

MANAGING EARNINGS PER SHARE

AN EMPIRICAL ANALYSIS OF GOODWILL IMPAIRMENT
IN EUROPE

TIM DANIEL

PHILIPP VON AICHBERGER

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Abstract

This study investigates the use of goodwill impairment to manage earnings per share (EPS) relative to consensus forecasts. The sample is comprised of firm-year observations between 2015 and 2021 covering IFRS-applying firms listed in the STOXX Europe 600. Within our analysis, we utilize a probit regression to test for the likelihood of impairment and a tobit regression for the impairment magnitude. Generally, our findings indicate that the discretion inherent in the goodwill impairment regulation (IAS 36) might be exercised to manage EPS utilizing consensus forecasts as a benchmark. Incorporating three managerial incentive proxies, our results suggest that managers exercise the discretion not only to overstate but also to understate goodwill impairment. Our additional analysis regarding the COVID-19 pandemic identifies the pre-crisis period as the driver of our main analysis' results. The implications of our findings extend to various stakeholders such as standard setters, auditors, and investors, particularly given the ongoing discussions on the impairment-only approach.

Keywords:

IFRS, goodwill, impairment-only approach, managerial incentives, earnings per share

Authors: Tim Daniel (42307), Philipp von Aichberger (42306)

Tutor: Irina Gazizova, Assistant Professor, Department of Accounting

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List of abbreviations

2SLS	Two Stage Least Squares
CEO	Chief Executive Officer
CGU	Cash-Generating Unit
COVID-19	Coronavirus Disease 2019
EPS	Earnings Per Share
EU	European Union
GAAP	Generally Accepted Accounting Principles
GDP	Gross Domestic Product
GW	Goodwill
GW	Goodwill Impairment
H	Hypothesis
IAS	International Accounting Standards
IASB	International Accounting Standards Board
ICB	Industry Classification Benchmark
IFRS	International Financial Reporting Standards
IQR	Interquartile Range
N	Number of Observations
OLS	Ordinary Least Squares
SFAS	Statement of Financial Accounting Standards
US	United States
VIF	Variance Inflation Factor
€	Euro
σ	Standard Deviation

1. Introduction

“Prediction is very difficult, especially if it's about the future!” - Niels Bohr

Assessing future economic benefits, the subsequent measurement of firms' goodwill is based on numerous predictions. Since goodwill makes up a significant part of many firms' reported assets, a truthful representation of the underlying economic value is of utmost importance. Stakeholders rely on accurate financial reporting to evaluate the economic prospects of businesses and make informed decisions. Establishing a framework that accommodates both a faithful representation of economic reality and the inherent uncertainty associated with goodwill's forward-looking nature presents a challenge to regulators.

Despite standard setters emphasizing increased value relevance and transparency following current goodwill regulations, criticism has been expressed by scholars and practitioners alike (Glaum et al., 2018; Lee, 2011). Until 2004, the goodwill balance had to be amortized periodically using a straight-line approach. Replacing this amortization regime, the impairment-only approach based on IAS 36 necessitates impairment tests at least on an annual basis. Those impairment tests require assumptions concerning future cash flows and growth as well as discount rates to determine whether goodwill needs to be impaired (IASB, 2004a). The International Accounting Standards Board (IASB) follows the largely comparable SFAS 142 within US GAAP that was introduced in 2001 (André et al., 2016). Although the required assumptions raised concerns regarding the use of discretion, the IASB opted to maintain this approach and voted for supplementary disclosure requirements following the end of the post-implementation review in 2022 (IASB, 2022).

While managerial discretion could be utilized to display private information (AbuGhazaleh et al., 2011), it might be exercised to manage earnings (Ramanna & Watts, 2012). Thereby, managers might use certain financial benchmarks as a threshold. Within the set of benchmarks, analysts' earnings per share (EPS) consensus forecasts serve as a relevant target alongside historic, industry, and zero earnings (Brown & Caylor, 2005; Carvajal et al., 2017; Degeorge et al., 1999). The consensus forecast is the median estimate of all analysts' EPS predictions for a given firm (Chung & Hribar, 2021; Gu & Wu, 2003). These predictions are based on firms' public disclosures as well as various other sources and utilized by several stakeholders to assess firms' performance. In general, the difference between the reported EPS and the EPS consensus forecast is referred to as the earnings surprise (Matsumoto, 2002).

Managers could take advantage of the flexibility granted by the goodwill impairment standard and manage EPS relative to consensus forecasts. Although IAS 36 prohibits the reversal of goodwill impairment, it is presumed that the discretion inherent in impairment decisions could be used in diverging directions. The desire to reach an EPS consensus

benchmark might serve as a managerial incentive to understate goodwill impairment. In contrast, firms might also face incentives to overstate impairment. These overstatement incentives could be relevant for firms with pre-impairment EPS clearly below or above the consensus. Integrating the previously mentioned managerial incentives in a European setting establishes the following research question:

Are listed European firms utilizing goodwill impairments to manage EPS relative to consensus forecasts?

By answering this research question, we aim to contribute to existing literature in the domain of goodwill impairment determinants which focuses on actual and industry earnings as benchmarks instead of EPS consensus forecasts. With respect to incentives to overstate goodwill impairment, we follow previous research and investigate the prevalence of big bath and earnings smoothing. Big bath refers to a one-time overstatement of charges against income in times of adverse profitability (Sevin & Schroeder, 2005). In times of excess profitability, earnings smoothing involves efforts to attain a stable and predictable earnings pattern (Zucca & Campbell, 1992). Although previously published literature finds a significant relation between big bath behavior and goodwill impairment (AbuGhazaleh et al., 2011; Kabir & Rahman, 2016), other studies cannot affirm these findings (Glaum et al., 2018; Iatridis & Senftlechner, 2014). Similarly, previous research observes exploitation of goodwill impairment for earnings smoothing purposes (AbuGhazaleh et al., 2011; Glaum et al., 2018), while overall evidence in this domain is mixed (Giner & Pardo, 2015). Regarding goodwill impairment understatement, sparse evidence suggests that motivations to reach an earnings threshold play a substantial role in goodwill impairment decisions (Gros & Koch, 2020).

Transitioning to our study design, we employ a STOXX Europe 600 sample covering the fiscal years 2015 to 2021. Our analysis focuses on the determinants of goodwill impairment incidences and magnitudes with respect to EPS consensus forecasts. To investigate this, we utilize a probit regression to test for the likelihood of impairment and a tobit regression for the impairment magnitude. After controlling for economic factors, our findings indicate that managers might exercise the discretion permitted by IAS 36 to manage EPS relative to consensus forecasts. We find significant positive associations between variables describing big bath as well as earnings smoothing incentives and the likelihood and magnitude of goodwill impairment. In addition, we observe a significant negative association between the target-beating incentive proxy and the likelihood as well as magnitude of impairment. For our additional analysis, we partition the time horizon into a pre-crisis and a crisis subsample to examine goodwill impairment determinants before and during the COVID-19 pandemic. Opposed to previous literature investigating goodwill impairment decisions during the financial crisis in 2008 and 2009 (Giner & Pardo, 2015), we identify the pre-crisis period as the driver of the main analysis' results.

Therefore, our study's findings from listed European companies illustrate that the discretion inherent in the goodwill impairment regulation based on IAS 36 might be

utilized to manage EPS relative to external analyst estimates. By using EPS consensus forecasts to describe managerial incentives to take a big bath or smooth earnings, we aim to provide a new perspective to this domain and complement previous literature focusing on firms' reported earnings parameters. With regards to companies meeting or slightly beating the EPS consensus, we aspire to combine target-beating literature and studies on goodwill impairment determinants. We build on the distributional approach to incorporate an interval to the right of the earnings threshold to define our managerial incentive variable and to provide insights into an area of high theoretical and practical relevance. Covering the COVID-19 crisis in our additional analysis, we aim to shed light on goodwill impairment determinants within a unique macroeconomic setting.

The remainder of this thesis is structured as follows. We commence by introducing the institutional setting of goodwill impairment and the relevant literature in this domain. This thesis continues by outlining our methodology, succeeded by a description of the underlying data and our sample. Subsequently, we present and discuss our results, including the findings from our additional analysis. Lastly, we summarize our study, outline limitations, and provide suggestions for future research.

2. Regulatory background

This section starts by focusing on the characteristics and guidelines of the current goodwill impairment regulations. Following this, the discretion inherent in the impairment-only approach is described.

2.1. Impairment-only approach

According to IFRS 3, goodwill represents the future economic benefits arising from other assets acquired in a business combination that are not individually identified and separately recognized (IFRS 3.A). These future economic benefits represent various aspects that are not covered by the accounting system. Among others, expected synergies from integrating the acquired business and the ability to generate monopoly profits after the acquisition are potential future economic benefits (Giner & Pardo, 2015). The amount of goodwill that needs to be recognized upon acquisition is computed as the excess of the consideration transferred over the net of the acquired identifiable assets and assumed liabilities (IFRS 3.32).

Subsequent to initial recognition, goodwill needs to be tested for impairment. Revised in 2004, IAS 36 requires companies to test goodwill for impairment at least on an annual basis. This impairment-only approach necessitates the comparison between the carrying and the recoverable amount of the respective cash-generating unit (CGU) (IAS 36.90). The recoverable amount reflects the higher of the value in use and the fair value less costs of disposal (IASB, 2004a). The value in use builds on the present value of future cash flows, discounted by an estimated discount rate (IASB, 2004a). In that context, the impairment-only approach mandates allocating goodwill to the CGUs of the acquiring entity expected to experience the synergistic effects stemming from the business combination (IAS 36.80). This differs from utilizing the acquired entity as the primary unit of measurement (Hellman & Hjelström, 2023).

If the need for an impairment is detected, the corresponding loss must be allocated to goodwill first and to the remaining assets of the CGU second (IAS 36.104). Regarding timing, the impairment test can be conducted at any point within the fiscal year, given that it is consistently performed at the same time each year. However, CGUs to which goodwill has been allocated may undergo impairment testing separately following differing schedules (IAS 36.96). In addition, impairment tests could also be undertaken outside the regular schedule once there is an indication of impairment (IAS 36.90).

2.2. Discretion within goodwill impairment

Following IAS 36, the impairment test and the required calculations demand several estimations that allow for discretion and judgment by management (Giner & Pardo, 2015; Jarva, 2009).

First, managers can assert discretion in allocating goodwill to the respective CGUs. Upon acquisition, the arising goodwill needs to be split between the CGUs that are expected to attain the future economic benefit of the business combination (IAS 36.80). This allocation involves a high level of discretion and simultaneously affects the incidence and size of future impairment charges (Beatty & Weber, 2006; Lapointe-Antunes et al., 2008; Ramanna & Watts, 2012). However, the allocation to the respective CGUs is a one-time event and subsequent discretion is limited (Avallone & Quagli, 2015).

Second, the standard permits discretion in estimating cash flows for the upcoming fiscal years. While emphasis should be placed on external evidence, managers are supposed to project cash flows based on the most recent financial budgets and best estimates of the underlying economic conditions. Those estimates should extend over a maximum period of five years and exclude future restructurings and alterations to enhance the assets' performance (IAS 36.33 (a), (b)). Consequently, firms possess considerable flexibility in including unverifiable estimates and assumptions in their goodwill impairment decisions (Avallone & Quagli, 2015; Lee, 2011; Watts, 2003), particularly compared to the previous amortization regime (Jarva, 2009).

Lastly, assumptions relating to long-term growth and discount rates allow for managerial discretion within impairment tests (Avallone & Quagli, 2015). Concerning the long-term growth rates, some limitations need to be followed. Unless an increasing long-term growth rate can be justified, a steady or declining rate is required. Furthermore, the long-term growth rate must not exceed the average growth rates of related products, industries, and the entity's operating countries and markets (IAS 36.33 (c)). In addition, the estimations of CGUs' fair values and values-in-use rely on expectations concerning the applicable discount rates that reflect the underlying risk profiles (Glaum et al., 2018). IAS 36.A17 suggests utilizing a CGU's weighted average cost of capital or incremental borrowing rate as a starting point. However, this rate needs to be adjusted subsequently to account for, among others, currency, country, and price risks (IAS 36.A18). Due to the forward-looking characteristics of long-term growth and discount rates, the degree of subjectivity is high while the verifiability by external parties such as auditors is low (Ramanna & Watts, 2012).

Generally, the allocation of goodwill to a CGU, the growth rate of future cash flows, and the discount rate, among others, are subject to several subjective and unverifiable assumptions. While the managerial discretion is limited to a certain degree by the standard, the remaining flexibility leaves room to substantially impact the amount of goodwill impairment recorded in the income statement (Avallone & Quagli, 2015).

3. Literature review & hypotheses development

This section begins by investigating previous research regarding the influence of the accounting standard on goodwill impairment determinants. Subsequently, applicable literature on earnings management is introduced, followed by a discussion of empirical evidence concerning earnings thresholds. The section is concluded by integrating the realms of goodwill impairment, earnings management, and earnings thresholds to establish our hypotheses.

3.1. Information content of goodwill impairment

While the impairment-only approach postulates more relevant reporting than the previous amortization regime, criticism has been voiced by different stakeholders (Jarva, 2009; Lee, 2011).

Several studies indicate that the impairment-only approach has improved decision usefulness contrasted with the amortization approach. Chalmers et al. (2011) compare the effectiveness of local GAAP and IFRS after adoption in Australia and find that the impairment-only approach resembles the underlying economic value better than amortization. Beyond that, the study by AbuGhazaleh et al. (2011) on firms in the United Kingdom reveals that managers use their discretion to signal private information about the future development of cash flows, mirroring the intentions of the accounting guidelines.

Despite this, concerns have been raised regarding the value relevance and timeliness of impairment. Based on their study using US companies with market indications of goodwill impairment, Ramanna & Watts (2012) cannot confirm an association between proxies for managers' private information on favorable future cash flows and goodwill non-impairment. However, they do find an association between non-impairment and CEO compensation, CEO reputation, as well as debt covenants. This aligns with agency theory and suggests that the revised goodwill accounting rules are used opportunistically rather than to convey private information (Ramanna & Watts, 2012). A decrease in the informational value of goodwill impairment is also implied by the findings of Bens et al. (2011) who compare stock market reactions following goodwill impairments before and after the introduction of SFAS 142.

