Lisbon School of Economics & Management
Universidade de Lisboa

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MASTER'S FINAL WORK

DISSERTATION

THE IMPACT OF FUNDAMENTAL VALUE DRIVERS ON VALUATION MULTIPLES: A CROSS-INDUSTRY ANALYSIS OF EUROPEAN EQUITIES (2016-2025)

RICARDO NOVIKOV

JUNE 2026

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JUNE 2026

Acknowledgements

This work would not have come to fruition without the many people in my life who made the journey worthwhile.

I would like to begin by thanking my supervisors, Professor Pedro and Professor Victor. Thank you for your deep engagement with this work, for your guidance throughout this year's CFA Research Challenge - which helped us bring the national trophy home - and for your inspiring classes, which made me enjoy corporate finance even more. Your guidance throughout this year has proved indispensable.

To my CFA Research Challenge colleagues - Jannik Schmid, Juliana Guerreiro, Thiago Ferreira and Tigran Andreasian – it was a pleasure to spend so many hours with such a bright group of people.

To my mother, who has always been a role model of hard work and perseverance, who pushed through every obstacle so that I could receive a good education.

To my grandmother, who instilled in me the intellectual curiosity that I carry with me to this day.

To my sister and my stepfather, thank you for your constructive presence and for always bringing joy and perspective to my life.

To Marta, thank you for being such a wonderful partner and a constant source of strength. Thank you for your patience and understanding of my goals and aspirations throughout this demanding year.

To my closest friends - André, Alex, and Martim. Here's to us, and to all the achievements still ahead.

Finally, I want to thank ISEG, and all faculty involved in the Master´s in Finance for providing me the opportunity to get such a solid education. At a time of profound technological and societal transformation, this master's taught me how to think and gave me a solid foundation on which to build my future.

I shall be telling this with a sigh,
Somewhere ages and ages hence:
Two roads diverged in a wood, and I –
I took the one less traveled by,
And that has made all the difference

The Road Not Taken – Robert Frost, 1915

ABSTRACT

This dissertation examines how European equity markets price the fundamental value drivers (profitability, growth and risk) embedded in the P/B, P/E, and EV/EBITDA multiples across ten non-financial sectors, from 2016 to 2025. Our main model employs firm fixed effects panels of 23,751 (P/B), 19,212 (P/E), and 19,089 (EV/EBITDA) firm-year observations, as indicated by Hausman tests. The central contribution is a decomposition of each multiple into its price and accounting components, which shows that the puzzling negative association of profitability with P/E and EV/EBITDA is not an economic penalty but a reflection of ratio construction: the price and accounting components respond asymmetrically to economic shocks. We confirm the mechanism in three ways - the sign reverses on the price components, the distortion disappears under forward profitability, and it propagates across sample sub-components and all ten sectors. Forward expectations then reveal that each multiple has a distinct economic identity: P/E is fundamentally a growth-expectations multiple, with this model capturing two-thirds of within-firm variation, while P/B prices forward profitability and EV/EBITDA prices forward operating growth and, more weakly, forward profitability. Profitability is the dominant and most robust driver, growth and risk price unevenly across industries, and the apparent risk effects are themselves shown to be mechanical. For practitioners, the findings caution against reading denominator-driven compression as undervaluation and provide a rule for selecting the multiple best suited to a firm's value proposition.

Keywords: Relative Valuation; Valuation Multiples; Price-to-Earnings Ratio; Price-to-Book Ratio; EV/EBITDA; Fundamental Value Drivers; European Markets.

JEL Codes: G12, G14, M41, G32, C23

Resumo

Esta dissertação examina como os mercados acionistas europeus precificam os determinantes fundamentais de valor (rendibilidade, crescimento e risco) incorporados nos múltiplos P/B, P/E e EV/EBITDA, em dez setores não financeiros, entre 2016 e 2025. O nosso modelo principal emprega painéis de efeitos fixos ao nível da empresa de 23 751 (P/B), 19 212 (P/E) e 19 089 (EV/EBITDA) observações empresa-ano, conforme indicado pelos testes de Hausman. O contributo central é uma decomposição de cada múltiplo nas suas componentes de preço e contabilística, que demonstra que a associação negativa e contraintuitiva da rendibilidade com o P/E e o EV/EBITDA não constitui uma penalização económica, mas um reflexo da construção do rácio: as componentes de preço e contabilística respondem assimetricamente a choques económicos. Confirmamos o mecanismo de três formas - o sinal inverte-se nas componentes de preço, a distorção desaparece sob rendibilidade futura, e propaga-se entre subcomponentes das amostras e nos dez setores. As expectativas futuras revelam que cada múltiplo possui uma identidade económica distinta: o P/E é essencialmente um múltiplo de expectativas de crescimento, com este modelo a captar dois terços da variação intra-empresa, enquanto o P/B precifica rendibilidade futura e o EV/EBITDA precifica crescimento operacional futuro e, mais fracamente, rendibilidade futura. A rendibilidade é o determinante dominante e mais robusto, o crescimento e o risco são precificados de forma desigual entre indústrias, e os aparentes efeitos do risco revelam-se, eles próprios, mecânicos. Para a comunidade profissional, os resultados alertam contra a leitura da compressão induzida pelo denominador como subavaliação e fornecem uma regra para selecionar o múltiplo mais adequado à proposta de valor de cada empresa.

Palavras-Chave: Avaliação Relativa; Múltiplos de Avaliação; Rácio Preço-Lucro (P/E); Rácio Preço-Valor Contabilístico (P/B); EV/EBITDA; Determinantes Fundamentais do Valor; Mercados Europeus.

Códigos JEL: G12, G14, M41, G32, C23

Glossary

BVPS	Book Value per Share
CAPM	Capital Asset Pricing Model
D&A	Depreciation and Amortization
DCF	Discounted Cash Flow
DPS	Dividends per Share
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
EM	Equity Multiplier
EPS	Earnings per Share
EV	Enterprise Value
EV/EBITDA	Enterprise Value-to-EBITDA
FCFF	Free Cash Flow to the Firm
FE	Fixed Effects
GICS	Global Industry Classification Standard
GMM	Generalized Method of Moments
IC	Invested Capital
IFRS	International Financial Reporting Standards
LM	Lagrange Multiplier
NAICS	North American Industry Classification System
NAV	Net Asset Value
NOPAT	Net Operating Profit After Tax
NPM	Net Profit Margin
OLS	Ordinary Least Squares
P/B	Price-to-Book
P/E	Price-to-Earnings
RE	Random Effects
ROA	Return on Assets
ROE	Return on Equity
ROIC	Return on Invested Capital
RR	Retention Rate
SIC	Standard Industrial Classification
SME	Small and Medium Enterprise
TFE	Two-Way Fixed Effects
VIF	Variance Inflation Factor
WACC	Weighted Average Cost of Capital

DISCLAIMER REGARDING THE USE OF ARTIFICIAL INTELLIGENCE

This master's thesis was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG - Lisbon School of Economics and Management.
The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency and to uphold my academic integrity and the academic integrity of ISEG standards, I voluntarily inform that artificial intelligence (AI) tools were employed in this work to support the following tasks:

- **Brainstorming of potential research angles**
- **Grammatical revision of the main text**
- **Coding in Stata**
- **Assistance in literature review and data collection**

I have ensured that AI tools have not compromised the originality, integrity, or academic judgment underlying this dissertation. All decisions regarding the research questions, theoretical frameworks, methodology, data collection, empirical analysis, interpretation of results, and conclusions are solely mine. The responsibility for every single piece of content in this dissertation, including errors, omissions, interpretations, and conclusions, remains with the author.

