IMPROVING PRICING ACCURACY OF THE ABNORMAL EARNINGS GROWTH MODEL

DOES A FADE-AWAY FACTOR DO THE TRICK?

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Abstract

In this thesis, we examine whether the pricing accuracy of the parsimonious AEG model can be improved when industry-specific fade-away factors of AEG are acknowledged in the model. In order to answer this question, the study uses three different methods, namely a simple linear regression, a graph analysis, and a calculation of implied fade-away factors, to derive industry-specific patterns. Then, in a second step, these results are used to assess the AEG model's pricing accuracy with and without the acknowledgement of these industry-specific factors. It was found that industry-specific factors enhance the pricing accuracy of the AEG model. Especially the fade-away factors estimated with the linear regression proved to be superior. These findings contribute to previous studies which investigate the validity of the AEG model, and which hypothesize how it could be improved without adding unnecessary complexity. The fact that industry-specific fade-away factors have a significant impact on the AEG model's pricing accuracy highlights that both academic researchers and practitioners who engage with the AEG model should account for the industry-specific factors derived in this study.

Keywords:

Equity valuation, accounting-based valuation, abnormal earnings, pricing accuracy

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Contents

1. Introduction

> Abnormal earnings growth methods [...] take an approach that focuses on the first derivative of abnormal earnings instead of abnormal earnings themselves, and this approach seems to lose information that is critical for valuation purposes and leads to less reliable forecasts. (Daske et al., 2010, p.33)

The Abnormal Earnings Growth (AEG) model is an accounting-based equity valuation approach which stands out thanks to its combination of theoretical validity and practicality in its application. However, despite being derived from the same underlying Discounted Dividend Model (DDM), the AEG model is often criticized for being less accurate than its direct peer, the Residual Income Valuation (RIV) model. Naturally, this leads to the question how the AEG model can be modified in order to yield an improved pricing accuracy.

Therefore, this study investigates the following research question:

Does introducing industry-specific fade-away factors of abnormal earnings growth improve the AEG model's pricing accuracy?

As the name indicates, accounting-based equity valuation models build on the usage of companies' reported accounting numbers. To transform them into a complete valuation model which also captures the future prospects of the valued company, this anchor in known accounting figures is subsequently complemented with forecasted numbers in the form of expected firm performance and analyst forecasts (Penman, 2013). To be complete, Penman (2005) identifies four key aspects which each valuation model needs to fulfill: First, it needs to specify what parameters are required to be forecasted for the valuation of a company. Second, it has to guide the model's user with regards to converting the collected and analyzed data into a forecast. Third, it is required to outline how to convert the forecast into a valuation. And forth, the model needs to allow the user to reverse engineer a valuation into a forecast in order to assess the future payoffs implied by observable market prices. However, it is also necessary that, while all of these aspects are fulfilled, the valuation model is utilitarian, meaning that it needs to ensure a high level of usefulness for a practical application at the same time (Penman, 2005). Consequently, the so-called parsimonious valuation models, requiring only a small number of different variables which are easily obtained, play a significant role in the professional investment context (Anesten et al., 2020).

Ohlson (2005) and especially Ohlson and Juettner-Nauroth (2005; OJ thereafter) argue that with the AEG model, they derived an accounting-based equity valuation model which fulfills all requirements stated above to a greater extent when compared to the more prominent RIV. Most strikingly, since investment practice is focused on earnings growth, not growth of book values, the AEG model's practical utility appears to be superior (Ohlson, 2005). However, several empirical studies comparing the different models' pricing accuracy indicate that the RIV is superior (e.g., Gode & Mohanram, 2003; Jorgensen et al., 2011; Anesten et al., 2020).

Therefore, our research is motivated by the ambition to investigate whether it is possible to improve the parsimonious version of the AEG model by including a pattern for an industry-specific development of AEG in the model. As mentioned above, the model's derivation from the same DDM and its numerous advantages in terms of practicability should make it a superior alternative to the RIV. However, the AEG model's inferior empirical performance effectively prevents it from becoming more influential. Hence, this study is motivated to apply adjustments to the model which might mitigate its current flaws. However, as described by Anesten et al. (2020), it is imperative to acknowledge that even theoretically correct adjustments do not improve the model's usefulness if they are difficult to apply in practice. Therefore, as the parsimonious AEG model already demands forecasts for both near-term and long-term AEG, the introduction of an industry-specific fade-away factor of the abnormal earnings growth could be done easily. Describing for each industry how near-term AEG decays towards an anticipated long-term AEG over time could potentially lead to significant improvements of the AEG model's pricing accuracy.

This research question has a high relevance independent of the outcome of this analysis. If the study shows that the AEG model's pricing accuracy can be improved by conducting such a low complexity adjustment, it might indicate that the model has indeed a realistic chance of taking over a more prominent role in equity valuations both in academic research and practical applications. If, however, this work concludes that considering industry-specific fade-away factors do not improve the model's validity, it provides further evidence that the AEG model requires more fundamental adjustments which might limit its utility.

To answer the research question, the analysis is split into two parts. While in Part I industry-specific fade-away factors are derived using three different methods, in Part II the pricing accuracy of these methods are tested. In the first method used in Part I, it is analyzed whether historically achieved AEG allows to isolate an industry-specific growth pattern for abnormal earnings with help of a simple linear regression over the whole sample period. In the second method, the historic data is aggregated into multiple 11-year timeframes on a rolling basis which are then used to derive an industry-specific fade-away factor. In the third method, it is analyzed what industry-specific fade-away factors are implied in historic market valuations by reverse engineering the AEG model with help of analyst forecasts. Building on these findings, in Part II of the analysis, the results of the three different methods are then inserted into the AEG model and the pricing accuracy will be compared between the different versions in order to conclude whether the model's validity improved.

Ultimately, the results of the analysis show that industry-specific fade-away factors exist and can be derived with help of different methods. Furthermore, acknowledging these industry-specific fade-away factors in the AEG model does increase the model's pricing accuracy compared to versions which use generic factors for all industries. In specific, the fade-away factors estimated by the linear regression yield the highest pricing accuracy of all the versions tested. Hence, it is concluded that utilizing an industry-specific development of AEG is a promising strategy to increase the AEG model's validity, and that further research should acknowledge that fact.

All in all, our study contributes to existing literature in several dimension. The analysis is a direct continuation of studies conducted by Jorgensen et al. (2011), Ho et al. (2017), and Anesten et al. (2020), who address the inferior empirical pricing accuracy of the AEG model and hypothesized on how to improve it further. Therefore, this study provides tangible insights regarding a possible way of improving the AEG model's validity. While existing research is mainly focused on comparing the AEG model's performance with other accounting-based valuation methods, this study explicitly focuses on a concrete area of improvement and investigates whether it is worth accounting for it.

The remainder of this work is organized in the following way. The second part of this study provides an overview of already existing research on the AEG model. This includes insight into the derivation of the AEG model, its advantages and disadvantages, as well as existing studies that have investigated the empirical validity of the model in comparison to other accounting-based equity valuation models. Part three outlines the different hypotheses which are tested in this study. Part four describes the methodology which is used to test the hypotheses and to answer the research question. This includes a description of the different methods and the data sample used for this analysis. Part five presents and interprets the results of the data analysis which can be observed, and which are then discussed in part six. Finally, the results of the study are summarized, and further areas of research are highlighted.

2. Literature Review

2.1. Derivation & Design of the AEG Model

The Abnormal Earnings Growth model is, compared to other accounting-based equity valuation models, a relatively new concept and one that was strongly promoted by Ohlson and Juettner-Nauroth (2005). Similarly, to the more widely known Residual Income Valuation model, it has its origin in the Discounted Dividend Model. Hence, it also follows the theoretical assumption that the sum of all future dividends distributed to shareholders defines the value of the company (Miller & Modigliani, 1961; Ohlson, 2000).

As stated in its name, the AEG model uses the growth of abnormal earnings to value a firm's equity. In general, this abnormal earnings growth – or, more precisely, the abnormal growth of earnings (Brief, 2007) – is defined as the difference between, on the one hand, the sum of next period's earnings and the interest on the theoretically reinvested current period's dividends, and, on the other hand, the current period's earnings growing at a rate equal to the cost of capital. In the case of the AEG model, which aims to value the company's equity, the cost of capital is defined as the cost of equity ρ_e. Formally, this can be represented by the following formula:

$$z_t = [EPS_{t+1} + \rho_e \cdot DPS_t] - (1 + \rho_e) \cdot EPS_t \tag{1}$$

where z equals the expected abnormal earnings growth, EPS stands for expected earnings per share, DPS stands for expected dividends per share, ρ_e stands for cost of equity, and t stands for the respective point in time.

In order to derive an equity valuation model based on AEG, one starts with the DDM model (e.g., Miller & Modigliani, 1961; Ohlson, 2005; Penman, 2016):

$$V_0 = \sum_{\tau=1}^{\infty} R^{-\tau} \cdot E_0\big(\widetilde{DPS}_\tau\big) \tag{2}$$

where V equals the company's equity value and $R = (1 + \rho_e)$. From this starting point, the model needs to be extended by utilizing a theory developed by Ohlson (2000) which allows to transform the DDM into a valuation model based on future abnormal earnings growth instead of future expected dividends. To achieve that, as a first step, the following algebraic equation is required (Ohlson, 2000):

$$0 = y_0 + R^{-1}(y_1 - Ry_0) + R^{-2}(y_2 - Ry_1) + \cdots \tag{3}$$

for which the sequence of $\{y_t\}_{t=0}^{\infty}$ can be any sequence of numbers as long as the condition $R^{-T} y_T \rightarrow 0$ for $T \rightarrow \infty$ is fulfilled. As a second step, the DDM presented in formula (2) can now be combined with the sequence shown in (3) to result in a generic valuation formula which forms the basis for the derivation of both the RIV and the AEG model (OJ, 2005):

$$V_0 = y_0 + \sum_{t=1}^{\infty} R^{-t} \cdot (y_t + E_0(DPS_t) - Ry_{t-1}) \tag{4}$$

Now, as the final step to arrive at the AEG model, one sets y_t equal to capitalized future earnings per share (EPS) for period t. By doing so, one arrives at the following equity valuation model, which is also called the non-parsimonious AEG model (OJ, 2005; Jennergren & Skogsvik, 2007):

$$V_0 = \frac{E_0(EPS_1)}{\rho_e} + \frac{1}{\rho_e} \sum_{t=1}^{T} \frac{1}{(1+\rho_e)^t} \cdot E_0(z_t) \tag{5}$$

The non-parsimonious AEG model shown in formula (5) illustrates vividly how the AEG model works: The firm's equity can be valued by the capitalized next period earnings and a valuation premium. This valuation premium, namely [V_0 – EPS_1 / ρ_e], consists of the capitalized present value of abnormal earnings growth in future periods. As shown in formula (1), the abnormal earnings growth results from cum dividend earnings which are growing at a faster rate than the cost of equity would suggest. Therefore, this valuation premium represents the capitalized present value of the difference between the growth rate of future earnings and the cost of equity (OJ, 2005).[1]

One challenge associated with the non-parsimonious AEG model, however, is that it requires the user to forecast z_t for all periods until the truncation period T. Naturally, this implies large and detailed amount of data, such as earnings and dividends forecasts per share for every forecasted year. This leads to the problem that for valuing companies, which are commonly assumed to exist for a long, often undefined period of time, the model requires an extensive number of financial forecasts. Yet, these long-term forecasts are often either not available or not accurate enough to yield valid results, indicating the need of a more parsimonious approach which allows equity valuations without the need of explicit periodical forecasts.

As a response to these issues, OJ (2005) outline the derivation of the parsimonious AEG model (Jennergren & Skogsvik, 2007) which is characterized by a significantly higher utility. Instead of requiring forecasts of all the individual parameters until the truncation date, OJ (2005) suggest implementing an assumed long-term, perpetual growth rate to z_t for future periods and thus to use a model which allows a more parsimonious application than the initial one. More specifically, in contrast to the non-parsimonious version, the

[1] It is important to note that notations such as EPS and DPS refer to the expected future EPS and DPS if the respective point in time indicates so. From now on, the paper will refrain from using more elaborate notations such as $\overline{EPS_t} = E_t[\widehat{EPS}_{t+1}]$ to enhance the readability of the paper.

parsimonious AEG model assumes that the abnormal earnings growth z_t will develop in the following way for all future periods:

$$z_{t+1} = \gamma \cdot z_t \tag{6}$$

The gamma, γ, represents a perpetual growth rate with which the abnormal earnings are expected to develop in the long-term, i.e., $\gamma = (1 + g_p)$. Consequently, depending on the assumptions made regarding the perpetual growth rate g_p, the factor γ can either represent future growth or act as a fade-away factor of AEG. For cases where $g_p > 0$, it is assumed that abnormal earnings grow perpetually, while $g_p < 0$ indicates that abnormal earnings will gradually disappear.

By integrating this factor into the AEG model, one arrives at the parsimonious AEG model (OJ, 2005):

$$V_0 = \frac{EPS_1}{\rho_e} + \frac{1}{\rho_e} \cdot \frac{z_1}{R - \gamma} \tag{7}$$

Clearly, in comparison to the non-parsimonious version shown in (5), the parsimonious AEG model (7) is characterized by its significantly lower complexity and reliance on fewer parameters. While the former one requires individual forecasts of z_t for each period, the latter one relies only on a near-term growth rate in AEG represented by z_1, and an assumption about the future development of abnormal earnings in form of γ.

OJ (2005) argue that some restrictions on the parameters of the parsimonious AEG model are necessary as they provide "certain natural restrictions on the set of admissible settings" (p.353). These restrictions, namely $z_1 > 0$; $1 \leq \gamma < R$; and $t = 1, 2, \ldots$, are not mathematically necessary as highlighted by the authors, and rather introduced as they "make intuitive sense" (p.354). However, these assumptions require further investigation.

