysis. However, coefficients may vary not only because there is an actual difference in correlation, but also due to distribution differences. Hence, it is necessary to conduct a test to understand whether there are structural breaks (i.e. significant differences in correlation across time). I use Chow tests (Chow, 1960) to understand whether there are structural breaks between each year-pair (i.e. 2001-2002, 2002-2003, …, 2017-2018). Chow examines whether the coefficients of two linear regressions on different sets are equal. For instance, Chow tests whether coefficients $\alpha_{2001,0}$, $\beta_{2001,1}$, $\beta_{2001,2}$ and $\beta_{2001,3}$ (from regression model (1a), i.e. when regressing decomposed profit margin from year 2001 on profit margin of 2002) are equal to $\alpha_{2002,0}$, $\beta_{2002,1}$, $\beta_{2002,2}$ and $\beta_{2002,3}$ (from regression model (2a), i.e. when regressing decomposed profit margin from year 2002 on profit margin of 2003).

H$_0$: $\alpha_{2001,0} = \alpha_{2002,0}$ and $\beta_{2001,1} = \beta_{2002,1}$ and $\beta_{2001,2} = \beta_{2002,2}$ and $\beta_{2001,3} = \beta_{2002,3}$ **(no structural break)**

H$_1$: $\alpha_{2001,0} \neq \alpha_{2002,0}$ or $\beta_{2001,1} \neq \beta_{2002,1}$ or $\beta_{2001,2} \neq \beta_{2002,2}$ or $\beta_{2001,3} \neq \beta_{2002,3}$ **(structural break)**

If the null hypothesis cannot be rejected, this implies that there is no structural break between regression model (1a) and (2a), i.e. differences in coefficients of these two models are not statistically significant, but instead they are caused by distribution differences. In contrast, if the null hypothesis is rejected, differences in coefficients imply that the correlations have changed significantly. As previously mentioned, I conduct Chow for each year-pair, meaning after having analysed whether the coefficients from regression (1a) and (2a) are statistically identical, I test whether the coefficients from regression (2a) and (3a) are identical and so on.

Finally, for my regression by sub-items (section 5.6), I modify my basic regression model in the sense that I replace negative special PM^{w}_{t} and positive special PM^{w}_{t} with one-time sub-items deflated with sales. COMPUSTAT provides a break-down of one-time items into the following sub-items: Acquisition/Merger Pretax (#360), Gain/Loss Pretax (#364), Impairment of Goodwill Pretax (#368), Settlement (Litigation/Insurance) Pretax (#372), Restructuring costs Pretax (#376), Writedowns Pretax (#380), Other Special Items Pretax (#384), In-process R&D pretax (#388) and Extinguishment of Debt Pretax (#406). Therefore, my regression model for section 5.6 looks as follows:

$$PM_{t+1}^{w} = \alpha_{4,0} + \beta_{4,1}^{w} * core\ PM_{t}^{w} + \beta_{4,2}^{w} * in-process\ R\&D_{t}^{w}$$

$$+ \beta_{4,3}^{w} * restructuring_{t}^{w} + \beta_{4,4}^{w} * gain\ loss_{t}^{w} + \beta_{4,5}^{w} * litigation_{t}^{w}$$

$$+ \beta_{4,6}^{w} * other\ SPI_{t}^{w} + \beta_{4,7}^{w} * M\&A_{t}^{w} + \beta_{4,8}^{w} * goodwill_{t}^{w} + \beta_{4,9}^{w} * writedown_{t}^{w}$$

$$+\beta_{4,10}^{w} * extinguish\ debt_{t}^{w} + \sum_{i=1}^{10} \beta_{4,11}^{i} * YEAR_{i} + \varepsilon_{t+1} \quad (2)$$

Table 1: Key variable definitions

Variable	Definition / Computation
Variables for basic regression (section 5.1) and regressions by geography (5.3), by industry (5.4), by time (5.5)	
Net operating income (NOI $_t$)	Net income (#172) + Extraordinary items & discontinued operations (#48) + Non-controlling interest income (#49) + Income taxes (#16) - Non-operating income / expense (#61) - Interest and related income (#62) + Interest and related expense (#15)
Special items $_t$	COMPUSTAT data item #17
Core earnings $_t$	NOI_t - Special $items_t$
Negative special items $_t$	Special $items_t$, assuming value is negative
Positive special items $_t$	Special $items_t$, assuming value is positive
Profit margin (PM $_t$)	NOI_t / $Revenue_t$
Core profit margin (core PM $_{t)}$	Core $earnings_t$ / $Revenue_t$
Neg. special PM	Negative special $items_t$ / $Revenue_t$
Pos. special PM	Positive special $items_t$ / $Revenue_t$
Additional variables for regression by profitability (section 5.2)	
Net operating asset (NOA $_t$)	Common stock (#60) + preferred stock (#130) + long term debt (#9) + debt in current liabilities (#34) + minority interest (#38) - cash and ST invest (#1)
Return on net operating assets (RNOA $_t$)	NOI_t / (0.5*(NOA_t + NOA_{t-1}))
Core RNOA	(NOI_t - Special $items_t$) / (0.5*(NOA_t +NOA_{t-1}))
Additional variables for regression by sub-items (section 5.6)	
In-process R&D $_t$	In-process R&D pretax (#388) / $Revenue_t$
Restructuring $_t$	Restructuring costs Pretax (#376) / $Revenue_t$
Gain loss $_t$	Gain/Loss Pretax (#364) / $Revenue_t$
Litigation $_t$	Settlement (Litigation/Insurance) Pretax (#372) / $Revenue_t$
Other special items $_t$	Other Special Items Pretax (#384) / $Revenue_t$
M&A gain / loss $_t$	Acquisition/Merger Pretax (#360) / $Revenue_t$
Goodwill impairment $_t$	Impairment of Goodwill Pretax (#368) / $Revenue_t$
Write-down $_t$	Writedowns Pretax (#380) / $Revenue_t$
Extinguish debt $_t$	Extinguishment of Debt Pretax (#406) / $Revenue_t$

3.2 Sample selection

Bradshaw & Sloan (2002) show that the data item “special items” (item #17) pursuant to COMPUSTAT is strongly correlated with the adjustments pursued by analysts when they try to compound a core earnings figure. This makes COMPUSTAT a suitable database for my research. Hence, I rely on the Annual Industrial COMPUSTAT database from 2001 to 2018. Despite of the fact that I examine differences in the relevance of one-time items across Europe and North America, I use the COMPUSTAT “North America – Daily” database, as the “Global – Daily” database does not provide a break-down of one-time items into sub-items, which is crucial for my empirical analysis in section 5.6. The “North America – Daily” database also captures European companies, which are listed in the US, meaning a geographic comparison is possible (section 5.3). In order to make sure that there are no significant discrepancies between the “North America – Daily” and the “Global – Daily” data, I reached out to the S&P Global Market Intelligence support. They informed me that key financial variables are identical between the two databases. However, there may be some variation with respect to special items – for instance, in the “North America – Daily” dataset, asset write-downs are always recorded as a special item, while, in the “Global – Daily” database, write-downs are recorded as a special item unless a company reports them in three or more consecutive years. Hence, it needs to be mentioned that those variations might create some minor distortions.

The observation period from 2001 to 2018 has been chosen deliberately for two reasons. First, after 2000 COMPUSTAT “North America – Daily” database provides a break-down of special items into sub-items. Second, for my regression analysis by time (section 5.5), I investigate how the predictive ability of one-time items changes during economic cycles to draw conclusions for the current situation in light of the COVID-19 pandemic. Given that there have been three major economic downturns between 2001 and 2018 – the dot-com bubble burst (2002 / 2003), the global financial crisis (2007 / 2008) and the euro crisis (2010 – 2012) – it is a suitable observation period for my research.

Between 2001 and 2018 the Annual Industrial COMOUSTAT database provides 9,850 active firms and 105,859 firm-year-observations. To ensure comparability with Fairfield et al. (2009), I apply very similar sample selection criteria, which are summarized in **Table 2**. In particular, like Fairfield et al. (2009) I exclude firms from the financial services sector, small firms with net operating assets or sales below $5 million as well as outliers with return on net operating assets or profit margin exceeding 100% or core profit margin or special profit margin exceeding 200%. Furthermore, I introduce two additional selection criteria. All firms must be headquartered either in North America or in Europe. Firms without 18 years of consecutive data are excluded, which is necessary for my regression analysis by time (section 5.5). These criteria impose a strong survivorship bias (addressed in section 6), but still leave me with a sufficient large sample with 1,165 total firms and 20,970 firm-year-observations.

Table 2: Sample selection criteria

Sample selection criteria	Total observations	Total firms
2001-2018 Annual Industrial Compustat (active firms)	105,859	9,850
Firms in financial services (SIC 6000s)	(38,544)	(3,817)
Firms outside of Europe or North America	(7,437)	(788)
NOA < $5m or Sales < $5m	(17,509)	(1,584)
Absolute value of RNOA or PM > 1; or CORE PM or SPECIAL PM > 2	(3,366)	(250)
Firms without 18 years consecutive data	(18,033)	(2,246)
Final sample	**20,970**	**1,165**

3.3 Descriptive statistics

The left pie chart in **Figure 1** shows that approximately 91% of my sample firms are headquartered in North America. The comparably low share of European companies (9%) can be traced back to the fact that I rely on the “North America – Daily” COMPUSTAT database as described in section 3.2. Nonetheless, my European sample still includes 100 companies and, thus, 1,800 firm-year-observations. It should be noticed, however, that the European companies are, on average, bigger than the North American ones (avg. revenue EU $26.8bn vs. NA $6.6bn). This is a direct consequence of my choice to rely on the “North America – Daily” database, which captures only those European companies, which are also listed in the US, i.e. usually globally operating, large companies.

One-time items by industry have so far not been investigated apart from Johnson et al. (2011) who test frequency of special items by industry. In contrast to their research, I allocate my sample into 12 Fama-French industry portfolios instead of 48. This is because my sample is too small for creating 48 portfolios. The right pie chart in **Figure 1** illustrates the breakdown of my sample into 12 Fama-French industry portfolios. The most common industry portfolios in my sample are Manufacturing (16%), Other (15%), Utilities (14%) and Wholesale (13%). In contrast, Telecom (3%), Energy (4%) and Chemicals (4%) are the least common portfolios. Notice that industry portfolio #11 is not included, as this portfolio captures the financial services industry, which I excluded in the sample selection.

Figure 1: Sample by geography (left) and industry (right)

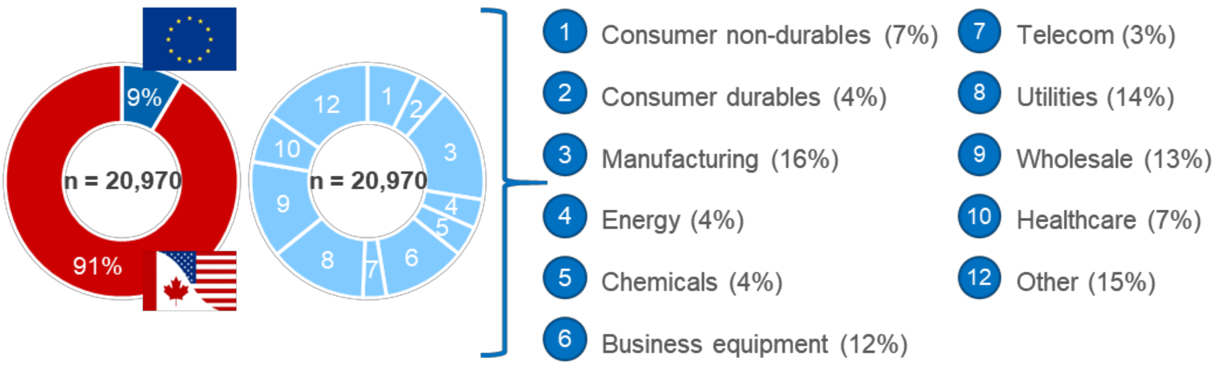

Table 3 reports descriptive statistics of key financial variables for firm-year-observations with positive special items, negative special items, and no special items. One-time charges are with 10,878 observations more frequent than no one-time items (7,169) and one-time revenues (2,923). Adding together the number of observations of one-time charges and one-time revenues, it becomes apparent that one-time items "are so prevalent now that they're not special anymore" (Fowler, 2006), as my sample includes approximately 1.9x more special items firm-year-observations than no special items ones. Furthermore, the first two variables – special items deflated with avg. total assets and sales – confirm prior research in the sense that negative special items

(2.2% and 2.9%) are, on average, larger than positive ones (1.2% and 1.7%). A more detailed analysis on frequency and magnitude of one-time items can be found in section 4.1 and 4.3, respectively.

Performance measures show that the performance of positive special items observations and no special items observations is very similar. Looking at return figures (RNOA, ROA, ROE), one-time revenue observations (17.6%, 9.7%, 27.9%), on average, marginally outperform no one-time item observation (16.5%, 9.5%, 22.3%). In return, with respect to operating margin and sales growth, no special items observations (12.0%, 8.3%) exceed positive special items (11.7%, 7.6%) observations. While one-time revenue- and no special items firm-year-observations perform on a similar level, negative special items observations perform significantly worse with respect to all five performance indicators. Despite being least profitable, one-time charges observations show the highest R&D expenses and lowest capital intensity (3.1%, 141.1%). This might potentially indicate future performance improvements for negative special items firm-year-observations.

My evidence suggest that mean market capitalization of one-time charges and one-time revenues observations is $1.2bn and $1.1bn, respectively, while the equity value of no special items firms is, on average, $0.8bn. Consequently, firms recording special items – positive and negative – tend to be larger than firms not recording one-time items. Finally, no special items observations show a higher Tobin's Q and a lower debt-to-equity ratio than special items observations.

In short, there are significant differences between one-time revenue and one-time expenses observations as well as between one-time items observations and no one-time items observations. Consequently, special items appear to be important, meaning it shall be questioned whether categorically excluding them when computing non-GAAP figures is justified.

In the Appendix, I report **Table 3** broken down by geography (**Table 21**) and by industry (**Table 22**). I do not report these tables in the main part of my thesis, because, fundamentally, my evidence suggests that the patterns discussed above for the entire sample also apply to my sub-samples by geography and industry. In particular, for all sub-samples, one-time expenses are, on average, bigger than one-time revenues. Furthermore, for all sub-samples, on average, positive special items observations and no special items observations outperform negative special items observations.

Table 3: Descriptive statistics across key financial variables by firm-year-observation with positive special items, negative special items, no special items **– total sample**

	Positive special items				Negative special items				No special items			
Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
SPI / Avg. Total Assets	2,923	1.2%	0.4%	0.027	10,877	-2.2%	-0.8%	0.045	7,168			
SPI / Sales	2,923	1.7%	0.4%	0.044	10,878	-2.9%	-0.9%	0.070	7,169			
RNOA	2,923	17.6%	14.7%	0.161	10,878	11.6%	11.6%	0.174	7,169	16.5%	12.6%	0.162
ROA	2,923	9.7%	9.0%	0.078	10,877	6.4%	6.9%	0.094	7,168	9.5%	8.1%	0.083
ROE	2,850	27.9%	21.5%	1.959	10,567	18.5%	17.3%	3.051	7,112	22.3%	20.3%	0.679
Op. Margin	2,923	11.7%	10.0%	0.118	10,878	7.4%	7.7%	0.131	7,169	12.0%	10.8%	0.118
Sales Growth	2,923	7.6%	6.1%	0.218	10,876	6.3%	4.6%	0.214	7,167	8.3%	6.1%	0.250
R&D Expense	1,503	2.8%	1.4%	0.038	6,583	3.1%	1.8%	0.040	2,703	2.6%	1.0%	0.038
Capital Intensity	2,923	145.9%	110.5%	1.161	10,878	141.1%	111.8%	1.032	7,169	166.8%	112.7%	1.393
Market Capitalization	2,806	11,211	1,498	29,568	10,478	12,209	2,286	30,258	5,718	7,778	757	31,314
Tobin's Q	2,683	1.681	1.414	0.938	9,831	1.715	1.463	0.969	5,538	1.851	1.455	1.224
Debt/Equity	2,841	100.0%	51.4%	2.620	10,539	133.1%	60.4%	6.489	7,083	89.0%	53.8%	4.840

Variable definitions:

SPI / Avg. Total Assets	=	ratio of COMPUSTAT data items SPECIAL ITEMS (#17) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
RNOA	=	ratio of NET OPERATING INCOME (NOI) from period t and average of NET OPERATING ASSETS (NOA) across period t and t-1 (as defined in Table 1).
ROA	=	ratio of NET OPERATING INCOME (NOI) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
ROE	=	ratio of NET OPERATING INCOME (NOI) from period t and average of COMMON EQUITY (#60) across period t and t-1 (negative obsv. excluded).
Op. Margin	=	ratio of NET OPERATING INCOME (NOI) from period t and REVENUES (#12) from period t.
Sales Growth	=	growth in REVENUES (#12) between period t and t-1.
R&D Expense	=	ratio of COMPUSTAT data items R&D EXPENSE (#46) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
Capital Intensity	=	ratio of COMPUSTAT data items TOTAL ASSETS (#6) from period t and REVENUES (#12) from period t.
Market Capitalization	=	product of COMPUSTAT data items CLOSING STOCK PRICE (#24) and COMMON SHARES OUTSTANDING (#25).
Tobin's Q	=	ratio of (TOTAL ASSETS (#6) + MARKET CAPITALIZATION - COMMON EQUITY (#60) - DEFERRED TAXES (#74)) and average of TOTAL ASSETS (#6) across period t and t-1 - in line with Johnson, et al. (2011).
Debt/Equity	=	ratio of COMPUSTAT data items (LONG-TERM DEBT (#9) + CURRENT DEBT (#34)) and COMMON EQUITY (#60).

4 One-time items – a descriptive analysis across four dimensions

Prior literature is focused on US only except of Cutillas-Gomariz et al. (2016), who investigate earnings relevance and non-recurring items for listed companies in Spain. Besides of that, the vast majority of the research papers do not provide an industry breakdown and capture data only until approximately 2010. Therefore, my sample adds to the existing literature by providing a break-down by geography (Europe and North America) and industry (12 Fama-French industry portfolios) as well as by extending the observation period until 2018. Given my unique sample, my research will put a strong emphasis on descriptive analysis of one-time items. In this regard, I took inspiration from the research paper of Johnson et al. (2011) "Special items: a descriptive analysis." In the following, I will examine one-time items across four dimensions – frequency (4.1), pesistence (4.2), magnitude (4.3) and sub-items (4.4). Each sub-section includes a short paragraph including my hypotheses, followed by an analysis over the entire sample, by geography and by industry.

4.1 Frequency of one-time items

Frequency is defined as the percentage of firms which report one-time items in a given year. I expect frequency of one-time items to follow an increasing trend, which is mainly driven by negative special items, while positive special items remain fairly constant (e.g. Riedl & Srinivasan, 2010; Johnson et al., 2011). I predict that frequency will be sensitive to economic downturns and crises, i.e. frequency is supposed to peak during and shortly after the dot-com bubble burst (2002 / 2003), the global financial crisis (2007 / 2008) and the euro crisis (2010 – 2012). Finally, Johnson et al. (2011) find an increase in frequency of positive special items and stagnating frequency of negative special items between 2002 and the global financial crisis. I expect that my evidence is in line with this finding, but I assume that this stagnation is just a temporary consequence of the significant frequency jump following the dot-com bubble burst and that this trend does not continue, as there is no valid reason for this development. Since there is no prior research on differences in frequency across Europe and North

America, I hypothesize that frequency of one-time items shall be similar. With respect to differences by industry, Johnson et al. (2011) find that the industries that report the fewest one-time charges also report the fewest one-time revenues, while the industries with the most one-time expenses are not the ones with the most one-time revenues.

Figure 2 confirms my hypotheses and is consistent with prior special items literature. While in 2001 approximately 52% of the firms in my sample reported one-time items, the frequency increased to 76% in 2018. As predicted, this growth is primarily driven by one-time charges, the frequency of which increased from 40% in 2001 to 63% in 2018. One-time expenses – and thus also total special items – are sensitive to crises, as **Figure 2** shows a jump after all three crises in my observation period. After every jump, negative special items stagnate for some years until the next economic downturn or crash arrives. Thus, my data shows, similarly to Johnson et al. (2011), fairly constant negative special items reporting frequency between 2002 and 2007, while positive special items became more frequent during this time period. However, after the financial crisis in 2007 / 2008, the frequency of positive special items remained stable between 13% and 15%. In contrast to one-time expenses, one-time revenues do not appear to be affected by economic downturns. This might indicate that analysts and investors should treat negative special items different during crises as well as different compared to positive special items.

Figure 3 shows the frequency of one-time items by geography. My evidence suggests that European companies report special items more frequently (85% of European firms in 2018) compared to North American companies (75% in 2018). This underlines that special items in Europe have not yet been investigated sufficiently by prior special items literature. This observation, however, might be enhanced due to the fact that my European sample captures, on average, bigger companies, assuming there is a positive correlation between size and special items frequency. While one-time revenues in North America are fairly constant (ranging between 11% and 19%) and reluctant to crises, they seem far more sensitive to downturns in Europe (ranging between 9% and 23%). In fact, before every crisis, we observe a peak in positive special items in Europe. In closing, the evidence is not in line with my initial hypothesis that frequency across Europe and North America is similar. I expect different predictive ability of one-time items across Europe and North America (section 5.3). Moreover, it is reasonable to believe that one-time revenues provide more useful information in Europe compared to North America – particularly during downturns.

Figure 2: Frequency of positive, negative, total special items **– total sample**

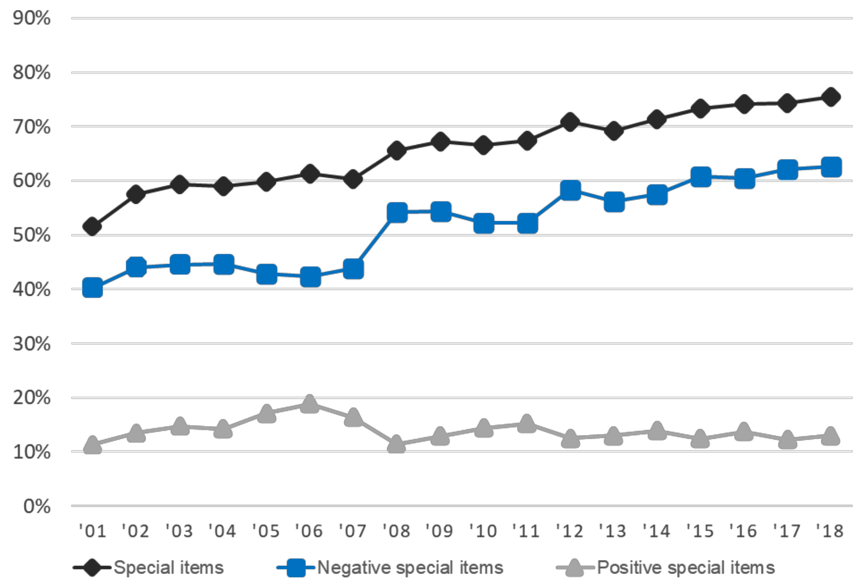

Figure 3: Frequency of positive, negative, total special items **– by geography**

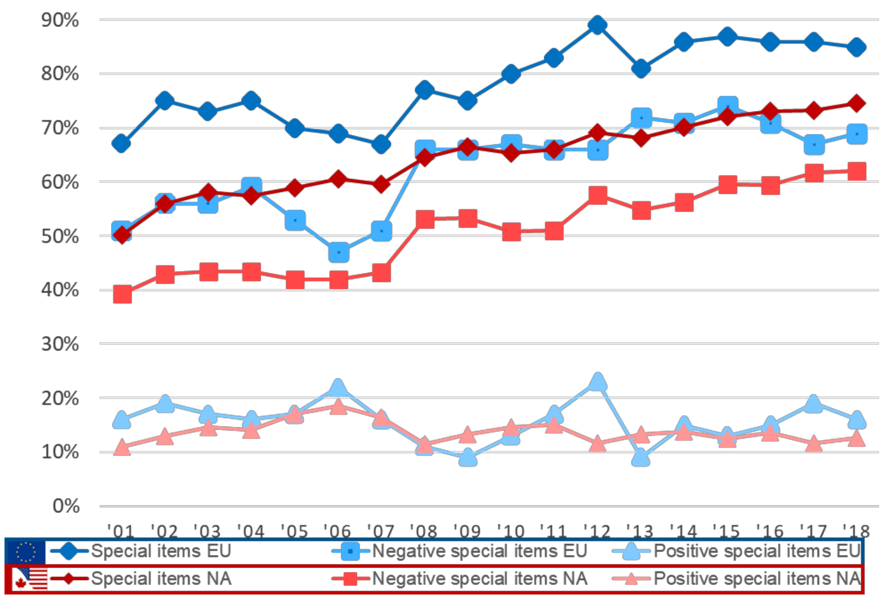

Table 4 shows the frequency of positive and negative special items by industry portfolios. In the Utilities sector one-time items are far less common than in all other industries. Over the entire observation period the average frequency of positive and negative special items in the Utilities sector has been 9% and 23%, respectively. In addition to that, standard deviation in the Utilities sector is low (3% and 7% for one-time revenues and charges), meaning special items in this industry appear to be insensitive to economic downturns. One-time expenses are most common in the following industries: Healthcare (avg. frequency: 66%), Chemicals (avg. frequency: 65%) and Consumer durables (avg. frequency: 63%). In contrast, the frequency of one-time revenues is most frequent in Energy (avg. frequency: 19%), Telecom (avg. frequency: 19%) and Other (avg. frequency: 18%). Thus, the industries with the most one-time expenses are not the ones with the most one-time revenues. Consequently, my evidence is in line with my hypothesis and the findings of Johnson et al. (2011).

Table 4: Frequency of positive, negative, total special items **– by industry**

	Positive special items					**Negative special items**				
Industry portfolio	Mean	Median	Min.	Max.	Std. Dev.	Mean	Median	Min.	Max.	Std. Dev.
Consumer non-durables	16%	16%	6%	27%	6%	58%	59%	38%	73%	10%
Consumer durables	13%	13%	4%	22%	6%	63%	63%	39%	84%	13%
Maunfacturing	14%	13%	9%	21%	3%	58%	59%	45%	72%	9%
Energy	19%	18%	9%	32%	7%	48%	45%	32%	66%	12%
Chemicals	17%	17%	4%	29%	6%	65%	65%	52%	83%	8%
Business equipment	14%	15%	7%	19%	3%	63%	65%	46%	76%	9%
Telecom	19%	18%	5%	32%	8%	61%	64%	37%	76%	11%
Utilities	9%	9%	4%	15%	3%	23%	23%	10%	35%	7%
Wholesale	12%	12%	6%	22%	3%	48%	47%	35%	60%	9%
Healthcare	12%	13%	5%	23%	4%	66%	67%	49%	81%	10%
Other	18%	17%	13%	23%	3%	49%	51%	29%	61%	9%

4.2 Persistence of one-time items

High persistence means that firms that reported special items in the past are more likely to do it again in the future. I expect high persistence, i.e. prior reporting frequency is correlated with future reporting frequency (e.g. Elliot & Hanna, 1996; Johnson et al., 2011). Furthermore, I postulate the hypothesis that this pattern is stronger for one-time charges than for one-time revenues. There is no prior literature on persistence by geography or by industry. However, applying my predictions, it is reasonable to expect that geographic regions and industries with a higher one-time item reporting frequency (section 4.1) show a stronger persistence.

The results on persistence can be found in **Table 5**, **Table 6** and **Table 7**. These tables should be interpreted as follows: assuming a sample firm reported between zero and five special items in the course of the prior four years and the current year (column on the very left), then, on average, how many one-time items did this company record over the subsequent three years. Given that I analyse how many one-time items are reported over a five-year- and over a three-year-window, the sums of firm-year-observations do not add-up to N = 20,970. This is because the first four years (2001 - 2004) and the last three years (2016 - 2018) of my observation period cannot be considered directly, as it is not possible to examine the previous four / subsequent three years for those years. Those years are still considered indirectly, when analysing the previous four years of year 2005 and the subsequent three years of year 2015.

Table 5: Persistence of positive and negative special items **– total sample**

			# of SPIs taken over subsequent 3 years				
	# of SPIs reported in prior 5 year	Firm-year observations	Mean	Median	25th	75th	Std. Dev.
Pos. special items	0	6,684	0.31	0	0	1	0.57
	1	3,830	0.45	0	0	1	0.67
	2	1,602	0.54	0	0	1	0.71
	3	540	0.73	1	0	1	0.84
	4	127	1.02	1	0	2	0.94
	5	32	2.00	3	1	3	1.19

			# of SPIs taken over subsequent 3 years				
	# of SPIs reported in prior 5 year	Firm-year observations	Mean	Median	25th	75th	Std. Dev.
Neg. special items	0	2,210	0.63	0	0	1	0.87
	1	1,979	1.15	1	0	2	1.04
	2	2,231	1.54	2	1	2	1.03
	3	2,215	1.94	2	1	3	1.00
	4	2,190	2.25	3	2	3	0.89
	5	1,990	2.55	3	2	3	0.71

My research is in line with my hypothesis as well as prior literature. Pursuant to **Table 5**, the number of one-time revenues and expenses recorded over three subsequent years is higher, the more one-time revenues and expenses a firm reported in the previous five years. If a sample company takes no positive or negative special items in a time period of five years, then, on average, this firm reports 0.31 and 0.63 positive and negative special items over the following three years. In contrast, a firm that reports a one-time revenue or expense five years in a row records, on average, 2.00 and 2.55 positive and negative special items over the subsequent three years. This supports the hypothesis that persistence is more pronounced for negative special items.