30th of June 2026,
Ricardo Novikov

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1 – Introduction

The law of one price, along with the no-arbitrage pricing principle, constitute the foundational principles of valuation in modern finance. The idea that equal investment opportunities or equivalent goods should trade at the same price is mediated by the market demand and supply mechanism, with deviations from this principle creating opportunities for market corrections (Berk & DeMarzo, 2023). Relative valuation relies on these principles to price target firms based on comparable peer sets, through standardized valuation ratios known as market multiples. This approach is used by 93% of equity analysts (Pinto, Robinson & Stowe, 2019) and is the dominant methodology in M&A advisory (Shaffer, 2024). However, the validity and accuracy of relative valuation rely on an understanding of what drives these valuation ratios. With this understanding, economic agents can identify, interpret, and correct for differences between the target firm they are valuing and the comparable peer group. If fundamental drivers are not understood, or if the ratio construction obscures genuine economic relationships, the no-arbitrage pricing logic breaks down, and valuation multiples become a source of mispricing rather than a tool that standardizes similar (but never perfectly identical) investment opportunities.

The problem that we are setting out to solve matters to practitioners, investors, regulators, and other economic players who are involved in capital allocation decisions. These capital allocation decisions materialize themselves in M&A transactions (Shaffer, 2024), IPO pricings (Kim & Ritter, 1999), valuation fairness opinions and portfolio decisions. The valuation ratios become also inevitably shaped by the accounting standards in place. The fact that IFRS standards have focused on improving accounting comparability (Young & Zeng, 2015) between firms, provides motivation to study valuation multiples in a European context. Because differences in the measurement of accounting denominators feed directly into the distortions that we document, the efforts of European regulators and accounting standard setters, to pursue further standardization of accounting information, bear direct implication into the reliability of relative valuation. Our study is also heavily motivated by the fragmentation in the relative valuation literature: most studies are US-based, rely on cross-sectional specifications, examine individual multiples, or take approaches that only consider a select set of industries.

We address these gaps by estimating firm-fixed effects panel regressions on the P/B, P/E, and EV/EBITDA valuation multiples across the 10 non-financial GICS industries in Europe, from 2016 to 2025. Our primary specification works with trailing accounting fundamentals and "current" market data. We further decompose each multiple into its price numerator and accounting denominator components to separate genuine economic pricing from mechanical effects. This framework, which helps understand and quantify the diverging response of the numerator and the denominator to shocks on valuation ratios, constitutes our central contribution from which all findings flow. The analysis becomes further supported by the inclusion of forward expectations in a separate sample which unveils the economic angles more strongly captured by each multiple. For practitioners, we also clarify when P/B, P/E, or

EV/EBITDA are most informative and caution against interpreting denominator-driven compressions as undervaluation.

The remainder of this work is organized as follows. Chapter 2 presents theoretical derivations that link discounted cash flow models to the valuation multiples under study, thereby deriving some of our independent variables from theory. Chapter 3 reviews the conceptual and empirical literature on relative valuation, covering valuation methods, valuation accuracy, peer selection, fundamental value drivers, and some ML approaches. Chapter 4 builds on Chapter 3 by identifying the research gap and formulating the hypothesis. Chapter 5 covers empirical strategy, including data and econometric methodology. Chapter 6 reports baseline results, additional variations of the main model, cross-industry regressions, and robustness checks. Chapter 7 extends the analysis to forward-consensus expectations under a new sample. Finally, Chapter 8 discusses the main findings and concludes.

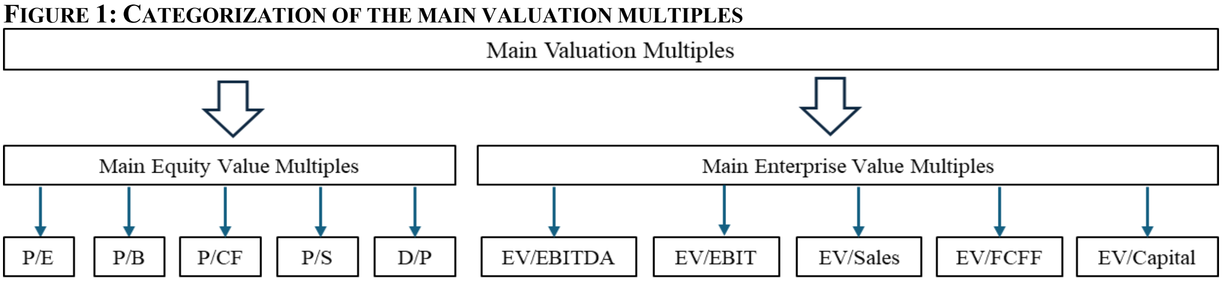
2 – Theoretical Foundations

In this chapter, we outline some of the conceptual building blocks that lay the foundation for the subsequent work.

2.1 Main Types of Multiples

As we outlined in the introduction, the law of one price, along with the no-arbitrage pricing principle, are at the heart of finance and valuation theory. Applying these principles to relative valuation involves valuing our target firm using a set of identical firms that mirror its profitability, growth, and risk patterns. Since identical firms are virtually impossible to find, what analysts do is express the value of the firm as a valuation multiple, which is the ratio of the firm's market value to some standardizing measure of the firm, which adjusts for differences in scale. Valuation multiples can be broadly classified into two main categories, depending on the claimholders that they represent: equity value multiples and enterprise value multiples.[1] Figure 1 categorizes some of the most used valuation multiples:

FIGURE 1: CATEGORIZATION OF THE MAIN VALUATION MULTIPLES



Source: Author Elaboration, based on Fernandez (2002), Damodaran (2007), and Pinto et al. (2015)

[1] This classification is not entirely exhaustive. Some multiples can be specific to an industry, such as enterprise value per subscriber in the cable TV industry. Industry-specific multiples were not considered in this description, and they are usually more applicable to companies in the earlier stages of their life cycle (Damodaran, 2017).

Equity value multiples focus only on the stake held by the firm's shareholders. The numerator is a market capitalization measure (or price per share), while the denominator is an equity-related value driver and is therefore measured after debt-related payments. The best-known multiples in this category are the P/E and P/B multiples, which link equity value to earnings and to book value of equity, respectively (Alford, 1992; Cheng & McNamara, 2000).

Enterprise value multiples value the firm´s core operations, which are available to both debt and equity investors. Since the numerator reflects the entire firm, the denominator must be an unlevered metric, and the most common examples of enterprise value multiples are EV/Sales, EV/EBIT, and EV/EBITDA (Bhojraj & Lee, 2002). A commonly cited advantage of enterprise value multiples is that they allow for comparisons between firms that are not affected by capital structure, whereas equity value multiples are quite sensitive to financial leverage (Lie & Lie, 2002; Schreiner & Spremann, 2007).

2.2 The Mechanics of Relative Valuation

The application of relative valuation to price a firm can be generally described as a three-step process (Damodaran, 2007)[2]:

1. **Defining the peer group**: The first step is to define the set of comparable firms that our target firm will be benchmarked against. Since finding perfectly identical comparables is virtually impossible, the goal is to identify firms that are more closely related to our target firm in terms of profitability, growth, and risk.
2. **Standardizing by choosing the appropriate multiple**: The analyst then needs to assess what is the most appropriate multiple to use, given the specific industry and company features, since different multiples are driven by distinct fundamental drivers. Once the market value is standardized by choosing the appropriate multiple, a central tendency measure for the peer group is extracted[3].
3. **Adjusting for differences**: Even with the previous steps correctly performed, differences in fundamentals will always exist, and further steps can be taken to increase comparability. This can be done by normalizing accounting figures, incorporating subjective adjustments (such as valuation premiums or discounts), and creating a modified multiple by mathematically incorporating a core value driver (Damodaran, 2007)[4]. Once these steps are completed, the

[2] The three-step process described was adapted from Damodaran (2007), but with relevant adaptations by the author, namely regarding the need to choose the appropriate multiple during the process, a topic not addressed by Damodaran (2007).