Focusing on the timeliness of goodwill impairment, Li & Sloan (2017) find an increase in goodwill balances and untimely impairments under SFAS 142 compared to the previous standard. A lack of timely goodwill impairment has also been associated with overconfident CEOs, who are assumed to inflate expectations of future cash flows (Chung & Hribar, 2021). Furthermore, the findings of André et al. (2016) suggest that American companies are more likely to impair and write off larger shares of their goodwill balance than European companies. This especially holds for the financial crisis in 2008 and 2009.

Although accounting standards for goodwill impairment are comparable between the US and Europe (André et al., 2016), there are differences in the institutional settings and public environments that could influence impairment behavior. Differing legal frameworks, market dynamics, financing choices, and company attributes such as ownership and governance could play a role in goodwill impairment reporting and might explain the deviating impairment decisions (Giner & Pardo, 2015; Hail et al., 2010).

The increase of discretion in goodwill impairment accounting driven by the intent to enrich informational value has sparked concerns regarding potential exploitation and decreased timeliness of impairment. While large parts of previous research focus on US settings when investigating the impairment-only approach, the findings of André et al. (2016) highlight the significant implications for European companies.

3.2. Earnings management through goodwill impairment

The discretion given to managers within the current goodwill impairment regulation may be exercised strategically in the form of earnings management. Earnings management can be described as the intentional intervention in the financial reporting process to attain a benefit (Schipper, 1989). There are numerous motivations for firms to engage in earnings management which include increasing executives' compensation, avoiding covenant breaches, and influencing stock market perceptions (Healy & Wahlen, 1999). Relevant forms of earnings management include earnings smoothing and big bath accounting. Companies employ various methods to manage earnings, for example, the use of real activities (Cohen et al., 2008; Dechow et al., 1995). Real activities are comprised of, among others, cutting advertising as well as research and development expenses (Baber et al., 1991; Bushee, 1998), and disposing assets the firm would typically retain (Bartov, 1993). Beyond that, accounting items allowing for managers' discretion, such as accruals, have proven to be vehicles of earnings management (Healy, 1985; Jones, 1991; Moehrlé, 2002).

While accruals such as accounts receivable and inventories are subject to a certain degree of discretion, the flexibility and potential scale are assumed to be greater within the current framework of goodwill impairment (Lee, 2011; Ramanna & Watts, 2012). Following section 2.2., the inherent uncertainty and subjectivity in projecting future cash flows is particularly pronounced for goodwill compared to other capitalized assets. This stems from goodwill typically embodying the present value of anticipated cash flows, which are contingent upon various internal and external factors influencing the company's competitive positioning. Additionally, the concept of moral hazard may come into play, as managers could potentially exploit goodwill impairment without fearing repercussions arising from unmet expectations in the future. This allows managers to exercise discretion in the goodwill impairment decisions to reach current objectives (Ramanna & Watts, 2012).

Furthermore, goodwill impairment is seen as a more cost-effective strategy compared to other methods of earnings management. Unlike manipulating cash flow relevant activities or items, impairing goodwill has no direct implications for the firm's business activities (Peasnell et al., 2005). Lastly, the potentially large impact on reported earnings and the flexible timing of goodwill impairment could serve as additional drivers of this earnings management method (Beatty & Weber, 2006; Lee, 2011).

Although firms might also manage earnings using real or accrual-based strategies, characteristics of the discretion inherent in the goodwill impairment regulation establish the relevance of this area for scholars and practitioners.

3.3. Earnings thresholds

When managing earnings, a few financial benchmarks gain importance that might be used as a threshold by managers. According to the study by Kirschenheiter & Melumad (2002) on earnings surprises in relation to stated targets, an equilibrium setting exists in which both taking a big bath and earnings smoothing are optimal for risk-neutral managers to maximize firm value. In addition, the earnings surprise is said to pivot to a level close to the right of zero.

This theoretical observation around a threshold is documented by prior empirical research. Brown's (2001) temporal analyses of earnings in the US indicate the same pattern. This study finds that the median earnings surprise has shifted from a negative to a small positive value over time, using a sample from 1984 to 1999. Degeorge et al. (1999) introduce a distributional model, which centers around the prediction of the number of observations close to a given threshold, to test for the expected earnings behavior. Using zero earnings, prior year earnings, and analyst forecasts, the authors find that results are less frequent in an interval to the left, and more common to the right of the target, indicating a discontinuity. In support, Burgstahler & Dichev (1997) use graphical and statistical evidence to demonstrate that companies manage earnings to prevent losses and small earnings decreases. Low frequencies for small losses and decreases as well as unusually high frequencies for small profits and small positive changes in earnings have been found. This distributional approach has been utilized in follow-up studies in different settings, such as for Australian companies by Holland & Ramsay (2003) who largely confirm previous findings regarding a discontinuity of earnings.

Furthermore, several studies determine a hierarchy of thresholds. First, Degeorge et al. (1999) identify preventing losses as the most relevant benchmark for managers, which is followed by recent performance and analyst forecasts. With regards to the prevention of losses and earnings decreases, Burgstahler & Dichev (1997) observe the same hierarchical order. This is investigated and compared to the relevance hierarchy for investors by Carvajal et al. (2017). This paper, studying an Australian setting, finds that managers focus on profits and positive earnings changes, but the market attaches a higher

value to analyst forecasts. This is supported by Brown & Caylor (2005), as the authors find that meeting or slightly beating the quarterly analyst forecast is most important, applying the methodologies of Burgstahler & Dichev (1997) and Degeorge et al. (1999). Considering analyst forecasts, Burgstahler & Eames (2006) underline the importance of EPS forecasts for managers due to the observed frequency of upward earnings and downward forecast management. Nevertheless, the threshold hierarchy is subject to several firm-level factors, such as analyst forecast accuracy and dispersion, firm size, growth prospects, and trading volume (Fang Li, 2010).

Multiple benchmarks can impose incentives to manage earnings. The EPS consensus forecast has been identified as one of the main targets internally as well as externally and, therefore, serves as the basis for our managerial incentive proxies.

3.4. Hypotheses development

Considering the previous subsegments and our research question, we integrate the realms of goodwill impairment, earnings management, and earnings thresholds to posit our hypotheses. For the purpose of this thesis, we differentiate between incentives to overstate and understate goodwill impairment. Taking a big bath and earnings smoothing represent the incentives to overstate goodwill impairment and are assumed to be optimal for managers in an equilibrium setting to maximize firm value (Kirschenheiter & Melumad, 2002). In addition, managers might be incentivized to understate goodwill impairment within certain areas to the right of earnings thresholds (Degeorge et al., 1999). Following previous literature, we examine over- and understatement incentives for both the decision to impair and the magnitude of impairment (Glaum et al., 2018; Han et al., 2021). Since taking a big bath, earnings smoothing, and reaching the EPS consensus are subject to different motivations and empirical evidence, they are outlined separately in the subsequent paragraphs.

3.4.1. Big bath

There are several motivations to take a big bath. Firms may prefer to overstate expenses in a period with already unusually low earnings to reduce future expenses and thereby increase prospective earnings (Sevin & Schroeder, 2005). Furthermore, this strategy may help managers maximize long-term bonus payments (Riedl, 2004). Zucca & Campbell (1992) stress the signaling effect as a potential motivation for taking a big bath, implying that challenging periods have been overcome and more prosperous times will follow. In addition, future stock returns might be positively affected by unanticipated earnings increases following big bath charges in a prior period (Dechow et al., 2010; McVay, 2006). Conversely, the existence of debt covenants might serve as a motivation to not follow a big bath strategy to prevent potential covenant breaches (Watts & Zimmerman, 1990). Moreover, managers might refrain from taking a big bath to avoid negative stock market reactions that follow unexpected goodwill impairments (Bens et al., 2011).

Shedding a light on goodwill impairment literature, AbuGhazaleh et al. (2011) find an association between big bath accounting and goodwill impairment losses, indicating that the discretionary nature of impairment is exploited. Giner & Pardo (2015) analyze the decision to impair and the magnitude of goodwill impairment for a Spanish sample. According to their dichotomous variable definition, a big bath is taken when firms report negative pre-impairment earnings that are also below the earnings of the previous year. While their study finds a significant positive relation between the described big bath variable and the likelihood of impairment, they do not find a significant association between big bath and the impairment magnitude.

Furthermore, in the study by Glaum et al. (2018) on companies applying IFRS, firm-years with negative income and a negative change in income indicate big bath behavior if the change is below the median of firms with a negative change in income. They do not find a significant relation between taking a big bath and the likelihood of goodwill impairment, which is confirmed by Iatridis & Senftlechner (2014) for an Austrian setting. Beatty & Weber (2006) find that delayed goodwill impairments are associated with more binding debt covenants. This illustrates the conflicting motivations that managers face when impairing goodwill, balancing the benefits and risks associated with taking a big bath.

Given these competing motivations and mixed evidence on the prevalence of big bath accounting through goodwill impairment, this area warrants additional research. While previous studies rely on actual and industry earnings as benchmarks (Giner & Pardo, 2015; Glaum et al., 2018), we use external estimates in the form of EPS consensus forecasts to investigate big bath. Given the abundance of motivations to engage in big bath accounting (Riedl, 2004; Sevin & Schroeder, 2005; Zucca & Campbell, 1992) and evidence that goodwill impairment is used for this purpose (AbuGhazaleh et al., 2011; Giner & Pardo, 2015), we posit the following hypotheses (both stated in alternative form):

H1a: There is a significant positive association between firm-years with pre-impairment EPS substantially below analysts' EPS consensus forecasts and the likelihood of goodwill impairment

H1b: There is a significant positive association between firm-years with pre-impairment EPS substantially below analysts' EPS consensus forecasts and the magnitude of goodwill impairment

3.4.2. Earnings smoothing

Goodwill impairment may be used by firms to take a big bath, however, there is also an incentive to overstate goodwill impairment in years with unusually good performance to smooth earnings. One of the main reasons to smooth earnings is the perception that investors attribute less risk to firms with smooth earnings paths (Graham et al., 2005; Zucca & Campbell, 1992). Another motivation to manage earnings downward in

prosperous periods is to build up so-called “cookie jar” reserves which can help to reduce expenses in financially adverse periods (Sevin & Schroeder, 2005). Managers might also have bonus arrangements with certain thresholds that motivate them to shift excess earnings to future periods (Moses, 1987). However, managers might refrain from overstating goodwill impairment to avoid adverse stock market reactions (Bens et al., 2011). In addition, potential cost considerations related to auditors and internal control instances that need to be persuaded that the reported impairment losses correspond to the economic reality constitute a motivation against engaging in earnings smoothing (Degeorge et al., 1999).

Considering applicable goodwill impairment literature, Glaum et al. (2018) find a significant positive relation between the earnings smoothing incentive proxy and the likelihood of impairment. In this context, firms are considered to smooth earnings when they report a profit and the increase in income compared to the previous year is larger than the median income increase of firms with a positive change in income. Using a similar smoothing definition, AbuGhazaleh et al. (2011) find an association between earnings smoothing and goodwill impairment. Contrasting these findings, Giner & Pardo (2015) do not observe a significant relationship between earnings smoothing and the decision to impair.

Pivoting toward EPS consensus forecasts as a benchmark for earnings smoothing, this study aims to introduce a new perspective to the goodwill impairment literature. Considering previous empirical evidence indicating the existence of earnings smoothing (AbuGhazaleh et al., 2011; Glaum et al., 2018), we establish the following hypotheses (both stated in alternative form):

H2a: There is a significant positive association between firm-years with pre-impairment EPS substantially above analysts’ EPS consensus forecasts and the likelihood of goodwill impairment

H2b: There is a significant positive association between firm-years with pre-impairment EPS substantially above analysts’ EPS consensus forecasts and the magnitude of goodwill impairment

3.4.3. Target-beating

In addition to overstating goodwill impairment to either take a big bath or smooth earnings, understating is another possibility for managers with regard to earnings targets. To be precise, managers may use their discretion to understate goodwill impairment to meet or slightly beat EPS consensus forecasts. Gros & Koch (2020) use Barua et al. (2006) and Davis et al. (2009) as a starting point to separate discretionary and predicted economic goodwill impairment on a firm level. Gros & Koch (2020) test for instances in which the reported EPS is equal to or above the forecast, and the EPS excluding discretionary

goodwill impairment is below the forecast. Their findings suggest that managers use negative discretionary goodwill impairments to meet or beat analysts' EPS forecasts.

While this matches prior evidence on target-beating behavior (Burgstahler & Eames, 2006; Degeorge et al., 1999), two competing theories could be applied to managers' understatement decisions. On the one side, pressuring effects could strengthen the motivations to meet or beat analysts' estimates as missing this benchmark is associated with reductions in market return (Bartov et al., 2002; Brown et al., 1987; Kasznik & McNichols, 2002; Skinner & Sloan, 2002). Additionally, executives' performance-based compensation posits another motivation to reach external earnings thresholds (Han et al., 2021; Matsunaga & Park, 2001). On the other side, monitoring effects could prevent upward earnings management since analysts have facilitated uncovering fraud and opportunistic behavior in the past, acting as an intermediary within capital markets (Chen et al., 2015; Han et al., 2021; Jensen & Meckling, 1976). In this context, the differentiation between street and GAAP earnings might be another force that limits opportunistic goodwill impairment as analysts may prefer estimates excluding non-recurring items (Gu & Chen, 2004; Philbrick & Ricks, 1991).

Given the competing motivations and scarce evidence on goodwill impairment understatements to meet or beat EPS consensus forecasts, this area merits additional research. Following ample empirical evidence on target-beating behavior around consensus forecasts (Bhojraj et al., 2009; Burgstahler & Eames, 2006; Degeorge et al., 1999; Holland & Ramsay, 2003; Matsumoto, 2002), we employ the following hypotheses (both stated in alternative form):

H3a: There is a significant negative association between firm-years with pre-impairment EPS meeting or slightly beating analysts' EPS consensus forecasts and the likelihood of goodwill impairment

H3b: There is a significant negative association between firm-years with pre-impairment EPS meeting or slightly beating analysts' EPS consensus forecasts and the magnitude of goodwill impairment

3.5. Contribution

Considering our hypotheses, this study aims to contribute to existing literature in various ways. Given the relevance of EPS consensus forecasts for managers, our research seeks to investigate the use of goodwill impairment to manage EPS relative to the consensus. While previous studies on big bath and earnings smoothing focus on firms' reported earnings parameters, the introduction of EPS consensus forecasts offers a new angle to the utilization of the discretion permitted within IAS 36.