Table 6: Persistence of positive and negative special items **– by geography**

Panel A: Persistence in **Europe**

	# of SPIs reported in prior 5 year	Firm-year observations	# of SPIs taken over subsequent 3 years: Mean	Median	25th	75th	Std. Dev.
Pos. special items	0	516	0.32	0	0	1	0.56
	1	392	0.46	0	0	1	0.66
	2	126	0.60	0	0	1	0.79
	3	52	0.87	1	0	2	0.89
	4	14	1.00	1	1	1	0.68
	5	0	0.00	0	0	0	0.00

	# of SPIs reported in prior 5 year	Firm-year observations	# of SPIs taken over subsequent 3 years: Mean	Median	25th	75th	Std. Dev.
Neg. special items	0	82	0.95	1	0	2	0.95
	1	132	1.45	2	0	2	1.11
	2	185	1.74	2	1	3	1.06
	3	189	1.97	2	1	3	1.09
	4	286	2.34	3	2	3	0.83
	5	226	2.54	3	2	3	0.70

Panel B: Persistence in **North America**

	# of SPIs reported in prior 5 year	Firm-year observations	# of SPIs taken over subsequent 3 years: Mean	Median	25th	75th	Std. Dev.
Pos. special items	0	6,168	0.31	0	0	1	0.57
	1	3,438	0.45	0	0	1	0.68
	2	1,476	0.53	0	0	1	0.71
	3	488	0.72	1	0	1	0.84
	4	113	1.02	1	0	2	0.97
	5	32	2.00	3	1	3	1.19

	# of SPIs reported in prior 5 year	Firm-year observations	# of SPIs taken over subsequent 3 years: Mean	Median	25th	75th	Std. Dev.
Neg. special items	0	2,128	0.62	0	0	1	0.87
	1	1,847	1.13	1	0	2	1.03
	2	2,046	1.52	2	1	2	1.03
	3	2,026	1.93	2	1	3	1.00
	4	1,904	2.24	3	2	3	0.90
	5	1,764	2.55	3	2	3	0.72

Table 6 compares persistence of special items by geography. The results are mostly consistent with my initial expectations, but there are some unforeseen patterns. As anticipated, the persistence of positive and negative special items is stronger in Europe than in North America. This is visible based on a higher mean of one-time charges taken over three subsequent years, assuming a firm recorded between zero and three one-time items over the five previous years. For one-time expenses, this mean ranges between 0.95 and 1.97 in Europe, while only between 0.62 and 1.93 in North America. For one-time revenues, this mean ranges between 0.32 and 0.87 in Europe, while only between 0.31 and 0.72 in North America. Somewhat surprising, my evidence suggests that this pattern reverses the more one-time items a company reports over the prior five years. For instance, if a firm reports five one-time charges over the previous five years, then, on average, this firm reports 2.55 one-time expenses over the subsequent three years in North America, but only 2.54 negative special items in Europe. This suggests that the persistence of special items is higher in North America for companies, which report those items extremely frequently. It needs to be mentioned, however, that this result may be distorted, as the European sample of companies, which take four of five one-time items in the five prior years is very small.

Table 7 shows the three industry portfolios with the highest and lowest persistence for positive (panel A) and negative (panel B) special items, respectively. Please notice that I restricted the number of one-time items reported over the previous five years (left column in the table) at three, as there are not sufficient sample firms within each industry which reported four or five special items in a row. The evidence is not in line with my initial hypothesis, i.e. persistence is not necessarily high for industries with a high frequency. For negative special items (panel B), my findings suggest the highest persistence in Consumer durables, Healthcare and Telecom, and the lowest persistence for Utilities, Energy and Other. Thereof, only Telecom is among the top three industries in terms of frequency of negative special items (4.1). The Utilities sector has the lowest frequency and also the lowest persistence of one-time expenses. For positive special items (panel A), I observe the highest persistence in Chemicals, Business equipment and Energy, and the lowest persistence for Healthcare, Wholesale / retail, and Consumer durables. Thereof, only Chemicals is among the top three industries in terms of frequency of positive special items (section 4.1). Despite of being the industry with the lowest one-time revenue frequency, the Utilities sector is not among the top 3 lowest persistence industry portfolios. In conclusion, it appears like there is no correlation between frequency and persistence for industries.

Table 7: Three industries with highest / lowest persistence of special items

Panel A: **Positive** special items

Highest persistence:	Chemicals		Energy		Business equipment	
	# of SPIs taken over subsequent 3 years					
# of SPIs reported in prior 5 year	Firm-year observations	Mean	Firm-year observations	Mean	Firm-year observations	Mean
0	267	0.27	206	0.37	748	0.35
1	123	0.54	172	0.64	494	0.41
2	79	0.59	79	0.63	189	0.49
3	30	1.27	46	0.91	50	0.82

Lowest persistence:	Healthcare		Wholesale		Consumer durables	
	# of SPIs taken over subsequent 3 years					
# of SPIs reported in prior 5 year	Firm-year observations	Mean	Firm-year observations	Mean	Firm-year observations	Mean
0	491	0.29	971	0.31	297	0.29
1	250	0.38	494	0.41	164	0.52
2	116	0.44	192	0.48	54	0.57
3	22	0.27	60	0.57	23	0.57

Panel B: **Negative** special items

Highest persistence:	Consumer durables		Healthcare		Telecom	
	# of SPIs taken over subsequent 3 years					
# of SPIs reported in prior 5 year	Firm-year observations	Mean	Firm-year observations	Mean	Firm-year observations	Mean
0	39	1.31	54	1.07	16	1.56
1	47	1.40	112	1.26	57	1.63
2	113	1.76	145	1.74	77	1.69
3	83	2.31	150	2.13	98	2.09

Lowest persistence:	Utilities		Energy		Others	
	# of SPIs taken over subsequent 3 years					
# of SPIs reported in prior 5 year	Firm-year observations	Mean	Firm-year observations	Mean	Firm-year observations	Mean
0	838	0.34	98	0.64	301	0.73
1	356	0.67	81	1.36	347	1.10
2	240	1.13	114	1.55	417	1.57
3	161	1.41	95	1.80	397	1.86

4.3 Magnitude of one-time items

Research defines magnitude as the relative size of one-time items in relation to revenues (e.g. Fairfield et al., 2009), total assets (e.g. Johnson et al., 2011) or operating expenses (e.g. Bradshaw & Sloan, 2002). Postulating hypotheses for magnitude is comparably difficult, as prior literature appears to be somewhat contradicting (discussed in section 2.3). Since I replicate the model by Fairfield et al. (2009) and they find that the relative size of one-time items did not change significantly, I do not expect that one-time items grew markedly in size during my observation period. However, I predict that the magnitude of special items will be sensitive to economic events and crises. This is supposed to be driven by one-time expenses, while one-time revenues stay constant. Given that I predict sensitivity to crises, I foresee North America to be more affected by the global financial crises (2007 / 2008) and Europe to show stronger aftereffects of the euro crisis (2010 – 2012). There is no prior research on magnitude of special items by industry, which is why it is not possible to postulate any hypothesis.

Figure 4 displays the magnitude of positive, negative, and total special items in relation to sales. I prepared the same analysis with total assets (instead of sales) in the denominator (**Figure 6** in the Appendix) – since the results are very similar, the focus will be on one-time items divided by sales in the following. Before discussing the implications of **Figure 4**, it needs to be pointed out that the magnitude of special items in my research paper is low in comparison to prior literature. This is most likely a consequence of the issue that primarily large companies (with high revenue figures) satisfy my sample selection criteria. While this affects the relative size of one-time items in relation to sales, it should not be a big issue for my analysis, as I use the same sample for my entire research. In absolute terms, total one-time items increased slightly from 1.3% of sales in 2001 to 1.7% of sales in 2018. However, the trajectory of the line graph shows strong fluctuations with a minimum of absolute 0.6% in 2004 and a maximum of absolute 3.2% in 2008. In line with my hypothesis, the line graph shows strong increases in 2002, 2008 and 2012, i.e. during every crisis in my observation period. The relative size of total special items remains at a constant, high level from 2015 onwards (between absolute 1.4% and absolute 1.8% of sales). While I do not have a definite explanation for this observation, this might be a consequence of Accounting Standard Update No. 2015-01 by the FASB. This standard implies that extraordinary items are not required to be segregated from ordinary operations anymore. Hence, it appears like many companies classified extraordinary items as a special item from 2015 onwards. In line with my hypothesis, total special items are negative throughout the entire observation period, i.e. negative one-time items exceed positive ones. In particular, one-time expenses are ranging between -0.86 % and -3.34% of sales, while one-time revenues are fairly constant between 0.15% and 0.31% of sales.

Figure 4: Positive, negative, total special items deflated with sales **– total sample**

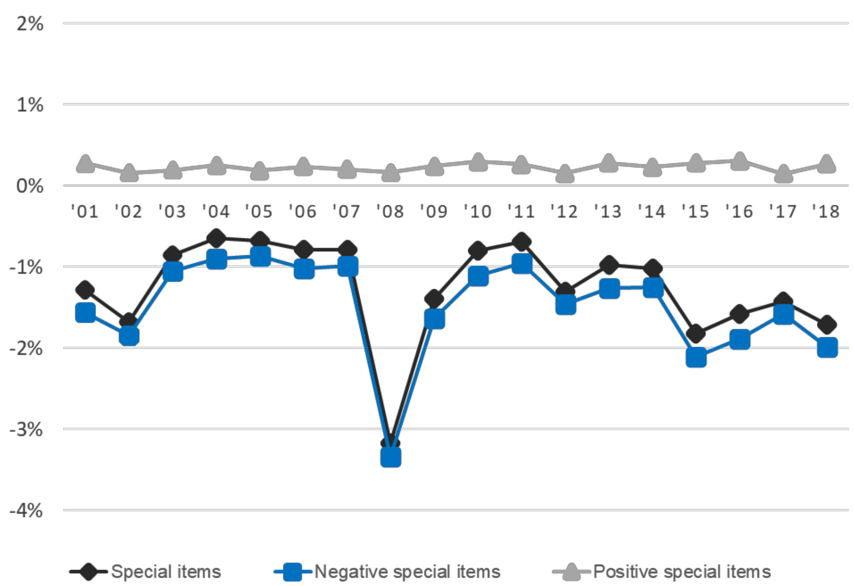

Figure 5 compares the magnitude of positive, negative, and total one-time items in relation to sales for Europe and North America. Overall, the magnitude of total one-time items is in a similar region across Europe and North America, ranging between absolute 0.5% and 3.2% of sales. While the magnitude of total special items in North America spiked in 2007 / 2008 (as a consequence of the financial crisis), the one in Europe shows a significant increase between 2010 and 2016 (as a consequence of

the euro crisis, even though the long duration of the decline is somewhat puzzling). In both geographic regions, one-time expenses are driving total special items. However, one-time revenues are not only more frequent in Europe (section 4.1), but they also tend to be bigger than in North America. In fact, positive special items averaged 0.53% of sales in 2018 in Europe, but only 0.25% in North America.

Figure 5: Positive, negative, total special items deflated with sales **– by geography**

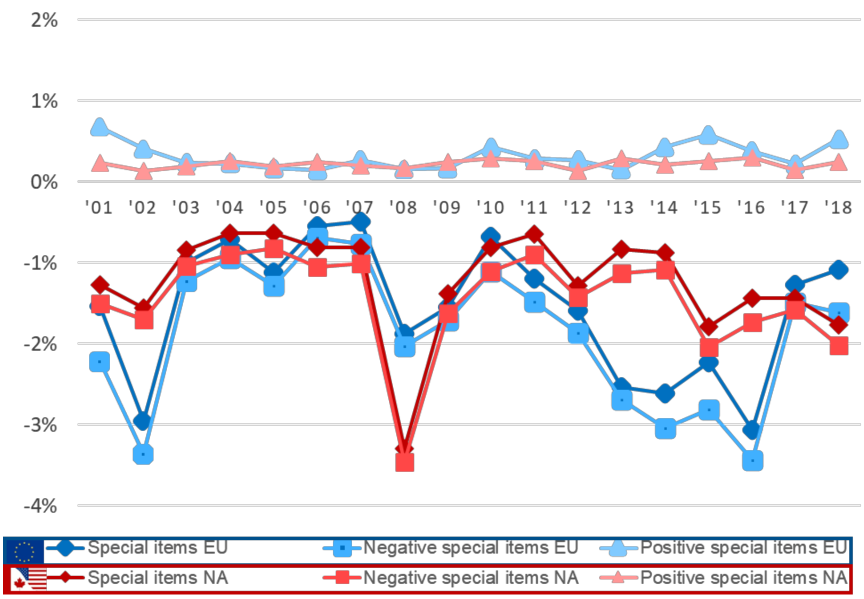

Table 8 displays minimum, maximum, average, median and standard deviation of positive and negative special items by industry. On average, the magnitude of both positive and negative one-time items is the largest within the Telecom (negative: -3.4%; positive: 0.6%) and the Energy (negative: -2.0%; positive: 0.4%) industry portfolio. Those two industry portfolios are also among the ones, which report negative special items most frequently (discussed in section 4.1). Thus, there appears to be some association between reporting frequency of one-time items and their magnitude. This association is not self-explanatory, as higher frequency could be an indicator of earnings management in the sense that companies are trying to distribute their one-time expenses and revenues instead of reporting all at once. The Wholesale

industry shows, on average, the smallest magnitude for both one-time expenses (-0.6%) and revenues (0.1%).

Table 8: Positive, negative, total special items deflated with sales **– by industry**

	Positive special items					Negative special items				
Industry portfolio	Mean	Median	Min.	Max.	Std. Dev.	Mean	Median	Min.	Max.	Std. Dev.
Consumer non-durables	0.2%	0.2%	0.0%	0.7%	0.2%	-1.2%	-0.9%	-3.5%	-0.6%	0.7%
Consumer durables	0.2%	0.1%	0.0%	0.8%	0.3%	-1.2%	-0.9%	-3.5%	-0.4%	0.9%
Maunfacturing	0.2%	0.2%	0.0%	0.5%	0.1%	-1.4%	-1.3%	-3.0%	-0.6%	0.7%
Energy	0.4%	0.3%	0.1%	1.9%	0.4%	-2.0%	-1.3%	-6.8%	-0.2%	1.8%
Chemicals	0.3%	0.2%	0.0%	0.6%	0.2%	-1.5%	-1.5%	-3.5%	-0.6%	0.7%
Business equipment	0.2%	0.2%	0.1%	0.4%	0.1%	-2.1%	-1.5%	-6.7%	-0.6%	1.6%
Telecom	0.6%	0.4%	0.0%	2.4%	0.6%	-3.4%	-2.3%	-15.9%	-1.0%	3.6%
Utilities	0.2%	0.1%	0.0%	1.1%	0.2%	-0.9%	-0.7%	-2.4%	-0.1%	0.7%
Wholesale	0.1%	0.1%	0.0%	0.3%	0.1%	-0.6%	-0.6%	-1.5%	-0.2%	0.3%
Healthcare	0.3%	0.2%	0.1%	0.7%	0.2%	-3.3%	-3.6%	-4.5%	-1.7%	0.8%
Other	0.3%	0.3%	0.1%	0.6%	0.1%	-1.2%	-1.2%	-3.0%	-0.5%	0.5%

4.4 Breakdown into sub-items

According to Johnson et al. (2011) “no one charge / gain dominates special items, suggesting that in any particular period firms are most often reporting multiple sub-types as part of their special item” (p. 520). Hence, I expect heterogeneity in my results for the entire sample as well as for my sub-samples by geography and industry.

Table 9 summarizes my evidence for special item sub-items of the entire sample. The tables shall be read as follows: the tables report sub-items, when a firm reports positive or negative total, net special items, i.e. the aggregate of all sub-items. This implies that some sub-items in the first table can still be negative, as all sub-items are considered as long as net total special items are positive (and vice versa for the second table). Most frequent sub-items when a firm reports net positive one-time items are one-time gains / losses (47%), litigation (37%) and restructuring (29%). With 0.53% of sales (median) one-time gains / losses is the sub-item with the biggest magnitude. Despite of total special items being positive in the first table, in process R&D, restructuring, goodwill impairment and PP&E write-offs are, on average, still negative in more than 80% of observations. In contrast, most frequent sub-items when a firm reports negative net one-time items are restructuring (56%), M&A related gains / losses (32%) and other special items (30%). Looking at the magnitude of the sub-items, however, goodwill impairments appear to be most significant (median 1.2% of sales). Finally, if total special items are negative, then, on average, all sub-items are in more than 80% of observations negative except of one-time gains / losses and litigation.

Table 9: Breakdown of one-time sub-items **– total sample**

Positive special items

Special item type	n	Percent of SPI obs.	Million $ Mean	Million $ Median	Percent of Sales Mean	Percent of Sales Median	Percent of item > < 0: < 0	Percent of item > < 0: > 0
In Process R&D	33	1%	-40.49	-7.00	-0.38%	-0.26%	97%	3%
Restructuring	861	29%	-53.34	-4.10	-0.20%	-0.19%	81%	19%
Gain/Loss	1,380	47%	198.40	10.30	2.01%	0.53%	2%	98%
Litigation	1,086	37%	24.96	3.94	1.02%	0.32%	10%	90%
Other	818	28%	58.16	2.02	0.77%	0.16%	34%	66%
M&A	599	20%	62.91	0.57	0.85%	0.07%	41%	59%
Goodwill	168	6%	-67.04	-5.00	-0.81%	-0.17%	99%	1%
PP&E Write-Offs	386	13%	-54.95	-4.19	-0.58%	-0.18%	92%	8%
Extinguish Debt	431	15%	2.32	-1.00	0.39%	-0.05%	63%	37%
All Observations	2,923		115.43	6.18	0.23%	0.00%		

Negative special items

Special item type	n	Percent of SPI obs.	Million $ Mean	Million $ Median	Percent of Sales Mean	Percent of Sales Median	Percent of item > < 0: < 0	Percent of item > < 0: > 0
In Process R&D	412	4%	-161.27	-13.73	-1.95%	-0.44%	100%	0%
Restructuring	6,110	56%	-93.18	-14.67	-1.03%	-0.55%	98%	2%
Gain/Loss	1,872	17%	36.73	3.56	0.17%	0.11%	27%	73%
Litigation	2,555	23%	-52.72	-2.36	-0.69%	-0.12%	65%	35%
Other	3,225	30%	-96.24	-6.00	-0.86%	-0.25%	84%	16%
M&A	3,475	32%	-48.14	-5.64	-0.69%	-0.23%	91%	9%
Goodwill	1,960	18%	-320.60	-33.77	-5.18%	-1.20%	100%	0%
PP&E Write-Offs	2,922	27%	-106.69	-9.60	-1.92%	-0.42%	99%	1%
Extinguish Debt	2,399	22%	-30.56	-6.57	-0.60%	-0.22%	92%	8%
All Observations	10,878		-202.57	-19.76	-1.49%	-0.04%		

Table 10 panel A and B shows sub-items for Europe and North America, respectively. For net negative special items, my evidence suggests similar patterns for both geographic regions. In both cases restructuring charges (Europe: 71%; NA: 54%), M&A related gains / losses (Europe: 31%; NA: 32%) and other special items (Europe: 35%; NA: 29%) are the most frequent sub-items. In Europe, sub-items-heterogeneity tends to be a bit lower compared to North America, as restructurings appear very frequent – if a European sample company reports negative net special items in one year, then there is a 71% chance that this company recorded a restructuring item in that year. The importance of restructurings is also visible based on the fact that it is the largest sub-item in Europe relative to sales (median of absolute 0.67%). In contrast, in North America goodwill remains the largest item in terms of absolute magnitude (1.44% of sales). Furthermore, even when a European firm reports net positive one-

time items restructuring is the second most frequent sub-item (45%) after one-time gains / losses (57%). This does not imply that restructuring revenues are particularly common, as restructurings are in 88% of my European sample negative. In North America, the most frequent sub-items, given net special items are positive, are one-time gain/loss (46%), litigation (39%) and restructuring (28%).

Table 10: Breakdown of one-time sub-items **– by geography**

Panel A: Sub-items in **Europe**

Positive special items

			Million $		Percent of Sales		Percent of item > < 0	
Special item type	n	Percent of SPI obs.	Mean	Median	Mean	Median	< 0	> 0
In Process R&D	4	1%	-16.28	-13.04	0.24%	-0.03%	75%	25%
Restructuring	128	45%	-192.43	-59.31	-0.65%	-0.34%	88%	13%
Gain/Loss	161	57%	750.12	160.39	2.58%	1.10%	1%	99%
Litigation	61	22%	87.35	15.45	0.48%	0.18%	25%	75%
Other	116	41%	145.50	18.58	0.98%	0.25%	31%	69%
M&A	74	26%	47.53	2.76	0.71%	0.03%	47%	53%
Goodwill	31	11%	-152.07	-35.53	-0.74%	-0.18%	100%	0%
PP&E Write-Offs	53	19%	-137.07	-23.71	-0.58%	-0.25%	79%	21%
Extinguish Debt	30	11%	79.21	1.45	1.14%	0.01%	50%	50%
All Observations	283		453.51	59.53	0.32%	0.00%		

Negative special items

			Million $		Percent of Sales		Percent of item > < 0	
Special item type	n	Percent of SPI obs.	Mean	Median	Mean	Median	< 0	> 0
In Process R&D	45	4%	-97.45	-12.58	-2.13%	-0.45%	98%	2%
Restructuring	799	71%	-255.35	-86.16	-1.18%	-0.67%	98%	2%
Gain/Loss	309	27%	69.41	13.86	0.29%	0.14%	25%	75%
Litigation	229	20%	-135.77	-23.00	-0.97%	-0.25%	72%	28%
Other	398	35%	-288.68	-22.00	-0.66%	-0.19%	71%	29%
M&A	347	31%	-78.99	-13.16	-0.72%	-0.14%	84%	16%
Goodwill	326	29%	-558.23	-97.30	-3.31%	-0.58%	98%	2%
PP&E Write-Offs	308	27%	-257.87	-51.04	-1.65%	-0.42%	96%	4%
Extinguish Debt	114	10%	-62.48	-20.32	-0.61%	-0.26%	88%	12%
All Observations	1,128		-559.69	-133.12	-1.87%	-0.31%		

Panel B: Sub-items in **North America**

Positive special items

			Million $		Percent of Sales		Percent of item > < 0	
Special item type	n	Percent of SPI obs.	Mean	Median	Mean	Median	< 0	> 0
In Process R&D	29	1%	-43.83	-6.80	-0.46%	-0.28%	100%	0%
Restructuring	733	28%	-29.05	-3.00	-0.13%	-0.16%	80%	20%
Gain/Loss	1,219	46%	125.53	7.25	1.93%	0.49%	3%	97%
Litigation	1,025	39%	21.24	3.90	1.05%	0.33%	9%	91%
Other	702	27%	43.73	1.77	0.74%	0.15%	35%	65%
M&A	525	20%	65.07	0.57	0.87%	0.08%	40%	60%
Goodwill	137	5%	-47.80	-4.00	-0.82%	-0.17%	99%	1%
PP&E Write-Offs	333	13%	-41.88	-3.80	-0.58%	-0.17%	94%	6%
Extinguish Debt	401	15%	-3.43	-1.00	0.33%	-0.06%	64%	36%
All Observations	2,640		79.19	5.23	0.22%	0.00%		

	Special item type	n	Percent of SPI obs.	Million $ Mean	Million $ Median	Percent of Sales Mean	Percent of Sales Median	Percent of item > < 0: < 0	Percent of item > < 0: > 0
Negative special items	*In Process R&D*	367	4%	-169.09	-14.00	-1.93%	-0.44%	100%	0%
	Restructuring	5,311	54%	-68.78	-12.00	-1.01%	-0.53%	98%	2%
	Gain/Loss	1,563	16%	30.27	2.80	0.14%	0.10%	27%	73%
	Litigation	2,326	24%	-44.54	-2.00	-0.66%	-0.12%	65%	35%
	Other	2,827	29%	-69.15	-5.35	-0.89%	-0.26%	86%	14%
	M&A	3,128	32%	-44.72	-5.12	-0.69%	-0.24%	92%	8%
	Goodwill	1,634	17%	-273.19	-25.64	-5.55%	-1.44%	100%	0%
	PP&E Write-Offs	2,614	27%	-88.88	-7.82	-1.95%	-0.41%	99%	1%
	Extinguish Debt	2,285	23%	-28.96	-6.00	-0.60%	-0.22%	92%	8%
	All Observations	9,750		-161.25	-16.34	-1.45%	-0.02%		

Table 11 shows the frequency of one-time sub-items by industry portfolios. Overall, my evidence suggests similar sub-item patterns for all industries with only few exceptions. When a firm reports net negative special items, restructuring charges are the most frequent sub-item for all industries but the Utilities portfolio. In the Utilities sector, PP&E write-offs are with 36% most common, whereas restructurings are recorded relatively seldom (21%). Besides of the Utilities sector, the Healthcare portfolio shows a unique sub-items pattern for net negative special items. While in-process R&D expenses are least common in all industry portfolios (with a frequency ranging between 0% and 10%), the Healthcare sector reports in-process R&D expenses with 22% comparably often. This is not surprising, as research clearly plays a crucial role in the Healthcare sector. Still, this implies that analysts may be able to better understand one-time items, by having knowledge about the industry of their targets. Most frequent sub-items when a firm reports net positive one-time items are in all 11 industry portfolios one-time gains / losses, litigation, restructurings and other special items.

Table 11: Breakdown of one-time sub-items **– by industry**

	Special item type	Consumer non-dur.	Consumer durables	Manu-facturing	Energy	Chemicals	Business equipment	Telecom	Utilities	Wholesale	Healthcare	Other
Positive special items	In Process R&D	0%	0%	0%	0%	0%	4%	0%	0%	0%	9%	0%
	Restructuring	36%	45%	37%	20%	44%	40%	27%	12%	23%	34%	21%
	Gain/Loss	56%	43%	47%	44%	48%	50%	61%	62%	41%	43%	40%
	Litigation	33%	44%	37%	50%	51%	35%	20%	17%	43%	45%	38%
	Other	30%	28%	27%	39%	38%	20%	31%	23%	25%	32%	29%
	M&A	25%	20%	20%	11%	28%	29%	20%	11%	16%	30%	19%
	Goodwill	8%	9%	6%	3%	6%	4%	13%	3%	5%	7%	6%
	PP&E Write-Offs	15%	10%	12%	16%	13%	13%	24%	13%	11%	13%	13%
	Extinguish Debt	12%	6%	11%	17%	26%	10%	29%	9%	15%	17%	18%

	Special item type	Consumer non-dur.	Consumer durables	Manu-facturing	Energy	Chemicals	Business equipment	Telecom	Utilities	Wholesale	Healthcare	Other
Negative special items	*In Process R&D*	0%	1%	1%	1%	4%	10%	0%	0%	0%	22%	0%
	Restructuring	69%	72%	68%	46%	73%	67%	48%	21%	42%	59%	43%
	Gain/Loss	23%	20%	20%	17%	27%	16%	27%	12%	12%	16%	12%
	Litigation	19%	22%	21%	25%	28%	20%	21%	15%	24%	41%	24%
	Other	32%	33%	29%	40%	40%	22%	33%	27%	27%	34%	28%
	M&A	34%	23%	29%	21%	32%	38%	28%	25%	28%	46%	33%
	Goodwill	19%	19%	19%	17%	17%	14%	39%	13%	18%	13%	20%
	PP&E Write-Offs	28%	25%	26%	30%	28%	22%	36%	36%	24%	27%	28%
	Extinguish Debt	17%	12%	21%	24%	23%	18%	31%	16%	27%	21%	29%

5 Regression results

This chapter discusses the results from my regression models, which I postulated and explained in section 3.1. My base model regresses lagged decomposed profit margin (consisting of core profit margin, positive and negative special profit margin) on future profit margin over increasing time windows from one to five years (section 5.1). Subsequently, I adjust my sample and / or model to analyse differences across profitability (section 5.2), geography (section 5.3), industry (section 5.4), time (section 5.5) and sub-items (section 5.6). All sub-sections include a brief repetition of the empirical model used, hypotheses in light of prior literature and the results of chapter 4, a discussion of my regression results as well as concluding remarks for investors.

5.1 Basic regression model

My base model analyses the association between past core earnings, past special items and future earnings. In particular, I regress core PM^{w}_{t}, negative special PM^{w}_{t} and positive special PM^{w}_{t} on PM^{w}_{t+1} for my pooled sample over earnings windows (w) from one to five years. All variables are normalized with sales. Furthermore, please notice that negative and positive special profit margin can never be ≠ 0 at the same time, as special items are netted. This model is in line with the approach used by Fairfield et al. (2009). For earnings window w = 1, they find a high, significant coefficient for core profit margin (0.785), while positive and negative special profit margin are not significantly different from zero. Extending the earnings windows, the evidence by Fairfield et al. (2009) suggests a decreasing, yet still significant persistence of core earnings (coefficient of core PM^{w}_{t} for w = 5 is 0.688). Neither one-time expenses, nor one-time revenues show a clear pattern for their pooled sample.

Table 12: Base regression model **– entire sample (N = 20,970)**

$$PM_{t+1}^{w} = \alpha_{0,0} + \beta_{0,1}^{w} * core\ PM_{t}^{w} + \beta_{0,2}^{w} * negative\ special\ PM_{t}^{w} + \beta_{0,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{0,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

Nbr. of years in earnings window	α	Core PM^{w}_{t}	Negative special PM^{w}_{t}	Positive special PM^{w}_{t}	R^2
1	0.001	0.713***	0.242***	0.018	0.425
	(0.004)	(0.014)	(0.030)	(0.076)	
2	0.039***	0.731***	0.209***	0.193**	0.461
	(0.003)	(0.012)	(0.035)	(0.079)	
3	0.044***	0.738***	0.240***	0.266***	0.459
	(0.002)	(0.012)	(0.042)	(0.091)	
4	0.030***	0.733***	0.241***	0.338***	0.464
	(0.003)	(0.013)	(0.045)	(0.090)	
5	0.025***	0.715***	0.199***	0.338***	0.469
	(0.003)	(0.014)	(0.041)	(0.115)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

My regression results are reported in **Table 12**. Similarly to Fairfield et al. (2009), core PM^{w}_{t} is significant for all periods with a coefficient ranging between 0.713 and 0.738. However, my results do not suggest that the persistence of core profit margin is monotonically decreasing with increasing window size, as the coefficient reaches its maximum at w = 3 with 0.738. This is probably because the smoothed earnings figure over several years provides a better estimate for future performance, given that my observation period captures several economic fluctuations. Furthermore, according to my evidence, negative and positive special items are (mostly) also significant. In fact, negative special PM^{w}_{t} is significantly different from zero across all five earnings windows – the coefficient is decreasing from 0.242 in w = 1 to 0.199 in w = 5. This implies that, while the persistence of core earnings is approximately three times bigger than the one of negative special items, one-time expenses still convey useful information for future profit margin. For the consolidated sample, investors should not categorically exclude one-time expenses. The coefficient of positive special PM^{w}_{t} is insignificant for the one-year earnings window, but significantly different from zero from w = 2 onwards, ranging between 0.193 (w = 2) and 0.338 (w = 5). Consequently, when averaging one-time revenues over longer time horizons and including this smoothed estimate in our earnings forecast model, we can improve forecast accuracy. While there is no definite explanation for the different results compared to Fairfield et al. (2009), one possible reason might be that Fairfield et al. (2009) investigated the period from 1984 – 2003, while my sample captures the period from 2001 – 2018. As reported by prior research and shown in chapter 4 of my paper, one-time items increasingly gained importance over the past decades. According to my evidence, this implies that one-time items are not completely transitory anymore like they used to be in the past. In the following chapters I analyse how the relevance of special items for earnings forecasts evolves across a number of different dimensions.