[3] The central tendency measure extracted is usually the mean, median, or the harmonic mean (Alford, 1992; Baker & Ruback, 1999).

[4] A well-known example of this type of adjustment is the PEG ratio, which is created by dividing the P/E ratio by the expected growth.

process to derive the predicted value relies on a simple mathematical relationship. We multiply the target firm's value driver by the benchmark multiple extracted from the comparable set as follows:

$$V(\tau) = \, Value\ Driver(\tau) \times \frac{Market\ Value(\tau)}{Value\ Driver(\tau)}(peers\ benchmark)$$

Where $V(\tau)$ represents either the market value of equity or the enterprise value, depending on whether the multiple used is enterprise-value-based or equity-value-based, respectively.

The central contribution of this dissertation lies in step three of the described three-step process. By quantifying the relationships among profitability, growth, risk, and market multiples within the same firm over time, we offer academia and practitioners a framework to understand the sources of observed differences in market multiples and to interpret them more accurately.

2.3 Derivations of Valuation Multiples in their Fundamental Value Drivers

Discounted cash flow (DCF) valuation is a function of three main variables: the capacity to generate cash flows, the expected growth in those cash flows, and the risk associated with those cash flows (Damodaran, 2007). In theory, every multiple is a function of these variables, but relative valuation makes implicit rather than explicit assumptions about them. We start with basic discounted cash flow models for equity and enterprise value to derive the theoretical drivers of the multiples to be explored in this research, linking fundamentals and firm value under strict theoretical assumptions. A range of authors have built on these derivations, which we base ourselves on and credit (Bhojraj & Lee, 2002; Damodaran, 2007; Knudsen, Kold, & Plenborg, 2017; Koller et al., 2020). A detailed explanation of the variables used in these derivations can be found in the Appendix section, under Table A.1.

2.3.1 Derivation of the P/E multiple

To derive the trailing P/E ratio, we start with the Gordon Growth Model (Gordon, 1959) and its assumption that the price of a firm is the present value of future expected dividends, which grow at a constant growth rate into perpetuity:

$$P(0) = \frac{DPS(1)}{Ke - g} \quad (1)$$

Since dividends are paid out of earnings, $DPS(1)$ can be expressed as the current trailing earnings $EPS(0)$ grown by one period $(1 + g)$ and multiplied by the $Payout\ Ratio$:

$$P(0) = \frac{EPS(0) \times (1 + g\ ) \times Payout\ Ratio}{Ke - g} \quad (2)$$

Further dividing both sides by $EPS(0)$ isolates the trailing P/E multiple on the left side and the value drivers on the right side:

$$\frac{P(0)}{EPS(0)} = \frac{Payout\ Ratio\ \times (1 + g)}{Ke - g} \quad (3)$$

We can further expand Equation 3 by considering that growth (g) is the product of Return on Equity (ROE) and the retention rate (RR). Rearranging, the retention rate (RR) can be expressed as $\frac{g}{ROE}$. As such, the payout ratio can be rewritten as $Payout\ ratio = 1 - \frac{g}{ROE}$ and we arrive at our trailing P/E multiple:

$$\frac{P(0)}{EPS(0)} = \frac{P}{E} = \frac{\left(1 - \frac{g}{ROE}\right) \times (1+g)}{Ke - g} \quad (4)$$

Equation 4 shows that growth (g) only expands a firm's valuation multiple if the Return on Equity (ROE) exceeds the cost of equity (Ke). It is important to note that this derivation is based on a steady-state assumption, which requires that earnings and dividends grow at the same rate into perpetuity, and hence, that payout and retention rates are constant into perpetuity as well.

2.3.2 Derivation of the EV/EBITDA multiple

We start with a simple DCF Free Cash Flow to the Firm (FCFF) model that assumes constant growth into perpetuity:

$$EV(0) = \frac{FCFF(1)}{WACC - g} \quad (5)$$

We now need to expand $FCFF(1)$ as $FCFF(1) = NOPAT(1) \times (1 - Reinvestment\ Rate)$. Since we are deriving the trailing multiple, we express $NOPAT(1) = NOPAT(0) \times (1+g)$. Furthermore, rearranging the ROIC formula[5], we can write $NOPAT(0) = ROIC \times IC(0)$. Substituting these expressions into equation 5, we get:

$$EV(0) = \frac{(ROIC \times IC(0) \times (1+g)) \times (1 - Reinvestment\ Rate)}{WACC - g} \quad (6)$$

Dividing both sides by $IC(0)$ and recognizing that $Reinvestment\ Rate = \frac{g}{ROIC}$ we get:

$$\frac{EV(0)}{IC(0)} = \frac{ROIC \times (1+g) \times (1 - \frac{g}{ROIC})}{WACC - g} \quad (7)$$

We then multiply $ROIC$ across the parentheses and further multiply both sides by $(\frac{1}{ROIC})$ to place $NOPAT(0)$ into the denominator as follows:

$$\frac{EV(0)}{NOPAT(0)} = \frac{ROIC - g}{WACC - g} \times \frac{(1+g)}{ROIC} \quad (8)$$

Finally, if we recognize that $NOPAT(0) = EBITDA(0) \times (1-t) \times (1 - Depreciation\ Rate)$ we arrive at our final expression for the trailing EV/EBITDA multiple:

$$\frac{EV(0)}{EBITDA(0)} = \frac{EV}{EBITDA} = \frac{ROIC - g}{WACC - g} \times \frac{(1+g) \times (1-t) \times (1 - Depreciation\ Rate)}{ROIC} \quad (9)$$

[5] $ROIC = \frac{NOPAT}{Invested\ Capital}$

This derivation shows that trailing EV/EBITDA is fundamentally driven by expected growth (g), risk (WACC), and profitability (ROIC). The multiple is also adjusted downward to account for a portion of EBITDA being lost to taxes and reinvested in maintenance capital expenditures. It is crucial to note that this derivation assumes that capital structure, WACC, expected growth, ROIC, tax rate, and depreciation rate will remain constant in perpetuity, consistent with the steady-state assumption used in the P/E derivation.

2.3.3 Derivation of the P/B multiple

To derive the P/B ratio, we start, once again, with the Gordon Growth Model:

$$P(0) = \frac{DPS(1)}{Ke - g} \quad (10)$$

We established in Equation 2 that $DPS(1) = EPS(0) \times (1 + g\ ) \times Payout\ Ratio$. Recognizing that next-period earnings can be written either as $EPS(1) = EPS(0) \times (1 + g)$ or as $EPS(1) = ROE\ \times BVPS(0)$, we substitute the latter into Equation 10:

$$P(0) = \frac{ROE\ \times BVPS\ (0)\ \times Payout\ Ratio}{Ke - g} \quad (11)$$

We then apply the same substitution as in Equation 4, replacing the payout ratio with $(1 - \frac{g}{ROE})$:

$$P(0) = \frac{ROE\ \times BVPS\ (0) \times (1 - \frac{g}{ROE})}{Ke - g} \quad (12)$$

We can simplify the numerator by distributing ROE across the parentheses, and the ROE terms cancel out to give:

$$P(0) = \frac{BVPS(0) \times (ROE - g)}{Ke - g} \quad (13)$$

Finally, dividing both sides by BVPS (0) isolates the P/B multiple on the left-hand side and its fundamental value drivers on the right side as follows:

$$\frac{P(0)}{BVPS(0)} = \frac{P}{B} = \frac{ROE - g}{Ke - g} \quad (14)$$

Equation 14 shows that the spread between ROE and the expected growth rate drives the P/B ratio. A key economic finding from this expression is that a firm will only trade above its book value if its Return on Equity exceeds its cost of equity ($ROE\ > Ke$), meaning the firm creates value above its required return.