Furthermore, this study examines firms' goodwill impairment decisions to meet or beat EPS consensus forecasts. Drawing on the distributional approach, we specify an interval to the right of the earnings threshold to define our managerial incentive variable. Thus, we aim to integrate previously published literature on target-beating behavior and studies on goodwill impairment determinants.

In light of the recent COVID-19 pandemic, goodwill impairment in times of economic stability and distress is the focus of our additional analysis. Unlike previous studies that concentrate on static benchmarks such as prior year earnings, our study analyzes EPS consensus forecasts, which account for revised expectations following an external shock. Representing a unique macroeconomic setting, investigating impairment behavior during the COVID-19 crisis aims to enhance current research focusing on impairment decisions during the financial crisis of 2008 and 2009.

Generally, this thesis aspires to contribute to existing literature by shedding light on the role of EPS forecasts within impairment decisions following IAS 36. While large parts of the academic literature in this domain focus on US firms, this study analyses companies in a European setting that is characterized by a different legal and market environment.

4. Methodology

This section commences with an introduction to the overall research design, which outlines the types of regressions and dependent variables. Subsequently, the focus shifts to the independent variables and the description of the managerial incentive proxies. Following this, the control variables are grouped into debt contracting, governance and monitoring, and firm-level control variables. The section ends with integrating dependent, independent, and control variables, presenting two regression formulas used for investigating goodwill impairment determinants.

4.1. Research design

To investigate the use of goodwill impairment to manage EPS relative to consensus forecasts, this thesis utilizes a probit and a tobit regression. In line with prior research, we employ a probit regression to test for the decision to impair. Since this decision has only two possible outcomes, impairment or non-impairment, a probit regression is used to analyze this dichotomous choice. Within this regression, the goodwill impairment incidence (GWI_INC) is used as the binary, dependent variable amounting to 1 if the company reports an impairment in the current fiscal year, and 0 otherwise (Beatty & Weber, 2006; Giner & Pardo, 2015). For the magnitude of goodwill impairment (GWI_MAG), we follow previous literature and utilize a tobit regression (Glaum et al., 2018; Li et al., 2011; Riedl, 2004; Zang, 2008). This type of regression censors the continuous dependent variable of goodwill impairment at zero and allows for an examination of the magnitude. For this, goodwill impairments are scaled by lagged total assets following previous research (AbuGhazaleh et al., 2011; Giner & Pardo, 2015). In addition, goodwill impairments are transformed into positive numbers for statistical conformity concerning the dependent variable of the tobit regression (AbuGhazaleh et al., 2011; Riedl, 2004). Both the probit and tobit analysis contain the same independent variables.

4.2. Managerial incentive proxies

The managerial incentives to over- or understate goodwill impairment are captured by three different dummy variables. Incentives to overstate are represented by BIGBATH and SMOOTH, while MEET_BEAT describes an incentive to understate goodwill impairment. To establish a uniform benchmark for the three managerial incentive variables, we employ a measure that aims to depict EPS consensus forecasts in relation to pre-impairment EPS. Therefore, we apply the concept of the earnings surprise that is commonly used to describe target-beating behavior (Burgstahler & Eames, 2006; Degeorge et al., 1999; Matsumoto, 2002).

The formula for the pre-impairment earnings surprise draws on Carvajal et al. (2017), as illustrated in Equation (1).

$$Pre\text{-}imp.\text{ earnings surprise} = \frac{(pre\text{-}imp.\text{ EPS} - consensus\text{ EPS}) * weighted\text{ avg. diluted shares}}{lagged\text{ total assets}} \quad (1)$$

The pre-impairment earnings surprise is the difference between the actual EPS adjusted for goodwill impairment and the EPS consensus multiplied by the weighted average number of diluted shares and scaled by lagged total assets. The conversion of EPS from a per-share basis and deflation by lagged assets should allow for an analysis of both relatively small and large EPS figures included in the sample. In the following paragraphs, the three managerial incentive proxies are discussed in detail.

4.2.1. Big bath

Goodwill impairment decisions might be driven by pre-impairment EPS that are substantially below the EPS consensus. This incentive to overstate goodwill impairment is described by the dummy variable BIGBATH. The median of negative pre-impairment earnings surprises serves as a threshold for identifying instances where the target is substantially missed, corresponding with prior research (AbuGhazaleh et al., 2011; Glaum et al., 2018). This leads to the BIGBATH variable taking the value of 1 if the pre-impairment earnings surprise is negative and below the median of negative pre-impairment earnings surprises, and 0 otherwise.

Beyond theoretical motivations to take a big bath such as reducing future expenses (Sevin & Schroeder, 2005) and increasing executives' long-term bonus payments (Riedl, 2004), there is evidence of big bath accounting through goodwill impairment outside the domain of EPS consensus forecasts (AbuGhazaleh et al., 2011; Giner & Pardo, 2015). In line with our hypotheses H1a and H1b, we expect a positive association between BIGBATH and the likelihood of goodwill impairment as well as the magnitude, implying that companies with pre-impairment earnings surprises below the median of negative pre-impairment earnings surprises are more prone to impair and report larger goodwill impairments.

4.2.2. Earnings smoothing

Earnings smoothing represents an incentive to overstate goodwill impairment in times of unusually good performance relative to the EPS consensus. Symmetrically to the big bath approach, SMOOTH utilizes the median of positive pre-impairment earnings surprises as the threshold used to define substantial target-beating instances, in line with previous research (AbuGhazaleh et al., 2011; Glaum et al., 2018). Applying this to the corresponding managerial incentive variable, SMOOTH takes the value of 1 if the pre-impairment earnings surprise is positive and above the median of positive pre-impairment earnings surprises, and 0 otherwise.

The aspirations to obtain a stable earnings path (Graham et al., 2005; Zucca & Campbell, 1992) and to build up “cookie jar” reserves (Sevin & Schroeder, 2005) are considered main drivers behind the decision to engage in earnings smoothing. Empirical evidence suggests the existence of smoothing through goodwill impairment with regard to firms’ reported earnings parameters (AbuGhazaleh et al., 2011; Glaum et al., 2018). In line with our hypotheses H2a and H2b, we predict a positive association between SMOOTH and the likelihood as well as magnitude of goodwill impairment. This implies that companies with pre-impairment earnings surprises above the median of positive pre-impairment earnings surprises are more likely to impair and report larger goodwill impairments.

4.2.3. Target-beating

In contrast to overstating goodwill impairment to either take a big bath or smooth earnings, the variable MEET_BEAT aims to capture the incentive to understate impairment. This rationale is assumed to be followed when earnings are close to the benchmark to meet or beat the target and prevent reductions in both market return (Bartov et al., 2002; Kasznik & McNichols, 2002) and annual cash bonuses (Matsunaga & Park, 2001). For the purpose of this thesis, the definition of “close” to the benchmark draws on the distributional approach developed by Burgstahler & Dichev (1997) and Degeorge et al. (1999). This approach tests whether more earnings observations are in the interval close to the right of the target than expected. For defining our target-beating incentive proxy (MEET_BEAT), we build on the distributional approach to incorporate an interval to the right of the earnings threshold.

When constructing an interval, the need for precision needs to be balanced with the need for fineness (Degeorge et al., 1999; Dichev & Skinner, 2002). Holland & Ramsay (2003) present five formulas¹ to estimate the optimal interval width for data approaching normality. Those formulas are derived by estimating the underlying density function and incorporate the variability of the data as well as the number of observations.

To determine the interval width used for the MEET_BEAT variable, those five formulas are employed on the sample. Given the nature of the managerial incentive proxies, the zero pre-impairment earnings surprise serves as the center of the earnings distribution and intervals are specified following distributional properties. Constituting our relevant range, the interval to the right of zero is presumed to comprise companies that either meet or slightly exceed analysts’ EPS consensus forecasts prior to the goodwill impairment decision. As two out of the five formulas suggest interval widths that are significantly different from the remaining three and conflict with the desired characteristic, this thesis opts for an average of the remaining three formulas, as shown in Equation (2).

¹ $3.5\sigma n^{-1/3}$ (Scott, 1979); $2(IQR)n^{-1/3}$ (Freedman & Diaconis, 1981); $0.79(IQR)n^{-1/5}$ (Silverman, 1986); $0.9(\min(\sigma; IQR/1.34))n^{-1/5}$ (Silverman, 1986); $1.06\sigma n^{-1/5}$ (Silverman, 1986)

$$Interval\ width = mean \left[2(IQR)n^{-\frac{1}{3}}; 0.9 \left(\min \left(\sigma; \frac{IQR}{1.34} \right) \right) n^{-\frac{1}{5}}; 0.79(IQR)n^{-\frac{1}{5}} \right]$$

(2)

Where IQR = interquartile range of the sample, n = number of observations within the sample, and σ = standard deviation of the sample.

By utilizing the sample companies' pre-impairment earnings surprise data and Equation (2), the interval width is determined to be 0.001152. Following this calculation, the variable MEET_BEAT equals 1 if the pre-impairment earnings surprise is within the range of 0 to 0.001152, and 0 otherwise. In light of theoretical motivations and empirical evidence, a negative association with the goodwill impairment dependent variables is expected, indicating that these companies show a lower likelihood of impairment and smaller magnitudes (Burgstahler & Eames, 2006; Degeorge et al., 1999; Gros & Koch, 2020). All variables utilized in the regressions are described in Table 1.

Table 1. Definition of variables

Variables	Type of variable	Description
<i>Dependent:</i>		
GW_INC	Indicator	Equals 1 if the firm impairs goodwill in year t, and 0 otherwise
GW_MAG	Continuous	Goodwill impairment in year t divided by total assets in year t-1
<i>Independent:</i>		
BIGBATH	Indicator	Equals 1 if the pre-impairment earnings surprise is negative and below the median of negative pre-impairment earnings surprises, and 0 otherwise
SMOOTH	Indicator	Equals 1 if the pre-impairment earnings surprise is positive and above the median of positive pre-impairment earnings surprises, and 0 otherwise
MEET_BEAT	Indicator	Equals 1 if the pre-impairment earnings surprise is within the range of 0 to 0.001152, and 0 otherwise
<i>Controls:</i>		
LEV	Continuous	Total liabilities divided by impairment-adjusted assets in year t
INSTI_OWEN	Continuous	Proportion of shares held by institutional owners in year t
AUDITOR	Indicator	Equals 1 if the firm is audited by a Big 4 company in year t, and 0 otherwise
ANALYSTS	Continuous	Natural logarithm of the sum of 1 and the analyst count in year t
SIZE	Continuous	Natural logarithm of assets adjusted for goodwill impairment in year t
GW_SIZE	Continuous	Impairment-adjusted goodwill balance divided by impairment-adjusted total assets in year t
MB	Continuous	Market value of equity divided by the impairment-adjusted book value of equity in year t
PRIOR_IMP	Indicator	Equals 1 if the firm has impaired goodwill in year t-1
RETURN	Continuous	Firm's market return in year t
ROA	Continuous	Impairment-adjusted net income in year t divided by total assets in year t-1

4.3. Control variables

In the domain of asset write-offs, it is imperative to control for economic factors to ensure the credibility of the empirical findings. In this context, falsely attributing economically induced impairments to opportunistic behavior should be avoided (Wilson, 1996). As management expectations are unobservable and public data for every CGU is unavailable, we follow previous literature in incorporating firm-level variables to proxy for economic impairment (AbuGhazaleh et al., 2011; Beatty & Weber, 2006; Francis et al., 1996; Giner & Pardo, 2015; Glaum et al., 2018; Riedl, 2004; Zang, 2008). Consequently, we establish debt contracting, governance and monitoring, and firm-level control variables to limit misleading qualitative inferences about goodwill impairment determinants. The following paragraphs are concerned with introducing the methodology and motivation of the control variables.

4.3.1. Debt contracting

Debt contracting is comprised of a variable describing firms' leverage (LEV), which is defined as liabilities divided by impairment-adjusted assets (Glaum et al., 2018). The incidence and magnitude of goodwill impairment might be impacted by considerations relating to leverage. Assuming that LEV serves as a proxy for the presence and strictness of debt covenants, managers might be incentivized to avoid goodwill impairment to prevent covenant breaches (Zang, 2008). Similarly, goodwill non-impairment could be motivated by efforts to protect a firm's credit rating (Glaum et al., 2018). Following this, we expect a negative association between LEV and the likelihood as well as magnitude of goodwill impairment. However, it should be noted that higher leverage can also be associated with a higher likelihood of asset write-downs due to increased monitoring by investors (Elliott & Shaw, 1988; Strong & Meyer, 1987).

4.3.2. Governance & monitoring

Governance and monitoring systems presumably influence goodwill impairment decisions by managers. While managers might exercise the discretion within IAS 36 to overstate or understate goodwill impairment, monitoring by stakeholders could limit this discretion (Glaum et al., 2018). Therefore, the goodwill impairment likelihood and magnitude might be influenced positively or negatively depending on the circumstances. Consequently, a directional prediction for the three control variables listed below is omitted.

As the first variable, INSTL_OWN represents the share of institutional ownership (Glaum et al., 2018) and accounts for the motivations of institutional shareholders to monitor firm performance (Matsumoto, 2002; Shleifer & Vishny, 1986). Second, AUDITOR is included and defined as a dummy variable amounting to 1 if the firm-year is audited by a Big 4 auditing firm, and 0 otherwise (Giner & Pardo, 2015). In line with previous

research, AUDITOR should serve as a monitoring proxy, implying that Big 4 auditors are associated with higher audit quality (Boone et al., 2010; DeAngelo, 1981).

Lastly, the variable ANALYSTS leverages Han et al. (2021) and uses the natural logarithm of the sum of 1 and the analyst count. By functioning as efficient monitoring instruments in capital markets, analysts play a crucial role in reducing agency costs (Jung et al., 2012; Moyer et al., 1989) and earnings management (Yu, 2008). Conversely, increased analyst coverage has the potential to stimulate improved corporate investments and thereby reduce the potential need for impairments in future periods (To et al., 2018). This illustrates the opposing views on the relationship between analyst coverage and goodwill impairment, which is further elaborated in section 3.4.3. Analysts not only monitor companies but might pressure managers to meet or beat analysts' forecasts.

