MASTER THESIS

PREDICTING VALUATION MULTIPLES

Implementing Fundamental Regression Approaches for Relative Valuation Purposes

Authors:
Peder Havander
Felix Goich

Supervisor:
Jannick Dam Mortensen

May, 2019

MSc Applied Economics & Finance

COPENHAGEN BUSINESS SCHOOL

Number of Characters: 263 731 Date of Submission: May 15th, 2019

Acknowledgments: We would like to sincerely thank our supervisor Jannick Dam Mortensen for his valuable knowledge, insights, and guidance throughout this academic undertaking. We would also like to extend our regards to Copenhagen Business School for providing the required resources for conducting the empirical study.

Student Numbers: 94062; 93972

- Abstract -

This study addresses the empirical deficit that surrounds the underlying relationship between theoretically derived value drivers and valuation multiples, and whether fundamental regressions approaches can generate accurate predictions of intrinsic firm value. Even though previous literature suggests that regression analysis can be utilized to account for heterogeneity amongst comparable firms, few studies have empirically evaluated the accuracy of predicted valuation multiples based on statistical approaches. In addition, while relative valuation is seen as the most commonly applied valuation technique, regression analysis is rarely used as a primary tool for this specific purpose in practice. Instead, relative valuation processes are often permeated by subjective adjustments that commonly hold limited theoretical and statistical substance. Guided by theoretical underpinnings on relative valuation as well as prior empirical findings, the conducted study consequently develops theoretically founded regression approaches that objectively account for individual firm performance in terms of growth, profitability and risk. It is subsequently tested whether these approaches are able to generate accurate predictions of observed EV/EBITDA multiples, which constitutes the sole dependent variable of the study.

Utilizing a sample of 965 publicly traded US firms obtained from the S&P Composite 1500 index, a series of multi-level regressions generate findings that vary significantly across studied sectors and industries. These results contradict the theoretical assumption that growth, profitability, and risk uniformly hold significant predictive power of the studied multiple across firms. On the other hand, it is discovered that valuation estimates based on fundamental value drivers are significant predictors of intrinsic firm value in a majority of instances. Yet, the accuracy of developed predictions is not found to be significantly superior to the accuracy of predictions based on simple peer group averages. With regards to the ultimate research question of the conducted study, a regression approach based on fundamental value drivers is concluded to be a valid methodology in predicting firm value, even though prediction accuracy should be considered limited for some of the studied sectors and industries. As such, utilizing regression approaches for the purpose of relative valuation should be seen as a complement rather than standalone tool in the search for intrinsic firm value. Overall, obtained results are argued to contribute from a holistic standpoint to the academic discourse within multiple accuracy. Apart from providing empirical evidence on the fundamental feasibility of applying a regression approach, the statistical analysis sheds light on the relative importance of value drivers across sectors and industries. Furthermore, the study demonstrates how a statistical method that is developed from theoretical underpinnings can handle differences between firms without being bound to subjective adjustments. Additionally, the research provides empirical insights to the prevalent discussion on the optimal level of analysis by adopting several definitions of peer groups.

- Table of Contents -

- List of Figures -

- List of Tables -

- 1. Introduction -

In its broadest sense, value can be argued to constitute the ultimate dimension of measurement in any market economy, since rational individuals invest with the expectation that benefits from an investment are sufficient enough to compensate for risk-taking. Thus, the ability to generate value, and the degree to which it does so, are both principal measures by which a firm should be assessed (Koller et al., 2010). Considering this notion from a holistic standpoint, theories and empirical evidence concerning how value is created and should be measured are vital for society as a whole. This furthermore implies a need for understanding the intrinsic value of a firm and its underlying drivers (Bernström, 2014). As such, corporate valuation is a fundamental component within finance and accounting theory.

The theoretical emphasis of corporate valuation generally resides in absolute valuation approaches, where the intrinsic value of a firm is determined by the present value of expected future cash flows. Models capturing this notion most notably include the discounted cash flow (DCF) model and the dividend discount (DDM) model, where firm value is captured either as total enterprise or equity value (Petersen et al., 2017). Nevertheless, absolute valuation can in many regards be seen as a cumbersome process that is highly sensitive to a multitude of subjective assumptions. As a consequence, practitioners often revert to relative valuation approaches in the form of multiples, where the value of a firm is determined in relation to comparable firms. A multiple can in simple terms be described as the ratio of a market price, such as total enterprise or equity value, to a particular value driver such as earnings or revenue. Thus, based on the market value of comparable firms or precedent corporate transactions, the implied value of a target firm of interest can be derived. As relative valuation exclusively refers to market values of comparable firms, the method of utilizing multiples can also be described as an indirect, market-based valuation approach (Schreiner, 2007).

The primary rationale for the increasing application of multiples amongst practitioners is driven by the inherent simplicity of the method, as the valuation technique can be conducted faster and with fewer assumptions compared to absolute valuation approaches. Additional appealing features include that multiples reflect the current mood of the market and are easy to understand and present to both clients and non-professionals (García, 2015). In line with these arguments, Pinto, Robinson & Stowe (2015) discovered that 98% of professionals utilize relative valuation methods on a regular basis[I]. Given these findings, they maintain that

[I] Findings from Pinto et al. (2015) were based on a sample of 1980 equity analysts from the CFA institute the multiples approach has become the most widely used valuation method in practice[I]. Regardless of preference, industry standard amongst practitioners has become to either utilize multiples on a standalone basis, or as a complement to more complex valuation techniques (Pandey, 2012; Gaughan, 2015). In sum, relative valuation constitutes a vital component within corporate valuation, which motivates an examination of its theoretical as well as empirical underpinnings.

Even though seemingly attractive due to its simplified nature, relative valuation through the use of multiples does not come without potential pitfalls and weaknesses. Since a multiple based on comparable firms reflects the mood of the market, the approach might lead to over- or undervaluation of intrinsic value, given certain market conditions. Moreover, while relative valuation is not dependent on the same subjective assumptions as absolute valuation approaches, the valuation technique is still vulnerable to manipulation and subject to bias. Lastly, as the relative valuation method builds upon the principle that two identical firms should be valued equally, any heterogeneity between a group of comparable firms and a target firm will need to be adjusted for. These adjustments on the other hand usually involve a high degree of subjectivity, which is why relative valuation in some regards has been referred to as *"more of an art than science"* (Rossi & Forte, 2016, p.2).

Apart from subjective adjustments, theory suggests that accounting for fundamental heterogeneity within relative valuation either entails modification of multiples to be scaled according to a value relevant measure or the implementation of statistical regression approaches (Bernström, 2014). Which value drivers to specifically adjust for remains disputed as a multitude of factors make up the value of a firm. However, according to theoretical assumptions and empirical evidence, only a handful of fundamental value drivers are particularly prominent in determining valuation multiples. In this regard, research into the drivers of multiples consistently returns to three factors that are considered to be the most influential determinants of firm value, namely growth, profitability and risk (Berk & Demarzo, 2017; Petersen et al., 2017). Thus, it is arguably crucial for relative valuation purposes to have a thorough understanding about the relationship between these key value drivers and valuation multiples, as well as how to effectively adjust for them, in order to overcome issues caused by peer group heterogeneity.

The inherent components of multiple valuation and potential implementation issues correspondingly make up the primary topics of interest within the academic discourse. These areas of interest can arguably be generalized

[I] Asquith, Mikhail and Au (2005) also found in their comparative study that 99% of financial analysts make use of multiples when performing valuations of firms, while only 12,8% expressed that they frequently apply present value approaches to include the selection of value relevant measures, the identification of comparable firms, the aggregation of peer group multiples and appropriate adjustments of synthetic multiples (Schreiner, 2007). Variations within these areas of interest ultimately determine the preconditions for a synthetic multiple to accurately predict the implied market value of a firm. Thus, in order to examine the legitimacy of multiple valuation and improve the understanding of how to optimally utilize the method, a significant amount of empirical research has been devoted to testing the accuracy of multiple valuation. Although modifications of the definition exist, accuracy in this setting is generally measured as the difference between a valuation estimate and the actual market value of a firm (Harbula, 2009).

While several insightful studies have added to the academic body on the accuracy of multiples in recent years, empirical evidence remains widely mixed. Furthermore, a majority of the literature that has been dedicated to evaluating the prediction accuracy of multiples has had a limited focus on solely comparing the performance of different multiples across industries and settings. That is, less attention has been given to the underlying relationship between multiples and their fundamental value drivers and its overall implications on multiple accuracy. More specifically, relatively few studies have explicitly focused on the derivation and ultimate valuation accuracy of multiples based on statistical regression approaches with fundamental value drivers as determinants. This observation serves as fundamental base of this paper, where it argued that further empirical investigation on the topic is needed.

1.1 Problem Formulation & Research Questions

Considering the above, it is argued that there is an informational deficit within the academic literature on relative valuation, especially with regards to how an understanding of fundamental value drivers can be used to generate accurate predictions of firm value. Furthermore, empirical evidence suggesting that practitioners applying multiple valuation predominantly rely on experience rather than scientifically proven methods to handle differences between firms, threatens the credibility of the approach as a whole (Bhojraj & Lee, 2002). Even though authors have suggested that application of regression analysis can be used to remedy subjectivity issues, few studies have empirically evaluated the accuracy of predicted valuation multiples from statistical approaches. For these reasons, the overarching research objective and aim of this study is to develop a statistical method based on previous literature that handles differences in fundamental value drivers between firms, produces relatively accurate valuation estimates, and is free from subjective adjustments. As will be outlined in a following section, the analysis is intentionally delimited in several ways. Perhaps most centrally, it is delimited to study a single enterprise multiple, namely EV/EBITDA. Given the singular focus on one individual multiple, the research objective is not meant to exhaustively cover multiples in general. It is expected that the impact of fundamental value drivers is complex in that it may vary considerably across different types of multiples. Accordingly, the inclusion of several dependent variables would arguably limit the ability to make the necessary efforts to produce an in-depth understanding of the topic at hand. This narrow focus is argued to contribute with more value to the academic discourse than a broader and less meticulous study would. Furthermore, enterprise multiples such as EV/EBITDA have the benefit of utilizing measures where accounting differences can be minimized, and the influence of capital structure can be avoided. Nonetheless, the narrow focus undeniably impacts the generalization of results, which is seen as a necessary limitation.

Overall, it is argued that two central components underlie the outlined problem formulation, which will have to be orderly addressed to approach the stated objective. Firstly, the relationship between fundamental value drivers and the studied multiple needs to be identified and investigated. Secondly, the accuracy of predictions has to be evaluated in isolation and in a comparative context to shed light on whether predicted multiples represent accurate estimates of actual market multiples. As such, the two following research questions are formulated to guide the study.

- Research Question 1: *What is the underlying relationship between EV/EBITDA and its fundamental value drivers?*

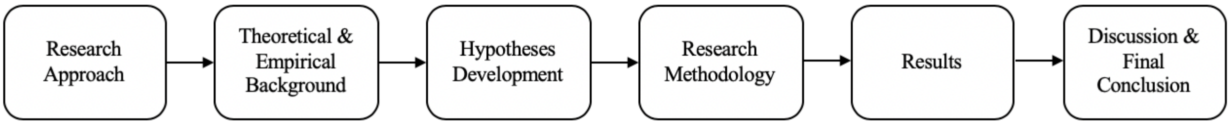
- Research Question 2: *Does a regression approach based on fundamental value drivers provide predicted EV/EBITDA multiples that represent accurate estimates of actual market multiples?*

1.2 Research Approach and Structure of the Paper

Regarding the process of theoretic construction, this study is conducted in line with a deductive approach with regards to hypothesis development and testing. That is, the research approach of this paper is dependent on existing theory which will be subject to examination through a number of propositions. More specifically, widely-acknowledged theoretical frameworks and empirical findings within the field of corporate valuation will guide the formulation of relevant hypotheses, which subsequently determine the research methodology. As this research is motivated partly by empirical observations and partly by an identified research gap within existing literature, as opposed to being purely theory driven, the research approach of this paper could arguably be characterized as abductive. However, in line with deduction, this study will follow a structured methodological research approach that facilitates replication and warrants reliability.

Thus, in the attempt of answering the stated research questions, this study is divided into sections that collectively handle the fundamental components of a deductive empirical research, as illustrated in Figure 1 below. Firstly, with the fundamental research approach outlined, overall delimitations will be presented, which ensure a specific and narrow research focus. Subsequently, theoretical foundations, relevant literature as well as empirical research underlining the chosen topic will be outlined in order to specify and formulate relevant hypotheses. Together with stated research questions, the formulated hypotheses will thereafter guide the research methodology, including selected variables and operationalizations, utilized sample as well as method of data analysis. Lastly, the discovered empirical findings will form the foundation for a summarizing discussion and final conclusion, where perspectivization of results will be considered from both an empirical as well as theoretical standpoint.

Figure 1. Structure of the Paper



1.3 Delimitations

The following study is delimited in several aspects with regards to research focus, theoretical framework, literature background and research methodology. Enforcing certain delimitations is in line with the deliberate aim of ensuring a narrow and specific focus that addresses a gap within existing literature on a more in-depth rather than general level. The following section will address the selected delimitations and outline their underlying rationale, which consequently serves as complimentary base for the subsequent sections of this paper.

On a general level, the theoretical framework is delimited to concern relative valuation within the field of corporate valuation. This implies that the conducted study does not attempt to examine other valuation approaches than relative valuation, including absolute valuation models such as the discounted cash flow (DCF) model, the residual income (RI) model, the dividend discount (DD) model, the economic value added (EVA) model or the adjusted present value (APV) model. Neither will this study concern alternative valuation approaches such as liquidation or contingent claims valuation. With that said, this study will still account for, on a fundamental level, the intrinsic connection between absolute and relative valuation.

The stated research questions and focus furthermore guide the delimitation in terms of relevant literature and empirical research. As will be outlined in subsequent sections, existing literature and empirical research within relative valuation primarily concerns multiple accuracy in predicting implied firm value, which in broad terms can be divided into four main research areas. These specifically include the selection of value relevant measures and drivers, the identification of comparable firms, the estimation of synthetic peer group multiples, and further adjustments in actual multiple valuation. While this paper implicitly covers all the relevant aspects above, academic literature and empirical background is explicitly delimited to fundamental value drivers and estimation of synthetic peer group multiples.

Accordingly, the conducted research methodology is delimited with regards to specific dependent and independent variables. Firstly, the primary variable of interest is delimited to only concern the enterprise multiple EV/EBITDA. As such, this study will not cover the underlying relationships for other valuation multiples and their corresponding value drivers. Neither will it examine several different constructs of EV/EBITDA. Consequently, the ambition of this paper is to conduct a thorough examination of a single valuation multiple, where inferences and statistical results are limited to a narrow area within relative valuation. Additional enterprise and equity multiples could arguably have been examined in this study in order to provide a more holistic view of underlying relationships between multiples and their fundamental value drivers. However, it is argued that the inclusion of additional dependent variables would compromise the ability to make necessary efforts to produce an in-depth understanding of the topic at hand. Furthermore, the EV/EBITDA multiple was chosen specifically due to its several advantages compared to both equity and other enterprise multiples. Firstly, compared to equity multiples, utilizing EV/EBITDA allows for minimizing the implications of accounting and capital structure differences between firms. Secondly, empirical evidence supports that EV/EBITDA, compared to other enterprise multiples, produces superior prediction accuracy in estimating intrinsic firm value.

In line with adopted delimitations for dependent variable, the independent variables are delimited to only concern theoretically derived value drivers of EV/EBITDA, namely growth, profitability and risk. In this regard, potential additions would have been to introduce a wide range of both independent and control variables, including depreciation rate, tax rate and firm size, amongst others. The inclusion of additional independent and control variables would arguably assist in determining observed EV/EBITDA multiples from a more holistic standpoint. However, the objective of this paper explicitly concerns the relationship between EV/EBITDA and its primary value drivers based on theoretical assumptions. Thus, introducing additional variables in the analysis is not considered consistent with a deductive approach. Moreover, even though it might seem intuitive that more comprehensive models should yield more precise valuations, that need not necessarily be the case. Greater complexity implies a greater number of inputs, which also increases the potential for errors. Thus, in line with arguments put forward by Damodaran (2012) in terms of parsimony with regards to valuation practices, only the identified fundamental value drivers of EV/EBITDA will be included for the purposes of this study[I].

Moreover, the utilized research methodology is furthermore delimited with regards to variable operationalization, where each individual value driver is delimited to single measures obtained from the Bloomberg Terminal database (Bloomberg)[II]. An alternative approach to potentially capture a more holistic picture of value drivers includes the aggregation of several performance measures, also known as an indexing approach[III]. However, it is argued that the aggregation of several measures might distort the individual importance of each value driver in isolation and is therefore not applied in the conducted study.

To continue, the study is also delimited with regards to utilized sample as well as time period considered. Firstly, the utilized sample in this study will only concern firms from a single market, and more specifically, public US firms included in the S&P Composite 1500 Index. Consequently, exogenous market factors across geographies will not be explicitly analyzed or accounted for, which would arguably distort the intended focus of this paper. Moreover, as the utilized sample in this study only concerns public firms from a single country, results should be viewed as limited in being representative for firms in different markets and geographies or for non-public firms. Even though it could be argued that public European firms to a large extent share the same underlying characteristics as public US firms, regulatory and other market-specific discrepancies still make accurate comparisons difficult. Secondly, the time period considered will for the purposes of this paper be delimited to the years between 2016 and 2018, with the aim of deliberately maintaining a precise time window for inferences. As valuation of a firm is based on firm-specific as well as market-wide data inputs, estimations fluctuate as new information becomes available. Thus, intertemporal differences in underlying relationships across time will not receive an explicit focus in this study.

[I] See Section 5.1

[II] That is, each value driver is based on a single proxy obtained from Bloomberg

[III] More specifically, an indexing approach involves a subjective ranking methodology where several measures are ranked and assigned a certain index score based on its relative performance (see Asness & Frazzini, 2013)

Lastly, the research methodology is additionally delimited with regards to method of data analysis. More specifically, the method of data analysis is delimited to ordinary least squares (OLS) regressions, based on aggregated cross-sectional data. Several alternatives to OLS regression analysis could have been applied, including general least squares (GLS) regression analysis based on cross-sectional data, or advanced panel data models such as the first difference estimator as well as fixed and random effects models. However, as most similar studies on the same topic have utilized OLS regression analysis, the applied statistical approach is argued to be appropriate in terms of robustness. Moreover, as the examination of intertemporal differences in underlying relationships across time is not explicitly a central focus of this study, applying time-series models based on panel data would not be appropriate to implement. Instead, cross-sectional data is aggregated over the studied time period in order to partly mitigate exogenous and time-invariant unobservable effects.

- 2. Theoretical Foundations -

The aim of the following section is to provide an overview of theoretical foundations underpinning the conducted research, which guide the selection of relevant literature as well as subsequent formulation of hypotheses and research methodology. As described in the previous section, the theoretical background mainly relates to relative valuation. However, absolute valuation which forms the basis for relative valuation will additionally be covered to form a holistic view of the study in question. In broad terms, the following sections will firstly cover absolute and relative valuation approaches as well as their respective limitations. Additionally, value drivers of enterprise multiples will be introduced on a fundamental level by presenting the intrinsic derivation of EV/EBITDA and the different ways in which peer group heterogeneity can be accounted for.

2.1 Approaches to Corporate Valuation

The varying nature of firms implies that valuation requires differing formats and sets of information, which has consequently generated several methods for estimating firm value. Thus, professionals employ a wide range of models for valuation purposes in practice that vary depending on the assumptions, inputs, and type of asset class considered (Gaughan, 2015). Even though different valuation models make different assumptions regarding the pricing of an asset, they all share some common fundamentals that make them categorizable in broad terms. It is widely accepted within the academic literature that four major valuation techniques can be identified, which include absolute valuation, relative valuation, liquidation value approaches and contingent claim valuation (Petersen et al., 2017). To keep to the topic of interest, the following sections do not cover these techniques exhaustively. Instead, absolute valuation will first be outlined as it lays the fundamentals for the following section on relative valuation. Moreover, limitations of both valuation methods will be highlighted for the purpose of perspectivization.

2.1.1 Absolute Valuation

On the most fundamental level, the value or price of an asset reflects the future value that it will produce (Brigham, 2014). The widely accepted fundamental principle for firm value creation is that companies create value by investing capital raised from investors to generate future cash flows at a rate of return that exceeds the investor cost of capital (Koller, 2010). Consequently, the faster companies can generate cash flows and deploy capital at appealing rates of return, the more value they create. As such, the absolute valuation method aims at estimating the intrinsic value of a firm based on projections of future cash flows. These projections are discounted to present value by a factor that takes the risk in generating the cash flows and the time value of money into account (Brigham, 2014). Intrinsic firm value is consequently derived based on individual firm fundamentals, without any relative considerations for other firms that display similar characteristics. As such, absolute valuation can be regarded as the fundamental valuation methodology that all other valuation approaches are built upon (Bernström, 2014). In basic terms, absolute valuation can be expressed by the following equation, where the value of an asset equals the present value of expected future cash flows generated by the asset of interest.

Equation 1.

$$Value_0 = \sum_{t=1}^{t=n} \frac{CF_t}{(1+r)^t}$$

where,

$n = Lifetime\ of\ the\ asset$

$CF_t = Cashflow\ in\ period\ t$

$r = risk\ adjusted\ discount\ rate\ or\ cost\ of\ capital$

As all of the different present value approaches are fundamentally based on the equation depicted above, they are all theoretically equivalent and should therefore yield identical value estimates if the same inputs are applied (Petersen et al., 2017). Different scholars apply various methodologies for categorizing present value approaches. However, on an overall level, the approaches are either used to value total equity of the business, which relates to shareholder claims only, or total enterprise value, which in addition to equity also accounts for claimholders of company debt (Damodaran, 2012)[I]. Within absolute valuation, the DCF model is by far the most utilized valuation method and can for the purposes of mathematical derivation be utilized to illustrate the fundamental connection between absolute and relative valuation[II]. Depending on whether the objective is to value the equity value or total enterprise value of a firm, the DCF model can in its simplest form be expressed by the following equations (Petersen et al., 2017).

Equation 2.

$$Market\ value\ of\ equity_0 = \sum_{t=1}^{t=n} \frac{FCFE_t}{(1+r_e)^t}$$

Equation 3.

$$Enterprise\ value_0 = Market\ value\ of\ equity_0 + NIBD_0 = \sum_{t=1}^{t=n} \frac{FCFF_t}{(1+WACC)^t}$$

where,

$FCFE_t = Free\ cash\ flow\ to\ equity\ owners\ in\ time\ period\ t$

$r_e = Investors\ required\ rate\ of\ return$

$NIBD_0 = Market\ value\ of\ net\ interest\ bearing\ debt$

$FCFF_t = Free\ cash\ flow\ to\ the\ firm\ in\ time\ period\ t$

$WACC = Weighted\ average\ cost\ of\ capital$

Limitations of Absolute Valuation

Being the fundamental and most theoretically founded methodology in valuing the intrinsic value of a firm, absolute valuation should in theory be applicable to value any kind of asset. Given the informational requirements for absolute valuation, present value approaches are most easily utilized in firm valuation where cash flows are positive and can be estimated with some reliability for future periods. An additional requirement is that proxies for risk are available in order to derive reasonable discount rates. However, the further the distance from this idealized situation in reality, the more difficult it is to derive accurate estimates utilizing

[I] In line with this overall categorization, the approaches for valuing the equity value of a firm includes the discounted cash flow (DCF) model, the residual income (RI) model and dividend discount (DD) model, whereas approaches for valuing the total enterprise value of a firm also includes the DCF model and additionally the economic value added (EVA) model as well as the adjusted present value (APV) model (Petersen et al., 2017)

[II] The intrinsic derivation of the EV/EBITDA multiple will explicitly be illustrated in Section 2.2.1

absolute valuation. Thus, some limitations in its applicability for firm valuation exists, which mainly relates to the nature of the firm in question as well as the process itself in practice (Koller, 2010; Brigham, 2014). Several scenarios for the current state of a firm exists where subjective and cumbersome adjustments using a DCF analysis are necessary. These problematic instances most notably include situations when a target firm of interest is in distress, have cyclical cash flows or unutilized assets, and when a firm undergoes restructurings or acquisitions (Brigham, 2014).

Given the implications above, absolute valuation is not always the preferred valuation method in practice. According to Koller, Goedhart & Wessels (2010), a thorough and well-executed DCF analysis offers superior accuracy compared to alternative approaches. However, as also highlighted in the paragraph above, the process often involves several adjustments and assumptions in order to estimate future cash flows and determine an appropriate discount rate. This furthermore implies that absolute valuation can often be tedious procedures susceptible to error (Kim & Ritter, 1999; Lie & Lie, 2002; Gupta, 2018). The fact that inputs and assumptions in valuation models are biased implies a final value that may not be a precise measure of intrinsic value. It is therefore unrealistic to assume complete certainty in absolute valuation as cash flows and discount rates are estimated with a degree of error, which can widely vary across different types of investments (Kim & Ritter, 1999). For these reasons, many professionals turn to relative valuation in practice.

2.1.2 Relative Valuation

While absolute valuation approaches have received predominant theoretical emphasis in the academic discourse on corporate valuation, industry practitioners regularly turn to relative valuation in practice (Lie & Lie, 2002). Even in cases where absolute valuation methods are the primary valuation tools, multiple valuation is most often used in cohesion to provide a second opinion given the heavy reliance on delicate assumptions (Rossi & Forte, 2016). This section will firstly provide an overview of the fundamentals that the multiple valuation method rests on as well as the mechanics associated with applying it in practice. The final section will subsequently shed light on its shortcomings, which constitute a great proportion of the motivation for conducting this empirical research.

As opposed to absolute valuation, relative valuation does not determine the value of a firm intrinsically but is instead anchored in the comparison of assets between firms (Damodaran, 2007). As stated by Baker & Ruback (1999), it builds on the most basic economic concept that assets which are perfect substitutes should be valued at the same price. Relative valuation applies the same logic on an enterprise level, postulating that two identical firms should be valued equally, which makes it possible to infer the value of one firm from observing the value of the other. As such, industry practitioners applying relative valuation often value privately held firms by drawing inference from market values of comparable publicly listed firms, which can be directly observed in the stock market. As such, relative valuation is said to represent an indirect, market-based method of valuation (Rossi & Forte, 2016).

In this regard, the notion of market efficiency plays a central role, as an efficient market is characterized by providing market prices with unbiased estimates of the intrinsic value of assets (Brigham, 2014)[I]. In the process of intrinsically valuing a firm through absolute valuation approaches, the underlying assumption is that markets can be inefficient and that over and undervaluation can be identified. On the other hand, the underlying assumption for relative valuation is that markets are largely efficient in that the law of one price holds. These assumptions furthermore imply that firm value has to be linearly proportional to identified value drivers, and that this linearity holds true for comparable firms (Rossi and Forte, 2016). As firms with similar underlying fundamentals should in theory be valued similarly, implied firm value based on comparables is therefore assumed to be close to the true intrinsic value of a firm (Berk & Demarzo, 2017).

To allow for the comparison across firms, relative valuation takes it form as a multiple in practice, which is merely a fractional expression of a firm's market value relative to a key performance statistic. The statistic in the denominator is used to scale firm value to a common accounting measure and must have a reasonable connection to the numerator (UBS, 2001). That is, the performance statistic in the denominator should be a fundamental determinant of the numerator, which allows the multiple to capture the effects of the main drivers behind valuation (Credit Suisse, 2016). For this reason, much research has been devoted to investigating the most appropriate choice of accounting variable to be used as a scaling statistic[II].

On the whole, multiple valuation entails inference of implied company value by calculating benchmark multiplies from a number of comparable public firms. Furthermore, to sum up, the method relies on two central assumptions. Firstly, those companies used as benchmarks have proportional future cash flow expectations and risk profiles as the company of interest. Secondly, the performance measure used as a scaling statistic is

[I] Necessary conditions for market efficiency to exist include that assets which are sources of inefficiencies are publicly traded, that deviations from the theoretically correct market price are random and that the law of one price holds, meaning that assets with similar underlying characteristics should trade at similar levels (Brigham, 2014)

[II] This specific area of the academic discourse will be expanded in a subsequent section of the literature review proportional to value. If these two assumptions hold, the multiple valuation method should arguably produce more accurate valuation estimates than a DCF approach since the multiple includes market expectations of future cash flows and discount rates (Kaplan & Ruback, 1995). In its simplest form, the method can be expressed as follows.

Equation 4.

$$\textit{Implied Value of Target Firm} =$$
$$\textit{Comparable Firm's Multiple} * \textit{Target Firm's Relevant Accounting Measure}$$

With regards to multiple valuation, it is appropriate to make a clarifying distinction. As within fundamental valuation, firm value can be categorized into total equity value or total enterprise value. Accordingly, there are two main categories of valuation multiples, namely equity multiples and enterprise value multiples. Both groups of multiples have inherent advantages and disadvantages. While equity multiples have the benefit of being highly relevant to shareholders and being more familiar to investors than most enterprise multiples, they are more sensitive to differing accounting practices across firms (UBS, 2001). Consequently, adjustments related to accounting issues have to be made to identified benchmarks in order to ensure comparability. Furthermore, the lack of attention to divergent capital structures and the exclusion of non-operating items may distort certain multiples, such as P/E multiples (Koller et al., 2010). On the other hand, enterprise value multiples have the benefit of utilizing measures where accounting differences can be minimized, and the influence of capital structure can be avoided. Yet, estimating enterprise multiples involves more subjectivity than equity multiples in general, especially when non-core assets are included in the valuation (UBS, 2001).

Limitations of Relative Valuation

As has been stated, multiple valuation is extensively used in practice as it is recognized to hold several advantages over other valuation methods. Nonetheless, the method is not without its drawbacks. Firstly, it relies heavily on the ability of an analyst to identify firms that are truly comparable in terms of cash flow streams (Baker & Ruback, 1999). However, identifying firms with identical cash flow streams would require a perfect projection of those cash flows, which would contradict the purpose of using comparables as a heuristic technique in the first place. Then again, too much dissimilarity within peer groups will cause biased valuation estimates. Thus, there is an apparent trade-off present between effort and quality within the relative valuation approach (Plenborg & Pimentel, 2016). Secondly, while it has the benefit of taking relative value into account, it is still susceptible to valuation errors caused by an entire sector being under- or overvalued (Kim & Ritter, 1997). That is, if a comparable underlying asset is mis-valued, it is highly likely that an asset of interest will be mis-valued as well. Finally, the lack of perfectly identical firms leads to a need for adjusting implied multiples generated from peer groups in order to arrive at a final valuation estimate. Meanwhile, there is a lack of recognized guidelines for how to deal with differences between firms. This drawback is central to the motivation for conducting this research, since industry practitioners often rely on field experience rather than theoretically and empirically proven principles (Rossi & Forte, 2016).

2.2 Value Drivers of Enterprise Multiples

While firms can differ in numerous ways, it is generally accepted that there are a handful of key value drivers that are particularly prominent in determining the value of a firm. More specifically, academics overwhelmingly agree that growth, profitability, and risk are the three fundamental factors that matter most to firm value (Damodaran, 2012). Thus, variation in such fundamental drivers should be decisive points of comparability between firms and largely explain why some firms are traded at a multiple above or below their peers (Knudsen et al., 2017). As such, understanding the relationship between these fundamental value drivers and value multiples, as well as how to account for differences in value drivers between firms, has the potential to provide insights for effectively implementing multiple valuation.

2.2.1 Intrinsic Derivation of EV/EBITDA

In accordance with the delimited focus on utilizing a single enterprise multiple, namely EV/EBITDA, this section will illustrate the intrinsic derivation of the EV/EBITDA multiple in order to show how growth, profitability and risk, relate to firm value mathematically. Several previous researchers of value drivers have included similar derivations in their papers as it clarifies and justifies the choice to study growth, profitability, and risk specifically. Yet, both the steps and the final mathematical expression varies across studies. Guided by derivations applied by Petersen et al. (2017), this section aims to show that the aforementioned value drivers are mathematically imbedded in the EV/EBITDA multiple[I].

Denoting free cash flow to the firm as $FCFF$, weighted average cost of capital as $WACC$, and assuming constant growth rate, the DCF model for enterprise valuation can be expressed as follows:

Equation 5.

$$EV = \frac{FCFF}{(1 + WACC)}$$

[I] The following mathematical derivation of EV/EBITDA does not include time scripts or equivalent notations, as the primary objective is to illustrate the fundamental relationship between absolute and relative valuation

Given that free cash flow to the firm is determined by what the firm earns minus what the firm reinvests in the company, one can also express $FCFF$ as $NOPAT * (1 - r)$, where $NOPAT$ is the Net Operating Profit After Tax, r is the reinvestment rate and g is growth in value relevant measure. The expression is now:

Equation 6.

$$EV = \frac{NOPAT * (1 - r)}{WACC - g}$$

Intuitively, $NOPAT$ can subsequently be rewritten as $ROIC * IC$, that is, Return on Invested Capital multiplied by Invested Capital. Substituting $NOPAT$ and dividing both sides with IC yields:

Equation 7.

$$\frac{EV}{IC} = \frac{ROIC * (1 - r)}{IC * (WACC - g)}$$

Given that r can be rewritten as $\frac{g}{ROIC}$, we can simplify the expression to obtain the $\frac{EV}{IC}$ multiple:

Equation 8.

$$\frac{EV}{IC} = \frac{ROIC - g}{WACC - g}$$

As $NOPAT = ROIC * IC$, multiplying the denominator on both sides with $ROIC$ gives the $\frac{EV}{NOPAT}$ multiple:

Equation 9.

$$\frac{EV}{NOPAT} = \frac{ROIC - g}{WACC - g} * \frac{1}{ROIC}$$

Substituting $NOPAT$ with $EBIT * (1 - t)$ and multiplying the equation with $(1 - t)$, where t is the corporate tax rate, generates the $\frac{EV}{EBIT}$ multiple:

Equation 10.

$$\frac{EV}{EBIT} = \frac{ROIC - g}{WACC - g} * \frac{1}{ROIC} * (1 - t)$$

Finally, replacing $EBIT$ with $EBITDA * (1 - D)$ and multiplying the equation with $(1 - D)$, where D is the depreciation rate measured as $\frac{Depreciation}{EBITDA}$, ultimately generates an expression for the $\frac{EV}{EBITDA}$ multiple:

Equation 11.

$$\frac{EV}{EBITDA} = \frac{ROIC - g}{WACC - g} * \frac{1}{ROIC} * (1 - t) * (1 - D)$$

The final expression shows that the growth, profitability and risk are indeed imbedded in the multiple through g, $ROIC$, and $WACC$. As stated by Petersen et al. (2017), the derivation is useful because it reveals what factors firms in a peer group have to demonstrate identical performance in for multiple valuation to be theoretically correct. Evidently, identical performance is unlikely in practice, thus, it rather shows what factors an analyst applying multiple valuation needs to understand when accounting for differences amongst comparable firms. Furthermore, the derivation can also be used to explain why some firms are traded at a multiple above or below their peers (ibid). In conclusion, the mathematical derivation supports the relevance of studying growth, profitability, and risk as fundamental value drivers of EV/EBITDA.

2.2.2 Accounting for Heterogeneity

In line with the consistency principle[I], accounting for differences in fundamental value drivers amongst peers is a necessary procedure within relative valuation in order to attain an accurate valuation of a target firm. Regardless of selection criteria employed in constructing peer groups, the resulting comparables will inherently be different by various degrees from the target firm (Brigham, 2014). According to Kim & Ritter (1999), many firm specific factors are not captured by sole reliance on average peer group multiples, and that adjustments for drivers such as profitability and growth consequently need to be made. In general, three methods are recognized as procedures to handle such differences, including subjective adjustments, modified multiples as well as statistical regression approaches, outlined below.

Subjective Adjustments

According to Gaughan (2015), even though relative valuation is principally driven by quantitative data, the approach often includes subjective assumptions. This statement is also supported by Damodaran (2007), who argues that relative valuation in many instances can be seen as a qualitative process permeated by subjectivity. Rossi & Forte (2016) additionally acknowledges that multiple valuation is widely accepted as more of an artform than science as the level of subjectivity required in many practical applications is inconsistent with a scientific standpoint. The subjective adjustment process in terms of multiple valuations implies that a derived

[I] As outlined in Section 2.1.2, the consistency principle concerns one of the basic assumptions of relative valuation average or median peer group multiple is revised based on subjective beliefs about the fundamentals of a target firm. If the fundamentals of the target firm are believed to be superior compared to a selected group of comparable firms, the subjective adjustment would include an increase in the multiple of the target firm and vice versa if fundamentals are considered to be inferior. Providing strong quantitative justification behind subjective adjustments can at many times be difficult, especially when several interrelated factors in coercion account for differences in implied firm valuation (Brigham, 2014). Consequently, this often results in adjustments based on little more than guesswork, which simply confirm inherent analyst biases about the firm in question (Damodaran, 2007).

Modified Multiples

An alternative approach to making adjustments includes the process in which multiples are modified to account for the most determining variable, known as a companion variable (Hermann & Richter, 2003). Arguably, accounting for companion variables provides a tool for handling fundamental differences between firms and allows for the detection of over- or undervaluation (Chandra, 2014). For example, if PE ratios were to be analyzed across firms with diverging growth rates, the multiple can be modified by dividing the ratio by the expected growth rate in EPS. This modification provides a growth-adjusted PE ratio, also known as the PEG ratio. Compared to the PE ratio, the PEG ratio more easily detects mispricing as it evens out a fundamental value driver across the comparable sample (Yoo, 2006). The inherent issue with the modified multiple approach is that it implicitly assumes only one factor to be the primary driver of interest, without taking into consideration the interrelationship of additional drivers that consequently are assumed to be uniform across firms. Moreover, the approach also assumes a strict linear relationship between the modified multiple and the independent value driver. If this assumption was not to hold up in practice, firms with high growth rates would mistakenly be seen as undervalued and vice versa when utilizing a PEG ratio (Damodaran, 2007).

Statistical Regression Approaches

To overcome the inherent flaws with subjective adjustments and modified multiples, a statistical regression-based approach can be utilized to more precisely account for differences in fundamental value drivers amongst comparable firms. The advantages of a regression approach are threefold. Firstly, regression analysis allows for testing the direction and strength of causality between valuation multiples and selected fundamental value drivers, both in isolation and in cohesion (Gaughan, 2015). The interrelationships between independent variables provides evidence of the relative importance and cross effects of value drivers, which arguably is crucial information in understanding why firms are valued differently. Secondly, regressions can be modified to account for non-linearity in the relationship between multiples and value drivers (Berk & Demarzo, 2017). Finally, regression models can be extended to include several value drivers as well as control factors of interest to allow for more complex relationships and provide a wider picture of multiple valuation fundamentals (Damodaran, 2012)[I].

Utilizing statistical regression approaches in terms of multiple valuation can in broad terms be conducted for sector or market level, each with separate implications (Bernström, 2014). Sector regressions imply that regressions are performed with a sample consisting of only one sector or industry at a time, which entails the implication of how the sector is defined. However, sector regressions also imply a risk of small sample sizes if sectors are defined too narrowly, which undercut the usefulness of the statistical approach. Market-wide regressions, on the other hand, do not restrict the sample to certain sectors. Rather, the whole market is considered in its entirety, where firms are consequently defined as comparables solely based on their underlying fundamentals (Bernström, 2014). By considering all firms in a market simultaneously, market regressions allow for meaningful comparisons of firms operating in small sectors and industries, where small sample sizes otherwise would deem regression analysis less useful. Moreover, market regressions also allow for statistical comparison between industries that may otherwise be subject to systematic over or undervaluation, as valuation estimates for each firm are obtained relative to the market as a whole (Damodaran, 2012) [II].

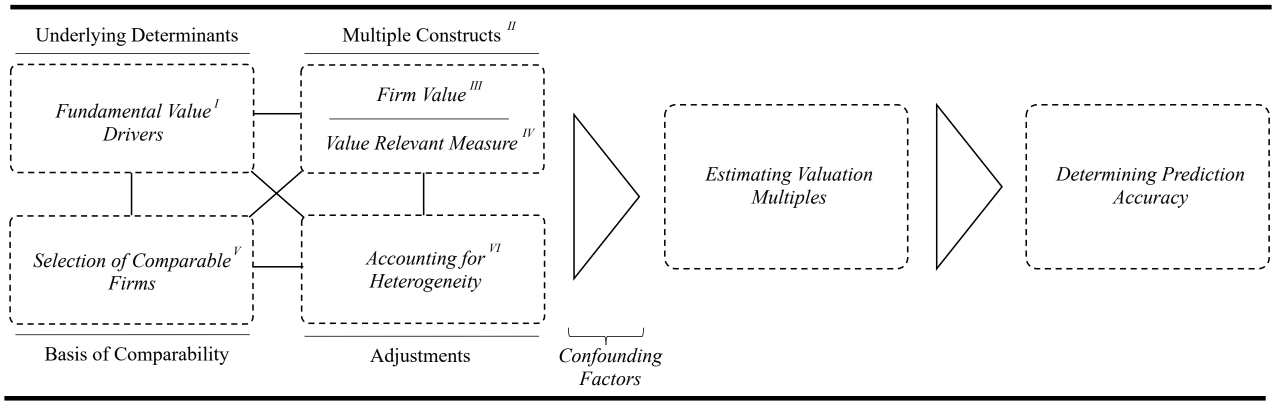
- 3. Review of Literature & Empirical Research -

With the theoretical foundations covered, the following section aims to outline the literature and previous empirical studies of major significance within multiple valuation, which will further guide hypothesis formulation and research methodology. Moreover, outlining the major research streams additionally assists in defining the value contribution to existing literature. To that point, academic studies concerning relative valuation can be said to ultimately focus on the accuracy of multiples in predicting firm value. It is argued that

[I] These advantages partly explain the utilization of statistical regression approaches within academic studies on multiple valuation, where the methodology have been applied in testing the relationships between multiples and value drivers as well as the performance and accuracy of different sets of multiples

[II] More specifically, as some industries systemically tend to be over or undervalued, the implied intrinsic value for a target firm of interest, derived based on comparables, might otherwise be distorted the most central literature streams under multiple accuracy can be further categorized into concerning either multiple constructs or the selection of comparables[I]. This will subsequently be outlined in the following sections together with research on fundamental value drivers as well as additional considerations within multiple valuation. For illustrative purposes, a simplified conceptualization of existing literature streams and central open-ended questions has been provided in Figure 2 below.

Figure 2. Conceptual Map on Central Literature Streams



[I] What drivers should be included and what proxies should be used?

[II] Forward, current, or historical measures?; What method for aggregating synthetic multiples?

[III] Enterprise or equity value?

[IV] What type of value measures?

[V] Based on fundamentals, industry affiliation, or alternative methods?

[VI] What method, and what factors to account for?

3.1 Accuracy of Multiples

To examine the legitimacy of multiple valuation and improve the understanding of how to optimally utilize the method, a significant amount of empirical research has been devoted to testing the accuracy of multiple valuation in practice as well as what specific types of multiples yield the most accurate valuation estimates[II]. Although variations of the definition exist, accuracy in this setting is generally measured as the difference between a valuation estimate, which is produced by using industry-wide multiples, and the actual market value

[I] Other possible categorizations of literature streams within relative valuation includes the selection of value relevant measures, the identification of comparable firms, the aggregation of peer group multiples and lastly adjustments of synthetic multiples to determine value of a target firm. It is however argued that the overall categorization of multiple constructs and selection of comparable firms implicitly provides an exhaustive overview

[II] For a comprehensive overview of seminal research papers on multiple accuracy, see Bagna & Ramusino (2017) of a firm (Harbula, 2009). Given that the specific focus on testing the accuracy of valuation estimates sheds light on both credibility issues as well as best practice, it is not surprising that the theme has a dominant role in the academic body. This section therefore provides an overview of the most prominent papers within different areas of multiple accuracy testing[I].