Table A.2 in the Appendix section summarizes the conclusions we have reached in this section.

The theoretically derived drivers from this chapter inform the variable selection and econometric approaches defined further in Chapter 5.

3 – Literature Review

The literature developed on relative valuation has evolved significantly throughout the decades. The main body of research in the field has focused on improving the prediction accuracy of multiples for firm valuation, either by better understanding the underlying value drivers or by selecting more comparable peer groups. We will start this chapter by drawing the bridge between firm value and fundamentals and, subsequently, fundamentals and relative valuation.

3.1 Relative Valuation in the Context of Valuation Methods

Firm valuation is an essential process in finance and accounting. Pinto et al. (2015) define valuation as "the estimation of an asset´s value based on variables perceived to be related to future investment returns or based on comparisons with closely similar assets". The process of valuing a company can be approached through various techniques and appears in various contexts. According to Koller et al. (2020), the intrinsic value of a firm is determined by its underlying fundamental drivers, and the firm generates economic value only by deploying capital at a ROIC that exceeds the WACC. Valuing a firm is also critical in strategic decision-making contexts such as corporate strategy (defining the optimal business mix) and M&A transactions (Shaffer, 2024). Valuation further helps analysts deal with stock market noise by allowing them to form their own benchmark of value, rather than relying solely on market price (Bhojraj & Lee, 2002).

Fernandez (2023) has developed a categorization of company valuation methods into six main groups, while Damodaran (2007) uses four categories. Pinto et al. (2015) use less granularity and classify valuation models into two broad categories: absolute valuation models (which specify an asset´s intrinsic value) and relative valuation models (which estimate an asset´s value relative to another asset). Table 1 merges the inputs from these authors into an integrated framework of the most common valuation approaches:

Table 1: Summary of the Most Common Valuation Approaches

Valuation Category	Where does value come from?	Main approaches
Absolute/Intrinsic Valuation	Asset´s ability to generate future cash flows or economic profit, adjusted for the time value of money and risk	**-Equity Valuation**: Dividend Discount Model (DDM), Free Cash Flow to Equity (FCFE) **-Enterprise Valuation**: Free cash Flow to the Firm (FCFF), Adjusted Present Value (APV) **-Value Creation**: Economic Value Added (EVA), Residual Income (RI), and Cash Flow Return on Investment (CFROI)
Relative Valuation (Multiples)	Benchmarking against how the market is pricing similar or comparable assets, through ratios standardized to a common value driver	**-Equity Multiples:** Such as Price-to-Earnings (P/E), Price-to-Book (P/B) and Price-to-Cash Flow (P/CF) **-Enterprise Multiples**: Such as EV/EBITDA, EV/EBIT, and EV/Sales

Valuation Category	Where does value come from?	Main approaches
Asset-Based/Accounting-Based Valuation	Value comes from a point-in-time assessment of the existing assets and liabilities on a firm´s books, either as reported or on an adjusted basis	**-Book Value (Historic Cost)** **-Adjusted Book Value** **-Substantial Value** **-Liquidation Value**
Mixed Valuation Approaches (Goodwill-based)	Value originates from a combination of a point in time valuation (Net Asset Value) and a capital gain resulting from future excess profits (Goodwill)	**-Classic Valuation Method** **-Simplified UEC Method** **-Anglo-Saxon Direct Method**

Source: Author Elaboration, based on Fernandez (2023) and Damodaran (2007)

Although Fernandez (2023) considers the discounted cash flow model the most "conceptually correct", other authors note that DCF analysis often faces criticism for its high complexity and sensitivity to subjective assumptions, such as long-term growth rates and discount rates (Damodaran, 2007; Lie & Lie, 2002). Due to these practical issues, practitioners overwhelmingly favor the relative valuation approach. Surveys by Pinto, Robinson & Stowe (2019) reveal that 93% of professional equity analysts use the market multiples approach in their valuations, compared to 79% who use a present discounted value approach. Market agents also favor multiples due to their simplicity and the speed at which a valuation can be performed, a crucial aspect in M&A transactions (Plenborg & Pimentel, 2016). In line with this, Shaffer (2024) notes that M&A advisors rely heavily on accounting multiples to counter the subjectivity of DCF valuations, which can subject the model to manipulation (Gupta, 2018).

However, the simplicity and intuitive nature of valuation multiples come at a cost. Mauboussin & Callahan (2024) highlight some of those limitations, such as the fact that we are comparing a long-term market-value numerator with a short-term accounting denominator, which does not provide insight into a firm´s long-term investments and whether these investments result in an adequate return for shareholders' risk exposure. Using accounting numbers also exposes the analyst to the assumptions underlying companies' reported numbers. Reporting assumptions can distort comparability and weaken the informational signal provided by valuation multiples (Mauboussin & Callahan, 2024; Plenborg & Pimentel, 2016; Young & Zeng, 2015). Relative valuation can also be subject to behavioral biases, whereby financial advisors twist their value estimates to align with their clients' needs (Bhojraj & Lee, 2002; Damodaran, 2012), creating a confirmation bias. Moreover, multiples rely on market sentiment and are therefore exposed to frequent market inefficiencies. If a particular sector is overvalued, valuation multiples will likely yield an inflated valuation for our target firm, with a prime historical example of this effect being the Dotcom bubble in the 2000s (Koller et al., 2020**)**. Indeed, Fernandez (2002) shows that multiples exhibit a broad cross-sectional dispersion and serve better as a confirmation to absolute valuation methods, questioning a mechanical reliance on them. This stresses the importance of this work´s purpose. Understanding what fundamentally drives valuation multiples across industries allows analysts to make more informed valuation decisions, mitigating some of the disadvantages of using valuation multiples.

3.2 The Performance of Relative Valuation

With relative valuation positioned within all valuation approaches, we turn to literature on its empirical performance. Previous authors have pursued variations of the stylized models we established in Chapter 2 through methodological choices - forward vs trailing metrics, time frame and different aggregation methods. As Liu, Nissim & Thomas (2002) outline, academic research evaluates the accuracy of multiples through the distribution of pricing errors, defined as the difference between the multiple-implied predicted value and the actual stock price.

A notable consensus is that forward-looking metrics outperform trailing ones in accuracy. Kim & Ritter (1999) found that P/E multiples based on forecasted earnings are more accurate than using reported earnings, which can be subject to temporary noise, since forecasts better reflect expected future payoffs (Plenborg & Pimentel, 2016). Moreover, two or three-year forecasted EPS outperforms using one-year forecasted EPS (Kim & Ritter, 1999; Liu et al., 2002). Additionally, Yoo (2006) shows that combining multiple historical valuation multiples adds no incremental information that goes beyond forward-looking multiples in valuation accuracy. While the literature evaluates forward multiples in terms of prediction accuracy, the question of whether forward fundamentals alter the structural relationship between drivers and "current" multiples remains largely unexplored.

Regarding the multiples we study, Cheng & McNamara (2000) found that P/E outperforms P/B individually, but a combined valuation using both outperforms either, indicating that book value provides complementary information beyond earnings. At the enterprise-level, Lie & Lie (2002) found that EV/EBITDA outperforms EV/EBIT by neutralizing the distorting effects of differing D&A schedules across firms. Damodaran (2009) noted a similar result in the case of cyclical industries, as EV/EBITDA exhibits lower volatility during economic downturns. This superiority of EV/EBITDA was also reflected in practice, as documented by Shaffer (2024), who show that enterprise-level multiples are employed significantly more than equity-level multiples in M&A transactions.