4.3.3. Firm-level control variables

Six distinct control variables constitute the firm-level controls. First, we introduce the variable SIZE which accounts for the firm size based on assets at the end of the reporting period. SIZE is defined as the natural logarithm of total assets adjusted for goodwill impairment (Giner & Pardo, 2015; Glaum et al., 2018). In line with prior research, we do not provide a directional prediction for the variable SIZE (AbuGhazaleh et al., 2011; Beatty & Weber, 2006; Zang, 2008).

To control for the proportion of goodwill on a firm's balance sheet, the variable GW_SIZE is included in the regression models. GW_SIZE is established as the pre-impairment goodwill balance divided by adjusted total assets at the end of the fiscal year (Glaum et al., 2018). Firms that have a higher share of goodwill on their balance sheet might report larger goodwill impairments due to a greater amount of goodwill that is exposed to impairment tests (Zang, 2008). Therefore, we predict a positive relationship between the variable GW_SIZE and the likelihood as well as magnitude of goodwill impairment (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Zang, 2008).

Following existing literature, we include a control variable for goodwill impairment in the prior period (Beatty & Weber, 2006; Francis et al., 1996; Glaum et al., 2018). PRIOR_IMP is a dummy variable and takes the value of 1 if the firm impaired goodwill in the previous fiscal year, and 0 otherwise. Firms reporting large non-recurring write-offs in the preceding fiscal year are significantly more likely to report such write-offs in the following fiscal year than firms without prior write-offs (Elliott & Hanna, 1996). Consequently, we expect a positive association between PRIOR_IMP and the dependent variables.

Pivoting from pure accounting towards market-based measures, we utilize MB to describe the market-to-book ratio of a firm at the end of the reporting period. MB represents the ratio of market value of equity to total shareholders' equity prior to goodwill impairment (Giner & Pardo, 2015; Glaum et al., 2018). The market-to-book ratio is used as a proxy

for growth options (Jarva, 2009). Firms with high growth options are less likely to impair goodwill (Beatty & Weber, 2006). Furthermore, instances of market-to-book ratios below 1 can be seen as indicators of a need to impair goodwill (Ramanna & Watts, 2012). We expect a negative association between MB and the dependent variables, corresponding with prior research (AbuGhazaleh et al., 2011; Beatty & Weber, 2006; Francis et al., 1996; Giner & Pardo, 2015).

The remaining two firm-level control variables aim to depict economic impairment resulting from firm performance. First, ROA is included in the model and calculated by dividing net income adjusted for goodwill impairment by lagged total assets (Francis et al., 1996; Riedl, 2004). Given the institutional setting of goodwill and the allocation across different segments, the performance of the firm potentially offers information concerning the underlying profitability of the CGUs to which goodwill has been allocated (Hayn & Hughes, 2006). Following previous literature, a negative association between ROA and the dependent variables is expected (AbuGhazaleh et al., 2011; Zang, 2008).

Similarly to accounting profitability, the market return variable RETURN covers the firms' performance during the fiscal year (Giner & Pardo, 2015). RETURN is defined as the stock market return and is assumed to serve as a proxy for the market's assessment of the firm's capability to generate future cash flows (Glaum et al. 2018). The variable is expected to be negatively associated with the goodwill impairment dependent variables (Francis et al., 1996, Zang, 2008).

4.4. Model specification

This thesis utilizes panel data describing firm-year observations over a time horizon from 2015 to 2021. With regards to intra-year reporting dates, companies reporting in the months of January to June are grouped with companies reporting in the months of July to December of the prior year. This implies that a company reporting on March 31, 2018, is counted towards the fiscal year 2017 and therefore grouped with companies reporting on December 31, 2017. For all regressions, we use year fixed effects and industry fixed effects. Companies are grouped following ICB categories (AbuGhazaleh et al., 2011) (Table A.1). Firms belonging to the same industry presumably show common effects regarding goodwill impairment since they are subject to similar competition and other industry-specific economic factors (Zang, 2008). Furthermore, all continuous variables are winsorized at the 1 and 99 percentiles to limit the effects of outliers within the data set (Han et al., 2021; Iatridis et al., 2022).

Transitioning to our regression models, a probit regression is used to test the three hypotheses concerning the likelihood of goodwill impairment. As the probit regression models a non-linear relationship between the dependent and explanatory variables, the interpretation of coefficients diverges from linear models. Acknowledging the underlying maximum likelihood estimation, the coefficients are interpreted as the change of the z-

score following a one unit increase in the independent variable. Due to the lack of linearity, the particular effect on z varies depending on the position within the cumulative standard normal distribution. To interpret our main independent variables, we employ a marginal analysis² to illustrate the expected change in the probability of an impairment associated with a discrete one unit increase in the respective independent variable (Liao, 1994).

Based on the dependent, independent, and control variables discussed above³, the following probit regression (Equation (3)) is established. In line with previous research, we cluster robust standard errors by firm (Petersen, 2009).

$$\begin{aligned} GWI_INC_{it} = & \beta_0 + \beta_1 BIGBATH_{it} + \beta_2 SMOOTH_{it} + \beta_3 MEET_BEAT_{it} + \beta_4 LEV_{it} + \beta_5 INSTI_OWN_{it} \\ & + \beta_6 AUDITOR_{it} + \beta_7 ANALYSTS_{it} + \beta_8 SIZE_{it} + \beta_9 GW_SIZE_{it} + \beta_{10} MB_{it} \\ & + \beta_{11} PRIOR_IMP_{it} + \beta_{12} RETURN_{it} + \beta_{13} ROA_{it} + \sum \beta_j INDUSTRY_{ji} + \sum \beta_t YEAR \\ & + \varepsilon_{it} \end{aligned} \quad (3)$$

We use a tobit regression to test our three hypotheses concerning the goodwill impairment magnitude. Since the tobit regression censors the dependent variable above or below a threshold, it integrates a probit regression for the probability of observing uncensored observations and a standard linear model equivalent to an OLS regression (Maddala, 1991; Osgood et al., 2002). Thus, the tobit regression accommodates the potential selection bias that might arise when solely analyzing observations with goodwill impairments⁴ (Lennox et al., 2012; Maddala, 1991). Consequently, the resulting coefficients display the estimated effect of the independent variable on the latent dependent variable (McDonald & Moffitt, 1980). Given that IAS 36 prevents companies from reporting positive impairments resulting from increased values of goodwill, the left-censoring limit is specified at zero (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018).

This leads to the following tobit regression (Equation (4)). Similar to the probit regression, robust standard errors are clustered on a firm level (Petersen, 2009).

$$\begin{aligned} GWI_MAG_{it} = & \beta_0 + \beta_1 BIGBATH_{it} + \beta_2 SMOOTH_{it} + \beta_3 MEET_BEAT_{it} + \beta_4 LEV_{it} + \beta_5 INSTI_OWN_{it} \\ & + \beta_6 AUDITOR_{it} + \beta_7 ANALYSTS_{it} + \beta_8 SIZE_{it} + \beta_9 GW_SIZE_{it} + \beta_{10} MB_{it} \\ & + \beta_{11} PRIOR_IMP_{it} + \beta_{12} RETURN_{it} + \beta_{13} ROA_{it} + \sum \beta_j INDUSTRY_{ji} + \sum \beta_t YEAR \\ & + \varepsilon_{it} \end{aligned} \quad (4)$$

² The marginal analysis describes the derivative of the covariate keeping the remaining variables at the population average (Liao, 1994).

³ We do not include interaction effects between variables since the computation and interpretation for the probit and tobit models deviate from a linear model and require the calculation of the cross derivative or cross difference (Ai & Norton, 2003).

⁴ In contrast, an OLS regression applied only for uncensored data would generate biased estimates (Greene, 1997; Maddala, 1991).

5. Data

This section starts by providing an overview of the sample selection process, including an outline of the geographic scope and adjustments to the final sample. Subsequently, the section details our data collection, followed by a description of quality tests employed on the empirical data.

5.1. Sample selection

This empirical study utilizes a sample of firms listed in the STOXX Europe 600 index as of January 2024. We focus on European companies in contrast to prior goodwill impairment research that primarily investigates single countries (AbuGhazaleh et al., 2011; Giner & Pardo, 2015), especially the US (Beatty & Weber, 2006; Bens et al., 2011; Chung & Hribar, 2021; Li & Sloan, 2017; Ramana & Watts, 2012). Our research period concerns the years 2015 to 2021. This time horizon allows for a reasonable overall sample size as well as a partitioning into a pre-crisis and crisis subsample in the realm of the additional analysis concerning COVID-19.

From our initial sample of 4,200 firm-years, we exclude several observations. First, all firm-years of companies in the broader financial (including real estate) industry are dropped. There are multiple reasons for the exclusion of this sector. Different regulatory requirements between firms in the financial and other industries might impact goodwill impairment decisions. Furthermore, capital structures and key financial statement ratios are subject to significant differences between financial and non-financial firms (Glaum et al., 2018). Second, we reduce our sample by all firm-year observations without positive goodwill balances since these companies do not have the option to impair any goodwill (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018). Third, we exclude firm-year observations with a negative book value of equity in line with prior research (Glaum et al., 2018; Gros & Koch, 2020). Finally, all firm-years with missing data are eliminated.

This results in a final unbalanced sample consisting of 408 firms across 9 industries, corresponding to 2,614 firm-years (Table 2).

Table 2. Derivation of the final sample

<i>Observations of STOXX Europe 600</i>	4,200
<i>Less:</i>	
Observations within the financial and real estate industry	994
Observations without goodwill	296
Observations with negative book value of equity	26
Observations with missing data	270
<i>Sample size (No. of firms = 408)</i>	2,614

The table shows the derivation of our final sample size, consisting of 2,614 observations across 408 firms between 2015 and 2021.

5.2. Data collection & quality

This thesis utilizes empirical data for the accounting and market-based measures from Thomson Reuters Datastream. In addition, data on actual and consensus EPS⁵, institutional ownership (INSTI_OWN), market capitalization, and weighted average number of diluted shares has been collected from Capital IQ. In this context, auditor engagements have been hand-collected from Capital IQ and categorized into Big 4 and non-Big 4 audit firms for the dummy variable serving as a proxy for audit quality (AUDITOR). All data used in our regressions have been gathered in February and March 2024.

Different data tests have been performed to ensure data quality and variable reliability. To be precise, 250 random observations, which translate to about 10 percent of the total sample, have been selected and checked for accuracy using a supplementary data source. This implies that for a given variable, data points reported within Thomson Reuters Datastream have been compared to Capital IQ and annual reports have been leveraged in selected cases. Only minor deviations have been observed on infrequent occasions during those tests, suggesting that the reliability of the underlying data is high and the results are likely not materially influenced by data quality concerns.

⁵ Both actual and consensus EPS are based on diluted shares. The EPS consensus relies on data sourced from reports that adhere to both the methodology specified in Capital IQ guidelines and the required actuality. All EPS estimates that are included in the consensus must not be issued more than 180 days before the EPS reporting date, indicating a stale policy of 180 days. The most recent estimate is used for analysts with multiple reports during this timeframe.

6. Results & analysis

This section begins by summarizing the descriptive statistics, detailing the dependent, independent, and control variables across impairment and non-impairment observations. Subsequently, the results of probit and tobit regressions are provided, followed by the main analysis. The section continues by covering the additional analysis concerning the COVID-19 pandemic. Furthermore, several checks are performed to guarantee the robustness of our inferences to alterations in definitions and assumptions. Lastly, the section is concluded by addressing statistical considerations.

6.1. Descriptive statistics

Descriptive statistics for the impairment incidence of the entire sample throughout the observation horizon are presented in Table 3. On average, 21.6 percent of the firm-year observations contain goodwill impairments. There are considerable differences between the fiscal years concerning goodwill impairment incidences. While 2020 marks the year with the highest share of goodwill impairers (28.8 percent), fiscal year 2021 records the lowest share (15.9 percent).

Table 3. Overview of goodwill impairment incidences

Fiscal Year	2015	2016	2017	2018	2019	2020	2021
Firms with GWI	88	70	73	63	95	113	63
Firms with GW	346	347	370	376	386	392	397
<i>GW incidence (in %)</i>	25.4%	20.2%	19.7%	16.8%	24.6%	28.8%	15.9%

The table displays the goodwill impairment incidence during the sample period. Due to adjustments to our final sample, specifically pertaining to firms without goodwill balances, the "Firms with GW" row indicates the total number of observations within the given fiscal year. This thesis utilizes panel data describing firm-year observations over a time horizon from 2015 to 2021. With regards to intra-year reporting dates, companies reporting in the months of January to June are grouped with companies reporting in the months of July to December of the prior year.

Table 4 displays descriptive statistics about the number of observations, means, and standard deviations. The sample can be divided into firm-years with and without goodwill impairment. To assess the significance of differences between these subsets, a t-test for the difference in means is conducted, corresponding with prior research (AbuGhazaleh et al., 2011; Glaum et al., 2018). Additionally, we examine the differences by utilizing Mann-Whitney U tests for all continuous (Glaum et al., 2018) and Pearson chi-squared tests for all indicator variables (AbuGhazaleh et al., 2011; Zucca & Campbell, 1992).

The variables are split into dependent, independent, and control variables. Our regressions contain the two dependent variables describing the goodwill impairment incidence (GWI_INC) and magnitude (GWI_MAG). Among the observations with goodwill impairment, the mean (median) impairment amounts to €199 million (€25 million), which reflects 0.8 percent of the firms' lagged total assets. The independent variables are

comprised of the managerial incentive proxies BIGBATH, SMOOTH, and MEET_BEAT. The share of firm-years with a managerial incentive to overstate goodwill impairment through taking a big bath (BIGBATH) is higher in the impairment sample (25.7 percent) compared to firm-years without goodwill impairment (21.1 percent). Similarly, the variable representing the incentive to smooth earnings (SMOOTH) is more prevalent among the impairment firm-years (32.0 percent) than among the observations without goodwill impairment (22.7 percent). The opposite holds for the incentive to understate goodwill impairment (MEET_BEAT). The impairment sample contains a lower share of MEET_BEAT observations (8.0 percent) than the non-impairment sample (15.6 percent). All the described differences are statistically significant based on the t-test and Mann-Whitney U test.