5.2 Regression by profitability

Prior literature indicates that the relevance of special items for future performance depends on the profitability of the company reporting those special items. For instance, Atiase et al. (2004) as well as Khurana & Lippincott (2000) find that restructuring charges are only associated with improved future performance for low profitability companies with fundamental operational problems. According to Fairfield et al. (2009), as “special items reported by low and high profitability firms are likely to be triggered by different economic circumstances and incentives, they may also have different implications for future profit margins” (p. 216).

For my analysis by profitability, I rank my sample according to core profitability (core RNOA) into three profitability groups (in line with Fairfield et al., 2009) and subsequently estimate my base regression model for each group separately. Core RNOA is defined as net operating income minus special items divided through average total assets. Since profitability will heavily depend on industry effects and on economic cycles, I rank the sample into three profitability groups for each year and each industry portfolio. Fairfield et al. (2009) comes to the following conclusions i) core earnings are always significant (for all three profitability groups across all five earnings windows), whereby the persistence is the highest for the middle rank of core RNOA and the lowest for the low profitability group, ii) for high profitability firms, one-time expenses provide significant predictive content for future profit margin and this association grows with increasing earnings windows, and iii) one-time revenues do not show a significant, predictable pattern for any profitability group. In the following, I discuss whether my results are consistent with the findings of Fairfield et al. (2009).

Table 13 reports my regression results for all three profitability groups. R^2 is the highest for the high core RNOA group (between 48% and 58%) and the lowest for the low profitability group (between 26% and 30%). In line with Fairfield et al. (2009), core PM^w_t is significant at the 1% level for all profitability groups and time windows, whereby the persistence is the highest for the medium profitability group (coefficient between 0.738 and 0.882) and the lowest for the low profitability group (coefficient between 0.593 and 0.621). Just like core earnings, negative special PM^w_t is significantly different from zero for all profitability groups and time windows. In the short-term ($w = 1$), one-time expenses are most relevant for the high profitability group (coefficient of 0.405, while only 0.224 and 0.222 for the medium and low profitability rank, respectively). The coefficient of negative special PM^w_t for all three profitability groups is decreasing with increasing earnings windows, whereby the one of the high profitability group shows the strongest decline. Hence, when smoothing one-time expenses over several earnings windows, they tend to be more useful for predicting future earnings of low and medium profitability companies. One-time revenues are insignificant for high profitability firms. For low profitability firms, one-time revenues have a positive, significant coefficient for the two, three and four-year time window, but an insignificant one for the one and five-year earnings window. Since there appears to be no predictable pattern for positive special items of low profitability firms, analysts can in most cases treat them as transitory. For the middle profitability rank, positive special items are irrelevant in the

Table 13: Regression model – **by rank of core RNOA (N = 20,970)**

$$PM_{t+1}^{w} = \sum_{j=1}^{3} \alpha_{1,0} + \sum_{j=1}^{3} \beta_{1,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{3} \beta_{1,2}^{w} * negative\ special\ PM_{t}^{w}$$

$$+ \sum_{j=1}^{3} \beta_{1,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{1,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

	Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
High Profitability	1	0.014**	0.723***	0.405***	0.003	0.484
		(0.006)	(0.026)	(0.093)	(0.062)	
	2	0.030***	0.796***	0.231***	0.001	0.58
		(0.004)	(0.021)	(0.073)	(0.074)	
	3	0.037***	0.771***	0.174***	0.138	0.564
		(0.004)	(0.024)	(0.065)	(0.136)	
	4	0.029***	0.738***	0.172**	0.2	0.538
		(0.005)	(0.027)	(0.070)	(0.158)	
	5	0.026***	0.711***	0.125*	0.243	0.532
		(0.005)	(0.029)	(0.074)	(0.198)	
	Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
Medium Profitability	1	-0.017**	0.882***	0.224***	-0.017	0.430
		(0.007)	(0.021)	(0.053)	(0.074)	
	2	0.022***	0.783***	0.248***	0.049	0.426
		(0.004)	(0.024)	(0.072)	(0.121)	
	3	0.037***	0.781***	0.314***	0.343***	0.444
		(0.004)	(0.021)	(0.091)	(0.092)	
	4	0.027***	0.761***	0.267***	0.677***	0.446
		(0.004)	(0.022)	(0.097)	(0.121)	
	5	0.022***	0.738***	0.172**	0.834***	0.460
		(0.004)	(0.025)	(0.071)	(0.121)	
	Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
Low Profitability	1	-0.011	0.593***	0.222***	-0.003	0.270
		(0.008)	(0.027)	(0.039)	(0.133)	
	2	0.052***	0.593***	0.188***	0.276**	0.275
		(0.005)	(0.022)	(0.047)	(0.122)	
	3	0.053***	0.597***	0.198***	0.248*	0.262
		(0.005)	(0.023)	(0.054)	(0.140)	
	4	0.035***	0.621***	0.203***	0.249**	0.286
		(0.004)	(0.022)	(0.058)	(0.126)	
	5	0.028***	0.606***	0.174***	0.179	0.296
		(0.004)	(0.024)	(0.057)	(0.146)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.

Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

short-term (for w = 1 and w = 2) but become significant and highly positive from w = 3 onwards (with coefficient amounting to 0.343, 0.677 and 0.834). Hence, analysts should consider smoothed positive special items when analysing companies, which are showing a profitability close to the median profitability of their peer group.

Consequently, while my results with respect to core earnings are consistent with Fairfield et al. (2009), my evidence on positive and negative special items leads to different conclusions. Analysts can use this evidence for their earnings forecast models in the following way. Ideally, they should select a peer group in the same industry as the firm they are analysing and compute core RNOA for all companies. If their target company shows profitability exceeding or below the median profitability of the peer group, they should take only one-time expenses into account. If the target's profitability is in line with the one of the peer group, both negative and positive special items should be considered, whereby for one-time revenues the analyst should compute an average over several years.

5.3 Regression by geography

In this sub-section, I run my base model separately for Europe and North America. As mentioned, there is no prior special items literature distinguishing between Europe and North America, making it difficult to postulate hypotheses. Cutillas-Gomariz et al. (2016) find that earnings relevance increased for publicly listed Spanish companies after including non-recurring items into operating income. This might potentially indicate that one-time items have a higher predictive ability in Europe compared to North America, as the majority of the US-focused literature suggests that earnings quality declines as a result of special items (e.g. Dichev & Tang, 2008). My evidence from chapter 4 shows that one-time items in Europe are more frequent (4.1), more persistent (unless firms report special items very frequently, i.e. more than four times over the past five years; section 4.2) and one-time revenues are bigger than in North America (4.3). Taken together, these results also suggest that one-time items in Europe might be more significant from an economic perspective. Before discussing my regression results in the following, it needs to be pointed out once more that my European sample is relatively small (1,800 firm-year-observations) and is mainly including very large companies. Therefore, implications of special items across Europe and North America in my research might not only be different due to geographic reasons, but also due to other distorting factors.

Table 14: Regression model – **by geography (N = 20,970)**

$$PM_{t+1}^{w} = \sum_{j=1}^{2} \alpha_{2,0} + \sum_{j=1}^{2} \beta_{2,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{2} \beta_{2,2}^{w} * negative\ special\ PM_{t}^{w} + \sum_{j=1}^{2} \beta_{2,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{2,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

	Nbr. of years in earnings window	α	Core PM^{w}_{t}	Negative special PM^{w}_{t}	Positive special PM^{w}_{t}	R^2
Europe	*1*	0.01	0.798***	0.626***	-0.04	0.582
		(0.012)	(0.044)	(0.124)	(0.104)	
	2	0.054***	0.806***	0.721***	-0.365*	0.602
		(0.011)	(0.045)	(0.152)	(0.215)	
	3	0.078***	0.795***	0.994***	-0.138	0.573
		(0.011)	(0.053)	(0.231)	(0.210)	
	4	0.084***	0.761***	1.201***	0.017	0.52
		(0.013)	(0.064)	(0.340)	(0.394)	
	5	0.071***	0.721***	0.854*	-0.172	0.47
		(0.013)	(0.070)	(0.441)	(0.562)	
	Nbr. of years in earnings window	α	Core PM^{w}_{t}	Negative special PM^{w}_{t}	Positive special PM^{w}_{t}	R^2
North America	*1*	0	0.699***	0.193***	0.017	0.407
		(0.004)	(0.015)	(0.026)	(0.083)	
	2	0.038***	0.719***	0.144***	0.231***	0.445
		(0.003)	(0.012)	(0.027	(0.083)	
	3	0.042***	0.728***	0.168***	0.279***	0.449
		(0.002)	(0.011)	(0.031)	(0.096)	
	4	0.026***	0.732***	0.186***	0.345***	0.464
		(0.003)	(0.012)	(0.035)	(0.093)	
	5	0.021***	0.720***	0.177***	0.359***	0.476
		(0.002)	(0.012)	(0.036)	(0.119)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

Table 14 reports my regression results. Core profit margin is significant for all five earnings windows in both Europe and North America. For short-term earnings windows, the coefficient in Europe is sightly higher (approximately 0.8, while in North America circa 0.7). Extending the windows, the persistence of core earnings in Europe is declining (to 0.721 in w = 5) and the one in North America is flat / slightly increasing (0.720 in w = 5). In line with the pooled sample, negative special PM^{w}_{t} is significant for all earnings windows across Europe and North America. Looking at the coefficients, however, it becomes visible that one-time expenses capture more useful information for future performances in Europe than in North America. In Europe, the coefficient of negative special PM^{w}_{t} is increasing from 0.626 (w = 1) to 1.201 (w = 4) and dropping back to 0.854 in w = 5. This implies that in Europe one-time expenses are approximately as important as core earnings for predicting future performances. Therefore, excluding one-time charges would mean a significant loss of useful information. In America, the coefficient of negative special PM^{w}_{t} ranges between 0.1 and 0.2, i.e. core earnings are three to five times more persistent than one-time expenses. Ignoring one-time expenses would still be an error, as all five coefficients are significantly different from zero, meaning there is an association between past negative special items and future profit margin. For one-time revenues the picture looks completely different. Despite of the higher frequency (4.1) and magnitude (4.3) of positive special items in Europe compared to North America, the coefficient of positive special PM^{w}_{t} for my European sample is only significantly different from zero for w = 2, but insignificant for all other earnings windows. Hence, analysts can usually neglect one-time revenues for European companies. In North America, positive special PM^{w}_{t} is insignificant in the short-term (w = 1), but from w = 2 onwards the coefficient is significant and in the area of 0.23 to 0.36.

Summarizing my analysis on geographic differences, I conclude that analysts should never exclude one-time expenses for European companies, while they can usually ignore one-time revenues. For companies headquartered in North America, analysts should consider negative special items and for longer time horizons also positive special items. Overall, however, one-time items are more relevant for predicting future performance of European companies – this is also reflected in a higher R^2 ranging between 47% and 60% in Europe and between 40% and 48% in North America.

5.4 Regression by industry

In this sub-section, I run my base model separately for my Fama-French industry portfolios. With the exception of Johnson et al. (2011), who investigated frequency of special items by industries, special items literature did not yet examine the relevance of one-time revenues and expenses by industry. Consistently with Johnson et al. (2011), my descriptive analysis in section 4.1 shows that the industries that report the fewest one-time charges also report the fewest one-time revenues, while the industries with the most one-time expenses are not the ones with the most one-time revenues. Furthermore, I concluded in section 4.3 that there appears to be some association between reporting frequency of one-time items and their magnitude in industry portfolios, as the Telecom and the Energy sector are among the industries with highest magnitude and frequency. Since special items are very prevalent in those industries, it would be reasonable to expect that one-time items convey more useful information compared to other industries.

My evidence suggests that for each industry portfolio either one-time revenues or one-time expenses or neither of them are significant. In other words, there is no industry portfolio where I observe that both positive and negative special items are relevant. **Table 15** reports my regression results for the industry portfolios where one-time revenues (panel A) and expenses (panel B) are significant, respectively. The regression outputs for the industries without foreseeable patterns for positive and negative special items can be found in **Table 23** in the Appendix.

My results suggest that positive special items are relevant in for the Consumer non-durables as well as for the Other industry portfolios (panel A). For the Other industry portfolio, one-time revenues gain significance when extending the time window. The coefficient is insignificant in w = 1, but significant with a monotonically increasing coefficient from w = 2 onwards (0.278 in w = 2; 0.863 in w = 5). This is similar to the pattern of positive special items observed in my basic regression model in section 5.1. In contrast, for the Consumer non-durables portfolio the coefficient is significant in the short-term (from w = 1 to w = 3), but irrelevant in the long-term.

Panel B shows that one-time expenses provide useful information for future earnings for the following industries: Consumer durables, Energy, Utilities, and Healthcare. For the Energy, Utilities, and Healthcare portfolios, negative special PM is significantly different from zero in all five earnings windows. For all three industries, the coefficient is high, positive and monotonically increasing the longer the earnings window. In contrast, in the Consumer durables industry portfolio, one-time expenses are significant only in the long-term, i.e. from w = 2 onwards. My analysis suggests that the relevance of one-time items for future performance does not simply depend on frequency and magnitude of those items in the respective industries. Sections 4.1, 4.2 and 4.3 showed that frequency, persistence and magnitude of one-time expenses is the lowest in the Utilities sector. Nonetheless, my regression results suggest that negative special items are significant at the 1% level for all five earnings windows in the Utilities sector. This suggests that one-time items appear very rarely in the Utilities sector, but when they do, they are important and should be considered. In contrast, section 4.1 and 4.3 suggested that frequency and magnitude of one-time revenues are very high in the Telecom sector, but my regression results in **Table 23** (Appendix) report that they do not provide significant useful information for future earnings.

In closing, analysts with basic knowledge about the industry of their targets can simplify their approaches with respect to one-time items, as my evidence suggest that, on average, in each industry either one-time revenues or one-time expenses or neither of them are relevant. Finally, it is important for investors to understand that low / high special items frequency, persistence and magnitude in an industry does not necessarily imply that one-time items can be excluded / should be included categorically, as we have seen at the example of the Utilities and the Telecom sector.

Table 15: Regression model **– by industry (N = 20,970)**

$$PM_{t+1}^{w} = \sum_{j=1}^{11} \alpha_{3,0} + \sum_{j=1}^{11} \beta_{3,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{11} \beta_{3,2}^{w} * negative\ special\ PM_{t}^{w}$$

$$+ \sum_{j=1}^{11} \beta_{3,3}^{w} * \ positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{3,4}^{i} * YEAR_{i} + \ \varepsilon_{t+1}$$

Panel A: Industries with significant **positive special items**

	Consumer Non-Durables					Other				
Nbr. of years in earnings window	α	Core $PM^w{}_t$	Negative special $PM^w{}_t$	Positive special $PM^w{}_t$	R^2	α	Core $PM^w{}_t$	Negative special $PM^w{}_t$	Positive special $PM^w{}_t$	R^2
1	0.005	0.822***	0.162	0.143**	0.618	0	0.633***	0.039	0.003	0.357
	(0.009)	(0.055)	(0.151)	(0.058)		(0.011)	(0.032)	(0.075)	(0.10)	
2	0.017**	0.846***	0.095	0.356***	0.689	0.041***	0.643***	0.027	0.278**	0.39
	(0.007)	(0.059)	(0.132)	(0.085)		(0.007)	(0.031)	(0.076)	(0.124)	
3	0.016*	0.817***	-0.220*	0.672***	0.671	0.059***	0.613***	-0.047	0.493***	0.359
	(0.009)	(0.074)	(0.123)	(0.182)		(0.007)	(0.031)	(0.086)	(0.120)	
4	0.014	0.763***	-0.422***	0.52	0.633	0.042***	0.598***	0.023	0.706***	0.352
	(0.011)	(0.087)	(0.141)	(0.360)		(0.007)	(0.030)	(0.071)	(0.123)	
5	0.018*	0.716***	-0.503***	0.164	0.617	0.031***	0.580***	-0.023	0.863***	0.352
	(0.011)	(0.096)	(0.153)	(0.602)		(0.007)	(0.029)	(0.076)	(0.146)	

Panel B: Industries with significant **negative special items**

	Consumer Durables					Energy				
Nbr. of years in earnings window	α	Core PMwt	Negative special PMwt	Positive special PMwt	R2	α	Core PMwt	Negative special PMwt	Positive special PMwt	R2
1	0.012	0.696***	0.187	-0.248	0.383	-0.028	0.548***	0.509***	0.095	0.460
	(0.009)	(0.049)	(0.136)	(0.381)		(0.020)	(0.055)	(0.111)	(0.295)	
2	0.023***	0.765***	0.235**	0.041	0.562	0.073***	0.498***	0.635***	-0.241	0.459
	(0.007)	(0.033)	(0.103)	(0.355)		(0.015)	(0.048)	(0.153)	(0.422)	
3	0.019***	0.764***	0.365***	0.091	0.564	0.150***	0.536***	0.795***	0.744	0.477
	(0.006)	(0.034)	(0.113)	(0.334)		(0.015)	(0.044)	(0.168)	(0.879)	
4	0.007	0.756***	0.627***	0.093	0.55	0.150***	0.518***	0.986***	0.45	0.463
	(0.007)	(0.038)	(0.125)	(0.346)		(0.017)	(0.044)	(0.228)	(0.929)	
5	0.003	0.730***	0.762***	0.146	0.521	0.108***	0.471***	1.144***	0.186	0.444
	(0.007)	(0.044)	(0.149)	(0.544)		(0.016)	(0.042)	(0.248)	(0.869)	

	Utilities					Healthcare				
Nbr. of years in earnings window	α	Core $PM^w{}_t$	Negative special $PM^w{}_t$	Positive special $PM^w{}_t$	R^2	α	Core $PM^w{}_t$	Negative special $PM^w{}_t$	Positive special $PM^w{}_t$	R^2
1	0.044***	0.717***	0.235***	-0.024	0.422	0.022	0.742***	0.407***	-0.027	0.457
	(0.016)	(0.053)	(0.064)	(0.123)		(0.017)	(0.044)	(0.095)	(0.112)	
2	0.053***	0.783***	0.251***	-0.013	0.556	0.054***	0.756***	0.629***	-0.035	0.523
	(0.010)	(0.031)	(0.070)	(0.114)		(0.011)	(0.037)	(0.103)	(0.203)	
3	0.031***	0.813***	0.577***	0.082	0.611	0.040***	0.746***	0.683***	-0.05	0.483
	(0.007)	(0.024)	(0.078)	(0.159)		(0.011)	(0.036)	(0.125)	(0.390)	
4	0.027***	0.812***	0.706***	0.063	0.622	0.026**	0.719***	0.650***	-0.061	0.422
	(0.006)	(0.022)	(0.113)	(0.183)		(0.013)	(0.040)	(0.131)	(0.606)	
5	0.040***	0.788***	0.775***	0.111	0.595	0.032**	0.686***	0.554***	-0.388	0.384
	(0.006)	(0.024)	(0.160)	(0.208)		(0.013)	(0.043)	(0.113)	(0.799)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.

Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

5.5 Regression by time

As discussed in section 3.1, for my regression analysis by time I estimate the basic regression model for each year of my observation period (i.e. from 2001 to 2018) separately. For instance, I regress lagged decomposed profit margin from year 2001 on profit margin of 2002 and so on. As opposed to sections 5.1 to 5.4, I do not run my regression model over earnings windows from one to five years, as I specifically try to examine whether there are annual differences in the association between past decomposed profit margin and future profit margin. This analysis leaves me with 17 regressions, providing me with one coefficient per year for each explanatory variable. I will discuss these coefficients in the first part of this sub-section. Since coefficients may vary not only because there is an actual difference in correlation, but also due to distribution differences, I analyse in the second part of this sub-section whether there are structural breaks between each year-pair (i.e. 2001-2002, 2002-2003, …, 2017-2018) using Chow tests (Chow, 1960). With my analysis by time I am trying to understand how the predictive ability of core earnings, one-time revenues and expenses for future profit margin has evolved over time and how it is affected by economic downturns. Thus, this analysis is particularly interesting in light of the current economic conditions as a consequence of the COVID-19 pandemic, even though it needs to be emphasized that each crisis is unique, which is why it is unclear whether patterns from past crises can be transferred to the current one. Sections 4.1 and 4.3 have shown that frequency and magnitude of one-time expenses behave differently during crises, while one-time revenues remain with few exceptions fairly constant. This might suggest that negative special items capture more useful information for future profits than during economic expansions or peaks.

Table 16 reports my regression results. The evidence suggests that core earnings are significant at the 1% level for all 17 regressions. The coefficients are ranging relatively stable between approximately 0.5 and 0.8. Given that the two lowest core PM coefficients appear in 2003 (0.502) and 2010 (0.595), there is a tendency for core earnings to be less persistent in the post crises periods. However, I do not observe a

Table 16: Regression model **– by time (N = 20,970)**

$$PM_{2002} = \alpha_{2001,0} + \beta_{2001,1} * core\ PM_{2001} + \beta_{2001,2} * negative\ special\ PM_{2001} + \beta_{2001,3} * positive\ special\ PM_{2001} + \varepsilon_{2002}$$

$$\dots$$

$$PM_{2018} = \alpha_{2017,0} + \beta_{2017,1} * core\ PM_{2017} + \beta_{2017,2} * negative\ special\ PM_{2017} + \beta_{2017,3} * positive\ special\ PM_{2017} + \varepsilon_{2018}$$

Year of PM_{t+1}	α	Core PM_t	Negative special PM_t	Positive special PM_t	R^2
2002	0.008	0.664***	0.520***	0.483*	0.284
	(0.008)	(0.073)	(0.096)	(0.260)	
2003	0.052***	0.502***	-0.016	-0.164	0.399
	(0.005)	(0.050)	(0.064)	(0.468)	
2004	0.034***	0.713***	0.055	0.272	0.452
	(0.004)	(0.036)	(0.110)	(0.175)	
2005	0.028***	0.743***	0.194	0.001	0.533
	(0.006)	(0.055)	(0.125)	(0.071)	
2006	0.014**	0.834***	0.262**	0.446	0.482
	(0.006)	(0.047)	(0.126)	(0.420)	
2007	0.017***	0.780***	0.275*	0.137	0.497
	(0.006)	(0.051)	(0.145)	(0.190)	
2008	-0.022***	0.847***	0.385**	-0.189	0.365
	(0.007)	(0.052)	(0.150)	(0.333)	
2009	0.002	0.772***	0.130***	0.031	0.47
	(0.006)	(0.048)	(0.049)	(0.168)	
2010	0.052***	0.595***	-0.041	0.384	0.394
	(0.005)	(0.051)	(0.107)	(0.333)	
2011	0.015***	0.835***	0.031	-0.008	0.621
	(0.004)	(0.034)	(0.070)	(0.069)	
2012	0.021***	0.721***	0.327***	0.301	0.433
	(0.006)	(0.050)	(0.10)	(0.358)	
2013	0.017***	0.796***	0.203***	-1.688***	0.461
	(0.006)	(0.056)	(0.063)	(0.510)	
2014	0.028***	0.735***	0.562***	-0.126	0.553
	(0.008)	(0.064)	(0.205)	(0.184)	
2015	0.019***	0.702***	0.836***	-0.455**	0.313
	(0.007)	(0.059)	(0.209)	(0.215)	
2016	0.01	0.820***	0.473***	0.213	0.489
	(0.009)	(0.071)	(0.124)	(0.172)	
2017	0.038***	0.631***	0.265**	0.065	0.501
	(0.007)	(0.051)	(0.117)	(0.098)	
2018	0.027***	0.662***	0.426***	0.449	0.389
	(0.008)	(0.062)	(0.123)	(0.385)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Model is not estimated over increasing earnings windows, as I specifically investigate whether there are annual differences in the correlation of lagged decomposed profit margin and future profit margin. I test whether the coefficients between each year-pair are significantly different (i.e. structural break) by using Chow – please refer to the appendix for the results. Year dummies are not reported. Huber–White clustered standard errors are reported below the coefficients, which are robust to heteroscedasticity.

similar pattern after the euro crisis. One possible explanation for this might be that the majority of my sample companies are headquartered in North America and, hence, have been less affected by the euro crisis. One-time expenses are significantly different from zero in 12 out of 17 regressions. Similarly to core earnings, negative special items appear to be less relevant in the post-crises periods. However, while core PM coefficients were lower but still significant shortly after crises, the ones of negative special PM are insignificant (in 2003, 2004, 2005, 2010 and 2011). In line with my initial hypothesis, the coefficient of one-time expenses is significant, positive, and relatively high during crises (e.g. 0.520 in 2002, 0.385 in 2008, 0.327 in 2012), implying that analysts should not exclude negative special items from their earnings forecast models. Finally, from 2015 onwards the coefficient of one-time expenses remains high and significant for each year. This is in line with section 4.3, showing that the magnitude of negative special items are at a constant high level after Accounting Standard Update No. 2015-01 by the FASB, which implies that extraordinary items are not required to be segregated from ordinary operations anymore, i.e. can be recorded as a special item. My evidence suggests that Accounting Standard Update No. 2015-01 increased the importance of negative special items. We need to supervise whether this development sustains in future periods, as four years are not yet sufficient to make final conclusions. Finally, looking at the coefficients of positive special PM, we can conclude that analysts can confidently exclude one-time revenues in most forecast scenarios. The coefficient is only significant in three out of 17 regressions (2002, 2013 and 2015) and it is difficult to find a reliable pattern when positive special PM is significantly different from zero.

As mentioned in section 3.1 as well as in the beginning of this sub-section, the coefficients of my 17 regressions may vary not only because there is an actual difference in correlation, but also due to distribution differences. I use Chow-tests for each year-pair (i.e. 2001-2002, 2002-2003, …, 2017-2018) of my observation period to understand whether there are structural breaks. The null hypothesis of Chow is that the coefficients of two linear regressions on different sets are equal (no structural break). If my F values exceed the critical value, this implies that the null hypothesis can be rejected, i.e. there are structural breaks between each year-pair or, in other words, there is an actual difference in correlation across time. My evidence suggests that the F values exceed the critical value for each year-pair except of 2003-2004, 2004-2005, 2005-2006, 2016-2017 (F values can be found in **Table 24** in the Appendix). Consequently, for all other years the differences among the coefficients are significant, meaning my conclusions from above are valid.

Summarizing my regression by time analysis, I conclude that analysts should consider core earnings and one-time expenses for their earnings forecast models. One-time expenses are particularly important during economic downturns and crises, but they can be ignored in the immediate post-crisis period. When forecasting without smoothing values, one-time revenues can be ignored, as there is no clear pattern.

5.6 Regression by sub-items

As discussed in section 3.1, I modify the basic regression model by Fairfield et al. (2009) for this analysis in the sense that I break down positive and negative special PM^w_t into one-time sub-items deflated with sales. Followingly, my explanatory variables are core earnings, M&A related gains / losses, one-time gains / losses, goodwill impairment, litigation expenses, restructuring charges, PP&E write-offs, other special items, in-process R&D expenses and extinguishments of debt. The motivation behind this analysis is that some sub-items may capture more useful information for future performance than others. This would make sense from a theoretical perspective, as, for instance, restructuring charges should ideally lead to improved future performances, while other items are not directly linked to future earnings. For example, goodwill impairments can be a sign that a company overpaid when acquiring another company and, hence, do not necessarily affect future performance. Prior literature suggests that restructuring charges are indeed positively associated with the real performance hypothesis (e.g. Bens & Johnston, 2007), even though there is some disagreement whether this applies to all companies or only to companies with low profitability (Atiase et al., 2004). For analysts and investors the results of my regression by sub-items is particularly interesting, because it might help them to understand whether they should include or exclude special items after looking up the sub-items in the financial statement of the company they are analysing.

Table 17 reports my regression results. Like in my previous sub-sections, core earnings are significant with coefficients ranging in the area of 0.7 for all five earnings windows. The only three sub-items which are significantly different from zero in all time windows are in-process R&D expenses, restructuring charges and M&A related gains / losses. With coefficients amounting to 0.341 (in-process R&D), 0.245 (restructuring) and 0.247 (M&A gains / losses) for w = 1, the explanatory power of those three sub-items is roughly two to three times below the one of core earnings in the short-term. When averaging the items over earnings windows of five years, the coefficient of in-process R&D is very big (1.925 for w = 5), underlining that research and development are one of the main drivers of future performance. Consequently, when analysts find those three sub-items in the financial statements of their target companies, they should definitely take them into account for any forecasts. This result is once again in line with my previous conclusion that higher frequency of special items does not necessarily imply higher predictive content for future earnings. In fact, in-process R&D expense is, on average, the sub-item with the lowest frequency (section 4.4).

One-time gains / losses and other special items are insignificant for the one- and two-year earnings windows and significant with high coefficients as of w = 3. This pattern very much reminds of the one of positive special PM from section 5.1. Not surprisingly, section 4.4 suggest that those two one-time sub-items are together with litigation expenses the most frequent sub-items when a company reports net positive special items. Litigations are insignificant for the one-, two- and five-year earnings window, i.e. it is difficult to extrapolate a pattern. However, for one-time gains / losses and other special items it makes sense to consider a smoothed average in the forecast model. Finally, goodwill impairment, write-offs and extinguishments of debt are significant in w = 1, but insignificant afterwards without a predictable pattern. Consequently, analysts should consider them for short-term forecasts, but can exclude them otherwise.