When it comes to accuracy relative to the size of the firms being valued, Cheng & McNamara (2000) showed that valuation accuracy is positively correlated with firm size, noting that size brings the most positive effect on accuracy when applying the P/E multiple. Plenborg & Pimentel (2016) explore that smaller firms have a lower information environment which shows why their valuations can become less accurate. The peer-group averaging method matters too: evidence favors the harmonic mean (Baker &

Ruback, 1999; Liu, Nissim & Thomas, 2002) over the median (Damodaran, 2012; Schreiner & Spremann, 2007; Alford, 1992) for mitigating the effect of outliers in the data.

Importantly, the empirical performance of relative valuation depends heavily on the target firm's industry, with Gupta (2018) and Fernandez (2002) showing that analysts exhibit a preference for multiples that best capture the economic realities of the distinct industries that they cover. This makes the selection of comparables a key methodological step in performing a relative valuation.

3.3 Selection of Comparables for Relative Valuation

The literature on peer selection has moved from industry heuristics to structured processes that use advanced econometric approaches and machine learning algorithms.

A clear benchmark in the literature is the use of industry classification systems, against which the authors test their models. Boatsman and Baskin (1981) found that matching firms based on historical earnings growth yielded lower valuation errors than random industry selection, while Alford (1992) concluded that combining risk and earnings growth is effective, but does not outperform the first three digits of the SIC code. Alford (1992) also highlighted a key tradeoff: matching on multiple variables simultaneously constrains sample size, putting theoretical precision in conflict with statistical reliability.

Subsequent approaches became more structured. Bhojraj & Lee (2002) introduced the “warranted multiple” approach, estimating a target multiple using cross-sectional regressions on value drivers and selecting peers based on the smallest absolute deviation of their warranted multiple from that of the target firms. Bhojraj, Lee, & Oler (2003) showed that GICS is superior to SIC and NAICS at explaining cross-sectional variations in valuation multiples – a finding that informs our industry selection process. Extending to Europe, Dittmann and Weiner (2005) found that matching based on total assets and ROA outperformed industry membership alone. Underlying all data-based peer selections, Young & Zeng (2015) showed that its success relies on accounting standardization, with mandatory IFRS adoption improving valuation accuracy, by reducing reporting driven measurement errors. As we outlined in the introduction, their work also provided motivation to study valuation drivers in Europe.

More recent econometric methods select peers based on shared structural relationships rather than industry membership. Asche and Misund (2016) test whether adding a new candidate to the peer set changes the baseline valuation equation, using Chow tests to identify “structural breaks” in the data. Knudsen, Kold & Plenborg (2017) rank firms by the Sum of Absolute Rank Differences (SARD) across profitability, growth and risk proxies - arguing that two firms can be peers across industries.

3.4 Fundamental Value Drivers of Valuation Multiples

As we showed in Chapter 2, valuation multiples can be mathematically derived from absolute valuation models. In theory, the cross-sectional differences in multiples are determined by differences in these parameters. However, the underlying premises of these stylized models are unstable in practice, and bridging theory with empirical reality is a key motivation for our work. A deeper understanding of what drives valuation multiples can also help address some of the limitations of relative valuation we have discussed. Most empirical work on the drivers of multiples uses cross-sectional specifications, whereas panel data methods that assess within-firm variation remain underrepresented, despite their ability to control for unobserved firm heterogeneity (Binoy, 2025; Muradova, 2026). We will further address this gap through our main model specification.

Starting with profitability, this channel reflects a firm's fundamental capacity to generate cash flows, which expands the valuation multiple (Damodaran, 2007). Gupta (2018) identifies financial parameters such as ROE, ROCE, and net profit margins as the primary determinants of the premium the market assigns to a firm´s trading multiples. However, the relevance of a specific profitability measure depends strictly on the type of multiple being analyzed. Geertsema and Lu (2023) show that ROE and net profit margins are the strongest empirical drivers of equity multiples (e.g., P/B), and ROA, ROIC, and operating margins are the primary drivers of enterprise-level multiples, such as EV/Sales and EV/Assets.

When it comes to growth, the intuition behind this driver is that expected future growth can increase future earnings, thereby expanding the valuation multiple (Damodaran, 2007). The most common proxy for growth in the literature is the analyst consensus forecast of long-term future earnings. As shown by Bhojraj & Lee (2002), the consensus analyst forecast of a firm´s earnings is a highly significant explanatory variable of the EV/Sales and P/B valuation multiples. Other authors have used trailing proxies for growth, such as the 10-year historical average earnings growth rate (Boatsman & Baskin, 1981). Geertsema and Lu (2023) incorporate multiple trailing metrics, such as one-year trailing sales growth and book equity growth, into their machine-learning valuation models. Zarowin (1990) identifies forecasted earnings growth as a major source of cross-sectional variation in earnings multiples. However, it is crucial to note that not all growth creates value. Growth leads to value creation only if ROIC is sufficient to cover the WACC; otherwise, growth becomes value destructive (Koller et al, 2020; Mauboussin & Callahan, 2024).

When it comes to risk, the economic intuition is that risk is inversely related to valuation multiples: higher uncertainty about future cash flows commands a higher discount rate, which naturally shrinks the multiple (Damodaran, 2007). This is empirically validated by Gupta (2018), who shows that beta exhibits a significantly negative coefficient when predicting multiples. In the literature, various proxies have been used to capture the effect of risk in addition to beta. Alford (1992) and Knudsen, Kold & Plenborg (2017) use firm size (measured by total assets) as a proxy, since smaller firms face lower liquidity and higher uncertainty. Researchers have also used capital structure to capture financial risk, through the net debt-to-EBIT ratio (Knudsen, Kold & Plenborg, 2017), and through book leverage to capture cross-sectional differences linked to the implied cost of capital (Bhojraj & Lee, 2002). More recently, Golubov & Konstantinidi (2019) highlighted operating leverage as a major risk driver, noting that it makes assets in-place riskier and explaining why certain firms trade at a meaningful discount to peers. A relevant stream of research also highlights that the traditional fundamental proxies for profitability, growth, and risk are not accurate in capturing the economic characteristics of firms with a high proportion of intangible assets (Lie & Lie, 2002). Schreiner & Spremann (2007) found that accrual-based multiples penalize firms that invest heavily in Research and Development (R&D), since intangible investments are expensed rather than capitalized, thereby artificially compressing earnings (Mauboussin & Callahan, 2024). To address this distortion, Bhojraj & Lee (2002) explicitly incorporate the R&D-to-Sales ratio as an additional fundamental value driver, showing that this metric is significant in capturing future profitability growth that can be masked by reported earnings, thereby justifying its inclusion in an empirical model as a control variable.

3.5 Machine Learning and Relative Valuation

Taking advantage of developments in artificial intelligence, researchers have begun applying machine learning techniques for two main purposes: algorithmic peer selection processes that leverage Big Data to improve comparability (Hoberg and Phillips, 2016; Lee, Ma, and Wang, 2015; Bonne et al.,2022; Jagric et al. ,2024), and machine learning valuation models that directly predict valuation multiples and implied equity values (Geertsema and Lu, 2023; Staňková, 2024; Gu, Kelly, and Xiu, 2020).