Table 4. Summary statistics

Variables	Total sample			Firm-years with GWI			Firm-years without GWI		
	n	Mean	σ	n	Mean	σ	n	Mean	σ
<i>Dependent</i>									
GW_INC	2,614	0.216	0.412	565	1	0	2,049	0	0
GW_MAG	2,614	0.002	0.010	565	0.008	0.019	2,049	0	0
<i>Independent</i>									
BIGBATH	2,614	0.221	0.415	565	0.257	0.437	2,049	0.211	0.408
SMOOTH	2,614	0.247	0.431	565	0.320	0.467	2,049	0.227	0.419
MEET_BEAT	2,614	0.140	0.347	565	0.080	0.271	2,049	0.156	0.363
<i>Controls</i>									
LEV	2,614	0.582	0.155	565	0.603	0.146	2,049	0.576	0.157
INSTI_OWN	2,614	0.457	0.231	565	0.444	0.227	2,049	0.461	0.233
AUDITOR	2,614	0.943	0.232	565	0.935	0.248	2,049	0.945	0.227
ANALYSTS	2,614	2.827	0.490	565	2.959	0.458	2,049	2.791	0.492
SIZE	2,614	9.071	1.438	565	9.665	1.385	2,049	8.908	1.410
GW_SIZE	2,614	0.188	0.150	565	0.184	0.140	2,049	0.189	0.153
MB	2,614	3.971	3.681	565	2.782	2.356	2,049	4.299	3.906
PRIOR_IMP	2,614	0.225	0.418	565	0.538	0.499	2,049	0.139	0.346
RETURN	2,614	0.165	0.306	565	0.113	0.297	2,049	0.179	0.307
ROA	2,614	0.069	0.067	565	0.046	0.059	2,049	0.076	0.068

The table displays the summary statistics for all variables utilized in the probit and tobit regression. The sample is divided into firm-years with and without goodwill impairment. Displayed descriptive statistics include the number of observations, means, and standard deviations. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Pivoting to the market-to-book ratio (MB) control variable, we find that companies without goodwill impairment tend to have larger market-to-book ratios compared to the impairment sample⁶. This is affirmed by a statistically significant t-test and Mann-Whitney U test. Furthermore, companies from the impairment sample are significantly more likely to have reported a goodwill impairment in the previous year (PRIOR_IMP)

⁶ The MB variable exhibits values exceeding those reported in previous studies within this domain (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018; Han et al., 2021; Iatridis et al., 2022). Consequently, we conducted an additional verification using a supplementary database, validating our findings.

as opposed to the non-impairment sample. While companies from the non-impairment sample recorded an impairment in the previous fiscal year in 13.9 percent of cases, the impairment sample displays a considerably higher share at 53.8 percent. Lastly, companies that reported an impairment show lower performance in terms of ROA and RETURN during the fiscal year. This is reflected by statistically significant t-tests and Mann-Whitney U tests for both variables. Results for the test of differences are presented in Table 5.

Table 5. Test of differences

Variables	Difference in means	t-test	Mann-Whitney U test	Pearson chi-squared test
<i>Independent</i>				
BIGBATH	-0.047	0.016**		0.016**
SMOOTH	-0.093	0.000***		0.000***
MEET_BEAT	0.075	0.000***		0.000***
<i>Controls</i>				
LEV	-0.027	0.000***	0.000***	
INSTI_OWN	0.017	0.115	0.095*	
AUDITOR	0.011	0.326		0.326
ANALYSTS	-0.168	0.000***	0.000***	
SIZE	-0.757	0.000***	0.000***	
GW_SIZE	0.004	0.543	0.690	
MB	1.517	0.000***	0.000***	
PRIOR_IMP	-0.399	0.000***		0.000***
RETURN	0.066	0.000***	0.000***	
ROA	0.030	0.000***	0.000***	

The table displays the test statistics for all variables utilized in the probit and tobit regression. To assess the significance of differences in means between the two subsets, a t-test is conducted. Additionally, we examine the differences by utilizing Mann-Whitney U tests for all continuous and Pearson chi-squared tests for all indicator variables. Values depicted in columns 3 to 5 refer to p-values. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

The correlations between all explanatory variables utilized in the regressions are examined with Pearson correlations, as illustrated in Table 6. Notably, the control variable SIZE displays the highest positive and negative correlations. While SIZE is significantly positively correlated with ANALYSTS (0.653) and LEV (0.348), it is significantly negatively correlated with both MB (-0.414) and ROA (-0.408). Furthermore, MB is significantly positively correlated with ROA (0.518). Regarding our managerial incentive proxies, SMOOTH is significantly negatively correlated with the variables BIGBATH (-0.305) and MEET_BEAT (-0.230). In addition, BIGBATH is significantly negatively correlated with the variable MEET_BEAT (-0.214).

Table 6. Pearson correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) GWI_INC	1.000														
(2) GWI_MAG	0.357 (0.000)	1.000													
(3) BIGBATH	0.045 (0.022)	0.047 (0.016)	1.000												
(4) SMOOTH	0.089 (0.000)	0.114 (0.000)	-0.305 (0.000)	1.000											
(5) MEET_BEAT	-0.090 (0.000)	-0.067 (0.001)	-0.214 (0.000)	-0.230 (0.000)	1.000										
(6) LEV	0.071 (0.000)	-0.001 (0.960)	0.045 (0.021)	-0.133 (0.000)	0.023 (0.245)	1.000									
(7) INSTL_OWN	-0.031 (0.115)	0.074 (0.000)	0.030 (0.125)	0.072 (0.000)	-0.040 (0.043)	0.008 (0.692)	1.000								
(8) AUDITOR	-0.019 (0.326)	0.012 (0.527)	-0.004 (0.830)	-0.005 (0.818)	0.008 (0.680)	0.005 (0.810)	0.090 (0.000)	1.000							
(9) ANALYSTS	0.141 (0.000)	0.050 (0.011)	0.085 (0.000)	-0.096 (0.000)	-0.067 (0.001)	0.193 (0.000)	-0.001 (0.977)	0.041 (0.038)	1.000						
(10) SIZE	0.217 (0.000)	0.031 (0.113)	0.085 (0.000)	-0.109 (0.000)	-0.048 (0.014)	0.348 (0.000)	-0.170 (0.000)	0.000 (0.990)	0.653 (0.000)	1.000					
(11) GW_SIZE	-0.012 (0.542)	0.079 (0.000)	-0.038 (0.055)	-0.025 (0.199)	0.039 (0.048)	-0.037 (0.056)	0.168 (0.000)	-0.028 (0.624)	-0.033 (0.093)	-0.125 (0.000)	1.000				
(12) MB	-0.170 (0.000)	-0.065 (0.001)	-0.015 (0.453)	0.013 (0.511)	0.023 (0.248)	0.046 (0.018)	0.040 (0.043)	0.030 (0.125)	-0.142 (0.000)	-0.414 (0.000)	0.111 (0.000)	1.000			
(13) PRIOR_IMP	0.393 (0.000)	0.120 (0.000)	0.026 (0.185)	0.046 (0.020)	-0.058 (0.003)	0.073 (0.000)	-0.021 (0.277)	-0.010 (0.624)	0.137 (0.000)	0.207 (0.000)	-0.014 (0.463)	-0.152 (0.000)	1.000		
(14) RETURN	-0.089 (0.000)	-0.073 (0.000)	-0.078 (0.000)	0.062 (0.002)	0.030 (0.128)	-0.109 (0.000)	-0.033 (0.093)	0.001 (0.976)	-0.195 (0.000)	-0.216 (0.000)	0.011 (0.577)	0.283 (0.000)	-0.032 (0.104)	1.000	
(15) ROA	-0.181 (0.000)	-0.099 (0.000)	-0.177 (0.000)	0.205 (0.000)	0.019 (0.328)	-0.367 (0.000)	0.082 (0.000)	0.010 (0.601)	-0.206 (0.000)	-0.408 (0.000)	-0.008 (0.697)	0.518 (0.000)	-0.147 (0.000)	0.214 (0.000)	1.000

The table displays the Pearson correlations for all variables utilized in the regressions. The p-values are displayed in brackets below the respective coefficients. The sample includes 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

6.2. Regression results

In light of all variables discussed above, a probit and a tobit regression are used to test for the decision to impair and the magnitude. The results are described in the following paragraphs and illustrated in Table 7 and Table 8.

Starting with the probit regression, the three managerial incentive proxies indicate significant results. BIGBATH shows a positive sign and proves slightly significant at the 10 percent level. SMOOTH is significant at the 1 percent level with a positive coefficient, which permits us to reject the null hypothesis that the coefficient is zero. This result shows that companies with a managerial incentive to smooth earnings by overstating goodwill impairment are associated with a higher likelihood of impairment. Pivoting to the variable MEET_BEAT, the probit regression displays a negative coefficient and significance at 5 percent, allowing us to reject the null hypothesis. This suggests that companies with small non-negative pre-impairment earnings surprises are associated with a lower likelihood of impairment.

Table 7. Probit regression results

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.148	1.70	0.090*
SMOOTH	+	0.435	5.25	0.000***
MEET_BEAT	-	-0.205	-2.08	0.037**
<i>Debt contracting</i>				
LEV	-	-0.162	-0.61	0.542
<i>Governance & monitoring</i>				
INSTI_OWEN	+/-	-0.100	-0.64	0.523
AUDITOR	+/-	-0.088	-0.52	0.605
ANALYSTS	+/-	0.042	0.36	0.716
<i>Firm-level controls</i>				
SIZE	+/-	0.122	2.86	0.004***
GW_SIZE	+	0.157	0.62	0.533
MB	-	-0.028	-1.70	0.090*
PRIOR_IMP	+	1.059	11.89	0.000***
RETURN	-	-0.201	-1.62	0.106
ROA	-	-2.160	-2.59	0.010***
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
N	2,614			
Pseudo R ²	0.2061			
Wald chi-squared test	373.32			
p-value	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the probit regression. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Transitioning to the remaining control variables, SIZE proves to be significant at 1 percent and shows a positive coefficient, suggesting that larger firms are associated with a higher likelihood of goodwill impairment. ROA is significant at the 1 percent level and the negative sign aligns with our prediction. In addition, PRIOR_IMP displays a positive coefficient significant at 1 percent. This implies that companies with a goodwill impairment in the preceding fiscal period are more prone to impair in the following period.

The results of the tobit regression mirror the findings of the probit regression to a considerable extent. For the variables BIGBATH and SMOOTH, the null hypotheses can be rejected. BIGBATH and SMOOTH display significance levels of 5 and 1 percent, respectively, indicating that firms with an incentive to overstate goodwill impairment are associated with larger impairment magnitudes. Furthermore, the variable MEET_BEAT exhibits a negative coefficient and is significant at the 5 percent level, which allows us to reject the null hypothesis. This implies that firms facing an incentive to understate goodwill impairment are associated with smaller impairments.

Table 8. Tobit regression results

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.005	2.23	0.026**
SMOOTH	+	0.012	5.77	0.000***
MEET_BEAT	-	-0.004	-2.34	0.019**
<i>Debt contracting</i>				
LEV	-	-0.006	-1.09	0.278
<i>Governance & monitoring</i>				
INSTI_OWEN	+/-	0.004	1.24	0.214
AUDITOR	+/-	-0.001	-0.27	0.790
ANALYSTS	+/-	0.002	0.71	0.478
<i>Firm-level controls</i>				
SIZE	+/-	0.001	1.58	0.113
GW_SIZE	+	0.013	2.30	0.021**
MB	-	-0.001	-1.56	0.119
PRIOR_IMP	+	0.017	5.97	0.000***
RETURN	-	-0.005	-2.35	0.019**
ROA	-	-0.059	-3.00	0.003***
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Model F-test</i>	3.25			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the tobit regression. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The interpretation of the *Pseudo R*² for a tobit regression deviates from the standard linear regression (Dhrymes, 1986). Due to our negative *Pseudo R*², we omit the result in this table. We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

In contrast to the probit regression, *GW_SIZE* is significant at the 5 percent level with a positive sign, implying that companies with larger goodwill balances are associated with higher magnitudes of goodwill impairment. Similarly, *RETURN* shows significance at the 5 percent level within the tobit regression. Looking at *ROA* as another return metric, a statistical significance of 1 percent is observed. Both return metrics coefficients display a negative sign that corresponds with our directional predictions and suggests that firms with lower performance are associated with larger goodwill impairments. Apart from firm-level performance, the control variable *SIZE* shows no statistical significance for the magnitude of impairment as opposed to the decision to impair. Lastly, *PRIOR_IMP* remains significant at the 1 percent level with a positive sign, which aligns with our directional expectations.

6.3. Regression analysis

This section starts by examining the results of the managerial incentive proxies to overstate goodwill impairment, followed by an analysis of the target-beating variable. We continue by investigating other determinants of goodwill impairment, which includes a comparison of the results to existing literature.

6.3.1. Big bath & earnings smoothing

Our empirical results indicate a relation between firms with pre-impairment EPS clearly below the consensus and an increased likelihood as well as magnitude of goodwill impairment. With regards to the likelihood of impairment, the marginal analysis suggests that a change in the *BIGBATH* variable from 0 to 1 implies an increase in the probability of impairment by 3.5 percentage points, keeping the remaining variables at the population average. In line with H1a and H1b, our findings indicate that firms exercise discretion within goodwill impairment decisions to engage in a big bath strategy taking the EPS consensus as a benchmark.

The findings are consistent with prior research on goodwill impairment employing actual and industry earnings as targets (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Kabir & Rahman, 2016). Expanding to the wider domain of asset write-offs, our findings on big bath behavior align with Riedl (2004) and Zucca & Campbell (1992). Furthermore, this corresponds with motivations put forward by Sevin & Schroeder (2005), arguing that engaging in a big bath strategy may arise from the intention to increase future earnings. Riedl (2004) sees the maximization of proceeds from managers' long-term bonus plans as a driver of big bath strategies. Although prior literature supports the prevalence of big bath behavior for firms that clearly miss relevant targets, the overall evidence on this matter is mixed. Our identification of big bath behavior both in the decision to impair and in the impairment magnitude stands in contrast to other studies in the realm of asset write-offs (Francis et al., 1996) and specifically goodwill impairment (Glaum et al., 2018; Han et al., 2021; Iatridis & Senftlechner, 2014).