Table 17: Regression model **– by sub-items (N = 20,970)**

$$PM_{t+1}^{w} = \alpha_{4,0} + \beta_{4,1}^{w} * core\ PM_t^w + \beta_{4,2}^{w} * in - process\ R\&D_t^w$$

$$+ \beta_{4,3}^{w} * restructuring_t^w + \beta_{4,4}^{w} * gain\ loss_t^w + \beta_{4,5}^{w} * litigation_t^w$$

$$+ \beta_{4,6}^{w} * other\ SPI_t^w + \beta_{4,7}^{w} * M\&A_t^w + \beta_{4,8}^{w} * goodwill_t^w + \beta_{4,9}^{w} * writedown_t^w$$

$$+ \beta_{4,10}^{w} * extinguish\ debt_t^w + \sum_{i=1}^{10} \beta_{4,11}^{i} * YEAR_i + \varepsilon_{t+1}$$

Nbr. of years in earnings window	α	Core PM^w_t	In process $R\&D^w_t$	Re-structuring^w_t	Gain/ $Loss^w_t$	$Litigation^w_t$
1	0	0.713***	0.341**	0.245**	0.042	0.179
	(0.004)	(0.015)	(0.165)	(0.113)	(0.093)	(0.172)
2	0.037***	0.736***	0.407**	0.349***	0.030	0.542*
	(0.003)	(0.012)	(0.189)	(0.088)	(0.155)	(0.321)
3	0.041***	0.746***	0.987***	0.323***	0.733**	1.349***
	(0.002)	(0.012)	(0.210)	(0.114)	(0.285)	(0.370)
4	0.027***	0.739***	1.575***	0.497***	2.129***	0.964**
	(0.003)	(0.013)	(0.176)	(0.134)	(0.414)	(0.480)
5	0.023***	0.717***	1.925***	0.390**	3.047***	0.185
	(0.002)	(0.014)	(0.233)	(0.165)	(0.720)	(0.243)

Nbr. of years in earnings window	Other SPI^w_t	$M\&A^w_t$	$Goodwill^w_t$	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R2
1	0.029	0.247*	0.239***	0.109*	0.448**	0.423
	(0.073)	(0.150)	(0.043)	(0.063)	(0.205)	
2	0.328	0.637***	0.119*	-0.083	0.371	0.46
	(0.210)	(0.240)	(0.063)	(0.068)	(0.280)	
3	0.845**	0.949***	0.203	0.117	0.042	0.463
	(0.378)	(0.338)	(0.146)	(0.182)	(0.516)	
4	2.470***	1.178***	0.018	0.634	-0.335	0.47
	(0.791)	(0.442)	(0.176)	(0.449)	(0.678)	
5	2.732**	0.717*	-0.640***	0.88	-0.934	0.473
	(1.134)	(0.384)	(0.230)	(0.861)	(0.841)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

6 Potential issues and robustness

6.1 Replication of one-time revenues and expenses

Despite of the fact that Bradshaw & Sloan (2002) show that “special items” (item #17) from COMPUSTAT are strongly correlated with the adjustments pursued by analysts when they try to compound a core earnings figure, the COMPUSTAT database might cause issues for my analysis for two reasons. First, data quality is not ideal, as the sum of the one-time sub-items is equal to net special items only in 93.6% of my observations. Second, COMPUSTAT does not provide numbers for positive and negative special items. Instead, the database provides only a netted number for each year. Existing literature as well as my research approach takes this netted number and allocates it to one-time expenses for each negative firm-year-observation and to one-time revenues for each positive firm-year-observation. Hence, negative and positive special profit margin can never be ≠ 0 at the same time, as mentioned several times throughout my research paper. There is one simple workaround, solving both issues. Instead of the prevalent approach, one could simply add up all negative and all positive one-time sub-items for each observation. Thereby, it is possible that both one-time revenues and expenses are ≠ 0 at the same time. I deliberately decided against using this approach in the main part of my thesis for two reasons. First, by using a different approach than Fairfield et al. (2009), comparability with their evidence would have been negatively affected. Second, this approach is less convenient and applicable for investors due to data availability issues. In fact, the COMPUSTAT “Global – Daily” database does not even provide a special item break-down into its sub-items, meaning the suggested workaround could not be conducted for all listed companies around the world.

Nevertheless, I estimate my basic regression model from section 5.1 for the same sample by using the suggested workaround. The results from this regression are reported in **Table 18**. Both negative special PM^{w}_{t} and positive special PM^{w}_{t} show a very similar pattern compared to section 5.1. In fact, one-time expenses are just like in section 5.1 significant at the 1% level for all five earnings windows with a coefficient ranging between 0.174 (in w = 5) and 0.217 (in w = 1), while positive special items are not relevant for the first earning windows and significant at the 1% level with a monotonically increasing coefficient from w = 2 onwards. As a conclusion, the evidence from table **Table 18** suggests that using net special items from COMPUSTAT is not an issue with regards to one-time items.

Table 18: Base regression model **– replication positive / negative special items (N = 20,970)**

$$PM_{t+1}^{w} = \alpha_{5,0} + \beta_{5,1}^{w} * core\ PM_{t}^{w} + \beta_{5,2}^{w} * negative\ special\ PM_{t}^{w} + \beta_{5,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{5,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

Nbr. of years in earnings window	α	Core PM^{w}_{t}	Negative special PM^{w}_{t}	Positive special PM^{w}_{t}	R^2
1	0.001	0.712***	0.217***	-0.001	0.423
	(0.004)	(0.014)	(0.031)	(0.068)	
2	0.039***	0.732***	0.178***	0.194***	0.459
	(0.003)	(0.012)	(0.037)	(0.074)	
3	0.044***	0.738***	0.219***	0.255***	0.459
	(0.002)	(0.012)	(0.042)	(0.083)	
4	0.030***	0.733***	0.218***	0.348***	0.463
	(0.003)	(0.013)	(0.044)	(0.083)	
5	0.024***	0.715***	0.174***	0.371***	0.468
	(0.003)	(0.014)	(0.040)	(0.106)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

6.2 Sample selection

As mentioned in section 3.2, my sample selection causes several issues, possibly distorting my research. First, since I had to use the COMPUSTAT “North America – Daily” database instead of the “Global – daily” one, my European sample is comparably small (firm-year-observations 1,800) and captures mainly large companies. Second, my sample selection criteria reducing my sample from initially 105,859 firm-year-observations to 20,970 observations imposes a strong survivorship bias.

While the issue with regards to my European sample cannot be solved and calls for additional research in this field, the sample selection criteria can be adjusted easily. In the following, I estimate my base regression model from section 5.1 for a sample with less strict selection criteria. I still exclude firms from the financial services sector and require that all firms must be headquartered in Europe or North America. Small firms and outliers are still excluded, but I use more generous cut-off points. I exclude small firms with net operating assets or sales below $1 million (before: $5 million) as well as outliers with return on net operating assets or profit margin exceeding 200% (before: 100%) or core profit margin or special profit margin exceeding 400% (before: 200%). Finally, instead of 18 years of consecutive data, I only require 10 years of consecutive data, which is the minimum necessary to still be able to create my earnings windows from one to five years. This leaves me with 35,807 firm-year-observations. **Table 25** in the Appendix summarizes the sample selection criteria.

Table 19 reports my regression results. All model parameters are identical to the ones used in section 5.1 with the only difference that I used a different sample. Just like in my base model, the coefficients of core earnings and negative special items are significantly different from zero for all five earnings windows. For both variables, the coefficients tend to be smaller than in my initial base model, which is probably because my sample in this sub-section underlies less strict selection criteria, i.e. outliers may create noise. In contrast to section 5.1, the coefficients from positive special items are insignificant. Consequently, one-time revenues may be less important for future earnings than my base regression model in section 5.1 implies. Since we require additional clarity on this matter, positive special items would be a suitable topic for future research, as the vast majority of special items literature has a strong focus on one-time expenses.

Table 19: Base regression model **– different sample selection criteria (N = 35,807)**

$$PM_{t+1}^{w} = \alpha_{6,0} + \beta_{6,1}^{w} * core\ PM_t^w + \beta_{6,2}^{w} * negative\ special\ PM_t^w + \beta_{6,3}^{w} * positive\ special\ PM_t^w + \sum_{i=1}^{10} \beta_{6,4}^{i} * YEAR_i + \varepsilon_{t+1}$$

Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.009*	0.631***	0.184***	0.071	0.337
	(0.005)	(0.015)	(0.031)	(0.064)	
2	0.051***	0.629***	0.166***	0.056	0.351
	(0.003)	(0.013)	(0.027)	(0.066)	
3	0.057***	0.634***	0.135***	0.004	0.343
	(0.003)	(0.013)	(0.031)	(0.096)	
4	0.034***	0.637***	0.108***	-0.007	0.345
	(0.003)	(0.013)	(0.032)	(0.105)	
5	0.028***	0.627***	0.075**	0.063	0.365
	(0.003)	(0.013)	(0.031)	(0.094)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

6.3 GAAP reformation for extraordinary items

My research indicates that the importance of negative special items from 2015 onwards is more significant than before. The magnitude of one-time expenses deflated with sales increased in absolute terms from 1.3% in 2014 to 2.1% in 2015 (section 4.3). Furthermore, my regression by time (5.5) suggest high, significant coefficients for negative special PM from 2015 onwards. This might be a consequence of Accounting Standard Update No. 2015-01 by the FASB. Before this reformation, special items were reported on a pre-tax basis, while extraordinary items were segregated on an after-tax basis. However, Update No. 2015-01 implies that extraordinary items are not required to be segregated from ordinary operations anymore. Thus, companies can classify extraordinary items as a special item from 2015 onwards. We need to observe whether this development persists in coming years. Given that I require at least ten years of consecutive data for my basic regression model with earnings windows from one to five years, I cannot run my model for the period after Update No. 2015-01.

7 Conclusion

In the core of my paper, I investigate how past core earnings and past special items are associated with future earnings over increasing time windows from one to five years. One-time items are, by definition, supposed to be transitory, which is why investors usually exclude those items when projecting earnings. This approach is only valid if there is no significant association between past one-time items and future earnings. Otherwise, the exclusion of special items implies a loss of information and can cause overvaluations, as the majority of those items are expenses, meaning an earnings figure excluding one-time charges exceeds the actual GAAP figure. My regression results from section 5.1 suggest that one-time items, indeed, provide predictive content for future profit margin. In fact, one-time expenses are relevant for future earnings in the short-term as well as in the long-term with a persistence that is approximately 1/3 compared to the one of core earnings. Positive special items are also significant, but only over longer time horizons, i.e. including a smoothed one-time revenues figure can improve forecast accuracy. The robustness checks in sections 6.2 indicates my research may overvalue the importance of one-time revenues, while the association between negative special items and future earnings is robust. Hence, we require additional research on the actual relevance of one-time revenues.

Despite of the fact that special items providing useful information for earnings forecasts contradicts with their definition, this result is not particularly surprising. My descriptive analysis of one-time items in chapter 4 shows that one-time items “are so prevalent now that they're not special anymore” (Fowler, 2006). In fact, while in 2001 approximately 52% of the firms in my sample reported one-time items, the frequency increased to 76% in 2018. The relative size of special items increased slightly from absolute 1.3% to 1.7% of sales during my observation period, whereby magnitude shows strong fluctuations with a minimum of absolute 0.6% in 2004 and a maximum of absolute 3.2% in 2008. Frequency and magnitude of one-time items are mainly driven by one-time expenses, which peak during economic downturns and crises. Most frequent one-time sub-items when a firm reports net negative one-time items are restructuring (56%), M&A related gains / losses (32%) and other special items (30%). One-time revenues, on the other hand, remain fairly constant and mainly contain one-time gains / losses (47%), litigation (37%) and other special items (28%). I extend prior literature in the sense that I perform the descriptive analysis of special items not only for my consolidated sample, but also by geography as well as by industry. One-time items in Europe are more frequent (4.1), more persistent (unless firms report special items very frequently, i.e. more than four times over the past five years; section 4.2) and one-time revenues are bigger than in North America (4.3). Given that my results suggest differences across Europe and North America, future research should examine geographic discrepancies even further. This would be particularly important, as my European sample is comparably small, which might possibly lead to distortions. My analysis of special items by industry shows that the industries that report the fewest one-time charges also report the fewest one-time revenues, while the industries with the most one-time expenses are not the ones with the most one-time revenues. Furthermore, there appears to be some association between reporting frequency of one-time items and their magnitude in industry portfolios, as the Telecom and the Energy sector are among the industries with highest magnitude and frequency.

Given that there are significant differences in the patterns of special items across geography, industry, economic cycles, and sub-items, my descriptive analysis implies that there is no “one size fits all”-approach with regards to one-time items. This would be in line with Fairfield et al. (2009), who provide evidence, suggesting that special items may have different association with future profit margins depending on a firm’s profitability. Therefore, I examine from section 5.2 to 5.6, whether the usefulness of one-time items for earnings forecasts indeed varies by profitability (5.2), geography (5.3), industry (5.4), time (5.5), and sub-items (5.6). My research provides analysts and investors with frameworks for different circumstances, hopefully improving their investment decisions. It needs to be emphasized, however, that my results may not be representative for all kinds of circumstances, meaning investors should not trust blindly my results without questioning whether they are applicable to their investment targets.

My results suggest that the predictive content of one-time items varies across those five dimensions. However, one of the most important take-aways of my research paper is that high / low special items frequency and magnitude in a certain country, industry or of one particular one-time sub-item does not necessarily imply high / low special items relevance. My evidence provides three examples, supporting this finding. First, the Utilities industry portfolio shows the lowest positive and negative special items frequency, while my regression by industry (5.4) suggests that one-time expenses are particularly relevant for earnings forecasts in this sector. Second, in-process R&D expense is, according to section 4.4, the sub-item with the lowest frequency, but my regression by sub-items (5.6) indicates that it is the one-time sub-item with the strongest association to future profit margin. And finally, third, despite of the fact that one-time revenues are bigger and more frequent in Europe compared to North America (4.3), my regression by geography (5.3) suggests that positive special items are insignificant for forecasting future earnings in Europe, while they are relevant for long-term forecasts in North America. This take-away cannot be emphasized enough and implies that investors should not jump to conclusions when considering whether to include or exclude one-time items.

Nevertheless, my regression analyses suggest that there are some foreseeable patterns with regards to one-time items. For high and low profitability companies, only one-time expenses are significant, whereby, in the short-term, they are particularly relevant for high profitability firms. In contrast, if the target's profitability is in line with the one of the peer group (medium profitability), both negative and positive special items should be considered. For European companies, one-time revenues can usually be neglected, while one-time expenses are almost as important as core earnings when projecting future profit margin. For companies headquartered in North America, negative special items are less persistent than in Europe (approximately 1/4 to 1/5 compared to the one of core earnings) but should still be considered for earnings forecasts. Furthermore, for long-term forecasts also positive special items are relevant in North America. My evidence suggests that for the Consumer durables, Energy, Utilities, and Healthcare industry portfolios negative special items are associated with future earnings. Positive special items appear to be relevant for the Consumer non-durables and the Other industry portfolio. Besides of that, my regression by industry (5.4) suggests that for each industry portfolio either one-time revenues or one-time expenses or neither of them are significant. Hence, analysts can usually focus on one-time revenues or one-time expenses once identified which one is more important in their targeted industry. In line with my initial expectations, my regression by time (5.5) indicates that one-time expenses are particularly important for earnings forecasts during economic downturns and crises. In contrast, they can usually be neglected in the immediate post-crisis period. When looking at short-term forecasts, i.e. forecasting without smoothing values, one-time revenues can be ignored, as there is no clear pattern. Finally, my regression by sub-items (5.6) shows that in-process R&D expenses, restructuring charges and M&A related gains / losses are the most important sub-items for forecasts.

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Appendix

Table 20: Data years included in one- and five-year windows

w = 1	
y	x
2002	2001
2003	2002
2004	2003
2005	2004
2006	2005
2007	2006
2008	2007
2009	2008
2010	2009
2011	2010
2012	2011
2013	2012
2014	2013
2015	2014
2016	2015
2017	2016
2018	2017

w = 5					
y			x		
2006	*to*	2010	2001	*to*	2005
2007	*to*	2011	2002	*to*	2006
2008	*to*	2012	2003	*to*	2007
2009	*to*	2013	2004	*to*	2008
2010	*to*	2014	2005	*to*	2009
2011	*to*	2015	2006	*to*	2010
2012	*to*	2016	2007	*to*	2011
2013	*to*	2017	2008	*to*	2012
2014	*to*	2018	2009	*to*	2013

In line with Fairfield et al. (2009), I perform my regression (section 5) over increasing earnings windows from one to five years, because one-time items tend to be irregular. There is no overlap between the time windows of the dependent and independent variables. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. Extending the time window to its maximum of w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Consequently, we require at least 10 years of consecutive data for w = 5.

Table 21: Descriptive statistics across key financial variables by firm-year-observation with positive special items, negative special items, no special items **– by geography**

Variables	Positive special items				Negative special items				No special items			
	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
SPI / Avg. Total Assets	283	1.3%	0.4%	0.027	1,128	-1.8%	-0.7%	0.032	389			
SPI / Sales	283	2.0%	0.6%	0.043	1,128	-3.0%	-1.0%	0.070	389			
RNOA	283	21.0%	16.0%	0.187	1,128	14.0%	12.9%	0.171	389	20.1%	15.6%	0.177
ROA	283	10.7%	9.4%	0.079	1,128	6.9%	6.6%	0.080	389	10.7%	9.6%	0.085
ROE	280	29.2%	24.7%	0.899	1,111	25.0%	19.1%	1.398	389	27.6%	22.9%	0.245
Op. Margin	283	15.6%	14.1%	0.115	1,128	9.5%	9.3%	0.143	389	15.6%	12.1%	0.164
Sales Growth	283	8.9%	6.3%	0.285	1,128	4.7%	3.4%	0.172	389	13.2%	8.7%	0.566
R&D Expense	196	2.7%	0.9%	0.036	820	3.7%	2.4%	0.042	210	2.8%	0.8%	0.040
Capital Intensity	283	166.4%	153.8%	0.851	1,128	162.8%	143.7%	0.915	389	167.8%	146.5%	1.036
Market Capitalization	279	31,593	13,059	42,113	1,121	30,442	14,062	38,973	379	23,784	10,079	31,992
Tobin's Q	276	1.742	1.469	1.244	1,104	1.680	1.450	0.885	376	1.939	1.507	1.415
Debt/Equity	280	104.7%	67.2%	1.467	1,111	122.6%	70.3%	3.273	389	84.9%	66.5%	0.774

Variables	Positive special items				Negative special items				No special items			
	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
SPI / Avg. Total Assets	2,640	1.2%	0.4%	0.027	9,749	-2.2%	-0.8%	0.046	6,779			
SPI / Sales	2,640	1.6%	0.4%	0.045	9,750	-2.9%	-0.9%	0.069	6,780			
RNOA	2,640	17.2%	14.5%	0.158	9,750	11.3%	11.4%	0.174	6,780	16.3%	12.4%	0.161
ROA	2,640	9.6%	9.0%	0.078	9,749	6.3%	6.9%	0.096	6,779	9.4%	8.0%	0.083
ROE	2,570	27.8%	21.2%	2.042	9,456	17.7%	17.0%	3.190	6,723	22.0%	20.3%	0.696
Op. Margin	2,640	11.3%	9.6%	0.118	9,750	7.1%	7.5%	0.130	6,780	11.8%	10.7%	0.114
Sales Growth	2,640	7.4%	6.1%	0.210	9,748	6.5%	4.7%	0.219	6,778	8.1%	6.0%	0.218
R&D Expense	1,307	2.8%	1.4%	0.038	5,763	3.1%	1.7%	0.039	2,493	2.5%	1.0%	0.038
Capital Intensity	2,640	143.7%	104.0%	1.187	9,750	138.6%	107.4%	1.042	6,780	166.8%	109.9%	1.411
Market Capitalization	2,527	8,961	1,244	26,920	9,357	10,025	1,822	28,264	5,339	6,642	644	30,955
Tobin's Q	2,407	1.674	1.411	0.896	8,727	1.720	1.465	0.979	5,162	1.844	1.449	1.209
Debt/Equity	2,561	99.5%	48.9%	2.717	9,428	134.3%	59.2%	6.768	6,694	89.2%	52.0%	4.975

Variable definitions:

SPI / Avg. Total Assets = ratio of COMPUSTAT data items SPECIAL ITEMS (#17) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

RNOA = ratio of NET OPERATING INCOME (NOI) from period t and average of NET OPERATING ASSETS (NOA) across period t and t-1 (as defined in Table 1).

ROA = ratio of NET OPERATING INCOME (NOI) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

ROE = ratio of NET OPERATING INCOME (NOI) from period t and average of COMMON EQUITY (#60) across period t and t-1 (negative obsv. excluded).

Op. Margin = ratio of NET OPERATING INCOME (NOI) from period t and REVENUES (#12) from period t.

Sales Growth = growth in REVENUES (#12) between period t and t-1.

R&D Expense = ratio of COMPUSTAT data items R&D EXPENSE (#46) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

Capital Intensity = ratio of COMPUSTAT data items TOTAL ASSETS (#6) from period t and REVENUES (#12) from period t.

Market Capitalization = product of COMPUSTAT data items CLOSING STOCK PRICE (#24) and COMMON SHARES OUTSTANDING (#25).

Tobin's Q = ratio of (TOTAL ASSETS (#6) + MARKET CAPITALIZATION - COMMON EQUITY (#60) - DEFERRED TAXES (#74)) and average of TOTAL ASSETS (#6) across period t and t-1 - in line with Johnson, et al. (2011).

Debt/Equity = ratio of COMPUSTAT data items (LONG-TERM DEBT (#9) + CURRENT DEBT (#34)) and COMMON EQUITY (#60).

Table 22: Descriptive statistics across key financial variables by firm-year-observation with positive special items, negative special items, no special items **– by industry**

Panel A: Industry portfolio **#1, #2, #3 and #4**

		Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Consumer non-durables	*SPI / Avg. Total Assets*	239	1.3%	0.4%	0.025	884	-2.0%	-0.9%	0.037	407			
	SPI / Sales	239	1.5%	0.4%	0.040	884	-2.0%	-0.9%	0.042	407			
	RNOA	239	17.8%	16.2%	0.126	884	13.9%	13.2%	0.147	407	19.5%	17.4%	0.155
	ROA	239	10.7%	10.6%	0.069	884	8.2%	8.5%	0.085	407	12.3%	11.3%	0.098
	ROE	234	28.6%	22.2%	0.309	864	26.4%	19.9%	0.645	406	16.3%	19.4%	1.417
	Op. Margin	239	10.2%	8.5%	0.088	884	8.4%	8.4%	0.093	407	10.9%	8.7%	0.155
	Sales Growth	239	5.9%	4.5%	0.149	884	4.7%	2.7%	0.166	407	10.3%	5.5%	0.542
	R&D Expense	104	1.1%	0.8%	0.013	417	1.1%	0.8%	0.012	83	1.2%	0.7%	0.013
	Capital Intensity	239	106.1%	82.1%	0.895	884	109.7%	92.0%	0.639	407	119.4%	76.7%	1.444
	Market Capitalization	231	7,283	1,615	16,809	855	13,904	3,168	29,208	389	2,610	538	7,143
	Tobin's Q	227	1.709	1.505	0.807	836	1.792	1.579	0.881	380	2.051	1.639	1.383
	Debt/Equity	234	79.2%	45.9%	1.596	864	108.5%	64.3%	3.880	406	45.4%	16.8%	1.477
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Consumer durables	*SPI / Avg. Total Assets*	117	1.9%	0.4%	0.061	556	-2.0%	-0.9%	0.040	209			
	SPI / Sales	117	1.5%	0.3%	0.048	556	-1.9%	-0.7%	0.054	209			
	RNOA	117	16.2%	15.4%	0.145	556	11.7%	12.7%	0.144	209	21.5%	19.8%	0.153
	ROA	117	8.9%	8.8%	0.075	556	6.5%	7.2%	0.079	209	12.4%	11.7%	0.086
	ROE	116	19.1%	19.0%	0.157	553	-20.0%	16.8%	8.270	205	27.5%	22.9%	0.436
	Op. Margin	117	7.2%	7.1%	0.061	556	5.0%	5.7%	0.080	209	10.2%	9.3%	0.076
	Sales Growth	117	5.9%	5.2%	0.163	556	4.5%	4.1%	0.169	209	9.1%	7.4%	0.182
	R&D Expense	88	2.9%	2.2%	0.021	459	3.4%	2.8%	0.028	168	3.3%	2.7%	0.034
	Capital Intensity	117	89.1%	83.6%	0.310	556	88.7%	82.3%	0.330	209	89.4%	82.5%	0.332
	Market Capitalization	117	8,367	799	19,029	555	5,662	1,655	11,107	209	4,448	557	9,102
	Tobin's Q	115	1.469	1.353	0.631	518	1.528	1.393	0.687	194	1.924	1.570	1.047
	Debt/Equity	116	59.8%	30.6%	0.877	552	78.6%	41.4%	1.665	205	100.9%	25.9%	3.652
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Manufacturing	*SPI / Avg. Total Assets*	460	1.1%	0.4%	0.022	1,968	-2.2%	-0.9%	0.039	937			
	SPI / Sales	460	1.4%	0.3%	0.039	1,968	-2.4%	-0.9%	0.051	938			
	RNOA	460	17.7%	15.4%	0.148	1,968	11.5%	11.9%	0.160	938	17.6%	14.6%	0.168
	ROA	460	9.9%	9.5%	0.077	1,968	6.3%	7.1%	0.085	937	10.2%	9.6%	0.089
	ROE	457	29.2%	20.9%	1.365	1,928	18.8%	17.2%	1.596	933	16.1%	18.2%	1.000
	Op. Margin	460	8.5%	8.3%	0.081	1,968	5.9%	6.7%	0.100	938	8.0%	8.0%	0.082
	Sales Growth	460	6.7%	6.5%	0.174	1,968	5.1%	4.0%	0.193	937	8.9%	7.0%	0.217
	R&D Expense	305	1.9%	1.2%	0.021	1,486	2.1%	1.4%	0.022	521	2.0%	1.5%	0.020
	Capital Intensity	460	107.1%	92.1%	0.740	1,968	107.8%	99.6%	0.487	938	93.5%	85.2%	0.424
	Market Capitalization	460	4,518	788	10,987	1,963	5,504	1,601	11,569	929	3,788	308	12,032
	Tobin's Q	428	1.607	1.375	0.864	1,808	1.582	1.428	0.727	886	1.618	1.365	0.995
	Debt/Equity	457	92.0%	39.4%	4.227	1,925	141.5%	57.6%	6.846	926	46.4%	27.6%	0.804
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Energy	*SPI / Avg. Total Assets*	161	1.1%	0.4%	0.019	402	-2.2%	-0.5%	0.045	283			
	SPI / Sales	161	2.2%	0.6%	0.052	402	-4.2%	-0.8%	0.090	283			
	RNOA	161	21.1%	18.5%	0.188	402	9.4%	8.6%	0.199	283	17.6%	16.5%	0.202
	ROA	161	12.3%	10.5%	0.103	402	5.3%	5.1%	0.116	283	10.3%	10.9%	0.108
	ROE	160	31.1%	23.5%	0.392	398	10.8%	13.1%	0.341	281	22.1%	22.3%	0.381
	Op. Margin	161	15.4%	14.3%	0.182	402	4.4%	7.3%	0.224	283	13.3%	12.2%	0.184
	Sales Growth	161	12.8%	11.9%	0.306	402	9.2%	9.3%	0.339	282	13.6%	13.8%	0.296
	R&D Expense	57	1.3%	0.3%	0.015	201	1.4%	0.9%	0.016	82	0.7%	0.3%	0.013
	Capital Intensity	161	181.7%	143.0%	1.279	402	201.1%	153.9%	1.498	283	179.8%	143.5%	1.091
	Market Capitalization	161	30,904	5,251	54,481	402	25,322	4,831	45,181	283	36,409	2,860	89,093
	Tobin's Q	155	1.896	1.507	1.588	370	1.507	1.272	0.968	282	1.715	1.580	0.839
	Debt/Equity	160	69.1%	50.3%	0.729	397	76.3%	56.7%	1.187	281	62.2%	40.4%	1.063