3.1.1 Multiple Constructs

Based on the landmark studies within multiple valuation, there is little consensus on which multiple constructs yield the most accurate valuation estimates. It is generally accepted that the first widely cited research to explicitly examine the overall performance of different multiple constructs was conducted by Lie & Lie (2002). Before that, empirical studies had indeed touched upon accuracy testing of multiple valuation, but on a less comprehensive level. Nonetheless, conducted research on optimal multiple constructs have primarily investigated the accuracy between different firm value estimates (choice of nominator), value relevant measures (choice of denominator), the timing of variables (the utilization of forward-looking versus current and trailing measures) as well as how synthetic multiples are ultimately adjusted for valuation purposes.

To begin with, most of the earlier influential studies focused on evaluating the usefulness of relative valuation by comparing valuation accuracy between multiples and absolute valuation approaches. For example, using a sample of 51 highly leveraged transactions, Kaplan & Ruback (1995) devoted a large part of their empirical study to benchmark the performance of valuation estimates from a thorough DCF analysis to the performance of valuation estimates obtained from multiple valuation. Their results suggest that multiple valuation generates useful predictions, especially when used in cohesion with a DCF valuation (Kaplan & Ruback, 1995). Kim & Ritter (1999), who examined the performance of multiples in the context of IPO valuations, added to the understanding of the usefulness of multiple valuation by comparing the accuracy of historic, current, and forward-looking multiples. They find that forward looking multiples result in much more accurate valuations as compared to when historical accounting numbers are used for multiple constructs[II].

Motivated by the lack of clarity provided by previous research regarding the performance of different multiples at the time, Lie & Lie (2002) examined bias and valuation accuracy of different multiples for several categories

[I] Additional aspects of multiple accuracy will be further scrutinized in the research methodology of this paper, as it specifically relates to practical implementation concerns for variable operationalization

[II] Since then, several landmark studies have supported this view (e.g. Lie & Lie 2002; Liu et al., 2007; Schreiner & Spearmann, 2007; Bernström 2014; Plenborg & Pimentel, 2016) of companies. This was conducted with the aim of aiding practitioners in their application of the method in practice, as well as academic researchers in choosing multiples that minimize bias embedded in the value measure. Their comprehensive research supported Kim & Ritter's (1999) conclusion about the superiority of forward-looking measures, but more importantly, shed light on several unexplored questions surrounding multiple performance. To name a few, they found that asset multiples generally outperform sales and earnings multiples in terms of precision and bias, EBITDA multiples generally produce better estimates than EBIT multiples, and that the relative performance of multiples depends on a number of factors, such as company size and profitability. Many of the researchers following Lie & Lie (2002) have compared their findings to this landmark paper and either confirmed or disputed the conclusions.

For example, in their study of the US equity market, Liu, Nissim & Thomas (2002) found that earnings multiples outperform both cash flow and asset multiples across industries and sample years, which was concluded to be in opposition to the findings of Lie & Lie (2002). Providing yet another view on optimal multiple choice, Harbula (2009) found that cash flow multiples produce the most superior valuation estimates in his study of European firms. Furthermore, Liu, et al. (2002) conclude that their findings contradict the popular notion that differences across industries in the relative importance of certain financial items determine the optimal multiple to be utilized, known as the best multiple notion. This has given rise to later empirical studies that have focused on examining the best multiple notion explicitly by attempting to identify the most suitable multiple by industry, as measured by prediction accuracy. In a recent study conducted by Gupta (2018), results from a rigorous regression analysis across a sample of publicly listed firms in India showed supporting empirical evidence for the best multiple notion. That is, he found that the accuracy of estimated valuations from various multiples differed significantly across industries, suggesting that industries are associated with different best multiples.

Lastly, as highlighted by Rossi & Forte (2016), a significant factor with regards to multiple constructs concerns the process of which individual firm multiples are aggregated into synthetic peer group multiples. Several techniques for constructing peer group multiples have been tested in previous studies, which includes the application of simple arithmetic means, medians, size-adjusted weighted averages, geometric means or harmonic means (Plenborg & Pimentel, 2016). Considered as one of the earliest studies that addressed the accuracy of different averaging processes, Baker & Ruback (1999) found evidence that strongly supported the use of harmonic means compared to other techniques. These results were subsequently supported by findings from studies conducted by Liu et al. (2002) as well as Dittman &. Maug (2008). Contradicting these results, however, Hermann & Richter (2003) as well as Schreiner (2007) found evidence that harmonic means in certain instances tend to under-estimate firm market value. As concluded by Plenborg & Pimentel (2017), even though superior to simple averages, the evidence for whether to apply harmonic means or median remains mixed, as both techniques avoid the impact of extreme observations.

3.1.2 Selection of Comparables

Similar to relative accuracy of various multiple constructs, there are further implementation issues within relative valuation where the academic research is divided. As described, practitioners performing multiple valuation rely on drawing inference from a group of close comparable firms given that no two firms are identical in practice. Naturally, this poses an important issue regarding the basis on which comparability is determined and thus how to identify a so-called peer group. As earlier stated, one of the two central assumptions of multiple valuation is that comparable firms have proportional cash flow expectations and risk profiles as the company of interest (Kaplan & Ruback, 1995). Given the centrality of the comparability assumption to the method as a whole, peer group identification is a vital component of multiple valuation and has implications for the usefulness of the approach. Academics mainly split into two central schools of thoughts regarding how peer groups should be identified, which will be outlined below.

The first school of thought argues for selecting comparable firms based on industry affiliation, considered to be the most commonly used basis for peer group selection in academic research (Gaughan, 2015; Berk & Demarzo, 2017). The theoretical idea is that industry affiliation enhances comparability because firms within the same industry are likely to apply similar accounting methods and are expected to be similar in terms of factors such as risk and earnings growth (Young & Zeng, 2015). Amongst others, Alford (1992) advocates for this approach in his seminal paper where he found that a substantial part of the cross-sectional variation in the determinants of multiples could be explained by industry affiliation, defined by Standard Industrial Classification (SIC) codes. Results from his empirical study showed that valuation accuracy increased with the number of SIC digits used, up to the third digit. A more comprehensive study that evaluates the most suitable type of industry classification system to apply in multiple valuation was conducted by Bhojraj, Lee, and Oler (2003). Comparing the obtained valuation accuracy statistics from estimates based on several industry classification systems, they consistently found that GICS codes outperformed other approaches in terms of prediction accuracy[I]. Bhojraj et al. (2003) postulate that the superior performance of GICS codes stems from several factors, such as the fact that it is highly financially-oriented in the sense that groupings are established

[I] Findings also showed that GICS codes explained variations in several key financial ratios as well as other important aspects, such as growth rates, better than the other classification systems to meet the need of investments professionals, and that the assignment of GICS codes to individual firms are conducted by specialists.

The second school of thought argues for basing comparability on similarity of fundamental values, e.g. growth, profitability and risk (Nel et al., 2014; Knudsen et al., 2017). In that sense, the theoretical idea is to directly base comparability on the factors that constitute cross variational differences between firms, rather than trying to find a grouping variable such as industry affiliation that indirectly captures similarity in these factors. In their study, Bhojraj & Lee (2002) investigate the impact of growth, profitability and risk as fundamental values to construct "warranted multiples", which are subsequently used to identify peer groups. By utilizing regression analysis, they find that their peer group identification technique outperforms other approaches such as industry classification. In a similar study, Dittman & Wiener (2005) studied a sample of European and US firms to examine what specific fundamental values yield the most accurate method for peer group selection. Their results indicate that grouping firms based on return on assets (ROA), or a combination of ROA and total assets, is the optimal approach to peer group selection.

Several implementation issues are common to the peer group selection approaches discussed above. Firstly, there is a trade-off associated with how narrow, or how broad, one chooses to define comparability. An overly narrow definition will enhance similarity, but result in a small set of comparable firms, which consequently hinders statistical analysis. Meanwhile, a very broad definition will successfully provide larger sample sizes that allow for statistical analysis, but compromise similarity between firms, which threatens the comparability assumption as a whole. Secondly, peer group selection is susceptible to inaccuracy of the information on which comparability estimates are based. As such, any bias in the data set will result in a biased analysis. Moreover, analysts play an important role in the selection of peer groups, which creates an opportunity for manipulation to follow subjective narratives. It is often suggested by industry practitioners that the selection of peer groups is more of an art than a science, which according Bhojraj & Lee (2002) is discomforting from a scientific perspective given the implied level of subjectivity.

To continue, two other central implementation issues with peer group identification include differences in accounting policies and normalization of earnings. Firstly, differences in accounting policies may distort comparability between firms and can make two dissimilar firms appear similar and vice versa. Such differences may therefore lead to bias in both peer selection and valuation output (Young & Zeng, 2015)[I]. This notion is supported by Lie & Lie (2002) who implicitly evaluate how differences in depreciation schedules affect the accuracy of multiples. By showing that multiples based on EBITDA outperformed multiples based on EBIT in terms of accuracy, they concluded that distorted accounting information in general creates biased valuation estimates, and that any divergent accounting information should be avoided[II]. Another study supporting this conclusion is that of Schreiner (2007), who showed that differences in the portion of intangible assets between firms cause bias in valuation estimates since intangible assets are amortized more aggressively than tangible assets under accrual-based accounting. Overall, the empirical evidence suggests that differences in accounting policies distort comparability and should therefore be avoided to the highest extent.

Secondly, reported earnings may include non-recurring items that do not reflect future cash flow streams, which may potentially distort comparability. Failing to adjust for such items by normalizing earnings can compromise the measure and cause bias in valuation estimates (Plenborg & Pimentel, 2016). However, simply using recurring income instead of net income does not necessarily provide a better alternative, as argued by Nissim (2013). The complexity stems from the fact that transitory items may be difficult to measure, where analysts and companies can differ in what they consider to be transitory in nature. Also, some companies use non-recurring items to smooth shocks to recurring items, which would make net income the more favorable item. Normalizing earnings is often a tedious process in practice, which is perhaps why the explicit research on this topic is limited, but several studies have implicitly supported the need for normalizing earnings by utilizing earnings items such as earnings before extraordinary items and discontinued operations[III].

3.2 Empirical Research on Fundamental Value Drivers

In relation to research streams on the accuracy of multiples, surprisingly few studies have handled the relationship between fundamental value drivers and valuation multiples. In most empirical studies on the topic, underlying drivers and multiple constructs are taken as given, without consideration for the significance of utilized inputs. However, while some studies[IV] have explicitly tested the significance of a wide array of potentially important value drivers, the theoretically founded value drivers of the EV/EBITDA multiple, as

[I] Beaver & Morse (1978) also found that firms with more conservative accounting policies are inclined to have higher P/E-ratios

[II] In line with this finding, Bhojraj & Lee (2002) found evidence that enhanced accounting comparability between firms had a significant impact on the accuracy of implied peer group multiples

[III] E.g. Alford (1992) and Bhojraj & Lee (2002), amongst others

[IV] E.g. Harbula (2009) and Gupta (2018), amongst others derived in Section 2.2.1, primarily includes growth, profitability and risk. The following subsections are therefore dedicated to providing a comprehensive overview of these fundamental value drivers in the literature, as well as related considerations.

3.2.1 The Effect of Growth

From a theoretical standpoint, an increase in the growth rate of a firm will increase expected cash flows, and thus increase its intrinsic value. Anecdotally, analysts generally perceive growth as being the most important value driver in terms of having the greatest impact on multiples (UBS, 2001). In line with this, Zarowin (1990) and Liu & Ziebart (1994) found in their respective studies that earnings growth has a positive and significant relationship with PE ratios. However, the relationship between growth and value multiples may also be dependent on the nature and source of growth. For example, top-line growth resulting from a general increase in price levels can theoretically decrease multiples through the increase in cost of investments, while growth resulting from an increase in efficiency gains undeniably adds to the value of a firm (UBS, 2001). In line with this, Damodaran (2007, 2012) suggests that value-adding growth could stem from persistence in growth through sustainable competitive advantage, rather than just growth itself. The notion is further supported by Koller et al. (2010), who show that sustainable revenue growth is one of the main drivers of multiples. Additionally, Harbula (2009) finds that both the level of expected future growth and the stability of growth are important determinants of firm value that have a significant and positive relationship with value multiples. As a final validation to this point, Yin et al. (2018) also find that firms that outperform their peers in terms of future expected growth are assigned premiums to their multiples.

Predominantly, empirical evidence from prior studies have concluded that growth is an important determinant of firm value. However, there are some empirical findings that dispute this. Gupta (2018), for example, found that growth was an important determinant of EV/EBITDA for several sectors, but not for the banking and steel sectors. Furthermore, Credit Suisse (2016) support that growth is one of the three most important determinants of multiples, but that its relative importance has decreased significantly over time. More specifically, they show in a comparative study that growth was the most important determinant of firm value in the pre-financial crisis period. However, their findings also indicate that growth was surpassed by profitability in the post-financial crisis period in terms of significance. Nonetheless, on the whole, it is evident that a majority of the literature on the subject suggests that there is a strong and positive relationship between growth and multiples.

3.2.2 The Effect of Profitability

Theoretically, an increase in a company's profitability will directly increase the company's expected future cash flows and should therefore increase intrinsic firm value. Providing empirical support to this notion, Koller et al. (2010), amongst others, highlight that a higher level of profitability leads to a higher valuation multiple. Substantiating their finding, Gupta (2018) showed that profitability was consistently significant and positively related to EV/EBITDA across all studied sectors, suggesting the relationship to be more persistent than that between growth and EV/EBITDA. Furthermore, Credit Suisse (2016) support this perspective by showing that an increase in profitability leads to greater multiple expansion than an equal increase in growth. In fact, they find that firms with above median performance in profitability receive twice the increase in their valuation multiple compared to firms with above median performance in growth. In combination, these finding suggest that profitability is both a more universal determinant of multiples, and a more impactful one. It would therefore seem that all firms should pursue strategies that increase profitability rather than growth. However, it should be pointed out that even if it holds true that profitability is superior to growth, the ease and appropriateness of pursuing one or the other differs greatly amongst firms (Ointo et al., 2015).

There is substantial theoretical and empirical support for profitability being a fundamental value driver of multiples, but some additional remarks should be made. To begin with, changes in profitability are only meaningful if the profit is indicative of future profit potential (UBS, 2001). To that point, both Harbula (2009) and Credit Suisse (2016) find that the sustainability of profitability matters. Furthermore, similar to growth, the nature of profitability improvements may matter. For example, Harbula (2009) found that absolute profitability measures did not show any significant relationship with value multiples, meanwhile, relative profitability measures as compared to peer groups did. Yet, altogether, the overwhelming research on the relationship between profitability and value multiples suggests a strong and positive relationship. Furthermore, as found in several studies, profitability appears to play an increasingly central role empirically in determining firm value since the financial crisis (Gaughan, 2015; García, 2017).

3.2.3 The Effect of Risk

As compared to growth and profitability, the relationship between risk and firm value is understood to be all the more complex. Much of the complexity arises from the fact that risk embodies several elements that may have paradoxical effects, e.g. market sentiment, capital structure, volatility of performance, perspectives on the quality of management, and the attractiveness of a company's business portfolio (Chandra, 2014). Koller et al. (2010) argue that the cost of capital is the most relevant measure of risk in valuation settings as it indicates the hurdle rate that investors require for bearing risks associated with the firm. Thus, the higher the risk, the higher the cost of capital. Adopting this perspective, the derived expression for EV/EBITDA in Equation 11 unambiguously suggests that risk (WACC) has a negative relationship with EV/EBITDA as it only appears in the denominator on the right-hand side of the equation. Multiple valuation hence relies on the same principles as the underlying absolute valuation approach, as value is an increasing function of a firm's payoffs and a decreasing function of risk (Rossi & Forte, 2016). Adding to this understanding, Damodaran (1994, 2002, 2006, 2012) shows that a firm that experiences increases in risk should also experience a decrease in enterprise value. Loughran & Wellman (2011) found similar results in their study on the determinants of stock returns using a sample period between 1963 and 2009, where firms with lower discount rates tended to have higher warranted enterprise multiples.

The suggested negative relationship between risk and firm value seems odd from the textbook perspective of investors being rewarded for taking on more risk. That is, risky assets should have a higher expected return than less risky assets. However, while risky assets are associated with more sizeable expected cash flows, these cash flows are also more uncertain and are therefore discounted more heavily, creating paradoxical forces affecting the value of the asset (Berk & Demarzo, 2017). Seemingly, the popular perspective that the cost of capital is the most appropriate measure of risk in firm valuation argues for considering the negative effect of risk that arises from uncertainty around future cash flows in isolation, rather than considering the effects of risk from a more comprehensive perspective. This makes sense for the purposes of multiple valuation, since variables of growth and profitability should capture the corresponding positive impact of risk on expected cash flows.

3.2.4 Alternative Value Drivers

Returning to the derived expression for EV/EBITDA in Equation 11, two other factors apart from growth, profitability, and risk directly impact the multiple. Namely, corporate tax rate and depreciation rate. Although growth, profitability, and risk are the value drivers most commonly mentioned in the literature in relation to EV/EBITDA, both corporate tax rate and depreciation rate have received some attention. Firstly, corporate tax rate has a direct impact on expected cash flows and hence the value of the firm. Accordingly, Gaughan (2015) argues that all EV based multiples are implicitly affected by the corporate tax rate, especially multiples that scale enterprise value to pre-tax measures such as EBIT or EBITDA. The reason for this can be observed in the derivation of EV/EBITDA in Equation 11, where corporate tax rate is added to the right-hand side of the expression in order to account for the scaling statistic being unaffected by the corporate tax rate, while enterprise value in the numerator is not. Harbula (2009) showed this empirically, where tax rate proved to be an important determinant of all multiples using pre-tax figures in his study. Accordingly, differences in tax rates make it difficult to utilize international samples that incorporate heterogenous taxation systems due to lack of comparability (Ointo et al., 2015). Secondly, as for corporate tax rate, depreciation rate appears in the expression for EV/EBITDA in Equation 11 since enterprise value is affected by changes in depreciation, even though the scaling statistic is not.

As an ending remark with regards to additional value drivers of EV/EBITDA multiples, it should be repeated that several scholars argue that using pre-tax and pre-depreciation measures is favorable for the very reason that they do not take corporate tax rate and deprecation rate into account (Gaughan, 2015). For example, Lie & Lie (2002) showed that EBITDA multiples proved to be more accurate than EBIT multiples because depreciation expenses that appeared to distort the information value of earnings were excluded from the scaling statistic. Thus, even though corporate tax rate and depreciation rate do not appear in the expression for multiples such as EV/NOPAT[I], they are instead embedded in the calculation of the scaling statistic directly.

3.3 Additional Considerations within Multiple Valuation

3.3.1 Confounding Factors

Yielding consistent and accurate valuation outputs by applying relative valuation entails the understanding of confounding factors that may impact the relationship between multiples and their fundamental value drivers (Plenborg & Pimentel, 2016). As such, confounding factors constitute an important aspect with regards to multiple prediction accuracy. Even though theoretical support as well as empirical findings remain mixed regarding confounding variables within relative valuation, several prior studies have particularly highlighted the distorting impact of industry affiliation, firm size, illiquidity discounts and control premiums.

In line with arguments supporting the selection of comparable firms based on industry classification, systematic differences between industries in terms of fundamentals can be argued to influence the accuracy of multiple valuation (Alford, 1992). Given the fact that valuation multiples reflect the current mood and expectations of the market, utilizing valuation multiples without consideration for industry differences may produce a distorted output as some industries might be overvalued and vice versa (Damodaran, 2012). Supporting the notion that cross-sectional variation in fundamental value drivers can be explained by industry affiliation, Bhojraj et al. (2003) and Harbula (2009) found that industry classification has a significant impact

[I] See Equation 10

on the accuracy of predicting valuation multiples. Thus, empirical evidence suggests that the relative and direct importance of fundamental value drivers in relation to valuation multiples varies depending on what industry a firm operates in.

To continue, empirical findings from previous studies emphasize the confounding impact of firm size in terms of multiple prediction accuracy. Smaller firms tend to be characterized by lower information environments, weaker internal controls, less managerial depth as well as more narrow product offerings compared to larger firms (Petersen & Plenborg, 2016). In addition, smaller firms also tend to have erratic earnings (Lie & Lie, 2002), which is why firm size also have been utilized as a proxy for risk in some studies[I]. Demonstrating the confounding impact of firm size, Alford (1992) finds in his study that prediction errors for valuation multiples of larger firms are only half the size as those for smaller firms. These results were later supported by Kim and Ritter (1999) as well as Cheng and McNamara (2000), who concluded that valuation accuracy of both enterprise and equity multiples increases with firm size. Thus, empirical findings suggest in general that firm size has a significant and positive impact on the accuracy of valuation multiples, which additionally may influence the underlying relationship between value drivers and multiples.

Lastly, in terms of confounding factors, several authors highlight the importance of adjusting for marketability and control in relative valuation processes[II]. In theory, investors favor liquidity in investments as it enables a more rapid conversion of ownership into cash with lower transaction costs, at a greater certainty of realizing proceeds (Silber, 1991; Officer, 2007). Thus, the value of a share in a public firm should be higher than an equivalent share in a private firm, due to higher marketability (Bernström, 2014). In line with this argument, Pratt, Reilly & Schweihs (2008) found that lack of marketability constitutes the most common valuation discount for firms. Thus, multiples acquired from a set of comparable public firms need to be adjusted for when valuing a private firm, known as the illiquidity discount (Brigham, 2014). Moreover, as for marketability, a controlling interest is also theorized to provide greater value as it allows investors to affect the overall business structure and policies of a firm. As public firms typically have dispersed ownership structures, adjustments to account for a control premium are necessary when using multiples based on public firms to value private firms.

[I] E.g. Fama & French, 1992; Gupta, 2018; Alford ,1992

[II] E.g. Damodaran, 2012; Bernström, 2014; Rossi & Forte, 2016; Petersen et al., 2017

3.3.2 Distributional Properties

In line with confounding factors, it is important to account for the relative impact of stated value drivers at different levels on multiples given distributional properties (Koller et al., 2010). As mentioned in Section 2.1.2, relative valuation rests on the assumption that the value of a firm is linearly proportional to an identified value driver, which should hold true for all its comparables in a peer group. Thus, relative valuation in practice assumes that there is a linear relationship between fundamentals and multiples. This implies, for example, that a firm with zero growth should have a firm value of zero. However, according to Harbula (2009), these relationships are rarely linear in reality. As a testament of this notion, utilizing a sample of all US stocks in July 2000, Damodaran (2012) highlights the inherent non-linear relationship between PEG ratios and growth in cross-section samples, which he accounts for by taking the natural log of the expected growth rate. Moreover, Credit Suisse (2016) demonstrate in their comparative study that earnings growth and profitability have a non-linear impact on EV/EBITDA multiples, where incremental changes have a decreasing marginal effect. In other words, empirical findings in this regard suggest that growth and profitability may not consistently imply a proportional change in the valuation multiple of interest.

3.3.3 Intertemporal Differences

Suggested to be the last topic of particular interest for the review of literature and empirical research, evidence suggests that intertemporal differences hold several implications for relative valuation. Several prior studies show that distributions of multiples change over time, making comparisons of valuation multiples across different time periods difficult[I]. While reversion to historic norms is a strong force within financial markets, changing macroeconomic fundamentals such as interest rates, inflation, expected growth in real GDP as well as overall behavior in a market, can dramatically distort any intertemporal conclusion (Garciá, 2015). Thus, when employing regression approaches aimed at explaining differences in valuation multiples across companies over time, the statistical significance of independent variables and predictive power of regression models might fluctuate as a result of changing market conditions (Damodaran, 2012). In the landmark study performed by Cragg & Malkei (1968), regression analysis revealed that independent variable coefficients for growth, profitability and risk fluctuated widely on a year-to-year basis when utilizing a sample covering the years 1961-1965. Moreover, their results also showed substantial differences in the predictive power and significance of the regression models employed between different time periods.

[I] See conducted studies by Kisor & Whitbeck, 1963; Cragg & Malkei, 1968; Damodaran, 1994, 2002, 2006, 2007, 2012; Harbula, 2009; Rossi & Forte, 2016

Regressions similar to those employed by Kisor & Whitbeck (1963) and Cragg & Malkei (1968) were later updated in studies made by Damodaran (1994, 2002)[I]. These following studies utilized a larger sample of listed firms and a wider range of valuation multiples with data for the years 1987-1991. His conclusions were in unison with earlier findings in that independent variable coefficients and R-squared statistics varied significantly over time. Specifically, R-squared ranged from 90% in 1987 to 30% in 1991. Additional findings from these studies also included that the sign of the coefficients of selected value drivers not always turn out to be in line with theoretical assumptions. Damodaran (1994, 2002) postulated that the variations in coefficients and predictive power may be partly driven by the volatile nature of earnings. Additionally, the results were argued to be caused by macroeconomic factors, where the recession around year 1991 increased uncertainty and risk levels as well as reduced analyst's earnings forecasts. In a later study conducted by Harbula (2009) utilizing data between 1986 to 2006, results indicated that the level of valuation errors in employing relative valuation techniques were greatest during the internet & dotcom bubble, another major recession around year 2000. In line with these results, Rossi & Forte (2016) conclude that the valuation accuracy of both trailing and forward-looking multiples fluctuates greatly across time. Furthermore, accuracy was found to vary considerably across periods of market stability and periods characterized as crises.

- 4. Hypothesis Development -

Following a process of theoretic construction that is deductive in nature, this section develops a number of hypotheses from the review of literature and empirical research that will thereafter be subject to rigorous testing through a series of propositions. That is, predictions and findings from previous literature and empirical research within multiple valuation are redeployed to address the stated research questions. This section is thus meant to demonstrate the logic and relevance of selecting the specific focus areas.

Firstly, the theoretical background provided compelling support for that a handful of key value drivers are particularly prominent in determining multiples. More specifically, growth, profitability, and risk are found to be generally accepted amongst scholars as the three most important fundamental value drivers to consider (Petersen et al., 2017). Based on earlier empirical evidence, growth and profitability are expected to have a positive relationship with the studied multiple. In contrast, risk is expected to exhibit a negative relationship

[I] The same sample was utilized in both studies conducted by Damodaran in 1994 and 2002 respectively, with some minor changes in terms of methodology. The same regressions with updated samples were later conducted by Damodaran, 2006, 2007 and 2012 with the studied multiple if measured as the cost of capital. Secondly, previous researchers furthermore agree that incremental differences in fundamental value drivers largely explain why some firms are traded at a multiple above or below their peers[I]. Since direct comparisons tie valuation premiums and discounts to relative performance in fundamental value drivers, it can be argued that such a methodology potentially provides a more accurate picture of under- and overvaluation of firms. For these reasons, the following hypotheses are formulated in relation to the first research question.

- Research Question 1: *What is the underlying relationship between EV/EBITDA and its fundamental value drivers?*

  - Hypothesis 1: *In isolation, growth has a positive and significant impact on EV/EBITDA*

  - Hypothesis 2: *In isolation, profitability has a positive and significant impact on EV/EBITDA*

  - Hypothesis 3: *In isolation, risk has a negative and significant impact on EV/EBITDA*

  - Hypothesis 4: *In cohesion, when accounting for differences amongst independent variables, growth, profitability and risk jointly have a significant impact on EV/EBITDA*

  - Hypothesis 5: *In cohesion, when accounting for differences amongst independent variables, relative performance in growth, profitability and risk jointly have a significant impact on deviations from a peer group EV/EBITDA multiple*

To continue, a great proportion of the academic discourse on multiple valuation has focused on testing the accuracy of multiples since it sheds light on the credibility of the approach. Given that empirical evidence from previous studies suggests that fundamental value drivers hold predictive power of enterprise multiples, it is expected that estimations developed from studying growth, profitability, and risk should represent relatively accurate predictions of actual market multiples. Furthermore, to assess the performance of predictions, researchers have commonly benchmarked results from their own methods to that of standard peer group averages. Conceptually, this allows for the direct comparison of results from a statistical method that considers differences between firms within peer groups, and a commonly used method that ignores such differences. As

[I] E.g. Kim & Ritter, 1999; Harbula, 2009; Gupta, 2018 the research objective of this study is to develop a statistical method that produces accurate valuation estimates, comparing results to simple peer group averages allows for assessment of whether or not the objective has been reached. For these reasons, the following hypotheses are formulated in relation to the second research question.

- Research Question 2: *Does a regression approach based on fundamental value drivers provide predicted EV/EBITDA multiples that represent accurate estimates of actual market multiples?*

  - Hypothesis 6: *Predicted EV/EBITDA multiples developed from a regression analysis of fundamental value drivers are significant determinants of actual market multiples*

  - Hypothesis 7: *Predicted EV/EBITDA multiples developed from a regression analysis of fundamental value drivers will have significantly lower prediction errors in determining actual market multiples than estimates based on simple peer group averages*

Given developed research questions and corresponding hypotheses, it is argued that this paper contributes to the existing literature in several regards. Firstly, the overarching focus on testing whether a regression approach based on fundamental value drivers can produce predicted multiples that represent accurate estimates of firm value has seldom been adopted in prior research. It is therefore argued that this paper will shed light on the fundamental feasibility of applying a regression approach and accordingly whether more frequent employment of the methodology is justified for accuracy testing. Also, this study will examine the predictive power of the theoretically derived value drivers included in the analysis and whether it is feasible to employ a regression approach that is based solely on these core factors. In the process of doing so, the study will contribute to the prevalent discussion regarding the optimal level of analysis by adopting several definitions of peer groups, where it is unclear whether a narrow definition that is associated with high comparability is better or worse than a broad definition that enhances statistical suitability.

For practitioners, this study provides further insights into the underlying drivers of the EV/EBITDA multiple and how an understanding of fundamental value drivers can be used to generate accurate predictions of firm value. In this regard, the methodological approach will provide empirical evidence on the relative importance of fundamental value drivers. Furthermore, the employed relative regression approach additionally attempts to shed light on how incremental differences in value drivers for a firm compared to a selected peer group warrants multiple premiums or discounts. As such, obtained findings will also imply empirical ramifications in terms of suitable multiple adjustments in practice. Consequently, this study will provide guidance for practitioners in accounting for differences between firms in a manner that is free from subjective adjustments, which otherwise threatens the credibility of the approach from a theoretical perspective. Finally, contrasting the results from the developed regression models to standard peer group averages sheds light on whether a predicted multiple based on regressions provides a more suitable point of departure for relative valuation purposes than a standard peer group multiple.

- 5. Research Methodology -

The research methodology of this empirical study consists of four main sections aimed at covering the vital components of answering stated research questions and formulated hypotheses. The individual sections are furthermore structured to cover the main implementation issues associated with accuracy studies on relative valuation[I]. The first section will provide an overview of variable operationalization of included dependent and independent variables as well as the underlying rationale and supporting evidence for each. The second section will concern the methodology for selecting comparable firms, where discussions on data selection and construction of the final data sample naturally follows. The third section describes the method of data analysis employed, together with connected discussions on limitations and caveats. Lastly, research model specifications are provided to explicitly outline the developed statistical models.

5.1 Variable Operationalization

The following section outlines the selected measures of dependent and independent variables included in the applied research models, where the operationalizations of measures are described and discussed. Before covering specifics, a common feature of all included variables includes the conducted normalization of values between the base years 2016 and 2018, in order to account for fluctuations and cyclicality in reported data[II]. Averaging of values across time is identified as the most common approach in similar studies, even though the process of normalization of financial data can take many different forms. Table 1 provides a summary of included variables as well as each respective operationalization.

[I] Direct implementation issues within relative valuation can be extended to include the selection of relevant variable measures, the selection of comparable firms, estimation of synthetic multiples and methods for testing valuation accuracy

[II] See Appendix 1 for mathematical representation of variable construction

The independent variables utilized in this paper constitutes proxies for the fundamental value drivers of EV/EBITDA multiples, namely growth, profitability and risk. Commonly within regression analysis, in order to obtain more causal relationships and isolate the effects of key independent variables of interest, confounding effects of other covariates are often accounted for in the form of control variables (Stock & Watson, 2012). However, in line with formulated research questions, the aim of this paper is to test whether regression analysis based on fundamental value drivers can accurately predict observed EV/EBITDA multiples on a standalone basis. This implicitly entails that the inclusion of additional control variables would arguably distort the predominant theoretical focus for the benefit of sole reliance on prior empirical observations. On the other hand, even though not explicitly included as control variables, systematic cross-section differences between industries as well as the impact of firm size will implicitly be taken into consideration throughout the analysis[I].

Table 1. Variable Operationalization

Variable	Operationalization	Time Horizon
Panel A: Dependent variable		
*EV/EBITDA**	Enterprise Value (FY) divided by BEst EBITDA (FY+2), aggregated between 2016-2018	FY+2 (forward-looking)
Panel B: Independent Variables		
Growth	Median EBITDA CAGR (FY1-FY3) between 2016-2018	FY+3 (forward-looking)
Profitability	Median ROIC (FY) between 2016-2018	FY (current)
Risk	WACC (LFY)	LFY (trailing)

**Referred to as MTPL*

5.1.1 Dependent Variable

As explicitly outlined in Section 1.3, the primary variable of interest for the conducted study is enterprise value (EV) over earnings before interest, tax, depreciation and amortization (EBITDA). The multiple estimation is obtained from the Bloomberg Terminal (Bloomberg) database, where EV is defined as the current market capitalization of a firm's equity plus the market value of a firms net interest-bearing debt, and EBITDA is defined as the average of two-year forward-looking BEst consensus estimates (Bloomberg, 2019). In order to mitigate cyclical fluctuations and time dependence, the harmonic mean of implied EV/EBITDA between the

[I] Moreover, according to Bernström (2014), when comparing public firms for valuation purposes, controlling for marketability and control holds lesser theoretical grounds, and are therefore factors not considered in this study, neither explicitly nor implicitly years 2016-2018 will correspondingly be utilized. The choice of focusing on the EV/EBITDA multiple specifically[I] is motivated by several theoretical and empirical advantages.

Firstly, from a theoretical standpoint, one clear advantage of the measure is that EBITDA is unaffected by differences in taxation as well as accounting practices regarding depreciation and amortization across firms (Rossi & Forte, 2016). As covered, potential differences in taxation and accounting policies between comparable firms has a negative influence on comparability, which consequently results in biased valuation estimates (Plenborg & Pimentel, 2016)[II]. Secondly, it is deemed more appropriate to employ a cashflow based measure such as EBITDA in the denominator rather than sales, as the aim of this paper is to ultimately predict an enterprise multiple. This notion is also supported by the extensive usage of EV/EBITDA by practitioners for enterprise valuation purposes (Credit Suisse, 2016). Lastly, scholars have also found empirical evidence supporting EV/EBITDA multiples as valid predictors of firm intrinsic value. For example, Kaplan & Ruback (1995) found in their comprehensive study[III] that the utilization of EV/EBITDA multiples produced comparable prediction accuracy as those produced by extensive DCF analyses for the purposes of estimating enterprise value.

On the other hand, even though several scholars support EV/EBITDA as a valid predictor of firm value across firms, empirical evidence also suggests that the specific multiple is appropriate for valuation purposes in certain types of sectors and industries (Lie & Lie, 2002). Building on the best multiple notion as outlined in Section 3.1.1, this implies that optimal multiple constructs generally depend on relative industry-specific importance of certain financial items, such as depreciation and amortization, leverage, CAPEX or earnings growth (Plenborg & Pimentel, 2016). Accordingly, Damodaran (2012) argues that the EV/EBITDA multiple is particularly useful for firms that operate in sectors that require large investments in infrastructure with long formation periods, which is widely supported by empirical evidence. For example, utilizing a sample of publicly listed firms in India, Gupta (2018) found that EV/EBITDA multiples provides optimal estimates for companies operating within the steel sector due to its capital-intensive nature[IV], while P/BV multiples proved to be more appropriate within the banking sector. In line with this finding, Rossi & Forte (2016) concluded that EV/EBITDA multiples should preferably be applied when estimating the value of firms operating in

[I] As opposed to other enterprise or equity multiples that could alternatively have been used

[II] One of the important take-aways from this notion includes that EV/EBITDA is highly applicable for diverse types of firms. Since this study employs a single multiple across industries, this notion is important to highlight

[III] Which focused on comparing the relative accuracy of absolute valuation and market multiples

[IV] I.e. an industry characterized by the requirement of large up-front investments, high depreciation rates as well as substantial leverage infrastructure or manufacturing industries where CAPEX and depreciation holds significant importance. Findings obtained by Harbula (2009) further support the notion that EV/EBITDA is suitable for a great variation of firms, as the multiple was found to be optimal in 10 out of 14 studied industries.

However, the empirical evidence on industry suitability for EV/EBITDA multiples is mixed. Examining the accuracy performance of a wide range of multiple constructs, Liu et al. (2007) finds that valuation accuracy of EV/EBITDA did not prove to be superior in industries characterized by low growth or high levels of amortization of goodwill. Moreover, Harbula (2009) shows in his study that the EV/EBITDA multiple is especially suboptimal within certain industries, primarily including the banking & insurance industry, the life sciences & healthcare industry as well as the real estate industry. Furthermore, Gupta (2018) finds in his comparative study that EV/EBITDA is highly unsuitable for the automobile sector due to wide variations in terms of capital intensity across firms. Nonetheless, for the sake of objectivity, this paper will consider EV/EBITDA as a valid multiple construct for all industries included, where the notion of industry best multiples will be examined by comparing accuracy estimates between different industries, both explicitly and implicitly.

A final crucial aspect to account for with regards to the choice and measurement of utilized dependent variable concerns the use of either trailing or forward-looking multiples. As outlined in Table 1, the EV/EBITDA multiple employed in this study is based on forward-looking earnings through BEst consensus estimates, which provides the arithmetic average for broker estimates of future earnings (Bloomberg, 2019). Even though forecasted estimates are inherently biased and subject to uncertainty, considerable evidence from similar studies highlights that forward-looking multiples, and more specifically 2-year forward-looking multiples, produce superior estimates compared to trailing multiples[I]. Kim and Ritter (1999) theorize that historical earnings generally underperform given their transitory nature, which potentially results in biased predictions of a firm's future earnings. In line with arguments put forward by Petersen et al. (2017), as the intrinsic value of a firm is the sum of expected future cash flows, it makes intuitive sense that forward-looking multiples should outperform trailing multiples that are based on historical earnings.

[I] E.g. Kim & Ritter, 1999; Lie & Lie, 2002; Liu et al., 2002; Schreiner, 2007; Harbula, 2009

5.1.2 Independent Variables

Growth

In line with similar studies where the relationship between EV/EBITDA and its underlying value drivers have been examined[I], the proxy utilized for growth in this paper is growth in EBITDA. More specifically, the proxy is constructed as the compounded annual growth rate (CAGR) of BEst EBITDA consensus estimates provided by Bloomberg between FY+1 and FY+3, where timing of the growth rate specifically follows the methodology as proposed by Bernström (2014)[II]. As for the dependent variable, cyclicality and time dependence will be partly accounted for by aggregating the aforementioned estimates between the base years 2016 and 2018[III].

The utilized construct and proxy for growth as a determinant of EV/EBITDA has considerable support both empirically and theoretically. Firstly, with regards to construct, operationalizing growth as compounded annual growth rate is frequently applied by both scholars and practitioners alike in order to obtain an average growth rate over a range of time periods. The reason for this resides in that it mitigates the effects of volatility but still accounts for the impact of compounding effects (Moutinho & Hutcheson, 2011). Secondly, with regards to utilizing growth in EBITDA, all else equal, firms with higher EBITDA generate higher cash flows which consequently should imply higher enterprise value (Petersen et al., 2017). Thus, when estimating firm value based on EV/EBITDA, a main underlying driver arguably includes future growth in EBITDA. This was empirically proved by Harbula (2009) who in his study on multiple accuracy concluded that higher expected earnings growth results in higher valuation multiples across firms. Lastly, in line with the rationale for operationalization of the dependent variable, it is argued that utilizing estimates of future growth explicitly rather than historical figures is more appropriate as it provides a more accurate picture of future earnings capacity.

Profitability

Intrinsically derived as a major driver of EV/EBITDA in Equation 11, the utilized proxy for profitability is return on invested capital (ROIC). The estimate for ROIC is also obtained from Bloomberg, where the variable is defined as trailing 12-month net operating profit after tax (NOPAT), divided by the average total invested

[I] Including Harbula (2009), Damodaran (2006, 2007, 2012) and Bernström (2014), amongst others

[II] See Appendix 1 for underlying computations

[III] In this instance, medians rather than harmonic means were used for aggregations as many firms in the included sample show negative growth rates capital for current period and invested capital for the same period one year back (Bloomberg, 2019). For the sake of consistency, cyclicality in profitability is also accounted for by taking averaging ROIC between the years 2016-2018 for all firms considered in the final sample[I].

In relation to growth, utilized proxies for profitability have varied more widely in previous literature. In studies with a predominant focus on the accuracy of equity multiples, Return on Equity (ROE) is arguably the most common measure of profitability[II]. In terms of studies with included focus on enterprise multiples[III], Return on Assets (ROA), Return on Capital Employed (ROCE), EBITDA margin, EBIT margin as well as Net Income margin have also been suggested as relevant proxies for profitability. Following the theoretical reasoning of Koller et al. (2010), Berk & Demarzo (2017) and Petersen et al. (2017), however, ROIC is utilized as proxy in this study as it most accurately represents the overall profitability of firm operations and in turn true value creation of economic value added. Consequently, all else equal, a higher return on invested capital should result in higher estimates of enterprise value.

The utilized operationalization for profitability in this study however includes inconsistent usage of current rather than forward-looking estimations of ROIC. This is a direct result of data unavailability, where forward-looking estimates of ROIC are not provided in the Bloomberg database. Different approaches in manually constructing a forward-looking measure for ROIC could potentially have been conducted by obtaining estimates for NOPAT, net interest-bearing debt (NIBD) and market value of equity (MVE). However, given that no forward-looking estimates with regards to these variables are available in Bloomberg either, it is argued that the included ROIC estimation, even though based on current data, provides a more reliable proxy than the alternative option. The negative impact of the inconsistency in using current rather than forward-looking ROIC is argued to be partly mitigated by averaging values over a historical three-year period in order to approximate a stable profitability ratio[IV].

[I] As for growth, medians rather than harmonic means were used for aggregations as many firms in the included sample show negative profitability

[II] The proxy of ROE for profitability was for example utilized in the studies conducted by Alford (1992), Liu et al. (2002) and Gupta (2018)

[III] E.g. studies conducted by Bhojraj & Lee (2002) and Harbula (2009), amongst others

[IV] Studies with similar limitations, where historical figures have been used as substitutes due to lack of forward-estimates, includes Damodaran (2012) who used historical growth rates as substitute for expected future growth rate in terms of earnings when determining PEG ratios. Another example includes Schreiner (2007), who due to data unavailability for R&D expenditure estimates decided to construct trailing rather than forward-looking knowledge-related multiples

Risk

Lastly, in terms of independent variables, the proxy for risk is defined as the weighted average cost of capital (WACC), an estimate provided by Bloomberg based on firm capital structure from last fiscal year (Bloomberg, 2019). The main rationale for including WACC as a proxy for risk relates to the intrinsic derivation of EV/EBITDA in Equation 11, where WACC is identified as a major value driver. However, several different proxies for risk have previously been utilized by scholars. In their respective studies, Alford (1992), Knudsen et al. (2017) and Gupta (2018) used firm size as a proxy for risk in the selection of comparable firms, with the underlying rationale that larger firms tend to be more liquid and thus more able to meet their financial liabilities. Apart from cost of capital and firm size, other proxies for risk also utilized in prior studies primarily include financial leverage (e.g. Harbula, 2009) as well as standard deviation in earnings (e.g. Alford, 1992).