The first assumption used, namely that $z_1 > 0$, is made by OJ (2005) because of two reasons. First, since any case for $z_t = 0$ would result in $z_{t+1} = 0$, such a case would eliminate any valuation premium and limit the equity value of the company to $V_0 = EPS_1/\rho_e$, a case described as "trite" (OJ, 2005, p.353). Second, any scenario where $z_t < 0$ would represent the "exceptional scenario in which the expected earnings performance always is inferior" (OJ, 2005, p.353). Therefore, on the grounds of its exceptional character, this case is excluded by the authors too.

The second assumption, namely the reason for $1 \leq \gamma < R$, can be split into its two components. The second restriction, $\gamma < R$, appears plausible as it is required for the model's convergence towards $\sum_{t=1}^{\infty}(1 + \rho_e)^{-t} \cdot z_t$ (OJ, 2005). However, the first part of the assumption, $1 \leq \gamma$, requires further investigation: OJ (2005) argue that situations where $\gamma < 1$ are unrealistic as that would force z_t to zero and thus violate the fact that conservative accounting enables lasting abnormal earnings growth. However, on the other hand, studies conducted by Ahmed (1994) and Astana and Zhang (2006) show that not only conservative accounting, but also competition has a significant impact on the development of abnormal earnings in the long-term. While conservative accounting biases increase abnormal earnings, competitive forces reduce them. Hence, OJ's (2005) claim that conservative accounting naturally results in lasting abnormal earnings growth might not hold. Another study by Skogsvik and Juettner-Nauroth (2013) investigates this assumption further. The two authors outline that not conservative accounting per se results in lasting abnormal earnings growth, but rather the development of abnormal conservative bias change over time determines the AEG in the long run. This, as a consequence, leads to the authors' conclusion that "an appropriate persistence factor for the abnormal earnings growth change would be equal to about 1.0" (Skogsvik & Juettner-Nauroth, 2013, p.79). Hence, the study reinforces the impression that this restriction implemented by OJ (2005) is not well reasoned. As a result, instead of assuming perpetual growth in abnormal earnings, existing studies suggest that no perpetual growth at all or maybe even a fade-away factor of $\gamma < 1$ are more appropriate to assume. However, OJ (2005) do state that their restriction is not mathematically required for the derivation of the model and therefore does not affect the model's theoretical validity.

All in all, it can be concluded that the AEG model is an equity valuation approach directly linked to the DDM and thus very similar to the wider known RIV. The two versions of the AEG model, the non-parsimonious and the parsimonious AEG model, differ mainly with regard to the fact that the latter one relies only on the expected near-term growth of abnormal earnings and a γ-factor which describes the perpetual development of AEG, while the former one requires yearly forecasts of AEG until the truncation date. While this simplification might possibly lead to inaccuracies, it significantly lowers complexity and thus increases utility, a key characteristic for every appreciated valuation method (Penman, 2005). Nevertheless, it also means that the γ-factor used needs to be as accurate as possible so that is does not diminish the model's validity. In line with pertinent literature, the present work will move forward by concentrating on the parsimonious AEG model as shown in formula (7). Hence, when referred to the AEG model throughout the remaining paper, the parsimonious AEG model is the one meant.

2.2. Advantages & Disadvantages of the AEG model

As described above, the AEG model relies on future expected earnings instead of discounted dividends or future book value of equity to value a company's equity. Several studies have discussed the implications of this concept and how its design might affect the model's usefulness.

2.2.1. Advantages of the AEG Model

The advantages of the parsimonious AEG model over other valuation models highlighted in previous studies can be summarized into three major areas: the AEG model's intuitive understandability owing to the usage of earnings forecasts, the model's ease of use due to its reliance on earnings forecasts, and the model's high theoretical reliability.

The first area of advantages, the intuitive understanding of the model, is mainly promoted by Penman (e.g., 2005; 2013) who argues that one of the main advantages of the AEG model is its intuitiveness with respect to the understanding of the model's logic. Since the AEG model's central idea is that the "value of a firm is based on what it can earn" (Penman, 2013, p.195), it appears very intuitive for investors, who commonly think in and buy earnings and earnings growth, by linking expected future earnings to a company's equity value. Hence, the AEG model represents a neat approach in which earnings are converted into a valuation that is consistent with the theoretical underpinnings of Miller and Modigliani (1961).

The second area of advantages is focused on the AEG model's ease of use. First, this argument is based on the fact that the model relies on earnings and earnings growth forecasts, both measures which are widely covered by analysts and therefore easy to obtain (Penman, 2013). In fact, the wide proliferation of earnings forecasts is further stressed by the fact that companies' price-to-earnings (P/E) ratios are one of the most commonly used multiples in praxis (Penman, 2005; 2013). Naturally, by using parameters which are widely available, the AEG model significantly lowers the hurdles for investors to engage with it. Second, several studies (e.g., Ohlson, 2005; Penman, 2005; Ho et al., 2017) prove that the AEG model does not require clean-surplus accounting and thus allows for an easy application. RIV, on the other hand, requires the clean surplus relation (CSR), i.e., the assumption that the book value of a company's equity is only affected by net income, dividends, and equity contributions in this specific period (Anesten et al., 2020), to hold. Hence, RIV suffers from the fact that Generally Accepted Accounting Principles (GAAP) regularly "violate CSR by allowing value-relevant accounting items to be charged directly to the book value without showing up in earnings" (Ho et al., 2017, p.565). This leads to a more cumbersome application of the RIV for practitioners as it must be applied on a total dollar basis (Penman, 2005), while the AEG model can simply be applied on a per share basis which facilitates its usage in practice by helping to accommodate any transaction that affects the anticipated earnings per share (Ohlson, 2005; Penman, 2005). Therefore, by relying mainly on parameters which are widely available and abandoning additional adjustments, the AEG model stands out due to its exceptional ease of use.

The third area of advantages is mainly concerned with the – theoretically – high degree of reliability of the AEG model. Ohlson (2005), Ohlson and Gao (2006), and Skogsvik and Juettner-Nauroth (2009) argue that the accounting conservatism included in the book value of equity, which in turn acts as an anchor in the RIV, tends to cause a negative bias in the valuation estimate. The AEG model, however, which operates with capitalized future earnings as an anchor, is not biased in the same way. In fact, the anchor value of the AEG model comes even closer to the equity's market value than the book value of equity (Ohlson, 2005). Additionally, it can also be argued that, by admitting changing growth rates represented in the near-term AEG and γ-factor, the parsimonious AEG model represents reality well. In contrast to that, other models such as the RIV rely solely on a constant rate, and thus try to handle this phenomenon with multi-stage growth models. Therefore, the AEG model accounts for the changing growth rates much more elegantly (Penman, 2005), ensuring a theoretically high degree of reliability.

However, as there are always two sides of the same coin, the AEG model is also subject to some serious critique which needs to be accounted for.

2.2.2. Disadvantages of the AEG Model

The disadvantages of the parsimonious AEG model can be summarized into two overarching areas: On the one hand, critics stress that the AEG model's reliance on future earnings undermines the model's accounting anchor and thus restricts insights into a company's value generation. On the other hand, critics claim that the parsimonious AEG model's conception gives rise to a low degree of reliability, a finding which was substantiated by several empirical studies.

First, critics of the AEG model argue that by anchoring its valuation on expected forward earnings received from analyst forecasts instead of the book value of equity, the AEG model goes against the advice of fundamental analysis to separate speculation from what is known. Since even the anchor is forward looking and not rooted on reported accounting metrics, it is argued that this undermines the AEG model's classification as a fundamental accounting-based equity valuation model altogether (Penman, 2005; 2013). As a consequence, this hurts the AEG model's ability to illustrate value creation of a company. Relying on future earnings does not provide insights into the company's value creation that are as accurate as the ones provided by anchoring in book values. While RIV explicitly provides insights whether investing in certain assets generates economic value, the AEG model does not have such a feature. Hence, the AEG model seems to be less suitable for strategic analyses compared to the RIV (Penman, 2013).

Building on this first aspect, critics also argue that the AEG model contains conceptual flaws, which lead to a lower degree of reliability. One argument for this claim is that the often-cited advantage of the AEG model, namely that it does not require the CSR to hold, ultimately turns out to be a disadvantage. Without the strict adherence to the CSR, and therefore allowing revenue or expense items to bypass the income statement, some of the accounting context is lost. This issue is further exacerbated by the omission of the balance sheet as the anchor value. The balance sheet might offer valuable information for forecasting, especially in cases where a mark-to-market accounting is used. However, by dropping the CSR, the AEG model negatively affects its reliability (Penman, 2005). In addition to that argument, both Jorgensen et al. (2011) and Anesten et al. (2020) emphasize that short-term earnings forecasts by analyst are a rather unreliable anchor due to the noise added by transitory items. Since “one-year-ahead earnings forecasts are likely to include more transitory earnings items than longer-term earnings forecasts” (Jorgensen et al., 2011, p.461) which do not reflect the company’s operations and are unlikely to reoccur, they provide an unreliable picture of the future. Furthermore, Jennergren and Skogsvik (2011) argue that the AEG model’s reliance on a single interest rate is not sufficient to incorporate the individual company’s situation adequately, hurting the model’s reliability further. The initial model is rather general and does not differentiate between the required unlevered rate of return on the equity, the borrowing rate, and the required rate of return on the equity under partial debt financing and treat them as the same. Instead, in order to better match the reality, it would be necessary for the AEG model to specify bottom-line earnings as operating earnings minus debt interest, and dividend as free cash flow minus interest on debt plus debt increase (Jennergren & Skogsvik, 2011).

These conceptual downsides of the AEG model are also affecting the model’s empirical performance as shown in the next section. Several empirical tests conclude that the AEG model underperforms in both pricing accuracy as well as estimation of implied cost of capital compared to its peers, namely the DDM and RIV. These findings highlight the need to modify the parsimonious AEG model.

2.3. Empirics on the AEG Model’s Performance

As mentioned above, the parsimonious AEG model benefits form several advantages regarding its usefulness, but also has conceptual shortcomings which hurt its reliability. Empirical studies have investigated the model’s reliability with help of two approaches: In the first approach, studies compare the AEG model’s pricing accuracy with RIV and DDM. In the second one, the implied cost of capital (ICC) of observable stock prices for the DDM, RIV, and the AEG model are investigated and evaluated. Both approaches rely on the assumption of efficient markets, meaning that every market participant has equal access to information, and thus observed stock prices reflect the right value of companies. Ultimately, both approaches conclude majoritarian that the AEG model suffers from a lower performance compared to its peers.

2.3.1. Pricing Accuracy

Commonly Used Methodology for the Analysis of Pricing Accuracy

The overall idea of investigating the AEG model’s validity by determining the model’s pricing accuracy is based on two parameters and rather intuitive: In a first step, it is calculated what value a company’s equity has according to different equity valuation models. As a second step, this value is then compared to the actual observable equity value in the market, i.e., the company's stock price. The relative difference between calculated values and observed prices is then aggregated per method used and compared between the different valuation methods.

To test the validity of the different approaches, a principal method has been established in the literature. Previous research is mainly concentrated on the use of the mean absolute error (MAE) and mean absolute percentage error (MAPE) for measuring accuracy (e.g., Jorgensen et al., 2011; Ho et al., 2017; Anesten et al., 2020), defined as:

$$MAPE_{0;i} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{V_{0;j} - P_{0;j}}{P_{0;j}}\right| \tag{8}$$

where V equals the valuation of company j's equity derived from the respective equity valuation model, and P equals the observed market price of the respective company's equity at the valuation date t = 0. In addition to that, to provide even deeper insights, such a pricing accuracy analysis is usually complemented by analyses about how large the part of the sample is where the absolute percentage pricing error exceeds 15%, namely the 15%APE, and how large the range between the third and first quartile of the pricing errors is, namely the inter-quartile range of pricing errors (IQRPE) (e.g., Jorgensen et al., 2011; Anesten et al., 2020).

Empirical Results of the Analysis of Pricing Accuracy

Several studies have dealt with the analysis of pricing accuracy of the AEG model. While these studies differ in their sample of companies and other model specifications, the vast majority concludes that the AEG model's pricing accuracy generally underperforms compared to its peers, namely the DDM and RIV.

The first study investigating pricing accuracy of the AEG model was conducted by Penman (2005). Focusing on US traded equities between 1975 and 2002, Penman (2005) calculates the value of the companies' equity with help of analyst forecasts for two years ahead and divides the result by the current price, resulting in a value-to-price ratio. While RIV yields a median ratio of 1.0 and thus corresponds to the market, the AEG model with a median value-to-price ratio of 2.02 significantly overestimates the value of the companies' equity. Hence, this evidence could mean that either the short-term growth forecasts by analyst are overly optimistic, or that one-year ahead earnings are often substantially depressed due to write-downs and restructuring expenses (Penman, 2005). Nevertheless, the results indicate that equity values derived by RIV appear more accurate than the ones derived by the AEG model. However, Penman (2005) stresses that his results do not mean that the AEG model is an invalid model due to his non-exhaustive research design.

A more elaborated study which compares that pricing accuracy of the AEG model and RIV was conducted by Jorgensen et al. (2011). Using US data of companies with fiscal year-end in December between 1984 and 2005, resulting in 24,886 observations, the authors compare the accuracy of several valuation models by calculating MAPE, 15%APE, and IQRPE. The study's key finding is that pricing accuracy of the AEG model is significantly inferior to RIV, and that this difference is largest for the shortest explicit forecast period of two years. The authors claim that the AEG model largely overestimate the firm's future development of return on equity (ROE), a matter which is mitigated by increasing the forecast horizon to five years. Their interpretation is that current earnings are often influenced by transitory items and that these transitory items affect next year's earnings expectations. Hence, when using this growth expectation to determine long-term earnings growth beyond the forecast horizon, the overall valuation becomes inaccurate. RIV estimates, however, being anchored on the current book value of equity, reduce the impact of noise in current earnings and yield more accurate results (Jorgensen et al., 2011).

The findings of Jorgensen et al. (2011) are also confirmed by Anesten et al. (2020). Focusing on Scandinavian data, their results show that the AEG model performs even worse than it does with US data. However, in contrast to Jorgensen et al. (2011), the authors present evidence that neither the use of longer forecast horizons nor the avoidance of transitory items have a strong influence on the AEG model's performance (Anesten et al., (2020), which means that the reason for the low accuracy of the AEG model must lie elsewhere than assumed by Jorgensen et al. (2011).