Even with clear predictive advantages, implementing machine learning in a relative valuation context requires special care regarding economic interpretability. This issue speaks to the bias-variance tradeoff (Hastie, Tibshirani, and Friedman, 2009). While linear models like OLS can suffer from high bias due to the rigid functional form imposed, machine learning models can reduce bias by identifying complex patterns, but are susceptible to high variance and overfitting. This tradeoff between statistical adequacy and economic interpretability informs our decision to employ traditional regressions. Given our clear focus on studying the drivers of valuation multiples (and not prediction), high interpretability is a non-negotiable feature of our model. Hence, such advanced methods will not be used in our study. While machine learning algorithms excel at out-of-sample prediction, we believe our estimator preserves the transparency needed to isolate the underlying economic mechanisms and the marginal effects of value drivers. (Damodaran, 2007; Gu, Kelly, & Xiu, 2020; Jagric et al., 2024; Staňková, 2024).

4 – Hypothesis Development

4.1 Research Gap

The literature review allowed us to identify empirical gaps that support our hypothesis development. While previous literature has clearly identified various proxies for profitability, growth, and risk as key drivers of valuation multiples, significant gaps remain in methodology, geographical focus, and in the treatment of forward versus trailing fundamentals.

4.1.1 The Methodological Gap

There is a clear methodological gap that this study aims to bridge. It concerns model specification and the breadth of industries covered. Most of the literature on fundamental value drivers examines effects using cross-sectional and pooled OLS specifications. Foundational contributions such as Alford (1992), Liu, Nissim, & Thomas (2002), and Bhojraj & Lee (2002) establish that profitability, growth, and risk proxies explain a significant share of cross-sectional variation in valuation multiples. However, their specifications are primarily designed to evaluate price prediction accuracy, with a specific focus on minimizing absolute pricing errors between their implied model valuation and the observed market price. This focus on prediction accuracy leaves ample room to study the structural and economic associations between valuation multiples and their fundamental determinants. Moreover, it is critical to understand whether the theory-predicted drivers explain valuation multiples, and to do so using an estimator that isolates economic relationships from unobserved firm heterogeneity (Gormley & Matsa, 2014). The literature is also underrepresented in comprehensive cross-industry approaches. The studies that focus on cross-industry explanations of fundamental determinants focus on a select number of industries (Gupta, 2018; Asche & Misund, 2016; Bagna & Cotta Ramusino, 2017), whereas our selection of industries is market-wide.

4.1.2 The Geographical Gap

The overwhelming majority of literature on relative valuation has focused on the US market rather than on the European market, arguably due to greater standardization of accounting standards, larger market size, greater availability of historical information, and the broader scope and depth of prior studies. While European panel data sets have been used to study specific pricing dynamics of valuation multiples (Barros & Gonçalves, 2025), we identify a significant empirical deficit in the study of the theoretically suggested value drivers of valuation multiples in European equity markets. Moreover, as we pointed out in Chapter 3, Young and Zeng (2015) show that mandatory IFRS adoption in the EU significantly improved cross-border accounting comparability and peer-based valuation accuracy, thereby motivating a comprehensive study of value drivers in a fully European sample across industries. Most studies that use the European equity market as a sample focus on peer selection (Dittmann & Weiner, 2005) and on specific structural anomalies, such as the impact of size on multiples or their behavior in cyclical industries (Bagna & Cotta Ramusino, 2017; Gracia, 2019).

4.1.3 The Forward vs Trailing Gap

We have also identified an important diagnostic debate, which concerns the hypothesized superiority of forward consensus estimates over trailing accounting metrics. However, this superiority is established by most authors through an evaluation of forward multiples, analyzing the distribution of pricing errors relative to the actual stock price in a cross-sectional context (Liu, Nissim, & Thomas, 2002; Kim &

Ritter, 1999; Lie & Lie, 2002; Schreiner & Spremann, 2007). This leaves a significant gap in unveiling the structural and economic relationships between forward fundamentals and "current" valuation multiples. After testing our main specification, which employs trailing variables, we will test this hypothesis in a separate analysis under Chapter 7, using a distinct sample from the main one. This approach is inspired by Bhojraj & Lee (2002), who applied forward metrics to trailing multiples.

4.2 Definition of the Object of Study

Our study focuses on the P/E, P/B, and EV/EBITDA multiples, as these ratios help address the identified research gaps. Firstly, they carry an unmatched relevance within the practitioner community, ensuring we are studying effects that motivate real-world capital allocation decisions. Asquith, Mikhail, and Au (2005), in a content analysis of 1,126 equity analyst reports, find that 99% rely on some form of earnings multiple. Other practitioner surveys found that P/E, P/B and EV/EBITDA are the defining metrics of market practice both in Europe (Bancel and Mittoo, 2014) and globally (Pinto, Robinson & Stowe, 2019).

These multiples are also complementary, providing an equity-value and an enterprise-value perspective. While the P/E is useful for overall market valuation, EV/EBITDA provides a more meaningful comparison when P/E is distorted by differing capital structures, depreciation schedules, and non-operating items (Koller et al., 2020). This potentially distortive nature of P/E justifies including P/B as a dependent variable. The P/B multiple carries significant theoretical valuation weight through the residual income framework (Ohlson, 1995), and book-to-market (inverse of P/B) is empirically among the most robust cross-sectional predictors of stock returns (Fama & French, 1992). P/B is also more stable, due to the cumulative balance-sheet denominator. It is also arguably more relevant in capital-intensive sectors such as Utilities, Materials, and Industrials, where the P/E signal can become distorted. Moreover, Penman (1996) ties P/B to persistent profitability, and Bhojraj & Lee (2002) point to it as a stable alternative when the P/E ratio becomes technically and economically undefined.

By assessing the three together, our study analyzes how the market prices a firm's earnings signal, core operating performance, and underlying equity base across different economic environments in Europe – the very ratios that guide capital allocation in market practice.

4.3 Hypothesis Formulation

With this setup in mind, we can now outline the research questions and the associated hypotheses that guide the empirical methodology of this study, summarized in Table 2:

Table 2: Research Hypotheses Under Study

Research Questions and Underlying Hypothesis
RQ1: To what extent do value drivers, derived from corporate finance theory and prescribed by previous literature, accurately determine firm-level variation in the most employed valuation multiples, in a cross-industry European setting?
H1: Within-firm variations in the P/E, P/B, and EV/EBITDA valuation multiples are significantly and positively determined by proxies for profitability and growth, and significantly negatively associated with proxies for risk, motivated by the derivations in Chapter 2.
H2: Models using forward-looking consensus expectations produce coefficient estimates more consistent with the predictions of corporate finance theory and exhibit stronger structural associations between fundamental drivers and valuation multiples than models that rely on trailing accounting metrics.
RQ2: Does the specific economic environment (GICS Industry) induce structural heterogeneity in how the market weights the previously tested fundamental value drivers?
H3: The marginal pricing weights and explanatory power of fundamental value drivers exhibit significant structural heterogeneity across the 10 non-financial GICS sectors.

Source: Author Elaboration

5 – Data & Research Methodology

5.1 Data Sources and Sample Construction

The primary dataset for this study was sourced from Refinitiv Eikon. Regarding industry composition, we will work with the 10 non-financial GICS Sectors. According to Bhojraj, Lee & Oler (2003), the focus on principal business activities makes this industry classification system superior to other classification systems in explaining cross-sectional variation in valuation multiples.