Panel B: Industry portfolio **#5, #6, #7 and #8**

		Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Chemicals	*SPI / Avg. Total Assets*	144	1.4%	0.5%	0.024	562	-2.1%	-1.1%	0.034	158			
	SPI / Sales	144	1.5%	0.5%	0.027	562	-2.3%	-1.2%	0.038	158			
	RNOA	144	19.7%	17.9%	0.144	562	16.4%	15.2%	0.161	158	18.6%	17.2%	0.169
	ROA	144	11.1%	10.9%	0.069	562	9.2%	9.5%	0.080	158	11.2%	12.3%	0.099
	ROE	127	34.7%	27.0%	1.437	519	27.5%	23.9%	0.294	158	28.1%	23.0%	0.365
	Op. Margin	144	11.6%	11.5%	0.079	562	9.7%	10.0%	0.096	158	10.5%	12.1%	0.113
	Sales Growth	144	6.1%	8.0%	0.182	562	6.2%	4.7%	0.213	158	7.0%	5.9%	0.161
	R&D Expense	122	2.1%	1.5%	0.023	529	2.3%	2.0%	0.019	115	4.0%	2.0%	0.039
	Capital Intensity	144	120.8%	109.3%	0.660	562	117.6%	109.0%	0.489	158	115.1%	100.3%	0.476
	Market Capitalization	132	12,698	1,879	23,426	504	21,175	4,697	38,395	157	15,200	715	39,350
	Tobin's Q	126	1.770	1.647	0.636	472	1.985	1.761	0.946	154	2.096	1.659	1.442
	Debt/Equity	127	88.2%	66.8%	1.367	519	96.0%	73.3%	0.897	155	60.7%	49.0%	0.896
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Business equipment	*SPI / Avg. Total Assets*	336	1.2%	0.4%	0.023	1,538	-2.6%	-0.9%	0.054	574			
	SPI / Sales	336	1.5%	0.5%	0.032	1,538	-3.4%	-1.1%	0.078	574			
	RNOA	336	20.1%	17.0%	0.182	1,538	10.4%	11.8%	0.213	574	17.6%	16.8%	0.188
	ROA	336	9.3%	8.3%	0.075	1,538	4.8%	6.2%	0.104	574	9.0%	9.3%	0.094
	ROE	335	17.6%	15.8%	0.827	1,519	0.3%	11.9%	4.981	574	16.9%	14.8%	0.296
	Op. Margin	336	11.5%	9.9%	0.106	1,538	6.2%	7.9%	0.151	574	9.5%	9.1%	0.126
	Sales Growth	336	9.1%	7.1%	0.187	1,538	7.9%	5.7%	0.230	574	10.3%	9.3%	0.200
	R&D Expense	297	6.9%	5.5%	0.050	1,319	6.9%	5.9%	0.050	495	6.1%	5.2%	0.045
	Capital Intensity	336	136.3%	124.9%	0.660	1,538	144.9%	130.1%	0.763	574	119.6%	110.8%	0.546
	Market Capitalization	336	12,467	1,251	30,870	1,538	9,831	1,986	26,291	573	3,511	361	12,431
	Tobin's Q	312	1.979	1.679	1.102	1,402	1.922	1.669	1.056	551	2.097	1.754	1.435
	Debt/Equity	335	58.5%	20.6%	1.606	1,517	97.0%	31.5%	9.341	574	80.9%	8.2%	11.609
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Telecom	*SPI / Avg. Total Assets*	127	1.6%	0.3%	0.038	415	-2.5%	-0.9%	0.060	142			
	SPI / Sales	127	3.2%	0.7%	0.075	415	-5.7%	-1.7%	0.145	142			
	RNOA	127	15.5%	13.0%	0.119	415	10.1%	9.6%	0.149	142	13.2%	11.9%	0.128
	ROA	127	9.8%	9.2%	0.063	415	5.9%	6.1%	0.089	142	8.8%	8.4%	0.080
	ROE	117	92.7%	24.6%	5.737	388	40.5%	20.7%	2.639	139	31.4%	22.2%	0.608
	Op. Margin	127	19.4%	18.7%	0.111	415	10.8%	13.2%	0.182	142	15.4%	15.7%	0.138
	Sales Growth	127	7.8%	4.9%	0.343	415	4.6%	1.7%	0.191	142	12.2%	7.2%	0.209
	R&D Expense	28	0.6%	0.2%	0.018	109	1.1%	0.3%	0.022	38	3.9%	0.6%	0.074
	Capital Intensity	127	219.7%	195.1%	0.879	415	216.0%	197.1%	0.860	142	209.3%	187.4%	1.160
	Market Capitalization	126	25,316	6,134	48,841	400	29,915	11,184	45,087	139	18,243	4,962	36,247
	Tobin's Q	126	1.429	1.369	0.527	399	1.402	1.263	0.566	139	1.657	1.434	0.969
	Debt/Equity	116	154.3%	98.3%	1.768	387	342.7%	135.6%	17.639	139	141.6%	74.3%	2.784
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Utilities	*SPI / Avg. Total Assets*	242	0.8%	0.2%	0.021	658	-1.2%	-0.4%	0.033	1,943			
	SPI / Sales	242	2.4%	0.6%	0.061	659	-3.9%	-1.1%	0.101	1,943			
	RNOA	242	11.9%	10.7%	0.102	659	7.3%	7.8%	0.070	1,943	9.9%	9.8%	0.042
	ROA	242	7.0%	6.7%	0.042	658	4.4%	4.9%	0.042	1,943	6.2%	6.0%	0.027
	ROE	242	28.6%	23.0%	0.681	651	31.2%	17.4%	3.328	1,934	22.2%	20.3%	0.183
	Op. Margin	242	20.1%	19.3%	0.158	659	13.5%	14.4%	0.129	1,943	18.1%	16.6%	0.104
	Sales Growth	242	6.3%	4.1%	0.326	658	3.4%	2.0%	0.318	1,943	3.7%	2.8%	0.222
	R&D Expense	0	.	.	.	0	.	.	.	0	.	.	.
	Capital Intensity	242	311.9%	288.5%	1.354	659	320.5%	306.5%	1.290	1,943	305.9%	293.0%	1.257
	Market Capitalization	178	9,053	3,317	13,489	439	12,996	9,439	13,343	619	5,665	2,362	8,606
	Tobin's Q	177	1.200	1.166	0.258	434	1.131	1.109	0.195	618	1.188	1.153	0.200
	Debt/Equity	242	147.2%	112.2%	2.306	649	155.2%	121.9%	2.040	1,930	130.0%	105.1%	1.742

Panel C: Industry portfolio **#9, #10, and #12**

		Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Wholesale	*SPI / Avg. Total Assets*	352	1.0%	0.3%	0.026	1,365	-1.9%	-0.6%	0.043	1,109			
	SPI / Sales	352	0.7%	0.2%	0.020	1,365	-1.3%	-0.4%	0.033	1,109			
	RNOA	352	19.8%	16.7%	0.171	1,365	13.1%	13.4%	0.177	1,109	21.6%	19.5%	0.173
	ROA	352	10.8%	10.0%	0.082	1,365	7.3%	7.9%	0.099	1,109	12.4%	11.5%	0.089
	ROE	343	13.5%	23.8%	3.937	1,288	29.1%	20.0%	1.968	1,087	30.2%	25.1%	0.991
	Op. Margin	352	6.3%	5.2%	0.060	1,365	4.4%	4.0%	0.073	1,109	6.8%	6.0%	0.065
	Sales Growth	352	5.4%	4.5%	0.163	1,364	6.1%	4.8%	0.176	1,109	8.8%	6.7%	0.157
	R&D Expense	220	0.0%	0.0%	0.002	891	0.0%	0.0%	0.002	748	0.0%	0.0%	0.001
	Capital Intensity	352	62.7%	53.7%	0.473	1,365	67.4%	54.3%	0.599	1,109	61.0%	53.5%	0.408
	Market Capitalization	343	8,026	1,154	23,198	1,343	7,767	1,323	24,941	1,079	6,176	794	20,621
	Tobin's Q	313	1.697	1.447	0.914	1,211	1.711	1.457	1.055	1,023	1.997	1.654	1.256
	Debt/Equity	341	110.9%	46.3%	3.072	1,277	123.1%	55.5%	3.777	1,078	97.2%	32.9%	8.206
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Healthcare	*SPI / Avg. Total Assets*	178	1.6%	0.5%	0.030	951	-3.2%	-1.5%	0.054	311			
	SPI / Sales	178	2.2%	0.5%	0.049	951	-5.1%	-2.0%	0.092	311			
	RNOA	178	21.5%	20.4%	0.168	951	13.8%	14.2%	0.204	311	19.5%	17.1%	0.244
	ROA	178	13.1%	13.7%	0.077	951	7.8%	9.1%	0.115	311	10.9%	11.6%	0.121
	ROE	167	33.5%	25.9%	0.422	919	21.9%	18.4%	1.073	307	21.4%	19.9%	0.665
	Op. Margin	178	15.6%	15.8%	0.107	951	10.4%	12.7%	0.171	311	11.6%	12.6%	0.139
	Sales Growth	178	11.2%	8.3%	0.197	951	8.9%	7.0%	0.190	311	10.6%	8.6%	0.163
	R&D Expense	157	4.2%	3.3%	0.039	855	5.2%	4.2%	0.045	288	4.6%	3.1%	0.048
	Capital Intensity	178	130.0%	119.9%	0.560	951	158.6%	136.9%	0.827	311	113.4%	102.0%	0.533
	Market Capitalization	178	17,144	1,504	40,788	948	26,427	3,475	52,136	310	5,768	299	22,037
	Tobin's Q	170	2.334	2.060	1.187	893	2.329	1.990	1.400	309	2.668	2.008	1.928
	Debt/Equity	166	99.0%	29.8%	2.593	915	116.3%	47.5%	5.340	304	29.6%	9.5%	0.460
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Other	*SPI / Avg. Total Assets*	567	1.1%	0.4%	0.024	1,578	-2.0%	-0.6%	0.045	1,095			
	SPI / Sales	567	1.7%	0.5%	0.047	1,578	-2.5%	-0.9%	0.052	1,095			
	RNOA	567	14.8%	12.6%	0.179	1,578	9.8%	9.9%	0.175	1,095	18.7%	15.1%	0.190
	ROA	567	8.1%	7.9%	0.084	1,578	5.5%	6.1%	0.098	1,095	9.9%	9.1%	0.084
	ROE	552	25.5%	19.5%	0.640	1,540	22.6%	16.3%	0.977	1,088	22.1%	20.0%	0.221
	Op. Margin	567	11.9%	10.7%	0.134	1,578	7.9%	7.7%	0.139	1,095	11.4%	9.7%	0.115
	Sales Growth	567	8.0%	6.6%	0.221	1,578	7.5%	5.5%	0.215	1,095	11.5%	8.7%	0.273
	R&D Expense	125	1.3%	0.1%	0.025	317	0.9%	0.0%	0.018	165	1.2%	0.0%	0.029
	Capital Intensity	567	177.0%	142.7%	1.410	1,578	166.6%	140.4%	1.224	1,095	160.9%	105.8%	1.596
	Market Capitalization	544	9,691	1,342	30,030	1,531	8,469	1,788	25,749	1,031	9,519	881	40,946
	Tobin's Q	534	1.518	1.307	0.760	1,488	1.562	1.348	0.855	1,002	1.865	1.504	1.145
	Debt/Equity	547	122.3%	65.4%	2.459	1,537	174.9%	70.6%	4.846	1,085	83.4%	37.3%	1.853

Variable definitions:

SPI / Avg. Total Assets = ratio of COMPUSTAT data items SPECIAL ITEMS (#17) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

RNOA = ratio of NET OPERATING INCOME (NOI) from period t and average of NET OPERATING ASSETS (NOA) across period t and t-1 (as defined in Table 1).

ROA = ratio of NET OPERATING INCOME (NOI) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

ROE = ratio of NET OPERATING INCOME (NOI) from period t and average of COMMON EQUITY (#60) across period t and t-1 (negative obsv. excluded).

Op. Margin = ratio of NET OPERATING INCOME (NOI) from period t and REVENUES (#12) from period t.

Sales Growth = growth in REVENUES (#12) between period t and t-1.

R&D Expense = ratio of COMPUSTAT data items R&D EXPENSE (#46) from period t and average of TOTAL ASSETS (#6) across period t and t-1.

Capital Intensity = ratio of COMPUSTAT data items TOTAL ASSETS (#6) from period t and REVENUES (#12) from period t.

Market Capitalization = product of COMPUSTAT data items CLOSING STOCK PRICE (#24) and COMMON SHARES OUTSTANDING (#25).

Tobin's Q = ratio of (TOTAL ASSETS (#6) + MARKET CAPITALIZATION - COMMON EQUITY (#60) - DEFERRED TAXES (#74)) and average of TOTAL ASSETS (#6) across period t and t-1 - in line with Johnson, et al. (2011).

Debt/Equity = ratio of COMPUSTAT data items (LONG-TERM DEBT (#9) + CURRENT DEBT (#34)) and COMMON EQUITY (#60).

Figure 6: Positive, negative, total special items deflated with assets **– total sample**

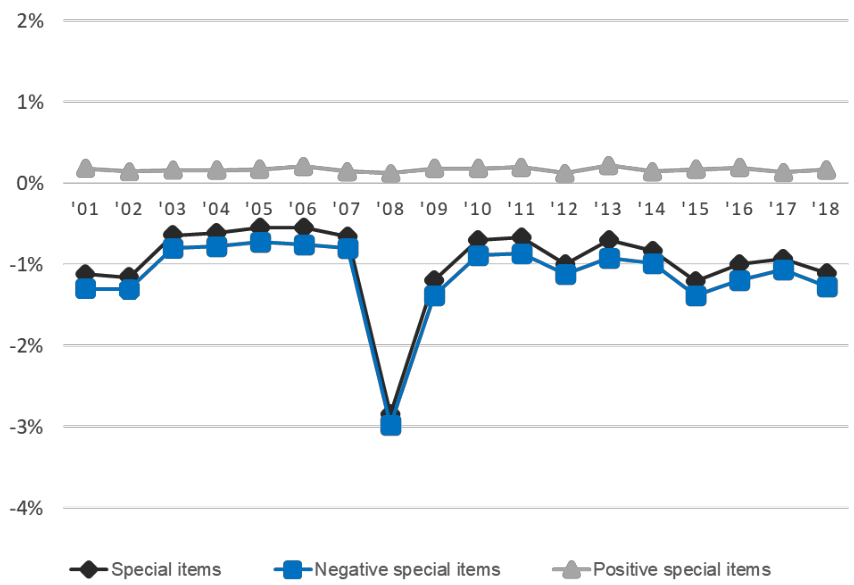

Figure 6 displays the magnitude of positive, negative, and total special items in relation to total assets. Since the results are very similar to the one in **Figure 4**, section 4.3 focuses only on special items deflated with sales.

Table 23: Regression model **– by industry; industries with insignificant one-time items (N = 20,970)**

Manufacturing

Nbr. of years in earnings window	α	Core PMwt	Negative special PMwt	Positive special PMwt	R2
1	-0.008	0.600***	0.200***	-0.152	0.31
	(0.008)	(0.044)	(0.052)	(0.460)	
2	0.023***	0.637***	0.114*	0.325	0.331
	(0.005)	(0.034)	(0.063)	(0.318)	
3	0.046***	0.626***	0.009	0.107	0.311
	(0.005)	(0.031)	(0.068)	(0.254)	
4	0.037***	0.652***	-0.135*	0.114	0.33
	(0.005)	(0.033)	(0.069)	(0.167)	
5	0.024***	0.658***	-0.184***	0.024	0.355
	(0.005)	(0.036)	(0.071)	(0.133)	

Chemicals

Nbr. of years in earnings window	α	Core PMwt	Negative special PMwt	Positive special PMwt	R2
1	0.028**	0.593***	0.230**	-0.15	0.356
	(0.013)	(0.091)	(0.096)	(0.156)	
2	0.017***	0.792***	0.126	0.026	0.553
	(0.006)	(0.039)	(0.084)	(0.412)	
3	0.021***	0.830***	0.119	0.197	0.594
	(0.008)	(0.037)	(0.118)	(0.421)	
4	0.021**	0.855***	0.267**	-0.444	0.611
	(0.009)	(0.041)	(0.120)	(0.336)	
5	0.021**	0.882***	0.320**	-0.634	0.619
	(0.010)	(0.054)	(0.129)	(0.392)	

Business Equipment

Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.045***	0.773***	0.147**	0.211	0.478
	(0.015)	(0.038)	(0.066)	(0.142)	
2	0.058***	0.709***	0.009	0.319	0.414
	(0.008)	(0.032)	(0.072)	(0.307)	
3	0.056***	0.740***	-0.090*	0.397	0.406
	(0.007)	(0.028)	(0.048)	(0.367)	
4	0.013	0.771***	-0.109**	0.643*	0.435
	(0.008)	(0.027)	(0.054)	(0.363)	
5	0.003	0.769***	-0.104*	0.848**	0.482
	(0.007)	(0.024)	(0.057)	(0.382)	

Telecom

Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	0.006	0.421***	0.234***	0.204	0.167
	(0.045)	(0.072)	(0.072)	(0.234)	
2	0.095***	0.567***	0.065	0.123	0.209
	(0.023)	(0.054)	(0.058)	(0.124)	
3	0.064***	0.592***	0.139*	0.107	0.233
	(0.021)	(0.051)	(0.078)	(0.126)	
4	0.039*	0.569***	0.091	0.409	0.225
	(0.021)	(0.056)	(0.082)	(0.318)	
5	0.044**	0.512***	-0.008	0.802	0.218
	(0.019)	(0.059)	(0.074)	(0.596)	

Wholesale

Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	0.007	0.799***	0.162**	0.068	0.551
	(0.007)	(0.035)	(0.063)	(0.089)	
2	0.017***	0.843***	0.062	0.215*	0.637
	(0.003)	(0.022)	(0.078)	(0.115)	
3	0.016***	0.854***	0.015	0.288*	0.645
	(0.003)	(0.018)	(0.071)	(0.166)	
4	0.006*	0.858***	-0.013	0.255	0.643
	(0.003)	(0.020)	(0.075)	(0.267)	
5	0.002	0.867***	-0.042	0.441	0.649
	(0.003)	(0.022)	(0.099)	(0.389)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 1. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

My evidence suggests that for each industry portfolio either one-time revenues or one-time expenses or neither of them are significant. Regression outputs for industries where one-time items are insignificant are reported above. Please notice that some of the coefficients of negative special PM^w_t and positive special PM^w_t are significant, but the results do not suggest predictable patterns.

Table 24: Results from Chow tests

	Regression 1 y	Regression 1 x	vs		Regression 2 y	Regression 2 x	F_t
(1a)	*2002*	*2001*		*(2a)*	*2003*	*2002*	20.80
(2a)	*2003*	*2002*		*(3a)*	*2004*	*2003*	3.21
(3a)	*2004*	*2003*		*(4a)*	*2005*	*2004*	1.25
(4a)	*2005*	*2004*		*(5a)*	*2006*	*2005*	0.96
(5a)	*2006*	*2005*		*(6a)*	*2007*	*2006*	0.59
(6a)	*2007*	*2006*		*(7a)*	*2008*	*2007*	14.08
(7a)	*2008*	*2007*		*(8a)*	*2009*	*2008*	4.57
(8a)	*2009*	*2008*		*(9a)*	*2010*	*2009*	25.14
(9a)	*2010*	*2009*		*(10a)*	*2011*	*2010*	10.49
(10a)	*2011*	*2010*		*(11a)*	*2012*	*2011*	4.26
(11a)	*2012*	*2011*		*(12a)*	*2013*	*2012*	3.27
(12a)	*2013*	*2012*		*(13a)*	*2014*	*2013*	3.05
(13a)	*2014*	*2013*		*(14a)*	*2015*	*2014*	4.69
(14a)	*2015*	*2014*		*(15a)*	*2016*	*2015*	3.19
(15a)	*2016*	*2015*		*(16a)*	*2017*	*2016*	3.10
(16a)	*2017*	*2016*		*(17a)*	*2018*	*2017*	1.96
					critical value:		2.38

For my regression by time, I run the basic regression model for each year of my observation period (i.e. from 2001 to 2018) separately (section 5.5):

$$PM_{2002} = \alpha_{2001,0} + \beta_{2001,1} * core\ PM_{2001} + \beta_{2001,2} * negative\ special\ PM_{2001} + \beta_{2001,3} * positive\ special\ PM_{2001} + \varepsilon_{2002} \quad (1a)$$

$$PM_{2003} = \alpha_{2002,0} + \beta_{2002,1} * core\ PM_{2002} + \beta_{2002,2} * negative\ special\ PM_{2002} + \beta_{2002,3} * positive\ special\ PM_{2002} + \varepsilon_{2003} \quad (2a)$$

…

$$PM_{2018} = \alpha_{2017,0} + \beta_{2017,1} * core\ PM_{2017} + \beta_{2017,2} * negative\ special\ PM_{2017} + \beta_{2017,3} * positive\ special\ PM_{2017} + \varepsilon_{2018} \quad (17a)$$

This leaves me with 17 regressions. Each regression gives me one coefficient per year for all my explanatory variable. I use Chow tests (Chow, 1960) to understand whether there are structural breaks between each regression (i.e. (1a) vs. (2a), …, (16a) vs. (17a)). Chow examines whether the coefficients of two linear regressions on different sets are equal. For instance, Chow tests whether coefficients $\alpha_{2001,0}$, $\beta_{2001,1}$, $\beta_{2001,2}$ and $\beta_{2001,3}$ (from regression model (1a), i.e. when regressing decomposed profit margin from year 2001 on profit margin of 2002) are equal to $\alpha_{2002,0}$, $\beta_{2002,1}$, $\beta_{2002,2}$ and $\beta_{2002,3}$ (from regression model (2a), i.e. when regressing decomposed profit margin from year 2002 on profit margin of 2003).

H_0: $\alpha_{2001,0} = \alpha_{2002,0}$ and $\beta_{2001,1} = \beta_{2002,1}$ and $\beta_{2001,2} = \beta_{2002,2}$ and $\beta_{2001,3} = \beta_{2002,3}$ **(no structural break)**

H_1: $\alpha_{2001,0} \neq \alpha_{2002,0}$ or $\beta_{2001,1} \neq \beta_{2002,1}$ or $\beta_{2001,2} \neq \beta_{2002,2}$ or $\beta_{2001,3} \neq \beta_{2002,3}$ **(structural break)**

If the null hypothesis cannot be rejected, this implies that there is no structural break between regression model (1a) and (2a), i.e. differences in coefficients of these two models are not statistically significant, but instead they are caused by distribution differences. In contrast, if the null hypothesis is rejected, differences in coefficients imply that the correlations have changed significantly. The null hypothesis can be rejected if the F-value exceeds the critical value. In **Table 24** all F-values exceeding the critical value are marked in green.

Table 25: Adjusted sample selection criteria **– robustness test**

Sample selection criteria	Total observations	Total firms
2001-2018 Annual Industrial Compustat (active firms)	105,859	9,850
Firms in financial services (SIC 6000s)	(38,544)	(3,817)
Firms outside of Europe or North America	(7,437)	(788)
NOA < $1m or Sales < $1m	(14,547)	(1,245)
Absolute value of RNOA or PM > 2; or CORE PM or SPECIAL PM > 4	(3,049)	(319)
Firms without 10 years consecutive data	(6,475)	(1,506)
Final sample	**35,807**	**2,175**

One-time items: Impact of firm life cycle

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Abstract:

My paper suggests that investors can leverage corporate life cycle theory to enhance their understanding of one-time items, helping them to decide whether those items shall be considered or neglected. One-time revenues are only associated with future performance for longer earnings windows in *mature* firms. One-time expenses, on the other hand, should primarily be considered for *growth* and *mature* businesses, as there is a significant, positive association to future performance for those two life cycle stages. For *shake-out* enterprises, there appears to be a weak correlation with future earnings in the short-term as well, but this might potentially be a consequence of earnings management. For *introduction* and *decline* firms, one-time expenses can be neglected. Extending my analysis by breaking down one-time items into their components, my research indicates deteriorating future performance of *introduction* firms following PP&E write-offs, while *growth* firms benefit from in-process R&D and M&A-related gains / losses. *Shake-out* firms have a higher chance of revival by focusing on in-process R&D and extinguishment of existing debt. *Decline* businesses can boost future performance by engaging in M&A activity, whereby this result needs to be taken with caution as the sample for declining firms reporting M&A related gains / losses is very small. Finally, my results suggest that goodwill impairment is the only one-time sub-item which shows a significant association to future profit margin in all five life cycle stages, while restructurings only create sustainable value for *mature* firms.

Keywords: Special items, One-time items, Firm life cycle, Earnings forecasts, Earnings persistence, Profit margins

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1 Introduction

Corporate life cycle theory suggests that businesses move in the course of their life through several cycles. Over the past decades, this theory has enjoyed successful applications to various different fields. Nagar & Sen (2017), for instance, suggest that corporate life cycle theory can be leveraged to help improving our understanding of special items. Special items – hereafter referred to as special items or one-time items – are, according to Accounting Principles Board (APB) Opinion No. 30, items that are unusual or infrequent but not both (FASB, 1973). One-time items are renowned to be one of the main reasons for the observed deteriorating earnings quality by many researchers (e.g. Dechow & Schrand, 2004), making it difficult for analysts and investors to predict future performances of their target companies. If we can use corporate life cycle theory to counteract or maybe even solve this issue, analysts and investors can significantly improve their investment decisions. Thus, this paper extends existing research by investigating whether investors and analysts can use firm life cycle theory to improve forecasts of future performance of their target companies. In particular, I examine whether special items should be included or excluded when projecting future profit margin for the respective life cycle stages.

One-time items are currently an important topic, as they tend to peak in frequency and magnitude during economic downturns (e.g. Johnson et al., 2011), i.e. it is reasonable to expect that they will become more prevalent in coming years as a direct consequence of the COVID-19 pandemic. So far, best practice by most investors and analysts is to categorically exclude one-time items and to base their forecasts on core earnings – in fact, research shows that the most significant pro-forma adjustments include special items and amortization (e.g. Ciesielski & Henry 2017). Taking a look at some of the most common one-time sub items, I have reasons to believe that their importance may vary by firm life cycle stage. For instance, Koh et al. (2015) find evidence supporting that restructuring strategies are influenced by corporate lifecycle. Assuming this implies disparity in the effectiveness of the respective restructuring strategies, it would be sound to infer the hypothesis that one-time items should be treated differently by investors, depending on the target life cycle stage. Hence, if investors decide to categorically exclude special items for all companies, this may imply a loss of information in some cases. Since special items are in most cases negative, adjusting for them will lead to a core earnings figure exceeding the actual GAAP figure. This means that excluding negative one-time charges may cause overvaluations, i.e. investors face the risk of seizing investments they should not. My paper is primarily aimed at investors, hopefully improving their investment decisions. It needs to be emphasized, however, that they should not trust blindly my results without questioning whether they are applicable to their specific investment opportunities.

To understand whether special items are relevant or whether investors should solely focus on core earnings for their forecasts, I regress for each life cycle stage lagged core profit margin, lagged negative and positive special profit margin on future profit margin over increasing time windows from one to five years (section 4.1). This approach is a replication of the one used by Fairfield et al. (2009) and is very intuitive, as it can be interpreted as the predictive content past core earnings and past one-time items provide for future earnings. In a next step, I examine whether the relevance of certain one-time sub-items varies by life cycle stage. Thus, I modify my regression model in the sense that I break down positive and negative special items into its components, i.e. I regress lagged core profit margin and lagged one-time sub-items on future profit margin for each life cycle stage separately (section 4.2).

In the next chapter, I discuss background literature on firm life cycle theory, earnings persistence, and special items. Subsequently, section 3 provides a discussion of the regression model and sample used for my empirical analysis, followed by a descriptive analysis of my sample. Section 4 reports my regression results, while section 5 discusses potential robustness issues. Finally, section 6 concludes.

2 Literature review

2.1 Firm life cycle theory

Dickinson (2011) defines firm life cycle stages as follows:

> Business firms are evolving entities, with the path of evolution determined by internal factors (e.g., strategy choice, financial resources, and managerial ability) and external factors (e.g., competitive environment and macroeconomic factors). Firm life cycles are distinct phases that result from changes in these factors, many of which arise from strategic activities undertaken by the firm. (p. 1969)

The corporate life cycle model consists of five stages: *introduction / birth*, *growth*, *maturity*, *shake-out / revival* and *decline* (e.g. Gort & Klepper, 1982; Dickinson, 2011). Miller & Friesen (1984) suggest that each stage lasts, on average, for six years, whereby business entities can move through the life cycle stages in a non-sequential manner, meaning that they can transition back and forth. Each stage is distinct and provides a corporate with unique organizational characteristics, challenges, and opportunities. During the *introduction* phase, corporates are young, have informal structures and are usually controlled by their owners (Miller & Friesen, 1984). Enterprises in this stage do not yet have an established customer base and still need to invest in growth, which they usually have to finance with debt (Dickinson, 2011). Consequently, the value of the firms in the *introduction* phase is based on their growth opportunities (Black, 1998), however, there is significant uncertainty with regards to this growth (Koh et al., 2015). Once firms transition to the *growth* phase, a separation between control and ownership emerges (Miller & Friesen, 1984). Enterprises in the *growth* stage are medium-sized, experience an increasing organizational complexity (Mueller, 1972), show a strong sales growth (Black, 1998) and continue to invest in growth, whereby those investments are still to a large extent financed with debt (Dickinson, 2011). Corporates in the *mature* life cycle stage operate in a well-defined market (Miller & Friesen, 1984), have a strong asset base, and maximized profitability (Black, 1998). They are less likely to take on innovations (Koh et al., 2015) and have exhausted positive net present value opportunities, which is why they usually have a negative cash flow from financing, despite of having minimum cost of capital and uncertainty (Dickinson, 2011). Firms in the *shake-out* stage are typically large firms with organizational complexities and inefficiencies, causing profitability declines (Mueller, 1972). As a consequence, they require more advanced control and planning systems (Miller & Friesen, 1984). Potential opportunities for business entities in this phase provide liquidation of assets (Dickinson, 2011), such as divestitures, and investments in new technologies (Black, 1998). Finally, corporates in the *decline* stage experience deteriorating growth rates, resulting in price cuts (Miller & Friesen, 1984) and eventually also in low earnings, low profitability (Black, 1998) and negative cash flow from operations (Dickinson, 2011). To support their operations and repay existing debt, *declining* firms can usually only liquidate their assets (Dickinson, 2011), i.e. they face a high probability of liquidation (Black, 1998).

Despite of the fact that research agrees on the view that businesses are evolving entities, there are a number of different approaches to determine life cycle stages. In the following, I will discuss three of the most prevalent methods and possible weaknesses of the respective approaches. Miller & Friesen (1984) allocate a pre-selected sample of 36 corporations into life cycle stages based on 54 variables relating to the strategy, situation, structure, and decision-making style of the respective firm. This strategy is difficult to implement, due to the tremendous amount of data one would have to gather for large samples. Anthony & Ramesh (1992) determine life cycle stages for their sample companies, using the following four life cycle descriptors: dividends, sales growth, capital expenditures and firm age. While this method is easier to apply than the one proposed by Miller & Friesen (1984), Dickinson (2011) criticizes the approach by Anthony & Ramesh (1992), as it assumes a uniform distribution of observations across life cycle phases. Thus, Dickinson (2011) suggests a model, which is free from distributional assumptions. In particular, Dickinson (2011) uses cash flow proxies to ascertain life cycle stages, meaning she sorts her sample into life cycle stages, based on the sign of cash flow from operating, investing and financing activities. One concern with respect to Dickinson's approach is that some firms may have relatively volatile life cycle patterns. Yan & Zhao (2010) illustrate that Apple

Computer Inc. experiences eleven changes in life cycle stages between 1989 and 2005 if one applies Dickinson’s cash flow proxies.

2.2 Life cycle theory, earnings persistence, and one-time items

Corporate life cycle theory has been applied to various different fields in the past. The earliest proponent, Dennis Mueller, uses life cycle theory in the context of corporate motivation. In particular, Mueller (1972) employs life cycle theory as possible explanation why managers use growth maximization instead of profit maximization policy. Later research applied firm life cycle theory, for instance, to the disciplines of management (Miller & Friesen, 1984), dividend policy (DeAngelo et al., 2006), and diversification (Arikan & Stulz, 2016).