However, the RIV model's superiority does not remain unchallenged. A comparative analysis of accounting-based valuation models from Ho et al. (2017), using a 34-year sample of US data from 1985 to 2013 and comparing the valuation estimates derived from the AEG model, the DDM, and two variations of RIV, concluded otherwise. When examining the relative valuation accuracy of these valuation models, the authors find that the AEG model's estimates have the lowest MAPE and thus yield the most reliable valuation estimates among all four models. Interestingly, this result occurs despite having a comparable research design as Jorgensen et al. (2011) since both studies rely on US data and use similar versions of the respective valuation models. However, the main difference in their research designs, besides differences in their samples' timeframe and conditions on what data to include, is that Jorgensen et al. (2011) assume a generic long-term AEG rate of γ = (1 + risk-free rate – 3%), whereas Ho et al. (2017) calculate a long-term AEG rate by using available analyst forecasts. As a result, the latter one arrives at the conclusion that capitalized next-year earnings forecast are the better anchor than book value, while the former one does not (Ho et al., 2017).

An overview about the different studies dealing with the pricing accuracy of different valuation models is shown in Table 1 below.

Table 1 – Prior Empirical Research on Pricing Accuracy of the AEG Model

Authors	Sample	AEG model specifications	Evaluation of pricing accuracy	Findings
Penman (2005)	US data; 1975 – 2002	t = 2; analyst forecasts for near-term AEG; g_p = 4%; ρ_e = 10%	Comparison of value-to-price ratios (V_0 / P_0)	RIV dominates AEG model
Jorgensen et al. (2011)	US data; 1984 – 2005	t = 2; analyst forecasts for near-term AEG; g_p = risk-free rate – 3%; ρ_e calculated with CAPM[2]	Comparison of MAPE, 15%APE, IQRPE	RIV dominates AEG model
Chang et al. (2012)	US data; 1980 – 2010	t = 5 and 15; analyst forecasts for entire time horizon AEG[3]; ρ_e calculated with CAPM[4]	Comparison of relative valuation differences ([V_0 – P_0] / P_0)	RIV dominates AEG model
Ho et al. (2017)	US data; 1985 – 2013	t = 2; analyst forecasts for near-term AEG; g_p calculated with analyst forecasts; ρ_e calculated with CAPM[5]	Comparison of MAPE	AEG model dominates DDM and RIV
Anesten et al. (2020)	Scandinavian data; 2004 – 2013	t = 2, 3, and 5; analyst forecasts for near-term AEG; g_p = 0; ρ_e calculated with CAPM[6]	Comparison of MAPE, 15%APE, AM-score (= [1 / IQRPE] / MAPE)	RIV and DDM dominate AEG model

[2] Capital Asset Pricing Model (CAPM) calculated with 30 prior monthly stock returns, risk-free rate = 10 year US treasury-bill rates, and market risk premium = 5%
[3] In contrast to the mainstream research, Chang et al. (2012) use the non-parsimonious AEG model.
[4] CAPM calculated with industry betas, risk-free rate = 10 year US treasury-bill rates, and market risk premium = 5%
[5] CAPM calculated with risk-free rate = 10 year US treasury-bill rates, and market risk premium = 5%
[6] CAPM calculated with 60 prior monthly stock returns, risk-free rate = 10 year government bond rates, and market risk premium = 5.5%

2.3.2. Implied Cost of Capital

Commonly Used Methodology for the Analysis of Implied Cost of Capital

While pricing accuracy tests are concerned with calculating companies' equity values and comparing it with observed market prices, another empirical method used in pertinent literature is to test the AEG model's validity with reverse engineering. For that, one starts with observed market prices and currently available analyst forecasts and calculates what cost of equity is required in each valuation model to arrive at the observed market prices. The result is then compared to the level of commonly cited risk characteristics for each individual company, concluding whether the implied cost of capital is justified (e.g., Gode & Mohanram, 2003; Botosan & Plumlee, 2005; Ho et al., 2017)

A company's cost of capital is a key parameter in accounting-based equity valuation models such as the AEG model and therefore has a significant impact on company valuations. However, because such a rate cannot directly be observed, several indirect approaches use established frameworks, which are supplemented with observable data, to derive implied cost of capital (ICC) (e.g., Gode & Mohanram, 2003; Daske et al., 2010; Ho et al., 2012; Larocque & Lyle, 2017). The idea behind the testing of the validity of valuation models is therefore to compare the calculated ICC with the commonly cited risk characteristics of the firm. In case of the parsimonious AEG model, the ICC can be expressed as a function of the forward earnings and the assumed development of future abnormal earnings growth in the long-term (Ohlson & Gao, 2006). Furthermore, common risk proxies are used to put the calculated ICC into perspective and to allow conclusions regarding the AEG model's validity. They include, among others, the company's leverage, size, and earnings variability (Gode & Mohanram, 2003; Chen et al., 2004; Botosan & Plumlee, 2005)

Empirical Results of the Analysis of Implied Cost of Capital

There are several studies existing which investigate and evaluate the cost of capital implied by the AEG model and compare it to the model's peers. The first study which compares the ICC of the parsimonious AEG model with RIV was performed by Gode and Mohanram (2003) who use US data between 1984 and 1998. In their study, the authors evaluate the implied cost of capital in the valuation methods in three different ways. First, they test how the calculated cost of capital correlates with five different risk factors: [1] systematic risk, [2] earnings variability, [3] unsystematic risk, [4] leverage, and [5] size. Second, they measure the relationship between the cost of capital implied in current prices and the one derived from the prices of the previous year. Third, the authors evaluate the ex-ante cost of capital and its correlation with ex-post realized returns. The study concludes that the implied cost of capital derived from the AEG model does correlate with the risk factors in the expected direction. However, the authors highlight that RIV outperforms the AEG model, especially in the second and third test conducted (Gode & Mohanram, 2003). Other studies arrive at similar conclusions, indicating that the ICC of the AEG model does have some merit, but does not keep up with that of other accounting-based equity valuation models such as the DDM (Botosan & Plumlee, 2005) and RIV, at least in countries where the clean surplus relation holds (Chen et al., 2004).

Another noteworthy study was performed by Daske et al. (2010) who used a simulation approach to evaluate the ability of RIV and the AEG model to estimate the true cost of capital. As the true cost of capital is unobservable in the market, the authors waive archival data and instead create a simulated economy that combines an econometric forecasting model, a business planning model, and a Discounted Cash Flow (DCF)-based valuation model which is then calibrated to the CRSP/COMPUSTAT universe to ensure neutrality with respect to the specific assumptions of the evaluated methods. The authors then calculate the implied cost of capital with help of methods based on residual income, AEG, and industry level, and compare the results to the true cost of capital, which is known for each company in the simulated economy. Despite the different approaches, the authors arrive at a similar conclusion as Gode and Mohanram (2003). In line with previous studies, Daske et al. (2010) conclude that methods based on RIV are more accurate for estimating the true cost of capital compared to methods based on AEG.

An overview about the different studies dealing with the investigation of the correlation of AEG model's implied cost of capital with common risk characteristics and comparing it to other accounting-based equity valuation methods is shown in Table 2 below.

2.4. Conclusion of the Literature Review

Taking all the empirical evidence presented above into account, it can be concluded that the parsimonious AEG model in general underperforms its accounting-based equity valuation model peers, the DDM and RIV. It can be argued that some empirical research (e.g., Ho et al., 2017) indicates that the AEG model is as valid as or even superior alternative to RIV, but taking the entirety of studies into account, these findings are rather isolated cases.

Building on that, the question about the reasons for these results arises, especially since both the AEG model and RIV are derived directly from the DDM. Jorgensen et al. (2011) suggest that transitory items may cause the lower validity, a claim that is in line with Penman's (2005) reservations towards the AEG model. However, this claim is effectively rejected by Anesten et al. (2020), at least for Scandinavian data.

Table 2 – Prior Empirical Research on Implied Cost of Capital in the AEG Model

Authors	**Sample**	**AEG model specifications**	**Evaluation of calculated ICC**	**Findings**
Gode & Mohanram (2003)	US data; 1984 – 1998	t = 5; analyst forecasts for near-term AEG; g_p = risk-free rate – 3%	Comparison of ICC with risk factors, previous year ICC, and ex-post realized returns	RIV dominates AEG model
Chen et al. (2004)	Seven countries[7]; 1993 – 2001	t = 2; analyst forecasts for near-term AEG; g_p = risk-free rate – 3%	Comparison of ICC with risk factors	RIV dominates when CSR holds, AEG model if not
Botosan & Plumlee (2005)	US data; 1983 – 1993	t = 5; analyst forecasts for near-term AEG; g_p = risk-free rate – 3%	Comparison of ICC with risk factors	DDM dominates RIV and AEG model
Daske et al. (2010)	Simulation model[8]	t = 2; integrated forecasting model for near-term AEG; g_p = risk-free rate – 3%	Comparison of ICC with known true cost of capital	RIV dominates AEG model
Ho et al. (2012)	US data; 1968 – 2008	t = 5; analyst forecasts for near-term AEG; g_p = risk-free rate – 3%	Comparison of ICC with ex-post realized returns	Model-based ICCs dominate analyst-based ICCs

[7] Australia, Canada, France, Germany, Japan, UK, US
[8] Calibrated with US data; 1970 – 2009

Therefore, one possible reason for the underperformance of the parsimonious AEG model is the generic use of long-term growth rates. As discussed in section 2.1, OJ (2005) suggest a perpetual growth rate of $1 < \gamma$ because of conservative accounting and the resulting AEG. However, as stated by Skogsvik and Juettner-Nauroth (2013), the long-term AEG is rather determined by abnormal conservative bias changes, leading to a factor of $\gamma = 1.0$. Despite this very relevant insight, their study also falls short of an important aspect: As outlined in multiple studies (e.g., Runsten, 1998; Zhang, 2000; Monahan, 2005), conservative accounting biases do not appear in every industry to a similar extent. Since they are mainly caused by balance sheet items such as intangible assets, conservative accounting biases appear mainly in industries with, among others, high R&D investments and marketing spending. Consequently, it can be argued that lasting abnormal earnings growth thanks to conservative accounting might hold for some industries, but not necessarily for all companies to the same extent. Hence, long-term growth of AEG might differ between industries. Additionally, studies show that competition forces abnormal earnings down, mitigating the described positive effect of conservative accounting biases, and potentially leading to a factor of $\gamma < 1$, i.e., implying a constant fade-away in abnormal earnings. The level of competition and therefore the negative impact on abnormal earnings differs significantly across industries (Ahmed, 1994; Asthana & Zhang, 2006). Consequently, this further strengthens the hypothesis that using one generic perpetual AEG pattern for all industries might not represent reality properly. This might also provide the reason why Ho et al. (2017), who estimate long-term AEG with analyst forecasts, conclude that the AEG model's pricing accuracy is superior compared to its peers, while Jorgensen et al. (2011) and Anesten et al. (2020), who use generic γ-factors, arrive at an opposite conclusion.

2.5. Own Contribution to Existing Literature

This research paper contributes to the existing literature on the AEG model by investigating whether the parsimonious AEG model can be improved by accounting for an industry-specific pattern of long-term AEG. One striking finding in previous research was that Ho et al. (2017), who use analyst forecasts to derive γ-factors, concludes that the AEG model outperforms RIV in terms of pricing accuracy, while studies relying on a generic development of AEG conclude otherwise (Jorgensen et al., 2011; Anesten et al., 2020). Obviously, these conflicting findings highlight the need for further investigation of more individualized patterns of long-term AEG, their development over time, and their impact on the pricing accuracy of the parsimonious AEG model.

In accordance with the findings of Runsten (1998) and Monahan (2005), who claim that industries differ significantly in terms of their conservative measurement biases, as well as the findings by Ahmed (1994) and Asthana and Zhang (2006), who argue that industry-specific competitive forces lead to different levels of abnormal earnings, this study focuses on the different industries' γ-factors. By doing so, this research paper not only contributes to existing literature by investigating whether a specific fade-away factor for AEG, which describes the decay from a near-term rate to a perpetual level, exists. It also differentiates between industries and investigates whether individual fade-away factors exist. The decision of limiting our investigation to the industry-level is motivated by the goal to maintain the AEG model's high level of feasibility and low degree of complexity, i.e., its high degree of utility (Penman, 2005). Firm-specific rates might be difficult to assess, but industry-specific fade-away factors for AEG are a feasible addition without adding too much complexity for practitioners. Consequently, to yield the highest amount of contribution, the focus of this study is limited to this level of granularity.

3. Hypothesis Development

In order to answer the research question of this study and to achieve the intended contribution to existing research, we investigate if a fade-away factor in AEG exists empirically, if yes then in what size and how acknowledging it affects the AEG model's pricing accuracy.

As described in the Literature Review, the parsimonious AEG model relies on a γ-factor which describes how abnormal earnings growth is assumed to develop over time (OJ, 2005; Skogsvik & Juettner-Nauroth, 2013). This factor is subject to contradicting influences, such as conservative accounting and competitive forces, which are highly industry-specific (e.g., Runsten, 1998; Asthana & Zhang, 2006) and therefore affect each companies' long-term development of AEG differently. Hence, by building upon these previous findings, this study investigates industry-specific patterns of abnormal earnings growth and whether acknowledging them increases the AEG model's validity. More precisely, we intend to derive an industry-specific fade-away factor using three different methods: a simple linear regression, a graph analysis, and an implied fade-away factor calculation. Therefore, in accordance with the overall research question, this study will test the following three hypotheses:

H1: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the simple linear regression of historic AEG.

H2: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the graph analysis of historic AEG.

H3: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the calculation of the long-term AEG rate implied in observed market prices.