Our methodology is to pair market data as of June 30th of year N with accounting data for the most recent fiscal year-end in year N-1. This is in line with Bhojraj & Lee (2002), Dittmann & Weiner (2005), and Golubov & Konstantinidi (2019). The rationale behind this methodology is that by setting a 6-month delay between year-end accounting and the market valuation date, we ensure that the financial statements have been published and assimilated by investors at the time the stock price is observed. With this approach in mind, we extracted a multi-year window of 15 valuation periods (2011-2025) during which we can assess multiples on the valuation date as of the 30th of June of each year (or the closest trading date). The initial screening process in Refinitiv adhered to methodological guidelines to ensure consistency from the outset. The universe consisted only of publicly listed firms with active trading status. Geographically, only firms domiciled in Europe and listed in Europe were considered, to avoid firms not domiciled in Europe, but with secondary European listings, whose valuations may be anchored to pricing dynamics in their primary market. We excluded Russia, Ukraine, and Belarus from the start, since multiples in these regions can be noisy due to ongoing geopolitical tensions and may fail to reveal meaningful economic dynamics. Moreover, there was a targeted aim to exclude small and medium enterprises from the study. Since we were going to deal with market data, lower liquidity, lower analyst coverage (on which some independent variables rely), and higher potential for extreme multiples were issues to avoid. This is well justified by foundational works in the literature (Liu, Nissim, & Thomas, 2002; Lie & Lie, 2002; Alford, 1992). This decision was also informed by Cheng & McNamara (2000) and by the positive correlation between firm size and valuation accuracy that they found. In that sense, a cutoff point was established based on the definition of Small and Medium Enterprise (SME) from the European Commission (European Commission, n.d.), where firms were only kept in the data set if they had a turnover above or equal to €50 million OR total assets above or equal to €43 million. From this initial raw sample, only observations with sufficient data to manually compute the multiples were retained. Table 3 provides the filtering process that was followed in Stata to arrive at the estimation sample of each multiple:

Table 3: Sample construction and filtering criteria

Sample Selection	Firms	Firm-Year Observations
Panel Before Cleaning	3,846	45,034
Less: Duplicate observations	-	(100)
Less: Observations missing all three multiples	(7)	(456)
Final unbalanced panel	3,839	44,478
Less: Financial sector (GICS)	(551)	(6717)
Non-financial estimation panel	**3,288**	**37,761**
Dependent variable estimation samples		
Less: Non-positive P/B (log transformation)	(3)	(427)
P/B estimation sample (2011-2025)	**3,285**	**37,334**
Less: Non-positive P/E (log transformation)	(140)	(7809)
P/E estimation sample (2011-2025)	**3,148**	**29,952**
Less: Non-positive EV/EBITDA (log transformation)	(103)	(3883)
EV/EBITDA estimation sample (2011-2025)	**3,185**	**33,878**

Source: Author Elaboration, with the filtering process being performed in Stata

While the raw data spans the valuation periods 2011-2025, the estimation sample that we present in subsequent chapters will cover the 10 valuation periods from 2016-2025, since market variables are only available starting in 2016. Specifically, the pre-2016 periods and listwise deletion reduce the estimation samples from 37,334, 29,952, and 33,878 to the 23,751 (P/B), 19,212 (P/E), and 19,089 (EV/EBITDA) observations reported in Tables 4 and 5. Boxplots of the valuation multiples on the pre-cut off samples (2011-2025) are presented in Figure A.3 of the Appendix section.

5.2 Variable Definition and Construction

Since we work with market and accounting variables, a clear principle was followed in variable construction. Market data was sourced from the Refinitiv database as is, and without adjustments from our side, as of 30/06 of year N, or the closest trading date. The accounting components of the main variables were taken in their raw form as of 31/12 of year N-1, with the accounting component available at the end of that fiscal year extracted. All variables that required accounting components were built by us, in line with the methodology followed by other authors (Bhojraj & Lee, 2002; Cheng & McNamara, 2000). In this way, we were able to ensure some level of control in the construction of the variables that rely on fundamental accounting data. This is important because ratios produced by financial data providers often have several (and sometimes conflicting) definitions, and hence, manually building the variables yields more interpretable results. Table A.3 in the Appendix section outlines the full list of variables that the reader will find throughout the results section of this study.

5.3 Data Cleaning and Treatment

After defining our independent and dependent variables, we constructed the final panel data sets for the parametric tests. The dependent variables were log-transformed, in line with standard econometric practices, to address extreme outliers, the inherent right-skewness of valuation multiples (see table 6), and concerns about heteroskedasticity (Gracia, 2019**).** The issue of negative multiples was also addressed by log-transformation of the dependent variables. After inspecting the boxplots and scatterplots of the non-log-transformed independent variables, severe outliers were identified that could distort least-squares coefficient estimates. In that sense, a 1/99 winsorization threshold was applied to every variable except for the log-transformed ones, since log-transformation already handles outliers well. This threshold was chosen as a compromise between smoothening the effect of extreme outliers on our results and conserving some economically meaningful variation in the context of a panel data set with 10 distinct industries. The financial industry (GICS Code: Financials) was excluded in line with other works in the field (Bartram & Grinblatt, 2018; Barth, Li, and McClure, 2023; Bagna & Cotta Ramusino,2017; Barros & Gonçalves, 2025) and under the recognition that the valuation of financial firms is inherently different from non-financial firms due to different accounting practices, regulatory environments, and the loss of economic and technical meaning of enterprise value multiples. For financial institutions, debt is an operating asset rather than a capital structure decision, rendering the enterprise value concept economically meaningless. The final samples used in parametric tests were constructed by listwise deletion - each sample is defined by non-missing values on all variables required for that specification (including robustness tests, where they are not related to the sample). Therefore, our final samples for parametric tests are lower than those previously presented in Table 3. The sample used in Chapter 7 was constructed separately and is smaller due to the requirement of non-missing consensus forecasts, reflecting a different economic profile of firms.

5.4 Descriptive Statistics

5.4.1 General Sample Characteristics

Across our samples, the largest sectors are consistently Industrials and Consumer Discretionary, while Energy and Utilities are consistently the least represented. This reflects the European economic fabric, and it is critical to acknowledge that the largest sectors will carry greater weight in our results; we unpack this in section 6.4, which explores industry heterogeneity in the main model results.

Table 4: Sample distribution by GICS sector

GICS Sector	P/B Sample - Frequency	P/B (%)	P/E Sample - Frequency	P/E (%)	EV/EBITDA Sample- Frequency	EV/EBITDA (%)
Communication Services	1,573	6.62	1,211	6.30	1,211	6.34
Consumer Discretionary	3,552	14.96	2,824	14.70	2,793	14.63
Consumer Staples	1,914	8.06	1,628	8.47	1,664	8.72
Energy	771	3.25	534	2.78	528	2.77
HealthCare	1,787	7.52	1,339	6.97	1,335	6.99
Industrials	6,287	26.47	5,242	27.29	5,268	27.60
Information Technology	2,684	11.30	2,146	11.17	2,130	11.16
Materials	1,798	7.57	1,514	7.88	1,632	8.55
Real Estate	2,465	10.38	1,971	10.26	1,736	9.09
Utilities	920	3.87	803	4.18	792	4.15
Total	23,751	100.00	19,212	100.00	19,089	100.00

Source: Author Elaboration, run in Stata

Regarding the sample composition by year (Table 5), the first valuation period under analysis is 2016. We observe a clear pattern of increasing coverage in observations, consistent with other studies in the field (Liu, Nissim, & Thomas, 2002).