However, apart from intrinsically being a driver of EV/EBITDA, the applicability of WACC as a suitable proxy for risk when estimating enterprise value relates to its ability to reflect the capital structure of a firm, and thus the implied risk for both lenders and investors (Brigham, 2014). Both lenders and investors require a higher rate of return for bearing more risk, where WACC is a composite risk-adjusted rate utilized for discounting future cash flows for enterprise valuation purposes. Thus, from a theoretical standpoint, an increase in implied risk of a firm should result in a higher WACC, which in turn should result in lower present value of a firm[I]. It could furthermore be argued, according to Bernström (2014), that WACC incorporates differences in firm size as smaller firms tend to be burdened with higher required rate of return, seen as another advantage of the proxy. In line with the proxy for profitability used in this study, it should be noted that utilizing a historical rather than forward looking measure for WACC constitutes another inconsistency, which again relates to data unavailability in the Bloomberg database. However, as historical discount rates are used for absolute valuation purposes, the negative implication of the inconsistency in using a historical measure of risk is argued to be limited.

5.2 Data Collection

5.2.1 Selection of Comparable Firms

A major aspect of this paper, in line with prior studies on the same topic, relates to how comparable firms are selected on both a methodological and conceptual level. In relation to prior empirical findings, where several methodologies for categorizing comparable firms have been presented, the major selection criteria for different

[I] This notion is greatly exemplified in Equation 11 on the intrinsic derivation of EV/EBITDA sets of comparable firms will in this study be based on industry affiliation. More specifically, selection of different peer groups is defined according to the Global Industry Classification Standard (GICS), ranging from 2-4 digits for sector and industry level respectively[I]. Other widely accepted classification systems include Standard Industrial Classification (SIC) and Industry Classification Benchmark (ICB). However, as highlighted by Bhojraj & Lee (2002), GICS classification has empirically proved to provide superior accuracy levels in previous studies when examining the accuracy of valuation multiples. A major advantage of GICS, primarily compared to SIC, is that the former is professionally managed and continuously updated to better capture transformations in the industrial environment (Schreiner, 2007). Applying pre-defined industry affiliations in the process of categorizing comparable firms is argued to partly mitigate potential selection bias of a more subjective methodology, which improves the probability of obtaining efficient and unbiased estimations (Rossi & Forte, 2016).

To continue, utilizing different sets of GICS codes, ranging from 2-4 digits for sector and industry level, will enable the implicit examination of peer group homogeneity and its implications for the conducted analysis. A common belief within the topic of relative valuation is that larger peer groups produce more accurate valuations by default as idiosyncrasies amongst firms are more likely to be accounted for (Schreiner, 2007). However, this benefit is only realized when a target firm in question is fully aligned with average sample performance, which is rarely the case in practice. Thus, a finer industry categorization down to 4-digit codes, where firms are more similar with respect to operating characteristics, would imply greater comparability and thus more accurate predictions (Schreiner & Spremann, 2007). However, even though a finer industry categorization in general is argued to provide comparatively better homogeneity amongst comparable firms, it is acknowledged that diversity amongst firms within the same industries with regards to levels of growth, profitability and risk will inherently exist in the utilized sample.

5.2.2 Sample Selection

Given the outlined research questions, hypotheses, and delimitations in terms of scope, the sample utilized for the conducted study is based on the public Standard & Poor Composite 1500 Index (S&P 1500). This combines the three leading US indices of S&P 500, the S&P Mid Cap 400 and the S&P Small Cap 600 (Us.spindices.com, 2019). The S&P 1500 index, which as of March 2019 includes 1506 firms, has been utilized by a number of prominent scholars within multiple accuracy research[II]. The sample choice is argued to have

[I] An industry classification supported by Bhojraj & Lee (2002), Schreiner (2007) and Rossi & Forte (2016), amongst others

[II] Including Lie & Lie (2002), Bhojraj et al. (2003) and Knudsen et al. (2015)

several advantages. Firstly, all included firms in the sample are public, which increases the availability and reliability of financial data as all public firms in the US are required to disclose extensive financial information. Additionally, from a statistical standpoint, the relatively large sample improves the overall efficiency of estimations and provides reasonably large sub-samples for examining different research models conducted on market, sector and industry levels[I].

Moreover, utilizing a sample from a single market arguably mitigates several aspects of unwanted heterogeneity, which improves the comparability amongst firms and thereby statistical inferences. Firstly, all firms in the S&P 1500 are required to follow the same fundamental accounting principles as dictated by the Generally Accepted Accounting Principles (GAAP). This implies that measurement, recognition and classification of accounting items should be carried out similarly across all firms in the sample. Secondly, the choice of sample furthermore mitigates heterogeneity amongst firms regarding diverging market factors such as interest rates, inflation and tax rates. As highlighted, identified fluctuations in macroeconomic variables across time periods are argued to distort the indicative value of valuation estimates over time. However, even though mitigating heterogeneity in several aspects, the utilized sample is by no means entirely homogenous. As the S&P 1500 index is a composite of three different indices ranging from small cap to large cap, significant differences exist in relevant fundamentals. As for systematic differences between different sectors and industries, firm heterogeneity and its potentially confounding impact on prediction accuracy of multiples will implicitly be examined through different levels of analysis.

5.2.3 Construction of the Final Data Set

From the available universe of 1506 publicly listed US firms in the S&P 1500 index, several restrictions were necessary to implement for the purposes of this study with reference to outlined variable operationalizations. The process for constructing the final data set is outlined in Table 2 below. Firstly, firms with missing values for given time periods of variable measurements were excluded. This includes estimates for enterprise value and ROIC in the period 2016-2018, BEst EBITDA estimates in the period 2017-2021 and WACC as reported for last fiscal year, which reduced the available sample down to 993 firms. Secondly, firms with reported negative values for BEst EBITDA in the period 2017-2021 were excluded in order to avoid mathematical issues with CAGR calculations as well as avoiding negative EV/EBITDA multiples in the sample, reducing the sample further to 976 firms. Thirdly, both the banking and insurance industries were excluded, as EV/EBITDA is generally considered as a non-representative valuation measure these types of firms due to

[I] This three-level analysis will be further described in the subsequent Section 5.3 on method of data analysis their inherently diverging accounting practices and capital structures. It should be noted that even though traditional banks and insurance companies were removed from the sample, the Diversified Financials Industry with GICS code 4020 was is still included, since it is argued that these firms differ from other financial companies with regards to balance sheet recognition of debt.

Table 2. Sample Construction

Sample Criteria	**N**
S&P Composite 1500 Index	1506
Exclusion of firms with lack of relevant measures:	
Enterprise Value between 2016-2018	1358
BEst EBITDA consensus estimates between 2017-2021	1001
ROIC estimates between 2016-2018	994
WACC estimates LFY	993
Positive values for BEst EBITDA 2017-2021	976
Exclusion of traditional banks	973
Exclusion of traditional insurance companies	969
Exclusion of outliers in terms of EV/EBITDA and ROIC	965
Final sample size utilized in study	965

In order to ensure more unbiased estimates in the subsequent method of data analysis, 4 apparent outliers were excluded[I]. With regards to individual sector and industry sub-samples, it could be argued that more observations in the final dataset could be considered as outliers. However, a conservative approach to the exclusion of observations has been adopted, which is mainly motivated by the fact that several previous researchers stress the statistical drawbacks of employing smaller samples. As such, given that some the obtained samples are small to begin with, further exclusion on sub-sample level may compound this issue further. On another note, it should be highlighted that some included sectors in the final sample only contain a single industry, which makes the two levels interchangeable. Sample characteristics as well as descriptive statistics of the final sample of 965 firms are illustrated in Table 3.

[I] These firms included Cardiovascular Systems Inc, Surmodics Inc and Rowan Companies plc, with implied EV/EBITDA multiples of 53x, 48x and 40x respectively, as well as Domino's Pizza Inc with an estimated ROIC of over 100%

Table 3. Sample Summary

Panel A: Sample Characteristics

Underlying index: S&P Composite 1500
Regional Coverage: US firms
Industry Classification: Global Industry Classification System (GICS) 2-digit sector and 4-digit industry group codes
Total public firms in the final sample: 965
Base period covered: 2016-2018
Utilised estimation period: 2016-2021

Panel B: Descriptive Statistics of the Sample

		MTPL		*Growth (%)*		*Profitability (%)*		*Risk (%)*	
Market/Sector/Industry	Number of Firms	Harmonic Mean	Stdev	Median	Stdev	Median	Stdev	Median	Stdev
Market	965	8,38	4,45	4,37	6,70	8,37	9,27	7,96	1,71
Energy Sector	69	5,60	4,07	7,40	8,68	2,13	7,87	7,84	1,30
Energy	69	5,60	4,07	7,40	8,68	2,13	7,87	7,84	1,30
Materials Sector	61	7,74	2,61	3,82	8,36	8,90	6,52	7,74	1,27
Materials	61	7,74	2,61	3,82	8,36	8,90	6,52	7,74	1,27
Industrials Sector	161	8,64	3,11	5,01	4,77	10,73	9,46	8,57	1,21
Capital Goods	104	9,12	2,70	5,01	5,49	9,53	10,75	8,61	1,07
Commercial & Professional Services	25	9,54	4,10	5,35	2,82	9,42	7,30	8,12	1,46
Transportation	32	6,96	2,87	4,53	3,04	12,58	5,92	8,55	1,38
Consumer Discretionary Sector	173	7,40	3,66	3,47	6,53	11,34	9,32	7,57	1,44
Automobiles & Components	14	5,09	3,19	2,77	3,00	12,26	5,46	7,57	1,80
Consumer Durables & Apparel	47	8,32	3,83	4,37	4,91	9,91	7,15	7,66	1,29
Consumer Services	40	8,70	4,23	4,49	5,93	11,18	9,89	7,38	1,23
Retailing	72	6,93	2,88	2,31	7,77	12,12	10,55	7,71	1,59
Consumer Staples Sector	55	10,88	3,49	3,03	3,60	11,82	8,77	6,83	0,98
Food Staples & Retailing	10	8,35	2,14	3,73	5,45	12,12	4,13	6,91	1,37
Food, Beverage & Tobacco	31	12,09	3,29	2,64	3,01	11,60	8,18	6,76	0,91
Household & Personal Products	14	10,81	3,70	3,49	3,12	13,61	11,87	6,91	0,88
Health Care Sector	130	8,85	4,96	6,24	7,55	7,98	9,30	8,84	1,67
Health Care Equipment & Services	80	8,00	5,04	6,29	6,72	7,88	6,83	8,84	1,67
Pharmaceuticals, Biotechnology & Life Sciences	50	10,65	4,87	5,76	8,77	8,15	12,14	8,83	1,67
Financials Sector	29	8,74	4,35	4,17	5,52	10,26	8,20	8,04	1,56
Diversified Financials	29	8,74	4,35	4,17	5,52	10,26	8,20	8,04	1,56
Information Technology Sector	131	8,50	4,81	5,22	6,94	9,05	11,38	9,21	1,58
Software & Services	54	11,68	4,45	6,53	5,68	8,88	14,08	9,16	1,42
Technology Hardware & Equipment	49	7,18	3,22	5,03	7,48	8,59	8,73	8,92	1,57
Semiconductors & Semiconductor Equipment	28	7,08	5,69	4,15	8,15	12,29	9,44	10,20	1,65
Communication Services Sector	41	7,44	3,97	4,72	9,01	7,76	6,38	7,52	1,70
Telecommunication Services	8	6,02	2,46	1,21	2,61	3,87	3,06	6,21	0,72
Media & Entertainment	33	7,89	4,14	6,13	9,49	8,06	6,79	8,04	1,68
Utilities Sector	39	10,26	1,98	3,94	2,47	4,96	1,82	4,96	0,54
Utilities	39	10,26	1,98	3,94	2,47	4,96	1,82	4,96	0,54
Real Estate Sector	76	14,68	4,00	2,27	4,21	4,39	3,00	6,02	0,85
Real Estate	76	14,68	4,00	2,27	4,21	4,39	3,00	6,02	0,85
Results by individual year before periodic aggregation									
Market 2018		8,19	4,96	4,50	9,51	9,08	12,30	N/A	N/A
Market 2017		9,35	7,42	4,37	8,34	8,53	10,12	N/A	N/A
Market 2016		7,75	8,28	4,57	11,56	7,99	11,97	N/A	N/A

5.2.4 Quality of Underlying Data

As highlighted in the previous Section 5.1, the data source for constructing the sample is the Bloomberg database, a software system provided by Bloomberg LP, also known as Bloomberg Professional Services (Bloomberg, 2019). Covering over 5 million bonds, equities, commodities and currencies, with over 320,000 subscribers, Bloomberg is considered as one of the largest and most credible sources of financial data in the world for businesses and professionals (Investopedia, 2019). Apart from extensive company coverage, a major advantage of Bloomberg is that it offers comprehensive forecast estimates on a wide range of variables, which hold great significance for variable constructs of this study. Also commonly used by previous researchers, the main alternative to the Bloomberg Terminal database arguably includes the Institutional Brokers Estimate System (IBES) provided by Thompson Reuters.

To continue, even though Bloomberg is deemed as a reliable and credible source of financial information, the potentially limiting factor of measurement errors will inherently exist for estimates of utilized variable constructs. As outlined in Table 1 on variable operationalization, several constructs are based on approximations where subjectivity is introduced, primarily including estimations for EV/EBITDA and ROIC. Firstly, as enterprise value cannot be observed directly, market value of net debt has to be approximated with book value of net debt. This procedure is seen as especially susceptible to noise, as the composition, recognition and accounting of net debt on the balance sheet can vary significantly between firms (Rossi & Forte, 2016). Secondly, with regards to the measure for ROIC, similar approximations as for enterprise value are necessary to implement in order to approximate NOPAT as well as average Invested Capital. Overall, both reported financial statements and approximations of market values through a third party inherently includes noise in the form of subjectivity. That is, sell-side estimations on which included variables are based upon may diverge from market expectations. This discrepancy may furthermore introduce additional measurement bias in the variable operationalizations. Considering the above, potential limitations are recognized and will explicitly be accounted for in a subsequent section[I].

5.3 Method of Data Analysis

In line with prior studies that examine the accuracy and implementation of multiple valuation, the method of data analysis will aim to ultimately evaluate the accuracy of estimated multiples. In this regard, stronger statistical association between reported accounting information and observed market values is regarded as

[I] See the subsequent Section 7 on validity of results more desirable than the opposite outcome. Under this definition, the value relevance of accounting information utilized in this study is determined by its ability to ultimately predict firm value through EV/EBITDA multiples. Following this way of interpretation, the significance of selected value drivers and the accuracy of predicted multiples is mainly evaluated through statistical significance, goodness of fit statistics, and measurement errors of the predicted values. Moreover, market values are for the purposes of this paper assumed to adequately represent the true intrinsic value of a firm, in that the law of one price holds[I]. Thus, market efficiency is assumed, where accuracy of predicted EV/EBITDA multiples is measured with error compared to the efficient values observed in the market. This section will firstly outline the fundamentals of the two major regression models developed as well as the utilized method for evaluating model prediction accuracy. Following, a discussion on statistical considerations and potential limitations of the employed methods will be presented. Subsequently, research model specifications underlining the developed models and accuracy testing will be outlined for purposes of replicability.

5.3.1 Impact of Fundamental Value Drivers: Research Question 1

Two separate types of regression models will constitute the main method for examining the first research question[II] that concerns the underlying relationship between EV/EBITDA and its fundamental value drivers. Both regression models will be conducted by utilizing the constructed data set of 965 firms on three separate levels, namely cross-sectional market level, sector level, and industry level. The rationale for conducting the regression models on three separate levels is based on the ambition to advance prior empirical evidence on optimal samples used in regressions for multiple accuracy testing and to provide further insights on systematic industry differences in terms of growth, profitability and risk. As described in the previous paragraph, value relevance of the employed regression models will overall be determined based on explanatory power and goodness of fit, together with statistical significance of estimated beta coefficients.

Standard Regression Analysis

The overall relationship between implied EV/EBITDA multiples and their corresponding fundamental value drivers will as a first step be tested through a series of single and multivariate ordinary least squares (OLS)

[I] The notion of the law of one price was explicitly outlined in Section 2.1.2 on theoretical foundations underlying the relative valuation method

[II] Corresponding to Hypotheses 1-5 outlined in Section 4 regression models. The reasoning for including single factor regressions[I] as a complement to multivariate models is mainly to provide additional empirical evidence on the impact of derived value drivers on a standalone basis. Moreover, utilizing multivariate OLS regressions is in line with similar empirical studies that have examined the impact of underlying drivers of valuation multiples[II], where utilized drivers as independent variables however differs from study to study. The theoretical and practical suitability of using multivariate regressions for the analysis is primarily related to the fact that it allows for testing the impact of identified value drivers simultaneously, while controlling for differences in each respective driver. This ability serves the aim of this study in that it provides a holistic understanding of the underlying relationship between EV/EBITDA and its fundamental value drivers. Moreover, multivariate regressions generate quantifiable measures of the direction and statistical impact of the independent variables, which sheds light on the relative importance of growth, profitability and risk. Additionally, the employed regressions can also be modified to account for potential non-linear relationships between included dependent and independent variables, which will be primarily mitigated through logarithmic and exponential transformation if observed.

Relative Regression Analysis

As an extension to the standard regression approach outlined above, some identified studies have introduced and incorporated different elements of relative measures and components in regression models. These approaches are generally argued to more effectively capture fundamental differences in value drivers amongst firms and thus provide more accurate predictions of firm value [III]. However, empirical findings from utilizing relative measures remains mixed. Even though not explicitly testing for the impact of underlying constructs of valuation multiples, Schreiner & Spearmann (2007) highlight the need for introducing adjustments of utilized peer group multiples in accuracy testing. They correct for this by introducing a subjective adjustment factor that theoretically accounts for accumulated relevant value differences in profitability, growth and risk between target firms and selected comparables.

In line with similar methodologies as employed by Bhojraj & Lee (2002) and Harbula (2009), the relative regression approach conducted in this study will be based on firm values relative to selected peer groups for both dependent and independent variables. Hence, each sample firm will correspondingly be assigned a

[I] As opposed to only include multivariate regressions

[II] E.g. Kaplan & Ruback, 1995; Damodaran, 1994, 2002, 2006, 2007, 2012; Bhojraj & Lee, 2002; Harbula, 2009, Gupta, 2018

[III] This notion is implicitly supported in studies conducted by Alford (1992), Kaplan & Ruback (1995), Kim & Ritter (1999), Bhojraj & Lee (2002) and Harbula (2009), amongst others selected peer group, based on comparable criteria outlined in Section 5.2.1, from which each individual value driver and multiple will be benchmarked against. The implied relative multiple premium or discount for each firm will consequently be regressed against relative value drivers, where obtained predictions will subsequently be utilized to compute predicted multiples. Overall, it can be argued that the employed relative regression approach provides a more precise picture of over or undervaluation of firms as it additionally attempts to shed light on how incremental differences in value drivers within peer groups warrant multiple premiums or discounts.

5.3.2 Model Prediction Accuracy: Research Question 2

As outlined, the second and ultimate research question of this paper relates to whether valuation estimates from regressions based on fundamental value drivers are accurate in predicting the studied multiple, and how these predictions compare with estimates based on simple peer group averages. This will be conducted in two steps. Firstly, predicted coefficients obtained from regressions will be utilized in order to compute predicted multiples. Secondly, the predicted multiples from standard and relative regression models will ultimately be compared to implied multiples based on simple peer group averages.

Following the methodology as outlined by Schreiner (2007) and Rossi & Forte (2016), amongst others, model prediction accuracy will be tested in two separate ways. As a first test, observed market multiples (dependent variable) will be regressed against predicted multiples (independent variable) derived from each separate model. In line with common practice, this first test will be evaluated based on goodness of fit as well as the statistical significance of the coefficients. The second test for accuracy will be based on calculations of prediction errors on market level, sector level and industry level for the studied sample. The prediction errors will subsequently be directly compared across the models, where the model associated with lowest predictions errors is deemed more accurate than the others.

5.3.3 Statistical Considerations and Potential Limitations of Employed Regression Models

As highlighted, the method of data analysis in this paper is mainly based on multivariate OLS regression models, which are ultimately utilized in examining various relationships between selected dependent and independent variables. On the most fundamental level, the OLS estimator selects regression coefficients so that the predicted regression line is as close as possible to the observed data, where closeness is determined by the sum of squared residuals made in predicting the dependent variable (Stock & Watson, 2012). In order for the OLS estimators to generate statistically efficient and unbiased results, a few main conditions and assumptions are necessary to be satisfied, which are outlined below.

- In line with underlying assumptions of relative valuation, the relationship between the studied multiple and fundamental value drivers is assumed to be linear in parameters, where the dependent variable is determined by a linear function of the independent variables and the error term[I]:

  Equation 12.

  $$Y_i = \alpha_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i, i = 1, \ldots, n$$

  where,

  $Y = Dependent\ variable$

  $X = Independent\ \ variables$

  $\alpha = Regression\ intercept$

  $\beta = Slope\ coefficient$

  $\varepsilon = Error\ term$

- The residual (or error term) of each regression model, denoted ε_i, has a conditional mean of zero and is normally distributed, mathematically described as:

  Equation 13.

  $$E(\varepsilon_i | X_{1i}, X_{2i} \ldots, X_{ki}) = 0$$

  Equation 14.

  $$\varepsilon_i \sim N(0, \sigma^2)$$

- The dependent variable and independent variables are independently and identically distributed across the employed sample, i.e. there is random sampling of observations, mathematically described as:

  Equation 15.

  $$(X_{1i}, X_{2i} \ldots, X_{ki}, Y_i), i = 1, \ldots, n$$

[I] It should here be noted that the basic construction of linear regressions includes regression intercepts, which implicitly allows for estimating the impact of omitted variable bias

- The assumption above furthermore implies the assumption that error terms have a homoscedastic distribution, mathematically described as:

Equation 16.

$$Var(\varepsilon_i | X_{1i}, X_{2i} \dots, X_{ki}) = \sigma^2$$

- Large outliers are unlikely, i.e. the dependent variable and independent variables have finite kurtosis

- No perfect multicollinearity between independent variables, i.e. the independent variables are linearly independent from each other

In order to test the efficiency and unbiasedness of the OLS estimator, the regression analysis will commence with a series of normality and heteroskedasticity tests of the underlying data employed, including skewness, kurtosis and Shapiro-Wilks tests for normality, as well as White test for heteroskedasticity. The null hypotheses of these tests are either that the variable distributions are normally distributed, have no skewness or kurtosis, and that no heteroskedasticity is present, which will be rejected below a p-value of 5%. Moreover, potential issues of multicollinearity will be examined through the use of Pearson correlation coefficients. The results of these tests will further indicate the generalizability of the regression models and their corresponding predictions, which ultimately determines the usefulness of results (Stock & Watson, 2012).

Hypothesis Testing and Measures of Fit

In order to test the significance of identified parameters of interest and determine whether formulated hypotheses should be accepted or rejected, statistical hypothesis testing based on t-statistics for single hypotheses and F-statistics for joint hypotheses will be conducted. When multiple restrictions are imposed, such as for the employed multivariate regression models of this paper, F-statistics is appropriate as it allows for testing model significance of numerous coefficients simultaneously (Stock & Watson, 2012). To increase robustness as well as efficiency of estimations, logarithmic transformation of individual variables and heteroskedasticity-robust estimates will be applied if concluded necessary. Following common practice, formulated hypotheses will be rejected at the 5% significance level. Inferences from regression results, on the other hand, will additionally be based on a 1%, 2,5% and 10% significance level. In essence, obtained test-statistics will at a first stage indicate whether selected value drivers have a significant impact on EV/EBITDA multiples[I], and at a second stage indicate whether implied synthetic multiples are accurate in predicting EV/EBITDA multiples[II]. Moreover, the sign and direction of each regression coefficient will provide further empirical evidence on examined relationships.

To continue, in order to analyze the measures of fit and predictive power of each regression model, adjusted R-squared statistics will be utilized. The standard regression R-squared is the fraction of sample variance of the dependent variable explained by the selected independent variables, where a high R-square signifies higher predictive power of the explanatory variables and vice versa (Stock & Watson, 2012). As standard R-squared increases by default when adding more than one independent variable, without regard for whether the added variables actually improves the fit of the model, adjusted R-squared provides a better measure given that it scales the figure to the number of regressors.

Moreover, for the sake of replicability, statistical regressions and hypothesis tests will be conducted utilizing the statistical software named R. The software is an environment and language for statistical computing as well as graphics, developed by Lucent Technologies, which provides a wide array of linear and nonlinear modelling tools that are suitable for the conducted research. Some of the strengths of the employed statistical program is the integrated publication-quality plotting options, data manipulation functionality, graphical display, as well as the options for adding additional functionality of defining new functions.

Potential Limitations of Employed Regression Models

Even though a highly suitable statistical methodology for the purposes of answering the formulated research questions and test stated hypotheses, the outlined regression approach of this study is expected to contain several limiting factors. In turn, these limitations may ultimately affect the external and internal validity of the study. Similar prior studies applying regression analysis have in particular highlighted some potential implications. These primarily include small sample sizes and corresponding heteroskedasticity issues, distributional properties of multiples and value drivers, multicollinearity issues as well as omitted variable bias[III].

[I] Corresponding to Hypotheses 1-5 in Section 4

[II] Corresponding to Hypotheses 6-7 in Section 4

[III] See Baker & Ruback, 1999; Liu et al., 2002, 2007; Bhojraj & Lee, 2002; Damodaran, 2007; Harbula, 2009

To begin with, in their research on development of minimum variance estimation models for valuation multiples, Baker & Ruback (1999) highlight the shortcomings of utilizing small sample sizes in relative valuation processes. When regressions are conducted on industry or sector basis, samples vary significantly in size and tend to be relatively small overall. These instances are often associated with heteroskedasticity issues, where residuals are not evenly distributed across the sample (Stock & Watson, 2012). In turn, heteroskedastic residual distributions distort the efficiency of OLS estimators in accurately predicting dependent variables. For these reasons, some scholars have suggested a transformation of the basic OLS regression model. For example, employing a sample of 225 firms across 22 industry groups, Baker & Ruback (1999) included the basis of substitutability (EBITDA) as dependent variable and the firm value metric (Enterprise value) as independent variable. This was done by dividing both sides of the equation by enterprise value. A similar transformation was later employed by Liu et al. (2002, 2007), with the underlying motivation that residuals in a standard OLS regression model based on small sample sizes might be approximately proportional to the dependent variable. Nonetheless, the model constructions employed in this paper are in line with constructions employed by Bhojraj & Lee (2002) and Harbula (2009) due to the similar research focus of those studies[I].

To continue, certain distributional properties of the selected multiple and theoretically derived value drivers may additionally contribute to biased OLS estimates. As the observed EV/EBITDA multiple for each firm in the sample has been manually restricted to values above zero[II], its distribution is potentially abnormal. In addition, distributions for multiples and their intrinsic value drivers can vary significantly over time. If taken as given, this fact consequently results in deteriorating predictive power for included regression models across different time periods, as the underlying relationships between multiples and value drivers are likely to fluctuate. In order to account for potentially abnormal distributions of included variables, data included for the sample is averaged over a three-year timespan and variable inputs are transformed to logarithmic scale, where applicable[III].

In relation to expected abnormal variable distributions, sample selection bias within the conducted research might be present. When testing for model prediction accuracy of developed regression models and the standard

[I] However, potential heteroskedasticity concerns in this study will be acknowledged and partly mitigated by utilizing heteroskedasticity-robust estimates

[II] By excluding firms displaying negative EV/EBITDA multiples

[III] As outlined in Section 5.1 on variable operationalization, the proxy for risk is only based on last fiscal year due to data unavailability in the Bloomberg database peer group approach, the same sample is consistently applied. That is, the same sample used to produce predictions of EV/EBITDA is subsequently used as benchmark for model accuracy, which practically implies that the target firm is included in the group of comparable firms[I]. As for small sample sizes and abnormal variable distributions, the potential selection bias might affect the efficiency of the OLS estimators, the distribution of prediction errors and consequently the validity of final results. However, in their study on multiple accuracy, Liu et al. (2002) found that the introduced bias from an in-sample regression approach is negligible when a cross-section sample is utilized, and that the dispersion of pricing errors decreases on industry level if in-sample harmonic means are used. Regardless, it is argued for the purposes of this study that an out-of-sample regression would not be appropriate to implement, as it would require the inclusion of either smaller, non-public or non-US firms, which would entail a lack of comparability given the comprehensiveness of the utilized S&P 1500 sample.

Moreover, it is expected that employed regression models might suffer from multicollinearity. In this setting, multicollinearity implies that at least one of the selected value drivers is highly correlated with a linear combination of the other value drivers. Based on intuitive logic, it could for example be argued that firms within the sample that report high earnings growth generally tend to be riskier, which implies that EBITDA CAGR would be highly correlated with WACC. As for abnormal variable distributions, detected multicollinearity could potentially undermine the efficiency of OLS estimators. A central remedy for this issue is to consider different sets of independent variables (Stock & Watson, 2012). However, given the formulated research questions, the aim of this paper is to analyze the impact of theoretically derived value drivers of EV/EBITDA, which for obvious reasons may be correlated by nature. Thus, potential multicollinearity observed from correlation analysis will not directly be counteracted but will rather form basis for discussion on internal validity of employed regression models.

Lastly, conducted statistical analysis in this study can only in essence provide inferred evidence of causal relationships as other potential predictors of EV/EBITDA might be omitted, known as omitted variable bias. Several previous studies that have examined the relationship between valuation multiples and value drivers over time[II] point out that the commonly obtained low R-squared statistics can mostly be attributed to omitted

[I] This notion is defined in previous research as an in-sample approach compared to an out-of-sample approach. See Rossi & Forte (2016) for a more elaborate discussion

[II] Most notably Kisor & Whitbeck (1963), Cragg & Malkei (1968) and Damodaran (1994, 2002, 2006, 2007, 2012) variable bias[I]. The statistical issue of omitted variable bias is a driving force of endogeneity, where either one or several regressors are correlated with an omitted variable. Alternatively, that an omitted variable is a determinant of the dependent variable, which distorts predictions (Stock & Watson, 2012). Some remedies for omitted variable bias involves either to introduce instrumental variables or simply add to the number of regressors in the models employed. Even though adding more value drivers could possibly counteract potential omitted variable bias, utilized independent variables will only include the theoretically derived value drivers of EV/EBITDA in line with stated problem formulation.

5.4 Research Model Specifications

5.4.1 Standard Regression Models

The first step of the standard regression analysis[II] is to conduct single regressions with each selected value driver separately included as independent variable and the studied multiple included as dependent variable. These single regressions will provide empirical evidence on the impact of each value driver on a standalone basis, which is argued to form valuable insights for subsequent multivariate regressions. Following prior empirical findings as well as theoretical assumptions, it is expected that growth and profitability will have a positive impact on EV/EBITDA[III], whereas risk is expected to have a negative impact. The constructions of employed single regressions for the standard regression analysis are illustrated below[IV].

Standard single regression models:

Equation 17.

$$MTPL_{i,t} = \alpha + \beta_1(Growth_{i,t}) + \epsilon_{i,t}$$

Equation 18.

$$MTPL_{i,t} = \alpha + \beta_1(Profitability_{i,t}) + \epsilon_{i,t}$$

Equation 19.

$$MTPL_{i,t} = \alpha - \beta_1(Risk_{i,t}) + \epsilon_{i,t}$$

[I] Most prior studies which explicitly have investigated the accuracy of various multiples over time have rarely obtained R-squared statistics over 70%, a figure varying greatly from study to study

[II] With the aim of specifically testing developed Hypotheses 1-3 in Section 4

[III] Referred to as MTPL in the subsequent equations

[IV] With reference to variable operationalization in Section 5.1

where,

$i = Firm\ i$

$t = Time\ t$

The second step of the standard regression analysis[I] is to employ multivariate regression models, where fundamental differences between firms in terms of growth, profitability and risk will be simultaneously controlled for. The construction of the employed standard multivariate model is illustrated below.

Standard Multivariate Model:

Equation 20.

$$MTPL_{i,t} = \alpha + \beta_1(Growth_{i,t}) + \beta_2(Profitability_{i,t}) - \beta_3(Risk_{i,t}) + \epsilon_{i,t}$$

where,

$i = Firm\ i$

$t = Time\ t$

5.4.2 Relative Regression Model

Following the same reasoning as for the standard regression analysis, a multivariate model is employed to simultaneously account for relative measures in growth, profitability and risk against peer group values[II]. The construction of the employed relative multivariate model is illustrated below.

Relative Multivariate Model:

Equation 21.

$$\left(\frac{MTPL_{i,t} - H_P(MTPL_{i,t})}{H_P(MTPL_{i,t})}\right) = \alpha + \beta_1\left(\frac{Growth_{i,t} - Med_P(Growth_{i,t})}{Med_P(Growth_{i,t})}\right) + \beta_2\left(\frac{Profitability_{i,t} - Med_P(Profitability_{i,t})}{Med_P(Profitability_{i,t})}\right) - \beta_3\left(\frac{Risk_{i,t} - Med_P(Risk_{i,t})}{Med_P(Risk_{i,t})}\right) + \epsilon_{i,t}$$

$$H_p(MTPL_{i,t}) = \frac{n}{\frac{1}{MTPL_{1,t}} + \frac{1}{MTPL_{2,t}} + \cdots + \frac{1}{MTPL_{n,t}}} = \frac{n}{\sum_{i=1}^{n}\frac{1}{MTPL_{i,t}}} = \left(\sum_{i=1}^{n}\frac{MTPL_{i,t}^{-1}}{n}\right)^{-1}$$

where,

$i = Firm\ i$

$t = Time\ t$

$P = Peer\ group\ multiple\ on\ market, sector\ and\ industry\ level$

$H_p(MTPL_{i,t}) = Harmonic\ mean\ of\ peer\ group\ multiple\ on\ market, sector\ and\ industry\ level$

[I] With the aim of specifically testing the developed Hypothesis 4 in Section 4

[II] With the aim of specifically answer developed Hypothesis 4 in Section 4

5.4.3 Model Prediction Accuracy

With the underlying relationships covered, the second and ultimate goal of the conducted research is to test prediction accuracy of developed regression models and subsequently to compare findings to prediction accuracy of estimates obtained from simple peer group averages. As such, the first step is to calculate predicted multiples for each firm using the different models on market, sector and industry level, illustrated below.

Simple Peer Group Model (SPGM):

Equation 22.

$$\widehat{MTPL_{i,t}^{SPGM}} = H\left(MTPL_{i,t}\right)$$

Standard Regression Model (SRM):

Equation 23.

$$\widehat{MTPL_{i,t}^{SRM}} = \hat{\alpha} + \widehat{\beta_1}\left(Growth_{i,t}\right) + \widehat{\beta_2}\left(Profitability_{i,t}\right) - \widehat{\beta_3}\left(Risk_{i,t}\right)$$

Relative Regression Model (RRM):

Equation 24.

$$\left(\frac{MTPL_{i,t} - \widehat{H_p\left(MTPL_{i,t}\right)}}{H_p\left(MTPL_{i,t}\right)}\right)^{RRM} = \alpha + \widehat{\beta_1}\left(\frac{Growth_{i,t} - Med_P\left(Growth_{i,t}\right)}{Med_P\left(Growth_{i,t}\right)}\right) + \widehat{\beta_2}\left(\frac{Profitability_{i,t} - Med_P\left(Profitability_{i,t}\right)}{Med_P\left(Profitability_{i,t}\right)}\right) - \widehat{\beta_3}\left(\frac{Risk_{i,t} - Med_P\left(Risk_{i,t}\right)}{Med_P\left(Risk_{i,t}\right)}\right)$$

Equation 25.

$$\widehat{MTPL_{i,t}^{RRM}} = \left(\frac{MTPL_{i,t} - \widehat{H_p\left(MTPL_{i,t}\right)}}{H_p\left(MTPL_{i,t}\right)}\right)^{RRM} * H_p\left(MTPL_{i,t}\right) + H_p\left(MTPL_{i,t}\right)$$

With obtained predicted multiples, it is subsequently possible to estimate and compare the accuracy of estimates based on the different approaches. The way in which prediction accuracy is measured is developed from previous literature, as outlined in Section 5.3. Firstly, the following regression is conducted for the predictions of observed multiples derived from utilized models[I].

Equation 26.

$$MTPL_{i,t} = \alpha + \widehat{MTPL_{i,t}} + \epsilon_{i,t}$$

[I] With the aim of specifically testing the developed Hypothesis 5 in Section 4

As common practice, the second test for scrutinizing the accuracy of valuation estimates finally includes the computation and comparison of the following formulation of scaled prediction errors.

Equation 27.

$$Error_{i,t} = \frac{\widehat{MTPL}_{i,t} - MTPL_{i,t}}{MTPL_{i,t}}$$

In line with similar studies on multiple accuracy testing[I], the computed prediction errors will serve as base for testing model bias in terms of average under or overvaluation, mean absolute deviation (MAD) as well as mean squared errors (MSE). The primary reasoning behind including several accuracy measures is to reduce the risk of distorted or incorrect conclusions. Bias as a sole measure of accuracy could potentially be misleading as it only takes into account whether predictions are positive or negative on average, but not their relative magnitude. Measures of MAD and MSE overcome this issue, where MSE furthermore assign a stronger penalty for large errors and thus diminishes estimated prediction accuracy in the case of outliers (Rossi & Forte, 2016). The equations utilized to estimate prediction error bias, MAD and MSE are outlined below[II].

Equation 28.

$$Bias = \frac{1}{N}\sum_{i=1}^{I} Error_{i,t}$$

Equation 29.

$$MAD = \frac{1}{N}\sum_{i=1}^{I} \left|Error_{i,t}\right|$$

Equation 30.

$$MSE = \frac{1}{N}\sum_{i=1}^{I} Error_{i,t}^{2}$$

where,

$i = Firm\ i$

$t = Time\ t$

$N = Number\ of\ observations$

$I = Total\ number\ of\ firms\ in\ each\ sub\ sample$

[I] E.g. Schreiner, 2007; Rossi & Forte, 2016

[II] With the aim of specifically testing the developed Hypothesis 7 in Section 4

- 6. Results -

The following section will outline all the statistical results obtained in the conducted research. Following the approach of a deductive empirical study, descriptive statistics as well as underlying correlations amongst included variables will firstly be presented. In line with the presentation of the underlying data, the evaluation of variable distributions as well as results from a series of normality tests will be outlined, which serves as base for the internal validity of overall results. Subsequently, this section will chronologically display obtained results in relation to stated research questions and the corresponding tests for developed hypotheses. Driven by empirical findings, each sub-section will additionally outline implemented post-hoc analyses, which were deemed necessary to perform in order to further investigate the underlying explanations for obtained results. Lastly, from a holistic standpoint, the overall external as well as internal validity of obtained results will be discussed in the subsequent Section 7, which together with actual empirical findings serves as base for the final discussion and perspectivization.

6.1 Descriptive Statistics

Descriptive statistics and correlation matrix for the full market sample of 965 firms is presented in Table 4 below. For comparative purposes, descriptive statistics and correlation matrices for all utilized sub-samples on sector and industry levels are presented in Appendix 2. It should be noted that descriptive statistics in Table 4 and Appendix 2 only display the standard operationalizations for selected variables, as underlying correlations of relative measures used in the relative regression model have similar direction and significance.

Table 4. Descriptive Statistics & Correlations

Sample: Cross-section (Market level)
Number of firms: 965

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,308	9,561	4,453	0,353	32,760			
2. Growth (%)	5,332	4,374	6,702	-18,233	45,432	0,096****		
3. Profitability (%)	9,945	8,366	9,274	-23,446	64,574	0,032	-0,122****	
4. Risk (%)	7,926	7,961	1,711	3,531	14,167	0,056*	0,347****	0,250****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

First of all, in terms of descriptive statistics of selected variables presented in Panel A, greatest standard deviations can be observed in measures of profitability and growth with 9,2% and 6,7% respectively, followed by EV/EBITDA with 4,4x and risk with 1,7%. As such, it is evident that the studied firms are least uniform in terms of profitability and most uniform in terms of risk. Furthermore, the measure for risk has a mean around 8%, which is a commonly applied discount rate in practice. Secondly, comparing means and medians shows that median values are lower for all variables, indicating right-skewness with large positive deviations in the cross-section sample. Thirdly, observed EV/EBITDA multiples in the cross-section sample range between 0,3x and 32,8x. Consequently, it is evident that multiple premiums for firms included in the sample have a considerable spread on cross-section level. As such, firms displaying the highest and lowest multiples could potentially be associated with underlying relationships between multiples and fundamental value drivers that deviate from theoretical assumptions. This would suggest that such observations should be excluded from the analysis. However, in terms of incremental differences amongst all firms included in the cross-section sample, these observations are not considered as outliers. Thus, including these observations is considered valid from a statistical standpoint.

To continue, in terms of correlations presented in Panel B, a high degree of multicollinearity can be observed between most of the independent variables. That is, all independent variables display highly significant correlations ($p<,01$) respective to each other. As outlined in Section 5.3.3, the observed multicollinearity between independent variables was excepted, where similar results have been obtained from previous studies. However, as can be observed in correlation matrices in Appendix 2, the significance and direction of correlations between independent variables vary greatly between sectors and industries. For example, the correlation matrices for the Utilities Sector, the Household & Personal Products Industry and the Technology Hardware & Equipment Industry demonstrate non-significant correlations between all independent variables. Nevertheless, the overall implications of the observed multicollinearity in certain samples will be further discussed in terms of internal validity of results[I].

Apart from observed multicollinearity, other interesting observations can be made with regards to the correlations between independent variables in the cross-section sample. First of all, profitability turns out to be significantly and negatively correlated with growth. Thus, across the sample on a market level, more profitable firms tend to have lower growth rates and vice versa. Furthermore, both profitability and growth are significantly and positively correlated with risk. That is, firms that are more profitable and enjoy high levels

[I] See Section 7

growth tend to be riskier and vice versa. From an intuitive standpoint, firms enjoying high growth levels are usually in the phase of conception, which is why the observation of a positive correlation between growth and risk arguably makes sense. Moreover, a possible explanation for the observed positive correlation between profitability and risk could be that riskier projects are associated with greater returns to compensate for additional risk taking. Yet again, as can be observed in Appendix 2, the significance and direction of correlations between independent variables however varies greatly between sectors and industries.