We will be able to find support for the above hypotheses if the pricing accuracy of the AEG model improves upon the introduction of different industry-specific fade-away factors. We assume that the various factors that influence the long-term development of AEG differ significantly across industries. Therefore, we expect that our analysis will yield different fade-away factors for each industry, which capture all of the industry-specific circumstances that influence the AEG properly. Hence, we expect that every method used will provide us with industry-specific γ-factors which, when applied to the parsimonious AEG model outlined in (7), will improve the model's pricing accuracy. Additionally, we will also investigate whether the fade-away factors achieved by the different methods will differ, which method's factors improve the pricing accuracy the most, and whether the presumed improvement is large enough to justify its application in practical issues.

4. Methodology

4.1. Research Design

In order to test the hypotheses and thus ultimately answer the overall research question of this study, the following course of action is divided into Part I and Part II. In Part I we derive industry-specific fade-away factors using three different methods, namely a simple regression analysis, a graph analysis, and an implied fade-away factor calculation. In Part II, we then test our hypotheses by following closely the approach of measuring pricing accuracy introduced by Jorgensen et al. (2011). Hence, by measuring the pricing accuracy of the AEG model with and without the derived industry-specific fade-away factors, the different results can be compared, and this study's research question can be answered.

4.1.1. Part I – Fade-Away Factor Derivation

Overview About the Methods Used

As introduced above, we will use three different methods to derive a fade-away factor which describes how abnormal earnings growth may develop in the long-term. While each method and its operationalization will be outlined in more detail below, a brief overview about the different methods is already provided here.

The first method used to derive such a γ-factor is a simple linear regression. For this method, a data set consisting of reported financial data from US companies from 1995 to 2015 is established. Then, for each company in the sample, the achieved abnormal earnings growth per year, as shown in formula (1), is calculated. Subsequently, to put each company's AEG into perspective and to allow cross-company comparisons, the yearly AEG is divided by the previous-year's reported book value of equity. As a result, the yearly company-specific Abnormal Profit Ratio (APR) is obtained. This yearly APR is then aggregated according to the companies' industries, and a simple linear regression is conducted for each industry in order to derive an estimation about how companies' APRs develop over time in each industry.

The second method is a graph analysis, based on the same data set used in Method I. In this method also, the calculated yearly APRs per company are used. However, instead of regressing the different yearly APRs, it is investigated whether the aggregated APRs per industry follow a certain pattern and converge to a stable state. After identifying the relevant timeframe until the APRs reach a stable level, the overall level of APR for each industry at this point of time is determined. Finally, the annual fade-away rate of the initial APR to the final APR, i.e., the compounded annual growth rate, is calculated per industry.

The third method used in this study builds on reverse engineering observed market valuations and on isolating the γ-factor which is implied in observed stock prices. For this method, historic stock prices at different points of time, namely the stock price observed at the end of May of each year from 1995 to 2015, will be reverse engineered. Hence, both the observed stock prices and the consensus of analyst forecasts announced during this month are entered into the AEG model as shown in formula (7). Then, the γ-factor which is required to arrive at the observed stock prices will be calculated for each company and aggregated to an industry-level.

In summary, all of these three methods follow a different logic, derive an industry-specific fade-away factor in a unique way, and thus complement each other well. As no previous research exists in which industry-specific fade-away factors are investigated, we are not able to follow any established approach. Instead, this study tests different scientific methods with the goal of achieving a better understanding about whether industry-specific fade-away factors exist, which method is best suited to derive them, and which method yields a fade-factor that produces the greatest improvement to the AEG model's pricing accuracy.

The first two approaches differ from the third one as both the linear regression and the graph analysis analyze achieved APRs in the past, estimate the average development of APRs in the long-term, and assume that this pattern is likely to occur in the future in a similar way. While Method I, the linear regression, estimates the yearly APR change for each company during the whole timeframe, Method II, the graph analysis, investigates whether the aggregated APR converges to a stable level, after how many years that happens, and estimates the average fade-away factor during the relevant time period. In contrast to this, Method III does not assess realized APRs. Instead, the method assumes that the market is in possession of additional, not explicitly reported or forecasted information, that needs to be accounted for when valuing companies. Here, it is also assumed that this implied information is valid for future periods too.

Method I – Simple Linear Regression

As described above, the first method used to derive an industry-specific fade-away factor for AEG builds on an estimation of γ with the help of a simple linear regression. As the required data cannot be readily obtained, the following steps are required to operationalize this approach.

As a first step of this method's operationalization, the yearly abnormal earnings growth is calculated for each company in the data sample based on reported net income (NI), dividends (Div), and cost of equity (ρ_e) with the help of the adjusted version of formula (1):

$$z_t = [NI_{t+1} + \rho_e \cdot Div_t] - (1 + \rho_e) \cdot NI_t \qquad (1a)$$

While companies' fundamentals such as net income and dividends can be sourced from renowned data bases, the cost of equity needs to be calculated separately. Similarly to existing research on the AEG model's pricing accuracy, ρ_e is derived with the help of the Capital Asset Pricing Model (CAPM), which represents a widely used approach of calculating cost of equity and is used in numerous previous studies (e.g., Jorgensen et al., 2011; Ho et al., 2017; Anesten et al., 2020). Following the example of Jorgensen et al. (2011), who use a comparable data sample, the following inputs are used to calculate ρ_e: [1] the company's market beta (β_{comp}), which is calculated using the last 30 monthly stock returns; [2] a yearly risk-free rate, which is set equal to the ten-year US treasury-bill yield (r_f); and [3] a market risk premium ($r_m - r_f$) which is set to 5%. To calculate the companies' individual cost of equity, the parameters are used for the following formula (Berk & DeMarzo, 2020):

$$\rho_e = r_f + \beta_{comp} * \left(r_m - r_f\right) \tag{9}$$

In order to eliminate outliers, to ensure reliable figures, and to obtain yearly cost of equity for all companies in the sample, sub-industry betas are calculated and entered into the CAPM. This is achieved by unlevering the calculated yearly betas of the individual companies, aggregating them per sub-industry and year, and calculating the median unlevered yearly beta per sub-industry. The median is used to mitigate the impact of outliers and extreme betas which might occur for individual companies, but do not represent the sub-industry properly. An overview of the unlevered yearly sub-industry betas, for presentation purposes aggregated to the average between 1995 and 2015, can be found in Appendix 1. This unlevered beta is then relevered for each individual company assigned to the respective sub-industry with help of the company's yearly debt-to-equity ratio (Berk & DeMarzo, 2020). This newly calculated beta is then used to calculate the companies' ρ_e.

$$\beta_{lev;t;j} = \beta_{unlev;t;j} \cdot \left[1 + \left[(1 - T_{C;t}) \cdot \frac{BV\left(D_{t;j}\right)}{MV\left(Eq_{t;j}\right)}\right]\right] \tag{10}$$

where T_C equals the effective tax rate for companies, BV(D) equals the book value of total debt, and MV(Eq) equals the market value of equity.

As a second step, the already mentioned yearly abnormal profit ratio (APR) is calculated for each company by dividing the companies' AEG with its book value of equity of the previous year. This step is necessary to transform the AEG into a relative metric which can be compared across companies and eventually aggregated to an industry-level.

$$APR_{t;j} = \frac{z_{t;j}}{BV_{t-1;j}} \tag{11}$$

As a result, for each company and year in the data sample an APR is obtained.

As a third step, to derive industry-specific fade-away factors, each company is assigned to an industry. For the allocation of companies into industries, the Standard Industrial

Classification (SIC) system is used throughout the study. As we focus our research on publicly listed US companies, and the US Securities and Exchange Commission (SEC) also classifies companies according to their SIC codes (US SEC, 2022), we follow their example. In general, the SIC system is broken down into ten divisions, each further divided into several major groups and finally into industry groups. For the calculation of the sub-industry betas outlined above, the SIC code's major groups, i.e., the first two digits of the SIC code, are used as long as at least ten companies are part of it. If that is not the case, comparable major groups are merged, so that each sub-industry comprises of at least ten companies. For the industry-specific fade-away factors, however, the first-level grouping with the ten different divisions is used. Although these divisions are rather broad, it enables us to obtain a large enough sample for each industry and to keep the analysis on an informative level. Hence, the following ten divisions are used for assigning the sample companies to industries. However, as companies classified as Public Administration represent a special case and are unlikely to engage in abnormal earnings, this division will be disregarded throughout the study.

Table 3. Sample breakdown to industries according to SIC codes (US DoL, 2022)

Division A	Agriculture, Forestry, and Fishing (Agriculture)
Division B	Mining
Division C	Construction
Division D	Manufacturing
Division E	Transportation, Communications, Electric, Gas, Sanitary Services (TCEGS)
Division F	Wholesale Trade
Division G	Retail Trade
Division H	Finance, Insurance, and Real Estate (Finance)
Division I	Services
Division J	Public Administration

As a fourth step of this method's operationalization, nine simple linear regressions are conducted, one for each industry. The dependent variable of the regressions is the company APR in period t, while the independent variable is the company APR in period t-1. As an additional restriction, only observations where the APR is positive are used for the regression to ensure conformity with the parsimonious AEG model. Since (OJ, 2005) build the model on positive AEG, as mentioned in the Literature Review, only such observations can be used when deriving a fade-away factor for the model. Additionally, in order to capture the assumed times series dynamics, the intercept of the regression is forced to zero. As a result, these regressions yield, for each industry, the level of the APR in relation to the previous years' APR. In other words, the regressions yield the industry-specific fade-away factor of the APR, as shown in formula (12):

$$\frac{z_{t+1}}{BV_t} = \gamma \cdot \frac{z_t}{BV_{t-1}} \tag{12}$$

Finally, the robustness of our industry-specific regression results will be assessed with three different types of robustness tests. First, the assumed market risk premium in the CAPM of 5% will be changed to 3% and to 7%. Second, the 21-year time period (1995-2015) used for the analysis is extended to a 31-year time period (1985-2015) as well as shortened to a 11-year time period (2005-2015). Lastly, our results are tested with another industry classification, allocating companies according to their GIC (Global Industry Classification) codes instead of the initially used SIC codes.

The first robustness test is motivated by the fact that the initially used market risk premium of 5% is only an estimate by previous studies such as Jorgensen et al. (2011). However, as the cost of equity has such a prominent role in the calculation of AEG, testing different assumptions for ρ_e allows valuable insights regarding the AEG model's validity. The second test helps us to understand whether the initially estimated fade-away factors are only valid for the selected time period or independent from the chosen timespan. The last robustness test validates whether our results are sensitive to the chosen industry classification according to SIC codes, or whether the results hold also for a different classification too.

Method II – Graph Analysis

As described above, the goal of Method II is to portray the development of the APR by aggregating the whole data sample's APRs on rolling time periods, identifying a stable level of APR per industry, and deriving the industry-specific fade-away factors from it.

To operationalize this approach, the first step is to split the overall used time period from 1995 to 2015 into timeframes of eleven years on a rolling basis. The choice of eleven years is motivated by a previous study by Nissim and Penman (2001) in which a time period of six years is chosen to investigate the evolution of various equity ratios. Therefore, six years can be regarded as the minimum number of years required, and to capture potential outliers we extend the time period for the analysis to eleven years.

Then, as a second step, each company's yearly APR is calculated in the same way as outlined in Method I. After that, the APRs for each company are entered into the smaller timeframes. For the same reasons outlined above, only observations where the APR in first year, i.e., Year 0, of the respective timeframe is positive, are used.

The third step of the method is then to aggregate the APRs according to the industries for Year 0 to Year 10 on a rolling basis. This allows us then to plot the graph for each industry for an eleven-year period and then to analyze whether the industry-specific APR follows a certain pattern, and whether a stable level of APR is reached at one point of time.

As the final step, the compounded average growth rate of APR is calculated for each industry between the first period and the industry-specific period where a stable level of APR is reached as illustrated in formula (13):

$$APR_{S,k} = \gamma^{S} \cdot APR_{0,k} \qquad (13)$$

where $APR_{t,k} = z_t / BV_{t-1}$ for each industry k, and S equals the point of time where APR reaches a stable level for this specific industry.

Method III – Implied Fade-Away Factor

For Method III, the implied industry-specific γ-factors in abnormal earnings growth by the market will be investigated. Following the example of Gebhardt et al. (2001) and Claus and Thomas (2001), who used a similar logic to research implied cost of capital in market prices, we will reverse engineer the stock price of the companies included in the data sample by using the AEG model and analyst forecasts and isolate the implied γ. For this method's operationalization, the parsimonious AEG model, outlined in formula (7), will be rearranged and filled with analyst forecasts of EPS and DPS as well as the observed stock price shortly after the forecasts' announcement date.

As a first step, the AEG model will be rearranged as illustrated below:

$$\gamma_j = -\left(\frac{z_{1;j}}{P_{0;j} - \frac{EPS_{1;j}}{\rho_{e;j}}} * \frac{1}{\rho_{e;j}}\right) + R_j \qquad (14)$$

where $P_{0;j}$ is the observed stock price of company j at the specific valuation point in time.

Then, formula (14) will be filled with data from each year between 1995 and 2015. First of all, only companies which have their financial year end in December are used in the data set to ensure consistency in the data used and to ensure comparability between companies. Secondly, the mean consensus analyst forecasts, announced in May of the respective year, are used. This is motivated by the goal to ensure that the companies have already published their previous year's annual report and thus all new information is integrated into the latest analyst forecasts, while, on the other hand, the influence of the current financial year is limited to the first quarter. Thirdly, the stock price observed at the end of May in the respective year are integrated into the model, allowing sufficient time for the market to adapt to the latest analyst forecasts. Finally, the cost of equity used in this method are also calculated with help of the CAPM, similar to the ones used in Method I and II.