Furthermore, literature suggests that life cycle theory can be exploited to improve forecast accuracy of profitability (e.g. Vorst & John, 2018) and earnings (e.g. Drake, 2013). This is a highly relevant finding, as research observes a deteriorating earnings quality, implying that earnings nowadays are less persistent and a less suitable figure for predicting future earnings than they have been in the past (e.g. Dechow & Schrand, 2004). There are at least three reasons why it may be beneficial for investors and analysts to consider firm life cycle stages in their forecast models. First, Vorst & John (2018) suggest that firm life cycle stages are a superior variable for estimating mean reversion. Since profitability and growth exhibit mean reversion (e.g. Fama & French, 2000), Vorst & John (2018) show that firm life cycle models outperform industry-specific and economy-wide forecast models when projecting profitability and growth. This is in line with the evidence by Dickinson (2011), which suggests that mean reversion of profitability differs across corporate life cycle stages. Second, Drake (2013) finds evidence suggesting that the association between large book-tax differences and low earnings persistence (Hanlon, 2005) can be explained using corporate life cycle theory. In other words, if the variation in earnings persistence can be traced back to life cycle theory, then analysts and investors can use this information to improve their earnings forecasts. Finally, third, Nagar & Sen (2017) suggest that the opportunistic usage of one-time items is correlated with life cycle stages. In particular, they show for an Indian sample that firms in the *declining* life cycle stage are more likely to opportunistically exploit one-time items to avoid reporting of operating losses. Since most analysts and investors exclude one-time items (Bradshaw & Sloan, 2002), being aware of the findings by Nagar & Sen (2017) can enhance their earnings forecasts.

Research views one-time items as one of the main reasons for the previously mentioned observed deterioration of earnings quality (e.g. Dechow & Schrand, 2004). Thus, this topic deserves additional attention. Special items are, according to Accounting Principles Board (APB) Opinion No. 30, items that are unusual or infrequent but not both (FASB, 1973). Consistently with that, research which dates back in time finds that one-time items are transitory (e.g. Fairfield et al., 1996). Analysts and investors, therefore, usually exclude one-time items when computing core earnings, non-GAAP figures and pro-forma financials (e.g. Bradshaw & Sloan, 2002). However, in contrast with the APB definition, recent special items literature finds an increasing importance of one-time items (e.g. Johnson et al., 2011), reflected in an increasing frequency, but also in a stable, slightly increasing magnitude of those items. “Special items are so prevalent now that they're not special anymore” (Fowler, 2006), making researchers wonder whether one-time items are truly transitory. Researchers who believe that special items capture useful information for future performance postulate two possible hypotheses. First, one-time items affect future earnings, because they signal future performance improvement or decline (real performance hypothesis). Second, one-time items could be relevant for future performance, because managers exploit them opportunistically to manage the earnings of their firms. Special items literature suggests two possible ways how companies can manage their earnings using one-time items. On the one hand, managers can transfer expenses or revenues from other periods into current period special items (e.g. Pierk, 2020). When managers use such an inter-period transfer, there will be a one-to-one earnings change from the opposite sign in a future period. Second, companies may engage in classification shifting to manage their earnings, meaning they misclassify current core expenses or revenues as one-time revenues or expenses (e.g. McVay, 2006). As previously mentioned, the findings of Nagar & Sen (2017) support the earnings management hypothesis for corporates in the *declining* life cycle stage.

Prior research did – to the best of my knowledge – not investigate the real performance hypothesis by firm life cycle. Breaking down one-time items into its components, there is a good chance that life cycle theory can help improving our understanding of special items. In fact, research suggests that two common one-time sub-items, restructuring charges and in-process R&D expenses, are influenced by corporate life cycle. As a consequence, it would be sound to infer the hypothesis that one-time items and one-time sub-items should be treated differently by investors, depending on the life cycle stage of the target. Using Sudarsanam and Lai's (2001) breakdown of restructuring strategies into managerial, operational, asset and financial restructuring, Koh et al. (2015) find that the choice of restructuring strategies by enterprises facing distress depends on the life cycle stage. For instance, corporates in the *introduction* stage are less likely to engage in managerial restructuring, as the owners of those firms usually manage those firms. Yoo et al. (2019) suggest that there is a higher likelihood for *mature* firms that R&D expenditures are positively associated with future performance. My paper investigates for each life cycle stage the association between past one-time items (section 4.1), past one-time sub-items (section 4.2) and future profit margin to get a better understanding of how corporate life cycle theory affects the importance of special items and its components.

3 Research design and descriptive statistics

3.1 Research model and variable definition

My empirical analysis aims to investigate whether the usefulness of one-time items for earnings forecasts varies by life cycle stages. In the following, I will first explain how I determine life cycle stages of my sample companies, followed by a discussion of the empirical model used to examine the relevance of special items for future performance.

There are several ways to allocate a sample into firm life cycle stages. In this paper, I decided to adopt cash flow proxies as proposed by Dickinson (2011). Namely, I determine the life cycle stage of my sample firms by using the signs of their cash flow from operating, investing, and financing activities (please refer to **Table 1**). This approach is employed separately for each year of my observation period to allow for temporary life cycle shifts.

Table 1: Cash flow proxies pursuant to Dickinson (2011)

	Life cycle stages							
Cash flow:	Birth	Growth	Mature	Revival	Revival	Revival	Decline	Decline
Operating activities	-	+	+	-	+	+	-	-
Investing activities	-	-	-	-	+	+	+	+
Financing activities	+	+	-	-	+	-	+	-

Dickinson's (2011) approach has several advantages compared to other life cycle measures. Cash flow life cycle proxies are free from distributional assumptions. Besides of that, the required information is readily available to investors and can be determined in an objective way, meaning that investors can easily apply cash flow proxies in a reliable way. Furthermore, it is useful to investigate one-time items from a cash flow perspective, as Johnson et al. (2011) find evidence showing that cash flow from operations are affected by special items. It needs to be pointed out, however, that the cash flow proxies by Dickinson (2011) also give rise to disadvantages – those issues are addressed in section 5.1.

To understand whether the relevance of one-time items for earnings forecasts varies by life cycle stage, I replicate the model used by Fairfield et al. (2009). They regress lagged decomposed profit margin – consisting of core profit margin, positive and negative special profit margin – on future profit margin over increasing time windows from one to five years. This approach is very intuitive, because the regression result can be interpreted as the predictive content past core earnings and past one-time items provide for future earnings. The regression is estimated over increasing windows because special items appear irregular, i.e. by computing smoothed averages over longer time periods I counteract this issue. There is no overlap between the time windows of the dependent and independent variables. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. Extending the time window to its maximum of w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Consequently, we require at least 10 years of consecutive data for w = 5 (**Table 10** in the Appendix shows a list of the years included in the one- and five-year windows).

Consistently with Fairfield et al. (2009), my model looks as follows:

$$PM_{t+1}^{w} = \sum_{j=1}^{5} \alpha_{0,0} + \sum_{j=1}^{5} \beta_{0,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{0,2}^{w} * negative\ special\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{0,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{0,4}^{i} * YEAR_{i} + \varepsilon_{t+1} \quad (1)$$

All the variables are derived from the Annual Industrial COMPUSTAT database between 2001 and 2018. Moreover, all variables are summarized and defined in **Table 2** as well as described below. The dependent variable PM^{w}_{t+1} is profit margin in period t+1, which is defined as net operating income (NOI) in t+1 divided by sales in t+1. Net operating income (NOI) is computed back-of-the-envelope as net income (#172) before extraordinary items and discontinued operations (#48), non-controlling interest income (#49), taxes (#16), non-operating income (#61), and interest income (#62) / expense (#15). In line with Fairfield et al. (2009), I exclude taxes, as I do not have any information on the tax deductibility of special items. Interest income and expenses are not considered, because otherwise capital structure changes might distort my analysis. Furthermore, I have chosen to compute NOI back-of-the-envelope, as this was the only way to make sure that my dependent variable reflects operating income including special items. In other words, if I had taken an operating income figure by COMPUSTAT instead, there would be the risk that COMPUSTAT already excluded some / all one-time items. This would be an issue, as my dependent variables decompose profit margin into lagged core profit margin (core PM^{w}_{t}), lagged negative special profit margin (negative special PM^{w}_{t}) and lagged positive special profit margin (positive special PM^w_t). Lagged core profit margin is defined as NOI minus special items in period t deflated with sales. Consequently, if my NOI did not include one-time items, my core profit margin would deduct special items twice. Lagged negative and positive special profit margin are derived by dividing negative / positive special items through sales in t. Since a company can only report negative or positive net special items (= sum of all one-time items), negative and positive special profit margin can never be ≠ 0 at the same time. As previously discussed, all variables are indexed with a superscripted w, implying the model will be estimated for time windows from one to five years.

As mentioned in section 2.2, I have reason to believe that one-time sub-items may have different implications for future performance depending on corporate life cycle stage. Thus, I examine in a next step how one-time sub-items are associated with future profit margin in the respective life cycle stage cohorts. COMPUSTAT provides a break-down of one-time items into the following sub-items: Acquisition/Merger Pretax (#360), Gain/Loss Pretax (#364), Impairment of Goodwill Pretax (#368), Settlement (Litigation/Insurance) Pretax (#372), Restructuring costs Pretax (#376), Writedowns Pretax (#380), Other Special Items Pretax (#384), In-process R&D pretax (#388) and Extinguishment of Debt Pretax (#406). I modify my basic regression model (1) in the sense that I replace negative special PM^w_t and positive special PM^w_t with all one-time sub-items deflated with sales, leaving me with the following regression model:

$$\begin{aligned} PM^w_{t+1} = {} & \textstyle\sum_{j=1}^{5} \alpha_{1,0} + \sum_{j=1}^{5} \beta^w_{1,1} * core\ PM^w_t + \sum_{j=1}^{5} \beta^w_{1,2} * in-process\ R\&D^w_t \\ & + \textstyle\sum_{j=1}^{5} \beta^w_{1,3} * restructuring^w_t + \sum_{j=1}^{5} \beta^w_{1,4} * gain\ loss^w_t \\ & + \textstyle\sum_{j=1}^{5} \beta^w_{1,5} * litigation^w_t + \sum_{j=1}^{5} \beta^w_{1,6} * other\ SPI^w_t + \sum_{j=1}^{5} \beta^w_{1,7} * M\&A^w_t \\ & + \textstyle\sum_{j=1}^{5} \beta^w_{1,8} * goodwill^w_t + \sum_{j=1}^{5} \beta^w_{1,9} * writedown^w_t \\ & + \textstyle\sum_{j=1}^{5} \beta^w_{1,10} * extinguish\ debt^w_t + \sum_{i=1}^{10} \beta^i_{1,11} * YEAR_i + \varepsilon_{t+1} \qquad (2) \end{aligned}$$

Table 2: Key variable definitions

Variable	Definition / Computation
Variables for basic regression (section 4.1)	
Net operating income (NOI $_t$)	Net income (#172) + Extraordinary items & discontinued operations (#48) + Non-controlling interest income (#49) + Income taxes (#16) - Non-operating income / expense (#61) - Interest and related income (#62) + Interest and related expense (#15)
Special items $_t$	COMPUSTAT data item #17
Core earnings $_t$	NOI_t - Special $items_t$
Negative special items $_t$	Special $items_t$, assuming value is negative
Positive special items $_t$	Special $items_t$, assuming value is positive
Profit margin (PM $_t$)	NOI_t / $Revenue_t$
Core profit margin (core PM $_t$)	Core $earnings_t$ / $Revenue_t$
Neg. special PM	Negative special $items_t$ / $Revenue_t$
Pos. special PM	Positive special $items_t$ / $Revenue_t$
Additional variables for regression by sub-items (section 4.2)	
In-process R&D $_t$	In-process R&D pretax (#388) / $Revenue_t$
Restructuring $_t$	Restructuring costs Pretax (#376) / $Revenue_t$
Gain loss $_t$	Gain/Loss Pretax (#364) / $Revenue_t$
Litigation $_t$	Settlement (Litigation/Insurance) Pretax (#372) / $Revenue_t$
Other special items $_t$	Other Special Items Pretax (#384) / $Revenue_t$
M&A gain / loss $_t$	Acquisition/Merger Pretax (#360) / $Revenue_t$
Goodwill impairment $_t$	Impairment of Goodwill Pretax (#368) / $Revenue_t$
Write-down $_t$	Writedowns Pretax (#380) / $Revenue_t$
Extinguish debt $_t$	Extinguishment of Debt Pretax (#406) / $Revenue_t$

3.2 Sample selection

Bradshaw & Sloan (2002) show that the COMPUSTAT data item “special items” (item #17) is strongly correlated with the adjustments conducted by analysts when they try to compound a core earnings figure. Thus, COMPUSTAT is a suitable database for my research. I rely on the Annual Industrial COMPUSTAT (“North America – Daily”) database from 2001 to 2018. Besides of that, I deliberately have chosen this time period, as COMPUSTAT provides a break-down into one-time sub items from 2001 onwards, which is crucial for my regression analysis by sub-items (section 4.2). Given that this observation period captures two global crises – the dot-com bubble burst (2002 / 2003) and the global financial crisis (2007 / 2008) –, it needs to be mentioned, however, that conclusions and implications from my research may be distorted.

Table 3 summarizes my sample selection criteria. These criteria are very similar to the ones applied by Fairfield et al. (2009) and the ones applied in part 1 of my thesis, in order to ensure consistency and comparability.

Table 3: Sample selection criteria

Sample selection criteria	Total observations	Total firms
2001-2018 Annual Industrial Compustat (active firms)	105,475	9,833
Firms in financial services (SIC 6000s)	(38,419)	(3,791)
Firms outside of Europe or North America	(7,407)	(792)
NOA < $5m or Sales < $5m	(17,414)	(1,598)
Absolute value of RNOA or PM > 1; or CORE PM or SPECIAL PM > 2	(3,358)	(250)
Firms without 10 years consecutive data	(7,375)	(1,508)
Final sample	**31,502**	**1,894**

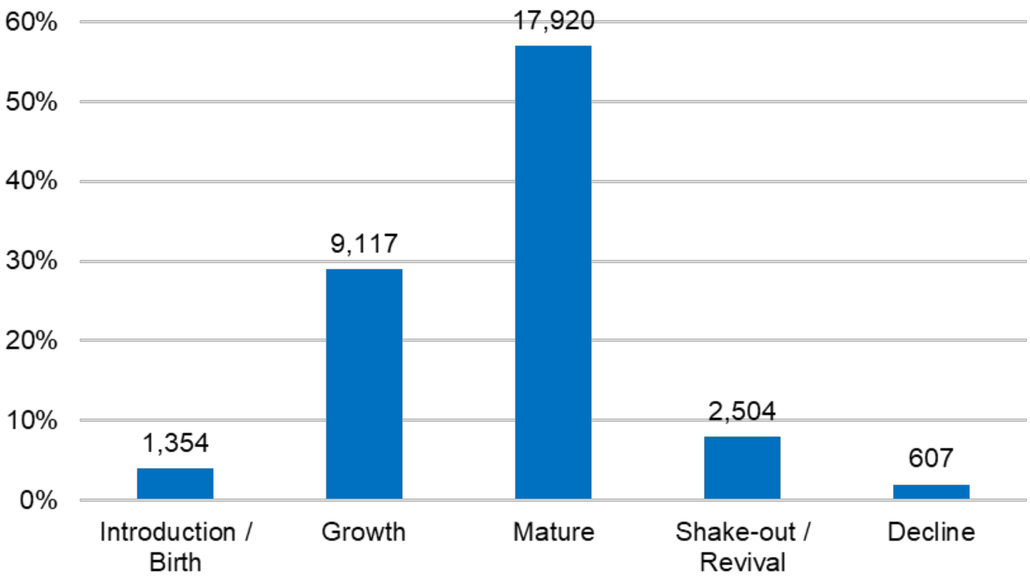
From the 105,475 firm-year-observations COMPUSTAT provides between 2001 and 2018, I exclude firms from the financial services sector, small firms with net operating assets or sales below $5 million as well as outliers with return on net operating assets or profit margin exceeding 100% or core profit margin or special profit margin exceeding 200%. Furthermore, all firms must be headquartered either in North America or in Europe. Notice that European companies are only considered if they are listed in the US and thus also captured in the "North America – Daily" COMPUSTAT database, making it unlikely that my sample suffers from tensions as a consequence of different accounting standards. Finally, firms without 10 years of consecutive data are excluded, as my regression analysis over earnings windows from one to five years requires at least 10 consecutive years (please refer to **Table 10** in the Appendix). This last criterion is different from the one I imposed in part 1 of my research, where all sample companies need to provide full documentation for all 18 years between 2001 and 2018, as I investigate differences by time during my observation period. Overall, my sample selection criteria impose a strong survivorship bias, but still leave me with a sufficient large sample with 1,894 total firms and 31,502 firm-year-observations.

3.3 Descriptive statistics

3.3.1 Life cycle distribution

Dickinson (2011) suggests the highest / lowest frequency of observations in the *mature / decline* life cycle stage. **Figure 1** shows that my evidence is in line with Dickinson's finding. 57% (17,920) of all firm-year-observations are classified as *mature*, while only 2% (607) of my sample observations are allocated to the *declining* life cycle stage. 29% (9,117), 8% (2,504) and 4% (1,354) of all firm-year-observations are categorized as *growth, shake-out / revival* and *introduction / birth*, respectively.

Figure 1: Distribution across life cycle stages



Numbers above bars refer to firm-year-observations in the respective life cycle stages.

The distribution in **Figure 1** is not very surprising – the *mature* stage is the most stable and persistent one, while the *introduction* and the *decline* stage are transitory. It needs to be mentioned, however, that this distribution is to some extent a consequence of my sample selection criteria, which impose a strong survivorship bias. Given that I exclude, for instance, firms with net operating assets or sales below $5m, there is a higher likelihood that firms from the *introduction* or *decline* stage are dropped. **Figure 2** in the Appendix suggests that less restrictive selection criteria would result in a similar life cycle pattern (i.e. highest / lowest frequency of observations in the *mature* / *decline* stage), but the distribution would show a higher density in the tails. Thus, the results from my regression analysis in section 4 should be transferred to enterprises not satisfying the sample selection criteria with caution.

3.3.2 Economic characteristics by life cycle stages

Being able to generate a reasonable life cycle distribution does not necessarily imply that a classification method is appropriate. Given that economic characteristics vary by life cycle stage, I would – besides of the distribution displayed in **Figure 1** – also expect significant differences across key financial variables in the five life cycle stages. **Table 4** summarizes key financial variables for all firm-year-observations as well as for firm-year-observations with positive special items, negative special items, and no special items in each life cycle stage. In the following, I first discuss whether the different life cycle stages reflect the characteristics projected by economic theory (i.e. focus on the left column of **Table 4** – "all observations"). Subsequently, in section 3.3.3, I analyse differences with respect to one-time items across the five life cycle stages (i.e. focus on the three columns on the right).

Economic theory predicts that firms are the smallest in their *introduction* stage, are growing the most in their *growth* phase and achieve maximum profitability in their *maturity* stage (please refer to section 2.1 for further details). My evidence with regards to firm size, growth and profitability is in line with these expectations. Enterprises are, on average, the smallest in the *introduction* stage (market capitalization: $1.3bn), while they are the largest in the *mature* life cycle (market capitalization: $12.0bn). Since those young, small firms usually have a small asset base, it is not surprising that capital intensity (136.1%) is, on average, the lowest during the *introduction* stage. Growth is, in median, the highest in the *growth* stage (sales growth of 10.1%), followed by the *introduction* (9.8%), *mature* (4.6%), *shake-out* (0.8%) and the *decline* stage (-3.1%). Given that *growth* firms do not yet have sufficient capital to finance this growth with equity, they usually have to take on a large amount of debt. Consistently with that, *growth* firms have, on average, the highest debt-to-equity ratio (141.4%). Profitability is, on average, the highest for the *mature* stage, which is visible based on several profitability metrics such as RNOA (16.8%), ROA (9.0%), ROE (24.2%) and operating margin (10.4%). In contrast, enterprises in the *declining* life cycle stages are, on average, the least profitable (RNOA: -12.8%; ROA: -5.7%; ROE: -21.6%; Operating margin: -9.0%).

Table 4: Descriptive statistics across key financial variables by firm-year-observation in each life cycle stage

		All observations				Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Introduction / Birth	*SPI / Avg. Total Assets*	1,351	-2.0%	0.0%	0.061	167	2.5%	0.6%	0.049	686	-4.6%	-1.7%	0.073	498			
	SPI / Sales	1,354	-2.4%	0.0%	0.082	168	3.1%	0.5%	0.069	687	-5.5%	-1.7%	0.100	499			
	RNOA	1,354	-4.8%	0.9%	0.255	168	3.7%	5.2%	0.226	687	-11.6%	-5.4%	0.261	499	1.6%	6.1%	0.229
	ROA	1,351	-1.9%	0.5%	0.128	167	2.3%	3.1%	0.098	686	-5.9%	-3.3%	0.130	498	2.3%	3.8%	0.117
	ROE	1,264	-6.6%	1.5%	2.072	159	18.7%	7.7%	0.751	621	-23.9%	-7.2%	2.912	484	7.2%	8.6%	0.290
	Op. Margin	1,354	-5.1%	0.4%	0.191	168	-1.0%	2.0%	0.174	687	-9.6%	-3.7%	0.194	499	-0.3%	2.1%	0.176
	Sales Growth	1,348	22.5%	9.8%	1.082	167	29.2%	12.3%	1.341	685	15.2%	7.2%	0.474	496	30.2%	14.4%	1.502
	R&D Expense	776	5.2%	2.2%	0.066	94	4.5%	1.7%	0.058	409	5.3%	2.4%	0.065	273	5.3%	2.1%	0.071
	Capital Intensity	1,354	136.1%	90.8%	1.722	168	148.2%	91.6%	1.799	687	142.2%	96.7%	1.929	499	123.7%	88.2%	1.349
	Market Capitalization	1,256	1,274	183	5,694	163	2,856	207	11,250	642	1,271	281	5,202	451	708	93	2,257
	Tobin's Q	1,188	1.742	1.318	1.425	155	1.662	1.272	1.149	596	1.636	1.276	1.236	437	1.916	1.406	1.711
	Debt/Equity	1,227	107.7%	51.8%	2.613	155	127.5%	53.5%	2.818	607	129.9%	57.0%	3.249	465	72.2%	40.2%	1.189
						12%	***of all observations***			***51%***	***of all observations***			***37%***	***of all observations***		

		All observations				Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Growth	*SPI / Avg. Total Assets*	9,108	-1.0%	0.0%	0.036	1,153	1.2%	0.4%	0.027	4,678	-2.2%	-0.9%	0.044	3,277			
	SPI / Sales	9,117	-1.4%	0.0%	0.066	1,155	2.4%	0.5%	0.066	4,682	-3.4%	-1.1%	0.081	3,280			
	RNOA	9,117	12.1%	10.3%	0.166	1,155	15.1%	12.5%	0.148	4,682	9.6%	9.3%	0.171	3,280	14.7%	10.7%	0.159
	ROA	9,108	6.8%	6.5%	0.082	1,153	8.6%	8.0%	0.069	4,678	5.4%	5.8%	0.087	3,277	8.3%	6.9%	0.075
	ROE	8,857	18.3%	17.7%	2.295	1,124	14.1%	20.1%	3.994	4,505	18.0%	15.0%	2.318	3,228	20.3%	19.3%	1.187
	Op. Margin	9,117	10.1%	9.3%	0.143	1,155	13.2%	10.9%	0.145	4,682	7.2%	7.2%	0.145	3,280	13.3%	11.7%	0.130
	Sales Growth	9,098	57.1%	10.1%	38.816	1,152	24.2%	10.4%	2.049	4,675	15.6%	10.0%	0.340	3,271	128.2%	10.2%	64.724
	R&D Expense	4,136	4.0%	2.0%	0.052	504	3.7%	1.8%	0.049	2,551	4.2%	2.1%	0.054	1,081	3.9%	1.8%	0.050
	Capital Intensity	9,117	199.8%	146.1%	1.712	1,155	204.4%	148.0%	1.702	4,682	184.6%	136.6%	1.555	3,280	220.0%	168.3%	1.899
	Market Capitalization	7,947	6,828	1,225	21,764	1,081	7,514	1,175	23,565	4,387	7,732	1,653	21,091	2,479	4,929	697	22,007
	Tobin's Q	7,596	1.917	1.535	1.363	1,046	1.781	1.469	1.124	4,147	1.846	1.541	1.156	2,403	2.098	1.563	1.723
	Debt/Equity	8,814	141.4%	72.4%	6.525	1,120	162.8%	72.3%	9.904	4,488	165.0%	71.8%	7.476	3,206	101.0%	72.8%	2.081
						13%	***of all observations***			***51%***	***of all observations***			***36%***	***of all observations***		

		All observations				Positive special items				Negative special items				No special items			
	Variables	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.	n	Mean	Median	Std. Dev.
Mature	*SPI / Avg. Total Assets*	17,903	-1.0%	-0.1%	0.037	2,475	1.1%	0.4%	0.029	9,652	-2.1%	-0.8%	0.044	5,776			
	SPI / Sales	17,920	-1.3%	-0.1%	0.055	2,479	1.6%	0.4%	0.047	9,661	-2.7%	-0.9%	0.068	5,780			
	RNOA	17,920	16.8%	13.9%	0.189	2,479	20.1%	16.3%	0.182	9,661	14.2%	12.8%	0.186	5,780	19.8%	14.6%	0.190
	ROA	17,903	9.0%	8.4%	0.092	2,475	10.7%	9.6%	0.082	9,652	7.5%	7.6%	0.094	5,776	10.8%	9.1%	0.088
	ROE	17,301	24.4%	20.2%	4.131	2,366	15.0%	22.5%	8.121	9,257	24.5%	18.4%	3.392	5,678	28.1%	21.4%	2.401
	Op. Margin	17,920	10.4%	9.4%	0.125	2,479	12.3%	10.2%	0.127	9,661	8.6%	8.4%	0.126	5,780	12.7%	10.9%	0.118
	Sales Growth	17,898	6.3%	4.6%	0.622	2,475	9.6%	5.6%	1.552	9,648	5.1%	3.9%	0.211	5,775	7.0%	5.2%	0.305
	R&D Expense	9,394	3.1%	1.5%	0.044	1,254	3.2%	1.4%	0.045	5,799	3.3%	1.7%	0.044	2,341	2.6%	0.8%	0.042
	Capital Intensity	17,920	142.8%	106.6%	1.208	2,479	137.7%	105.2%	1.097	9,661	138.2%	108.7%	1.183	5,780	152.5%	102.4%	1.288
	Market Capitalization	16,028	12,016	1,733	33,725	2,334	12,239	1,706	30,782	9,130	13,477	2,399	33,734	4,564	8,978	760	34,932
	Tobin's Q	15,234	1.825	1.487	1.144	2,219	1.784	1.459	1.124	8,598	1.764	1.484	1.014	4,417	1.964	1.509	1.361
	Debt/Equity	17,233	118.9%	49.8%	5.816	2,352	108.1%	44.8%	3.119	9,226	142.6%	55.3%	6.536	5,655	84.7%	41.5%	5.397
						14%	***of all observations***			***54%***	***of all observations***			***32%***	***of all observations***		

	Variables	All observations n	Mean	Median	Std. Dev.	Positive special items n	Mean	Median	Std. Dev.	Negative special items n	Mean	Median	Std. Dev.	No special items n	Mean	Median	Std. Dev.
Shake-out / Revival	*SPI / Avg. Total Assets*	2,503	-1.0%	-0.1%	0.048	491	2.8%	1.2%	0.043	1,381	-2.9%	-1.2%	0.051	631			
	SPI / Sales	2,504	-1.6%	-0.2%	0.092	491	4.8%	1.4%	0.091	1,381	-4.6%	-1.7%	0.101	632			
	RNOA	2,504	10.6%	9.4%	0.258	491	17.6%	13.9%	0.208	1,381	6.7%	7.1%	0.263	632	13.6%	10.7%	0.266
	ROA	2,503	5.1%	5.4%	0.118	491	9.0%	8.3%	0.097	1,381	3.2%	3.9%	0.121	631	6.3%	6.1%	0.116
	ROE	2,410	-14.9%	11.7%	13.964	470	42.3%	18.6%	2.959	1,316	0.2%	9.2%	7.466	624	-89.9%	13.0%	25.077
	Op. Margin	2,504	6.7%	6.3%	0.196	491	12.3%	10.5%	0.172	1,381	4.5%	4.8%	0.198	632	7.4%	6.7%	0.201
	Sales Growth	2,496	241.7%	0.8%	117.841	491	6.9%	1.6%	0.644	1,377	2.8%	0.0%	0.305	628	949.0%	2.1%	234.926
	R&D Expense	1,479	4.6%	2.3%	0.054	283	4.1%	1.5%	0.056	885	4.9%	2.5%	0.054	311	4.2%	2.4%	0.051
	Capital Intensity	2,504	161.5%	122.4%	1.364	491	166.4%	122.7%	1.507	1,381	159.8%	125.0%	1.264	632	161.3%	113.8%	1.457
	Market Capitalization	2,382	8,070	668	25,208	470	8,969	862	27,580	1,347	9,391	992	26,672	565	4,171	167	18,228
	Tobin's Q	2,267	1.569	1.279	1.043	453	1.551	1.323	0.883	1,264	1.527	1.272	0.979	550	1.679	1.265	1.276
	Debt/Equity	2,388	113.6%	35.1%	5.547	463	92.4%	39.7%	2.142	1,309	145.3%	44.3%	7.305	616	62.1%	7.4%	1.405
						20%	***of all observations***			***55%***	***of all observations***			***25%***	***of all observations***		

	Variables	All observations n	Mean	Median	Std. Dev.	Positive special items n	Mean	Median	Std. Dev.	Negative special items n	Mean	Median	Std. Dev.	No special items n	Mean	Median	Std. Dev.
Decline	*SPI / Avg. Total Assets*	606	-1.6%	-0.4%	0.076	127	5.5%	1.6%	0.089	338	-5.0%	-2.4%	0.065	141			
	SPI / Sales	607	-2.4%	-0.3%	0.140	127	8.5%	1.8%	0.185	338	-7.5%	-3.0%	0.123	142			
	RNOA	607	-12.8%	-9.5%	0.300	127	0.5%	0.7%	0.269	338	-19.2%	-17.2%	0.308	142	-9.6%	-8.2%	0.262
	ROA	606	-5.7%	-5.1%	0.147	127	0.1%	0.3%	0.129	338	-8.8%	-7.9%	0.151	141	-3.4%	-4.7%	0.135
	ROE	554	-21.6%	-9.8%	3.104	117	-61.7%	-2.0%	6.660	304	-13.4%	-16.2%	0.705	133	-5.2%	-6.8%	0.246
	Op. Margin	607	-9.0%	-5.4%	0.245	127	-2.6%	0.3%	0.193	338	-12.6%	-9.3%	0.243	142	-6.3%	-4.8%	0.274
	Sales Growth	606	1.5%	-3.1%	0.397	127	-1.6%	-2.3%	0.252	338	0.0%	-5.9%	0.434	141	7.7%	2.8%	0.408
	R&D Expense	383	7.0%	5.3%	0.071	91	5.9%	2.5%	0.071	206	7.0%	5.1%	0.072	86	8.2%	7.1%	0.068
	Capital Intensity	607	151.9%	112.2%	1.354	127	148.7%	108.2%	1.367	338	148.9%	106.8%	1.365	142	161.7%	122.4%	1.322
	Market Capitalization	578	1,608	121	11,991	122	1,387	146	3,532	326	1,996	172	15,649	130	841	54	3,662
	Tobin's Q	545	1.343	1.113	0.947	119	1.403	1.130	1.186	305	1.242	1.081	0.728	121	1.539	1.215	1.127
	Debt/Equity	547	103.6%	22.7%	2.820	117	135.3%	26.9%	4.460	301	110.0%	31.6%	2.470	129	60.1%	7.1%	1.146
						21%	***of all observations***			***56%***	***of all observations***			***23%***	***of all observations***		

Variable definitions:

SPI / Avg. Total Assets	=	ratio of COMPUSTAT data items SPECIAL ITEMS (#17) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
RNOA	=	ratio of NET OPERATING INCOME (NOI) from period t and average of NET OPERATING ASSETS (NOA) across period t and t-1 (as defined in Table 1).
ROA	=	ratio of NET OPERATING INCOME (NOI) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
ROE	=	ratio of NET OPERATING INCOME (NOI) from period t and average of COMMON EQUITY (#60) across period t and t-1 (negative obsv. excluded).
Op. Margin	=	ratio of NET OPERATING INCOME (NOI) from period t and REVENUES (#12) from period t.
Sales Growth	=	growth in REVENUES (#12) between period t and t-1.
R&D Expense	=	ratio of COMPUSTAT data items R&D EXPENSE (#46) from period t and average of TOTAL ASSETS (#6) across period t and t-1.
Capital Intensity	=	ratio of COMPUSTAT data items TOTAL ASSETS (#6) from period t and REVENUES (#12) from period t.
Market Capitalization	=	product of COMPUSTAT data items CLOSING STOCK PRICE (#24) and COMMON SHARES OUTSTANDING (#25).
Tobin's Q	=	ratio of (TOTAL ASSETS (#6) + MARKET CAPITALIZATION - COMMON EQUITY (#60) - DEFERRED TAXES (#74)) and average of TOTAL ASSETS (#6) across period t and t-1 - in line with Johnson, et al. (2011).
Debt/Equity	=	ratio of COMPUSTAT data items (LONG-TERM DEBT (#9) + CURRENT DEBT (#34)) and COMMON EQUITY (#60).