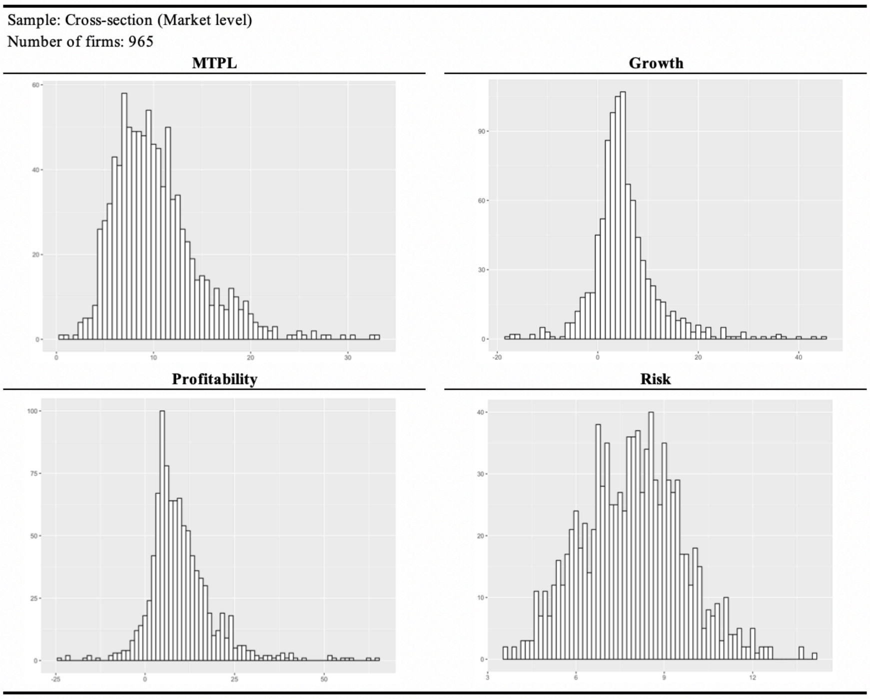
Moreover, the correlations for EV/EBITDA and selected value drivers indicate both theoretically expected and unexcepted results. First of all, across all firms in the sample, EV/EBITDA is significantly ($p<,01$) and positively correlated with growth. This finding is in line with theoretical assumptions, where higher earnings growth should warrant higher valuation multiples. However, EV/EBITDA is at the same time positively, but non-significantly ($p>,1$) correlated with profitability. The reason behind this result is argued to either stem from systematic industry differences across firms in the sample or potential measurement errors. In that regard, it can be observed in Appendix 2 that the relative importance of profitability with respect to EV/EBITDA varies greatly between sectors and industries. For example, the correlation is positive and significant ($p<,05$) in several instances such as within the Consumer Discretionary Sector, the Communication Services Sector and the Consumer Staples Sector, but negative and significant ($p<,05$) within the Real Estate Sector as well as non-significant in many other instances. These systematic differences are therefore theorized to cancel out the positive significance of profitability with regards to EV/EBITDA on an aggregate level when the sample across sectors and industries is employed. To continue, the observed non-significant correlation between EV/EBITDA and profitability could be the result of a measurement error in estimating ROIC. As the studied multiple is forward-looking, whereas profitability is constructed using current measures due to data unavailability, the observed result may indicate that current profitability and future value simply does not correlate. This potential explanation is however seen as less likely, as past performance should in theory also be able to significantly determine the future value of a firm. Thus, it is concluded to be most likely that systematic industry differences drive the observed correlation between the studied multiple and profitability.

Furthermore, another interesting finding in terms of correlations between the dependent variable and selected value drivers is that EV/EBITDA is positively but non-significantly ($p>,05$) correlated with risk. This finding implies that across the sample, higher risk warrants higher multiples, which goes against theoretical assumptions. As for the correlation between EV/EBITDA and profitability, the sign and significance of the correlation between EV/EBITDA and risk may be explained by systematic industry differences or measurement errors. However, in this instance it is also reasonable that it could be a result of underlying multicollinearity between risk and other independent variables. As risk is positively and significantly correlated with both growth and profitability in the cross-section sample, it is argued that the theoretically assumed negative relationship between risk and the studied multiple is outweighed on an aggregate level.

6.2 Variable Distributions

Variable distributions are for illustrative purposes presented in Table 5 below. In line with expectations, it can be observed that distributions for measures of EV/EBITDA, growth and profitability are all rightly skewed across the full sample. Meanwhile, the measure for risk displays a more normal distribution.

Table 5. Variable Distributions



In order to evaluate the normality of the underlying variable distributions, and thereby ensure less biased OLS estimators in the subsequent regression models, a series of normalization attempts were conducted. These attempts included different combinations of exponential and logarithmic transformations, where the outcome from each attempt was evaluated based on Shapiro-Wilks tests, skewness and kurtosis tests, as well as White tests for heteroskedasticity. Based on these results, it was concluded that a logarithmic transformation improved the distributions for EV/EBITDA as well as the measure for risk, whereas measures of growth and profitability provided higher normality and lower heteroskedasticity when kept in its original state. More specifically, normality tests indicated that logarithmic transformations of growth and profitability performed slightly better based on Shapiro-Wilks tests, but substantially underperformed in terms of skewness, kurtosis and heteroskedasticity[I]. The final tests for normality and heteroskedasticity, with EV/EBITDA and risk in logarithmic form as well as growth and profitability in its original state, are presented in Appendix 3 and Appendix 4.

Firstly, with the null hypotheses of no skewness and no kurtosis, it can be concluded from Appendix 3 that the operationalization of EV/EBITDA display no skewness or kurtosis in many sectors and industries, but that skewness and kurtosis is present on an overall market level. Similar conclusions can be made with regards to risk, which additionally displays no kurtosis on market level. On the other hand, only a few sectors and industries are free from skewness and kurtosis in terms of profitability and growth. To continue, with a null hypothesis of normal distribution, the results from the Shapiro-Wilks tests furthermore confirms that on a market level, as well as for most sectors and industries, the selected independent variables are non-normally distributed. It should be noted that the test statistics may be influenced by the varying sample sizes, where the ability to make statistical conclusions is limited in smaller samples. Nonetheless, conducted Shapiro-Wilks tests also show that EV/EBITDA is normally distributed in a majority of sub-samples. This observation is argued to outweigh the abnormal distributions of the independent variables, given that normal distribution of the dependent variable is the most central assumption for variable distribution of OLS estimators (Stock & Watson, 2012).

To continue, based on White tests with a null hypothesis of no heteroskedasticity presented in Appendix 4, it can be concluded that both single and multiple regressions on a market level contain heteroskedasticity in all instances but one. Meanwhile, regressions on a sector and industry level generally performs better. In order to partly mitigate the negative impact of existing heteroskedasticity, regression models will be conducted using heteroskedasticity-robust estimates, a statistical software function provided in R. To summarize, given the test results for both normality and heteroskedasticity, some bias will inherently exist in the subsequent regression outputs, the implications of which will be further discussed in terms of internal validity of results[II].

[I] Specific transformations performed included logarithmic as well as exponential transformation of independent variables. As these transformations turned out to perform worse in terms of normality for the included proxies of growth and profitability, only measures for the studied multiples and risk were transformed into logarithmic scales

[II] See Section 7

6.3 Linear Regression Results: Research Question 1

6.3.1 Single Regression Output

As outlined in previous sections, the first step in evaluating the underlying relationships between EV/EBITDA and its theoretically derived value drivers is to conduct single regressions based on market, sector and industry levels. The output from these tests is illustrated in Table 6. It should again be noted that even though single regressions fail to capture the interactions of each individual value driver in relation to other selected independent variables, they are argued to provide illustrative indications of underlying relationships.

To begin with, when examining the beta coefficients for growth in Panel A, it can be concluded that growth has a positive but non-significant (p>,05) relationship with EV/EBITDA on a market level. Furthermore, it can be observed that the relationship differs considerably across different sectors and industries. For example, growth turns out to have a positive and significant (p<,05) relationship with EV/EBITDA in the Health Care Sector[I], the Information Technology Sector[II], and the Telecommunication Services Industry. Meanwhile, a negative and significant (p<,05) relationship with EV/EBITDA can be observed within the Consumer Staples Sector[III]. Thus, it can be concluded that the significance of the relationship between growth and EV/EBITDA on a single regression level is somewhat sporadic across sectors and industries, but that most observations support a positive correlation in line with theoretical assumptions.

To continue, similar observations can be made with regards to profitability as shown in Panel B. On a market level, profitability has a positive and significant (p<,05) relationship with EV/EBITDA, which also turns out to be the case within the Consumer Discretionary Sector[IV], the Consumer Staples Sector[V], the Financials Sector, and the Communication Services Sector[VI]. Meanwhile, profitability has a negative and significant (p<,05) relationship with EV/EBITDA within the Real Estate Sector. In line with findings for growth, it is thus concluded that the significance of the relationship between profitability and EV/EBITDA on a single regression level is somewhat sporadic across sectors and industries, but that most observations support a positive correlation in line with theoretical assumptions.

[I] Including Pharmaceuticals, Biotechnology & Life Sciences Industry

[II] Including Software & Services Industry and Semiconductors & Semiconductor Equipment Industry

[III] Including Household & Personal Products Industry

[IV] Including Consumer Services Industry

[V] Including Household & Personal Products Industry

[VI] Including Media & Entertainment Industry

Table 6. Single Regression Output

		Panel A: MTPL ~ Growth		Panel B: MTPL ~ Profitability		Panel C: MTPL ~ Risk	
Market/Sector/Industry	N	Alpha	Growth	Alpha	Profitability	Alpha	Risk
Market	965	2,223****	0,004	2,212****	0,003**	2,239****	0,002
		(0,018)	(0,003)	(0,022)	(0,001)	(0,143)	(0,070)
Energy Sector	69	1,822****	0,005	1,884****	-0,008	1,512	0,173
		(0,098)	(0,009)	(0,060)	(0,009)	(0,958)	(0,476)
Energy	69	1,822****	0,005	1,884****	-0,008	1,512	0,173
		(0,098)	(0,009)	(0,060)	(0,009)	(0,958)	(0,476)
Materials Sector	61	2,061****	0,005*	2,081****	0,001	2,709****	-0,303
		(0,044)	(0,003)	(0,071)	(0,006)	(0,557)	(0,268)
Materials	61	2,061****	0,005*	2,081****	0,001	2,709****	-0,303
		(0,044)	(0,003)	(0,071)	(0,006)	(0,557)	(0,268)
Industrials Sector	161	2,201****	0,001	2,161****	0,004*	1,963****	0,115
		(0,043)	(0,006)	(0,038)	(0,002)	(0,487)	(0,228)
Capital Goods	104	2,259****	-0,002	2,211****	0,003	1,721****	0,245
		(0,044)	(0,006)	(0,041)	(0,002)	(0,496)	(0,230)
Commercial & Professional Services	25	2,394****	-0,016	2,130****	0,016	1,364	0,450
		(0,105)	(0,021)	(0,115)	(0,011)	(0,847)	(0,423)
Transportation	32	1,926****	0,016	1,932****	0,005	2,971****	-0,465
		(0,106)	(0,017)	(0,183)	(0,012)	(0,858)	(0,406)
Consumer Discretionary Sector	173	2,065****	0,006	1,979****	0,008**	1,966****	0,060
		(0,034)	(0,005)	(0,068)	(0,004)	(0,395)	(0,195)
Automobiles & Components	14	1,603****	0,052	1,347****	0,035	-0,701	1,251****
		(0,240)	(0,051)	(0,347)	(0,025)	(0,672)	(0,304)
Consumer Durables & Apparel	47	2,208****	-0,007	2,277****	-0,010	2,218***	-0,022
		(0,064)	(0,010)	(0,122)	(0,009)	(0,795)	(0,395)
Consumer Services	40	2,308****	-0,012	1,947****	0,020****	2,565***	-0,162
		(0,078)	(0,012)	(0,091)	(0,005)	(1,067)	(0,535)
Retailing	72	1,996****	0,007	1,909****	0,007	2,376****	-0,182
		(0,044)	(0,005)	(0,096)	(0,005)	(0,375)	(0,191)
Consumer Staples Sector	55	2,538****	-0,035***	2,299****	0,011***	1,229***	0,630***
		(0,049)	(0,012)	(0,068)	(0,004)	(0,494)	(0,257)
Food Staples & Retailing	10	2,279****	-0,027	1,755****	0,037*	0,610	0,816***
		(0,091)	(0,017)	(0,269)	(0,020)	(0,725)	(0,356)
Food, Beverage & Tobacco	31	2,585****	-0,026*	2,442****	0,007	1,636****	0,466*
		(0,050)	(0,013)	(0,084)	(0,005)	(0,473)	(0,251)
Household & Personal Products	14	2,554****	-0,035***	2,240****	0,012***	1,094	0,691
		(0,074)	(0,015)	(0,100)	(0,004)	(0,990)	(0,532)
Health Care Sector	130	2,335****	0,013***	2,420****	0,000	0,675**	0,810****
		(0,047)	(0,005)	(0,065)	(0,004)	(0,305)	(0,149)
Health Care Equipment & Services	80	2,316****	0,015*	2,360****	0,007	0,473	0,907****
		(0,075)	(0,009)	(0,111)	(0,009)	(0,380)	(0,193)
Pharmaceuticals, Biotechnology & Life Sciences	50	2,353****	0,011**	2,459****	-0,003	1,020*	0,646***
		(0,056)	(0,005)	(0,074)	(0,004)	(0,556)	(0,255)
Financials Sector	29	2,260****	0,001	1,985****	0,020***	2,416***	-0,073
		(0,067)	(0,018)	(0,142)	(0,008)	(0,999)	(0,475)
Diversified Financials	29	2,260****	0,001	1,985****	0,020***	2,416***	-0,073
		(0,067)	(0,018)	(0,142)	(0,008)	(0,999)	(0,475)
Information Technology Sector	131	2,114****	0,019***	2,220****	0,002	1,373***	0,394
		(0,053)	(0,007)	(0,063)	(0,004)	(0,553)	(0,257)
Software & Services	54	2,360****	0,019**	2,470****	0,003	0,375	0,978***
		(0,088)	(0,010)	(0,078)	(0,004)	(0,702)	(0,318)
Technology Hardware & Equipment	49	2,036****	0,002	2,065****	-0,002	0,841	0,551
		(0,058)	(0,008)	(0,087)	(0,005)	(0,754)	(0,353)
Semiconductors & Semiconductor Equipment	28	1,876****	0,035****	2,183****	-0,008	2,590***	-0,220
		(0,105)	(0,011)	(0,125)	(0,009)	(1,060)	(0,490)
Communication Services Sector	41	2,010****	0,008	1,879****	0,025****	-0,083	1,065****
		(0,080)	(0,010)	(0,070)	(0,006)	(0,521)	(0,267)
Telecommunication Services	8	1,677****	0,095***	1,601****	0,049*	-0,159	1,091
		(0,081)	(0,030)	(0,116)	(0,029)	(1,863)	(1,056)
Media & Entertainment	33	2,101****	0,003	1,955****	0,021***	0,017	1,020***
		(0,090)	(0,011)	(0,084)	(0,007)	(0,665)	(0,331)
Utilities Sector	39	2,299****	0,011	2,258****	0,017	1,239***	0,683***
		(0,072)	(0,016)	(0,091)	(0,020)	(0,470)	(0,295)
Utilities	39	2,299****	0,011	2,258****	0,017	1,239***	0,683***
		(0,072)	(0,016)	(0,091)	(0,020)	(0,470)	(0,295)
Real Estate Sector	76	2,742****	-0,007	2,867****	-0,029***	3,892****	-0,645**
		(0,040)	(0,007)	(0,062)	(0,013)	(0,554)	(0,307)
Real Estate	76	2,742****	-0,007	2,867****	-0,029***	3,892****	-0,645**
		(0,040)	(0,007)	(0,062)	(0,013)	(0,554)	(0,307)

**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

The relationship between risk and EV/EBITDA shown in Panel C, on the other hand, is positive but non-significant (p>,05) on a market level. It is further observed to be positive and significant (p<,05) within the Automobiles & Components Industry and the Consumer Staples Sector[I], amongst others. The only instances of a negative and significant (p<,05) relationship between risk and EV/EBITDA, in line with theoretical assumptions, can be observed within the Materials Sector and the Retailing Industry. However, as outlined in the previous section on descriptive statistics, it is argued that the observed positive relationship between risk and EV/EBITDA is mainly driven by the strong multicollinearity between risk and the other independent variables. As a result, when not controlling for growth and profitability, risk turns out to have a positive impact on EV/EBITDA.

Lastly, and on a more general level for all single regressions in Panel A-C, it can be observed that regression intercepts (alpha) are positive and highly significant (p<,01) in most instances. As outlined in Section 5.3.3, the decision to include a regression intercept stems from that it allows to account for omitted variable bias when predicting observed valuation multiples. Thus, the positive and highly significant intercepts indicate a strong omitted variable bias in the conducted single regressions, indicating that there are potentially numerous omitted value drivers in the models.

6.3.2 Multiple Regression Output

The second step for analyzing the underlying relationships between EV/EBITDA and its theoretically derived value drivers is to conduct multivariate regressions in order to simultaneously control for differences in terms of growth, profitability and risk. As noted in earlier sections, a second regression methodology is here additionally introduced, where relative measures of EV/EBITDA, growth, profitability and risk in relation to selected peer groups for each individual firm is employed. The output from conducted multiple regressions for both the standard and relative regression models is displayed in Table 7 and Table 8.

Standard Regression Model Output

To begin with, in terms of the standard regression output illustrated in Table 7, it can be observed that the direction and significance of beta coefficients for growth, profitability and risk differ in several instances compared to obtained coefficients from single regressions. This result is primarily explained by the fact that relative differences in value drivers are simultaneously controlled for in the multiple regression setting. On

[I] Including Food Staples & Retailing Industry and Food, Beverage & Tobacco Industry market level, it can be concluded that growth and profitability have a positive impact on EV/EBITDA, whereas risk has a negative impact in line with theoretical assumptions. Even though the coefficients for growth and risk do not turn out to be significant on a 5% level, the overall regression on market level is jointly significant (p<,05) as determined by the provided F-statistic of 3,348.

Moreover, as for conducted single regressions, the direction and significance of value drivers included in conducted multiple regressions differs substantially across sectors and industries. For example, growth is found to have a positive and significant (p<,05) impact on EV/EBITDA within the Materials Sector, the Retailing Industry, and the Information Technology Sector[I], but a negative and significant (p<,05) impact within the Consumer Staples Sector[II]. Profitability, on the other hand, is additionally found to have a positive and significant (p<,05) impact on EV/EBITDA within the Consumer Discretionary Sector[III], the Pharmaceuticals, Biotechnology & Life Sciences Industry, the Financials Sector and the Communication Services Sector[IV]. Meanwhile, profitability has a negative and significant relationship (p<,05) within the Pharmaceuticals, Biotechnology & Life Sciences Industry. Lastly, in line with theoretical assumptions, risk turns out to have a negative and significant (p<,05) relationship with EV/EBITDA within the Materials Sector and the Retailing Industry, but results also show that risk has a positive and significant (p<,05) impact within several other sectors and industries, contradicting the theorized direction.

To continue, several sector and industry regressions display significant F-statistics, even though not all coefficients on independent variables included show significance simultaneously. That is, within the Consumer Discretionary Sector[V], the Consumer Staples Sector[VI], the Health Care Sector, the Information Technology Sector[VII], the Communication Services Sector[VIII] and the Real Estate Sector, selected measures for growth, profitability and risk are found to jointly and significantly determine observed EV/EBITDA multiples. These results should however be conservatively viewed, given the fact that there in most cases is a single value driver that drives the joint significance.

[I] Including Semiconductors & Semiconductor Equipment Industry

[II] Including Food, Beverage & Tobacco Industry and Household & Personal Products Industry

[III] Including Consumer Services Industry

[IV] Including Media & Entertainment Industry

[V] Including Consumer Services and Retailing Industry

[VI] Including Food, Beverage & Tobacco Industry

[VII] Including Software & Services Industry and Semiconductors & Semiconductor Equipment Industry

[VIII] Including Media & Entertainment Industry

Table 7. Standard Multivariate Regression Output

							Beta		
Market/Sector/Industry	N	R^2	Adj R^2	SE	F-Stat	Alpha	Growth	Profitability	Risk
Market	965	0,010	0,007	0,437	3,348***	2,369****	0,005*	0.004***	-0,096
						(0,149)	(0,003)	(0,002)	(0,078)
Energy Sector	69	0,023	-0,022	0,510	0,505	1,575	0,004	-0,008	0,134
						(1,019)	(0,010)	(0,008)	(0,526)
Energy	69	0,023	-0,022	0,510	0,505	1,575	0,004	-0,008	0,134
						(1,019)	(0,010)	(0,008)	(0,526)
Materials Sector	61	0,121	0,075	0,291	2,627*	3,240****	0,014****	0,008	-0,636**
						(0,636)	(0,004)	(0,006)	(0,311)
Materials	61	0,121	0,075	0,291	2,627*	3,240****	0,014****	0,008	-0,636**
						(0,636)	(0,004)	(0,006)	(0,311)
Industrials Sector	161	0,015	-0,004	0,319	0,773	2,051	0,001	0,004	0,049
						(1,019)	(0,010)	(0,008)	(0,526)
Capital Goods	104	0,025	-0,004	0,276	0,859	1,784****	-0,002	0,002	0,208
						(0,500)	(0,006)	(0,002)	(0,231)
Commercial & Professional Services	25	0,150	0,028	0,340	1,233	2,192***	-0,023	0,017	0,023
						(0,835)	(0,022)	(0,015)	(0,835)
Transportation	32	0,170	0,081	0,332	1,915	3,122****	0,026	0,018	-0,702
						(0,860)	(0,020)	(0,011)	(0,438)
Consumer Discretionary Sector	173	0,055	0,038	0,401	3,271***	2,198****	0,009*	0,010***	-0,136
						(0,421)	(0,006)	(0,004)	(0,214)
Automobiles & Components	14	0,441	0,273	0,438	2,626	-1,309**	-0,026	-0,018	1,702****
						(0,637)	(0,040)	(0,025)	(0,484)
Consumer Durables & Apparel	47	0,067	0,002	0,352	1,026	1,944***	-0,013	-0,012	0,208
						(0,723)	(0,009)	(0,010)	(0,376)
Consumer Services	40	0,269	0,208	0,354	4,422***	2,063***	-0,006	0,020****	-0,036
						(0,907)	(0,014)	(0,005)	(0,471)
Retailing	72	0,131	0,092	0,361	3,405***	2,745****	0,014**	0,011**	-0,451**
						(0,413)	(0,007)	(0,005)	(0,220)
Consumer Staples Sector	55	0,376	0,339	0,242	10,223****	1,241***	-0,041****	0,008***	0,636***
						(0,378)	(0,008)	(0,003)	(0,210)
Food Staples & Retailing	10	0,703	0,554	0,185	4,731*	0,660	-0,020*	0,020*	0,720***
						(0,415)	(0,011)	(0,012)	(0,245)
Food, Beverage & Tobacco	31	0,321	0,246	0,214	4,256***	1,292***	-0,045****	0,008	0,652***
						(0,427)	(0,010)	(0,005)	(0,238)
Household & Personal Products	14	0,327	0,126	0,293	1,623	1,521	-0,033***	0,009*	0,464
						(0,975)	(0,012)	(0,005)	(0,548)
Health Care Sector	130	0,128	0,107	0,447	6,143****	0,700*	0,004	-0,005	0,807****
						(0,386)	(0,005)	(0,004)	(0,207)
Health Care Equipment & Services	80	0,117	0,083	0,514	3,371***	0,518	0,003	-0,001	0,883***
						(0,620)	(0,010)	(0,011)	(0,359)
Pharmaceuticals, Biotechnology & Life Sciences	50	0,189	0,136	0,327	3,575***	1,065*	0,006	-0,006**	0,641***
						(0,546)	(0,005)	(0,003)	(0,252)
Financials Sector	29	0,196	0,100	0,406	2,038	2,993***	-0,004	0,025***	-0,504
						(1,095)	(0,017)	(0,010)	(0,546)
Diversified Financials	29	0,196	0,100	0,406	2,038	2,993***	-0,004	0,025***	-0,504
						(1,095)	(0,017)	(0,010)	(0,546)
Information Technology Sector	131	0,114	0,093	0,423	5,442***	1,645***	0,021***	0,005	0,184
						(0,550)	(0,007)	(0,004)	(0,264)
Software & Services	54	0,334	0,295	0,262	8,376****	0,602	0,011	0,001	0,828**
						(0,774)	(0,008)	(0,004)	(0,376)
Technology Hardware & Equipment	49	0,073	0,011	0,382	1,175	0,784	-0,001	-0,005	0,603*
						(0,736)	(0,007)	(0,005)	(0,340)
Semiconductors & Semiconductor Equipment	28	0,367	0,288	0,430	4,639***	3,267****	0,041****	0,008	-0,666*
						(0,821)	(0,010)	(0,009)	(0,380)
Communication Services Sector	41	0,501	0,460	0,276	12,362****	-0,361	-0,005	0,020***	1,145****
						(0,430)	(0,007)	(0,008)	(0,217)
Telecommunication Services	8	0,724	0,516	0,217	3,489	2,902**	0,109***	0,025*	-0,747
						(1,387)	(0,037)	(0,013)	(0,763)
Media & Entertainment	33	0,480	0,426	0,282	8,920****	-0,492	-0,007	0,019**	1,217****
						(0,551)	(0,007)	(0,009)	(0,256)
Utilities Sector	39	0,194	0,125	0,171	2,808*	1,117***	0,012	0,012	0,689***
						(0,408)	(0,014)	(0,018)	(0,236)
Utilities	39	0,194	0,125	0,171	2,808*	1,117***	0,012	0,012	0,689***
						(0,408)	(0,014)	(0,018)	(0,236)
Real Estate Sector	76	0,161	0,126	0,251	4,613***	3,687****	-0,007	-0,022*	-0,464
						(0,566)	(0,007)	(0,012)	(0,323)
Real Estate	76	0,161	0,126	0,251	4,613***	3,687****	-0,007	-0,022*	-0,464
						(0,566)	(0,007)	(0,012)	(0,323)

**** $p < 0,01$
*** $p < 0,025$
** $p < 0,05$
* $p < 0,1$

Table 8. Relative Multivariate Regression Output

							Beta		
Market/Sector/Industry	N	R^2	Adj R^2	SE	F-Stat	Alpha	Growth	Profitability	Risk
Market	965	0,011	0,008	0,529	3,673***	0,219****	0,034**	0,020	0,029
						(0,018)	(0,017)	(0,019)	(0,099)
Energy Sector	69	0,051	0,007	0,724	1,166	0,301****	0,025	-0,014	0,876
						(0,085)	(0,106)	(0,032)	(0,856)
Energy	69	0,051	0,007	0,724	1,166	0,301****	0,025	-0,014	0,876
						(0,085)	(0,106)	(0,032)	(0,856)
Materials Sector	61	0,133	0,088	0,323	2,919**	0,070*	0,063****	0,059	-0,856***
						(0,040)	(0,017)	(0,061)	(0,367)
Materials	61	0,133	0,088	0,323	2,919**	0,070*	0,063****	0,059	-0,856***
						(0,040)	(0,017)	(0,061)	(0,367)
Industrials Sector	161	0,019	0,000	0,359	0,988	0,101****	0,008	0,041	0,168
						(0,028)	(0,036)	(0,031)	(0,296)
Capital Goods	104	0,025	-0,004	0,296	0,864	0,072***	-0,006	0,018	0,304
						(0,030)	(0,037)	(0,022)	(0,261)
Commercial & Professional Services	25	0,190	0,074	0,414	1,637	0,078	-0,082	0,230	0,089
						(0,062)	(0,126)	(0,188)	(0,486)
Transportation	32	0,151	0,060	0,400	1,662	0,085	0,092	0,210	-1,076
						(0,053)	(0,099)	(0,152)	(0,845)
Consumer Discretionary Sector	173	0,048	0,031	0,487	2,859**	0,165****	0,046*	0,114*	-0,218
						(0,038)	(0,024)	(0,068)	(0,268)
Automobiles & Components	14	0,297	0,087	0,600	1,411	0,326***	-0,123	-0,290	2,042****
						(0,135)	(0,150)	(0,340)	(0,601)
Consumer Durables & Apparel	47	0,095	0,032	0,453	1,509	0,149**	-0,055	-0,198	0,247
						(0,068)	(0,054)	(0,134)	(0,554)
Consumer Services	40	0,293	0,234	0,425	4,975***	0,079	0,025	0,300****	-0,179
						(0,056)	(0,079)	(0,089)	(0,567)
Retailing	72	0,091	0,051	0,405	2,273*	0,141***	0,034*	0,108	-0,385
						(0,050)	(0,018)	(0,066)	(0,290)
Consumer Staples Sector	55	0,296	0,254	0,277	7,141****	0,090***	-0,116****	0,092**	0,647***
						(0,037)	(0,031)	(0,044)	(0,255)
Food Staples & Retailing	10	0,701	0,552	0,172	4,691*	0,120***	-0,043	0,277**	0,765****
						(0,043)	(0,035)	(0,136)	(0,231)
Food, Beverage & Tobacco	31	0,348	0,275	0,232	4,795***	0,049	-0,136****	0,080	0,820****
						(0,039)	(0,034)	(0,065)	(0,244)
Household & Personal Products	14	0,260	0,038	0,336	1,173	0,081	-0,094*	0,130*	0,477
						(0,076)	(0,053)	(0,071)	(0,662)
Health Care Sector	130	0,251	0,233	0,491	14,057****	0,406****	0,047	-0,079***	1,385****
						(0,045)	(0,047)	(0,034)	(0,253)
Health Care Equipment & Services	80	0,320	0,293	0,530	11,900****	0,572****	0,051	-0,060	1,789****
						(0,058)	(0,095)	(0,078)	(0,390)
Pharmaceuticals, Biotechnology & Life Sciences	50	0,167	0,113	0,431	3,079**	0,148**	0,036	-0,071**	0,808**
						(0,066)	(0,034)	(0,033)	(0,378)
Financials Sector	29	0,247	0,157	0,457	2,735*	0,126	0,019	0,322***	-0,696
						(0,089)	(0,058)	(0,139)	(0,510)
Diversified Financials	29	0,247	0,157	0,457	2,735*	0,126	0,019	0,322***	-0,696
						(0,089)	(0,058)	(0,139)	(0,510)
Information Technology Sector	131	0,166	0,146	0,523	8,405****	0,161****	0,158****	0,044	0,419
						(0,048)	(0,056)	(0,059)	(0,302)
Software & Services	54	0,312	0,271	0,326	7,551****	0,134**	0,049	-0,021	1,294***
						(0,066)	(0,055)	(0,050)	(0,487)
Technology Hardware & Equipment	49	0,096	0,036	0,440	1,598	0,158***	0,006	-0,068	0,748*
						(0,061)	(0,040)	(0,063)	(0,410)
Semiconductors & Semiconductor Equipment	28	0,541	0,484	0,577	9,444****	0,148*	0,336****	0,270*	-0,650
						(0,089)	(0,096)	(0,155)	(0,454)
Communication Services Sector	41	0,449	0,404	0,412	10,040****	0,120**	-0,011	0,162*	1,457****
						(0,054)	(0,051)	(0,083)	(0,409)
Telecommunication Services	8	0,685	0,449	0,303	2,901	0,019	0,150***	0,081	-0,165
						(0,076)	(0,058)	(0,061)	(1,120)
Media & Entertainment	33	0,421	0,361	0,419	7,036***	0,140**	-0,017	0,163*	1,553***
						(0,065)	(0,068)	(0,097)	(0,486)
Utilities Sector	39	0,248	0,184	0,174	3,850***	0,011	0,050	0,095	0,770***
						(0,026)	(0,053)	(0,095)	(0,245)
Utilities	39	0,248	0,184	0,174	3,850***	0,011	0,050	0,095	0,770***
						(0,026)	(0,053)	(0,095)	(0,245)
Real Estate Sector	76	0,150	0,115	0,257	4,239***	0,098***	-0,022	-0,085	-0,416
						(0,031)	(0,021)	(0,058)	(0,268)
Real Estate	76	0,150	0,115	0,257	4,239***	0,098***	-0,022	-0,085	-0,416
						(0,031)	(0,021)	(0,058)	(0,268)

**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

Lastly, strikingly low R-squared statistics can be observed across conducted regressions, especially on market level where the output shows an adjusted R-squared of only 0,7%. This indicates that the included value drivers can only explain 0,7% of variance in EV/EBITDA multiples across firms in the sample. As highlighted in prior studies on the same topic, a low R-squared from conducted regressions is to be expected on an empirical level, as the ultimate value of a firm may depend on a multitude of observable as well as unobservable factors[I]. For example, in his single factor regression analysis, Harbula (2009) obtained an R-squared of 1% for EBITDA margins in explaining EV/EBITDA. However, as for the other test-statistics of interest, results show that R-squared varies significantly across sectors and industries, where for example adjusted R-squared is observed to be 33,9% and 51,6% within the Consumer Staples Sector and the Telecommunication Services Industry respectively. Thus, a part conclusion at this stage is that the employed regression models are better in explaining residuals of EV/EBITDA as the homogeneity of the sample increases, moving from market to sector and industry level.

Relative Regression Model Output

Moving over to the output for the relative regression model presented in Table 8, the fundamental differences between the standard and relative regression model should again be highlighted. As the relative regression model directly utilizes values that are computed relative to a peer group, the output should be interpreted as demonstrating the relationship between relative performance in selected value drivers and a premium or discount in EV/EBITDA. In other words, the output in Table 8 provides evidence of the impact and significance of growth, profitability and risk in determining premiums and discounts of EV/EBITDA relative to a peer group multiple.

As can be observed when comparing the output in Table 7 and Table 8, the direction and significance for coefficients obtained by the relative regression model is similar to results obtained through the standard regression model, with some exceptions. On market level, it can be concluded that growth and profitability have a positive impact on EV/EBITDA in line with theoretical assumptions in both models. However, risk has a positive impact on EV/EBITDA in the relative regression model, which goes against theoretical assumptions. Moreover, while the standard regression model on a market level displays a significant coefficient on profitability and a non-significant coefficient on growth, the opposite can be observed in the output from the relative regression model. However, even though the coefficients for profitability and risk do not turn out to be significant at a 5% level, the overall regression on market level is jointly significant ($p<,05$) as determined

[I] In this regard, unobservable factors concern other potentially confounding factors not included in the conducted study by the resulting F-statistic of 3,673. Thus, it can be concluded that relative measures of growth, profitability and risk jointly have a significant impact on premiums and discounts of EV/EBITDA on market level.

To continue, relative measures of growth exhibit a similar impact on premiums and discounts as absolute measures of growth on the studied multiple. More specifically, a positive and significant (p<,05) relationship is found within the Materials Sector, the Information Technology Sector[I] and the Telecommunication Services Industry. Meanwhile, a negative and significant relationship is observed within the Consumer Staples Sector[II]. The relative measure for profitability, on the other hand, is only found to have a positive and significant (p<,05) relationship within the Consumer Services Industry, the Consumer Staples Sector[III] and the Financials Sector. Thus, only within these sub-samples do greater relative profitability compared to a peer group average warrant higher valuation premiums on a statistically significant level. Lastly, as for the standard regression model, the relative measure of risk only turns out to have a negative and significant (p<,05) impact within the Materials Sector, which contradicts theoretical assumptions.

Moreover, in line with results obtained from the standard regression model, several sector and industry regressions display significant F-statistics for the relative regression model, even though not all variables included show significance simultaneously. That is, within the Materials Sector, the Consumer Discretionary Sector[IV], the Consumer Staples Sector[V], the Health Care Sector, the Information Technology Sector[VI], the Communication Services Sector[VII], the Utilities Sector and the Real Estate Sector, selected relative measures for growth, profitability and risk are found to jointly and significantly determine observed premiums or discounts of observed EV/EBITDA. As for obtained results from the standard regression model in Table 7, these results should however be conservatively viewed, given the that there in most cases is a single value driver that observably drives the joint significance.

Lastly, relative measures of growth, profitability and risk turn out to jointly imply a low R-squared statistic, which is primarily observed on market level, but also in several instances across sectors and industries.

[I] Including Semiconductor & Semiconductor Equipment Industry

[II] Including Food, Beverage & Tobacco Industry

[III] Including Food, Staples and Retailing Industry

[IV] Including Consumer Services Industry

[V] Including Food, Beverage & Tobacco Industry

[VI] Including Software & Services Industry and Semiconductors & Semiconductor Equipment Industry

[VII] Including Media & Entertainment Industry

Specifically, adjusted R-squared turns out to be merely 0,8% on market level. Other examples of low adjusted R-squared include 0,7% for the Energy Sector and 3,1% for the Consumer Discretionary Sector. On the other hand, the applied relative regression model also produces relatively high R-squared statistics within some sectors and industries, including the Consumer Staples Sector, the Communication Services Sector, the Food Staples & Retailing Industry and the Semiconductors & Semiconductor Equipment Industry. Here, the adjusted R-squared turns out to be 25,4%, 40,4%, 55,2% and 44,9% respectively. Moreover, while constituting two different methodologies, it is argued that the fundamental similarities between the standard and relative regression model can explain the comparable results in terms of R-squared. That is, if the predictive power of the fundamental value drivers turns out to be low on market level as well as within certain sectors and industries, relative measures of the same drivers should arguably have similar predictive power in explaining relative measures of the dependent variable. In line with this, findings in Table 8 also indicate that the predictive power of relative measures in explaining premiums and discounts depends on the level of analysis.

6.3.3 Part-Conclusion: Research Question 1

Given the linear as well as multivariate regression results presented in the previous Tables 6-8, conclusions can be made with regards to the underlying relationship between EV/EBITDA and its fundamental value drivers. To conclusively respond to Research Question 1, the underlying relationship between EV/EBITDA and its fundamental value drivers is found to be sporadic across sectors and industries included in the sample, where theoretical assumptions are confirmed in some instances but contradicted in others. A summary of conducted hypothesis testing supporting this conclusion is illustrated in Table 9.

Developed hypotheses are accepted or rejected based on t-statistics with a one-sided significance level of 5%. Table 9 shows that Hypothesis 1 and Hypothesis 2 are confirmed (i.e. the null hypothesis of no significance and non-positive relationship is inversely rejected) in 6 and 9 instances out of the 34 sub-samples respectively. Moreover, Hypothesis 3 is confirmed (i.e. the null hypothesis of no significance and non-negative relationship is inversely rejected) in 2 instances out of the 34 sub-samples. On a general note, instances where Hypotheses 1-3 is accepted is in the minority across the included sectors and industries. This result can partly be explained by the fact that single regressions do not account for relative differences in other independent variables simultaneously, which might produce a distorted picture of the actual impact of the included value drivers. As such, it is firstly concluded that the inability to simultaneously account for relative differences in other performance measures appears to render single regressions unsuitable for the purposes of studying the true relationship between fundamental value drivers and the studied multiple.

Table 9. Hypothesis Testing: Research Question 1

Market/Sector/Industry	Hypothesis 1	Hypothesis 2	Hypothesis 3	Hypothesis 4	Hypothesis 5
Market	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Energy Sector	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Energy	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Materials Sector	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***
Materials	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***
Industrials Sector	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Capital Goods	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Commercial & Professional Services	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Transportation	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Consumer Discretionary Sector	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Automobiles & Components	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Consumer Durables & Apparel	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Consumer Services	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Retailing	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***	*Not Confirmed*
Consumer Staples Sector	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Food Staples & Retailing	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Food, Beverage & Tobacco	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Household & Personal Products	*Not Confirmed*	***Confirmed***	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Health Care Sector	***Confirmed***	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Health Care Equipment & Services	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Pharmaceuticals, Biotechnology & Life Sciences	***Confirmed***	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Financials Sector	*Not Confirmed*	***Confirmed***	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Diversified Financials	*Not Confirmed*	***Confirmed***	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Information Technology Sector	***Confirmed***	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Software & Services	***Confirmed***	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Technology Hardware & Equipment	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Semiconductors & Semiconductor Equipment	***Confirmed***	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***
Communication Services Sector	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Telecommunication Services	***Confirmed***	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*
Media & Entertainment	*Not Confirmed*	***Confirmed***	*Not Confirmed*	***Confirmed***	***Confirmed***
Utilities Sector	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***
Utilities	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	*Not Confirmed*	***Confirmed***
Real Estate Sector	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***	***Confirmed***
Real Estate	*Not Confirmed*	*Not Confirmed*	***Confirmed***	***Confirmed***	***Confirmed***

Research Question: What is the underlying relationship between EV/EBITDA and its fundamental value drivers?
- H1: In isolation, growth has a positive and significant impact on EV/EBITDA
- H2: In isolation, profitability has a positive and significant impact on EV/EBITDA
- H3: In isolation, risk has a negative and significant impact on EV/EBITDA
- H4: In cohesion, when accounting for differences amongst independent variables, growth, profitability and risk jointly have a significant impact on EV/EBITDA
- H5: In cohesion, when accounting for differences amongst independent variables, relative performance in growth, profitability and risk jointly have a significant impact on deviations from a peer group EV/EBITDA multiple

To continue, based on F-statistics with a one-sided significance level of 5%, Hypothesis 4 and Hypothesis 5 are confirmed (i.e. the null hypothesis of no joint significance is inversely rejected) in 16 and 19 instances out of the 34 sub-samples respectively. Thus, based on these results, it is concluded that introducing multivariate regressions appear to produce a picture that is closer in line with theoretical assumptions. In other words, simultaneously controlling for relative differences amongst the included value drivers arguably appears to render a more suitable approach in studying the impact of growth, profitability and risk in relation to EV/EBITDA. However, it is argued that the joint significance is in most cases driven by strong predictive power of a single independent variable, an observation that will be taken into consideration in the final perspectivization of results. On another note, as the relative regression model is observed to produce joint significance in a larger number of instances compared to the standard regression model, it appears that the relative performance in value drivers hold more predictive power than absolute performance. Thus, comparative performance appears to alter the added value that an increase in fundamental value drivers yields. Nonetheless, the difference in the quality of output from the two models is argued to be negligible and does not allow for any general conclusions in this regard.

6.3.4 Post-Hoc Analysis 1

As discovered, it appears that employed regression models are better in explaining residuals of EV/EBITDA as the homogeneity within the sample increases, moving from market to sector and industry level. That is, test-statistics are found to generally be dependent on industry affiliation, which will be further scrutinized in this post-hoc analysis. Moreover, in order to examine other possible explanations for the weak relationships identified between fundamental value drivers and the studied multiple, the potential negative confounding impact of intertemporal differences will also be tested.

Sample Homogeneity

Results indicate that test-statistics generally improve in terms of significance and predictive power when samples employed becomes more homogenous. In order to gain a better understanding of why the developed regression models based on fundamental value drivers fail to produce more instances of significant results, the first post-hoc analysis consequently includes tests for the statistical impact of industry affiliation. This is specifically conducted by introducing an additional sector and industry dummy variable in established regression models. The corresponding output from separately introducing sector and industry dummy variables to the standard regression model on market and sector level is illustrated in Table 10.

Table 10 illustrates how R-squared statistics and F-statistics change as both sector and industry dummies are introduced in the utilized standard regression model. It can firstly be concluded from Table 10, Panel A, that introducing sector or industry dummies significantly increases F-statistics and adjusted R-squared. More specifically, adjusted R-squared increases from 0,7% to 23,6% and 29,3% with sector and industry dummies respectively. Moreover, it can also be concluded that introducing an industry rather than sector dummy results in the highest adjusted R-squared, in line with expectations that greater sample homogeneity results in greater predictive power of independent variables. This conclusion is further supported by the presented results in Panel B that shows output from regressions with introduced industry dummies conducted on sectors containing more than 1 industry. Specifically, results in Panel B demonstrate that most sector regressions generally show an improvement in predictive power as industry dummies are included. Further analysis of the statistical impact on fundamental value drivers of growth, profitability and risk from introducing sector and industry dummies on market and sector level is illustrated in Appendix 5.