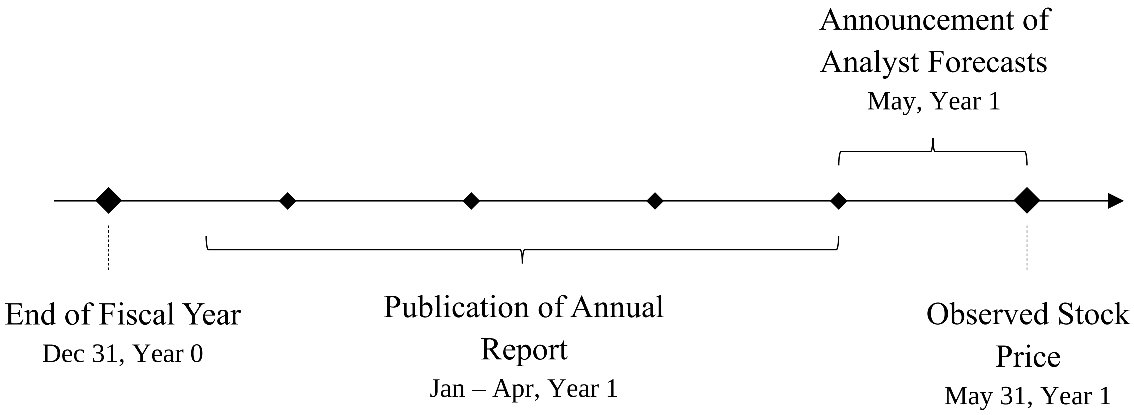


Figure 1. Overview of Timeline

The industry-specific γ-factor is derived by calculating its mean of all companies assigned to the individual industry, using the same industry classification as described above. As a result, the fade-away factor per industry, implied by the market, is obtained.

Finally, the results are subjected to similar robustness tests as the results in the previous methods, motivated by similar reasons: First, the assumed market risk premium of 5% will be altered to 3% and to 7% due to the high influence of ρ_e in the AEG model. Second, instead of using 21 years of analyst forecasts (1995-2015), both 31 years and 11 years are tested to conclude whether the investigated timespan matters. Third, the results are validated by changing the industry classification towards GIC codes to study the analysis' sensitivity regarding the industry classification used.

4.1.2. Part II – Pricing Accuracy Testing

Overview About the Pricing Accuracy Test

In Part II, this study will test whether introducing industry-specific γ-factors, derived from the three methods outlined above, improves the pricing accuracy of the parsimonious AEG model. In order to do so, stock valuations will be calculated with help of the parsimonious AEG model, outlined in formula (7), and publicly available information such as analyst forecasts. For the required γ-factor, five different versions are used: Two generic versions of γ, which are valid for every company and are used as a benchmark, and the three version derived in Part I, which are industry-specific. The calculated stock valuations with these five versions are then compared to the observed stock prices in the market, and each tested version's pricing accuracy is evaluated.

For the pricing accuracy test, we follow the approach introduced by Jorgensen et al. (2011) which was, at least to a large part, also used in several related studies (e.g., Ho et al., 2017; Anesten et al., 2020). More precisely, the three accuracy measures discussed in the Literature Review are used to evaluate any change in pricing accuracy: First, the mean absolute percentage error (MAPE) between the calculated value per share and the observed stock price, as outlined in formula (8) in the Literature Review, is calculated. Second, the share of absolute percentage pricing errors which exceeds 15% (15%APE) is compared between each of the AEG model's version. Third, the inter-quartile range of pricing errors (IQRPE), namely the range between the third and first quartile of the pricing errors for each version of the model, is evaluated. The MAPE provides the average pricing error of each version, taking both under- and overvaluations into account, and therefore providing an overall picture about each version's validity. The 15%APE indicates how many observations per version differ substantially from the observed stock prices, providing additional context for the interpretation of the MAPE. Lastly, the IQRPE is used to provide insights about the spread of the observations. In contrast to standard deviation or variance, the IQRPE is not affected by any outliers, which in turn are already analyzed with the 15%APE, and therefore is expected to yield results which are more stable. Hence, these three metrics allow a holistic picture about the pricing accuracy of the different versions of the AEG model.

Once more, it is worth highlighting that this pricing accuracy test does not evaluate the parsimonious AEG model's validity compared to other valuation models as other studies (e.g., Jorgensen et al., 2011; Anesten et al., 2020) have done. Instead, the goal of the pricing accuracy test conducted in this study is to assess whether the AEG model's pricing accuracy improves when using industry-specific fade-away factors relative to when generic estimates are used.

However, to conduct the pricing accuracy test in a consistent manner, several aspects need to be taken into account, both for operationalizing the stock valuations with help of the AEG model and for operationalizing the subsequent pricing accuracy tests.

Operationalization of Stock Valuation by the AEG Model

First of all, as the different fade-away factors are derived by using data up to and including the year 2015, the pricing accuracy tests are solely based on data available from 2016 onwards, namely data from 2016 to 2020. This split into two time horizons, one period for the estimation of industry-specific fade-away factors and one period for the assessment of the pricing accuracy, is motivated by the goal of avoiding circularity.

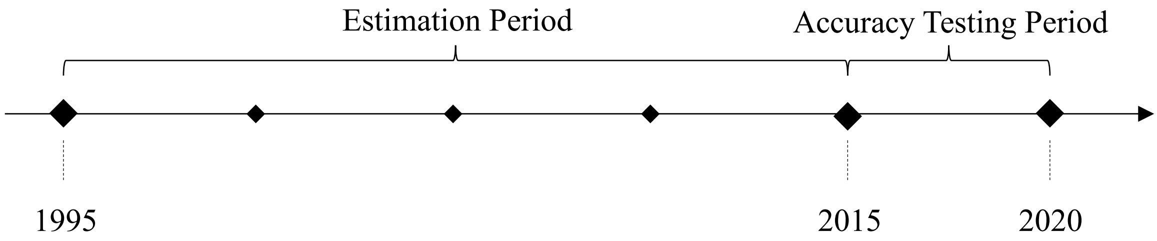


Figure 2. Differentiation between Estimation and Accuracy Testing Period

Second, with the same motivation as outlined in Method III, the data sample used is restricted to companies with their fiscal year end in December. This allows us to use consensus analyst forecasts announced in May of each year for the stock valuation, and to compare the calculated stock valuations to observed stock price at the end of May.

Third, the parsimonious AEG model needs to be adjusted to allow fade-away factors derived from Method I and II to be implemented. As outlined in formula (7) in the Literature Review, the parsimonious AEG model relies only on four distinct parameters: [1] expected future earnings per share EPS_1; [2] cost of equity ρ_e; [3] near-term growth in abnormal earnings z_1; and [4] the fade-away factor γ. While the implied fade-away factor derived from Method III can be inserted directly into the model, the fade-away factor derived from Method I and II describes the decay pattern of APR, not AEG. Hence, for the fade-away factors estimated by these two methods, the following adjusted version of the parsimonious AEG model will be used instead:

$$\frac{V_0}{BV_0} = \frac{\frac{NI_1}{BV_0}}{\rho_e} + \frac{1}{\rho_e} \cdot \frac{\frac{z_1}{BV_0}}{R - \gamma} \tag{7a}$$

As this version does not yield a stock valuation which can be compared to observed stock prices, the calculated ratio of V_0 / BV_0 must be multiplied by the current book value of equity before it can be used for the final pricing accuracy test.

Operationalization of the Pricing Accuracy Measurement

In total, five versions of the parsimonious AEG model are tested, consisting of two base-case versions with a generic fade-away factor, and three versions which integrate the industry-specific fade-away factors obtained in Part I of this analysis. For the first base-case version, a fade-away factor of γ = (1 + risk-free rate – 3%), which is standard practice in previous studies (e.g., Gode & Mohanram, 2003; Jorgensen et al., 2011), is used. For the second base-case valuation, we follow the recommendation by Skogsvik and Juettner-Nauroth (2013) of setting γ = 1.0. These two versions of the parsimonious AEG model provide the benchmark for the assessment of any potential pricing accuracy improvements achieved by integrating industry-specific fade-away factors.

4.2. Data sample

The empirics in our study are obtained from databases provided by Wharton Research Data Services (WRDS). In this study, we are using US company data to attain a large and consistent sample. This is an important criterion to achieve accurate research result which then can be generalized. For our analysis, we are investigating a time frame of 21 years (1995-2015) as this provides us with a large amount of observation without adding too much noise from far in the past. CRSP/COMPUSTAT Merged is used to obtain annual historical data from financial statements, while I/B/E/S is used to obtain analyst estimates. Observed stock prices are received from CRSP. BetaSuite, an additional service provided by CRSP, is used to calculate individual company betas for companies where company-specific data is available, which then is manually aggregated to sub-industry betas as outlined in Part I. Lastly, the yearly risk-free rates, which are set equal to the yield of ten-years US treasury-bills, and the yearly effective tax rate, which is used to unlever and relever yearly company betas, are provided by the Federal Reserve Bank of St. Louis.

To limit our data sample only to relevant observations and to eliminate unrealistic data points which would bias the analysis, several criteria, inspired by the approaches of Jorgensen et al. (2011) and Gode and Mohanram (2003), need to be fulfilled. Regarding data availability, we only include companies in our data set if first their financial statement data, such as book value of equity, are available on COMPUSTAT, second their analysts' earnings forecasts are available on I/B/E/S, and third their yearly stock price are reported on CRSP. Furthermore, we only select firm-year observations of companies for the data sample if they [1] are incorporated in the US; [2] have a positive book value of equity; [3] have sales larger or equal to three million USD; [4] have a fiscal year end in December; [5] have analysts' earnings forecasts that are non-negative; and [6] do not belong to an industry major group that is classified as "Nonclassifiable Establishments" according to the company's SIC code. These limitations were enforced to eliminate any outliers in the sample, which comes from accounting particularities, and to eliminate companies with extreme relative changes in their reported figures due to their small size. The fourth criterion is chosen to ensure consistency in the derivation of implied γ-factors and pricing accuracy tests as outlined above. The fifth restriction is needed to fulfill the parsimonious AEG model's requirements. The sixth criterion is needed as companies with the mentioned characteristic would disrupt the analysis of industry-specific fade-away factors. Additionally, to mitigate the effects of outliers, all input data is winsorized at 1% and 99%. The size of the sample resulting from the use of these constraints, and which is used for the derivation of the fade-away factors, equals 85,191 observations of 8,879 US firms between 1995 and 2015. The sample for the subsequent pricing accuracy test comprises observations of 4,086 US firms. After implementing all of the different criteria to the data sample, only four companies with an industry classification "Agriculture, Forestry, and Fishing" ("Agriculture") remain. Since such a small number of companies is hardly representative of the whole industry and unlikely to yield reliable results, the industry "Agriculture" is excluded from the analysis.

Table 4. Descriptive Statistics Part I

	Mean	**SD**	**Min.**	**1st Qu.**	**Median**	**3rd Qu.**	**Max.**
Equity	1,207.1	3,001.6	2.2	59.6	215.4	825.3	19,093.6
Assets	4,797.8	13,443.8	6.5	156.2	678.7	2,709.4	93,094.3
Sales	2,134.6	5,389.3	4.4	76.9	312.6	1,329.7	34,562.6
Net Income	148.8	476.5	-487.3	-0.1	12.7	78.2	3,105.0
Dividends	55.6	181.4	0.0	0.0	0.0	18.7	1,224.3
Return on Equity	7.6%	27.9%	-79.4%	-0.2%	9.4%	17.0%	137.0%
EBIT Margin	10.3%	28.9%	-156.9%	3.2%	10.6%	22.1%	82.0%
Sales Growth	11.6%	30.5%	-54.9%	-2.5%	6.9%	19.7%	162.7%
Cost of Equity	9.9%	3.8%	4.5%	7.5%	9.2%	11.2%	29.9%
z(t)/BV(t-1)	4.5%	34.1%	-75.2%	-4.9%	0.7%	6.5%	209.0%

Table 5. Descriptive Statistics Part II

	Mean	**SD**	**Min.**	**1st Qu.**	**Median**	**3rd Qu.**	**Max.**
Equity	3,865.5	8,963.8	27.8	382.4	938.8	2,895.4	60,851.6
Assets	15,885.1	39,202.3	65.1	1,251.1	3,361.9	10,085.5	257,515.4
Sales	6,090.7	14,479.3	37.9	454.1	1,484.5	4,797.6	98,593.0
Net Income	521.7	1,388.2	-834.4	20.6	96.0	362.2	9,074.0
Return on Equity	14.5%	21.5%	-41.7%	6.0%	11.5%	19.5%	125.5%
EBIT Margin	17.8%	15.4%	-11.2%	6.8%	13.2%	26.0%	59.3%
Sales Growth	8.5%	22.9%	-86.5%	-0.6%	6.0%	14.3%	515.4%
Cost of Equity	7.8%	2.9%	3.5%	6.2%	7.3%	8.6%	22.7%

5. Empirical Results

5.1. Part I – Fade-Away Factor Derivation

5.1.1. Description of Results of Part I

Method I – Simple Linear Regression

Method I estimates the development of companies' APRs over time for each industry with a simple linear regression. More precisely, for every year the company's APR is calculated and regressed against the previous year's APR. The then resulting regressions' coefficients represent the fade-away factor γ shown in formula (12) above. The regression results for each industry are summarized in Table 6.

Table 6. Overview about Regression Results

Industry	**Metric**[9]			
	Coefficient (γ-Factor)	Adjusted R^2	F Statistic	Observations
Construction	0.247***	0.042	11.587***	190
Finance	0.358***	0.043	227.906***	4,078
Manufacturing	0.310***	0.034	243.933***	3,723
Mining	0.165***	0.119	107.748***	486
Retail Trade	0.019	0.001	0.740	414
Services	0.108***	0.038	115.927***	1,821
TCEGS	0.253***	0.038	67.653***	1,303
Wholesale Trade	0.110***	0.132	84.477***	365

All in all, each regression per industry yield positive coefficients under 1.0 in the span between 0.019 and 0.358. Furthermore, all coefficients except for the one in "Retail Trade" are significant with a p-value < 0.01. However, since this is the only industry where an insignificant coefficient is estimated, it is still included in the following pricing accuracy test to ensure comparability between the results of the different methods. Additionally, the regressions' R^2 differs between regressions, ranging between 0.1% to 13.2%.