In addition, our findings suggest that firms exercise discretion within IAS 36 to engage in earnings smoothing taking the EPS consensus as a benchmark. Confirming our hypotheses H2a and H2b, our regressions exhibit statistical significance for the earnings smoothing proxy (SMOOTH) with regard to the likelihood and magnitude of goodwill impairment. Concerning the likelihood of impairment, the marginal analysis suggests that changing the SMOOTH variable from 0 to 1 is associated with a 10.8 percentage point increase in the probability of reporting an impairment.

This is consistent with previous literature investigating earnings smoothing as a determinant of goodwill impairment and revolving around firms' reported earnings parameters as benchmarks (AbuGhazaleh et al., 2011; Glaum et al., 2018; Han et al., 2021). Additionally, this aligns with existing research that extends beyond the goodwill impairment context and focuses on asset write-downs (Zucca & Campbell, 1992). Beyond that, this likely affirms theoretical motivations with regard to the establishment of "cookie jar" reserves (Sevin & Schroeder, 2005) and performance bonus considerations (Moses, 1987). Nonetheless, it is worth emphasizing that the research domain of earnings smoothing shows mixed evidence. Previous studies find no significant association between earnings smoothing and asset write-offs (Francis et al., 1996) as well as goodwill impairment (Giner & Pardo, 2015).

The results for the variables BIGBATH and SMOOTH affirm managerial incentives to overstate goodwill impairment. This aligns with theoretical predictions in Kirschenheiter & Melumad (2002), which suggest that both taking a big bath and earnings smoothing can be optimal for managers. Considering that the EPS consensus forecast stands as a key benchmark for various stakeholders (Brown & Caylor, 2005), our research demonstrates that the discretion permitted within IAS 36 could be exercised to manage EPS relative to the consensus.

6.3.2. Target-beating

Our study finds a link between companies meeting or slightly beating EPS consensus forecasts before reporting an impairment and a decreased likelihood as well as magnitude of goodwill impairment. This is consistent with our hypotheses H3a and H3b. In terms of the likelihood of impairment, the marginal analysis indicates that changing the MEET_BEAT variable from 0 to 1 results in a decrease in the probability of impairment by 4.5 percentage points. These findings imply that firms with small non-negative pre-impairment earnings surprises exercise the discretion within goodwill impairment decisions to meet or beat the consensus.

This aligns with the results from Gros & Koch (2020), who focus on economic impairment and suggest that EPS consensus forecasts play a significant role in goodwill impairment decisions. Considering this limited evidence on goodwill impairment determinants with regard to EPS consensus forecasts, our variable definition (MEET_BEAT) drawing on the distributional model presents a complementary

alternative within this area. The distributional model has been employed in previous studies on target-beating behavior outside the domain of goodwill impairment (Burgstahler & Eames, 2006; Degeorge et al., 1999; Dichev & Skinner, 2002; Holland & Ramsay, 2003). Those studies find that companies manage earnings in relation to analyst forecasts.

Echoing these findings, our empirical results suggest that motivations to reach targets influence goodwill impairment decisions. Describing potential motivations for target-beating behavior by utilizing pressuring and monitoring effects, our findings suggest that managers are inclined to follow the motivations consistent with the pressuring effect. Given that companies failing to meet analyst expectations are linked to declines in market returns (Bartov et al., 2002; Kasznik & McNichols, 2002) and CEO cash bonuses (Han et al., 2021; Matsunaga & Park, 2001), the exerted pressure may serve as a contributing factor to the observed association.

6.3.3. Other goodwill impairment determinants

In the regression analyses examining the determinants of goodwill impairment decisions, we include firms' leverage (LEV) as a proxy for debt contracting. In both regressions, we observe no significant association between LEV and goodwill impairment. Previous literature presents a conflicting view on this matter. Some studies indicate a significant negative relationship (Han et al., 2021; Zang, 2008) aligning with the motivations to avoid covenant breaches (Zang, 2008) and credit rating deteriorations (Glaum et al., 2018). However, other researchers investigating various geographies fail to find significant associations (AbuGhazaleh et al., 2011; Beatty & Weber, 2006; Giner & Pardo, 2015; Glaum et al., 2018), corresponding with our findings in a European setting.

Describing the dimensions of governance and monitoring, both regressions include a control variable indicating the level of institutional ownership (INSTI_OWN), the level of audit quality (AUDITOR), and the number of analysts following a firm (ANALYSTS). The three variables show similar results in terms of significance within the probit and tobit regression. Concerning institutional ownership, our findings suggest no significant association between INSTI_OWN and the respective goodwill impairment dependent variable. This stands in contrast to results based on a sample of non-financial firms in Glaum et al. (2018). Proceeding to the proxy for audit quality (AUDITOR), we find no significant relation between the control variable and the dependent variables. While this aligns with Giner & Pardo (2015), other studies on goodwill impairment determinants observe both significant positive (Han et al., 2021) and negative associations (Glaum et al., 2018). This contributes to the conflicting evidence on the role of audit quality within goodwill impairment decisions. Similarly, we find an insignificant relation between ANALYSTS and the dependent variables, corresponding with findings in Glaum et al. (2018) and contrasting to a significant negative association in Han et al. (2021).

In addition to controlling for debt contracting and governance and monitoring, we incorporate several firm-level control variables into our models. We find a significant positive association between the variable SIZE and the likelihood of goodwill impairment, consistent with existing literature (Beatty & Weber, 2006; Giner & Pardo, 2015; Glaum et al., 2018; Han et al., 2021). Conversely, when examining the magnitude of goodwill impairment, we do not find a significant link with the firm size. While firm size influences the decision to impair, it is assumed to play a lesser role when determining the extent of the impairment. This could be attributed to potential cost considerations for smaller companies regarding the implementation of impairment tests, which only influence the impairment likelihood but not the magnitude (Bens et al., 2011; Giner & Pardo, 2015). Interestingly, the opposite holds for the size of the goodwill balance (GW_SIZE). Contrary to our initial prediction and prior research (Giner & Pardo, 2015; Glaum et al., 2018), which suggests a positive relation between the size of the goodwill balance and the likelihood of impairment, we do not find statistical significance. Despite this, we do observe a significant positive association between GW_SIZE and the magnitude of impairment. This likely affirms the expectation that the increased goodwill balance exposed to impairment testing influences goodwill impairment decisions (Zang, 2008).

The presence of a goodwill impairment in the previous fiscal year is found to be significantly associated with both the likelihood and the magnitude of goodwill impairment. Consistent with our directional prediction and prior research (Glaum et al., 2018), we find a significant positive relation. This suggests that companies impairing goodwill in the prior fiscal year are more likely to report impairments and incur larger impairments in the subsequent period.

Transitioning to a market-based control variable, we find a slightly significant (10 percent level) negative association between MB and the likelihood of goodwill impairment. This aligns with prior literature's theoretical (Beatty & Weber, 2006; Ramanna & Watts, 2012) and empirical analyses (Giner & Pardo, 2015; Glaum et al., 2018). However, we are unable to replicate these results concerning the magnitude of impairment.

RETURN and ROA serve to measure firm-level performance. ROA exhibits a statistically significant negative association with both the likelihood and magnitude of goodwill impairment. This aligns with the findings of previously published literature (Glaum et al., 2018; Han et al., 2021), indicating that companies with lower accounting rates of return are more prone to impair and incur larger impairments. Nonetheless, evidence regarding this relationship is mixed (AbuGhazaleh et al., 2011). The variable RETURN is also subject to conflicting evidence. Our results indicate an insignificant coefficient for the market return proxy with regard to the likelihood of impairment. While this result is mirrored by Giner & Pardo (2015), Glaum et al. (2018) find a significant negative association with the likelihood of impairment. Concerning the tobit regression, we identify that firms with lower market returns impair to a larger extent. Overall, our results

indicate that both performance metrics influence the magnitude of impairment, but only ROA shows a statistically significant relationship with the decision to impair.

Generally, the regression analysis shows that the likelihood and magnitude of goodwill impairment are driven by both managerial incentives and economic factors. The findings suggest that managers exercise the discretion permitted by IAS 36 to manage EPS relative to consensus forecasts by overstating as well as understating goodwill impairment. The impairment decisions are, however, not entirely driven by managerial incentives but also economic factors such as stock performance (MB and RETURN) and profitability (ROA) prove to be significant aspects.

6.4. Additional analysis

The additional analysis is concerned with goodwill impairment decisions before and during the COVID-19 pandemic. The section commences with an introduction of the crisis setting, outlining the macroeconomic environment and theoretical motivations for opportunistic goodwill impairment under these circumstances. Subsequently, the results of the regressions are provided and analyzed.

6.4.1. Crisis setting

In our main analysis, we cover a sample comprising the fiscal years 2015 to 2021. However, falling within our research horizon, the onset of the COVID-19 pandemic in 2020 represents one of the most disruptive events of recent decades (ECB, 2021). COVID-19 is a disease that was declared a pandemic in March 2020 (EU Parliament, 2021). The emergence of this disease led to disruptions on a global scale, affecting economic, social, and health aspects. In 2020, the economy of the European Union witnessed a more than 5 percent decline in the gross domestic product (GDP), resulting from the substantial impact of the crisis on multiple industries (EU Parliament, 2021). While the valuation of goodwill balances in the realm of impairment tests is concerned with future cash flows (IASB, 2004a), the ramifications of the COVID-19 pandemic were likely to extend beyond the immediate crisis period. The need for judgment and the uncertainty in the estimations necessary for goodwill impairment tests likely intensified due to the pandemic (BDO, 2020).

As suggested by prior literature, periods of distress may see a rise in opportunistic behavior, driven by heightened pressure on managers and lower earnings levels (Glaum et al., 2018). Moreover, the increasing reluctance of credit institutions to lend during uncertain periods posits another challenge, especially for highly leveraged companies. Concerning the managerial incentives to overstate impairment, firms may opt to impair goodwill to preserve earnings for the periods following a recession (Giner & Pardo, 2015; Hayn, 1995). Hence, we expect firms to more frequently exercise discretion in the goodwill impairment regulation to manage EPS.

Research investigating the financial crisis of 2008 and 2009 finds mixed evidence (Giner & Pardo, 2015; Glaum et al., 2018; Iatridis et al., 2022). Drawing on the inconclusive findings concerning periods of economic instability, we aim to contribute an altered perspective by focusing on EPS consensus forecasts as a relevant benchmark. Unlike previous studies that center on static targets such as prior year earnings, EPS consensus forecasts incorporate revised expectations following a macroeconomic shock.

Consequently, we conduct an additional analysis regarding goodwill impairment determinants before and during the COVID-19 pandemic. In this context, the sample is split into two subsamples based on fiscal year. The pre-crisis period covers fiscal years 2015 to 2019, while the crisis period contains the fiscal years 2020 and 2021. For the year 2020, observations with reporting dates between January and November are excluded from the additional analysis since these observations cannot clearly be assigned to either the pre-crisis or crisis period. We utilize both probit and tobit regressions for each of the two subsamples, incorporating identical control variables and fixed effects as for our main analysis. In addition, robust standard errors remain clustered by firm.

6.4.2. Results & analysis

Transitioning to the summary statistics for the crisis (pre-crisis) subsample, the goodwill impairment incidence amounts to 21.7 percent (21.1 percent). While the incidence of impairment remains stable, the average magnitude of impairment increases from €189 million in the pre-crisis period to €227 million during the crisis period. Notably, market return (RETURN) and accounting profitability (ROA) remain relatively stable throughout the pre-crisis and crisis period. The average profitability marginally decreased during the crisis to 6.6 percent compared to 7.1 percent before the pandemic. The return metric even increased during the crisis period from 16.6 percent to 17.8 percent (Table A.2).

Proceeding to the regression outputs (Table 9; Table 10), deviating results in terms of significance for the pre-crisis and crisis subsamples can be observed. In line with our main analysis, the managerial incentive proxy SMOOTH shows statistical significance with a positive sign consistently across both periods. This suggests that irrespective of the macroeconomic environment within our research horizon, managers follow an earnings smoothing strategy with regard to EPS consensus forecasts. Even in times of crisis, managers are more likely to impair goodwill and incur larger impairments when EPS forecasts are clearly exceeded. This could be motivated by a perceived decrease in risk (Graham et al., 2005) and the aim of accumulating reserves for post-crisis periods (Giner & Pardo, 2015; Sevin & Schroeder, 2005).

BIGBATH shows deviating results for the two periods. For the pre-crisis period, BIGBATH shows a positive sign and proves significant at the 10 and 5 percent level for the probit and tobit regressions, respectively. Conversely, the variable displays coefficients that are insignificant for both regressions within the crisis period. This suggests that while big bath motivations influence goodwill impairment decisions in pre-

crisis periods, they are assumed to play a lesser role during the COVID-19 pandemic. This could be attributed to the heightened sensitivity of the stock market to negative news during a recession, particularly during the COVID-19 period. Throughout the pandemic, the stock market demonstrated a more pronounced reaction to negative earnings announcements compared to the pre-crisis phase (Kale & Kale, 2023). Thus, managers may be inclined to refrain from impairing goodwill to manage EPS relative to consensus forecasts. Additionally, managers may have sought to maintain their attractiveness to sources of capital during this period of distress (Giner & Pardo, 2015), further limiting motivations to decrease EPS by impairing goodwill.