Table 10. Dummy Regressions

Panel A: Market Regressions

	Without Dummy	With Sector Dummy	With Industry Dummy
R^2	0,010	0,246	0,311
Adj. R^2	0,007	0,236	0,293
F Stat	3,348***	23,848****	17,639****

Panel B: Sector Regressions

	Consumer Discretionary Sector		*Communication Services Sector*		*Consumer Staples Sector*	
	Without Dummy	With Industry Dummy	Without Dummy	With Industry Dummy	Without Dummy	With Industry Dummy
R^2	0,055	0,157	0,501	0,501	0,376	0,500
Adj. R^2	0,038	0,127	0,460	0,446	0,339	0,449
F Stat	3,271***	5,164****	12,362****	9,046****	10,223****	9,804****

	Health Care Sector		*Information Technology Sector*		*Industrials Sector*	
	Without Dummy	With Industry Dummy	Without Dummy	With Industry Dummy	Without Dummy	With Industry Dummy
R^2	0,128	0,128	0,114	0,343	0,015	0,130
Adj. R^2	0,107	0,100	0,093	0,317	-0,004	0,102
F Stat	6,143****	4,571***	5,442***	13,052****	0,773	4,648****

**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

Evaluating the results in Appendix 5 provides a number of findings. Firstly, it can be observed in Panel A that measures of growth and profitability turn out to be positive and highly significant (p<,025) determinants of EV/EBITDA for the standard regression model when sector dummy variables are introduced. Moreover, Panel B shows that profitability turns out to have a positive and significant (p<,05) impact on EV/EBITDA when industry dummies are introduced as well. Growth, on the other hand, turns out to have a positive but non-significant (p>,05) impact when industry dummies are introduced. Secondly, most sector and industry dummies in Appendix 5 turn out to have a significant (p<,05) impact on EV/EBITDA themselves, which is theorized to drive the results behind the insignificance of growth in Panel B.

Thus, based on these observations it is concluded that both sector and industry affiliation have a profound impact on statistical results in terms of predictive power. In addition, a lack of such control variables is argued to potentially distort the significance of fundamental value drivers in relation to EV/EBITDA in market regressions. However, as also outlined in Section 1.3, even though the introduction of control variables appears to make sense from a statistical standpoint, it is argued to contradict theoretical assumptions and similar studies on the same topic. That is, on the most fundamental level, measures of growth, profitability and risk should have a significant impact on EV/EBITDA multiples regardless of factors such as industry affiliation, which is why no control variables have been introduced in this study. Nevertheless, these observations will be further considered and put into perspective in the final discussion on the obtained results.

Intertemporal differences

Even though not being an explicitly handled topic of this paper, several previous studies within the field have highlighted the confounding impact of intertemporal differences on the relationship between valuation multiples and their respective fundamental value drivers. To partly mitigate for cyclicality and other potential intertemporal differences, measures utilized in this study have been averaged across a three-year time period where applicable. To gain further insights to whether intertemporal differences aid in explaining the relatively weak relationship between fundamental value drivers and the studied multiple, the second post-hoc analysis includes yearly comparisons in terms of multiple regression output, as presented in Table 11.

The results in Table 11 illustrate relatively sporadic test-statistics and relationships between EV/EBITDA multiples and fundamental value drivers of growth, profitability and risk over the studied years. More specifically, a limited number of regressions on market, sector or industry level appear to indicate stable results in the timespan between 2016-2018. For example, within the Consumer Discretionary Sector, measures for the fundamental value drivers of growth, profitability and risk turn out to produce an adjusted R-squared ranging between 0,2% and 22%. Furthermore, the measure of growth appears to have a negative and significant ($p<,05$) impact on EV/EBITDA in 2016, but a positive and highly significant ($p<,025$) impact in 2018. Possible explanations for the significant intertemporal differences could either be the that underlying relationships between EV/EBITDA and its fundamental value drivers simply vary to a great extent on a year-to-year basis. Alternatively, and arguably more likely, measurement issues may distort the obtained results. For example, as CAGR is applied when measuring growth in EBITDA, it could be the case that values for the ending and beginning years in the CAGR equation vary significantly for many firms in the sample. This would consequently produce partly biased estimates as growth would not be effectively captured by the variable. Nevertheless, the results confirm the notion that intertemporal differences may have a confounding impact on the relationship between EV/EBITDA and its fundamental value drivers. This is argued to partly distort results obtained in this study, which will be further discussed in the perspectivization of this paper.

Table 11. Intertemporal Differences in Underlying Data

	Adj. R^2			*F-Statistic*			*Growth*			*Profitability*			*Risk*		
Market/Sector/Industry	2018	2017	2016	2018	2017	2016	2018	2017	2016	2018	2017	2016	2018	2017	2016
Market	0,036	0,011	0,070	12,984****	4,614***	25,056****	0,608***	0,268	-1,136****	0,006****	0,004*	0,001	0,016	0,105	-0,032
Energy Sector	0,078	0,022	0,101	2,923**	1,498	3,534***	1,849***	0,394	-1,674**	0,003	-0,005	0,004	-0,294	0,557	0,874
Energy	0,078	0,022	0,101	2,923**	1,498	3,534***	1,849***	0,394	-1,674**	0,003	-0,005	0,004	-0,294	0,557	0,874
Materials Sector	0,011	0,127	-0,025	1,215	3,898***	0,511	-0,095	1,664**	0,189	-0,003	0,011*	0,004	-0,467	-0,360	-0,094
Materials	0,011	0,127	-0,025	1,215	3,898***	0,511	-0,095	1,664**	0,189	-0,003	0,011*	0,004	-0,467	-0,360	-0,094
Industrials Sector	0,107	0,015	0,055	7,399****	1,825	4,086***	2,544***	-0,922**	-0,994*	0,010****	0,000	0,002	0,032	0,211	-0,047
Capital Goods	0,103	0,037	0,012	4,954***	2,337*	1,405	1,894***	-0,967***	-0,677	0,007***	0,002	0,002	0,384	0,289	0,069
Commercial & Professional Services	0,237	0,113	0,181	3,482**	2,014	2,770*	9,110**	-3,643*	-3,286****	0,025***	0,023	0,008	-0,736	0,022	-0,063
Transportation	0,281	-0,065	0,158	5,029***	0,370	2,932*	6,343***	-0,665	-1,127	0,036****	0,002	0,002	-0,941***	-0,332	-0,598*
Consumer Discretionary Sector	0,224	0,014	0,022	17,522****	1,794	2,271*	1,808***	0,589	-0,766**	0,017****	0,006	0,002	-0,166	-0,258	0,319
Automobiles & Components	0,332	0,361	0,263	3,156*	3,451*	2,549	1,467	-5,992	-2,941***	0,020	0,007	-0,016	0,868	1,395***	1,654****
Consumer Durables & Apparel	0,017	0,000	0,243	1,272	1,000	5,930***	0,778**	0,699	-2,161****	-0,004	0,001	-0,004	0,098	-0,637	0,768
Consumer Services	0,452	0,049	0,229	11,715****	1,664	4,853***	6,534***	-1,321	-1,065	0,017****	0,010	0,023****	-1,127**	-0,015	0,196
Retailing	0,347	0,017	0,023	13,589****	1,404	1,558	2,635***	0,174	0,905**	0,020****	0,007*	0,003	-0,596***	-0,330	-0,232
Consumer Staples Sector	0,200	0,348	0,111	5,495***	10,596****	3,237**	-3,201*	-3,484****	-1,430**	0,008**	0,007**	0,004*	0,683***	0,709***	0,182
Food Staples & Retailing	0,369	0,430	0,065	2,754	3,267	1,210	-4,681	-2,255***	0,377	0,031	0,009	0,007	1,005*	0,410	0,345***
Food, Beverage & Tobacco	0,034	0,279	0,002	1,353	4,867***	1,022	-1,776	-3,481***	-0,865	0,009	0,006	0,003	0,235	1,038***	0,263
Household & Personal Products	0,124	0,329	0,126	1,613	3,123*	1,625	-0,547	-4,310****	-2,907***	0,012	0,005	0,007*	0,832	0,695	-0,445
Health Care Sector	0,248	0,120	0,351	15,182****	6,844****	24,254****	0,359	0,183	-2,354***	-0,002*	0,005	-0,007**	1,099****	0,823***	1,148****
Health Care Equipment & Services	0,384	0,195	0,520	17,382****	7,374****	29,511****	1,628	0,129	-3,174****	0,000	0,013	0,000	1,061****	0,901***	1,200****
Pharmaceuticals, Biotechnology & Life Sciences	0,065	0,011	0,070	2,128	1,187	2,234*	0,026	0,069	-0,626	-0,001	-0,003	-0,007**	0,783***	0,677*	0,706***
Financials Sector	0,030	0,134	0,069	1,285	2,443*	1,690	0,842	-0,486	-1,592	0,015	0,022***	0,008	0,017	0,160	-1,049
Diversified Financials	0,030	0,134	0,069	1,285	2,443*	1,690	0,842	-0,486	-1,592	0,015	0,022***	0,008	0,017	0,160	-1,049
Information Technology Sector	0,105	0,123	0,012	6,087****	7,055****	1,547	0,203	0,944	-0,822	0,001	0,001	0,004	0,807***	0,824***	-0,097
Software & Services	0,476	0,221	0,090	17,048****	6,017***	2,743*	2,783***	0,420	-0,333	0,003	-0,001	0,002	0,977***	1,001***	0,645*
Technology Hardware & Equipment	0,118	0,168	0,050	3,133**	4,223***	1,850	-0,001	-0,693	-1,438*	0,000	-0,006*	-0,004	0,906***	1,293***	0,034
Semiconductors & Semiconductor Equipment	-0,004	0,241	-0,044	0,963	3,864***	0,617	1,052*	2,259**	-1,184	-0,001	0,016*	-0,009	0,631	0,212	-0,739
Communication Services Sector	0,485	0,401	0,351	13,541****	9,910****	8,198****	-0,246	-1,167	-0,945***	0,011	0,021***	0,007	1,155****	1,492****	1,176****
Telecommunication Services	0,942	0,146	0,116	38,898****	1,399	1,306	8,654****	8,584**	-5,403*	0,009	-0,004	0,034	-0,211	0,004	1,668
Media & Entertainment	0,387	0,417	0,319	7,724****	8,628****	5,990***	-0,437	-1,214	-0,961***	0,009	0,026***	0,004	1,188****	1,638****	1,121***
Utilities Sector	0,165	0,109	0,085	3,503**	2,554*	2,176	3,074***	-0,142	0,725	0,007	0,013	-0,005	0,599*	0,747***	0,693***
Utilities	0,165	0,109	0,085	3,503**	2,554*	2,176	3,074***	-0,142	0,725	0,007	0,013	-0,005	0,599*	0,747***	0,693***
Real Estate Sector	0,140	0,111	0,224	5,077***	4,124***	8,213****	2,679***	-1,585	-1,384***	-0,007	-0,025	-0,010	-0,641*	-0,209	-0,817***
Real Estate	0,140	0,111	0,224	5,077***	4,124***	8,213****	2,679***	-1,585	-1,384***	-0,007	-0,025	-0,010	-0,641*	-0,209	-0,817***

**** $p < 0,01$
*** $p < 0,025$
** $p < 0,05$
* $p < 0,1$

6.4 Model Prediction Accuracy: Research Question 2

6.4.1 Model Prediction Accuracy Test 1

The second and ultimate research question for the conducted study concerns the valuation accuracy of predicted multiples derived from utilizing a regression methodology based on fundamental value drivers. The first step in this regard is to compute predicted multiples by utilizing the regression output produced in the previous section. The equations utilized in order to derive predicted multiples are illustrated in Appendix 6 for both the standard and relative regression approaches. The second step is subsequently to test for the statistical significance of predicted multiples in determining observed EV/EBITDA multiples for each individual firm in order to assess their absolute prediction accuracy. The output for this first multiple accuracy test is presented in Table 12.

To begin with, it can be observed in Table 12, Panel A, that predicted multiples turn out to be significant ($p<,05$) in determining observed EV/EBITDA multiples in most of the studied sub-samples with few exceptions[I]. The same instances of significant predictions can be observed in Panel B that shows output for the relative regression methodology. In other words, instances where predicted multiples turn out to be significant predictors of observed EV/EBITDA multiples are the same regardless whether multiples are constructed through a standard or relative regression methodology.

To continue, several observations can be made with regards to R-squared statistics for both regression models. Firstly, even though predicted multiples turn out to be significant predictors of observed multiples on market level and within most sectors and industry groups, R-squared statistics for both models are relatively low across sub-samples. However, as also discovered in relation to the first research question of this paper, adjusted R-squared generally improves as the utilized sample becomes more homogenous. For example, predicted EV/EBITDA multiples have an adjusted R-squared statistic of 0,9% and 0,5% for the standard and relative regression model on market level respectively. Meanwhile, adjusted R-squared turns out to be 39,5% and 38,5% for the standard and relative model within the Automobiles & Components Industry respectively. Secondly, R-squared appears to vary significantly across different sectors and industries. For example, the Energy Sector shows an adjusted R-squared of 0,8% whereas the Communication Services Sector shows an adjusted R-squared of 48,8% for the standard regression model.

[I] Including the Energy Sector, the Industrials Sector, the Consumer Durables & Apparel Industry as well as the Technology Hardware & Equipment Industry

Table 12. Model Prediction Accuracy Test 1

		Panel A: Standard Regression						**Panel B: Relative Regression**					
Market/Sector/Industry	N	R^2	Adj R^2	SE	F-Stat	Alpha	LN.MTPL	R^2	Adj R^2	SE	F-Stat	Alpha	LN.MTPL
Market	965	0,010	0,009	0,437	10,045***	-0,126	1,058***	0,006	0,005	0,438	5,746***	0,514	0,741**
						(0,842)	(0,376)					(0,866)	(0,372)
Energy Sector	69	0,023	0,008	0,502	1,560	0,060	0,969	0,012	-0,003	0,505	0,805	0,930	0,472
						(1,587)	(0,848)					(1,119)	(0,571)
Energy	69	0,023	0,008	0,502	1,560	0,060	0,969	0,012	-0,003	0,505	0,805	0,930	0,472
						(1,587)	(0,848)					(1,119)	(0,571)
Materials Sector	61	0,121	0,106	0,286	8,152****	-0,009	1,003***	0,135	0,121	0,284	9,230***	0,006	0,978***
						(0,732)	(0,352)					(0,665)	(0,316)
Materials	61	0,121	0,106	0,286	8,152****	-0,009	1,003***	0,135	0,121	0,284	9,230***	0,006	0,978***
						(0,732)	(0,352)					(0,665)	(0,316)
Industrials Sector	161	0,015	0,008	0,317	2,344	0,137	0,937	0,015	0,009	0,317	2,463	0,194	0,892
						(0,587)	(1,300)					(1,429)	(0,632)
Capital Goods	104	0,025	0,015	0,273	2,613	-0,203	1,093	0,027	0,017	0,273	2,789*	-0,090	1,024
						(1,593)	(0,708)					(1,530)	(0,668)
Commercial & Professional Services	25	0,150	0,113	0,325	4,051*	-0,003	1,003	0,144	0,106	0,326	3,860**	0,315	0,846
						(1,487)	(0,656)					(1,245)	(0,539)
Transportation	32	0,170	0,143	0,320	6,154***	-0,001	1,000*	0,108	0,078	0,332	3,636*	0,337	0,811
						(1,052)	(0,533)					(1,134)	(0,561)
Consumer Discretionary Sector	173	0,055	0,049	0,399	9,919***	0,008	0,996***	0,049	0,043	0,400	8,777***	-0,042	0,983***
						(0,785)	(0,373)					(0,854)	(0,393)
Automobiles & Components	14	0,441	0,394	0,400	9,454***	-0,003	1,004****	0,432	0,385	0,403	9,122***	-0,462	1,208****
						(0,389)	(0,195)					(0,453)	(0,231)
Consumer Durables & Apparel	47	0,067	0,046	0,344	3,220*	0,003	0,999	0,051	0,030	0,347	2,403	0,816	0,608
						(1,544)	(0,716)					(1,154)	(0,522)
Consumer Services	40	0,269	0,250	0,345	14,002****	0,001	0,998****	0,258	0,238	0,348	13,181****	-0,094	1,016****
						(0,583)	(0,256)					(0,536)	(0,232)
Retailing	72	0,131	0,118	0,356	10,507***	0,031	0,982***	0,104	0,091	0,361	8,145***	-0,225	1,079***
						(0,720)	(0,350)					(0,947)	(0,452)
Consumer Staples Sector	55	0,375	0,364	0,237	31,867****	0,015	0,995****	0,386	0,374	0,235	33,290****	0,121	0,940****
						(0,347)	(0,146)					(0,243)	(0,103)
Food Staples & Retailing	10	0,703	0,666	0,161	18,920***	-0,020	1,011****	0,731	0,697	0,153	21,695***	0,173	1,075****
						(0,478)	(0,217)					(0,581)	(0,259)
Food, Beverage & Tobacco	31	0,321	0,297	0,206	13,704****	-0,003	1,003****	0,305	0,281	0,209	12,724***	0,182	0,921****
						(0,562)	(0,223)					(0,625)	(0,246)
Household & Personal Products	14	0,327	0,271	0,268	5,840**	0,048	0,977****	0,337	0,281	0,266	6,091**	-0,300	1,109****
						(0,545)	(0,224)					(0,603)	(0,248)
Health Care Sector	130	0,128	0,121	0,443	18,718****	0,003	1,000****	0,123	0,117	0,444	18,013****	0,481	0,780****
						(0,435)	(0,188)					(0,355)	(0,151)
Health Care Equipment & Services	80	0,117	0,106	0,508	10,374***	0,025	0,987****	0,113	0,102	0,509	9,939***	0,566	0,744****
						(0,433)	(0,206)					(0,385)	(0,170)
Pharmaceuticals, Biotechnology & Life Sciences	50	0,189	0,172	0,320	11,187***	0,008	0,996****	0,175	0,158	0,323	10,215***	0,372	0,829****
						(0,679)	(0,281)					(0,586)	(0,238)
Financials Sector	29	0,196	0,167	0,390	6,601***	-0,021	1,010***	0,214	0,185	0,386	7,348***	-0,119	1,023***
						(0,933)	(0,404)					(0,888)	(0,375)
Diversified Financials	29	0,196	0,167	0,390	6,601***	-0,021	1,010***	0,214	0,185	0,386	7,348***	-0,119	1,023***
						(0,933)	(0,404)					(0,888)	(0,375)
Information Technology Sector	131	0,114	0,107	0,419	16,578****	0,046	0,976****	0,107	0,100	0,421	15,417****	0,465	0,766****
						(0,611)	(0,276)					(0,484)	(0,213)
Software & Services	54	0,334	0,322	0,257	26,131****	-0,019	1,009****	0,308	0,294	0,262	23,094****	0,525	0,781****
						(0,722)	(0,285)					(0,658)	(0,256)
Technology Hardware & Equipment	49	0,072	0,053	0,374	3,673*	0,025	0,988*	0,060	0,040	0,377	3,002*	0,387	0,786
						(1,146)	(0,571)					(1,082)	(0,523)
Semiconductors & Semiconductor Equipment	28	0,367	0,343	0,413	15,072****	-0,009	1,008****	0,300	0,273	0,435	11,137***	0,614	0,689***
						(0,551)	(0,260)					(0,527)	(0,247)
Communication Services Sector	41	0,500	0,488	0,269	39,062****	-0,002	1,001****	0,487	0,474	0,273	37,091****	0,227	0,877****
						(0,418)	(0,209)					(0,349)	(0,170)
Telecommunication Services	8	0,724	0,677	0,177	15,701***	0,010	0,993****	0,558	0,484	0,224	7,577**	0,453	0,751***
						(0,473)	(0,266)					(0,581)	(0,315)
Media & Entertainment	33	0,480	0,463	0,272	28,601****	-0,009	1,006****	0,476	0,459	0,273	28,150****	0,169	0,906****
						(0,508)	(0,248)					(0,413)	(0,198)
Utilities Sector	39	0,194	0,172	0,166	8,905***	-0,005	1,003***	0,185	0,163	0,167	8,380***	0,317	0,860***
						(0,771)	(0,331)					(0,723)	(0,308)
Utilities	39	0,194	0,172	0,166	8,905***	-0,005	1,003***	0,187	0,165	0,167	8,518***	0,374	0,883***
						(0,771)	(0,331)					(0,677)	(0,305)
Real Estate Sector	76	0,161	0,150	0,248	14,222****	0,041	0,986***	0,201	0,190	0,242	18,597****	-0,465	1,158****
						(0,911)	(0,334)					(0,902)	(0,327)
Real Estate	76	0,161	0,150	0,248	14,222****	0,041	0,986***	0,201	0,190	0,242	18,597****	-0,465	1,158****
						(0,911)	(0,334)					(0,902)	(0,327)

**** $p < 0,01$
*** $p < 0,025$
** $p < 0,05$
* $p < 0,1$

Lastly, R-squared statistics across utilized samples appear to be potentially correlated with sample size. Examples supporting this observation include the Automobiles & Components Industry, the Food Staples & Retailing Industry and the Telecommunication Services Industry. These industries are associated with sample sizes of 14, 10, and 8 firms respectively. The corresponding adjusted R-squared within these relatively small samples ranges from 39,4% to 67% for the standard regression model and 38,5% to 69,7% for the relative regression model. Generally, for regression analyses, along with other conditions for normality, R-squared becomes less biased as sample size increases (Stock & Watson, 2012). Thus, the relatively high R-squared statistic observed for industries with small sample sizes should be viewed conservatively.

6.4.2 Model Prediction Accuracy Test 2

In line with prior landmark studies on the same topic, the second part for accuracy testing in this study includes the computation of scaled prediction errors for the standard and relative regression model, as outlined in Equation 32. In turn, the computed prediction errors for each model are compared against each other as well as benchmarked against estimates obtained from simple peer group averages. In essence, the computed prediction errors will indicate how accurate each model is in determining observed EV/EBITDA multiples, but also determine accuracy in relation to commonly applied peer group multiples. Thus, the second part of accuracy testing will more clearly indicate whether the application of a regression methodology is feasible and suitable in predicting EV/EBITDA multiples, where prediction errors closer to zero signifies greater accuracy. As outlined in Section 5.4.3, the computed prediction errors will be utilized to derive measures of bias in terms of average under or overvaluation, mean absolute deviation (MAD) as well as mean squared prediction errors (MSE). The results of prediction error bias, MAD and MSE for multiples derived based on standard and relative regression methodologies as well as for multiples based on simple peer group averages are illustrated in Table 13.

First of all, several observations can be made with regards to prediction error bias. As can be observed in Table 13, simple peer group averages in Panel C are fully unbiased predictions of observed multiples on market, sector and industry level. That is, prediction errors of simple peer group averages do not contain inherent bias for over- or undervalued predictions of EV/EBITDA. This first observation can simply be explained by the fact that simple peer group multiples are naturally unbiased as they are based on a sample average. For the utilized standard and relative regression models in Panel A and B, on the other hand, both models appear to contain upward bias in prediction errors on all levels of analysis. Moreover, except for within the Energy Sector and the Food, Beverage & Tobacco Industry, the relative regression model appears to contain higher upward bias than the standard regression model in all instances.

To continue, as can be observed through the highlighted areas in Panel A and B, prediction errors from both utilized regression models outperform simple peer group averages in several instances. Even though simple peer group averages outperform both models on market level in terms of MAD and MSE, the standard regression model outperforms in 21 sub-samples in terms of both MAD and MSE. Thus, in 21 instances out of a total of 34, corresponding to 61,7% of all conducted regressions, the developed standard regression model produces smaller prediction errors in determining true EV/EBITDA than utilizing simple peer group averages. The relative regression model, while in fewer instances than the standard regression model, outperforms simple peer group averages in 53% of instances in terms of MAD and 44% of instances in terms of MSE. An overview and ranking of average accuracy performance of the utilized regressions and simple peer group model are presented in Table 14.

Table 13. Model Prediction Accuracy Test 2

		Panel A: Standard Regression			**Panel B: Relative Regression**			**Panel C: Simple Peer Group**		
Market/Sector/Industry	N	Bias	MAD	MSE	Bias	MAD	MSE	Bias	MAD	MSE
Market	965	0,117	0,384	0,951	0,228	0,429	1,263	0,000	0,362	0,811
Energy Sector	69	0,151	0,410	0,797	0,133	0,416	0,912	0,000	0,358	0,597
Energy	69	0,151	0,410	0,797	0,133	0,416	0,912	0,000	0,358	0,597
Materials Sector	61	0,043	0,234	0,090	0,082	0,243	0,102	0,000	0,246	0,089
Materials	61	0,043	0,234	0,090	0,082	0,243	0,102	0,000	0,246	0,089
Industrials Sector	161	0,053	0,259	0,121	0,104	0,274	0,141	0,000	0,253	0,109
Capital Goods	104	0,032	0,228	0,080	0,075	0,238	0,091	0,000	0,226	0,077
Commercial & Professional Services	25	0,046	0,261	0,108	0,103	0,288	0,137	0,000	0,252	0,099
Transportation	32	0,051	0,287	0,121	0,108	0,311	0,151	0,000	0,273	0,120
Consumer Discretionary Sector	173	0,082	0,328	0,211	0,171	0,362	0,274	0,000	0,325	0,194
Automobiles & Components	14	0,058	0,278	0,119	0,161	0,340	0,196	0,000	0,417	0,256
Consumer Durables & Apparel	47	0,054	0,264	0,111	0,121	0,303	0,149	0,000	0,250	0,094
Consumer Services	40	0,060	0,272	0,126	0,121	0,292	0,171	0,000	0,305	0,157
Retailing	72	0,069	0,302	0,148	0,134	0,332	0,192	0,000	0,319	0,162
Consumer Staples Sector	55	0,024	0,190	0,058	0,054	0,193	0,063	0,000	0,236	0,102
Food Staples & Retailing	10	0,007	0,137	0,021	0,020	0,133	0,021	0,000	0,212	0,099
Food, Beverage & Tobacco	31	0,108	0,155	0,042	0,041	0,158	0,046	0,000	0,186	0,056
Household & Personal Products	14	0,037	0,206	0,062	0,064	0,211	0,070	0,000	0,262	0,092
Health Care Sector	130	0,287	0,507	9,585	0,388	0,556	11,795	0,000	0,470	4,574
Health Care Equipment & Services	80	0,446	0,671	15,327	0,569	0,745	19,583	0,000	0,603	6,022
Pharmaceuticals, Biotechnology & Life Sciences	50	0,050	0,248	0,094	0,103	0,273	0,116	0,000	0,260	0,097
Financials Sector	29	0,074	0,332	0,192	0,147	0,340	0,240	0,000	0,347	0,240
Diversified Financials	29	0,074	0,332	0,192	0,147	0,340	0,240	0,000	0,347	0,240
Information Technology Sector	131	0,109	0,355	0,348	0,194	0,385	0,452	0,000	0,345	0,261
Software & Services	54	0,026	0,184	0,056	0,062	0,200	0,067	0,000	0,237	0,091
Technology Hardware & Equipment	49	0,075	0,299	0,225	0,149	0,334	0,287	0,000	0,286	0,173
Semiconductors & Semiconductor Equipment	28	0,079	0,346	0,241	0,162	0,405	0,339	0,000	0,380	0,318
Communication Services Sector	41	0,034	0,200	0,069	0,070	0,220	0,087	0,000	0,275	0,118
Telecommunication Services	8	0,015	0,134	0,024	0,027	0,172	0,040	0,000	0,183	0,062
Media & Entertainment	33	0,030	0,200	0,068	0,071	0,216	0,087	0,000	0,266	0,120
Utilities Sector	39	0,011	0,127	0,029	0,026	0,130	0,031	0,000	0,140	0,032
Utilities	39	0,011	0,127	0,029	0,026	0,130	0,031	0,000	0,140	0,032
Real Estate Sector	76	0,028	0,208	0,070	0,060	0,209	0,073	0,000	0,226	0,087
Real Estate	76	0,028	0,208	0,070	0,060	0,209	0,073	0,000	0,226	0,087

Shaded areas highlight sub-samples in which the predictions from a developed model outperforms predictions drawn from the Simple Peer Group approach.

As can be observed in Table 14, Panel A, models based on industry and sector levels generally appear to outperform models utilizing a full market sample. As for mean absolute deviations in predictions, for example, industry regressions[I] rank highest in terms of producing the most accurate predictions, whereas market models rank in the bottom for all three models. What can furthermore be observed in Table 14 is that simple peer

[I] As can be observed in Table 14, the Standard Market Model using industry as control variable is also considered for comparative purposes, even though the model is not a main part of the conducted research group averages in general appear to perform better in relative terms compared to utilized regression models, where they outperform standard and relative regression models on market, sector and industry level in terms of MSE. However, as highlighted in Section 5.4.3, as the measure of MSE assigns a stronger penalty for the existence of outliers amongst prediction errors, the outperformance of peer group averages in this regard is not surprising. Nevertheless, the tests for whether relative accuracy between the regression methodologies and predictions based on simple peer group averages statistically and significantly differs are outlined in Table 15.

Table 14. Ranking of Model Predictions

Panel A: Ranking

Bias	MAD	MSE
Simple Peer Group Model (Market)	*Standard Industry Model*	*Simple Peer Group Model (Industry)*
Simple Peer Group Model (Sector)	*Simple Peer Group Model (Industry)*	*Simple Peer Group Model (Sector)*
Simple Peer Group Model (Industry)	*Standard Market Model (Industry Dummy)*	*Simple Peer Group Model (Market)*
Standard Sector Model	*Simple Peer Group Model (Sector)*	*Standard Market Model*
Standard Industry Model	*Relative Industry Model*	*Standard Market Model (Industry Dummy)*
Standard Market Model (Industry Dummy)	*Relative Sector Model*	*Relative Market Model*
Standard Market Model	*Standard Sector Model*	*Standard Industry Model*
Relative Industry Model	*Simple Peer Group Model (Market)*	*Standard Sector Model*
Relative Sector Model	*Standard Market Model*	*Relative Sector Model*
Relative Market Model	*Relative Market Model*	*Relative Industry Model*

Panel B: Figures

Predictive Model	Bias	MAD	MSE
Standard Market Model	0,117	0,384	0,951
Relative Market Model	0,228	0,429	1,263
Simple Peer Group Model (Market)	0,000	0,362	0,811
Standard Market Model (Industry Dummy)	0,091	0,308	1,178
Standard Sector Model	0,052	0,347	1,509
Relative Sector Model	0,158	0,335	1,816
Simple Peer Group Model (Sector)	0,000	0,311	0,779
Standard Industry Model	0,085	0,288	1,416
Relative Industry Model	0,148	0,317	1,824
Simple Peer Group Model (Industry)	0,000	0,295	0,642

Given the results in Table 15, it can be concluded that even though the utilized regression methodologies outperform prediction accuracy compared to simple peer group averages in most individual cases, the difference in prediction errors for MAD and MSE turn out to be statistically insignificant (p>,05) in general based on t-statistics. Put differently, it appears that utilizing a regression methodology offers promising results in terms of valuation accuracy, but that it does not produce estimates that are significantly better than simple peer group averages based on harmonic means. It is likely that the inability to generate significant results regarding this matter is partly driven by the way in which prediction errors are defined. That is, scaling the observed difference between actual market multiples and predicted multiples to a peer group average centers computed errors closely around zero, which makes the absolute difference between the models quite small. As such, it may have been possible to draw statistical conclusions regarding the relative accuracy of the different models if errors had not been scaled, yet this approach would not carry the same theoretical and empirical support as the adopted definition.

Table 15. Comparing Model Prediction Accuracy

		Panel A: Standard Regression vs Simple Peer Group				Panel B: Relative Regression vs Simple Peer Group			
		MAD		*MSE*		*MAD*		*MSE*	
Market/Sector/Industry	N	Direction	p-value	Direction	p-value	Direction	p-value	Direction	p-value
Market	965	*Worse than SPG*	0,582	*Worse than SPG*	0,866	*Worse than SPG*	0,118	*Worse than SPG*	0,648
Energy Sector	69	*Worse than SPG*	0,686	*Worse than SPG*	0,793	*Worse than SPG*	0,664	*Worse than SPG*	0,716
Energy	69	*Worse than SPG*	0,686	*Worse than SPG*	0,793	*Worse than SPG*	0,664	*Worse than SPG*	0,716
Materials Sector	61	*Better than SPG*	0,709	*Worse than SPG*	0,950	*Better than SPG*	0,920	*Worse than SPG*	0,625
Materials	61	*Better than SPG*	0,709	*Worse than SPG*	0,950	*Better than SPG*	0,920	*Worse than SPG*	0,625
Industrials Sector	161	*Worse than SPG*	0,802	*Worse than SPG*	0,656	*Worse than SPG*	0,417	*Worse than SPG*	0,300
Capital Goods	104	*Worse than SPG*	0,961	*Worse than SPG*	0,867	*Worse than SPG*	0,643	*Worse than SPG*	0,435
Commercial & Professional Services	25	*Worse than SPG*	0,873	*Worse than SPG*	0,815	*Worse than SPG*	0,565	*Worse than SPG*	0,425
Transportation	32	*Worse than SPG*	0,791	*Worse than SPG*	0,980	*Worse than SPG*	0,508	*Worse than SPG*	0,550
Consumer Discretionary Sector	173	*Worse than SPG*	0,948	*Worse than SPG*	0,748	*Worse than SPG*	0,318	*Worse than SPG*	0,201
Automobiles & Components	14	*Better than SPG*	0,168	*Better than SPG*	0,151	*Better than SPG*	0,498	*Better than SPG*	0,619
Consumer Durables & Apparel	47	*Worse than SPG*	0,729	*Worse than SPG*	0,592	*Worse than SPG*	0,234	*Worse than SPG*	0,209
Consumer Services	40	*Better than SPG*	0,542	*Better than SPG*	0,518	*Better than SPG*	0,829	*Worse than SPG*	0,836
Retailing	72	*Better than SPG*	0,664	*Better than SPG*	0,772	*Worse than SPG*	0,782	*Worse than SPG*	0,608
Consumer Staples Sector	55	*Better than SPG*	0,191	*Better than SPG*	0,264	*Better than SPG*	0,235	*Better than SPG*	0,333
Food Staples & Retailing	10	*Better than SPG*	0,369	*Better than SPG*	0,305	*Better than SPG*	0,345	*Better than SPG*	0,305
Food, Beverage & Tobacco	31	*Better than SPG*	0,395	*Better than SPG*	0,404	*Better than SPG*	0,464	*Better than SPG*	0,593
Household & Personal Products	14	*Better than SPG*	0,337	*Better than SPG*	0,414	*Better than SPG*	0,416	*Better than SPG*	0,589
Health Care Sector	130	*Worse than SPG*	0,908	*Worse than SPG*	0,633	*Worse than SPG*	0,805	*Worse than SPG*	0,564
Health Care Equipment & Services	80	*Worse than SPG*	0,894	*Worse than SPG*	0,570	*Worse than SPG*	0,800	*Worse than SPG*	0,506
Pharmaceuticals, Biotechnology & Life Sciences	50	*Better than SPG*	0,731	*Better than SPG*	0,896	*Worse than SPG*	0,751	*Worse than SPG*	0,459
Financials Sector	29	*Better than SPG*	0,856	*Better than SPG*	0,733	*Better than SPG*	0,933	*Better than SPG*	1,000
Diversified Financials	29	*Better than SPG*	0,856	*Better than SPG*	0,733	*Better than SPG*	0,933	*Better than SPG*	1,000
Information Technology Sector	131	*Worse than SPG*	0,847	*Worse than SPG*	0,523	*Worse than SPG*	0,494	*Worse than SPG*	0,262
Software & Services	54	*Better than SPG*	0,109	*Better than SPG*	0,150	*Better than SPG*	0,290	*Better than SPG*	0,341
Technology Hardware & Equipment	49	*Worse than SPG*	0,853	*Worse than SPG*	0,672	*Worse than SPG*	0,521	*Worse than SPG*	0,457
Semiconductors & Semiconductor Equipment	28	*Better than SPG*	0,746	*Better than SPG*	0,693	*Worse than SPG*	0,831	*Worse than SPG*	0,923
Communication Services Sector	41	*Better than SPG*	0,077	*Better than SPG*	0,097	*Better than SPG*	0,217	*Better than SPG*	0,394
Telecommunication Services	8	*Better than SPG*	0,499	*Better than SPG*	0,302	*Better than SPG*	0,886	*Better than SPG*	0,569
Media & Entertainment	33	*Better than SPG*	0,189	*Better than SPG*	0,167	*Better than SPG*	0,350	*Better than SPG*	0,467
Utilities Sector	39	*Better than SPG*	0,635	*Better than SPG*	0,770	*Better than SPG*	0,714	*Better than SPG*	0,935
Utilities	39	*Better than SPG*	0,635	*Better than SPG*	0,770	*Better than SPG*	0,714	*Better than SPG*	0,935
Real Estate Sector	76	*Better than SPG*	0,540	*Better than SPG*	0,502	*Better than SPG*	0,561	*Better than SPG*	0,608
Real Estate	76	*Better than SPG*	0,540	*Better than SPG*	0,502	*Better than SPG*	0,561	*Better than SPG*	0,608

Shaded areas highlight sub-samples in which the predictions from a developed model outperforms predictions drawn from the Simple Peer Group approach.

6.4.3 Part-Conclusion: Research Question 2

Given the results illustrated in Table 12-13, conclusions can be made with regards to the accuracy of fundamentally derived predictions. To conclusively respond to Research Question 2, a regression approach based on fundamental value drivers provides significant prediction estimates of actual market multiples, but do not significantly outperform estimates based on simple peer group averages. A summary of conducted hypothesis testing supporting this conclusion is illustrated in Table 16.

Developed hypotheses are accepted or rejected based on t-statistics with a one-sided significance level of 5%. Table 16 shows that Hypothesis 6 and Hypothesis 7 are confirmed (i.e. the null hypothesis of no significance and non-positive relationship is inversely rejected) in 26 and 0 instances out of the 34 sub-samples respectively for both the standard as well as relative regression models. Hence, it is concluded that predicted multiples derived from a regression methodology are found to be significant determinants of observed multiples in a majority of cases. However, even though predicted multiples turn out to be significant within several sub-samples, predictive power as measured by R-squared statistics generally appear to be low. Moreover, results further show that developed predictions are not significantly more accurate than simple peer group averages based on harmonic means. One explanation for this observation is that peer group averages simply hold relatively high underlying explanatory power in determining EV/EBITDA multiples. Alternatively, the antecedent low predictive power of fundamental value drivers in determining predicted multiples may hamper the accuracy of developed predictions.

Table 16. Hypothesis Testing: Research Question 2

Market/Sector/Industry	Hypothesis 6	Hypothesis 7
Market	***Confirmed***	*Not Confirmed*
Energy Sector	*Not Confirmed*	*Not Confirmed*
Energy	*Not Confirmed*	*Not Confirmed*
Materials Sector	***Confirmed***	*Not Confirmed*
Materials	***Confirmed***	*Not Confirmed*
Industrials Sector	*Not Confirmed*	*Not Confirmed*
Capital Goods	*Not Confirmed*	*Not Confirmed*
Commercial & Professional Services	*Not Confirmed*	*Not Confirmed*
Transportation	*Not Confirmed*	*Not Confirmed*
Consumer Discretionary Sector	***Confirmed***	*Not Confirmed*
Automobiles & Components	***Confirmed***	*Not Confirmed*
Consumer Durables & Apparel	*Not Confirmed*	*Not Confirmed*
Consumer Services	***Confirmed***	*Not Confirmed*
Retailing	***Confirmed***	*Not Confirmed*
Consumer Staples Sector	***Confirmed***	*Not Confirmed*
Food Staples & Retailing	***Confirmed***	*Not Confirmed*
Food, Beverage & Tobacco	***Confirmed***	*Not Confirmed*
Household & Personal Products	***Confirmed***	*Not Confirmed*
Health Care Sector	***Confirmed***	*Not Confirmed*
Health Care Equipment & Services	***Confirmed***	*Not Confirmed*
Pharmaceuticals, Biotechnology & Life Sciences	***Confirmed***	*Not Confirmed*
Financials Sector	***Confirmed***	*Not Confirmed*
Diversified Financials	***Confirmed***	*Not Confirmed*
Information Technology Sector	***Confirmed***	*Not Confirmed*
Software & Services	***Confirmed***	*Not Confirmed*
Technology Hardware & Equipment	*Not Confirmed*	*Not Confirmed*
Semiconductors & Semiconductor Equipment	***Confirmed***	*Not Confirmed*
Communication Services Sector	***Confirmed***	*Not Confirmed*
Telecommunication Services	***Confirmed***	*Not Confirmed*
Media & Entertainment	***Confirmed***	*Not Confirmed*
Utilities Sector	***Confirmed***	*Not Confirmed*
Utilities	***Confirmed***	*Not Confirmed*
Real Estate Sector	***Confirmed***	*Not Confirmed*
Real Estate	***Confirmed***	*Not Confirmed*

Research Question: Does a regression approach based on fundamental value drivers provide predicted EV/EBITDA multiples that represent accurate estimates of actual market multiples?
- H6: Predicted multiples developed from a regression analysis of fundamental value drivers are significant determinants of actual market multiples.
- H7: Predicted multiples developed from a regression analysis of fundamental value drivers will have significantly lower prediction errors in determining actual market multiples than estimates based on simple peer group averages.

6.4.4 Post-Hoc Analysis 2

As demonstrated, results show that predicted multiples developed from the regression analysis are significant determinants of actual market multiples. Meanwhile, the relative accuracy of these predictions proved to be statistically similar to simple peer group multiples that do not consider individual firm differences. In order to gain a better understanding of why the developed regression models fail to produce significantly more accurate predictions than a simple peer group approach, this post-hoc analysis is included to scrutinize the results further.

Model Prediction Accuracy & Sample Size

As illustrated in previous sections, literature suggests that there is an inherent trade-off associated with the choice between adopting a narrow versus broad definition of peer groups. Again, the trade-off stems from the fact that a broad definition provides larger sample sizes that are more suitable to statistical analysis, while a narrow definition provides smaller, but more homogenous samples. While the advantages and disadvantages of the two options are clear, previous literature is less conclusive regarding whether a narrow or broad definition of peer groups is favorable on the whole. Since the analysis of this paper has covered three different levels of peer group definition, namely on market, sector and industry level, the results can be extended to shed further light on this matter.

As has been conducted throughout this paper, defining peer groups on a market, sector, and industry level divides the 965 investigated firms into 1, 11, and 22 individual samples respectively. In sum, this provides 34 different sample sizes that can be examined to learn how the number of firms in a sample relates to the accuracy of predictions developed from a regression analysis. The following Table 17 shows results from three single OLS regressions where mean absolute deviation errors from the standard regression model, relative regression model, and simple peer group approach, act as dependent variables[I].

Results in Table 17, Panel A, show that sample size is a significant determinant of prediction errors in all three models. Furthermore, the positive beta coefficient indicates that regression models based on larger sample sizes tend to generate less accurate predictions of firm value. This suggests that the loss of homogeneity caused by less narrow definitions of peer groups outweigh the statistical benefits from larger sample sizes. Moreover, while F-statistics are insignificant for all models, judging by adjusted R-squared statistics, it appears that the independent variable best explains the prediction errors associated with the relative regression model.

[I] The 34 different sample sizes that result from defining peer groups on a market, sector, and industry basis constitute the independent variable in all three regressions in this particular test

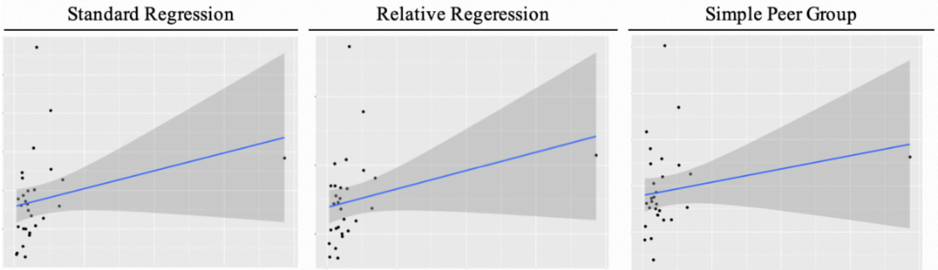
Table 17. Model Prediction Accuracy & Sample Size (1)

Panel A: Regression Output

	Dependent Variable		
	MAD (Standard Regression)	MAD (Relative Regression)	MAD (Simple Peer Group)
Sample Size	0,0002***	0,0002***	0,0001***
	(0,0001)	(0,0001)	(0,00004)
Alpha	0,258****	0,277****	0,279****
	(0,020)	(0,022)	(0,017)
Observations	34	34	34
R^2	0,069	0,074	0,039
Adj. R^2	0,040	0,045	0,009
Std. Error	0,111	0,124	0,092
F Stat	2,636	2,553	1,316

Panel B: Scatterplots

y-axis: MAD
x-axis: Sample Size



**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

To continue, the associated scatterplots in Panel B illustrate the relationship between mean absolute deviation errors and sample size for the standard regression model, relative regression model, and simple peer group approach respectively. While the beta coefficients are positive for all three models, it is evident that the inclusion of the large sample that is generated from defining peer groups on a market level constitutes an apparent outlier in terms of sample size. Thus, this observation is removed from the analysis leaving 33 different sample sizes left to study, outlined in Table 18.