Looking at the achieved coefficients from the regressions, substantial differences between the individual industries can be observed. Especially noteworthy are the industries "Finance, Insurance, and Real Estate" ("Finance") and "Manufacturing" which have

[9] Significance at the 10%, 5% and 1% levels are indicated by *, **, and ***, respectively.

coefficients of 0.358 and 0.310, respectively, and which form the upper end of the range. The industry “Retail Trade” forms then the lower end with a coefficient of only 0.019.

The robustness tests, namely [1] the change of the market risk premium used in the calculation of the cost of equity, [2] the different timespans used for the regression, and [3] the allocation of companies into industries according to GIC codes, all conclude that our regression results are in general robust.

When testing for sensitivity regarding the cost of equity, no major differences between the base case and the versions with a market risk premium of 3% and 7% are observed. The coefficients are in the range of 0.019 to 0.353 for the 3% and of 0.018 to 0.364 for the 7% market risk premium, putting the results in the same span as the base case. Also, every individual industry’s coefficient stays almost the same, indicating that the results are robust with respect to the used cost of equity. Additionally, all of the coefficients besides “Retail Trade” stay statistically significant.

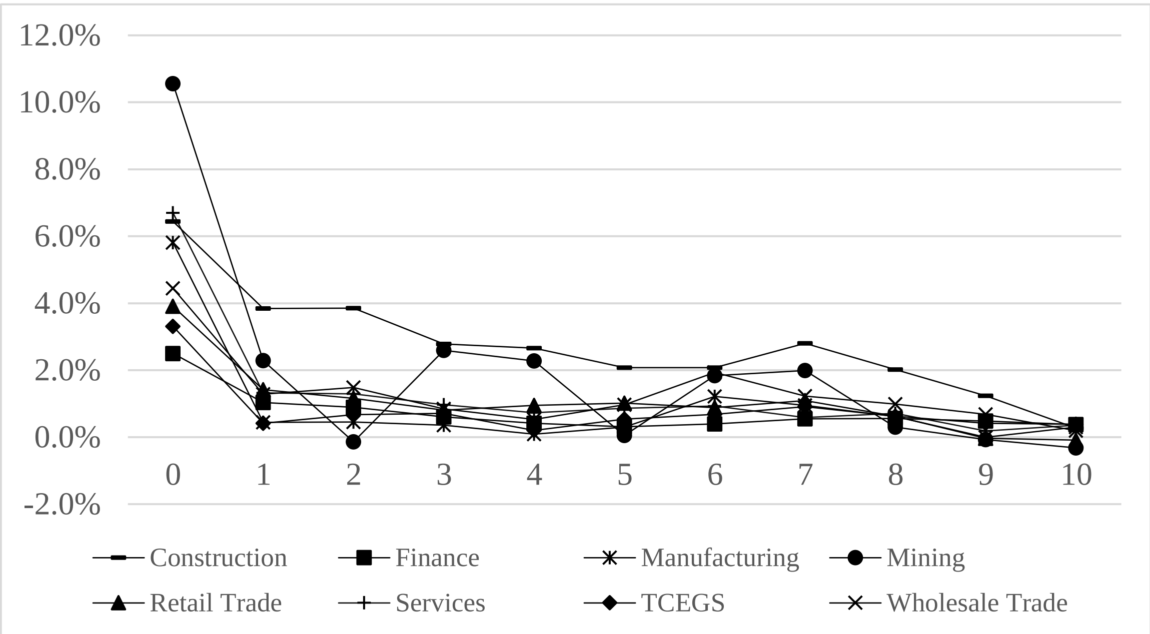
When it comes to estimating the development of APR in different timespans, namely 1985-2015 and 2005-2015, some larger differences can be observed. For example, the estimated coefficient for the industry “Finance” differs between 0.114 and 0.529, indicating that this particular industry is rather sensitive to the data sample used for the regression. However, most of the results do not differ in a major way, for example “Services” stays in a range of 0.122 and 0.086. Hence, despite some industries appear to be more sensitive than others with respect to the choice of analyzed time periods, it can be concluded that in general the regressed coefficients are robust.

The third robustness test conducted, which evaluates whether our results are sensitive to the chosen industry classification, comes to the same conclusion as our first two robustness tests, namely that the regression results are robust. In general, the span of received coefficients stays comparable, reaching from 0.056 to 0.466, and similar industries such as for example “Mining” (SIC) vs. “Materials” (GIC) yield similar coefficients. Also, every industry yields a significant result. Hence, our results are also robust with regards to the chosen industry classification.

Method II – Graph Analysis

In Method II the aim is also to derive industry-specific fade-away factors by measuring each company’s yearly APR and estimating its development over time. However, in contrast to the first method where the change of APR is estimated with a linear regression, it is now analyzed whether the APR aggregated per industry reaches a stable level at a certain point in time. Then, the development of the initial APR towards the stable level is described with help of formula (13) above. The calculated compounded annual growth rate represents the fade-away factor of the APR per industry.

Figure 3 presents the median APR per industry and its development over time on a rolling eleven-year basis. As illustrated, it can be concluded that each industry-specific APR follows the same declining trend. While this decline happens quickly for some industries such as “Mining” and reaches an APR of about 0% already after two years, other industries such as “Construction” are subject to a rather slow and gradual decline. Additionally, it can also be observed that the APR across all industries converges to comparable levels. While the initial difference between the highest and lowest industry-specific APR was around eight percent, it was only about one percent at the end of the investigated eleven-years period. Hence, taking these two observations into account, it can be concluded that [1] APRs in general decline to levels of around 0% with some slightly above and others slightly below zero, and that [2] APRs from different industries converge to similar levels eventually.



Note: The x-axis represents periods of time in years; the y-axis represents the level of APR

Figure 3. Development of APR per Industry

Table 7. Level of APR per Industry

Industry	Level of APR[10]						
	Y0	Y1	Y2	Y3	Y4	Y5	Y6
Construction	6.4%	3.8%	3.9%	2.8%	2.7%	2.1%	2.1%
Finance	2.5%	1.0%	0.9%	0.6%	0.4%	0.3%	0.4%
Manufacturing	5.8%	0.4%	0.5%	0.4%	0.1%	0.3%	1.2%
Mining	10.6%	2.3%	-0.1%	2.6%	2.3%	0.1%	1.8%
Retail Trade	3.9%	1.4%	1.2%	0.8%	0.9%	1.0%	0.9%
Services	6.7%	1.3%	1.3%	1.0%	0.7%	0.9%	0.9%
TCEGS	3.3%	0.4%	0.7%	0.7%	0.2%	0.5%	0.7%
Wholesale Trade	4.4%	1.3%	1.5%	0.8%	0.5%	1.0%	1.9%

However, as explained in the Methodology, the observed APRs need to be further operationalized before they can be interpreted and used for further analyses.

First, for each industry the relevant time period needs to be defined as the period when the APR reaches a stable level. In our case, we defined the relevant point in time when the APR either reaches 0% or, if that is not the case, the point in time when the APR increases for the first time after its initial decrease. This decision is motivated by the fact that after this point, the industry APR levels off at a similar level for almost every industry, with only incremental changes between periods. Expanding the time period to a later point in time would therefore add significant noise to the analysis without adding much value. Consequently, the industry-specific cut-off period was chosen according to this logic. The only exception to this rule, however, is the industry "Construction" which experiences a slight increase of 0.1% in period 2 but levels down to about 2.1% in the long run. Hence, for this industry, an exception is made, and the stable level is established in period 6 instead. The individual industry's maturity periods can be derived from Table 7.

Second, after identifying the relevant period in which the industry-specific APRs reach a stable level, the fade-away factors need to be calculated, following formula (13) presented in the Methodology. The fade-away factor equals the compound annual growth rate of the APR from the initial level to the stable level. As this calculation is not possible with negative values, the APR for the industry "Mining" in period 2 will be set to 0.1%. Following then formula (13), the γ-factor for each industry is calculated. The results are shown in Table 8.

[10] For presentation purposes and since the level of APR after reaching a stable level is irrelevant, Y7-10 are not presented here. Each industry-specific point in time when the stable level is reached is highlighted.

Table 8. γ-Factors Derived from Method II

Industry	**γ-Factors**
Construction	0.828
Finance	0.659
Manufacturing	0.077
Mining	0.097
Retail Trade	0.592
Services	0.575
TCEGS	0.127
Wholesale Trade	0.290

As shown, the calculated γ-factor for each industry differs significantly. For example, "Construction" forms the upper end with $\gamma = 0.82816$, while "Manufacturing" forms the lower end with $\gamma = 0.07688$. In general, these results indicate a larger variance between the different industries than Method I. Nevertheless, Method II yields results which can also be integrated in the adjusted parsimonious AEG model, shown in formula (7a).

Method III – Implied Fade-Away Factor

The results of the third method, namely the analysis of the long-term AEG implied in analyst forecasts, are presented in Table 9. As described, the γ-factor is calculated by rearranging the parsimonious AEG model to isolate it, as shown in formula (14), entering both analyst forecasts and observed stock prices of multiple different points of time into the rearranged formula, and calculating the average of the received γ per industry.

Table 9. γ-Factors Derived from Method III

Industry	**γ-Factors**
Construction	0.981
Finance	1.017
Manufacturing	0.952
Mining	0.933
Retail Trade	0.977
Services	0.991
Transportation	0.963
Wholesale Trade	1.013

As presented in Table 9, the difference between the by the market implied fade-away factor per industry is rather small. Additionally, while most industries have fade-away factors, “Finance” and “Wholesale Trade” have a $\gamma > 1$. Hence, the market seems to imply no fade-away of AEG for these two industries, but rather a perpetual increase of AEG.

The robustness tests conducted yield valuable insights. One the one hand, the two robustness tests regarding the different timeframes and industry classifications do not indicate any specific sensitivity to neither the years analyzed nor the allocation of companies into different industries. For example, also for the two other timeframes of 1985-2015 and 2005-2015, “Finance” and “Wholesale Trade” still have a $\gamma > 1$. On the other hand, the robustness test regarding the market risk premium used for the calculation of the cost of equity ρ_e shows a high degree of sensitivity. For instance, using a market risk premium of 3% leads to fade-away factors for all industries between 0.797 and 0.980 while pushing the fade-away factor of “Finance” up to 1.088. When using a market risk premium of 7%, every industry’s γ-factor becomes larger than 1.0, implying perpetual growth of AEG for all industries.

Hence, the robustness tests conclude that the calculation of implied fade-away factors by the market is not exceptionally sensitive to the analyzed period of time and industry classification, but to the level of market risk premium used for calculation ρ_e.

5.1.2. Interpretation of Results of Part I

To interpret the results of the three distinct methods correctly, it is imperative to first understand what the different levels of fade-away factors achieved by each method imply.

As explained in the Literature Review, the γ in the parsimonious AEG model is driven by long-term, perpetual growth in abnormal earnings as $\gamma = (1 + g_p)$. As a consequence, when $\gamma < 1$, a negative perpetual growth rate is indicated, leading to a decline in AEG and forcing it to zero eventually, i.e., $z_t \rightarrow 0$ (OJ, 2005). On the other hand, when $\gamma > 1$, perpetual growth of abnormal earnings is assumed. While Method III derives a γ-factor which can be integrated into the model directly, Method I and II yield a γ-factor which describes the development of the APR. Consequently, any $\gamma < 1$ derived from Method I and II indicates that the APR declines over time, meaning that abnormal earnings increase (decrease) in a slower (faster) pace than the book value of equity does.

In general, there are two contradicting effects which mainly influence the perpetual growth rate in abnormal earnings for the firms. One the one hand, as outlined by, among others, Zhang (2000), OJ (2005), and Skogsvik and Juettner-Nauroth (2013), conservative accounting practices can lead to abnormal earnings growth in the future. If the company is subject to abnormal changes in conservative biases, the company’s abnormal earnings grow (Skogsvik & Juettner-Nauroth, 2013). On the other hand, however, competition limits companies' opportunities to achieve and sustain abnormal earnings in the long-run. Due to the positive correlation between abnormal earnings and industry entry barriers such as the industry's R&D intensity, low barriers of entry will result in low AEG for companies operating in that industry (Ahmed, 1994; Asthana & Zhang, 2006).

Method I yields γ-factors between 0.358 and 0.019 for all of the industries. Hence, as they are clearly below 1.0, the linear regression estimates that each industries' APR converges to zero. Taking the two major effects into account, it can therefore be concluded that the regression estimates that the negative impact of competition is substantially higher than the positive impact of conservative accounting bias. As a consequence, the APRs will be forced to zero in the long-term. Moreover, since the fade-away factor is stronger the smaller the estimated coefficient, i.e., the γ-factor, of the regression is, Method I indicates that there are large differences between industries. For example, a fade-away factor of 0.310 for "Manufacturing" means that the APR in the upcoming period will be about 31% of the current year's APR, while a factor of 0.019 for "Retail Trade" indicates that next period's APR equals less than 2% of the current level. Hence, it means that companies operating in retail trade are subject to either exceptionally high competitive pressure, which eliminates every growth in abnormal earnings almost immediately, or to low conservative bias, which therefore cannot compensate for it. On the other hand, manufacturing companies experience these two effects less drastically, despite being also subject to declining APRs over time.

However, as described in the first paragraph of this part, it needs to be highlighted that APR = z_t / BV_{t-1}. Hence, the AEG is only measured in relation to the level of book value of equity and therefore declining APRs do not necessarily mean that abnormal earnings disappear in absolute terms. Instead, it can be the case that abnormal earnings grow, but due to even larger increases in book value of equity, the abnormal profit ratio declines.

Similar to the first one, Method II also yields different fade-away factors for each industry. Analyzing the development of APR, it can be concluded that the industry "Construction" with $\gamma = 0.828$ is subject to the smallest decay factor, while "Mining" companies in general have a $\gamma = 0.097$, indicating that any abnormal profit ratio in this industry vanishes almost immediately. Following the same logic outlined above, it can be concluded that according to this analysis, especially mining firms are subject to either high competitive pressure or low conservative accounting bias, while construction firms benefit from contrary effects.