Table 9. Additional analysis – Probit regression results

Variables	Pre-crisis subsample			Crisis subsample		
	Coefficient	z-value	p-value	Coefficient	z-value	p-value
<i>Managerial incentives</i>						
BIGBATH	0.170	1.66	0.097*	0.097	0.60	0.549
SMOOTH	0.484	4.84	0.000***	0.293	1.96	0.050**
MEET_BEAT	-0.291	-2.48	0.013**	-0.073	-0.36	0.717
<i>Debt contracting</i>						
LEV	-0.152	-0.49	0.626	-0.464	-1.09	0.276
<i>Governance & monitoring</i>						
INSTL_OWN	-0.039	-0.22	0.825	-0.309	-1.18	0.238
AUDITOR	0.024	0.13	0.897	-0.143	-0.77	0.444
ANALYSTS	0.012	0.10	0.922	0.105	0.51	0.612
<i>Firm-level controls</i>						
SIZE	0.133	2.91	0.004***	0.138	1.93	0.054*
GW_SIZE	0.376	1.41	0.159	-0.182	-0.45	0.650
MB	-0.037	-1.87	0.062*	-0.021	-0.92	0.359
PRIOR_IMP	1.006	9.58	0.000***	1.199	8.96	0.000***
RETURN	-0.059	-0.36	0.717	-0.201	-0.91	0.361
ROA	-1.372	-1.41	0.160	-4.322	-2.88	0.004***
<i>Industry indicator variables</i>	Yes			Yes		
<i>Year indicator variables</i>	Yes			Yes		
<i>N</i>	1,779			765		
<i>Pseudo R²</i>	0.1961			0.2657		
<i>Wald chi-squared test</i>	242.14			174.51		
<i>p-value</i>	0.0000			0.0000		

The table displays coefficients, z-values, and p-values for all variables utilized in the probit regressions. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,544 firm-year observations (1,779 observations within the pre-crisis subsample and 765 observations within the crisis subsample). All variables are defined in Table 1.

The findings for the MEET_BEAT variable show similar results as the BIGBATH variable with regard to statistical significance. While there is a significant negative association between MEET_BEAT and the likelihood as well as magnitude of goodwill impairment for the pre-crisis period, we do not find significance for the crisis subsample. This could indicate that the motivations to reach EPS consensus forecasts diminish during the crisis period. Consequently, strategies aimed at understating goodwill impairment

become less pertinent for companies that meet or slightly exceed the EPS consensus compared to the pre-crisis phase.

Table 10. Additional analysis – Tobit regression results

Variables	Pre-crisis subsample			Crisis subsample		
	Coefficient	z-value	p-value	Coefficient	z-value	p-value
<i>Managerial incentives</i>						
BIGBATH	0.006	2.16	0.031**	0.000	0.06	0.951
SMOOTH	0.013	4.60	0.000***	0.009	3.57	0.000***
MEET_BEAT	-0.006	-2.45	0.014**	-0.001	-0.50	0.620
<i>Debt contracting</i>						
LEV	-0.007	-0.89	0.372	-0.013	-1.58	0.115
<i>Governance & monitoring</i>						
INSTI_OWN	0.007	1.52	0.129	-0.001	-0.21	0.832
AUDITOR	0.001	0.17	0.867	0.000	0.09	0.926
ANALYSTS	0.001	0.53	0.594	0.001	0.47	0.641
<i>Firm-level controls</i>						
SIZE	0.002	1.60	0.110	0.001	1.11	0.268
GW_SIZE	0.019	2.46	0.014**	0.006	0.92	0.358
MB	-0.001	-1.60	0.109	0.000	-0.77	0.442
PRIOR_IMP	0.018	4.98	0.000***	0.015	6.85	0.000***
RETURN	-0.003	-0.94	0.345	-0.005	-1.50	0.135
ROA	-0.050	-1.92	0.055*	-0.096	-3.18	0.002***
<i>Industry indicator variables</i>	Yes			Yes		
<i>Year indicator variables</i>	Yes			Yes		
<i>N</i>	1,779			765		
<i>Model F-test</i>	1.94			3.09		
<i>p-value</i>	0.0035			0.0000		

The table displays coefficients, z-values, and p-values for all variables utilized in the tobit regressions. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The interpretation of the *Pseudo R*² for a tobit regression deviates from the standard linear regression (Dhrymes, 1986). Due to our negative *Pseudo R*² for both tobit regressions, we omit the results in this table. We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,544 firm-year observations (1,779 observations within the pre-crisis subsample and 765 observations within the crisis subsample). All variables are defined in Table 1.

Concerning our control variables, we identify ROA to be more influential for the impairment likelihood and magnitude during the crisis period. While ROA displays significance at the 1 percent level for both regressions within the crisis period, coefficients are found to be insignificant (slightly significant) for the probit (tobit) regression in the pre-crisis horizon. Moreover, in line with our general analysis, SIZE proves significant only for the likelihood of impairment, displaying a 1 percent significance for the pre-crisis and 10 percent for the crisis subsample. Conversely, GW_SIZE only exhibits statistical significance for the magnitude of impairment during the pre-crisis phase. This indicates that both size indicators play a more prominent role in the decision-making process for goodwill impairment within the pre-crisis subset, with their relevance diminishing to some extent during the crisis period. Lastly, the variable PRIOR_IMP remains significant at the 1 percent level within all regressions and subsamples, further supporting the results from our main analysis.

In general, these findings suggest that the managerial incentives described by our three proxies have a greater influence on the goodwill impairment likelihood and magnitude during the pre-crisis compared to the crisis period. This stands in contrast to our expectations and evidence from prior research on the financial crisis that identifies the crisis period as the driver of opportunistic impairment behavior (Giner & Pardo, 2015). However, due to the uniqueness of the COVID-19 crisis, the evidence for the financial crisis is not inherently transferable.

6.5. Robustness tests

In the subsequent paragraphs, we conduct several robustness checks to evaluate the impact of alternative assumptions within our underlying models and methodology on the analysis. Initially, we focus on the three managerial incentive proxies that form the basis of our hypotheses.

In the main analysis, we incorporate all proxies into a single model for both the probit and tobit regression. Consequently, our models include variables for the incentives to overstate and understate goodwill impairment simultaneously. Notably, existing literature on goodwill impairment determinants frequently covers only the incentives to overstate impairment in the form of earnings smoothing and big bath (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018; Han et al., 2021). Therefore, we run a probit and tobit regression without the variable MEET_BEAT in our robustness test. For both regressions, the results mirror the findings of the main analysis. Besides the variable BIGBATH which exhibits slightly higher statistical significance, there are no changes in the significance of any other independent or control variable. Within the probit regression, BIGBATH shows a coefficient that is significant at the 5 percent level with a positive sign, contrasting to 10 percent significance in the initial model. The variable's coefficient in the tobit model increases in significance from 5 percent to 1 percent (Table A.3; Table A.4).

Additionally, we conduct separate regressions excluding the proxies for goodwill impairment overstatement, focusing solely on the MEET_BEAT variable as a managerial incentive proxy. Similarly, we observe only minor changes compared to the main analysis. In both regressions, MEET_BEAT exhibits statistical significance at the 1 percent level as opposed to 5 percent when testing all managerial incentive variables simultaneously. Overall, separating the overstatement and understatement proxies does not substantially affect the regression outcomes (Table A.5; Table A.6).

Concerning the variable representing the incentive to understate goodwill impairment (MEET_BEAT), we draw on target-beating literature and test our model for robustness by using different interval widths (Holland & Ramsay, 2003). Following section 4.2.3.,

we employ the three formulas⁷ separately to estimate interval widths compared to the previous approach outlined in Equation (2). Accordingly, the variable MEET_BEAT is separately defined and incorporated into both the probit and tobit regression while keeping the remaining variables unchanged. The number of observations captured by the MEET_BEAT variable using the three distinct definitions is marginally different from the initial setting. In addition, the coefficients' significance levels and signs largely remain unchanged from the setup employed in the main analysis. The only alteration occurs with the method proposed by Freedman & Diaconis (1981), where the significance level for the MEET_BEAT variable shifts from 5 to 10 percent within the probit regression. Thus, the results for the incentive proxy reflecting firms that meet or slightly beat the EPS consensus forecast pre-impairment are robust to various interval widths.

As an alternative to probit models, some studies opt for logit regressions to test for the decision to impair goodwill (Glaum et al., 2018; Jarva, 2009; Li & Sloan, 2017). Unlike the normal distribution underpinning probit, logit regressions operate with a logistic distribution, resulting in a density function characterized by thinner tails (Stone & Rasp, 1991). As a result, the coefficient in a logit regression represents the shift in log odds corresponding to a one unit change in the independent variable (Maddala, 1983). Following the initial model, the logit regression utilizes the same dependent, independent, and control variables as the probit regression. There are only minor changes in the statistical significance of the coefficients. While the managerial incentive proxies SMOOTH and MEET_BEAT maintain their significance levels, the variable BIGBATH displays a coefficient that is insignificant compared to a significance of 10 percent in the initial model. The remaining variables show similar results compared to the probit regression. Therefore, the findings of the main analysis prove robust to a change of the underlying statistical model (Table A.7).

Following previous literature investigating goodwill impairment determinants in different countries (Glaum et al., 2018), we add country fixed effects to our regressions as an additional robustness test⁸. Given that our sample comprises companies from 18 different European countries, the inclusion of an additional fixed effect aims to limit the influence of country-specific factors. In that context, Polish firms are omitted from the probit regression sample since it is the only country without observations exhibiting incidences of impairment. Generally, the results change only marginally compared to the main analysis for both the probit and tobit regression. The BIGBATH coefficient is not significant for the probit regression and only slightly significant for the tobit regression,

⁷ $2(IQR)n^{-1/3}$ (Freedman & Diaconis, 1981); $0.79(IQR)n^{-1/5}$ (Silverman, 1986); $0.9(\min(\sigma; IQR/1.34))n^{-1/5}$ (Silverman, 1986)

⁸ We do not include firm fixed or industry $\times$ year fixed effects in our robustness tests due to the incidental parameter problem associated with small group sizes within non-linear regression models (Greene, 2004).

while the significance of the remaining two managerial incentive proxies remains unchanged (Table A.8; Table A.9; Table A.10).

In our additional analysis, we exclude observations with reporting dates falling between January and November 2020 because these cannot be distinctly categorized into either the pre-crisis or crisis period. We perform a robustness test by excluding only firm-year observations with reporting dates between January and June 2020. The findings remain consistent in terms of significance levels for both the probit and tobit regression, thus demonstrating robustness to variations in the definition of the crisis period.

We conduct several robustness checks to assess the sensitivity of our models. Among our three managerial incentive variables, BIGBATH displays the highest sensitivity to changes. Based on the preceding paragraphs and tests, we conclude that our models and variable definitions are robust to alterations in design and specification.

6.6. Statistical considerations

Our models might be subject to statistical concerns. First, the specification of both the probit and tobit regression might include endogenous variables. Endogeneity occurs when an explanatory variable is correlated with a component of the error term. In addition to simultaneity and measurement error, the correlation between explanatory variables and the error term could emerge because of an unobserved or omitted variable that affects both independent and dependent variables. Measurement error denotes instances where independent variables are inaccurately measured and the model does not incorporate this measurement imprecision. Consequently, the variable would include a noise term. Moreover, simultaneity implies that two variables are jointly determined, potentially leading to reverse causality, which indicates that the independent variable might be influenced by the dependent variable (Antonakis et al., 2010).

In our model specification, the market-based measures (MB, RETURN) could be subject to endogeneity due to reverse causality. A firm's market value might be influenced by goodwill impairment announcements (Bens et al., 2011). Mitigating endogeneity in non-linear regression models such as probit and tobit necessitates careful analysis of the causal structure and suitable econometric methods. Instrumental variable approaches like 2SLS and the Hausman test provide potential solutions, given appropriate instrumental variables are available and underlying assumptions are met (Han et al., 2021; Hausman, 1978; Iatridis et al., 2022). In line with prior research focusing on goodwill impairment determinants, endogeneity concerns are acknowledged but are assumed to not prevent interpretations concerning associations between variables (AbuGhazaleh et al., 2011; Denis, 2001).

In addition to endogeneity, our models' variables might also be subject to multicollinearity. Multicollinearity refers to the existence of correlations among independent variables in a multiple regression model. This phenomenon can render

statistical results inaccurate and might inflate standard errors since it would be challenging to discern the individual effects of each variable (Farrar & Glauber, 1967). To assess multicollinearity, we analyze the variance inflation factors (VIF). A VIF score above 10 is considered a severe form of multicollinearity (Wooldridge, 2016). The variables utilized in our regressions display VIF scores below 3, which suggests that multicollinearity is unlikely to have a substantial impact on our qualitative inferences (Table A.11).

In general, we adjust applicable firm-specific variables using the same deflator based on assets to mitigate potential issues related to heteroscedasticity (AbuGhazaleh et al., 2011; Riedl, 2004; Zang, 2008). Furthermore, it is worth mentioning that our additional analysis regarding COVID-19 might be limited in statistical power due to a relatively low number of observations within the pandemic subsample.

7. Conclusion

Since the introduction of the impairment-only approach in 2004, criticism has been voiced by different stakeholders regarding the use of discretion (Glaum et al., 2018; Lee, 2011). Mirroring the intentions of the standard, managerial discretion might be utilized to signal private information about future developments (AbuGhazaleh et al., 2011). Conversely, managers might exercise the discretion to manage earnings in relation to certain thresholds. Representing a key financial metric, EPS consensus forecasts can serve as a relevant benchmark for managers (Burgstahler & Eames, 2006). Therefore, our study focuses on the use of goodwill impairment to manage EPS relative to consensus forecasts in listed European companies. In our analysis, we introduce three different managerial incentive proxies and examine both the decision to impair as well as the magnitude by utilizing a probit and a tobit regression, respectively.

After controlling for economic factors, our results suggest that goodwill impairments are utilized by listed European firms to manage EPS relative to consensus forecasts. Firms that are either clearly below or above the EPS consensus prior to goodwill impairment are more likely to impair and report larger magnitudes of impairment. Marginal analyses show that firm-years subject to potential incentives to take a big bath or smooth earnings are associated with an increase in the probability of impairment by 3.5 and 10.8 percentage points, respectively. This contributes to an area of mixed evidence from prior research that focuses on firms' historic, industry, or zero earnings as relevant benchmarks (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018). In addition, firms that are meeting or slightly beating the EPS consensus before reporting an impairment are less likely to impair and incur smaller impairments. Concerning the likelihood of impairment, firm-years subject to a target-beating incentive are associated with a 4.5 percentage point decreased probability of reporting an impairment. This suggests that motivations to reach the EPS consensus play a significant role in impairment decisions, which aligns with scarce evidence in this domain (Gros & Koch, 2020).

With regards to our additional analysis, we find that the pre-crisis horizon from 2015 to 2019 serves as the driver of the main analysis' results, compared to the crisis period during the COVID-19 pandemic. Although the three managerial incentive proxies are statistically significant within the pre-crisis subsample, we find coefficients that are insignificant for the variables indicating big bath and target-beating behavior during the crisis. This stands in contrast to previous evidence, which identifies increases in opportunistic impairment behavior during the crisis period when analyzing the financial crisis of 2008 and 2009 (Giner & Pardo, 2015).