While the expectations with regards to profitability, growth and size are straightforward, it is more difficult to postulate hypotheses for other financial variables. For instance, it is tough to predict which life cycle stage has the highest / lowest R&D expense (deflated with average assets). Early-stage firms require research and development, as they still need to build their infrastructure and technology, but they do not necessarily have the required capacities and capital. *Mature* firms do have the funds to finance R&D expenses, but are generally less innovative than early-stage firms. Later-stage firms, again, may struggle to gather sufficient capital to finance R&D costs, but they require new innovations to achieve a turnaround. Dickinson (2011) provides evidence suggesting that innovations appear most often in the *introduction* and in the *decline* stage. My findings are in line with this, as R&D expenses are, on average, the highest for sample enterprises in the *decline* (7.0%) and in the *introduction* (5.2%) phase.

In closing, the life cycle classification according to Dickinson (2011) yields not only a reasonable distribution, but also the respective life cycle stages reflect the characteristics in line with economic theory.

3.3.3 One-time items by life cycle stages

The three columns on the right of **Table 4** show how key financial variables in the five life cycle stages differ across firm-year-observations with positive special items, negative special items, and no special items.

The first two rows refer to the magnitude of special items. Magnitude is in existing literature defined as special items deflated with sales (e.g. Fairfield et al., 2009) or with total assets (e.g. Johnson et al., 2011). Overall, my findings show that magnitude of one-time items is particularly large for enterprises in the *decline, shake-out* and *introduction* stage. In contrast, the relative size of special items appears to be comparably small for enterprises in the *growth* and in the *mature* life cycle stage. Special items literature finds that, on average, the magnitude of one-time expenses exceeds the one of one-time revenues (e.g. Johnson et al., 2011). My evidence suggests that this, however, holds only for early-stage and *mature* firms. For sample firms in the *shake-out* and in the *decline* stage, mean positive special items divided by average total assets and sales (*shake-out*: 2.8% and 4.8%; *decline*: 5.5% and 8.5%) exceed the one of negative special items (*shake-out*: -2.9% and -4.6%; *decline*: -5.0% and -7.5%). This is particularly surprising, as it would be from a theoretical perspective more likely that *shake-out* and *decline* firms are regularly confronted with restructurings and write-offs – two common one-time charges. Overall, the descriptive analysis with regards to magnitude of special items across firm life cycles indicates that there may very well be differences in the usefulness of one-time items for earnings forecasts of the various life cycle stages.

Special items literature investigates – besides of magnitude – frequency of one-time items. Frequency is defined as the percentage of firms which report one-time items. Prior research finds that this percentage is growing and that the growth can mainly be traced back to negative special items (e.g. Johnson et al., 2011). **Table 4** suggests that special items frequency over the entire observation period (from 2001 to 2018) is indeed very high for all life cycle stages, whereby frequency is monotonically increasing throughout the stages. Taking together one-time revenue and one-time expense firm-year-observations, special items frequency ranges from 63% in the *introduction* stage to 77% in the *decline* stage. Furthermore, in line with prior research, frequency of negative special items exceeds the one of one-time revenues in all life cycle stages. The difference between frequency of positive and negative special items is monotonically decreasing throughout the life cycle stages – in the *introduction* stage one-time expenses appear 4.1x more often than one-time revenues, while in the *decline* stage the difference is only 2.7x. This again suggests that one-time revenues appear to be more common in later stages like my previous discussion on one-time items magnitude already indicated. It needs to be mentioned, however, that recording positive special items in the *decline* stage could also be an earnings management attempt, as this might help these companies, for instance, to avoid reporting losses or violate bank covenants. Looking at the key financial variables listed in **Table 4**, this presumption may very well be true. For the first four life cycle stages, debt-to-equity ratio is higher for negative special item firm-year-observations than for positive ones, which is in line with the evidence provided in part 1 of my thesis, where I provide the same analysis for my consolidated sample. In contrast, for the *decline* stage, debt-to-equity ratio is higher for one-time revenue observations, which might indicate that these businesses face debt issues (e.g. violate covenants) and use positive special items to manipulate their earnings.

The other variables listed in **Table 4** suggest similar findings as part 1 of my thesis. Namely, on average, positive special items observations and no special items observations outperform negative special items observations, which is visible based on higher RNOA, ROA and operating margin in all five life cycle stages. In return, negative special items firm-year-observations have higher R&D expenses, which might potentially indicate future performance improvements. Finally, firms reporting special items (both positive and negative) are, on average, larger than firms not reporting one-time items in terms of market capitalization. In conclusion, the descriptive analysis shows that there are significant differences between firms reporting one-time items and firms not reporting those items. Furthermore, while my evidence suggests similar special items patterns across the life cycle stages, there are still some distinctions across the stages. Consequently, it shall be questioned whether applying the same treatments to one-time items across different life cycle stages is justified.

3.3.4 One-time sub-items by life cycle stages

Johnson et al. (2011) suggests that “no one charge / gain dominates special items” (p. 520). Consistently with that, part 1 of my thesis finds heterogeneity in one-time sub-items for my consolidated sample. However, as explained in my literature review in section 2.2, it is likely that the pattern of one-time sub-items differs across firm life cycle stages. For instance, one could argue that later-stage firms are more likely to restructure their companies, as they require change to achieve a turnaround.

Table 5 and **Table 6** shed light on the question whether we in fact observe differences in frequency and magnitude of one-time sub-items across the life cycle stages. Please notice that these tables should be interpreted in the following way: the tables report one-time sub-item frequency (**Table 5**) and magnitude / relative size deflated with sales (**Table 6**) for each life cycle stage, assuming total net special items are positive (left side) or negative (right side). This implies that some sub-items on the left side (listed in the positive special items category) can still be negative, as all sub-items are considered as long as total net special items are positive (and vice versa for the right side, i.e. net negative special items). Moreover, the sum of the frequency of all sub-items by life cycle exceeds 100%, as it is common that companies reports several sub-items in the same year.

Table 5 suggests that for all life cycle stages, but the *growth* phase, the three most frequent one-time sub-items are one-time gain / loss, litigation, and restructuring, assuming a firm reports positive net total special items (left side of the table). The *growth* stage shows only a slightly different pattern with other special items being the third most frequent sub-item instead of restructurings. Heterogeneity of sub-items tends to decrease throughout the life cycle stages, as the relative frequency of the above-mentioned items increases for later stages. For instance, if an *introduction* firm reports net positive special items, then in 36% of observations this company records a litigation, in 35% a one-time gain / loss and in 24% a restructuring. For an enterprise in the *decline* stage, those percentages are significantly higher – in 56% a one-time gain / loss, in 38% a litigation and in 37% a restructuring. The fact that restructurings are increasingly common for later stage enterprises is in line with economic theory. However, **Table 6** shows that, on average, restructuring items are positive for the *decline* stage (0.8% of sales), while they are negative for all other life cycle stages. This is very surprising, as part 1 of my research has shown that restructurings are almost always negative – even when net total special items are positive for a year, restructurings are negative in 81% of firm-year-observations in my consolidated sample. Moreover, **Table 6** suggests that the largest sub-item for net positive special items in all life cycle stages is one-time gain / loss, ranging between 0.6% of sales in the *mature* stage and 5.1% of sales in the *decline* stage. However, there is more variety with respect to the magnitude compared to frequency of sub-items for net positive special items.

If a sample firm reports net negative special items (right side of **Table 5** and **Table 6**), the most common sub-item in all life cycle stages are restructuring charges (ranging between 48% and 59% depending on the life cycle stage). In line with my initial expectations, the frequency is higher for later stages, as these companies require change to achieve turnaround. The second and third most frequent sub-items in the *introduction*, *growth* and *mature* stages are M&A related gains / losses and other special items. M&A related gains / losses are particularly frequent in the *growth* stage (with 43%) – this implies that companies in this life cycle stage do not only realize organic growth, but also to a significant extent inorganic growth. In contrast to the early and *mature* stages, the second and third most common sub-items in the *shake-out* stage are PP&E write-offs (31%) and extinguishments of debt (28%), while in the *decline* stage PP&E write-offs (35%) and other special items (30%). Again, it is reasonable from an economic perspective that later-stage companies with poor performance face write-offs more frequently.

Consequently, **Table 5** suggests that one-time sub-item frequency differs across life cycle stages and that those differences can be traced back to the economic challenges faced in the respective stages. One would therefore expect that the importance of certain sub-items for earnings forecasts varies by corporate life cycle. Magnitude of sub-items when a firm reports net negative special items, on the other hand, shows a less volatile pattern across life cycle stages. In fact, in all life cycle stages, goodwill impairment, restructuring charges and PP&E write-offs are, on average, the largest sub-items (**Table 6**).

Table 5: One-time sub-items frequency by life cycle stages

Special item type	Positive special items					Negative special items				
	Birth	Growth	Mature	Revival	Decline	Birth	Growth	Mature	Revival	Decline
In Process R&D	1%	1%	1%	2%	1%	4%	4%	3%	5%	2%
Restructuring	24%	23%	30%	36%	37%	48%	46%	56%	59%	58%
Gain/Loss	35%	39%	43%	66%	56%	11%	13%	16%	25%	21%
Litigation	36%	36%	38%	33%	38%	19%	21%	22%	23%	19%
Other	23%	28%	27%	27%	28%	27%	28%	29%	27%	30%
M&A	20%	24%	22%	17%	16%	26%	43%	30%	27%	19%
Goodwill	5%	4%	5%	9%	8%	20%	14%	19%	22%	26%
PP&E Write-Offs	17%	12%	12%	17%	17%	26%	26%	26%	31%	35%
Extinguish Debt	24%	17%	17%	21%	24%	23%	25%	24%	28%	25%

Table 6: One-time sub-items magnitude by life cycle stages

Special item type	Positive special items					Negative special items				
	Birth	Growth	Mature	Revival	Decline	Birth	Growth	Mature	Revival	Decline
In Process R&D	-0.1%	0.0%	0.0%	0.0%	0.0%	-0.2%	-0.2%	0.0%	-0.1%	-0.1%
Restructuring	-0.2%	-0.1%	-0.1%	-0.3%	0.8%	-0.9%	-0.5%	-0.6%	-0.8%	-1.7%
Gain/Loss	1.4%	1.0%	0.6%	3.9%	5.1%	0.1%	0.0%	0.0%	0.1%	0.0%
Litigation	0.7%	0.6%	0.5%	0.7%	0.5%	-0.2%	-0.2%	-0.1%	-0.2%	-0.3%
Other	0.5%	0.3%	0.2%	0.5%	0.2%	-0.5%	-0.3%	-0.2%	-0.4%	-0.6%
M&A	0.1%	0.4%	0.1%	0.1%	0.1%	-0.5%	-0.5%	-0.1%	-0.3%	-0.3%
Goodwill	0.0%	-0.1%	0.0%	-0.2%	0.0%	-1.7%	-0.9%	-1.0%	-1.8%	-2.4%
PP&E Write-Offs	-0.1%	-0.1%	-0.1%	-0.3%	-0.2%	-0.9%	-0.6%	-0.5%	-0.8%	-1.6%
Extinguish Debt	0.9%	0.2%	0.2%	0.1%	1.7%	-0.6%	-0.2%	-0.2%	-0.2%	-0.4%

4 Regression results

4.1 Basic regression model by life cycle stages

For my base model, I regress lagged core earnings, lagged negative and positive special items on future earnings over earnings windows (w) from one to five years for each life cycle stage separately. All variables are normalized with sales. Negative and positive items can never be ≠ 0 at the same time, as special items are netted. This approach is a replication of Fairfield et al. (2009) – they find that one-time revenues are irrelevant, while one-time expenses provide useful information for earnings forecasts in high profitability firms. Given that profitability is higher for the *growth* and *mature* life cycle stages, one would expect negative special items to be more relevant for these stages. Part 1 of my research extends the one by Fairfield et al. (2009) for a more recent observation period (2001 to 2018, i.e. same period as used in this paper). While my evidence suggests – in conformity with Fairfield et al. (2009) – that one-time expenses are particularly important for earnings forecasts in high profitability firms, it also indicates that one-time expenses are associated with future performance for medium and low profitability firms. This reflects the increasing importance of negative special items for all companies. Moreover, my findings show that for enterprises with a profitability in line with the one of its peer group (i.e. medium profitability group), one-time revenues can also be relevant for earnings forecasts in the long-term. It needs to be emphasized, however, that previous results on one-time items by profitability cannot be automatically transferred to my life cycle analysis, as life cycle theory captures differences in profitability, growth, and risk (Dickinson, 2011). **Table 7** reports my regression results separately for each life cycle stage.

Introduction. My results suggest that only core PM^{w}_{t} is relevant for projecting PM^{w}_{t+1}. The coefficient of lagged core profit margin is positive, significant at the 1% level for all five earnings windows, ranges between 0.479 (w = 3) and 0.604 (w = 1) and tends to decrease over time. It is not surprising that the coefficient shows a decline for long-term forecasts, as enterprises in the *introduction* stage are usually young and dynamic, meaning forecast accuracy will not improve by creating smoothed averages. Both negative and positive special PM^{w}_{t} are not significantly different from zero. This indicates that investors should consider core earnings from the previous period (i.e. no smoothed average), while they can usually exclude one-time revenues and expenses when projecting future performance of businesses in the *introduction* phase.

Growth. Both core earnings and negative special items are associated with future performance in the short-term as well as in the long-term. The coefficient of core PM^{w}_{t} is ranging between 0.669 (w = 5) and 0.725 (w = 1), indicating that core earnings have a stronger correlation with future earnings compared to the *introduction* stage. The coefficient of negative special PM^{w}_{t} is significant at the 1% level for all five time windows and is in the area of 0.274 (w = 5) to 0.364 (w = 3). This implies that one-time expenses should not be neglected for earnings forecasts in the *growth* stage, as the persistence of those expenses is only roughly 2 to 2.5x lower than the one of core earnings. One-time revenues are not associated with future profitability of enterprises in the *growth* stage, which is visible based on a non-significant coefficient of positive special PM^w_t for all five time windows.

Mature. All three independent variables of my regression are relevant for projecting future profit margin. Core PM^w_t is different from zero for all five earnings windows, whereby the coefficient is very stable at approximately 0.75. Core earnings have, therefore, a higher persistence for *mature* enterprises compared to all other life cycle stages. Similarly to the *growth* stage, negative special PM^w_t is significant at the 1% level for all five time windows – the coefficient, ranging between 0.115 (w = 2) and 0.167 (w = 5), is lower for *mature* businesses, however. This implies that the persistence of core earnings is roughly 4.5 to 6.5x higher than the one of one-time expenses. Finally, one-time revenues are also positively associated with future performance for firms in the *maturity* stage as well. In fact, the coefficient of positive special PM^w_t is insignificant for w = 1, but significantly different from zero from w = 2 onwards with very high coefficients between 0.277 (w = 2) and 0.574 (w = 5). In closing, when analysts and investors attempt to project earnings of *mature* companies, both negative and positive special items should be considered, whereby for one-time revenues the analyst should compute an average over several years.

Shake-out. My evidence suggests that mainly core PM^w_t is relevant for projecting PM^w_{t+1}. The coefficient of lagged core profit margin is positive, significant at the 1% level for all five earnings windows, ranges between 0.473 (w = 1) and 0.639 (w = 5) and monotonically increases over time. In this sense the *shake-out* stage is unique, as it is the only life cycle stage where analysts should consider smoothed averages for core earnings in their forecasts instead of core earnings from the previous year. While one-time revenues are irrelevant for all five earnings windows, one-time expenses (negative special PM^w_t.) are significant at the 5% level for w = 1 (0.155), but irrelevant from w = 2 onwards.

There are two possible explanations for the observed pattern of negative special PM^w_t in the *shake-out* stage. First, the fact that one-time expenses are only significant in w = 1 might suggest that firms in this stage engage in earnings management using special items. As mentioned in my literature review in section 2.2, managers can exploit one-time items opportunistically by transferring expenses from future periods into current one-time expenses, leading to lower current earnings and a one-to-one increase in future earnings. Second, the pattern of one-time expenses might indicate that *shake-out* firms attempt to achieve a turnaround (for instance through in-process R&D and restructurings), but are not able to create long-term value.

Decline. Only core PM^{w}_{t} is relevant for projecting PM^{w}_{t+1} with significant coefficients for all five earnings windows, ranging between 0.321 (w = 5) and 0.541 (w = 2). This suggests, however, that the coefficients of core earnings are smaller than in all other life cycle stages. Furthermore, neither one-time revenues nor one-time expenses show a significant association with future profitability for any of the five earnings windows.

My evidence with respect to positive and negative special PM^{w}_{t} in the *decline* stage is somewhat surprising, as Nagar & Sen (2017) suggest that firms in this stage engage in classification shifting, i.e. misclassifying core revenues / expenses as one-time revenues / expenses in order to manage their earnings . My descriptive analysis in section 3.3.3 also showed that positive special items are, on average, significantly bigger in magnitude for firms in the *decline* stage, which might potentially have been an indicator for earnings management. However, the regression results in **Table 7** are not in conformity with this finding, as one would expect significant coefficients for negative and positive special PM^{w}_{t} if managers misclassified core expenses and revenues as one-time expenses and revenues, respectively. One possible explanation why Nagar & Sen (2017) find supporting evidence for the earnings management hypothesis in the *decline* stage could be that they perform their analysis for an Indian sample, as earnings management is more likely in countries with low investor protection and weak corporate governance. My sample, in contrast, captures only companies headquartered in Europe and North America, i.e. geographic regions with stronger corporate governance.

Table 7: Base regression model – by life cycle stages (N = 31,502)

$$PM_{t+1}^{w} = \sum_{j=1}^{5} \alpha_{0,0} + \sum_{j=1}^{5} \beta_{0,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{0,2}^{w} * negative\ special\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{0,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{0,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

	Introduction / Birth					Growth				
Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.022	0.604***	0.131	0.251	0.342	-0.005	0.725***	0.276***	0.131	0.393
	(0.022)	(0.057)	(0.094)	(0.254)		(0.007)	(0.022)	(0.046)	(0.083)	
2	0.032**	0.516***	0.138	0.143	0.310	0.050***	0.708***	0.313***	0.152*	0.402
	(0.015)	(0.058)	(0.133)	(0.314)		(0.005)	(0.019)	(0.058)	(0.087)	
3	0.046***	0.479***	0.027	-0.147	0.262	0.050***	0.716***	0.364***	0.166	0.412
	(0.012)	(0.080)	(0.159)	(0.504)		(0.005)	(0.019)	(0.078)	(0.134)	
4	-0.003	0.562***	-0.079	-0.111	0.304	0.031***	0.700***	0.356***	0.203	0.414
	(0.012)	(0.091)	(0.176)	(0.431)		(0.005)	(0.020)	(0.096)	(0.160)	
5	0.001	0.514***	0.089	-0.333	0.306	0.030***	0.669***	0.274***	0.027	0.408
	(0.012)	(0.097)	(0.195)	(0.541)		(0.004)	(0.022)	(0.085)	(0.223)	

	Mature					Shake-out / Revival				
Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	0.001	0.767***	0.150***	0.089	0.454	-0.025	0.473***	0.155**	-0.046	0.276
	(0.004)	(0.016)	(0.027)	(0.106)		(0.020)	(0.032)	(0.067)	(0.101)	
2	0.032***	0.755***	0.115***	0.277***	0.482	0.060***	0.551***	0.09	0.204	0.326
	(0.003)	(0.014)	(0.028)	(0.087)		(0.010)	(0.031)	(0.060)	(0.147)	
3	0.041***	0.745***	0.128***	0.383***	0.479	0.063***	0.617***	0.083	0.063	0.384
	(0.003)	(0.013)	(0.034)	(0.114)		(0.007)	(0.033)	(0.071)	(0.148)	
4	0.030***	0.748***	0.155***	0.390***	0.494	0.046***	0.627***	0.053	0.124	0.401
	(0.003)	(0.013)	(0.036)	(0.134)		(0.007)	(0.039)	(0.084)	(0.159)	
5	0.021***	0.749***	0.167***	0.574***	0.517	0.036***	0.639***	0.014	0.037	0.448
	(0.003)	(0.014)	(0.039)	(0.124)		(0.010)	(0.042)	(0.096)	(0.152)	

	Decline				
Nbr. of years in earnings window	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.057	0.429***	0.154	0.192	0.257
	(0.065)	(0.073)	(0.167)	(0.143)	
2	0.049*	0.541***	0.271	-0.25	0.371
	(0.027)	(0.072)	(0.193)	(0.210)	
3	0.041*	0.491***	0.268	-0.405	0.347
	(0.023)	(0.073)	(0.272)	(0.390)	
4	0.074***	0.348***	0.247	-0.697	0.278
	(0.028)	(0.051)	(0.286)	(0.437)	
5	0.035*	0.321***	0.148	-0.182	0.241
	(0.020)	(0.055)	(0.171)	(0.492)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 2. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

Concluding remarks. Overall, my evidence suggests that corporate life cycle theory helps to improve our understanding when one-time revenues and expenses should be considered by analysts and investors. In short, one-time revenues should only be taken into account for *mature* firms – ideally, analysts and investors compute smoothed averages of positive special items, as the association with future profit margin increases for longer time windows. One-time expenses should primarily be considered for *growth* and *mature* businesses. For *shake-out* enterprises, there appears to be a weak correlation with future earnings in the short-term as well, but this might potentially be a consequence of earnings management. For *introduction* and *decline* firms, one-time expenses can be neglected. Generally, predictability of future performance is most difficult in those two stages, which is reflected in a comparably low R^2 (26% to 34% in the *introduction* stage; 24% to 37% in the *decline* stage) – this is not surprising, given that *introduction* and *decline* firms face a high level of uncertainty.

4.2 Modified regression by one-time sub-items and life cycle stages

In this sub-section, I modify the regression model from section 4.1 in the sense that I break down positive and negative special $PM^w{}_t$ into one-time sub-items. Followingly, I regress for each life cycle stage lagged core earnings and lagged one-time sub-items provided by COMPUSTAT – M&A related gains / losses, one-time gains / losses, goodwill impairment, litigation expenses, restructuring charges, PP&E write-offs, other special items, in-process R&D expenses and extinguishments of debt – on future earnings over time windows (w) from one to five years. All variables are normalized with sales. I conducted the same analysis in part 1 of my thesis for my consolidated sample, finding that the one-time sub-items with the highest association to future performance are in-process R&D expenses, restructuring charges and M&A related gains / losses. From a theoretical perspective, it makes sense that some sub-items are more relevant for earnings forecasts than others. While, for instance, goodwill impairments are usually a sign that a company overpaid when acquiring another company and do not necessarily affect future performance, restructuring charges should ideally boost future earnings. This sub-section adds an additional dimension to this analysis, as life cycle stages may affect the relevance of certain sub-items. As an example, section 3.3.4 has shown that *growth* businesses actively engage in M&A activity to enhance inorganic growth – thus, it is likely that M&A related gains / losses are positively associated with future profit margin in this life cycle stage. Furthermore, my descriptive analysis as well as prior research suggests that restructurings are influenced by corporate life cycle. Koh et al. (2015) find that the choice of restructuring strategies by enterprises facing distress depend on the life cycle stage. Section 3.3.4 has shown that frequency of restructurings is higher for later stages, as these companies require change to achieve turnaround. Adding to this, Atiase et al. (2004) find that find that restructuring charges are only associated with improved future performance for low profitability companies with negative earnings. As a consequence, it appears to be reasonable that certain one-time sub-items should be treated differently by investors, depending on the life cycle stage of the target. **Table 8** reports my regression results for each life cycle stage. Please notice that the conclusions on core earnings (core PM^{w}_{t}) would be identical to section 4.1, which is why I will focus on discussing **Table 8** with respect to one-time sub-items in the following. Moreover, please notice that I will only discuss significant sub-items with predictable patterns.

Introduction. My findings suggest that the only two relevant one-time sub-items for projecting future profit margin are goodwill impairments and PP&E write-offs. The coefficient of goodwill impairment is insignificant for w = 1, but significant and high from w = 2 onwards at approximately 0.5. The coefficient of PP&E write-offs, on the other hand, is significant and negative from w = 3 onwards, ranging between -0.443 (w = 3) and -0.662 (w = 5). It is puzzling that goodwill impairments are associated with future performance improvements – as previously mentioned, goodwill impairments are usually a sign that a company overpaid when acquiring another company and do not affect future performance. In line with this, Cready et al. (2012) find that “goodwill impairment charges have little empirical relation to future earnings or operating cash flows” (p. 1168). In contrast, it is sounds from a theoretical perspective why write-offs go hand in hand with value destruction for early-stage firms. This is because enterprises in the *introduction* stage do not yet have a substantial asset base and require those assets to ensure a successful transition to the *growth* stage. Write-offs are therefore counterproductive for young firms. Besides of those two sub-items, all other sub-items are not significantly different from zero for all five earnings windows, meaning they are transitory and can be neglected by analysts and investors.

Growth. The most important sub-items in the *growth* stage are in-process R&D, restructuring, other special items, M&A related gains / losses and goodwill impairments. Similarly to the *introduction* stage, the positive and significant association between goodwill impairments and future profit margin is puzzling. In-process R&D and M&A-related gains / losses are both as well significantly associated with future performance in four out of five time windows with high, positive coefficients (in-process R&D: ranges from 0.417 in w = 2 to 0.847 in w = 5; M&A related gains / losses: ranges from 0.218 in w = 1 to 0.594 in w = 4) – this is in line with my initial expectations, as *growth* companies require both R&D and M&A to enhance their growth activities. Restructuring as well as other special items are positively correlated with PM^{w}_{t+1} for the first two time windows and insignificant afterwards. This may indicate that *growth* companies use these two sub-items to manage their earnings – *growth* companies are usually less accused of managing their earnings, but it would be a conceivable solution to boost earnings, for instance, before a new financing round. Alternatively, the fact that restructuring charges only persist until w = 2 may also be traced back to the fact that *growth* companies are not able to create long-term value.

Mature. My evidence suggests that mainly restructuring charges, litigation, other special items, and goodwill impairments are relevant for projecting future profit margin. Goodwill impairment is significantly different from zero for all five time windows, ranging between 0.159 (w = 1) and 0.181 (w = 4) – like in the previous two life cycle stages, there is no valid explanation for this finding. Restructuring is significant from w = 2 onwards with a coefficient in the area of 0.3. This implies that restructurings should definitely be considered for *mature* businesses, as the persistence is only 2.5-3x lower than the one of core earnings. As mentioned in the introduction of this sub-section, I expected restructurings to be more relevant for low profitability companies – thus, my findings for the *mature* phase, the stage with the highest profitability, contradict with my initial hypothesis. Litigations are particularly important for short-term forecasts – the coefficient of litigation is positive and significant at the 10%, 5% and 1% level in w = 1, w = 2 and w = 3, respectively, but insignificant afterwards. Other special items, on the other hand, are relevant for long-term forecasts, as the coefficient is significant from w = 3 onwards – the coefficient increases monotonically and reaches a magnitude of 0.636 in w = 5, i.e. the long-term persistence is only 1.2x lower than the one of core earnings. Unfortunately, it is impossible to provide additional discussions on the sub-item “other special items”, as it is unclear which economic transactions hide behind this plug item.

Shake-out. Not a single one-time sub-item shows a significant coefficient for more than two out of five earnings windows, meaning it is difficult to draw any conclusions, as the patterns of the respective items are not very reliable and predictable. Some findings are still notable, however. Goodwill impairment is again important for our projection model, but only in the short-term, as the coefficient is positively correlated with future profit margin in the first two earnings windows. Furthermore, my evidence indicates that *shake-out* firms have a higher chance of recovery if they focus on in-process R&D and extinguishment of existing debt – both sub-items are significant at the 10% level in w = 5 with a highly positive coefficient (in-process R&D: 1.247; extinguishment of debt: 0.814). Finally, in contrast to my initial expectation that restructurings are more important for later-stage firms, the coefficient of restructuring is significant and negative from w = 4 onwards. This indicates that, on average, restructurings are not successful for *shake-out* firms and do not contribute to achieve a turnaround. The same inference applies to PP&E write-offs, which shows a significant coefficient of -0.512 in w = 5. It needs to be mentioned that PP&E write-offs are, unlike restructurings, not by choice, however.