The third method used, i.e., the analysis of implied γ-factors in observed stock prices, also concludes that most industries are subject to a fade-away of AEG in the long-term. However, in contrast to the other two methods, the market assumes that firms operating in the industries "Finance" and "Wholesale Trade" are able to sustain AEG in the long-term, as displayed in the implied $\gamma > 1$ for these two industries. Hence, observed market valuations imply that companies in these two industries are able to keep the abnormal earnings, predicted by analysts, growing. Additionally, as the robustness test shows, assuming a market risk premium of 7% instead of the initial 5% leads to the conclusion that every industry is able to maintain positive AEG in the long-term according to observed stock prices. Consequently, the interpretation of this finding is that, at least in the past, market participants expected that conservative accounting bias can be impactful enough to compensate for competition and thus keeping the growth of abnormal earnings positive.

All in all, it can be concluded that all of the three methods used to derive industry-specific fade-away factors yield relevant results which can be utilized for Part II of this study. Especially Method I and II, but also Method III as long as the assumed market risk premium is smaller than 7%, outline that AEG will decay over time, However, it could also be observed that the assumed γ-factor is highly dependent on the industry. While investigating the reasons for that issue in depth is not part of this study, the results can be interpreted that some industries, for example "Mining", might be subject to especially high competitive pressure or low conservative accounting bias, while other industries are not.

5.2. Part II – Pricing Accuracy Testing

5.2.1. Description of Results of Part II

As outlined in the Methodology, the estimated fade-away factors from Method I and II as well as the calculated implied γ-factors from Method III are used jointly with analyst forecasts of EPS and DPS to calculate stock valuations with the help of the parsimonious AEG model. While Method III can use the model presented in formula (7), the factors derived from Method I and II need formula (7a). Then, each company's results stemming from formula (7a) need to be multiplied with the reported book value per share (BPS) to yield the relevant equity valuation. As the following step, these calculated valuations are then compared to observed stock prices at the same point in time. Additionally, the three versions are compared with two base-cases which use common, generic γ-factors for all companies in the sample: Base-Case I assumes $\gamma = (1 + \text{risk-free rate} - 3\%)$ (e.g., Gode & Mohanram, 2003; Jorgensen et al., 2011) while Base-Case II assumes $\gamma = 1.0$ (Anesten et al., 2020). The results of the comparison between the calculated valuations and observed stock prices are presented in Table 10.

As illustrated, the results show large differences between the five versions tested. With regards to the MAPE, it can be observed that the average of all yearly MAPEs for each case ranges from 0.52 for Method I to 2.34 for Base-Case II. At the same time, when looking at the individual yearly MAPEs, the lowest MAPE is achieved by Method I in 2017 with 0.46, whereas the highest one is the 3.88 of Base-Case II in 2020. Overall, it can be observed that the MAPE of Method I and II is at similarly low levels, while Base-Case I, II, and Method III yield a substantially larger MAPE. Additionally, it is striking that MAPE is smaller in year 2016 to 2018 than in 2019 and 2020 for all versions tested. Looking at the 15%APE, a similar picture can be observed. While Method I and II have values of 0.77 and 0.78, respectively, both base-cases and Method III stand out again with a 15%APE of 0.86 and 0.87. However, the variation between the different years and versions is not as large as in the other metrics investigated, resulting in a more balanced picture. Finally, with regards to the average IQRPE, similar observations than the ones concerning MAPE can be made. Again, a large difference between Method I and II on the one hand and Base-Case I, II, and Method III on the other hand can be observed, ranging from 0.72 to 2.64. Moreover, the IQRPE in 2020 is significantly larger for all versions than for the ones observed before that, with the highest level of 5.46 for Base-Case II.

Looking at each version's industry MAPE, presented in Table 11, a similar picture can be drawn: The pricing accuracy of Method I for each individual industry outperforms all other versions constantly, followed by Method II. The two base-cases form the lower end of the spectrum. It can also be observed that some industry-specific pricing errors of different cases differ significantly from each other while others do not. For example, the MAPE in "Construction" and "Finance" is significantly lower in Method I compared to Method II, while others such as "Manufacturing" and "Wholesale Trade" are almost identical. Additionally, while Method III performs better than Base-Case I and II in most of the industries, "Finance" and "Wholesale Trade" of Method III underperform substantially. Furthermore, for all versions tested, the MAPE for the industry "Mining" is a constant outlier, surpassing the average MAPE of each version by two to three times.[11]

Overall, it can therefore be concluded that in all three metrics evaluated, Method I and Method II yield comparable results with only slight differences. However, Method I yields the smallest average of MAPE, 15%APE, and IQRPE over all assessed points in time and the smallest average MAPE over all industries, putting it in front of Method II.[12] In contrast to that, Base-Case I, Base-Case II, and Method III have significantly higher values in all three metrics, with Base-Case II yielding the highest average pricing errors.

[11] The remaining two accuracy metrics, namely 15%APE and IQRPE, are presented in Appendix 2

[12] The differences in mean values for MAPE in Table 10 and 11 arises from the fact that an unbalanced sample is used throughout the analysis.

Table 10. Comparison of Pricing Accuracy Metrics According to Years

Metric	**Year**	**Version**				
		Base-Case I γ = 1 + r(f) – 3%	Base-Case II γ = 1.0	Method I Linear Regression	Method II Graph Analysis	Method III Implied γ
MAPE	2016	2.04	2.20	0.50	0.54	1.92
	2017	1.53	1.66	0.46	0.48	1.46
	2018	1.46	1.52	0.47	0.48	1.25
	2019	2.11	2.42	0.62	0.65	2.04
	2020	2.88	3.88	0.57	0.66	3.84
	Mean	**2.01**	**2.34**	**0.52**	**0.56**	**2.10**
15%APE	2016	0.84	0.85	0.76	0.77	0.82
	2017	0.85	0.86	0.75	0.78	0.84
	2018	0.83	0.84	0.75	0.77	0.83
	2019	0.86	0.87	0.78	0.77	0.85
	2020	0.94	0.95	0.78	0.80	0.94
	Mean	**0.86**	**0.87**	**0.77**	**0.78**	**0.86**
IQRPE	2016	1.83	1.98	0.65	0.67	1.73
	2017	1.79	1.96	0.64	0.68	1.65
	2018	1.41	1.46	0.66	0.68	1.21
	2019	2.06	2.37	0.75	0.75	2.01
	2020	4.05	5.46	0.88	0.96	4.95
	Mean	**2.23**	**2.64**	**0.72**	**0.75**	**2.31**

Table 11. Comparison of MAPE According to Industries

Industry	**MAPE per Version**				
	Base-Case I γ = 1 + r(f) – 3%	Base-Case II γ = 1.0	Method I Linear Regression	Method II Graph Analysis	Method III Implied γ
Construction	1.31	1.46	0.37	0.56	1.20
Finance	2.04	2.44	0.46	0.57	3.39
Manufacturing	1.57	1.80	0.43	0.43	1.12
Mining	6.68	7.46	1.89	1.87	4.43
Retail Trade	1.65	1.87	0.70	0.72	1.44
Services	1.58	1.82	0.48	0.52	1.61
TCEGS	2.39	2.89	0.53	0.52	1.73
Wholesale Trade	1.58	1.88	0.37	0.38	2.33
Mean	**2.35**	**2.70**	**0.65**	**0.69**	**2.16**

5.2.2. Interpretation of Results of Part II

As outlined above, it can be concluded that the highest degree of pricing accuracy was achieved by Method I, followed by Method II. In contrast to that, Method III, which uses implied γ-factors, yields results which are similar to those of Base-Case I and II, but clearly underperforms compared to its two direct peers.

The results of the pricing accuracy test can be explained by the different levels of fade-away factors utilized in each tested version. As presented in Part I, Method I relies on fade-away factors in the range of 0.019 and 0.358, and Method II on factors between 0.077 and 0.828. This means that in the pricing accuracy test for both methods, a clear and fast fade-away of AEG is assumed. In contrast to that, Method III assumes only slow decays or even small increases in AEG over time, with γ-factors between 0.933 and 1.017. The two base-cases assume a development of AEGs which is very close to Method III: With risk-free rates around 2% for all points in time of the accuracy testing, Base-Case I assumes a slight fade-away of AEG for all industries. Base-Case II assumes a constant level of AEG with a $\gamma = 1.0$, putting it close to both Base-Case I and Method III.

Taking the results of the pricing accuracy test into account, it becomes evident that stronger fade-away assumptions lead to more precise results. On average, Method I assumes $\gamma = 0.196$ and yields the most precise results. Method II, assuming a slightly higher $\gamma = 0.406$ on average, yields a slightly lower accuracy in all three metrics. The other three versions, which assume a substantially higher γ of close or equal to 1.0, yield significantly less accurate results. Hence, the results of the pricing accuracy test can therefore be interpretated as that AEG declines quickly for all companies. This means that assuming that AEG decays quickly yields highly precise estimates for stock prices. However, if only a slow decrease in AEG or no decrease at all is assumed, the pricing accuracy decreases significantly, as shown by the other three versions. This interpretation is even further strengthened by the fact that the largest differences in pricing accuracy between Method I and II arise from “Construction” and “Finance”. While the linear regression estimates a γ-factor of 0.247 and 0.358, respectively, the graph analysis estimates γ-factors of 0.828 and 0.659. Consequently, the stronger fade-away assumption in Method I yields the more accurate results.

Another interesting finding is that the pricing accuracy of Method III is better for most industries than that of Base-Case I and II but underperforms in “Finance” and “Wholesale Trade”. In accordance with the previous interpretation, it most likely stems from the fact that Method III calculates an implied γ for “Finance” and “Wholesale Trade” that is larger than 1, implying perpetual growth of abnormal earnings. However, as Method I and also Method II have shown, pricing accuracy improves when AEG is assumed to converge to zero instead. Since risk-free rates r(f) are smaller than 3% for all the years from 2016 to 2020, Base-Case I coincidentally acknowledged that fact for all industries, although only slightly. As a consequence, the pricing accuracy of Method III is better as long as $\gamma < 1.0$, but worse for industries where a $\gamma > 1.0$ is calculated and utilized. However, one needs to be aware that for periods where r(f) > 3%, Base-Case I assumes growing AEGs in the long-term for all industries, which most likely will have significant negative impact on the version's pricing accuracy in general.

On an additional note, the already mentioned weaker performance of all versions in 2020 is worth assessing further. As all accuracy tests are based on data obtained in May of each year, a certain sensitivity to external events which happened around that time is likely. As the Covid-19 pandemic happened in the beginning of 2020, the market volatility around that time might have been higher than that in the previous years, which in turn might negatively influence each version's pricing accuracy. As a consequence, the calculated values between 2016 and 2019 might be more representative of each version's pricing accuracy.

All in all, it can be concluded that especially Method I yields a clear improvement in the pricing accuracy of the parsimonious AEG model compared to the two generic base-cases. While Method II arrives at almost similar levels, Method III clearly underperforms its peers. The reason for the strong pricing accuracy of Method I are likely because of the assumption of a quick fade-away of AEG. However, then the question arises what extend of the improved pricing accuracy stems from the assumed stronger fade-away factor, and what extend stems from the differentiation between individual industries. More specifically, the question is whether the pricing accuracy is already significantly improved if a substantial fade-away factor without any industry specifications is built into the model. If that is the case, then it is crucial to investigate whether the introduction of industry-specific fade-away factors, in contrast to a generic fade-away factor at a comparable level, improves the pricing accuracy to an extent that justifies the additional complexity.

To test this, we set up an additional version of the AEG model, called the Complexity Test. Here, a generic γ-factor of 0.2 is used for all companies, which equals the average fade-away factor used in the best-performing Method I. Then, the MAPE of Method I, II and the Complexity Test are compared in Table 12 and 13. As it can be observed, the Complexity Test does deliver a better pricing accuracy than Base Case I and II, but it still lags behind Method I and II. Both the overall yearly MAPE and the MAPE for each industry is larger when a generic γ-factor is used compared to the versions where industry-specific fade-away factors are used. Consequently, this provides additional evidence for the claim that industry-specific γ-factors improve the AEG model's pricing accuracy the most. The additional complexity, arising from the differentiation between industries, pays off.

Table 12. Comparison of MAPE According to Years

Year		**MAPE per Version**	
	Method I Linear Regression	Method II Graph Analysis	Complexity Test $\gamma = 0.2$
2016	0.50	0.54	0.78
2017	0.46	0.48	0.62
2018	0.47	0.48	0.62
2019	0.62	0.65	0.92
2020	0.57	0.66	1.03
Mean	**0.52**	**0.56**	**0.79**

Table 13. Comparison of MAPE According to Industries

Industry		**MAPE per Version**	
	Method I Linear Regression	Method II Graph Analysis	Complexity Test $\gamma = 0.2$
Construction	0.37	0.56	0.55
Finance	0.46	0.57	0.76
Manufacturing	0.43	0.43	0.62
Mining	1.89	1.87	2.99
Retail Trade	0.70	0.72	0.80
Services	0.48	0.52	0.65
TCEGS	0.53	0.52	0.83
Wholesale Trade	0.37	0.38	0.61
Mean	**0.65**	**0.69**	**0.98**

6. Discussion of Results

6.1. Evaluation of Results

All in all, the results presented above show two main aspects: First, we find evidence that industry-specific fade-away factors exist and they can be derived with different methods. Furthermore, we also find evidence that accounting for these industry-specific fade-away factors improves the pricing accuracy of the parsimonious AEG model compared to versions using a generic one.

Starting with Part I, namely the derivation of γ-factors with different methods, it can be concluded that each method tested yielded an industry-specific factor which describes the long-term development of APRs or AEG. Hence, the first finding of this study is that both historical achieved AEGs and γ-factors implied in past stock prices can be used to estimate a pattern of how abnormal earnings will grow in the future. However, a comparison between the different γ-factors achieved shows that each version yields different factors. The large difference between the first two methods and Method III can be, at least partially, explained by the fact that Method I and II estimate γ for industry APRs, while Method III calculates the γ-factors of AEG. The small difference between the industry-specific fade-away factors estimated by Method I and II can be explained by the different analysis designs used.