The refined results in Table 18 demonstrate a clearer picture of the relationship between sample size and prediction accuracy. That is, the F-statistics are now significant for both the standard regression model and the relative regression model, which strengthens the finding that a narrower definition of peer groups generates more accurate predictions. Meanwhile, sample size is not a significant determinant of prediction errors for the simple peer group approach after having refined the analysis. This result suggests that the accuracy of predictions from the simple peer group approach is statistically independent from sample size, as long as peer groups are defined on either an industry or sector level.

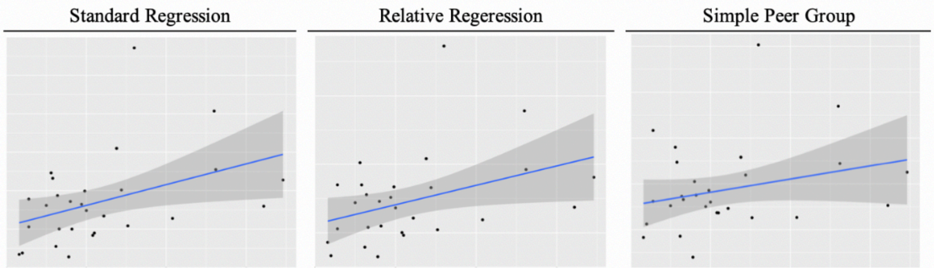
Table 18. Model Prediction Accuracy & Sample Size (2)

Panel A: Regression Output

	Dependent Variable		
	MAD (Standard Regression)	MAD (Relative Regression)	MAD (Simple Peer Group)
Sample Size	0,001***	0,001***	0,001
	(0,0004)	(0,0005)	(0,0004)
Alpha	0,207****	0,225****	0,253****
	(0,024)	(0,027)	(0,024)
Observations	33	33	33
R^2	0,152	0,136	0,065
Adj. R^2	0,125	0,108	0,034
Std. Error	0,106	0,119	0,092
F Stat	5,577***	4,886**	2,138

Panel B: Scatterplots

y-axis: MAD
x-axis: Sample Size



**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

Model Prediction Accuracy & Deviations from Peer Group Averages

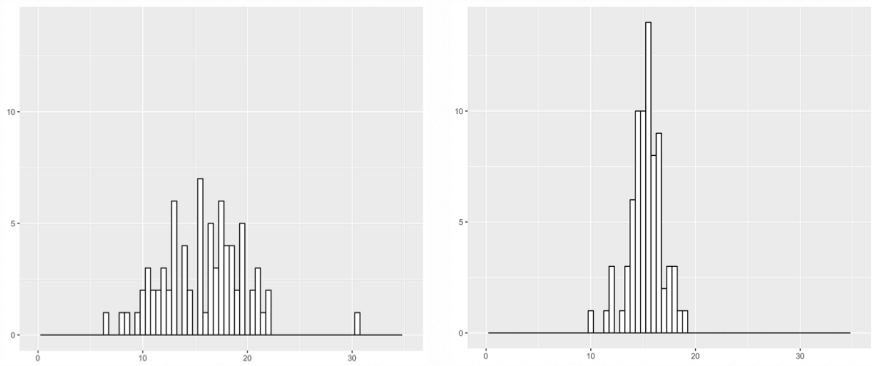
As the studied fundamental value drivers proved to hold relatively low predictive power of the studied multiple in relation to the first research question, the beta coefficients on the independent variables used in predictive models are generally quite small and close to zero. Consequently, it is theorized that predictions based on these regression models are not predominately influenced by individual performance in terms of growth, profitability and risk. Instead, predictions of market multiples are argued to be mainly driven by peer group affiliation, which should naturally cause predictions to be closely centered around a sample average, given their underlying computations[I]. As an illustrative example, the distribution of actual market multiples and the distribution of predicted multiples from the standard regression model for the Real Estate Sector are shown in Table 19.

[I] See predictive equations in Appendix 6

Table 19. Deviations from Peer Group Averages

Sample: Real Estate Sector
Number of firms: 76

Panel A: Distribution of Actual Multiples **Panel B: Distribution of Predicted Multiples**



The graphs in Table 19 indicate that predicted multiples are indeed more closely centered around a sample average as compared to actual market multiples. As a consequence of this general issue, it is expected that prediction errors will be larger for firms that have an actual market multiple that deviates far from the sample average. To statistically test this notion, single OLS regression analysis is adopted. Specifically, absolute prediction errors act as the dependent variable and deviation from the sample, defined as the absolute difference between the actual market multiple and the peer group average multiple, acts as the independent variable.

Results from the analysis on the relationship between model prediction accuracy and deviations from peer group averages are summarized in Appendix 7. As expected, prediction errors are significantly determined by deviations from the sample average in a large majority of the studied cases. In fact, the beta coefficient on the independent variable is significantly (p<,05) positive in 27 out of the 34 sub-samples for the standard regression model and 24 out of the 34 sub-samples for the relative regression model. Furthermore, as can be observed in Appendix 7, the F-statistic is significant in 22 and 18 sub-samples for each utilized model respectively. This suggests that the inability to effectively capture large deviations from sample averages constitute a notable shortcoming of the developed regression models. Moreover, results also indicate that the standard regression model is more susceptible to this issue than the relative regression model. Indeed, the adjusted R-squared for this specific post-hoc analysis is higher for the standard regression model than for the relative regression model in all but one sample.

As a result of the identified inability to capture deviations from the sample average, it is expected that measures of model performance are largely driven by outliers given that both MAD and MSE are computed based on mean values, which are naturally susceptible to such influences. In line with this, Appendix 8 shows that, in terms of median prediction errors that are less affected by outliers, the standard regression model and the relative regression model outperform the simple peer group approach in 27 and 25 sub-samples respectively, providing a different picture of relative model accuracy. Nonetheless, it is argued that MAD and MSE provide a more holistic view of model accuracy given that the measures consider all prediction errors in cohesion. Overall, the post-hoc analysis demonstrates that this general issue provides an important understanding of the systematic errors that are associated with the developed regression models. More importantly, it shows that the inability to capture deviations from the sample average lead predictions to be largely driven by peer group affiliation, which renders them susceptible to large outliers.

Model Prediction Accuracy & Firm Size

As discussed in previous sections, several important studies within the field of multiple valuation have found that firm size has a significant confounding impact on the relationship between fundamental value drivers and valuation multiples. More specifically, research has shown that relative valuation accuracy tends to significantly increase with firm size[I]. Thus, to investigate whether the results of this paper are distorted by this notion, an OLS regression analysis is conducted with absolute prediction errors as the dependent variable and firm size, measured as the natural logarithm of total assets, as the independent variable. Results from the conducted post-hoc analysis on the relationship between model prediction accuracy and firm size are summarized in Appendix 9.

Contrary to previous research, the output presented in Appendix 9 generally shows that prediction errors from the developed regression models are independent of firm size. In fact, the F-statistic is significant on a 5% level in merely 2 out of 34 sub-samples for the standard regression model and in 3 out of 34 sub-samples for the relative regression model. Additionally, in one of the utilized samples, the direction of the relationship is significantly inverted. That is, prediction error increases with firm size rather than the other way around. Altogether, the analysis fails to support previous empirical findings regarding the relationship between prediction accuracy and firm size. It is argued to be likely that the independence of prediction errors from firm size stems from the fact that there are other more important systematic issues with the developed regression models that cause this effect. Furthermore, the studied firms are all quite large given that they are exclusively

[I] This notion is believed to stem from the fact that smaller firms are often associated with characteristics such as lower information environments, weaker internal controls, less managerial depth, more narrow product offerings, and more erratic earnings (Plenborg & Pimentel, 2016) drawn from the S&P Composite 1500 Index, which constitutes the largest publicly listed firms in the US. Thus, even the relatively small firms in the sample may be large enough to be unaffected by the characteristics of smaller firms that in line with theoretical assumption might have a negative effect on prediction accuracy.

- 7. Validity of Statistical Results -

Given the overall findings presented throughout Section 6, it is suitable to comment on the external and internal validity of results from a holistic standpoint. The external and internal validity of results serves as vital components for the generalizability of discovered statistical relationships and determines the usefulness of utilized regression models from which inferences can be drawn. The following section aims to more specifically assess whether, and for what populations, the obtained results are generalizable as well as to what degree the results are free from errors.

To begin with, it is argued that the conducted study of this paper holds reasonably high external validity in several regards. Since the sample includes 965 public US firms drawn from the S&P Composite 1500 index, it is argued that the sample offers a sufficient base from which conclusions are generalizable for the population of public firms in the US. This is also strengthened by the fact that firms included in the sample were selected based on market index affiliation rather than individual firm characteristics, which reduces selection bias. However, the statistical findings are concluded to be less generalizable for non-public firms, firms based outside the US as well as smaller public firms. Thus, inferences based on findings from the conducted study should be applied conservatively in other markets, contexts, as well as for privately held firms. Moreover, given that intertemporal differences in the underlying data were discovered to be considerable, the generalizability of results for other time periods than between 2016 and 2018 is additionally deemed to be limited. Mitigating efforts geared towards increasing the external validity of results could have been to also include non-public firms, firms from different markets and utilizing data over longer time periods.

To continue, the internal validity of statistical findings is in some regards limited. As found from a series of conducted tests, several sub-samples display non-normal distributions in terms of skewness and kurtosis as well as multicollinearity for included variables. In line with these observations, descriptive statistics furthermore indicates that some of the included sub-samples contain observations for the dependent variable that significantly deviates from sample averages. Moreover, when regressing EV/EBITDA multiples against independent variables, several instances of heteroskedastic residual distributions were also discovered. These results compromise the stated OLS assumptions in Section 5.3.3, suggesting that some of the findings should be viewed as biased. Additionally, as can also be observed in several instances across utilized sub-samples, R-squared statistics generally turn out to be low. Consequently, the predictive power and thus internal validity is questionable for both theoretically derived value drivers and predicted multiples in several sub-samples. The observed instances of limited predictive power are argued to be primarily driven by a combination of omitted variable bias, peer group heterogeneity, sample size effects and potential measurement errors. Out of these, the former three factors are argued to have the greatest impact. Nevertheless, measurement errors in the form of discrepancies between sell-side estimates and market expectations potentially constitute a confounding factor with regards to internal validity as well. In order to partly mitigate time-invariant unobservable effects that potentially drives the high levels of omitted variable bias, time-series analysis based on panel data could have been applied. However, as also outlined in Section 1.3 on delimitations, no such effort was undertaken in line with most prior studies on the same topic.

Moreover, another potential methodological issue stems from the utilization of an in-sample as opposed to an out-of-sample approach in the second part of the conducted study. That is, employing an approach where predictions are utilized as determinants of firm values drawn from the same sample may cause prediction bias, which ultimately compromises internal validity. Nevertheless, it is argued that conducting an out-of-sample approach would not have been feasible given the broad sample utilized in this study. As the sample contains the largest firms in the US across all industries included in the S&P 1500 index, out-of-sample firms would have needed to be smaller public firms, non-public firms, or firms from other markets. It is therefore argued that an in-sample approach, compared to other available options, generates the most comparable results.

However, the internal validity of results is deemed sufficient in several regards as well. That is, numerous instances across utilized sub-samples were also found to satisfy stated OLS assumptions and display sufficient predictive power of estimators. For example, except for within the Energy Sector, the Consumer Durables & Apparel Industry, the Health Care Sector and the Real Estate Sector, the utilized measure for EV/EBITDA multiples turn out to be normally distributed. Even though less common, several instances of normality were also found for the included independent variables. As most of the central normality assumptions with regards to OLS estimators concern the distribution of the dependent variable, introduced bias from abnormal distributions of the independent variables is therefore argued to be partly mitigated. Additionally, even though high levels of multicollinearity are found on market level, several sectors and industries are found to free of such statistical issues.

Nevertheless, much of the obtained results are in line with previous empirical findings. As highlighted in earlier sections, the inherent statistical issues in relative valuation is widely recognized in several studies on the same topic. Thus, non-normal distributions, multicollinearity and low predictive power throughout conducted regressions were expected to some degree. As such, even though several limitations with regards to internal validity of results exists, it is concluded that the overall results provide vital insights into underlying relationships as well as the feasibility of introducing regression approaches to a greater extent within relative valuation.

- 8. Discussion -

Even though several of the theoretically derived hypotheses were not confirmed based on empirical evidence, it is argued that the statistical analysis of this empirical research provides several findings that are valuable from both an academic and professional perspective. Reflecting on the underlying reasons for why the developed methodological approach does not produce findings that consistently match theoretical assumptions provides revealing insights into the somewhat counterintuitive results. This section is therefore dedicated to discussing the results produced by the underlying research methodology in both an empirical and theoretical context to gain further comprehension of the empirical data.

8.1 The Predictive Power of Value Drivers

With some exceptions, the statistical analysis of this study demonstrates a relatively weak and sporadic relationship between the studied fundamental value drivers and the EV/EBITDA multiple. While there are several instances where identified relationships are in line with theory, output from both single and multiple regressions largely suggests that the primary fundamental value drivers, namely growth, profitability, and risk, are found to hold low explanatory power of the studied multiple. Hence, instances where beta coefficients are statistically different from zero are in the minority. Furthermore, the goodness of fit statistics suggest that the independent variables are poor predictors of residual variance in the regression models, especially for larger sub-samples. Altogether, there is a discrepancy between the empirical findings and the theoretical notion that these firm characteristics are the sole determinants of firm value. Consequently, at face value, the results of this paper in some regards dispute the theoretical proposition that fundamental value drivers hold the key to effectively implementing multiple valuation.

Given that the research methodology follows a stepwise structure, the low predictive power of included value drivers has implications for the rest of the statistical analysis. However, results showed that the low predictive power of value drivers does not hinder predictions from being significant determinants of actual market multiples. Put differently, the results demonstrate that an insignificant underlying model is at times able to produce significant predictions, which is evidently counterintuitive. Yet, further contemplation in the form of included post-hoc analyses shed some light on obtained results. Namely, the first post-hoc analysis on the impact of sample homogeneity suggested that collective peer group values appear to be significant determinants of observed market multiples. Furthermore, this fact became more apparent when considering the relative accuracy of predictions as a next step. That is, direct comparison of prediction errors revealed that although developed predictions from regression models are significant determinants of actual market multiples, they fail to significantly outperform predictions from simple peer group averages. It is argued that the inability to statistically conclude on the relative performance of developed models may be partly driven by the way in which prediction errors are defined, where scaling of deviations from actual market multiples centers computed errors closely around zero. This makes the absolute difference between the models quite small and thus difficult to statistically compare.

While other explanations potentially exist, it is argued that there are two central issues not associated with statistical properties that may constitute the reason for why the observed relationship between studied fundamental value drivers and EV/EBITDA is misaligned with theory. Firstly, the sporadic nature of the identified relationship could be attributed to issues concerning the best multiple notion. Again, previous researchers have suggested that different industries are associated with different best multiples, which implies that it may be inappropriate to solely utilize the EV/EBITDA multiple across the studied samples. Regardless, this study has deliberately adopted such a singular approach to keep a delimited focus on the feasibility of implementing a fundamental regression approach in determining the studied multiple. Consequently, the use of EV/EBITDA as a sole dependent variable could distort the true relationship between fundamental value drivers and the value of a firm from a holistic standpoint.

Moreover, the discrepancy between the empirical findings and the theoretical relationship between fundamental value drivers and multiples may be caused by intertemporal issues. The main concern with intertemporal differences is that both the dependent variable and independent variables are susceptible to cyclicality and non-normal observations. Demonstrating the importance of this, the post-hoc analysis in Section 6.3.4 showed that disaggregating the developed regression analysis and performing it on a year-by-year basis produced substantially different views on the relationship between fundamental value drivers and the EV/EBITDA multiple. It is argued that these discrepancies are predominately caused by measurement issues where individual yearly observations are less likely to be representative of long-term performance. This shortcoming constitutes the motivation for using aggregate measures throughout the analysis. Notwithstanding, the results from the post-hoc analysis suggest that the variations caused by intertemporal issues are likely to negatively impact the predictive power of the utilized aggregate measures.

8.2 Relative Importance of Value Drivers

Another interesting finding deductible from the statistical analysis concerns the relative importance of value drivers. That is, the analysis sheds light on which fundamental value driver appears to be the most important determinant of multiples in relative terms. Given the differing magnitude and significance level of beta coefficients in the regression models, one can infer that variations in these value drivers do not impact the EV/EBITDA multiples to an equal extent. Granted, directly comparing the magnitude of beta coefficients is rendered difficult given that the risk variable is in logarithmic form. Thus, it is argued that to be more appropriate to evaluate the relative importance of value drivers based on significance level. As such, when investigating the results from multiple regression models, risk appears to be the most important determinant of firm value as it is significant on a 5% level in the most sub-samples for both the standard regression model and the relative regression model. More specifically, for the standard regression model, the beta coefficient on risk, profitability and growth is significant in 15, 10 and 9 sub-samples respectively. Moreover, for the relative regression model, the beta coefficient on risk, growth and profitability is significant in 14, 7 and 8 sub-samples respectively.

Given the common understanding that growth and profitability are the most important determinants of enterprise multiples, this result is somewhat unexpected. Furthermore, it is also noticeable that the beta coefficient for risk is positive in a majority of instances since, according to theory, an increase in WACC should have a negative impact on EV/EBITDA. In this regard, it is argued that the observed inverted relationship between risk and the studied multiple is most likely caused by multicollinearity issues. As outlined in earlier sections, risk is an inherently difficult factor to effectively capture since it embodies several elements that may have paradoxical effects. That is, an increase in risk can have both negative and positive effects on expected future cash flows. Indeed, looking at the correlation tables presented in Appendix 2, there are evident multicollinearity issues in a large number of the studied sub-samples, where firms with high growth and high profitability are often associated with high risk. In fact, risk is significantly correlated with growth and profitability in 18 and 16 samples respectively. This may result in risk reflecting performance in other value drivers rather than the intended effect.

It is possible to alternatively interpret this result as being indicative of sensitivity of the studied multiple to changes and volatility in the value driver. Looking at the sample summary in Table 3, it is evident that risk is the most stable and uniform variable in terms of standard deviation. Furthermore, the correlation table presented in Table 4 shows that the difference between the highest and lowest risk profile is 10,6 percentage points. Meanwhile, the difference is 63,7 and 88,0 percentage points for growth and profitability respectively. Since it is evident that growth and profitability exhibit more volatility than risk, it would make sense that firm value is more susceptible to a percentage change in risk than an equal percentage change in growth or profitability. As a result, the beta coefficient on risk should be higher, and thus more significant, as compared to the beta coefficients on growth and profitability.

To continue, apart from suggesting that risk is a more important determinant of firm value than growth and profitability, these results further indicate that the relative importance of value drivers depends on peer group affiliation. The standard regression model based on the Materials Sector sub-sample, for example, strongly suggests that growth is the most important value driver. In contrast, the standard regression model based on the Consumer Services Industry sub-sample suggests that profitability is the most important value driver. Furthermore, results generally show that the beta coefficient is significant for only one of the three studied value drivers for each sub-sample utilized. While there may be internal validity issues causing this result, it is not unlikely that the relative importance of individual performance in growth, profitability, and risk does indeed differ depending on peer group affiliation. Specifically, some firms may operate in environments where investors value high growth profiles more than high profit margins, while other firms operate in environments where return on investment is the main concern[I].

As a final point with regards to the relative importance of value drivers, comparing the results from the standard regression model and the relative regression model also sheds light on whether absolute performance or relative performance holds more informational value. Judging by the number of samples in which the two different types of regression models produce significant F-statistics, it appears that relative performance in value drivers hold more predictive power than absolute performance in value drivers. That is, the relative regression model is significant in 19 sub-samples, while the standard regression model is significant in 16 sub-samples. This would suggest that, all else equal, a firm that outperform relative to its peer group should have a higher multiple than a firm that underperforms relative to its peer group. Put another way, comparative performance appears

[I] It should be noted, however, that the informational value of cross sample comparisons is negatively affected by the varying sample sizes to alter the added value that an increase in fundamental value drivers yields. However, with that said, the number of samples in which beta coefficients are significant on a 5% level is higher for the standard regression model than the relative regression model for all three value drivers. More generally, it is theorized that the relative regression model produces significant estimations in more sub-samples than the standard regression model due to utilized constructs of relative measures. Specifically, computations of relative measures inherently include peer group averages, which were found to hold substantial explanatory power throughout the study. Regardless, it is concluded that the standard regression model and the relative regression model produce highly similar results, and that further research on the differences between the two approaches is deemed necessary.

8.3 The Predictive Power of Homogeneity

As has been highlighted at several points in this study, the statistical analysis indicates that industry affiliation has a significant impact on the predictive power of developed models. For instance, results from both the standard and the relative regression models indicate that test-statistics generally improve in terms of significance and predictive power as samples employed become more homogenous. This finding was further strengthened by the post-hoc analysis in Section 6.3.4, which demonstrated that test-statistics improved dramatically when sector and industry dummies were separately included in the regression model. Indeed, the adjusted R-squared increased from 0,7% to 29,3% when incorporating industry dummies for the cross-section sample.

Furthermore, subsequent accuracy tests showed that the low predictive power of value drivers does not hinder developed predictions from being significant determinants of actual market multiples. These results further validate the importance of peer group homogeneity, since it is theorized that the predictive power of the developed models stems from peer group affiliation rather than individual performance in fundamental value drivers. Finally, and most importantly, direct comparison of prediction errors revealed that although developed predictions from regression models are significant determinants of actual market multiples, they fail to significantly outperform predictions from simple peer group averages. As such, the findings of this paper strongly support the theoretical notion that a substantial part of cross-sectional variation in fundamentals can be explained by industry affiliation. More generally, findings suggest that it is unsuitable to perform relative valuation without taking base in highly comparable firms, since the systematic value of growth, profitability, and risk varies across different types of firms.

Overall, the above indicates that more narrow definitions of peer groups may be preferable in general. As such, the GICS classification system could be utilized on a 6-digit level, which divides the S&P Composite 1500 Index into 69 sub-samples. An even more narrow definition would be to utilize the GICS classification system on a 10-digit level, which divides the index into 158 sub-samples. This is likely to substantially increase the comparability between firms within a peer group, which should eliminate many of the heterogeneity issues that blur the relationship between fundamental value drivers and multiples in larger samples. Accordingly, such an approach would more likely satisfy the basic assumption of the relative valuation method stating that companies used as benchmarks should have proportional future cash flow expectations and risk profiles as the company of interest. However, the small size of such peer groups would entail several statistical issues that would render regression analysis theoretically unsuitable. Thus, this discussion returns to the inherent trade-off associated with the choice between adopting a narrow versus broad definition of peer groups, where sample homogeneity and statistical benefits have to be balanced. Furthermore, it is interesting to reflect on the fact that sacrificing suitability of statistical methods for more narrowly defined peer groups moves the method of analysis close to how multiple valuation is carried out in practice. Meanwhile, the statistical flaws associated with such an approach largely motivated this research in the first place.

8.4 Industry Considerations

As has been highlighted, several researchers have presented theoretical arguments and empirical evidence for the notion that different industries are associated with different best multiples. Consequently, it is argued that the singular use of EV/EBITDA as dependent variable likely distorts the true relationship between fundamental value drivers and the studied multiple in several sub-samples. Nonetheless, the choice to utilize EV/EBITDA specifically was motivated by the theoretical arguments and empirical findings from previous researchers supporting that EV/EBITDA holds several advantages over other enterprise multiples, making it the most attractive option for this purpose.

On an overall level, as mentioned in Section 5.1.1, a clear advantage of the EV/EBITDA multiple is that it is unaffected by differences in taxation and diverging accounting practices concerning depreciation and amortization schedules across firms. Furthermore, the multiple is argued to be more easily comparable across firms that have varying financial leverage as opposed to other earnings multiples. However, empirical evidence in prior studies suggest that the EV/EBITDA multiple is suitable for certain types of sectors and industries, but unsuitable for others[I]. Suitable sectors and industries are mainly characterized by large investments in infrastructure, long formation periods, high depreciation rates as well as high leverage.

With this in mind, it is possible to evaluate whether the proposed level of applicability of the EV/EBITDA multiple in certain samples seem to determine the accuracy of results. To begin with, the sectors in which the F-statistic is significant on a 5% level in the standard regression model are the Real Estate Sector, the Consumer Staples Sector, the Communication Services Sector, the Consumer Discretionary Sector, the Health Care Sector, and the Information Technology Sector. Intuitively, this list of sectors is similar to those that generate more accurate predictions than the simple peer group approach, namely the Utilities Sector, the Real Estate Sector, the Consumer Staples Sector, the Communication Services Sector, the Materials Sector, and the Financials Sector. Unintuitively, however, several of these sectors are theoretically proposed to be unsuitable for the EV/EBITDA multiple. As such, the results do not provide uniform support for the theoretical predictions outlined above. However, it argued that these findings do not justifiably dispute the best multiple notion. Rather, it is theorized that there are other methodological issues causing this result, such as differing sample sizes and potential measurement issues.

8.5 Usefulness & Generalizability of the Study

While the value of this study is limited by several factors that mainly resonate from stated delimitations, it is argued that this research contributes with both theoretical and practical value from a holistic standpoint. These contributions mainly reside in the informational value of the methodological approach and the empirical evidence generated from the statistical analysis. As such, the argued value contributions should be individually outlined and weighted with corresponding limitations in mind.

To begin with, while the mathematical derivation of EV/EBITDA suggests that there are only a handful of factors that theoretically drive the multiple, findings from this study suggest otherwise. In fact, results indicate that the predictive power of these fundamental value drivers is relatively low, especially for larger samples. This constitutes a valuable finding as it questions the theoretical notion that growth, profitability and risk have a consistent relationship with the studied multiple. Yet, it is argued that the findings do not necessarily indicate

[I] As outlined in Section 5.1.1, Harbula (2009) finds that the EV/EBITDA multiple is suboptimal in the banking & insurance industry, the life sciences & healthcare industry, and the real estate industry. Furthermore, Gupta (2018) finds in his comparative study that EV/EBITDA is highly unsuitable for the automobile sector due to wide variations in terms of capital intensity across firms that the relationship between these fundamental value drivers and the studied multiple is weak. Rather, it is theorized that the relationship is much more complex than what the developed statistical models can capture. Consequently, as intended, this study sheds light on the fundamental feasibility of applying a regression approach. In this regard, findings indicate that while more frequent employment of the approach may be justified, more complex statistical models are required.

Secondly, the statistical analysis provides understanding of the relative importance of value drivers, where results indicate that variations in growth, profitability, and risk, do not impact the EV/EBITDA multiple to an equal extent. Furthermore, the varying results across samples indicate that the relative importance of value drivers differs depending on peer group affiliation. However, the ability to infer relative importance is somewhat compromised by internal validity issues, which renders a robust conclusion about the ranking difficult. Nonetheless, it is argued that the methodological approach to identifying beta coefficients on the studied fundamental value drivers provide practical value. It does so by demonstrating how a statistical method can handle differences between firms without being bound to subjective adjustments. While accuracy tests showed that predictions based on such beta coefficients are imperfect, the methodological approach provides guidance for the implementation of fundamental statistical analysis. Moreover, the adoption of dual regression models expands the research on whether absolute performance or relative performance holds more informational value in determining EV/EBITDA multiples. As results proved that developed approaches produce similar results, it is argued that further research is needed to conclude on which methodology is more reliable.

Thirdly, this study provides value in demonstrating that peer group affiliation holds a substantial amount of predictive power in determining the studied multiple. More specifically, the analysis shows that the high degree of sample homogeneity that is associated with narrow definitions of peer groups outweighs statistical drawbacks associated with small sample sizes. This provides valuable insights to the discussion on the optimal level of analysis, which is prevalent within the academic discourse. Furthermore, this study generally shows that the most narrow peer group definition included in this study generates superior predictions of multiples. Indeed, utilization of narrow definitions turn out to provide a better base for studying the relationship between EV/EBITDA and fundamental value drivers. Moreover, it also found to generate superior accuracy of predictions. Additionally, direct comparison of prediction accuracy from the studied models further demonstrates that the predictive power of peer group affiliation generates prediction accuracy that is statistically on par with models that consider individual differences between firms. As such, it is concluded that while the statistical method developed from previous literature produces relatively accurate valuation estimates, it does not produce statistically superior estimates compared to simple peer group averages.

Even though the obtained findings provide value in various aspects, several identified limitations throughout the study should be highlighted when evaluating the practical usage of results in their entirety. Thus, it is appropriate to extend the discussion on internal and external validity from Section 7 to also include general limitations for the paper as a whole. First of all, even though a highly suitable methodology for the purpose of answering the formulated research questions, the outlined regression approach was expected and proven to contain statistical issues in many instances. These issues mainly related to distributional properties of multiples and value drivers, multicollinearity between independent variables, heteroskedastic error terms as well as high levels of omitted variable bias. Additionally, considering that utilized sector and industry sub-samples often turn out to be relatively small, the unbiasedness of obtained OLS estimators is inherently distorted. These issues have direct implications for the internal validity of results, which limits the accuracy and reliability of inferences. With that said, it should again be stressed EV/EBITDA multiples displayed normal distributions in majority of included sub-samples, which partly mitigates introduced bias from abnormal distributions of the independent variables.

In line with this, uncontrollable external factors related to lack of oversight, control, and availability of data in the utilized Bloomberg database additionally increases the eventuality of measurement errors. This issue mainly permeates the utilized measures for profitability and risk where data unavailability forced the utilization of current and historical rather than forward-looking measures. Moreover, several directly obtained constructs from Bloomberg are also based on approximations where subjectivity is inherently present[I]. Lastly, related to potential measurement errors, whether the variable operationalizations utilized in this paper effectively captures the true effects of growth, profitability and risk with regards to EV/EBITDA could also be questioned, as only single measures are applied for each respective value driver.

To continue, the outlined delimitations imply a tradeoff between a narrow research focus and generalizability of results obtained from the conducted study. Firstly, delimitations for included variables of interest imply that inferences are restricted to a single valuation multiple, i.e. EV/EBITDA, and its corresponding value drivers. Inversely, findings from the conducted study should not be seen as generalizable for other types of valuation

[I] Primarily with regards to operationalizations of EV/EBITDA and ROIC multiples in general. Furthermore, given that EV/EBITDA is inherently less applicable within certain sectors and industries, the utilization of a single dependent variable implies that comparisons between sub-samples may be inconsistent.

Secondly, as the utilized sample in this study only concerns public firms from a single country, results should be viewed as limited in being representative for firms domiciling in other markets and geographies as well as for non-public firms. Even though it could be argued that public European firms share the same underlying characteristics as US firms to a large extent, market-specific discrepancies still make statistically accurate comparisons difficult. Lastly, as the conducted study in this paper does not explicitly consider intertemporal variances for the underlying relationship between EV/EBITDA and its fundamental value drivers, the generalizability of inferences for past and future underlying relationships should also be considered limited.

Having contrasted both the usefulness and limitations of the conducted study, obtained results are argued to contribute from a holistic standpoint to the academic discourse within multiple accuracy. Apart from providing empirical evidence on the fundamental feasibility of applying a regression approach, the statistical analysis sheds light on the relative importance of value drivers across sectors and industries. Furthermore, the study demonstrates how a statistical method that is developed from theoretical underpinnings can handle differences between firms without being bound to subjective adjustments and provides insights to the prevalent discussion on the optimal level of analysis. Nonetheless, the practical and empirical contributions in terms of research methodology and obtained results are argued to be restricted to certain contexts and a single period of time.

- 9. Conclusion –

This study addresses the empirical deficit that surrounds the underlying relationship between fundamental value drivers and valuation multiples, and whether fundamental regressions approaches can generate accurate predictions of intrinsic firm value. Even though previous literature suggests that regression analysis can be utilized to account for heterogeneity amongst comparable firms, few studies have empirically evaluated the accuracy of predicted valuation multiples based on statistical approaches. In addition, while relative valuation is seen as the most commonly applied valuation technique, regression analysis is rarely used as a primary tool for this specific purpose in practice. Instead, relative valuation processes are often permeated by subjective adjustments that commonly hold limited theoretical and statistical substance. These observations served as a fundamental base of the conducted study, where research questions were developed with the intent to address the identified issues. Guided by theoretical underpinnings on relative valuation as well as prior empirical findings, the conducted study consequently develops theoretically founded regression approaches that objectively account for individual firm performance. It is subsequently tested whether these approaches are able to generate accurate predictions of observed market multiples. To maintain a narrow research focus, the conducted study was delimited in several ways. Most centrally, the analysis solely concerns EV/EBITDA and its theoretically derived value drivers of growth, profitability and risk.

Following a process of theoretic construction that is deductive in nature, a careful review of literature and empirical research produced a number of hypotheses that were thereafter subject to rigorous testing through a series of propositions. Firstly, with regards to the relationship between EV/EBITDA and its fundamental value drivers, it was hypothesized that growth, profitability, and risk all hold significant predictive power of the studied multiple. Secondly, with regards to accuracy of valuation estimates, it was hypothesized that predicted multiples derived from fundamental regression approaches are significant determinants of actual market multiples and should outperform estimates based on simple peer group averages.

The developed research methodology utilized to answer stated research questions was built around three central components that mirror prior studies within the field of multiple valuation. Firstly, variable operationalizations were guided by previous empirical findings, with EV/EBITDA as dependent variable and selected measures for growth, profitability and risk as independent variables. In this regard, where applicable, variables were based on normalized values that covered a three-year period to avoid cyclicality issues. Secondly, studied firms were drawn from the S&P Composite 1500 Index and peer groups were defined according to the Global Industry Classification Standard on a market, sector, and industry level. This approach divided the 965 firms included in the final sample into 1, 11, and 22 individual sub-samples respectively. Finally, as generally advocated amongst leading scholars, a series of single and multivariate ordinary least squares regression models were selected to form the method of data analysis. More specifically, two distinct categories of regression models were developed based on absolute and relative measures respectively. The accuracy of predictions generated by these models were subsequently tested through regression analysis and direct comparison of prediction errors.

In relation to the first research question of this study, the statistical analysis showed that the developed methodological approach does not produce empirical findings that consistently match theoretical predictions. More specifically, results demonstrated a sporadic relationship between the studied fundamental value drivers and the EV/EBITDA multiple as findings varied significantly across sectors and industries. In several sub-samples, findings indicated that EV/EBITDA multiples cannot solely be determined by utilized measures of growth, profitability and risk, which suggested that other unobservable factors play a significant role. That is, output from both single and multiple regressions across samples largely suggested that the included value drivers hold low explanatory power of the studied multiple. The observed instances of limited predictive power are argued to be primarily driven by a combination of omitted variable bias, peer group heterogeneity, sample size effects and potential measurement errors. Nonetheless, results indicated that test-statistics generally improved as more homogenous samples are employed. A subsequent post-hoc analysis further supported this finding by demonstrating that the inclusion of sector and industry controls significantly improved the quality of output from employed regression models. Furthermore, motivated by empirical findings, an additional post-hoc analysis found that variations caused by intertemporal issues are likely to negatively affect the predictive power of the utilized aggregate measures.

In relation to the second research question of this study, predicted multiples developed from a fundamental regression analysis were found to be significant determinants of actual market multiples in a large majority of the studied sub-samples. As such, it was found that the low explanatory power of value drivers did not hinder developed predictions from being significant determinants of actual market multiples. Meanwhile, direct comparison of mean prediction errors revealed that estimates fail in generating significantly higher accuracy than estimates based on simple peer group averages. Thus, it was theorized that a large part of the explanatory power obtained from developed models likely stems from peer group affiliation rather than individual performance in fundamental value drivers. Accordingly, another post-hoc analysis confirmed that the low beta coefficients for the independent variables cause an inability to effectively capture deviations from the sample average. Further scrutinization of prediction errors also revealed that the loss of homogeneity associated with less narrow peer group definitions outweigh the statistical benefit from utilizing large sample sizes.

Thus, to conclusively respond to the first research question of this study, the underlying relationship between EV/EBITDA and its fundamental value drivers is found to be sporadic across sectors and industries included in the sample, where theoretical assumptions do not uniformly hold true. Moreover, to conclusively respond to the second research question of this study, a regression approach based on fundamental value drivers provides significant prediction estimates of actual market multiples, but do not significantly outperform estimates based on simple peer group averages. Thus, while the mathematical derivation of EV/EBITDA suggests that there are only a handful of factors that theoretically drive the multiple, findings from this study suggest otherwise. As such, it is concluded that utilizing regression approaches for the purpose of relative valuation should be considered a complement rather than a standalone tool in the search for intrinsic firm value.

This research is argued to contribute with both theoretical and practical value from a holistic standpoint. Firstly, the study sheds light on the fundamental feasibility of applying a regression approach for relative valuation purposes. In this regard, while more frequent employment of the approach may be justified, the inability to identify a strictly linear relationship between fundamental value drivers and the studied multiple indicates that more complex statistical models may be required. Secondly, it is argued that the methodological approach to identifying the underlying impact of fundamental value drivers provides practical value in several capacities. Most centrally, the employed methodology demonstrates how fundamental regression approaches can account for peer group heterogeneity without reliance on subjective adjustments. Finally, this study provides insights to the prevalent discussion regarding the trade-off associated with the optimal level of analysis for regression approaches within multiple valuation. That is, the analysis shows that the high degree of sample homogeneity associated with narrow definitions of peer groups outweighs statistical drawbacks associated with small sample sizes. In sum, this academic undertaking is argued to contribute with empirical evidence to the discourse on relative valuation in several dimensions.

- 10. Proposed Future Research & Extensions -

Given both the advantages and shortcomings of this research, it is argued that there are several extensions that can be applied for the purpose of validating and replicating the conducted study. To begin with, it is suggested that future studies investigate the impact of employing other measures of growth, profitability and risk than those applied in this study. While the adopted proxies have theoretical and empirical support, there are several alternative accounting measures representing the same performance indicators that could potentially capture the intended effect more effectively. Also, future researchers could consider aggregating several accounting measures into indexed constructs for each individual value driver, which may provide a more accurate and holistic view of fundamental value drivers. However, it is postulated that such an approach may oversee the effect of individual measures in isolation, which would have to be considered.

Apart from employing different measures, it is suggested that future researchers study the effect of including additional value drivers in a similar analysis. Even though it is argued that there is strong theoretical and empirical support for considering growth, profitability, and risk as being the most important value drivers, other factors could have been potentially included in the study as well. Adding more independent variables is expected reduce the influence of omitted variable bias and thus enhance informational value by increasing the predictive power of developed models. However, while additional value drivers will likely increase explanatory power, it is argued that such additions need to be motivated by intuitive theoretical reasoning. Even though a multitude of factors determine the value of a firm, adding variables to a developed model with sole intent to increase explanatory power does not provide practical value without logical justification.

To continue, another suggestion for future research includes utilization of international samples. Given that the adopted sample in this study exclusively incorporates US firms, the results are limited in their generalizability for other markets and diverging market factors. As it is theorized that the relationship between fundamental value drivers and the studied multiple is likely to differ across geographies and corresponding economic environments, this extension would allow for analysis of the confounding effect of specific market conditions. However, such international samples would exhibit substantial heterogeneity, which may complicate statistical analysis. Nonetheless, a deeper understanding of confounding market factors would arguably contribute with significant informational value to the discourse on multiple valuation.

Furthermore, given that intertemporal considerations appear to substantially influence the relationship between fundamental value drivers and the studied multiple, it is additionally suggested that future researchers direct significant attention to the issue when conducting similar studies. Such studies could potentially take several different forms. As an example, researchers could aggregate variables over a longer time period to mitigate the impact of non-normal observations, which would provide a more holistic view of the firm's historical performance. Alternatively, future researchers could perform a statistical analysis that explicitly tests how the relationship between fundamental value drivers and the studied multiple varies with intertemporal fluctuations.

Also, it is suggested to extend this study by incorporating several enterprise and equity multiples as dependent variables in a similar regression analysis. Since it appears that the suitability of multiples in specific industries may influence the accuracy of results, this would likely provide a better understanding of the relationship between multiples and their respective fundamental value drivers. However, due to various discrepancies in underlying relationships between different multiples and their corresponding value drivers, the inclusion of additional multiples of interest might potentially distort the practical usability of such a comprehensive study. Thus, it may be preferable to continuously investigate the underlying relationships of a single multiple per study, exclusively including firms for which the specific multiple in question is suitable. In this regard, the utilization of cross-market samples may be necessary in order to ensure sufficiently large sample sizes.

Moreover, as the research methodology is deliberately delimited with regards to method of data analysis, other statistical methods than OLS regression analysis is suggested to be implemented in the attempt of replicating obtained findings. Suggested alternatives in this regard firstly includes general least squares (GLS) regression analysis based on cross-sectional data, where the potential advantage resides in added robustness of estimates. Additionally, advanced panel data models such as the first difference estimator as well as fixed and random effects models could also be considered as primary method of data analysis for future reference. Applying time-series models based on panel data could potentially mitigate the statistical implications of exogenous and time-invariant unobservable effects, which would also improve general robustness of estimates. Moreover, a general implementation of time-series data in future research would allow for meaningful comparisons of intertemporal differences in studied relationships, as well as the intertemporal impact on multiple accuracy across different time periods.

Finally, it is suggested that future researchers extend the analysis of optimal peer group definition. More specifically, it is proposed to examine whether fundamental regression analysis utilizing sub-samples defined on the basis of other levels of GICS codes provides more accurate estimates of valuation multiples. It is expected that such an exercise would shed further light on the inherent trade-off associated with the choice between a narrow versus broad definition of peer groups. As also proposed in previous studies, future researchers could alternatively adopt a different approach by directly categorizing comparable firms that exhibit similar levels of growth, profitability and risk, regardless of industry classifications. If such an approach is found to enhance comparability between firms within peer groups, it is likely such samples may constitute a better point of departure in providing a more accurate picture of the relationship between fundamental value drivers and multiples.

- 11. References -

Alford, A. (1992). The Effect of the Set of Comparable Firms on the Accuracy of the Price-Earnings Valuation Method. *Journal of Accounting Research, 30*(1), 94-108.

Asquith, P., Mikhail, M., & Au, A. (2005). Information content of equity analyst reports. *Journal of Financial Economics, 75*(2), 245-282.

Asness, C., Frazzini, A., & Pedersen, L. (2013). Quality minus junk (Working Paper). *SSRN Electronic Journal.*

Asquith, P., Mikhail, M., & Au, A. (2005). Information content of equity analyst reports. *Journal of Financial Economics, 75*(2), 245-282.

Bagna, E. and Ramusino, E. (2017). Market Multiples and the Valuation of Cyclical Companies. *International Business Research*, 10(12), p.246.