Decline. Before discussing regression results for the *decline* stage, it needs to be mentioned that my sample for this stage is very small, creating a lot of noise. As displayed in **Figure 1**, there are 607 sample companies in the *decline* stage. Thereof, only 84 observations report, for instance, M&A related gains / losses. Thus, conclusions from my regression in the *decline* stage need to be drawn with caution.

According to my results for the *decline* stage, M&A related gains / losses is significant for all five time windows and shows a very high, positive coefficient of above 1. This is surprising, as sub-section 3.3.4 indicated that M&A related gains / losses are recorded comparably seldom in the *decline* stage – in fact, if a *decline* firm reports net positive / negative special items, this firm reports in only 16% / 19% of observations M&A related gains / losses. Nevertheless, my results indicate that M&A related gains / losses are the most successful attempt for *decline* firms to achieve a turnaround. Besides of M&A related gains / losses, goodwill impairment is significant in all earnings windows, but the third one. In contrast to my initial hypothesis, restructurings are insignificant in all five earnings windows, indicating investors can neglect them in their earnings forecast models. Finally, in-process R&D shows a huge positive and significant coefficient for w = 5 – this theoretically indicates that *decline* firms benefit from R&D in the long-term, helping them to achieve a turnaround. It needs to be emphasized, however, once more that my results may be distorted of the small sample in the *decline* stage.

Concluding remarks. In closing, this sub-section suggests that corporate life cycle theory helps to improve our understanding of which one-time sub-items are relevant. For instance, future performance of *introduction* firms is negatively affected by PP&E write-offs. In-process R&D and M&A-related gains / losses are particularly important for projections in the *growth* stage. Furthermore, my results suggest a number of conclusions contradicting with my initial expectations. Goodwill impairments appear to be relevant for earnings forecasts in all life cycle stages. Restructurings only create sustainable value for *mature* firms and short-term earnings improvements for *growth* firms. *Shake-out* firms have a higher chance to achieve a turnaround if they focus on in-process R&D and extinguishment of existing debt. Finally, *decline* businesses can boost future performance by engaging in M&A activity – however, this result may be distorted due to a small sample for the *decline* stage.

Table 8: Modified regression model – by sub-items and life cycle stages (N = 31,502)

$$PM_{t+1}^{w} = \sum_{j=1}^{5} \alpha_{1,0} + \sum_{j=1}^{5} \beta_{1,1}^{w} * core\ PM_t^w + \sum_{j=1}^{5} \beta_{1,2}^{w} * in-process\ R\&D_t^w + \sum_{j=1}^{5} \beta_{1,3}^{w} * restructuring_t^w + \sum_{j=1}^{5} \beta_{1,4}^{w} * gain\ loss_t^w + \sum_{j=1}^{5} \beta_{1,5}^{w} * litigation_t^w + \sum_{j=1}^{5} \beta_{1,6}^{w} * other\ SPI_t^w + \sum_{j=1}^{5} \beta_{1,7}^{w} * M\&A_t^w + \sum_{j=1}^{5} \beta_{1,8}^{w} * goodwill_t^w + \sum_{j=1}^{5} \beta_{1,9}^{w} * writedown_t^w + \sum_{j=1}^{5} \beta_{1,10}^{w} * extinguish\ debt_t^w + \sum_{i=1}^{10} \beta_{1,11}^{i} * YEAR_i + \varepsilon_{t+1}$$

Introduction / Birth

Nbr. of years in earnings window	α	Core PM^w_t	In-process $R\&D^w_t$	Re-structuring^w_t	Gain/ Loss^w_t	Litigation^w_t	Other SPI^w_t	$M\&A^w_t$	Goodwill^w_t	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R^2
1	-0.022	0.603***	0.431	-0.241	0.07	-0.074	0.106	0.051	0.126	0.225	0.198	0.346
	(0.022)	(0.057)	(0.408)	(0.190)	(0.444)	(0.249)	(0.187)	(0.318)	(0.133)	(0.225)	(0.153)	
2	0.028*	0.518***	0.096	0.019	-0.128	-0.033	-0.027	0.225	0.495***	-0.225	0.128	0.323
	(0.015)	(0.059)	(0.310)	(0.378)	(0.579)	(0.383)	(0.286)	(0.463)	(0.189)	(0.191)	(0.299)	
3	0.045***	0.481***	0.186	0.283	-0.654	-0.125	0.078	0.161	0.570***	-0.443**	-0.275	0.287
	(0.012)	(0.082)	(0.745)	(0.589)	(0.514)	(0.506)	(0.655)	(0.50)	(0.203)	(0.224)	(0.415)	
4	-0.003	0.555***	0.852	0.313	-0.93	-0.47	-0.014	0.869	0.402**	-0.622***	-0.349	0.33
	(0.012)	(0.091)	(1.028)	(0.623)	(0.775)	(0.572)	(0.690)	(1.081)	(0.202)	(0.165)	(0.662)	
5	0.002	0.506***	1.016	0.72	-1.025**	-0.245	-0.396	0.581	0.480**	-0.662**	0.906	0.332
	(0.012)	(0.097)	(1.087)	(0.734)	(0.514)	(0.585)	(0.683)	(1.549)	(0.196)	(0.261)	(0.976)	

Growth

Nbr. of years in earnings window	α	Core PM^w_t	In-process $R\&D^w_t$	Re-structuring^w_t	Gain/ Loss^w_t	Litigation^w_t	Other SPI^w_t	$M\&A^w_t$	Goodwill^w_t	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R^2
1	-0.005	0.723***	0.137	0.624***	0.219**	0.264*	0.436***	0.218**	0.259***	0.143	0.4	0.394
	(0.007)	(0.022)	(0.103)	(0.176)	(0.105)	(0.153)	(0.136)	(0.107)	(0.075)	(0.095)	(0.244)	
2	0.050***	0.710***	0.417***	0.409**	0.06	0.422	0.312**	0.324***	0.242***	0.176*	0.566**	0.402
	(0.005)	(0.020)	(0.150)	(0.196)	(0.139)	(0.340)	(0.144)	(0.114)	(0.076)	(0.105)	(0.243)	
3	0.050***	0.721***	0.578***	0.291	-0.155	0.648	0.229	0.545***	0.307***	0.144	0.432*	0.414
	(0.005)	(0.019)	(0.209)	(0.199)	(0.208)	(0.434)	(0.376)	(0.134)	(0.091)	(0.120)	(0.226)	
4	0.030***	0.705***	0.793***	0.188	0.065	0.769	0.004	0.594***	0.295***	0.183	0.508	0.417
	(0.005)	(0.020)	(0.293)	(0.269)	(0.221)	(0.527)	(0.337)	(0.163)	(0.111)	(0.172)	(0.340)	
5	0.030***	0.671***	0.847***	0.341	0.001	0.286	-0.006	0.500	0.16	0.161	0.637*	0.41
	(0.004)	(0.022)	(0.30)	(0.272)	(0.390)	(0.367)	(0.380)	(0.345)	(0.098)	(0.226)	(0.369)	

Mature

Nbr. of years in earnings window	α	Core PM^w_t	In-process $R\&D^w_t$	Re-structuring^w_t	Gain/ Loss^w_t	Litigation^w_t	Other SPI^w_t	$M\&A^w_t$	Goodwill^w_t	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R^2
1	0.001	0.768***	0.295	0.18	0.245**	0.190*	0.061	0.193*	0.159***	-0.011	0.12	0.454
	(0.005)	(0.016)	(0.329)	(0.126)	(0.124)	(0.101)	(0.119)	(0.114)	(0.038)	(0.054)	(0.113)	
2	0.032***	0.756***	-0.044	0.312***	0.194*	0.222***	0.174	0.382***	0.122***	-0.078	0.194	0.483
	(0.003)	(0.014)	(0.219)	(0.089)	(0.101)	(0.081)	(0.131)	(0.129)	(0.038)	(0.056)	(0.186)	
3	0.040***	0.748***	0.148	0.239**	0.061	0.344***	0.236*	0.216	0.170***	-0.180**	0.126	0.480
	(0.003)	(0.013)	(0.224)	(0.104)	(0.137)	(0.105)	(0.134)	(0.149)	(0.043)	(0.085)	(0.311)	
4	0.029***	0.750***	0.332	0.310**	0.271	0.199	0.455***	0.11	0.181***	-0.240**	0.381	0.496
	(0.003)	(0.013)	(0.239)	(0.121)	(0.249)	(0.166)	(0.176)	(0.195)	(0.041)	(0.111)	(0.314)	
5	0.021***	0.753***	0.785**	0.294**	0.578***	0.084	0.636***	0.074	0.163***	-0.224	0.891***	0.519
	(0.003)	(0.014)	(0.337)	(0.150)	(0.194)	(0.203)	(0.240)	(0.257)	(0.042)	(0.149)	(0.339)	

Shake-out / Revival

Nbr. of years in earnings window	α	Core PM^w_t	In-process $R\&D^w_t$	Re-structuring^w_t	Gain/ $Loss^w_t$	$Litigation^w_t$	Other SPI^w_t	$M\&A^w_t$	$Goodwill^w_t$	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R^2
1	-0.025	0.472***	1.307	0.19	0.006	-0.135	-0.09	0.415	0.210**	-0.07	-0.07	0.281
	(0.019)	(0.033)	(1.350)	(0.181)	(0.083)	(0.203)	(0.091)	(0.344)	(0.087)	(0.101)	(0.300)	
2	0.058***	0.548***	-0.153	0.109	0.125	-0.225	0.024	0.505	0.160*	-0.129	0.164	0.328
	(0.010)	(0.032)	(0.423)	(0.189)	(0.115)	(0.281)	(0.159)	(0.347)	(0.089)	(0.103)	(0.325)	
3	0.059***	0.624***	0.566	-0.291	-0.105	0.234	-0.096	0.763**	0.137	-0.21	-0.165	0.390
	(0.007)	(0.034)	(0.354)	(0.261)	(0.155)	(0.224)	(0.169)	(0.357)	(0.094)	(0.160)	(0.415)	
4	0.044***	0.634***	1.011	-0.571**	-0.121	0.28	-0.008	0.202	0.072	0.014	0.136	0.406
	(0.008)	(0.040)	(0.626)	(0.266)	(0.218)	(0.243)	(0.300)	(0.528)	(0.102)	(0.274)	(0.491)	
5	0.031***	0.650***	1.247*	-0.493*	-0.118	0.052	-0.608	-0.036	0.123	-0.512***	0.814*	0.461
	(0.010)	(0.043)	(0.686)	(0.289)	(0.213)	(0.208)	(0.541)	(0.494)	(0.120)	(0.147)	(0.433)	

Decline

Nbr. of years in earnings window	α	Core PM^w_t	In-process $R\&D^w_t$	Re-structuring^w_t	Gain/ $Loss^w_t$	$Litigation^w_t$	Other SPI^w_t	$M\&A^w_t$	$Goodwill^w_t$	PP&E write-offs^w_t	Extinguish $Debt^w_t$	R^2
1	-0.048	0.454***	-0.89	0.172	0.161	0.013	0.441**	1.086***	0.267**	-0.518	0.892***	0.308
	(0.068)	(0.076)	(1.157)	(0.115)	(0.201)	(0.252)	(0.215)	(0.202)	(0.115)	(0.327)	(0.263)	
2	0.031	0.538***	0.006	-0.717	-0.392	0.201	-0.334	2.310***	0.717***	-0.149	-0.947	0.43
	(0.023)	(0.073)	(1.781)	(0.465)	(0.269)	(0.284)	(0.234)	(0.695)	(0.183)	(0.244)	(1.696)	
3	0.037	0.487***	3.615	-0.159	-0.822**	-0.178	0.15	3.524***	0.419	-0.344	-1.108	0.413
	(0.023)	(0.075)	(5.761)	(0.792)	(0.413)	(0.362)	(0.281)	(1.299)	(0.303)	(0.323)	(1.459)	
4	0.065**	0.332***	8.668	1.109	-0.926**	-1.042	-0.594	3.994**	0.554*	-0.743*	-0.644	0.356
	(0.025)	(0.050)	(5.863)	(1.008)	(0.399)	(0.631)	(1.203)	(1.693)	(0.295)	(0.378)	(1.590)	
5	0.050**	0.319***	19.231***	0.231	-0.017	-0.323	3.642***	2.394***	0.726**	-1.402***	-0.122	0.308
	(0.020)	(0.059)	(4.769)	(1.015)	(0.541)	(1.168)	(1.288)	(0.568)	(0.338)	(0.401)	(1.033)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 2. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.

5 Robustness

My analysis faces several issues, potentially making it difficult to transfer my results to other samples or time periods. First, my observation period covers two global crises – the dot-com bubble burst (2002 / 2003) and the global financial crisis (2007 / 2008). Since the frequency and magnitude of special items peak during crises (e.g. Johnson et al., 2011), this may distort my analysis. Second, in 2015 the FASB introduced Accounting Standard Update No. 2015-01, implying that extraordinary items are not required to be segregated from ordinary operations anymore, i.e. companies could potentially classify them as special items from 2015 onwards. This might hamper comparisons of special items pre and post 2015. Third, my sample selection criteria impose a strong survivorship bias, possibly distorting the allocation of my sample into life cycle stages – this aspect is addressed in section 3.3.1 as well as in **Figure 2** (Appendix). Fourth, while the adopted methodology to determine life cycle stages pursuant to Dickinson (2011) has several advantages, it also gives rise to some issues. The main concern with respect to Dickinson's approach is that some firms may have relatively volatile life cycle patterns – this aspect is addressed in section 5.1. Finally, data quality from COMPUSTAT is not ideal, as the sum of the one-time sub-items is equal to net special items only in 92.7% of my observations – this aspect is addressed in section 5.2.

5.1 Life cycle classification pursuant to Dickinson (2011)

As previously mentioned, the approach suggested by Dickinson (2011) may create volatile life cycle patterns. Yan & Zhao (2010) illustrate that Apple Computer Inc. experiences eleven life cycle changes between 1989 and 2005 if one applies Dickinson's (2011) cash flow proxies. My sample also includes examples with unstable patterns – e.g. Orion Energy Systems shows nine different life cycle stages between 2006 and 2018. It is theoretically possible that enterprises rapidly move back and forth through the life cycle, as the current stage is not only the result from internal, but also from external factors, which the company cannot influence. However, extreme fluctuations in a very short time appear to be unlikely from a rational perspective. For instance, it seems to be unlikely for a *growth* company to jump to the *decline* stage next year and then to the *introduction* stage the year after. In line with this, Miller & Friesen (1984) suggest that each stage lasts, on average, for six years. However, the life cycle pattern of Orion between 2013 and 2018 reads as follows: *mature – introduction – shake-out – decline – shake-out – introduction.* This emphasizes that Dickinson's (2011) cash flow proxies give rise to some weaknesses, which might possibly distort my results. In order to test the validity of Dickinson's (2011) life cycle proxies, one should ideally apply different life cycle classification methods and subsequently compare the results. This, however, would exceed the scope of my thesis, as most life cycle classification methods require a sizable amount of data. Instead, **Table 9** shows a transition matrix of life cycle stages in my sample, illustrating the percentage of firm-year-observations which remain in period t+1 in the same life cycle stage as in period t (diagonal items – shown in bold).

Table 9: Transition matrix of life cycle stages

	Life cycle in t+1:				
Life cycle in t:	Introduction	Growth	Mature	Shake-out	Decline
Introduction	**25.3%**	27.3%	32.1%	8.5%	6.7%
Growth	3.8%	**44.5%**	45.1%	5.6%	1.0%
Mature	2.1%	22.2%	**67.9%**	6.9%	0.9%
Shake-out	4.9%	17.9%	52.3%	**20.1%**	4.8%
Decline	17.2%	15.5%	25.2%	20.9%	**21.3%**

Notice that t = 2018 is not considered in this table, as there would be no following year (t+1).

Table 9 suggests, for instance, that 67.9% of *mature* enterprises are remaining in their life cycle stage in t+1. In contrast, 2.1% move to the *introduction* stage, 22.2% to the *growth* stage, 6.9% to the *shake-out* stage and 0.9% to the *decline* stage. Overall, the transition matrix indicates a reasonable pattern – this is visible based on three observations. First, my data suggests a convergence to the *mature* stage. Second, a significant amount of sample companies remains in their current life cycle stage – the percentage ranges between 21.3% in the *decline* stage and 67.9% in the *mature* stage. It makes perfectly sense that the percentage is lower for extreme stages (i.e. to the *introduction* or *decline* stage), as these companies require change to survive. Third, jumps to extreme stages are rare for all other stages. In fact, the likelihood for a sample company to move to the *decline* stage in t+1 is 6.7% for *introduction*, 1.0% for *growth*, 0.9% for *mature* and 4.8% for *shake-out* firms. In closing, my findings indicate that extremely volatile and unrealistic life cycle patterns appear only seldom, suggesting that Dickinson’s (2011) cash flow proxies are an appropriate classification method.

5.2 Replication of one-time revenues and one-time expenses

COMPUSTAT might cause issues for my analysis, as data quality is not ideal – in fact, the sum of the one-time sub-items is equal to net special items only in 92.7% of my observations. Furthermore, COMPUSTAT does not provide values for positive and negative special items, but only a netted number for each year. Existing literature as well as my research approach takes this netted number and allocates it to one-time expenses for each negative firm-year-observation and to one-time revenues for each positive firm-year-observation. Hence, negative and positive special profit margin can never be ≠ 0 at the same time, as mentioned several times throughout my research paper. There is one simple workaround, solving both issues. Instead of the prevalent approach, one could simply add up all negative and all positive one-time sub-items for each observation. Thereby, it is possible that both one-time revenues and expenses are ≠ 0 at the same time. I deliberately decided against using this approach in the main part of my thesis for two reasons. First, by using a different approach than Fairfield et al. (2009), comparability with their evidence would have been negatively affected. Second, this approach is less convenient and applicable for investors due to data availability issues. In fact, the COMPUSTAT "Global – Daily" database does not even provide a special item break-down into its sub-items, meaning the suggested workaround could not be conducted for all listed companies around the world.

I estimate my basic regression model from section 4.1 for the same sample by using the suggested workaround. The results from this regression are reported in **Table 12** in the Appendix. Since the results are almost identical to the ones from section 4.1, I conclude that data quality from COMPUSTAT does not create any distortions.

6 Conclusion

My research examines whether corporate life cycle theory can be leveraged to improve our understanding of one-time items. This is an important topic, as special items are renowned to be a major reason for the observed deterioration of earnings quality by researchers (e.g. Dechow & Schrand, 2004), making it difficult for practitioners to project future earnings of their targets. Thus, investors usually neglect one-time items categorically and base their forecasts on core earnings (Bradshaw & Sloan, 2002). Assuming special items can under certain conditions be associated with future performance, this technique implies a loss of information and can cause overvaluations, as special items are usually negative, i.e. core earnings exceeds GAAP earnings.

In the core of my paper, I regress lagged decomposed profit margin – core profit margin, positive and negative special profit margin – on future profit margin over increasing time windows from one to five years (section 4.1). My results suggest that investors can indeed use corporate life cycle theory to enhance their understanding of when positive and negative special items should be considered. In fact, one-time revenues are only associated with future performance for longer earnings windows in *mature* firms. One-time expenses, on the other hand, should primarily be considered for *growth* and *mature* businesses, as negative special profit margin shows a significant, positive association to future profit margin in the short-term as well as in the long-term for those two life cycle stages. For *shake-out* enterprises, there appears to be a weak correlation with future earnings in the short-term as well, but this might potentially be a consequence of earnings management. For *introduction* and *decline* firms, one-time expenses can be neglected.

In a next step, I try to identify which one-time sub-items are relevant in the respective life cycle stages. Thus, I modify my regression model in the sense that I break down positive and negative special profit margin into one-time sub-items provided by COMPUSTAT (section 4.2). For early-stage firms, relevant sub-items are in line with economic theory in the sense that they are reflecting the specific challenges and opportunities of the respective life cycle stages. For instance, my evidence suggests deteriorating future performance of *introduction* firms following PP&E write-offs, which is plausible, because young and small businesses require their asset base to grow and move on the *growth / mature* stage. For *growth* firms, in-process R&D and M&A-related

gains / losses show a significant and positive association to future profits, reflecting their corporate objective of achieving organic and inorganic growth. For later-stage firms my results are less straightforward – they should also be interpreted with caution, as my sample is comparably small. Nevertheless, my regression analysis indicates that *shake-out* firms have a higher chance of revival by focusing on in-process R&D and extinguishment of existing debt, while *decline* businesses can boost future performance by engaging in M&A activity. Finally, my results suggest that goodwill impairment is the only sub-item which shows a significant association to future profit margin in all five life cycle stages, while restructurings only create sustainable value for *mature* firms – both results are somewhat surprising. Goodwill impairments are usually a sign that a company overpaid when acquiring another company, which should in theory not affect future performance as Cready et al. (2012) suggest. Restructurings, on the other hand, should theoretically be more relevant for later-stage business, as these businesses require change to achieve a turnaround. In line with this, my descriptive analysis in sub-section 3.3.4 confirms that the frequency of restructurings is higher for *shake-out* and *decline* firms. However, my regression results indicate that restructurings only show the desired effects for the *mature* stage. For *shake-out* firms, restructurings are even associated with long-term value destruction. Hence, we require additional research on goodwill impairments and restructurings to understand the discrepancy between theoretical economic expectations and my findings.

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Appendix

Table 10: Data years included in one- and five-year windows

w = 1	
y	x
2002	2001
2003	2002
2004	2003
2005	2004
2006	2005
2007	2006
2008	2007
2009	2008
2010	2009
2011	2010
2012	2011
2013	2012
2014	2013
2015	2014
2016	2015
2017	2016
2018	2017

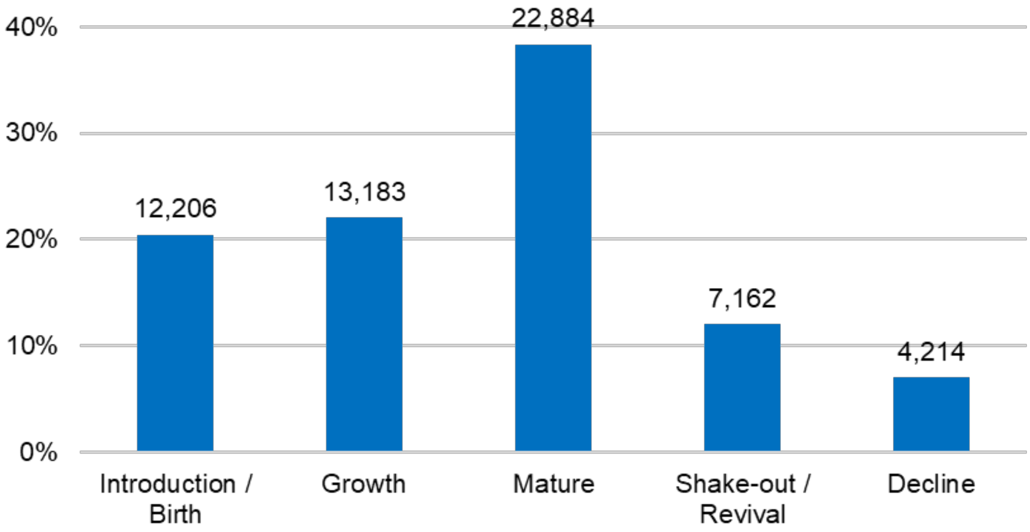
w = 5					
y			x		
2006	*to*	2010	2001	*to*	2005
2007	*to*	2011	2002	*to*	2006
2008	*to*	2012	2003	*to*	2007
2009	*to*	2013	2004	*to*	2008
2010	*to*	2014	2005	*to*	2009
2011	*to*	2015	2006	*to*	2010
2012	*to*	2016	2007	*to*	2011
2013	*to*	2017	2008	*to*	2012
2014	*to*	2018	2009	*to*	2013

In line with Fairfield et al. (2009), I perform my regression (section 4) over increasing time windows from one to five years, because one-time items tend to be irregular. There is no overlap between the time windows of the dependent and independent variables. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. Extending the time window to its maximum of w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Consequently, we require at least 10 years of consecutive data for w = 5.

Table 11: Adjusted sample selection criteria

Sample selection criteria	Total observations	Total firms
2001-2018 Annual Industrial Compustat (active firms)	105,475	9,833
Firms in financial services (SIC 6000s)	(38,419)	(3,791)
Firms outside of Europe or North America	(7,407)	(792)
Final sample	**59,649**	**5,250**

Figure 2: Distribution across life cycle stages based on adjusted sample selection criteria (Table 11)



Numbers above bars refer to firm-year-observations in the respective life cycle stages.

The derived life cycle distribution in section 3.3.1 is to some extent a consequence of my sample selection criteria, which impose a strong survivorship bias. Given that I exclude, for instance, firms with net operating assets or sales below $5m, there is a higher likelihood that firms from the *introduction* or *decline* stage are dropped. **Figure 2** illustrates the life cycle distribution, assuming less restrictive sample selection criteria (**Table 11**). Namely, enterprises are only excluded, if they are inactive between 2001 and 2018, operate in the financial services sector, and / or are headquartered outside of Europe / North America. The results suggest a similar life cycle pattern (i.e. highest / lowest frequency of observations in the *mature* / *decline* stage), but the distribution shows a higher density in the tails. While in section 3.3.1 only 4% and 2% of firm-year-observations are classified as *introduction* and *decline* respectively, the corresponding percentages in **Figure 2** are 20% and 7%. It would not be sound to base my regression analysis on the final sample from **Table 11**, however, as i) this sample includes numerous outliers, and ii) firms without 10 years of consecutive data are included, meaning I could not perform my regression analysis over earnings windows from one to five years. It needs to be emphasized, however, that the results of my regression analysis in section 4 should be transferred to enterprises not satisfying the sample selection criteria with caution.

Table 12: Base regression model – replication positive / negative special items (N = 31,502)

$$PM_{t+1}^{w} = \sum_{j=1}^{5} \alpha_{2,0} + \sum_{j=1}^{5} \beta_{2,1}^{w} * core\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{2,2}^{w} * negative\ special\ PM_{t}^{w} + \sum_{j=1}^{5} \beta_{2,3}^{w} * positive\ special\ PM_{t}^{w} + \sum_{i=1}^{10} \beta_{2,4}^{i} * YEAR_{i} + \varepsilon_{t+1}$$

Nbr. of years in earnings window	Introduction / Birth					Growth				
	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.02	0.599***	0.143	0.069	0.341	-0.005	0.724***	0.274***	0.11	0.393
	(0.022)	(0.057)	(0.099)	(0.213)		(0.007)	(0.022)	(0.045)	(0.069)	
2	0.034**	0.508***	0.175	-0.069	0.312	0.050***	0.707***	0.292***	0.149*	0.401
	(0.015)	(0.059)	(0.136)	(0.264)		(0.005)	(0.019)	(0.058)	(0.078)	
3	0.048***	0.465***	0.064	-0.571	0.268	0.051***	0.716***	0.341***	0.158	0.411
	(0.012)	(0.083)	(0.159)	(0.413)		(0.005)	(0.019)	(0.077)	(0.116)	
4	-0.002	0.553***	-0.044	-0.431	0.306	0.031***	0.700***	0.342***	0.255**	0.414
	(0.012)	(0.092)	(0.186)	(0.439)		(0.005)	(0.019)	(0.093)	(0.129)	
5	0.002	0.506***	0.117	-0.541	0.31	0.030***	0.668***	0.245***	0.16	0.408
	(0.012)	(0.099)	(0.203)	(0.467)		(0.004)	(0.022)	(0.082)	(0.171)	

Nbr. of years in earnings window	Mature					Shake-out / Revival				
	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	0.001	0.767***	0.126***	0.133*	0.453	-0.026	0.473***	0.111*	0.016	0.274
	(0.004)	(0.016)	(0.029)	(0.073)		(0.020)	(0.033)	(0.062)	(0.090)	
2	0.031***	0.756***	0.095***	0.288***	0.482	0.059***	0.552***	0.056	0.199*	0.325
	(0.003)	(0.014)	(0.029)	(0.062)		(0.010)	(0.031)	(0.060)	(0.112)	
3	0.040***	0.746***	0.119***	0.389***	0.479	0.062***	0.618***	0.066	0.121	0.385
	(0.003)	(0.013)	(0.034)	(0.086)		(0.007)	(0.033)	(0.070)	(0.125)	
4	0.029***	0.748***	0.137***	0.443***	0.495	0.045***	0.628***	0.051	0.153	0.402
	(0.003)	(0.013)	(0.036)	(0.101)		(0.007)	(0.039)	(0.082)	(0.131)	
5	0.020***	0.749***	0.154***	0.538***	0.517	0.035***	0.640***	-0.011	0.101	0.448
	(0.003)	(0.014)	(0.038)	(0.103)		(0.010)	(0.042)	(0.095)	(0.139)	

Nbr. of years in earnings window	Decline				
	α	Core PM^w_t	Negative special PM^w_t	Positive special PM^w_t	R^2
1	-0.054	0.427***	0.180	0.179	0.258
	(0.065)	(0.072)	(0.163)	(0.130)	
2	0.051*	0.539***	0.272	-0.284	0.376
	(0.026)	(0.072)	(0.181)	(0.189)	
3	0.041*	0.493***	0.183	-0.443	0.349
	(0.023)	(0.073)	(0.261)	(0.351)	
4	0.071***	0.348***	0.071	-0.712*	0.279
	(0.027)	(0.051)	(0.297)	(0.377)	
5	0.034*	0.323***	0.128	-0.118	0.240
	(0.020)	(0.055)	(0.174)	(0.455)	

Coefficients marked with *, ** or *** are significant at the 10%, 5% 1% level, respectively. Variables are as defined in Table 2. Model is postulated in section 3.1. Subscript w refers to the earnings windows, ranging from 1 to 5 years. For w = 1, the dependent variable captures period t+1, while the independent variables are collected from period t. For w = 5, the dependent variable is computed as the average from period t+1 until t+5, while the independent variables are defined as average from period t-4 until t. Year dummies are not reported.
Huber–White clustered standard errors are reported below the coefficients, which are robust to serial correlation and heteroscedasticity.