Another important finding of the first part of this study is that there is a significant difference in the development of APR and AEG between the different industries as described above, meaning that the derived fade-away factors are very dependent on the individual industries. While it might be relevant for both academic research and practitioners to investigate why that is the case, this further analysis is out of scope for this work. Hence, in this study, the different γ-factors across industries are only assessed under consideration of competitive pressure and conservative accounting bias, where the former potentially limits the prospect of future abnormal earnings, and the latter potentially allows abnormal earnings to grow perpetually.

Looking at Part II of this study, namely the pricing accuracy test, also some interesting conclusions can be drawn. First of all, the calculated pricing accuracy of the two base-cases matches to previous studies which conduct similar calculations. For instance, the average MAPE of 2.01 and 2.34 for Base-Case I and Base-Case II, respectively, corresponds well to the one calculated by Anesten et al. (2020), who yield a MAPE of the AEG model between 1.20 and 9.45, depending on which version is taken into account.

Furthermore, as presented above, taking industry-specific γ-factors into account leads to significant pricing accuracy improvements for all of the three methods compared to both Base Case I and Base Case II. While the improvements yielded from Method III are sensitive to the different point of time evaluated, i.e., performing similar to Base-Case II in

2020 but better in all remaining years, the improvements of Method I and II are highly stable. Apparently, the industry-specific fade-away factors of AEG derived from reported accounting figures by a linear regression retain their validity even in an exceptional situation such as the Covid-19 pandemic.

Additionally, it appears unintuitive that both Method I and Method II, despite estimating slightly different fade-away factors of APRs per industry, yield pricing accuracies which are almost identical for some industries. The question therefore arises how both methods could yield a similar pricing accuracy. A potential explanation for the similarity of the calculated MAPE between Method I and II is that, although the Complexity Test has shown that industry-specific factors outperform generic ones in general, in few selected industries the difference does not matter as much as in others. It might be the case that in "Construction" and "Finance" the marginal difference matters, while it does not in "Manufacturing". However, as shown by the Complexity Test, this does not mean that industry-specific factors are not relevant or not worth the additional complexity. Generic fade-away factors, despite being at a similar level, still underperform their industry-specific peers. Therefore, the conclusion that it is worthwhile to continue working with an industry split when using the AEG model still holds.

Nevertheless, another finding is that especially companies in the "Mining" industry are inaccurately evaluated by every tested version of the AEG model, even those which utilize the industry-specific γ-factors. Hence, one possible explanation of this finding is that neither of the three methods used to derive industry-specific fade-away factors is well-suited to describe the long-term development of abnormal earnings growth of mining companies. Alternatively, since the low degree of pricing accuracy appears to be systematic across all versions, it could also mean that the validity of available data such as analyst forecasts are below average for mining companies, at least in our sample, and that even an industry-specific fade-away factor cannot compensate for that.

6.2. Answering of Hypotheses and Research Question

As outlined above, three hypotheses were formulated before conducting the analysis. Assessing these hypotheses will then enable us to answer the overall research question of this study.

The first hypothesis stated was the following:

H1: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the simple linear regression of historic AEG.

The analysis yields strong support to the hypothesis that the introduction of industry-specific fade-away factors will improve the pricing accuracy of the AEG model. The results from Method I lead to significant improvements in pricing accuracy compared to both Base-Case I and II at every point in time. In specific, the mean MAPE across all years of Method I is 0.52 and thus far more superior than the same metric for Base Case I and II with 2.01 and 2.34, respectively. Furthermore, when it comes to the two other pricing accuracy metrics 15%APE and the IQRPE, Method I outperforms both Base Case I and II. Consequently, the first hypothesis of the study can be confirmed.

The second hypothesis investigated throughout this study was the following:

H2: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the graph analysis of historic AEG.

Here, similar conclusions as the ones for H1 can be drawn: The parsimonious AEG model modified with industry-specific fade-away factors derived from the graph analysis yield significantly better pricing accuracies than generic model of Base-Case I or II. Hence, in consistency with the argumentation above, H2 is also to be confirmed.

The final hypothesis tested was the following:

H3: The pricing accuracy of the AEG model increases when it acknowledges an industry-specific fade-away factor for abnormal earnings growth that is derived from the calculation of the long-term AEG rate implied in observed market prices.

In accordance with the conclusions drawn for H1 and H2, H3 was also confirmed by our analysis. Despite yielding a less improved pricing accuracy compared to Method I and II, it still outperforms both Base Case I and II in the majority of cases. Hence, similar to the other two hypotheses, H3 was also confirmed.

As a result, when looking at the initial research question of this study, the confirmation of all three hypotheses leads to the conclusion that introducing an industry-specific fade-away factor for the abnormal earnings growth improves the AEG model's pricing accuracy. The industry-specific γ-factors derived from the three different methods leads to the universal improvement of the pricing accuracy of the parsimonious AEG model compared to the generic Base-Case I and II. Furthermore, even the additional Complexity Test does not yield as accurate results as Method I and II. Hence, this study concludes that accounting for industry-specific fade-away factors is a promising approach of increasing the AEG model's validity further.

7. Conclusion

This study has investigated whether industry-specific fade-away factors of AEG can be derived and whether acknowledging them can lead to an improvement in pricing accuracy of the AEG model compared to using generic γ-factors. The results of the study show that this is the case, and that especially the industry-specific fade-away factors estimated with a linear regression on past, realized abnormal earnings growth increase the model's pricing accuracy substantially.

The AEG model, an accounting-based equity valuation model building on the DDM as a foundation, has multiple advantages in terms of practicability compared to other models. However, previous studies have shown that the AEG model's pricing accuracy is inferior (e.g., Gode & Mohanram, 2003; Jorgensen et al., 2011; Anesten et al., 2020). Therefore, improving the AEG model without increasing its complexity or reducing its practicability is a highly relevant topic which creates significant value for academics and practitioners.

In order to achieve this, the study was structured in two main parts: First, it was analyzed whether industry-specific fade-away factors of AEG can be derived from historic data. For this part, three different methods were utilized – a linear regression, a graph analysis, and a calculation of implied fade-away factors by the market – each of them following a different logic. Then, as a second part, it was analyzed whether acknowledging the derived industry-specific fade-away factors in the AEG model increases the model's pricing accuracy, measured by several metrics such as the MAPE and IQRPE. The results of the analysis show that each method used in Part I yields a different set of industry-specific fade-away factors, and that every set of factors achieves an improvement in the pricing accuracy of the AEG model. Therefore, the overall research question of this study, i.e., whether the introduction of industry-specific fade-away factors of abnormal earnings growth improves the AEG model's pricing accuracy, was answered. However, it was also shown that the different sets of derived fade-away factors lead to different levels of improvement. In specific, the results of the simple linear regression, which estimated the development of APRs over time, lead to the largest improvement, while the implied fade-away factors in previous stock prices yield only a marginal improvement.

The most striking aspect that explains the study's results is that the methods which yield the largest pricing accuracy improvements imply stronger fade-away factors than the other versions, which assume only a small or no decay at all of AEG in the long-term. Hence, it appears that stock prices can be better estimated when a quick decay of AEG is assumed. Nevertheless, additional testing has shown that differentiating between industries is yet highly relevant when predicting the long-term development of AEG.

However, we acknowledge that this study is subject to numerous limitations. First of all, only US data is used. Although this increases conformity throughout the sample, it reduces the usefulness of our results in other jurisdictions. Second, using only firms which fulfill several criteria such as positive book values of equity or sales of more than three million USD helped to reduce the impact of outliers. However, it limits the results of the study to firms which fulfill these criteria too. Third, the industry classifications according to SIC codes might be too broad to yield relevant results. The industry classification was chosen as it provides a useful overview and ensures that sufficient companies are included per industry to yield robust results. However, using more granular industry classifications might have led to greater pricing accuracy improvements. Forth, as mentioned in the ef-markets. As calculated valuations are compared to observed stock prices, mispricing of stocks by market participants might affect the result of the pricing accuracy test. Fifth, the accuracy testing is conducted with data available in May of each year. As there are several practical reasons for this analysis design as outlined in the Methodology, it is possible that pricing accuracy tests conducted at different points in time lead to other results.

Nevertheless, the study adds an important building block to the already existing research on the AEG model. It directly follows up on previous studies, mainly the ones conducted by Jorgensen et al. (2011), Ho et al. (2017), and Anesten et al. (2020), and highlights that industry-specific fade-away factors are an important aspect to consider when using the AEG model for equity valuations. Therefore, this study contributes significantly to the current research.

Additionally, this study highlights relevant areas for further research. First of all, future research could focus on investigating whether other methods for the estimation of industry-specific fade-away factors of AEG exist and whether they yield even better results. Second, our study's results could be used for pricing accuracy tests which compare the AEG model, equipped with the derived γ-factors from Method I, to the DDM and RIV. By such an assessment, it could be evaluated whether the AEG model's validity improved sufficiently to become a valid alternative to other accounting-based equity valuation models. Third, instead of focusing on industries, conducting a similar analysis with another sample split might yield additional insights about how AEG develops in the long-term. Such additional insights could then be used to further increase the AEG model's validity. Fourth, as mentioned in the Empirical Results section, there might be other factors than conservative accounting and competition that influence the development of AEG in the long-term. As it was out of scope of this study to investigate whether any other reasons exist, separate research could be dedicated to this topic. Lastly, further research could also investigate how abnormal operating income growth (AOIG), in contrast to earnings, develops over time. As operating income arises from operating assets which in turn are financed by both equity and debt, an analysis of AOIG might rely on more stable data and thus might lead to a more stable pattern of its long-term development.

8. References

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9. Appendix

Appendix 1. Average sub-industry unlevered betas 1995 – 2015

Agriculture, Forestry, And Fishing	0.5625
Amusement And Recreation Services	0.7282
Apparel And Accessory Stores	1.0959
Apparel And Other Finished Products Made From Fabrics And Similar Materials	0.8892
Automotive Dealers And Gasoline Service Stations	0.8757
Automotive Repair, Services, And Parking	0.6419
Building Construction General Contractors And Operative Builders	0.8026
Building Materials, Hardware, Garden Supply, And Mobile Home Dealers	0.8987
Business Services	1.2897
Chemicals And Allied Products	1.0665
Coal Mining	0.7884
Communications	0.7231
Construction Special Trade Contractors	0.9974
Depository Institutions	0.4722
Eating And Drinking Places	0.7537
Educational Services	0.8088
Electric, Gas, And Sanitary Services	0.3163
Electronic And Other Electrical Equipment And Components, Except Computer Equipment	1.4498
Engineering, Accounting, Research, Management, And Related Services	0.9406
Fabricated Metal Products, Except Machinery And Transportation Equipment	0.7749
Food And Kindred Products	0.5525
Food Stores	0.5660
Furniture And Fixtures	0.9490
General Merchandise Stores	1.1599
Health Services	0.7226
Heavy Construction Other Than Building Construction Contractors	1.0420
Holding And Other Investment Offices	0.4472
Home Furniture, Furnishings, And Equipment Stores	0.9844

Hotels, Rooming Houses, Camps, And Other Lodging Places	0.6788
Industrial And Commercial Machinery And Computer Equipment	1.1120
Insurance Agents, Brokers, And Service	0.6166
Insurance Carriers	0.6674
Leather And Leather Products	1.0374
Lumber And Wood Products, Except Furniture	0.9057
Measuring, Analyzing, And Controlling Instruments	1.0215
Metal Mining	1.0774
Mining And Quarrying Of Nonmetallic Minerals, Except Fuels	0.7967
Miscellaneous Manufacturing Industries	0.8501
Miscellaneous Retail	1.0273
Motion Pictures	0.6193
Motor Freight Transportation And Warehousing	0.6751
Non-depository Credit Institutions	0.5599
Oil And Gas Extraction	0.8018
Paper And Allied Products	0.7334
Personal Services	0.5269
Petroleum Refining And Related Industries	0.7817
Pipelines, Except Natural Gas	0.2093
Primary Metal Industries	1.1367
Printing, Publishing, And Allied Industries	0.8278
Railroad Transportation	0.7689
Real Estate	0.5063
Rubber And Miscellaneous Plastics Products	0.8414
Security And Commodity Brokers, Dealers, Exchanges, And Services	1.0975
Social Services	0.6695
Stone, Clay, Glass, And Concrete Products	1.0096
Textile Mill Products	0.8655
Tobacco Products	0.4649
Transportation By Air	0.7301
Transportation Equipment	0.9326
Transportation Services	0.8314
Water Transportation	0.6232
Wholesale Trade-durable Goods	0.8813
Wholesale Trade-non-durable Goods	0.6967

Appendix 2. Comparison of 15%APE and IQRPE According to Industries

Metric	Industry	Version				
		Base-Case I	Base-Case II	Method I	Method II	Method III
		γ = 1 + r(f) – 3%	γ = 1.0	Linear Regression	Graph Analysis	Implied γ
15%APE	Construction	0.87	0.87	0.73	0.82	0.85
	Finance	0.90	0.91	0.71	0.76	0.92
	Manufacturing	0.83	0.85	0.78	0.79	0.81
	Mining	0.92	0.92	0.89	0.88	0.86
	Retail Trade	0.90	0.90	0.76	0.71	0.89
	Services	0.81	0.82	0.82	0.78	0.80
	TCEGS	0.92	0.92	0.79	0.79	0.91
	Wholesale Trade	0.80	0.84	0.75	0.76	0.86
	Mean	**0.87**	**0.88**	**0.78**	**0.79**	**0.86**
IQRPE	Construction	2.04	2.27	0.68	0.93	1.87
	Finance	2.81	3.37	0.70	0.85	4.75
	Manufacturing	1.78	2.09	0.68	0.70	1.28
	Mining	4.11	4.58	1.13	1.14	2.54
	Retail Trade	2.39	2.83	0.74	0.73	2.03
	Services	1.48	1.72	0.79	0.77	1.55
	TCEGS	2.82	3.41	0.71	0.69	2.06
	Wholesale Trade	2.18	2.65	0.67	0.69	3.27
	Mean	**2.45**	**2.87**	**0.76**	**0.81**	**2.42**