Baker, M., & Ruback, R. (1999). Estimating Industry Multiples (Working Paper). Harvard University

Beaver, W., & Morse, D. (1978). What Determines Price-Earnings Ratios? *Financial Analysts Journal, 34*(4), 65-76.

Berk, J., & Demarzo, P. (2017). Corporate Finance (4th ed.). Harlow: Pearson Education Ltd.

Bernström, S. (2014). Valuation: The Market Approach*.* Chichester: John Wiley & Sons Ltd.

Bhojraj, S., & Lee, C. (2002). Who Is My Peer? A Valuation-Based Approach to the Selection of Comparable Firms. *Journal of Accounting Research, 40*(2), 407-439.

Bhojraj, S., Lee, C., & Oler, D. (2003). What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research. *Journal of Accounting Research, 41*(5), 745-774.

Bloomberg.com. (2019). Bloomberg Professional Services. [online] Available at: https://www. Bloomberg .com/professional/solution/bloomberg-terminal/.

Boatsman, J., & Baskin, E. (1981). Asset Valuation with Incomplete Markets. *The Accounting Review, 56*(1), 38-53.

Brigham, E., & Ehrhardt, M. (2014). Financial Management: Theory & Practice (14th ed.). Mason, OH: South-Western Cengage Learning.

Chandra, P. (2014). Corporate Valuation: A Guide for Analysts, Managers and Investors. New Delhi: McGraw Hill Education (India).

Cheng, C.A., and R. McNamara. (2000). The Valuation Accuracy of the Price-Earnings and Price-Book Benchmark Valuation Methods. *Review of Quantitative Finance and Accounting*, Vol. 15, No. 4, pp. 349-370.

Cragg, J., & Malkei, B. (1968). The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings. *The Journal of Finance, 23*(1), 67-84.

Credit Suisse. (2016). Managing the multiple: Weighing growth against profitability. New York: Credit Suisse Securities LLC.

Damodaran, A. (1994). Damodaran on Valuation: Security Analysis for Investment and Corporate Finance. New York: John Wiley & Sons Inc.

Damodaran, A. (2002). Investment valuation: Tools and techniques for determining the value of any asset (2nd ed.). New York: John Wiley & Sons Inc.

Damodaran, A. (2006). Damodaran on Valuation: Security Analysis for Investment and Corporate Finance (2nd ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.

Damodaran, A. (2007). Valuation Approaches and Metrics: A Survey of the Theory and Evidence. *Foundations and Trends in Finance, 1*(8), 693-784.

Damodaran, A. (2012). Investment valuation: Tools and techniques for determining the value of any asset (3rd ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.

Demirakos, E., Strong, N., & Walker, M. (2004). What Valuation Models Do Analysts Use? *Accounting Horizons, 18*(4), 221-240.

Dittmann, I., & Weiner, C. (2005). Selecting Comparables for the Valuation of European Firms. Berlin: Humboldt-Universität zu Berlin.

Emory Sr, J., Dengel, F., & Emory Jr, J. (2002). Discounts for Lack of Marketability, Emory Pre-IPO Discount Studies 1980–2000, As Adjusted October 10, 2002. *Business Valuation Review, 21*(4), 190-191.

Fama, F., & French, K. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.

García, F. (2017). Financial Risk Management: Identification, Measurement and Management. Cham: Palgrave Macmillan.

Gaughan, P. (2015). Mergers, Acquisitions, and Corporate Restructurings (6th ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.

Gupta, V. (2018). Predicting Accuracy of Valuation Multiples Using Value Drivers: Evidence from Indian Listed Firms. *Theoretical Economics Letters, 8*, 755-772.

Harbula, P. (2009). Valuation Multiples: Accuracy and Drivers - Evidence from the European Stock Market. *Business Valuation Review, 28*(4), 186-200.

Herrmann, V., & Richter, F. (2003). Pricing with Performance-Controlled Multiples. *Schmalenbach Business Review, 55*(3), 194-219.

Investopedia. (2019). Bloomberg Definition. [online] Available at: https://www. investopedia.com/terms/b /bloomberg.asp.

Kaplan, S., & Ruback, R. (1995). The Valuation of Cash Flow Forecasts: An Empirical Analysis. *Journal of Finance, 50*(1), 1059-1093.

Kim, M., & Ritter, J. (1999). Valuing IPOs. *Journal of Financial Economics, 53*, 409-437.

Kisor Jr, M., & Whitbeck, V. (1963). A New Tool in Investment Decision-Making. *Financial Analysts Journal, 19*(3), 55-62.

Knudsen, J., Kold, S., & Plenborg, T. (2017). Stick to the Fundamentals and Discover Your Peers. *Financial Analysts Journal, 73*(3), 85-105.

Koller, T., Goedhart, M., & Wessels, D. (2010). Valuation: Measuring and Managing the Value of Companies (5th ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.

Lie, E., & Lie, H. (2002). Multiples Used to Estimate Corporate Value. *Financial Analysts Journal, 58*(2), 44-54.

Liu, C., & Ziebart, D. (1994). Explaining earnings quality: A market-based test of a simple measure of sustainable earnings (Working Paper).

Liu, J., Nissim, D., & Thomas, J. (2002). Equity Valuation Using Multiples. *Journal of Accounting Research, 40*(1), 135-172.

Liu, J., Nissim, D., & Thomas, J. (2007). Is Cash Flow King in Valuations? *Financial Analysts Journal, 63*(2), 56-65.

Loughran, T., & Wellman, J. (2011). New Evidence on the Relation between the Enterprise Multiple and Average Stock Returns. *Journal of Financial and Quantitative Analysis, 46*(6), 1629-1650.

Moutinho, L., & Hutcheson, G. (2011). The Sage dictionary of quantitative management research. London: Sage Publications Ltd.

Nel, S., Bruwer, W., & le Roux, N. (2014). An Emerging Market Perspective on Peer Group Selection Based on Valuation Fundamentals. *Applied Financial Economics, 24*(9), 621-637.

Nissim, D. (2013). Relative Valuation of US Insurance Companies. *Review of Accounting Studies*, Vol. 18, No. 2 (2013), pp. 324-359.

Officer, M. (2007). The price of corporate liquidity: Acquisition discounts for unlisted targets. *Journal of Financial Economics, 83*(3), 571-598.

Ointo, J., Robinson, T., & Stowe, J. (2015). Equity Valuation: A Survey of Professional Practice (Working Paper).

Pandey, A. (2012). Relative Valuation: A Sectoral View for Indian Capital Market. *Management and Labour Studies, 37*(3), 179-193.

Petersen, C., Plenborg, T., & Kinserdal, F. (2017). Financial Statement Analysis: Valuation-Credit analysis-Performance Evaluation. Bergen: Fagbokforlaget.

Pinto, J., Robinson, T., & Stowe, J. (2015). Equity Valuation: A Survey of Professional Practice (Working Paper). CFA Institute

Plenborg, T., & Pimentel, R. (2016). Best Practices in Applying Multiples for Valuation Purposes. *The Journal of Private Equity, 19*(3), 55-64.

Pratt, S., Reilly, R., & Schweihs, R. (2008). Valuing a Business (5th ed.). New York: McGraw-Hill.

Rossi, E., & Forte, G. (2016). Assessing Relative Valuation in Equity Markets: Bridging Research & Practice. London: Macmillan Publishers Ltd.

Schreiner, A. (2007). Equity Valuation Using Multiples: An Empirical Investigation (Dissertation). *Deutscher Universitäts-Verlag Wiesbaden.* St. Gallen.

Schreiner, A., & K. Spremann. (2007). Multiples and their Valuation Accuracy in European Equity Markets. *Working paper*, http://ssrn.com/abstract=957352.

Silber, W. (1991). Discounts on Restricted Stock: The Impact of Illiquidity on Stock Prices. *Fiancial Analysts Journal, 47*(4), 60-64.

Stock, J., & Watson, M. (2012). Introduction to Econometrics (3rd ed.). Harlow: Pearson.

UBS. (2001). Valuation Multiples: A Primer. London: UBS Warburg.

Us.spindices.com. (2019). S&P Composite 1500® - S&P Dow Jones Indices. [online] Available at:https ://us.spindices.com/indices/equity/sp-composite-1500.

Yin, Y., Peasnell, K., & Hunt III, H. (2018). How do sell-side analysts obtain price-earnings multiples to value firms? *Accounting and Business Research, 48*(1), 108-135.

Yoo, Y. (2006). The valuation accuracy of equity valuation using a combination of multiples. *Review of Accounting and Finance, 5*(2), 108-123.

Young, S., & Zeng, Y. (2015). Accounting Comparability and the Accuracy of Peer-Based Valuation Models. *The Accounting Review, 90*(6), 2571-2601.

Zarowin, P. (1990). What determines earnings-price ratios: revisited. *Journal of Accouting Auditing and Finance, 5*(3), 439-454.

- 12. Appendices -

Appendix 1. Variable Construction

Dependent Variable:

$$MTPL_i = H\left(MTPL_{i,2018}, MTPL_{i,2017}, MTPL_{i,2016}\right) = H\left(\frac{EV_{i,2018}}{EBITDA_{i,2020}}, \frac{EV_{i,2017}}{EBITDA_{i,2019}}, \frac{EV_{i,2016}}{EBITDA_{i,2018}}\right) = \frac{3}{\frac{1}{\frac{EV_{i,2018}}{EBITDA_{i,2020}}} + \frac{1}{\frac{EV_{i,2017}}{EBITDA_{i,2019}}} + \frac{1}{\frac{EV_{i,2016}}{EBITDA_{i,2018}}}}$$

Independent Variables:

Growth:

$$Growth_i = Med\left(CAGR_{i,2018}, CAGR_{i,2017}, CAGR_{i,2016}\right) = Med\left(\left(\frac{EBITDA_{i,2021}}{EBITDA_{i,2019}}\right)^{\frac{1}{3}} - 1, \left(\frac{EBITDA_{i,2020}}{EBITDA_{i,2018}}\right)^{\frac{1}{3}} - 1, \left(\frac{EBITDA_{i,2019}}{EBITDA_{i,2017}}\right)^{\frac{1}{3}} - 1\right)$$

Profitability:

$$Profitability_i = Med(ROIC_{i,2018}, ROIC_{i,2017}, ROIC_{i,2016})P$$

Risk:

$$Risk_i = WACC_{i,LFY}$$

Appendix 2. Descriptive Statistics & Correlation Tables

Sector Sub-Samples

Sample: Consumer Discretionary Sector
Number of firms: 173

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,742	8,118	3,664	2,531	24,505			
2. Growth (%)	3,656	3,468	6,534	-18,233	28,730	0,115		
3. Profitability (%)	12,737	11,337	9,316	-23,446	52,438	0,154**	-0,139*	
4. Risk (%)	7,551	7,570	1,444	3,531	11,588	0,012	0,393****	0,143*

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Communication Services Sector
Number of firms: 41

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,553	7,676	3,968	4,312	27,467			
2. Growth (%)	7,338	4,721	9,014	-10,435	35,928	0,296*		
3. Profitability (%)	7,684	7,760	6,383	-8,116	23,734	0,314**	-0,138	
4. Risk (%)	7,716	7,520	1,702	4,937	12,403	0,618****	0,599****	0,096

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Consumer Staples Sector
Number of firms: 55

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	11,867	11,565	3,489	4,484	21,475			
2. Growth (%)	3,090	3,030	3,604	-6,921	17,584	-0,359****		
3. Profitability (%)	12,539	11,816	8,766	-3,883	38,385	0,282**	0,074	
4. Risk (%)	6,806	6,830	0,982	4,691	9,940	0,284**	0,186	0,3478****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Energy Sector
Number of firms: 69

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	7,324	5,860	4,073	0,851	25,078			
2. Growth (%)	8,465	7,402	8,678	-5,663	42,790	0,126		
3. Profitability (%)	2,159	2,127	7,871	-22,153	21,913	-0,054	-0,058	
4. Risk (%)	7,871	7,842	1,303	5,427	12,536	0,211*	0,406****	0,085

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Financials Sector
Number of firms: 29

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	**mean**	**median**	**s.d.**	**min**	**max**	**1**	**2**	**3**
1. MTPL	10,445	9,926	4,349	3,032	24,016			
2. Growth (%)	2,660	4,166	5,516	-11,299	12,606	0,123		
3. Profitability (%)	13,621	10,263	8,197	4,339	36,343	0,420**	0,049	
4. Risk (%)	8,381	8,037	1,555	4,607	11,287	-0,088	-0,172	0,370**

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Health Care Sector
Number of firms: 130

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	**mean**	**median**	**s.d.**	**min**	**max**	**1**	**2**	**3**
1. MTPL	12,295	11,264	4,963	0.3529242	32,760			
2. Growth (%)	6,897	6,236	7,554	-16,683	45,432	0,298****		
3. Profitability (%)	9,743	7,980	9,296	-13,061	64,574	-0,026	0,060	
4. Risk (%)	8,815	8,842	1,666	4,257	14,167	0,464****	0,443****	0,282***

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Information Technology Sector
Number of firms: 131

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	**mean**	**median**	**s.d.**	**min**	**max**	**1**	**2**	**3**
1. MTPL	10,363	9,310	4,809	2,223	32,760			
2. Growth (%)	6,685	5,222	6,936	-11,257	35,028	0,366****		
3. Profitability (%)	11,658	9,046	11,379	-15,661	62,918	0,026	-0,277****	
4. Risk (%)	9,216	9,206	1,584	4,857	13,621	0,215	0,172*	0,235****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Industrials Sector
Number of firms: 161

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	**mean**	**median**	**s.d.**	**min**	**max**	**1**	**2**	**3**
1. MTPL	9,561	9,205	3,106	3,475	22,407			
2. Growth (%)	5,674	5,011	4,770	-11,409	33,247	0,023		
3. Profitability (%)	11,997	10,730	9,456	-21,462	64,574	0,118	-0,027	
4. Risk (%)	8,517	8,572	1,210	3,576	12,165	0,096	0,086	0,286****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Materials Sector
Number of firms: 61

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,463	8,244	2,614	4,243	16,794			
2. Growth (%)	5,520	3,824	8,364	-11,123	45,432	0,119		
3. Profitability (%)	8,962	8,900	6,523	-5,681	28,776	0,005	-0,407****	
4. Risk (%)	7,778	7,744	1,274	4,719	11,491	-0,203	0,562****	-0,103

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Real Estate Sector
Number of firms: 76

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	15,763	16,157	4,002	6,716	30,269			
2. Growth (%)	2,589	2,273	4,214	-10,409	15,913	-0,157		
3. Profitability (%)	4,950	4,392	2,997	-0,752	20,373	-0,292***	-0,002	
4. Risk (%)	6,162	6,020	0,850	4,580	8,773	-0,298****	0,023	0,374****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Utilities Sector
Number of firms: 39

Panel A: Descriptive statistics						Panel B: Correlation matrix		
Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,603	10,603	1,981	7,242	16,091			
2. Growth (%)	4,128	3,944	2,467	-2,169	10,069	0,140		
3. Profitability (%)	5,046	4,961	1,818	-0,825	9,229	0,223	0,130	
4. Risk (%)	5,075	4,958	0,540	4,187	6,737	0,427****	-0,102	0,049

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Industry Sub-Samples

Sample: Automobiles & Components Industry
Number of firms: 14

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	6,475	6,057	3,194	2,531	13,529			
2. Growth (%)	2,841	2,767	2,997	-0,959	7,816	0,183		
3. Profitability (%)	11,484	12,264	5,457	1,460	18,364	0,227	0,485*	
4. Risk (%)	7,316	7,575	1,798	3,957	10,817	0,495*	0,639***	0,692****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Capital Goods Industry
Number of firms: 104

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	9,824	9,400	2,695	4,575	18,695			
2. Growth (%)	6,091	5,012	5,488	-11,409	33,247	-0,014		
3. Profitability (%)	12,005	9,527	10,753	-21,462	64,574	0,098	-0,022	
4. Risk (%)	8,658	8,608	1,073	4,206	12,165	0,141	0,085	0,214**

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Consumer Durables & Apparel Industry
Number of firms: 47

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	9,389	8,255	3,832	4,727	20,315			
2. Growth (%)	4,863	4,374	4,911	-4,802	20,004	-0,050		
3. Profitability (%)	10,282	9,906	7,149	-9,489	28,373	-0,284*	-0,143	
4. Risk (%)	7,474	7,659	1,292	5,469	11,164	0,003	0,446****	0,086

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Consumer Services Industry
Number of firms: 40

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,155	9,299	4,231	4,352	24,505			
2. Growth (%)	5,667	4,489	5,930	-3,566	28,730	-0,051		
3. Profitability (%)	14,316	11,180	9,893	1,865	52,438	0.538****	-0,157	
4. Risk (%)	7,523	7,378	1,227	5,570	11,588	-0,041	0,542****	-0,030

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Commercial & Professional Services Industry
Number of firms: 25

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,692	10,147	4,099	5,789	22,407			
2. Growth (%)	5,383	5,349	2,817	-0,473	11,107	-0,035		
3. Profitability (%)	11,146	9,424	7,300	1,717	31,621	0,423**	0,154	
4. Risk (%)	8,269	8,116	1,456	5,702	10,880	0,299	0,042	0,643****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Diversified Financials Industry
Number of firms: 29

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,445	9,926	4,349	3,032	24,016			
2. Growth (%)	2,660	4,166	5,516	-11,299	12,606	0,123		
3. Profitability (%)	13,621	10,263	8,197	4,339	36,343	0,420**	0,049	
4. Risk (%)	8,381	8,037	1,555	4,607	11,287	-0,088	-0,172	0,370**

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Energy Industry
Number of firms: 69

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	7,324	5,860	4,073	0,851	25,078			
2. Growth (%)	8,465	7,402	8,678	-5,663	42,790	0,126		
3. Profitability (%)	2,159	2,127	7,871	-22,153	21,913	-0,054	-0,058	
4. Risk (%)	7,871	7,842	1,303	5,427	12,536	0,211*	0,406****	0,085

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Food, Beverage & Tobacco Industry
Number of firms: 31

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	12,821	12,501	3,289	7,851	21,475			
2. Growth (%)	2,425	2,644	3,014	-6,921	7,536	-0,348*		
3. Profitability (%)	11,831	11,604	8,184	-3,883	37,940	0,175	0,346*	
4. Risk (%)	6,750	6,760	0,909	5,060	9,940	0,280	0,369**	0,409***

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Food Staples & Retailing Industry
Number of firms: 10

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,950	9,310	2,143	4,484	12,483			
2. Growth (%)	4,380	3,726	5,452	-2,701	17,584	-0,403		
3. Profitability (%)	10,838	12,123	4,134	4,039	15,674	0,565*	-0,374	
4. Risk (%)	6,812	6,912	1,374	4,984	8,742	0,664**	-0,030	0,177

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Health Care Equipment & Services Industry
Number of firms: 80

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	12,464	11,385	5,042	0,353	28,225			
2. Growth (%)	7,244	6,293	6,722	-6,244	29,078	0,353****		
3. Profitability (%)	8,676	7,876	6,832	-13,061	31,332	0,102	0,060	
4. Risk (%)	8,760	8,842	1,672	4,257	14,167	0,553****	0,505****	0,334****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Household & Personal Products Industry
Number of firms: 14

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	11,838	11,789	3,702	7,220	20,345			
2. Growth (%)	3,642	3,492	3,122	-0,927	12,046	-0,268		
3. Profitability (%)	15,323	13,606	11,874	-2,731	38,385	0,439	-0,143	
4. Risk (%)	6,924	6,909	0,877	4,691	7,992	0,278	0,142	0,410

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Materials Industry
Number of firms: 61

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,463	8,244	2,614	4,243	16,794			
2. Growth (%)	5,520	3,824	8,364	-11,123	45,432	0,119		
3. Profitability (%)	8,962	8,900	6,523	-5,681	28,776	0,005	-0,407****	
4. Risk (%)	7,778	7,744	1,274	4,719	11,491	-0,203	0,562****	-0,103

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Media & Entertainment Industry
Number of firms: 33

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	9,037	8,312	4,138	4,312	27,467			
2. Growth (%)	8,719	6,130	9,486	-10,435	35,928	0,218		
3. Profitability (%)	8,405	8,060	6,791	-8,116	23,734	0,264	-0,245	
4. Risk (%)	8,074	8,044	1,682	5,946	12,403	0,587****	0,538****	-0,017

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Pharmaceuticals, Biotechnology & Life Sciences Industry
Number of firms: 50

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	12,024	10,859	4,871	6,918	29,304			
2. Growth (%)	12,024	5,762	8,767	-16,683	35,660	0,231		
3. Profitability (%)	11,450	8,151	12,141	-8,941	57,280	-0,137	0,077	
4. Risk (%)	8,902	8,833	1,668	5,432	12,255	0,323***	0,383****	0,250*

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Real Estate Industry
Number of firms: 76

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	15,763	16,157	4,002	6,716	30,269			
2. Growth (%)	2,589	2,273	4,214	-10,409	15,913	-0,157		
3. Profitability (%)	4,950	4,392	2,997	-0,752	20,373	-0,292***	-0,002	
4. Risk (%)	6,162	6,020	0,850	4,580	8,773	-0,298****	0,023	0,374****

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Retailing Industry
Number of firms: 72

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	7,977	7,617	2,879	2,798	16,075			
2. Growth (%)	1,909	2,309	7,771	-18,233	24,532	0,171		
3. Profitability (%)	13,706	12,124	10,548	-23,446	40,415	0,153	-0,146	
4. Risk (%)	7,662	7,707	1,588	3,531	11,080	-0,050	0,373****	0,169

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Semiconductors & Semiconductor Equipment Industry
Number of firms: 28

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	9,164	8,179	5,686	2,223	32,760			
2. Growth (%)	5,849	4,149	8,152	-5,276	35,028	0,697****		
3. Profitability (%)	12,483	12,292	9,443	-2,588	27,136	-0,089	0,394**	
4. Risk (%)	10,108	10,197	1,649	7,395	13,621	0,059	0,174	0,183

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Software & Services Industry
Number of firms: 54

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	12,858	12,070	4,454	5,981	32,590			
2. Growth (%)	7,517	6,532	5,678	-4,434	22,212	0,315***		
3. Profitability (%)	12,887	8,882	14,076	-15,661	62,918	0,041	-0,314***	
4. Risk (%)	8,943	9,160	1,416	4,857	11,933	0,534****	0,334***	0,314***

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Technology Hardware & Equipment Industry
Number of firms: 49

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	8,299	7,584	3,216	3,475	18,246			
2. Growth (%)	6,247	5,028	7,479	-11,409	25,137	0,093		
3. Profitability (%)	9,832	8,589	8,732	-21,462	44,993	-0,105	-0,244*	
4. Risk (%)	9,008	8,920	1,567	3,576	12,517	0,267*	0,121	0,185

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Telecommunication Services Industry
Number of firms: 8

Panel A: Descriptive statistics / **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	6,556	6,039	2,457	4,316	12,285			
2. Growth (%)	1,639	1,208	2,609	-1,887	6,569	0,814***		
3. Profitability (%)	4,709	3,869	3,065	2,110	11,285	0,421	0,348	
4. Risk (%)	6,237	6,210	0,718	4,937	7,459	0,555	0,709**	0,253

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Transportation Industry
Number of firms: 32

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	7,819	7,634	2,874	3,475	18,607			
2. Growth (%)	4,550	4,525	3,043	-5,601	10,389	0,078		
3. Profitability (%)	12,637	12,583	5,920	3,391	24,493	0,032	-0,218	
4. Risk (%)	8,253	8,550	1,379	3,576	10,723	-0,314*	0,048	0,415***

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Sample: Utilities Industry
Number of firms: 39

Panel A: Descriptive statistics | **Panel B: Correlation matrix**

Variable	mean	median	s.d.	min	max	1	2	3
1. MTPL	10,603	10,603	1,981	7,242	16,091			
2. Growth (%)	4,128	3,944	2,467	-2,169	10,069	0,140		
3. Profitability (%)	5,046	4,961	1,818	-0,825	9,229	0,223	0,130	
4. Risk (%)	5,075	4,958	0,540	4,187	6,737	0,427****	-0,102	0,049

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Appendix 3. Normality Tests

Market/Sector/Industry	N	LN.MTPL						Growth					
		No Skewness		No Kurtosis		Shapiro-Wilk Test		No Skewness		No Kurtosis		Shapiro-Wilk Test	
		Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value
Market	965	-0,673	0,000***	6,856	0,000***	0,972	0,000***	1,369	0,000***	8,987	0,000***	0,885	0,000***
Energy Sector	69	-0,366	0,184	6,206	0,000***	0,925	0,000***	1,461	0,000***	6,685	0,000***	0,897	0,000***
Energy	69	-0,366	0,184	6,206	0,000***	0,925	0,000***	1,461	0,000***	6,685	0,000***	0,897	0,000***
Materials Sector	61	0,087	0,758	2,399	0,267	0,989	0,872	2,903	0,000***	14,272	0,000***	0,696	0,000***
Materials	61	0,087	0,758	2,399	0,267	0,989	0,872	2,903	0,000***	14,272	0,000***	0,696	0,000***
Industrials Sector	161	-0,063	0,744	3,197	0,585	0,996	0,913	2,041	0,000***	13,333	0,000***	0,795	0,000***
Capital Goods	104	-0,068	0,762	2,431	0,174	0,986	0,347	1,957	0,000***	10,981	0,000***	0,782	0,000***
Commercial & Professional Services	25	0,530	0,209	2,928	0,939	0,957	0,361	0,231	0,575	2,872	0,882	0,971	0,683
Transportation	32	0,077	0,834	3,326	0,666	0,974	0,615	-0,750	0,053*	5,336	0,006***	0,935	0,055*
Consumer Discretionary Sector	173	-0,124	0,501	3,214	0,529	0,995	0,835	-0,055	0,754	5,825	0,000***	0,941	0,000***
Automobiles & Components	14	-0,153	0,764	2,028	0,286	0,966	0,817	0,154	0,761	1,636	0,067*	0,929	0,294
Consumer Durables & Apparel	47	0,819	0,02**	3,067	0,929	0,931	0,008***	0,556	0,102	4,141	0,043**	0,959	0,096*
Consumer Services	40	0,078	0,814	2,764	0,742	0,984	0,848	1,692	0,000***	7,211	0,000***	0,861	0,000***
Retailing	72	-0,302	0,262	2,454	0,277	0,979	0,280	-0,266	0,320	4,146	0,027**	0,957	0,016**
Consumer Staples Sector	55	-0,284	0,359	3,614	0,264	0,980	0,480	0,850	0,008***	7,557	0,000***	0,899	0,000***
Food Staples & Retailing	10	-1,282	0,032**	4,368	0,101	0,876	0,116	1,361	0,027**	4,670	0,026**	0,856	0,068*
Food, Beverage & Tobacco	31	0,269	0,475	2,728	0,745	0,977	0,715	-1,131	0,008***	4,883	0,018**	0,911	0,014**
Household & Personal Products	14	-0,032	0,947	2,140	0,369	0,936	0,364	1,167	0,033**	4,956	0,017**	0,896	0,001***
Health Care Sector	130	-2,815	0,000***	23,560	0,000***	0,799	0,000***	0,855	0,000***	5,377	0,000***	0,932	0,000***
Health Care Equipment & Services	80	-3,276	0,000***	22,933	0,000***	0,750	0,000***	1,150	0,000***	4,989	0,005***	0,908	0,000***
Pharmaceuticals, Biotechnology & Life Sciences	50	0,726	0,031**	3,028	0,968	0,944	0,019**	0,688	0,041**	5,107	0,006***	0,942	0,017**
Financials Sector	29	-0,439	0,258	3,620	0,404	0,975	0,704	-0,893	0,032**	3,701	0,331	0,928	0,049**
Diversified Financials	29	-0,439	0,258	3,620	0,404	0,975	0,704	-0,893	0,032**	3,701	0,331	0,928	0,049**
Information Technology Sector	131	-0,221	0,288	3,887	0,025**	0,986	0,197	0,866	0,000***	4,850	0,001***	0,950	0,000***
Software & Services	54	0,385	0,212	3,761	0,158	0,980	0,493	0,726	0,026**	3,464	0,409	0,953	0,034**
Technology Hardware & Equipment	49	-0,195	0,527	3,406	0,520	0,980	0,579	0,427	0,183	3,379	0,541	0,960	0,093*
Semiconductors & Semiconductor Equipment	28	0,124	0,767	4,603	0,024**	0,948	0,173	1,789	0,000***	7,164	0,001***	0,849	0,001***
Communication Services Sector	41	0,703	0,053*	4,257	0,036**	0,957	0,119	1,364	0,001***	5,139	0,007***	0,869	0,000***
Telecommunication Services	8	1,222	0,050*	3,999	0,408	0,863	0,130	0,636	0,278	2,744	0,881	0,965	0,855
Media & Entertainment	33	0,655	0,090*	4,626	0,022**	0,950	0,129	1,103	0,008***	4,418	0,029**	0,894	0,004***
Utilities Sector	39	0,136	0,704	3,155	0,830	0,970	0,371	0,377	0,279	3,865	0,147	0,949	0,073*
Utilities	39	0,136	0,704	3,155	0,830	0,970	0,371	0,377	0,279	3,865	0,147	0,949	0,073*
Real Estate Sector	76	-0,596	0,029**	3,459	0,349	0,965	0,035**	0,575	0,034**	5,712	0,000***	0,918	0,000***
Real Estate	76	-0,596	0,029**	3,459	0,349	0,965	0,035**	0,575	0,034**	5,712	0,000***	0,918	0,000***

Market/Sector/Industry	N	Profitability						LN.Risk					
		No Skewness		No Kurtosis		Shapiro-Wilk Test		No Skewness		No Kurtosis		Shapiro-Wilk Test	
		Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value
Market	965	1,467	0,000***	8,892	0,000***	0,892	0,000***	-0,421	0,000***	3,022	0,885	0,987	0,000***
Energy Sector	69	-0,404	0,148	3,834	0,087*	0,983	0,451	0,080	0,766	2,853	0,787	0,988	0,752
Energy	69	-0,404	0,148	3,834	0,087*	0,983	0,451	0,080	0,766	2,853	0,787	0,988	0,752
Materials Sector	61	0,370	0,209	3,786	0,125	0,972	0,178	-0,484	0,101	3,890	0,074*	0,973	0,189
Materials	61	0,370	0,209	3,786	0,125	0,972	0,178	-0,484	0,101	3,890	0,074*	0,973	0,189
Industrials Sector	161	1,869	0,000***	11,562	0,000***	0,837	0,000***	-1,727	0,000***	9,630	0,000***	0,890	0,000***
Capital Goods	104	1,878	0,000***	10,522	0,000***	0,819	0,000***	-1,540	0,000***	10,041	0,000***	0,901	0,000***
Commercial & Professional Services	25	1,279	0,006***	4,329	0,047**	0,883	0,008***	-0,165	0,682	2,114	0,228	0,970	0,635
Transportation	32	0,300	0,429	2,255	0,272	0,964	0,360	-2,276	0,000***	9,901	0,000***	0,792	0,000***
Consumer Discretionary Sector	173	0,775	0,000***	6,050	0,000***	0,930	0,000***	-0,650	0,000***	4,145	0,006***	0,972	0,001***
Automobiles & Components	14	-0,618	0,244	2,271	0,480	0,921	0,228	-0,593	0,248	2,896	0,932	0,950	0,559
Consumer Durables & Apparel	47	0,094	0,764	3,892	0,102	0,973	0,354	-0,028	0,938	2,369	0,288	0,968	0,229
Consumer Services	40	1,783	0,000***	7,070	0,000***	0,844	0,000***	0,521	0,139	3,857	0,153	0,964	0,230
Retailing	72	0,228	0,393	4,683	0,007***	0,934	0,001***	-0,981	0,001***	4,250	0,019**	0,943	0,003***
Consumer Staples Sector	55	1,026	0,003**	4,444	0,020**	0,927	0,002***	-0,222	0,475	3,491	0,382	0,977	0,356
Food Staples & Retailing	10	-0,438	0,418	1,851	0,227	0,907	0,262	-0,146	0,787	1,710	0,144	0,924	0,394
Food, Beverage & Tobacco	31	0,996	0,014**	4,673	0,021**	0,933	0,053*	0,399	0,300	4,677	0,020**	0,951	0,172
Household & Personal Products	14	0,506	0,325	2,537	0,683	0,947	0,521	-1,435	0,011**	5,110	0,011**	0,861	0,031**
Health Care Sector	130	1,807	0,000***	9,862	0,000***	0,873	0,000***	-0,673	0,002***	4,110	0,011**	0,972	0,008***
Health Care Equipment & Services	80	0,336	0,202	4,573	0,009***	0,971	0,062*	-0,794	0,005***	4,751	0,008***	0,954	0,006***
Pharmaceuticals, Biotechnology & Life Sciences	50	1,759	0,000***	7,179	0,000***	0,852	0,000***	0,446	0,168	2,799	0,755	0,968	0,195
Financials Sector	29	1,108	0,012**	3,485	0,537	0,884	0,004***	-0,796	0,057*	3,828	0,231	0,953	0,220
Diversified Financials	29	1,108	0,012**	3,485	0,537	0,884	0,004***	-0,796	0,057*	3,828	0,231	0,953	0,220
Information Technology Sector	131	1,840	0,000***	8,190	0,000***	0,846	0,000***	-0,607	0,006***	4,275	0,005***	0,972	0,007***
Software & Services	54	1,853	0,000***	6,920	0,000***	0,783	0,000***	-1,392	0,000***	5,909	0,002***	0,896	0,000***
Technology Hardware & Equipment	49	1,661	0,000***	7,599	0,000***	0,875	0,000***	-0,126	0,693	2,810	0,768	0,985	0,794
Semiconductors & Semiconductor Equipment	28	0,126	0,752	1,762	0,051*	0,938	0,098*	-0,069	0,860	2,463	0,493	0,971	0,597
Communication Services Sector	41	0,108	0,746	3,602	0,351	0,980	0,661	0,447	0,196	2,581	0,524	0,960	0,156
Telecommunication Services	8	1,293	0,036**	3,678	0,650	0,836	0,068*	-0,486	0,410	3,317	0,841	0,942	0,632
Media & Entertainment	33	-0,156	0,671	3,483	0,509	0,970	0,488	0,394	0,290	2,342	0,337	0,953	0,162
Utilities Sector	39	-0,458	0,189	4,874	0,016**	0,958	0,150	0,624	0,091*	3,237	0,738	0,965	0,266
Utilities	39	-0,458	0,189	4,874	0,016**	0,958	0,150	0,624	0,091*	3,237	0,738	0,965	0,266
Real Estate Sector	76	2,360	0,000***	12,011	0,000***	0,802	0,000***	0,595	0,031**	3,474	0,325	0,968	0,055*
Real Estate	76	2,360	0,000***	12,011	0,000***	0,802	0,000***	0,595	0,031**	3,474	0,325	0,968	0,055*

*** p < 0,01
** p < 0,05
* p < 0,1

Appendix 4. Heteroscedasticity Tests

		MTPL ~ Growth		*MTPL ~ Profitability*		*MTPL ~ Risk*		*MTPL ~ Growth, Profitability, Risk*	
Market/Sector/Industry	N	BP	p-value	BP	p-value	BP	p-value	BP	p-value
Market	965	6,539	0,038**	9,340	0,009***	3,593	0,058*	7,566	0,023**
Energy Sector	69	2,244	0,326	1,002	0,606	4,643	0,098*	0,378	0,828
Energy	69	2,244	0,326	1,002	0,606	4,643	0,098*	0,378	0,828
Materials Sector	61	0,891	0,641	0,747	0,688	5,148	0,076*	1,390	0,499
Materials	61	0,891	0,641	0,747	0,688	5,148	0,076*	1,390	0,499
Industrials Sector	161	1,042	0,594	0,305	0,858	11,546	0,003***	0,411	0,814
Capital Goods	104	3,299	0,192	2,086	0,352	0,836	0,658	3,316	0,191
Commercial & Professional Services	25	2,367	0,306	8,171	0,017**	9,421	0,009***	8,960	0,011**
Transportation	32	0,915	0,633	4,635	0,099*	3,102	0,212	11,699	0,003***
Consumer Discretionary Sector	173	1,895	0,388	23,851	0,000***	8,415	0,015**	11,088	0,004***
Automobiles & Components	14	7,032	0,030**	1,161	0,560	2,242	0,326	1,921	0,383
Consumer Durables & Apparel	47	0,947	0,623	11,546	0,003***	10,056	0,007***	9,468	0,009***
Consumer Services	40	2,978	0,226	0,123	0,940	4,668	0,097*	0,620	0,734
Retailing	72	0,868	0,648	17,342	0,000***	4,622	0,099*	8,166	0,017**
Consumer Staples Sector	55	0,786	0,675	1,310	0,520	0,091	0,956	1,435	0,488
Food Staples & Retailing	10	1,408	0,495	2,671	0,263	1,650	0,438	1,352	0,509
Food, Beverage & Tobacco	31	0,126	0,939	1,318	0,517	1,502	0,472	0,412	0,814
Household & Personal Products	14	2,791	0,248	2,540	0,281	3,743	0,154	1,573	0,456
Health Care Sector	130	0,378	0,828	0,614	0,736	0,777	0,678	0,837	0,658
Health Care Equipment & Services	80	0,300	0,861	0,421	0,810	0,564	0,754	0,618	0,734
Pharmaceuticals, Biotechnology & Life Sciences	50	0,190	0,909	2,740	0,254	0,186	0,911	0,125	0,940
Financials Sector	29	11,498	0,003***	0,457	0,796	1,181	0,554	2,880	0,237
Diversified Financials	29	11,498	0,003***	0,457	0,796	1,181	0,554	2,880	0,237
Information Technology Sector	131	6,388	0,041**	3,891	0,143	15,411	0,000***	4,128	0,127
Software & Services	54	11,262	0,004***	25,871	0,000***	6,500	0,039**	5,575	0,062*
Technology Hardware & Equipment	49	2,799	0,247	1,759	0,415	3,843	0,146	4,088	0,130
Semiconductors & Semiconductor Equipment	28	0,968	0,616	1,305	0,521	3,215	0,200	0,329	0,848
Communication Services Sector	41	10,849	0,004***	0,945	0,624	3,946	0,139	6,688	0,035**
Telecommunication Services	8	1,172	0,557	2,380	0,304	6,134	0,047**	4,409	0,110
Media & Entertainment	33	8,960	0,011**	0,667	0,717	3,455	0,178	6,405	0,041**
Utilities Sector	39	3,631	0,163	9,953	0,007***	3,570	0,168	0,727	0,695
Utilities	39	3,631	0,163	9,953	0,007***	3,570	0,168	0,727	0,695
Real Estate Sector	76	2,363	0,307	5,979	0,050*	15,076	0,001***	6,867	0,032**
Real Estate	76	2,363	0,307	5,979	0,050*	15,076	0,001***	6,867	0,032**

**** p < ,01
*** p < ,025
** p < ,05
* p < ,1

Appendix 5. Dummy Regressions

Panel A: Sector Dummies

	Dependent Variable
	LN.MTPL
Growth	0,007***
	(0,015)
Profitability	0,004***
	(0,002)
Risk	0,168*
	(0,097)
Consumer Discretionary Sector	0,025
	(0,062)
Consumer Staples Sector	0,390****
	(0,066)
Energy Sector	-0,194***
	(0,081)
Financials Sector	0,187**
	(0,095)
Health Care Sector	0,324****
	(0,067)
Industrials Sector	0,114*
	(0,060)
Information Technology Sector	0,130*
	(0,067)
Materials Sector	0,025
	(0,066)
Real Estate Sector	0,732****
	(0,064)
Utilities Sector	0,374****
	(0,067)
Alpha	1,651****
	(0,015)
Observations	965
R^2	0,246
Adj. R^2	0,236
Std. Error	0,384
F Statistic	23,848****

Panel B: Industry Dummies

	Dependent Variable
	LN.MTPL
Growth	0,005*
	(0,003)
Profitability	0,003**
	(0,002)
Risk	0,196**
	(0,095)
Consumer Durables & Apparel	0,409***
	(0,133)
Commercial & Professional Services	0,520****
	(0,138)
Capital Goods	0,442****
	(0,124)
Consumer Services	0,457****
	(0,136)
Diversified Financials	0,477****
	(0,144)
Energy	0,101
	(0,137)
Food, Beverage & Tobacco	0,783****
	(0,130)
Food Staples & Retailing	0,416***
	(0,146)
Health Care Equipment & Services	0,622****
	(0,133)
Household & Personal Products	0,666****
	(0,144)
Media & Entertainment	0,337***
	(0,135)
Materials	0,319***
	(0,128)
Pharmaceuticals, Biotechnology & Life Sciences	0,613****
	(0,131)
Real Estate	1,025****
	(0,129)
Retailing	0,245*
	(0,130)
Software & Services	0,683****
	(0,128)
Semiconductors & Semiconductor Equipment	0,248
	(0,152)
Technology Hardware & Equipment	0,239*
	(0,133)
Telecommunication Services	0,136
	(0,157)
Transportation	0,209
	(0,137)
Utilities	0,675****
	(0,132)
Alpha	1,316****
	(0,227)
Observations	965
R^2	0,311
Adj. R^2	0,293
Std. Error	0,369
F Statistic	17,639****

Appendix 6. Predictive Equations

Standard Market Model

$$LN.\widehat{MTPL}_{i,t} = 2{,}369 + 0{,}005(Growth_{i,t}) + 0{,}004(Profitability_{i,t}) - 0{,}096(LN.Risk_{i,t})$$

Standard Sector Model

Consumer Discretionary

$$LN.\widehat{MTPL}_{i,t} = 2{,}198 + 0{,}009(Growth_{i,t}) + 0{,}010(Profitability_{i,t}) - 0{,}136(LN.Risk_{i,t})$$

Communication Services

$$LN.\widehat{MTPL}_{i,t} = -0{,}361 - 0{,}005(Growth_{i,t}) + 0{,}020(Profitability_{i,t}) - 1{,}145(LN.Risk_{i,t})$$

Consumer Staples

$$LN.\widehat{MTPL}_{i,t} = 1{,}241 - 0{,}041(Growth_{i,t}) + 0{,}008(Profitability_{i,t}) + 0{,}636(LN.Risk_{i,t})$$

Energy

$$LN.\widehat{MTPL}_{i,t} = 1{,}575 + 0{,}004(Growth_{i,t}) - 0{,}008(Profitability_{i,t}) + 0{,}134(LN.Risk_{i,t})$$

Financials

$$LN.\widehat{MTPL}_{i,t} = 2{,}993 - 0{,}004(Growth_{i,t}) + 0{,}025(Profitability_{i,t}) - 0{,}504(LN.Risk_{i,t})$$

Health Care

$$LN.\widehat{MTPL}_{i,t} = 0{,}700 + 0{,}004(Growth_{i,t}) - 0{,}005(Profitability_{i,t}) + 0{,}807(LN.Risk_{i,t})$$

Information Technology

$$LN.\widehat{MTPL}_{i,t} = 1{,}645 + 0{,}021(Growth_{i,t}) + 0{,}005(Profitability_{i,t}) + 0{,}184(LN.Risk_{i,t})$$

Industrials

$$LN.\widehat{MTPL}_{i,t} = 2{,}051 + 0{,}001(Growth_{i,t}) + 0{,}004(Profitability_{i,t}) + 0{,}049(LN.Risk_{i,t})$$

Materials

$$LN.\widehat{MTPL}_{i,t} = 3{,}240 + 0{,}014(Growth_{i,t}) + 0{,}008(Profitability_{i,t}) - 0{,}636(LN.Risk_{i,t})$$

Real Estate

$$LN.\widehat{MTPL}_{i,t} = 3{,}687 - 0{,}007(Growth_{i,t}) - 0{,}022(Profitability_{i,t}) - 0{,}464(LN.Risk_{i,t})$$