However, our study design is subject to limitations. First, the focus on European firms does not permit generalizations of our findings for companies exposed to other institutional settings. Covering only listed entities and excluding firms from the financial

industry further limits the transferability of our findings. Second, we acknowledge that our study focuses on determinants of goodwill impairment with respect to EPS consensus forecasts as a relevant benchmark. We do not cover other potential targets used by managers such as prior year and zero earnings that might incentivize deviating impairment behavior. Third, it should be noted that while the impairment tests are conducted on a CGU level, we utilize control variables on a firm level to account for economic impairment, such as return on assets. Due to the absence of public data for each CGU, we follow previous literature in incorporating firm-level variables to proxy for economically induced impairment (AbuGhazaleh et al., 2011; Giner & Pardo, 2015; Glaum et al., 2018). In this context, our study is limited by the number of control variables. The results might be affected by other observable or unobservable factors. In the domain of goodwill impairment determinants, previous studies use additional control variables related to management, including CEO tenure, CEO change, or management compensation (Beatty & Weber, 2006; Han et al., 2021; Iatridis & Senftlechner, 2014; Ramanna & Watts, 2012). Although we recognize the relevance, we do not include these variables for our sample due to issues of data availability.

The potential areas for future research are extensive. Investigating several benchmarks, including EPS consensus forecasts as well as previous year, industry, and zero earnings, simultaneously might provide a more comprehensive picture of the relevance of different thresholds within goodwill impairment decisions. In addition, future studies could widen the scope and cover multiple activities to manage EPS beyond goodwill impairment, including accruals and real activities. Moreover, future research might focus on analyzing the disclosure quality of companies that are identified to potentially exercise discretion within IAS 36 to manage EPS relative to consensus forecasts. Since we observe deviating results for the COVID-19 crisis, scholars might examine the persistence of this development beyond the pandemic. In this context, prospective studies might target the impact of the additional requirements put forward following the finalization of the post-implementation review in 2022 (IASB, 2022).

Overall, our findings indicate that managers exercise the discretion permitted by IAS 36 both to overstate and to understate goodwill impairment. The implications affect several stakeholders. Standard setters should continue to monitor empirical evidence concerning value relevance and potential exploitation of the current goodwill impairment regulation. This is assumed to be particularly relevant following the probable introduction of the revised disclosure requirements. Auditors should consider managerial incentives revolving around pre-impairment earnings surprises when reviewing firms' impairment decisions. Similarly, this is also required for investors and other financial statement users when evaluating goodwill impairments to make informed decisions. Ultimately, the impairment-only approach enables managers to convey a nuanced reflection of economic reality at the expense of relying on several predictions that provide flexibility to follow managerial incentives.

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Appendix

Table A.1. Industry overview

Country	Number of observations
Basic Materials	244
Consumer Discretionary	446
Consumer Staples	286
Energy	125
Health Care	272
Industrials	792
Technology	165
Telecommunications	128
Utilities	156
Total	2,614

The table displays the number of observations for each of the 9 industries used within our analysis, totaling to 2,614 observations across 408 firms. Industries are grouped by ICB categories.

Table A.2. Additional analysis – Summary statistics

Variables	Pre-crisis period			Crisis period		
	n	Mean	σ	n	Mean	σ
<i>Dependent</i>						
GW_INC	1,779	0.211	0.408	765	0.217	0.412
GW_MAG	1,779	0.002	0.010	765	0.002	0.008
<i>Independent</i>						
BIGBATH	1,779	0.228	0.420	765	0.186	0.389
SMOOTH	1,779	0.233	0.423	765	0.286	0.452
MEET_BEAT	1,779	0.148	0.356	765	0.122	0.327
<i>Controls</i>						
LEV	1,779	0.578	0.154	765	0.590	0.158
INSTI_OWN	1,779	0.452	0.227	765	0.455	0.232
AUDITOR	1,779	0.942	0.235	765	0.944	0.230
ANALYSTS	1,779	2.830	0.500	765	2.824	0.469
SIZE	1,779	9.007	1.461	765	9.247	1.371
GW_SIZE	1,779	0.190	0.150	765	0.185	0.153
MB	1,779	3.724	3.317	765	4.473	4.236
PRIOR_IMP	1,779	0.212	0.409	765	0.265	0.442
RETURN	1,779	0.166	0.295	765	0.178	0.324
ROA	1,779	0.071	0.063	765	0.066	0.073

The table displays the summary statistics for all variables utilized in the probit and tobit regressions in the additional analysis. The sample is divided into firm-years belonging to the pre-crisis and crisis subsample. The pre-crisis period covers fiscal years 2015 to 2019, while the crisis period contains the fiscal years 2020 and 2021. For the year 2020, observations with reporting dates deviating from the end of the calendar year are excluded from the additional analysis since these observations cannot clearly be assigned to either the pre-crisis or crisis period. The model uses a sample of 2,544 firm-year observations (1,779 observations within the pre-crisis subsample and 765 observations within the crisis subsample). Displayed descriptive statistics include the number of observations, means, and standard deviations. All variables are defined in Table 1.

Table A.3. Robustness test – Probit regression results (excl. MEET_BEAT)

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.193	2.29	0.022**
SMOOTH	+	0.483	6.10	0.000***
<i>Debt contracting</i>				
LEV	-	-0.175	-0.66	0.510
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	-0.095	-0.61	0.541
AUDITOR	+/-	-0.086	-0.51	0.612
ANALYSTS	+/-	0.049	0.43	0.670
<i>Firm-level controls</i>				
SIZE	+/-	0.123	2.86	0.004***
GW_SIZE	+	0.145	0.58	0.562
MB	-	-0.028	-1.67	0.095*
PRIOR_IMP	+	1.062	11.92	0.000***
RETURN	-	-0.202	-1.63	0.104
ROA	-	-2.196	-2.62	0.009***
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
N	2,614			
Pseudo R ²	0.2047			
Wald chi-squared test	363.53			
p-value	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the probit regression for the robustness test excluding the variable MEET_BEAT. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.4. Robustness test – Tobit regression results (excl. MEET_BEAT)

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.006	2.61	0.009***
SMOOTH	+	0.013	6.09	0.000***
<i>Debt contracting</i>				
LEV	-	-0.007	-1.13	0.260
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	0.004	1.27	0.206
AUDITOR	+/-	-0.001	-0.24	0.810
ANALYSTS	+/-	0.002	0.77	0.441
<i>Firm-level controls</i>				
SIZE	+/-	0.001	1.59	0.113
GW_SIZE	+	0.013	2.27	0.023**
MB	-	-0.001	-1.53	0.125
PRIOR_IMP	+	0.017	5.97	0.000***
RETURN	-	-0.006	-2.34	0.019**
ROA	-	-0.060	-3.02	0.003***
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Model F-test</i>	3.28			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the tobit regression for the robustness test excluding the variable MEET_BEAT. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The interpretation of the *Pseudo R*² for a tobit regression deviates from the standard linear regression (Dhrymes, 1986). Due to our negative *Pseudo R*², we omit the result in this table. We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.5. Robustness test – Probit regression results (excl. BIGBATH and SMOOTH)

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentive</i>				
MEET_BEAT	-	-0.374	-4.07	0.000***
<i>Debt contracting</i>				
LEV	-	-0.199	-0.75	0.455
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	-0.038	-0.24	0.808
AUDITOR	+/-	-0.096	-0.56	0.577
ANALYSTS	+/-	0.017	0.15	0.883
<i>Firm-level controls</i>				
SIZE	+/-	0.115	2.71	0.007***
GW_SIZE	+	0.142	0.56	0.574
MB	-	-0.032	-1.94	0.053*
PRIOR_IMP	+	1.069	12.10	0.000***
RETURN	-	-0.202	-1.67	0.095*
ROA	-	-1.632	-2.03	0.042**
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Pseudo R²</i>	0.1949			
<i>Wald chi-squared test</i>	344.13			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the probit regression for the robustness test excluding the variables BIGBATH and SMOOTH. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.6. Robustness test – Tobit regression results (excl. BIGBATH and SMOOTH)

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentive</i>				
MEET_BEAT	-	-0.009	-4.34	0.000***
<i>Debt contracting</i>				
LEV	-	-0.008	-1.31	0.191
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	0.006	1.65	0.100*
AUDITOR	+/-	-0.001	-0.37	0.713
ANALYSTS	+/-	0.001	0.44	0.661
<i>Firm-level controls</i>				
SIZE	+/-	0.001	1.38	0.169
GW_SIZE	+	0.013	2.26	0.024**
MB	-	-0.001	-1.76	0.078*
PRIOR_IMP	+	0.018	6.08	0.000***
RETURN	-	-0.006	-2.52	0.012**
ROA	-	-0.049	-2.48	0.013**
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Model F-test</i>	2.99			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the tobit regression for the robustness test excluding the variables BIGBATH and SMOOTH. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The interpretation of the *Pseudo R*² for a tobit regression deviates from the standard linear regression (Dhrymes, 1986). Due to our negative *Pseudo R*², we omit the result in this table. We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.7. Robustness test – Logit regression results

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.250	1.60	0.110
SMOOTH	+	0.745	5.06	0.000***
MEET_BEAT	-	-0.361	-2.01	0.045**
<i>Debt contracting</i>				
LEV	-	-0.281	-0.59	0.554
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	-0.206	-0.75	0.456
AUDITOR	+/-	-0.037	-0.13	0.900
ANALYSTS	+/-	0.094	0.44	0.660
<i>Firm-level controls</i>				
SIZE	+/-	0.219	2.86	0.004***
GW_SIZE	+	0.325	0.72	0.471
MB	-	-0.056	-1.81	0.070*
PRIOR_IMP	+	1.792	11.70	0.000***
RETURN	-	-0.341	-1.49	0.135
ROA	-	-3.905	-2.47	0.014**
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Pseudo R²</i>	0.2058			
<i>Wald chi-squared test</i>	338.03			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the logit regression. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles, include year and industry fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.8. Country overview

Country	Number of observations
Austria	35
Belgium	47
Denmark	98
Faroe Islands	7
Finland	98
France	392
Germany	375
Ireland	60
Italy	144
Luxembourg	45
Netherlands	121
Norway	73
Poland	18
Portugal	21
Spain	105
Sweden	266
Switzerland	200
United Kingdom	509
Total	2,614

The table displays the number of observations for each of the 18 countries used within our analysis, totaling to 2,614 observations across 408 firms.

Table A.9. Robustness test –Probit regression results incl. country fixed effects

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.106	1.22	0.224
SMOOTH	+	0.419	4.98	0.000***
MEET_BEAT	-	-0.200	-2.02	0.043**
<i>Debt contracting</i>				
LEV	-	-0.156	-0.57	0.567
<i>Governance & monitoring</i>				
INSTI_OWN	+/-	-0.176	-0.62	0.533
AUDITOR	+/-	0.117	0.57	0.567
ANALYSTS	+/-	0.069	0.59	0.558
<i>Firm-level controls</i>				
SIZE	+/-	0.113	2.58	0.010***
GW_SIZE	+	0.255	0.94	0.348
MB	-	-0.028	-1.58	0.114
PRIOR_IMP	+	1.015	11.78	0.000***
RETURN	-	-0.193	-1.53	0.125
ROA	-	-2.150	-2.46	0.014**
<i>Industry indicator variables</i>				
<i>Year indicator variables</i>				
<i>Country indicator variables</i>				
N	2,596			
Pseudo R ²	0.2138			

The table displays coefficients, z-values, and p-values for all variables utilized in the probit regression. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). We winsorize all continuous variables at the 1 and 99 percentiles, include year, industry, and country fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,596 firm-year observations (565 observations with GWI and 2,031 observations without GWI). All variables are defined in Table 1.

Table A.10. Robustness test –Tobit regression results incl. country fixed effects

Variables	Expected sign	Coefficient	z-value	p-value
<i>Managerial incentives</i>				
BIGBATH	+	0.004	1.94	0.053*
SMOOTH	+	0.011	5.68	0.000***
MEET_BEAT	-	-0.004	-2.28	0.023**
<i>Debt contracting</i>				
LEV	-	-0.006	-1.01	0.313
<i>Governance & monitoring</i>				
INSTL_OWN	+/-	-0.003	-0.58	0.563
AUDITOR	+/-	0.001	0.32	0.747
ANALYSTS	+/-	0.003	1.06	0.291
<i>Firm-level controls</i>				
SIZE	+/-	0.001	1.10	0.270
GW_SIZE	+	0.016	2.46	0.014**
MB	-	-0.001	-1.67	0.095*
PRIOR_IMP	+	0.016	5.93	0.000***
RETURN	-	-0.005	-2.13	0.033**
ROA	-	-0.058	-2.89	0.004***
<i>Industry indicator variables</i>	Yes			
<i>Year indicator variables</i>	Yes			
<i>Country indicator variables</i>	Yes			
<i>N</i>	2,614			
<i>Model F-test</i>	2.43			
<i>p-value</i>	0.0000			

The table displays coefficients, z-values, and p-values for all variables utilized in the tobit regression. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively (two-tailed). The interpretation of the *Pseudo R*² for a tobit regression deviates from the standard linear regression (Dhrymes, 1986). Due to our negative *Pseudo R*², we omit the result in this table. We winsorize all continuous variables at the 1 and 99 percentiles, include year, industry, and country fixed effects, and cluster robust standard errors by firm (Petersen, 2009). The intercept is not tabulated. The model uses a sample of 2,614 firm-year observations (565 observations with GWI and 2,049 observations without GWI). All variables are defined in Table 1.

Table A.11. Variance inflation factors

Variables	VIF score
<i>Independent</i>	
BIGBATH	1.29
SMOOTH	1.31
MEET_BEAT	1.19
<i>Controls</i>	
LEV	1.64
INSTL_OWN	1.16
AUDITOR	1.03
ANALYSTS	2.10
SIZE	2.88
GW_SIZE	1.27
MB	2.16
PRIOR_IMP	1.08
RETURN	1.27
ROA	1.97

The table displays VIF scores for all independent and control variables utilized in the probit and tobit regressions. All variables are defined in Table 1.