Utilities

$$LN.\widehat{MTPL}_{i,t} = 1{,}117 + 0{,}012(Growth_{i,t}) + 0{,}012(Profitability_{i,t}) + 0{,}689(LN.Risk_{i,t})$$

Standard Industry Model

Automobiles & Components

$$LN.\widehat{MTPL}_{i,t} = -1{,}309 - 0{,}026(Growth_{i,t}) - 0{,}018(Profitability_{i,t}) + 1{,}702(LN.Risk_{i,t})$$

Capital Goods

$$LN.\widehat{MTPL}_{i,t} = 1{,}784 - 0{,}002(Growth_{i,t}) + 0{,}002(Profitability_{i,t}) + 0{,}208(LN.Risk_{i,t})$$

Consumer Durables & Apparel

$$LN.\widehat{MTPL}_{i,t} = 1{,}944 - 0{,}013(Growth_{i,t}) - 0{,}012(Profitability_{i,t}) + 0{,}208(LN.Risk_{i,t})$$

Consumer Services

$$LN.\widehat{MTPL}_{i,t} = 2{,}063 - 0{,}006(Growth_{i,t}) + 0{,}020(Profitability_{i,t}) - 0{,}036(LN.Risk_{i,t})$$

Commercial & Professional Services

$$LN.\widehat{MTPL}_{i,t} = 2{,}192 - 0{,}023(Growth_{i,t}) + 0{,}017(Profitability_{i,t}) + 0{,}023(LN.Risk_{i,t})$$

Diversified Financials

$$LN.\widehat{MTPL}_{i,t} = 2{,}993 - 0{,}004(Growth_{i,t}) + 0{,}025(Profitability_{i,t}) - 0{,}504(LN.Risk_{i,t})$$

Energy

$$LN.\widehat{MTPL}_{i,t} = 1{,}575 + 0{,}004(Growth_{i,t}) - 0{,}008(Profitability_{i,t}) + 0{,}134(LN.Risk_{i,t})$$

Food, Beverage & Tobacco

$$LN.\widehat{MTPL}_{i,t} = 1{,}292 - 0{,}045(Growth_{i,t}) + 0{,}008(Profitability_{i,t}) + 0{,}652(LN.Risk_{i,t})$$

Food & Staples Retailing

$$LN.\widehat{MTPL}_{i,t} = 0{,}660 - 0{,}020(Growth_{i,t}) + 0{,}020(Profitability_{i,t}) + 0{,}720(LN.Risk_{i,t})$$

Health Care Equipment & Services

$$LN.\widehat{MTPL}_{i,t} = 0{,}518 + 0{,}003(Growth_{i,t}) - 0{,}001(Profitability_{i,t}) + 0{,}883(LN.Risk_{i,t})$$

Household & Personal Products

$$LN.\widehat{MTPL}_{i,t} = 1{,}521 - 0{,}033(Growth_{i,t}) + 0{,}009(Profitability_{i,t}) + 0{,}464(LN.Risk_{i,t})$$

Materials

$$LN.\widehat{MTPL}_{i,t} = 3{,}240 + 0{,}014(Growth_{i,t}) + 0{,}008(Profitability_{i,t}) - 0{,}636(LN.Risk_{i,t})$$

Media & Entertainment

$$LN.\widehat{MTPL}_{i,t} = -0{,}492 - 0{,}007(Growth_{i,t}) + 0{,}019(Profitability_{i,t}) + 1{,}217(LN.Risk_{i,t})$$

Pharmaceuticals, Biotechnology & Life Sciences

$$LN.\widehat{MTPL}_{i,t} = 1{,}065 + 0{,}006(Growth_{i,t}) - 0{,}006(Profitability_{i,t}) + 0{,}641(LN.Risk_{i,t})$$

Real Estate

$$LN.\widehat{MTPL}_{i,t} = 3{,}687 - 0{,}007(Growth_{i,t}) - 0{,}022(Profitability_{i,t}) - 0{,}464(LN.Risk_{i,t})$$

Retailing

$$LN.\widehat{MTPL}_{i,t} = 2{,}745 + 0{,}014(Growth_{i,t}) + 0{,}011(Profitability_{i,t}) - 0{,}451(LN.Risk_{i,t})$$

Semiconductors & Semiconductor Equipment

$$LN.\widehat{MTPL}_{i,t} = 3{,}267 + 0{,}041(Growth_{i,t}) + 0{,}008(Profitability_{i,t}) - 0{,}666(LN.Risk_{i,t})$$

Software & Services

$$LN.\widehat{MTPL}_{i,t} = 0{,}602 + 0{,}011(Growth_{i,t}) + 0{,}001(Profitability_{i,t}) + 0{,}828(LN.Risk_{i,t})$$

Technology Hardware & Equipment

$$LN.\widehat{MTPL}_{i,t} = 0{,}784 - 0{,}001(Growth_{i,t}) - 0{,}005(Profitability_{i,t}) + 0{,}603(LN.Risk_{i,t})$$

Telecommunication Services

$$LN.\widehat{MTPL}_{i,t} = 2{,}902 + 0{,}109(Growth_{i,t}) + 0{,}025(Profitability_{i,t}) - 0{,}747(LN.Risk_{i,t})$$

Transportation

$$LN.\widehat{MTPL}_{\iota,t} = 3{,}122 + 0{,}026(Growth_{i,t}) + 0{,}018(Profitability_{i,t}) - 0{,}702(LN.Risk_{i,t})$$

Utilities

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}117 + 0{,}012(Growth_{i,t}) + 0{,}012(Profitability_{i,t}) + 0{,}689(LN.Risk_{i,t})$$

Relative Market Model

$$\left(\frac{\widehat{MTPL_{\iota,t} - 8{,}378}}{8{,}378}\right) = 0{,}219 + 0{,}034\left(\frac{Growth_{i,t} - 4{,}374}{4{,}374}\right) + 0{,}020\left(\frac{Profitability_{i,t} - 8{,}366}{8{,}366}\right) + 0{,}029\left(\frac{Risk_{i,t} - 7{,}961}{7{,}961}\right)$$

Relative Sector Model

Consumer Discretionary

$$\left(\frac{\widehat{MTPL_{\iota,t} - 7{,}389}}{7{,}389}\right) = 0{,}165 + 0{,}046\left(\frac{Growth_{i,t} - 3{,}468}{3{,}468}\right) + 0{,}114\left(\frac{Profitability_{i,t} - 11{,}337}{11{,}337}\right) - 0{,}218\left(\frac{Risk_{i,t} - 7{,}570}{7{,}570}\right)$$

Communication Services

$$\left(\frac{\widehat{MTPL_{\iota,t} - 7{,}435}}{7{,}435}\right) = 0{,}120 - 0{,}011\left(\frac{Growth_{i,t} - 4{,}721}{4{,}721}\right) + 0{,}162\left(\frac{Profitability_{i,t} - 7{,}760}{7{,}760}\right) + 1{,}457\left(\frac{Risk_{i,t} - 7{,}520}{7{,}520}\right)$$

Consumer Staples

$$\left(\frac{\widehat{MTPL_{\iota,t} - 10{,}876}}{10{,}976}\right) = 0{,}090 - 0{,}016\left(\frac{Growth_{i,t} - 3{,}030}{3{,}030}\right) + 0{,}092\left(\frac{Profitability_{i,t} - 11{,}816}{11{,}816}\right) + 0{,}647\left(\frac{Risk_{i,t} - 6{,}830}{6{,}830}\right)$$

Energy

$$\left(\frac{\widehat{MTPL_{\iota,t} - 5{,}602}}{5{,}602}\right) = 0{,}301 + 0{,}025\left(\frac{Growth_{i,t} - 7{,}402}{7{,}402}\right) - 0{,}014\left(\frac{Profitability_{i,t} - 2{,}127}{2{,}127}\right) + 0{,}876\left(\frac{Risk_{i,t} - 7{,}842}{7{,}842}\right)$$

Financials

$$\left(\frac{\widehat{MTPL_{\iota,t} - 8{,}742}}{8{,}742}\right) = 0{,}126 + 0{,}019\left(\frac{Growth_{i,t} - 4{,}166}{4{,}166}\right) + 0{,}322\left(\frac{Profitability_{i,t} - 10{,}623}{10{,}623}\right) - 0{,}696\left(\frac{Risk_{i,t} - 8{,}037}{8{,}037}\right)$$

Health Care

$$\left(\frac{\widehat{MTPL_{\iota,t} - 8{,}850}}{8{,}859}\right) = 0{,}406 + 0{,}047\left(\frac{Growth_{i,t} - 6{,}236}{6{,}236}\right) - 0{,}079\left(\frac{Profitability_{i,t} - 7{,}980}{7{,}980}\right) + 1{,}385\left(\frac{Risk_{i,t} - 8{,}841}{8{,}841}\right)$$

Information Technology

$$\left(\frac{\widehat{MTPL_{\iota,t} - 8{,}501}}{8{,}501}\right) = 0{,}161 + 0{,}158\left(\frac{Growth_{i,t} - 5{,}222}{5{,}222}\right) + 0{,}044\left(\frac{Profitability_{i,t} - 9{,}046}{9{,}046}\right) + 0{,}419\left(\frac{Risk_{i,t} - 9{,}206}{9{,}206}\right)$$

Industrials

$$\left(\frac{\widehat{MTPL_{\iota,t} - 8{,}644}}{8{,}644}\right) = 0{,}101 + 0{,}008\left(\frac{Growth_{i,t} - 5{,}011}{5{,}011}\right) + 0{,}041\left(\frac{Profitability_{i,t} - 10{,}730}{10{,}730}\right) + 0{,}168\left(\frac{Risk_{i,t} - 8{,}572}{8{,}572}\right)$$

Materials

$$\left(\frac{\widehat{MTPL_{\iota,t} - 7{,}736}}{7{,}736}\right) = 0{,}070 + 0{,}063\left(\frac{Growth_{i,t} - 3{,}824}{3{,}824}\right) + 0{,}059\left(\frac{Profitability_{i,t} - 8{,}900}{8{,}900}\right) - 0{,}856\left(\frac{Risk_{i,t} - 7{,}744}{7{,}744}\right)$$

Real Estate

$$\left(\frac{\widehat{MTPL_{i,t} - 14{,}676}}{14{,}676}\right) = 0{,}098 - 0{,}022\left(\frac{Growth_{i,t} - 2{,}273}{2{,}273}\right) - 0{,}085\left(\frac{Profitability_{i,t} - 4{,}392}{4{,}392}\right) - 0{,}416\left(\frac{Risk_{i,t} - 6{,}020}{6{,}020}\right)$$

Utilities

$$\left(\frac{\widehat{MTPL_{i,t} - 10{,}264}}{10{,}264}\right) = 0{,}011 + 0{,}050\left(\frac{Growth_{i,t} - 3{,}944}{3{,}944}\right) + 0{,}095\left(\frac{Profitability_{i,t} - 4{,}961}{4{,}961}\right) + 0{,}770\left(\frac{Risk_{i,t} - 4{,}958}{4{,}958}\right)$$

Relative Industry Model

Automobiles & Components

$$\left(\frac{\widehat{MTPL_{i,t} - 5{,}091}}{5{,}091}\right) = 0{,}326 - 0{,}123\left(\frac{Growth_{i,t} - 2{,}767}{2{,}767}\right) - 0{,}290\left(\frac{Profitability_{i,t} - 12{,}264}{12{,}264}\right) + 2{,}042\left(\frac{Risk_{i,t} - 7{,}574}{7{,}574}\right)$$

Capital Goods

$$\left(\frac{\widehat{MTPL_{i,t} - 9{,}118}}{9{,}118}\right) = 0{,}072 - 0{,}006\left(\frac{Growth_{i,t} - 5{,}012}{5{,}012}\right) + 0{,}018\left(\frac{Profitability_{i,t} - 9{,}527}{9{,}527}\right) + 0{,}304\left(\frac{Risk_{i,t} - 8{,}608}{8{,}608}\right)$$

Consumer Durables & Apparel

$$\left(\frac{\widehat{MTPL_{i,t} - 8{,}317}}{8{,}317}\right) = 0{,}149 - 0{,}055\left(\frac{Growth_{i,t} - 4{,}374}{4{,}374}\right) - 0{,}198\left(\frac{Profitability_{i,t} - 9{,}906}{9{,}906}\right) + 0{,}247\left(\frac{Risk_{i,t} - 7{,}659}{7{,}659}\right)$$

Consumer Services

$$\left(\frac{\widehat{MTPL_{i,t} - 8{,}705}}{8{,}705}\right) = 0{,}079 + 0{,}025\left(\frac{Growth_{i,t} - 4{,}489}{4{,}489}\right) + 0{,}300\left(\frac{Profitability_{i,t} - 11{,}180}{11{,}180}\right) - 0{,}179\left(\frac{Risk_{i,t} - 7{,}378}{7{,}378}\right)$$

Commercial & Professional Services

$$\left(\frac{\widehat{MTPL_{i,t} - 9{,}536}}{9{,}536}\right) = 0{,}078 - 0{,}082\left(\frac{Growth_{i,t} - 5{,}349}{5{,}349}\right) + 0{,}230\left(\frac{Profitability_{i,t} - 9{,}424}{9{,}424}\right) + 0{,}089\left(\frac{Risk_{i,t} - 8{,}116}{8{,}116}\right)$$

Diversified Financials

$$\left(\frac{\widehat{MTPL_{i,t} - 8{,}742}}{8{,}742}\right) = 0{,}126 + 0{,}019\left(\frac{Growth_{i,t} - 4{,}166}{4{,}166}\right) + 0{,}322\left(\frac{Profitability_{i,t} - 10{,}623}{10{,}623}\right) - 0{,}696\left(\frac{Risk_{i,t} - 8{,}037}{8{,}037}\right)$$

Energy

$$\left(\frac{\widehat{MTPL_{i,t} - 5{,}602}}{5{,}602}\right) = 0{,}301 + 0{,}025\left(\frac{Growth_{i,t} - 7{,}402}{7{,}402}\right) - 0{,}014\left(\frac{Profitability_{i,t} - 2{,}127}{2{,}127}\right) + 0{,}876\left(\frac{Risk_{i,t} - 7{,}842}{7{,}842}\right)$$

Food, Beverage & Tobacco

$$\left(\frac{\widehat{MTPL_{i,t} - 12{,}091}}{12{,}091}\right) = 0{,}049 - 0{,}136\left(\frac{Growth_{i,t} - 2{,}644}{2{,}644}\right) + 0{,}080\left(\frac{Profitability_{i,t} - 11{,}604}{11{,}604}\right) + 0{,}820\left(\frac{Risk_{i,t} - 6{,}760}{6{,}760}\right)$$

Food & Staples Retailing

$$\left(\frac{\widehat{MTPL_{i,t} - 8{,}345}}{8{,}345}\right) = 0{,}120 - 0{,}043\left(\frac{Growth_{i,t} - 3{,}726}{3{,}726}\right) + 0{,}277\left(\frac{Profitability_{i,t} - 12{,}123}{12{,}123}\right) + 0{,}765\left(\frac{Risk_{i,t} - 6{,}911}{6{,}911}\right)$$

Health Care Equipment & Services

$$\left(\frac{\widehat{MTPL_{i,t} - 8{,}004}}{8{,}004}\right) = 0{,}572 + 0{,}051\left(\frac{Growth_{i,t} - 6{,}293}{6{,}293}\right) - 0{,}060\left(\frac{Profitability_{i,t} - 7{,}876}{7{,}876}\right) + 1{,}789\left(\frac{Risk_{i,t} - 8{,}841}{8{,}841}\right)$$

Household & Personal Products

$$\left(\frac{\widehat{MTPL_{i,t}} - 10{,}813}{10{,}813}\right) = 0{,}081 - 0{,}094\left(\frac{Growth_{i,t} - 3{,}492}{3{,}492}\right) + 0{,}130\left(\frac{Profitability_{i,t} - 13{,}606}{13{,}606}\right) + 0{,}477\left(\frac{Risk_{i,t} - 6{,}908}{6{,}908}\right)$$

Materials

$$\left(\frac{\widehat{MTPL_{i,t}} - 7{,}736}{7{,}736}\right) = 0{,}070 + 0{,}063\left(\frac{Growth_{i,t} - 3{,}824}{3{,}824}\right) + 0{,}063\left(\frac{Profitability_{i,t} - 8{,}900}{8{,}900}\right) - 0{,}856\left(\frac{Risk_{i,t} - 7{,}744}{7{,}744}\right)$$

Media & Entertainment

$$\left(\frac{\widehat{MTPL_{i,t}} - 7{,}885}{7{,}885}\right) = 0{,}140 - 0{,}017\left(\frac{Growth_{i,t} - 6{,}130}{6{,}130}\right) + 0{,}163\left(\frac{Profitability_{i,t} - 8{,}060}{8{,}060}\right) + 1{,}553\left(\frac{Risk_{i,t} - 8{,}044}{8{,}044}\right)$$

Pharmaceuticals, Biotechnology & Life Sciences

$$\left(\frac{\widehat{MTPL_{i,t}} - 10{,}650}{10{,}650}\right) = 0{,}148 + 0{,}036\left(\frac{Growth_{i,t} - 6{,}762}{5{,}762}\right) - 0{,}071\left(\frac{Profitability_{i,t} - 8{,}151}{8{,}151}\right) + 0{,}808\left(\frac{Risk_{i,t} - 8{,}833}{8{,}833}\right)$$

Real Estate

$$\left(\frac{\widehat{MTPL_{i,t}} - 14{,}676}{14{,}676}\right) = 0{,}098 - 0{,}022\left(\frac{Growth_{i,t} - 2{,}273}{2{,}273}\right) - 0{,}085\left(\frac{Profitability_{i,t} - 4{,}392}{4{,}392}\right) - 0{,}416\left(\frac{Risk_{i,t} - 6{,}020}{6{,}020}\right)$$

Retailing

$$\left(\frac{\widehat{MTPL_{i,t}} - 6{,}931}{6{,}931}\right) = 0{,}141 + 0{,}034\left(\frac{Growth_{i,t} - 2{,}309}{2{,}309}\right) + 0{,}108\left(\frac{Profitability_{i,t} - 12{,}124}{12{,}124}\right) - 0{,}385\left(\frac{Risk_{i,t} - 7{,}706}{7{,}706}\right)$$

Semiconductors & Semiconductor Equipment

$$\left(\frac{\widehat{MTPL_{i,t}} - 7{,}075}{7{,}075}\right) = 0{,}148 + 0{,}336\left(\frac{Growth_{i,t} - 4{,}149}{4{,}149}\right) + 0{,}270\left(\frac{Profitability_{i,t} - 12{,}292}{12{,}292}\right) - 0{,}650\left(\frac{Risk_{i,t} - 10{,}196}{10{,}196}\right)$$

Software & Services

$$\left(\frac{\widehat{MTPL_{i,t}} - 11{,}679}{11{,}679}\right) = 0{,}134 + 0{,}049\left(\frac{Growth_{i,t} - 6{,}532}{6{,}532}\right) - 0{,}021\left(\frac{Profitability_{i,t} - 8{,}882}{8{,}882}\right) + 1{,}294\left(\frac{Risk_{i,t} - 9{,}159}{9{,}159}\right)$$

Technology Hardware & Equipment

$$\left(\frac{\widehat{MTPL_{i,t}} - 7{,}176}{7{,}176}\right) = 0{,}158 + 0{,}006\left(\frac{Growth_{i,t} - 5{,}028}{5{,}028}\right) - 0{,}068\left(\frac{Profitability_{i,t} - 8{,}589}{8{,}589}\right) + 0{,}748\left(\frac{Risk_{i,t} - 8{,}920}{8{,}920}\right)$$

Telecommunication Services

$$\left(\frac{\widehat{MTPL_{i,t}} - 6{,}018}{6{,}018}\right) = 0{,}019 + 0{,}150\left(\frac{Growth_{i,t} - 1{,}208}{1{,}208}\right) + 0{,}081\left(\frac{Profitability_{i,t} - 3{,}869}{3{,}869}\right) - 0{,}165\left(\frac{Risk_{i,t} - 6{,}209}{6{,}209}\right)$$

Transportation

$$\left(\frac{\widehat{MTPL_{i,t}} - 6{,}960}{6{,}960}\right) = 0{,}085 + 0{,}092\left(\frac{Growth_{i,t} - 4{,}525}{4{,}525}\right) + 0{,}210\left(\frac{Profitability_{i,t} - 12{,}583}{12{,}583}\right) - 1{,}076\left(\frac{Risk_{i,t} - 8{,}550}{8{,}550}\right)$$

Utilities

$$\left(\frac{\widehat{MTPL_{i,t}} - 10{,}264}{10{,}264}\right) = 0{,}011 + 0{,}050\left(\frac{Growth_{i,t} - 3{,}944}{3{,}944}\right) + 0{,}095\left(\frac{Profitability_{i,t} - 4{,}961}{4{,}961}\right) + 0{,}770\left(\frac{Risk_{i,t} - 4{,}958}{4{,}958}\right)$$

Simple Peer Group Model – Market

$$\widehat{MTPL}_{i,t} = 8{,}378$$

Simple Peer Group Model -Sector

Consumer Discretionary
$\widehat{MTPL}_{\iota,t} = 7{,}398$

Communication Services
$\widehat{MTPL}_{\iota,t} = 7{,}435$

Consumer Staples
$\widehat{MTPL}_{\iota,t} = 8{,}378$

Energy
$\widehat{MTPL}_{\iota,t} = 10{,}876$

Financials
$\widehat{MTPL}_{\iota,t} = 8{,}742$

Health Care
$\widehat{MTPL}_{\iota,t} = 8{,}850$

Information Technology
$\widehat{MTPL}_{\iota,t} = 8{,}501$

Industrials
$\widehat{MTPL}_{\iota,t} = 8{,}644$

Materials
$\widehat{MTPL}_{\iota,t} = 7{,}736$

Real Estate
$\widehat{MTPL}_{\iota,t} = 14{,}676$

Utilities
$\widehat{MTPL}_{\iota,t} = 10{,}264$

Simple Peer Group Model - Industry

Automobiles & Components
$\widehat{MTPL}_{\iota,t} = 5{,}091$

Capital Goods
$\widehat{MTPL}_{\iota,t} = 9{,}118$

Consumer Durables & Apparel
$\widehat{MTPL}_{\iota,t} = 8{,}317$

Consumer Services
$\widehat{MTPL}_{\iota,t} = 8{,}705$

Commercial & Professional Services
$\widehat{MTPL}_{\iota,t} = 9{,}536$

Diversified Financials
$\widehat{MTPL}_{\iota,t} = 8{,}742$

Energy
$\widehat{MTPL}_{\iota,t} = 5{,}602$

Food, Beverage & Tobacco
$\widehat{MTPL}_{\iota,t} = 12{,}091$

Food & Staples Retailing
$\widehat{MTPL}_{\iota,t} = 8{,}345$

Health Care Equipment & Services
$\widehat{MTPL}_{\iota,t} = 8{,}004$

Household & Personal Products
$\widehat{MTPL}_{\iota,t} = 10{,}813$

Materials
$\widehat{MTPL}_{\iota,t} = 7{,}736$

Media & Entertainment
$\widehat{MTPL}_{\iota,t} = 7{,}885$

Pharmaceuticals, Biotechnology & Life Sciences
$\widehat{MTPL}_{\iota,t} = 10{,}650$

Real Estate
$\widehat{MTPL}_{\iota,t} = 14{,}676$

Retailing
$\widehat{MTPL}_{\iota,t} = 6{,}931$

Semiconductors & Semiconductor Equipment
$\widehat{MTPL}_{\iota,t} = 7{,}075$

Software & Services
$\widehat{MTPL}_{\iota,t} = 11{,}679$

Technology Hardware & Equipment
$\widehat{MTPL}_{\iota,t} = 7{,}176$

Telecommunication Services
$\widehat{MTPL}_{\iota,t} = 6{,}018$

Transportation
$\widehat{MTPL}_{\iota,t} = 6{,}960$

Utilities
$\widehat{MTPL}_{\iota,t} = 10{,}264$

Standard Market Model – Industry Dummy

Automobiles & Components

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t})$$

Capital Goods

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}442$$

Consumer Durables & Apparel

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}409$$

Consumer Services

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}457$$

Commercial & Professional Services

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}520$$

Diversified Financials

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}477$$

Energy

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}101$$

Food, Beverage & Tobacco

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}783$$

Food & Staples Retailing

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}416$$

Health Care Equipment & Services

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}622$$

Household & Personal Products

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}666$$

Materials

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}319$$

Media & Entertainment

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}337$$

Pharmaceuticals, Biotechnology & Life Sciences

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}613$$

Real Estate

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 1{,}025$$

Retailing

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}245$$

Semiconductors & Semiconductor Equipment

$$LN.\widehat{MTPL}_{i,t} = 1{,}316 + 0{,}005(Growth_{i,t}) + 0{,}003(Profitability_{i,t}) + 0{,}196(LN.Risk_{i,t}) + 0{,}248$$

Software & Services

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}316 + 0{,}005\left(Growth_{i,t}\right) + 0{,}003\left(Profitability_{i,t}\right) + 0{,}196\left(LN.Risk_{i,t}\right) + 0{,}683$$

Technology Hardware & Equipment

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}316 + 0{,}005\left(Growth_{i,t}\right) + 0{,}003\left(Profitability_{i,t}\right) + 0{,}196\left(LN.Risk_{i,t}\right) + 0{,}239$$

Telecommunication Services

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}316 + 0{,}005\left(Growth_{i,t}\right) + 0{,}003\left(Profitability_{i,t}\right) + 0{,}196\left(LN.Risk_{i,t}\right) + 0{,}136$$

Transportation

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}316 + 0{,}005\left(Growth_{i,t}\right) + 0{,}003\left(Profitability_{i,t}\right) + 0{,}196\left(LN.Risk_{i,t}\right) + 0{,}209$$

Utilities

$$LN.\widehat{MTPL}_{\iota,t} = 1{,}316 + 0{,}005\left(Growth_{i,t}\right) + 0{,}003\left(Profitability_{i,t}\right) + 0{,}196\left(LN.Risk_{i,t}\right) + 0{,}675$$

Appendix 7. Deviations from Peer Group Averages

		Panel A: Standard Regressions						Panel B: Relative Regressions					
Market/Sector/Industry	N	R^2	Adj R^2	SE	F-Stat	Alpha	Absolute Deviation	R^2	Adj R^2	SE	F-Stat	Alpha	Absolute Deviation
Market	965	0,036	0,035	0,881	35,748****	0,211****	0,050****	0,017	0,016	1,031	16,451****	0,292****	0,040***
						(0,016)	(0,011)					(0,016)	(0,011)
Energy Sector	69	0,051	0,037	0,784	3,592*	0,279****	0,050***	0,017	0,002	1,007	1,143	0,409****	0,037
						(0,062)	(0,107)					(0,079)	(0,023)
Energy	69	0,051	0,037	0,784	3,592*	0,279****	0,050***	0,017	0,002	1,007	1,143	0,409****	0,037
						(0,062)	(0,107)					(0,079)	(0,023)
Materials Sector	61	0,264	0,252	0,165	21,166****	0,113****	0,058****	0,146	0,132	0,195	10,085***	0,143****	0,047****
						(0,026)	(0,086)					(0,029)	(0,011)
Materials	61	0,264	0,252	0,165	21,166****	0,113****	0,058****	0,146	0,132	0,195	10,085***	0,143****	0,047****
						(0,026)	(0,086)					(0,029)	(0,011)
Industrials Sector	161	0,315	0,310	0,194	73,039****	0,115****	0,060****	0,199	0,194	0,231	39,559****	0,148****	0,053****
						(0,018)	(0,081)					(0,019)	(0,009)
Capital Goods	104	0,439	0,434	0,127	79,927****	0,082****	0,066****	0,273	0,266	0,16	38,366***	0,110****	0,058****
						(0,016)	(0,077)					(0,018)	(0,009)
Commercial & Professional Services	25	0,191	0,156	0,187	5,444**	0,179****	0,029****	0,062	0,021	0,235	1,522	0,233****	0,019**
						(0,049)	(0,078)					(0,060)	(0,010)
Transportation	32	0,089	0,059	0,195	2,941*	0,227****	0,028***	0,042	0,01	0,237	1,319	0,262****	0,023**
						(0,043)	(0,087)					(0,048)	(0,011)
Consumer Discretionary Sector	173	0,165	0,160	0,296	33,826****	0,193****	0,048****	0,074	0,068	0,365	13,583****	0,257****	0,038****
						(0,023)	(0,008)					(0,026)	(0,008)
Automobiles & Components	14	0,041	-0,039	0,216	0,514	0,228***	0,019	0,001	-0,082	0,307	0,016	0,327***	0,005
						(0,087)	(0,141)					(0,107)	(0,027)
Consumer Durables & Apparel	47	0,297	0,282	0,175	19,030****	0,165****	0,038****	0,101	0,081	0,232	5,058**	0,235****	0,026****
						(0,027)	(0,044)					(0,036)	(0,006)
Consumer Services	40	0,188	0,166	0,211	8,784***	0,174****	0,031***	0,076	0,052	0,289	3,142*	0,211****	0,026***
						(0,040)	(0,086)					(0,047)	(0,011)
Retailing	72	0,157	0,145	0,222	13,076****	0,172****	0,053****	0,068	0,054	0,281	5,091**	0,230****	0,042***
						(0,031)	(0,085)					(0,036)	(0,014)
Consumer Staples Sector	55	0,115	0,098	0,053	6,866***	0,758****	0,008***	0,097	0,08	0,157	5,720***	0,133****	0,022****
						(0,008)	(0,033)					(0,025)	(0,006)
Food Staples & Retailing	10	0,001	-0,124	0,052	0,004	0,136****	0,001	0,099	-0,014	0,059	0,879	0,110****	0,013
						(0,026)	(0,102)					(0,025)	(0,020)
Food, Beverage & Tobacco	31	0,214	0,187	0,122	7,884***	0,088***	0,027***	0,138	0,108	0,14	4,633**	0,099***	0,024**
						(0,029)	(0,136)					(0,030)	(0,011)
Household & Personal Products	14	0,184	0,116	0,138	2,700	0,119***	0,028****	0,117	0,043	0,162	1,583	0,134***	0,026***
						(0,041)	(0,092)					(0,044)	(0,008)
Health Care Sector	130	0,011	0,004	3,060	1,461	0,186****	0,670	0,008	0,0004	3,402	1,046	0,254****	0,071
						(0,054)	(0,562)					(0,058)	(0,070)
Health Care Equipment & Services	80	0,006	-0,007	3,895	0,433	0,350**	0,514	0,004	-0,009	4,409	0,307	0,439***	0,061
						(0,168)	(0,482)					(0,189)	(0,068)
Pharmaceuticals, Biotechnology & Life Sciences	50	0,219	0,203	0,163	13,492****	0,170****	0,023****	0,084	0,065	0,199	4,395**	0,218****	0,016****
						(0,028)	(0,035)					(0,034)	(0,004)
Financials Sector	29	0,121	0,089	0,278	3,722*	0,224****	0,032*	0,065	0,03	0,354	1,879	0,242****	0,029
						(0,057)	(0,148)					(0,069)	(0,018)
Diversified Financials	29	0,121	0,089	0,278	3,722*	0,224****	0,280*	0,065	0,03	0,354	1,879	0,242****	0,029
						(0,057)	(0,148)					(0,069)	(0,018)
Information Technology Sector	131	0,072	0,065	0,458	10,041***	0,239****	0,033***	0,032	0,025	0,547	4,325**	0,294****	0,026***
						(0,036)	(0,083)					(0,040)	(0,010)
Software & Services	54	0,234	0,220	0,132	15,911****	0,115****	0,022****	0,079	0,061	0,16	4,463**	0,157****	0,014****
						(0,018)	(0,034)					(0,023)	(0,004)
Technology Hardware & Equipment	49	0,180	0,163	0,341	10,325***	0,149****	0,064***	0,095	0,075	0,407	4,908**	0,210****	0,053***
						(0,033)	(0,140)					(0,039)	(0,022)
Semiconductors & Semiconductor Equipment	28	0,010	-0,028	0,359	0,267	0,321****	0,007	0,0002	-0,038	0,435	0,004	0,408****	-0,001
						(0,071)	(0,063)					(0,089)	(0,007)
Communication Services Sector	41	0,196	0,176	0,157	9,529***	0,140****	0,024****	0,088	0,065	0,192	3,770*	0,174****	0,018****
						(0,027)	(0,005)					(0,032)	(0,005)
Telecommunication Services	8	0,097	-0,054	0,083	0,641	0,117****	0,012**	0,002	-0,165	0,119	0,009	0,175****	-0,002
						(0,032)	(0,035)					(0,045)	(0,008)
Media & Entertainment	33	0,213	0,188	0,153	8,402***	0,142****	0,023****	0,09	0,061	0,198	3,076*	0,170****	0,018****
						(0,029)	(0,031)					(0,034)	(0,005)
Utilities Sector	39	0,386	0,369	0,092	23,245****	0,047***	0,054****	0,286	0,266	0,105	14,804****	0,057***	0,049***
						(0,017)	(0,138)					(0,019)	(0,015)
Utilities	39	0,386	0,369	0,092	23,245****	0,047***	0,054****	0,286	0,266	0,105	14,804****	0,057***	0,049***
						(0,017)	(0,138)					(0,019)	(0,015)
Real Estate Sector	76	0,306	0,297	0,137	32,700****	0,083***	0,037****	0,235	0,225	0,153	22,754****	0,092***	0,035****
						(0,030)	(0,145)					(0,030)	(0,010)
Real Estate	76	0,306	0,297	0,137	32,700****	0,083***	0,037****	0,235	0,225	0,153	22,754****	0,092***	0,035****
						(0,030)	(0,145)					(0,030)	(0,010)

**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1

Appendix 8. Median Prediction Errors

Market/Sector/Industry	N	Median Prediction Error		
		Standard Regression Model	Relative Regression Model	Simple Peer Group
Market	965	-0,015	0,070	-0,124
Energy Sector	69	0,061	0,123	-0,044
Energy	69	0,061	0,123	-0,044
Materials Sector	61	-0,003	0,026	-0,062
Materials	61	-0,003	0,026	-0,062
Industrials Sector	161	0,012	0,041	-0,061
Capital Goods	104	-0,004	0,027	-0,030
Commercial & Professional Services	25	-0,029	0,019	-0,060
Transportation	32	-0,108	-0,062	-0,086
Consumer Discretionary Sector	173	-0,022	0,053	-0,089
Automobiles & Components	14	0,035	0,077	-0,158
Consumer Durables & Apparel	47	0,011	0,066	0,008
Consumer Services	40	-0,014	0,064	-0,064
Retailing	72	-0,021	0,055	-0,090
Consumer Staples Sector	55	-0,021	0,024	-0,060
Food Staples & Retailing	10	-0,027	-0,008	-0,103
Food, Beverage & Tobacco	31	-0,018	0,005	-0,033
Household & Personal Products	14	0,059	0,038	-0,083
Health Care Sector	130	-0,036	0,029	-0,214
Health Care Equipment & Services	80	-0,051	0,007	-0,297
Pharmaceuticals, Biotechnology & Life Sciences	50	0,032	0,075	-0,019
Financials Sector	29	0,033	0,032	-0,119
Diversified Financials	29	0,033	0,032	-0,119
Information Technology Sector	131	-0,033	0,014	-0,087
Software & Services	54	0,039	0,065	-0,032
Technology Hardware & Equipment	49	0,023	0,090	-0,054
Semiconductors & Semiconductor Equipment	28	-0,092	0,027	-0,135
Communication Services Sector	41	0,013	0,031	-0,031
Telecommunication Services	8	0,033	0,048	-0,002
Media & Entertainment	33	0,012	0,049	-0,051
Utilities Sector	39	-0,013	0,002	-0,032
Utilities	39	-0,013	0,002	-0,032
Real Estate Sector	76	0,033	0,004	-0,092
Real Estate	76	0,033	0,004	-0,092

Shaded areas highlight sub-samples in which the predictions from a developed model outperforms predictions drawn from the Simple Peer Group approach.

Appendix 9. Model Prediction Accuracy & Firm Size

		Panel A: Standard Regression						Panel B: Relative Regression					
Market/Sector/Industry	N	R^2	Adj R^2	SE	F-Stat	Alpha	Size	R^2	Adj R^2	SE	F-Stat	Alpha	Size
Market	965	0,000	-0,001	0,897	0,096	0,435	-0,006	0,000	-0,001	1,040	0,062	0,476****	-0,006
						(0,088)	(0,011)					(0,102)	(0,013)
Energy Sector	69	0,001	-0,014	0,805	0,085	0,595	-0,020	0,001	-0,014	1,015	0,090	0,744	-0,026
						(0,446)	(0,056)					(0,571)	(0,072)
Energy	69	0,001	-0,014	0,805	0,085	0,595	-0,020	0,001	-0,014	1,015	0,090	0,744	-0,026
						(0,446)	(0,056)					(0,571)	(0,072)
Materials Sector	61	0,002	-0,015	0,192	0,126	0,161	0,008	0,002	-0,015	0,211	0,140	0,158	0,010
						(0,184)	(0,021)					(0,198)	(0,022)
Materials	61	0,002	-0,015	0,192	0,126	0,161	0,008	0,002	-0,015	0,211	0,140	0,158	0,010
						(0,184)	(0,021)					(0,198)	(0,022)
Industrials Sector	161	0,001	-0,006	0,234	0,084	0,292***	-0,004	0,001	-0,005	0,258	0,128	0,319***	-0,005
						(0,112)	(0,013)					(0,121)	(0,014)
Capital Goods	104	0,001	-0,009	0,169	0,052	0,251***	-0,003	0,000	-0,010	0,188	0,018	0,253***	-0,002
						(0,101)	(0,012)					(0,108)	(0,013)
Commercial & Professional Services	25	0,087	0,047	0,199	2,185	0,690***	-0,053*	0,064	0,023	0,234	1,566	0,715***	-0,053'
						(0,226)	(0,029)					(0,251)	(0,031)
Transportation	32	0,007	-0,026	0,204	0,203	0,187	0,011	0,017	-0,016	0,240	0,521	0,122	0,022
						(0,205)	(0,024)					(0,245)	(0,029)
Consumer Discretionary Sector	173	0,017	0,011	0,321	2,894*	0,084	0,030	0,008	0,002	0,378	1,320	0,168	0,024
						(0,224)	(0,029)					(0,263)	(0,034)
Automobiles & Components	14	0,155	0,085	0,203	2,204	-0,111	0,044	0,461	0,416	0,225	10,258***	-0,592*	0,106***
						(0,296)	(0,036)					(0,314)	(0,039)
Consumer Durables & Apparel	47	0,001	-0,022	0,208	0,025	0,231	0,004	0,000	-0,022	0,245	0,016	0,273	0,004
						(0,184)	(0,023)					(0,212)	(0,025)
Consumer Services	40	0,111	0,087	0,220	4,731**	0,720****	-0,055***	0,084	0,060	0,288	3,482*	0,794****	-0,061***
						(0,201)	(0,023)					(0,201)	(0,023)
Retailing	72	0,001	-0,014	0,242	0,049	0,339***	-0,005	0,012	-0,002	0,289	0,864	0,518***	-0,023
						(0,137)	(0,016)					(0,159)	(0,019)
Consumer Staples Sector	55	0,006	-0,013	0,056	0,305	0,755****	0,003	0,017	-0,002	0,164	0,898	0,065	0,014
						(0,053)	(0,006)					(0,163)	(0,018)
Food Staples & Retailing	10	0,004	-0,121	0,051	0,030	0,123*	0,002	0,008	-0,116	0,062	0,065	0,158**	-0,003
						(0,074)	(0,007)					(0,079)	(0,007)
Food, Beverage & Tobacco	31	0,101	0,070	0,130	3,270*	-0,140	0,032**	0,075	0,043	0,145	2,342	-0,120	0,030*
						(0,141)	(0,016)					(0,161)	(0,018)
Household & Personal Products	14	0,238	0,174	0,134	3,739*	0,617****	-0,049***	0,321	0,264	0,142	5,675**	0,751****	-0,064****
						(0,177)	(0,018)					(0,178)	(0,019)
Health Care Sector	130	0,000	-0,007	3,077	0,050	0,230	0,033	0,001	-0,007	3,415	0,065	0,207	0,042
						(0,204)	(0,053)					(0,227)	(0,059)
Health Care Equipment & Services	80	0,002	-0,011	3,902	0,157	-0,118	0,097	0,002	-0,011	4,413	0,175	-0,196	0,115
						(0,461)	(0,105)					(0,521)	(0,119)
Pharmaceuticals, Biotechnology & Life Sciences	50	0,109	0,091	0,174	5,898***	0,526****	-0,033***	0,081	0,061	0,200	4,210**	0,543****	-0,032**
						(0,125)	(0,014)					(0,137)	(0,015)
Financials Sector	29	0,101	0,068	0,282	3,049*	0,769****	-0,050***	0,116	0,083	0,344	3,550*	0,916****	-0,066***
						(0,206)	(0,020)					(0,270)	(0,026)
Diversified Financials	29	0,101	0,068	0,282	3,049*	0,769****	-0,050***	0,116	0,083	0,344	3,550*	0,916****	-0,066***
						(0,206)	(0,020)					(0,270)	(0,026)
Information Technology Sector	131	0,021	0,013	0,470	2,705	0,725***	-0,044	0,018	0,011	0,551	2,394	0,793***	-0,049
						(0,256)	(0,029)					(0,301)	(0,034)
Software & Services	54	0,000	0,019	0,151	0,015	0,198	-0,002	0,001	-0,038	0,435	0,018	0,465	-0,007
						(0,129)	(0,015)					(0,456)	(0,052)
Technology Hardware & Equipment	49	0,028	0,008	0,371	1,375	0,634**	-0,041	0,001	-0,018	0,166	0,050	0,172	0,003
						(0,288)	(0,031)					(0,132)	(0,016)
Semiconductors & Semiconductor Equipment	28	0,002	-0,036	0,360	0,063	0,251	0,011	0,026	0,005	0,422	1,253	0,699**	-0,044
						(0,397)	(0,049)					(0,328)	(0,035)
Communication Services Sector	41	0,002	-0,023	0,175	0,086	0,160	0,004	0,005	-0,021	0,201	0,195	0,288	-0,008
						(0,173)	(0,019)					(0,251)	(0,026)
Telecommunication Services	8	0,480	0,393	0,063	5,537*	0,371****	-0,024****	0,105	-0,044	0,113	0,706	0,324***	-0,016
						(0,071)	(0,007)					(0,109)	(0,010)
Media & Entertainment	33	0,041	0,010	0,169	1,314	0,025	0,020	0,003	-0,029	0,208	0,092	0,159	0,006
						(0,219)	(0,024)					(0,330)	(0,035)
Utilities Sector	39	0,000	-0,027	0,117	0,006	0,115	0,001	0,002	-0,025	0,124	0,065	0,086	0,004
						(0,137)	(0,014)					(0,131)	(0,013)
Utilities	39	0,000	-0,027	0,117	0,006	0,115	0,001	0,002	-0,025	0,124	0,065	0,086	0,004
						(0,137)	(0,014)					(0,131)	(0,013)
Real Estate Sector	76	0,001	-0,013	0,164	0,043	0,173	0,004	0,003	-0,011	0,175	0,208	0,290**	-0,009
						(0,133)	(0,015)					(0,136)	(0,016)
Real Estate	76	0,001	-0,013	0,164	0,043	0,173	0,004	0,003	-0,011	0,175	0,208	0,290**	-0,009
						(0,133)	(0,015)					(0,136)	(0,016)

**** p < 0,01
*** p < 0,025
** p < 0,05
* p < 0,1