Table 5: Sample distribution by Year

Sample by Year	**P/B – Frequency**	**P/B (%)**	**P/E – Frequency**	**P/E (%)**	**EV/EBITDA – Frequency**	**EV/EBITDA (%)**
2016	1,801	7.58	1,492	7.77	1,473	7.72
2017	1,894	7.97	1,622	8.44	1,596	8.36
2018	2,024	8.52	1,741	9.06	1,740	9.12
2019	2,170	9.14	1,853	9.65	1,839	9.63
2020	2,306	9.71	1,922	10.00	1,924	10.08
2021	2,454	10.33	1,782	9.28	1,768	9.26
2022	2,635	11.09	2,198	11.44	2,153	11.28
2023	2,785	11.73	2,236	11.64	2,230	11.68
2024	2,821	11.88	2,153	11.21	2,139	11.21
2025	2,861	12.05	2,213	11.52	2,227	11.67
Total	23,751	100.00	19,212	100.00	19,089	100.00

Source: Author Elaboration, run in Stata

It is important to present the distribution of the non-log-transformed (but winsorized at the 1/99 level) valuation multiples under study (pooled statistics, across all firm-year observations). Although we study their log-transformed versions, analyzing them is critical to assess the statistical and economic picture of the dependent variables. The results show a median P/B of 1.68x, median P/E of 17.7x, and median EV/EBITDA of 10.7x. These median levels are consistent with moderate valuations characteristic of European large-cap equities, which trade at a discount to US equities (Koller et al., 2020). However, as one can observe, the means are substantially above the medians, confirming the right-skewness we identified earlier as a reason to use the log-transformed multiple in the econometric specification. Table 6 presents these descriptive features:

Table 6: Distribution of the Non-Log Transformed Valuation Multiples

Multiple	N	Mean	Std. Dev.	p25	Median	p75
Price-to-Book (P/B)	23,751	3.491	6.362	0.925	1.680	3.348
Price-to-Earnings (P/E)	19,212	41.887	99.212	10.665	17.699	30.980
EV/EBITDA	19,089	21.488	46.507	6.622	10.668	18.723

Source: Author Elaboration, run in Stata

5.4.2 Descriptive Analysis of Independent Variables

Table A.4 in the Appendix section summarizes the key descriptive features of the samples used for each valuation multiple. The samples reflect large and mid-cap European firms with median total assets ranging from €775 million (P/B) to €927 million (EV/EBITDA). The variation in sample size is driven by listwise deletion. The P/B multiple has the largest sample size because P/E requires positive earnings, and EV/EBITDA requires distinct enterprise-level variables such as ROIC and WACC. There is a noticeable difference in the behavior of certain regressors between samples, by construction. For instance, the mean ROE for the P/E sample is 14%, while the mean ROE for the P/B sample is 7%. Since the P/E sample requires positive earnings, it represents only profitable firms, which is an important consideration to take when analyzing the results. These variations across samples become less pronounced in the 50th percentile. The mean top-line revenue growth across samples is more consistent, hovering between 12% and 13%. The EV/EBITDA sample (Panel C) shows an average WACC of 6.38% against a 13.25% ROIC, indicating that the average firm in this data set successfully creates economic value added, on average, across the 2016-2025 period. Market beta (Panels A and B) is stable between samples (between 0.8 and 0.9) and is consistent with a sample skewed towards larger European firms, which exhibit lower systematic risk than the overall market. Firms exhibit moderate leverage levels with D/E ratios between 0.78 and 0.89.

5.4.3 Correlation Analysis and Multicollinearity Diagnostics

Our Appendix section (Tables A.5, A.6 and A.7) presents the correlation matrices for the three samples under study, which allow us to conduct a preliminary univariate analysis and assess multicollinearity. We highlight the positive correlation between ln(P/B) and ROE (0.136) and the negative correlations of ln(P/E) with ROE (-0.329) and with NPM (-0.240), indicating a likely mechanical transmission effect between P/E and ROE through earnings, which appears in both. The negative correlation between ln (EV/EBITDA) and ROIC also stands out at (-0.119). On the multicollinearity analysis, the extremely high correlation between the equity multiplier and the leverage variable was expected and clearly stands out (+0.859 for the P/B sample and +0.829 for the P/E sample). For this reason, leverage will be excluded as a control variable when we present the model addressing the ROE and ROIC decompositions in Section 6.3.2. Aside from this relationship, all pairwise correlations among independent variables are weak to moderate (<0.60), which allows us to assume the non-presence of multicollinearity between the variables employed. Furthermore, Variance Inflation Factors (VIFs) computed for the independent variables across the three samples are all close to one (mean VIF between 1.03 and 1.06, with no individual value exceeding 1.12), well below the conventional threshold of 5 and confirming the absence of multicollinearity concerns.

5.5 Econometric Specification and Estimation Strategy

To test the impact of fundamental value drivers on valuation multiples, we employ an unbalanced panel data framework. The main econometric model employed for the three valuation multiples is a two-way fixed effects model:

Price-to-Book ratio:

$$\textit{Price/Book (ln)}_{it} = \beta_0 + \beta_1 \textit{ROE}_{it} + \beta_2 \textit{Revenue Growth}_{it} + \beta_3 \textit{Beta}_{it} + \textit{Controls}_{it} + \theta_i + \varphi_t + \varepsilon_{i,t} \quad (15)$$

Controls: Size, Leverage, and Intangibility

Price-to-Earnings ratio:

$$\textit{Price/Earnings (ln)}_{it} = \beta_0 + \beta_1 \textit{ROE}_{it} + \beta_2 \textit{Revenue Growth}_{it} + \beta_3 \textit{Beta}_{it} + \textit{Controls}_{it} + \theta_i + \varphi_t + \varepsilon_{i,t} \quad (16)$$

Controls: Size, Leverage, and Intangibility

EV/EBITDA ratio:

$$\textit{EV/EBITDA (ln)}_{it} = \beta_0 + \beta_1 \textit{ROIC}_{it} + \beta_2 \textit{Revenue Growth}_{it} + \beta_3 \textit{WACC}_{it} + \textit{Controls}_{it} + \theta_i + \varphi_t + \varepsilon_{i,t} \quad (17)$$

Controls: Size, and Intangibility

Where i indexes the firm, and t indexes the valuation year. β_1 through β_3 capture the sensitivities of the primary fundamental drivers, and $\textit{Controls}_{it}$ represents a vector of control variables (Size, Leverage, and Intangibility). $\varepsilon_{i,t}$ is the idiosyncratic error term. Firm fixed effects (θ_i) absorb time-invariant unobservable characteristics, while Year Fixed effects (φ_t) control for macroeconomic shocks that affect all firms present in the panel. Standard errors are clustered at the firm level to account for serial correlation within firm observations (Petersen, 2009). A detailed explanation of the theoretical and literature justifications that back the selection of variables for the models can be found in the Appendix section (Table A.3). Our main specification employs trailing accounting measures. This ensures we avoid analyst coverage selection bias inherent to forward consensus data, although we still explore these samples (which are inherently different from our main one) in Chapter 7. At the same time, we ensure maximum sample coverage and comparability across industries. Therefore, our coefficients measure the "current" association between trailing accounting fundamentals and current market variables with trailing valuation multiples.

6– Results Of Empirical Tests

6.1 Diagnostic Tests

The process to select the most suitable estimator for this study required us to conduct two diagnostic tests. Specifically, the Breusch-Pagan Lagrange Multiplier (LM) test was employed to assess the adequacy of a pooled OLS estimator. Given that the null hypothesis for this test was rejected, we conclude that unobserved individual effects are present in our panel sample and that a random-effects or fixed-effects estimator is required. A further Hausman test rejects the orthogonality assumption underlying the random-effects estimator, and we conclude that the fixed-effects estimator is consistent, in line with Gormley & Matsa (2014). Using this estimator as our main model allows us to address unobserved firm heterogeneity, which, according to Roberts and Whited (2013), is a critical step toward isolating true economic relationships in corporate finance. The testing process and results of these tests are outlined in Figure A.1 in the Appendix section.

6.2 Main Model: Drivers and Impact on Valuation Multiples

This section evaluates whether the empirical evidence aligns with the theoretical relationships we established in Chapter 2 and with H1 from Chapter 4. Table 7 reports results under three specifications: Pooled OLS including sector and year fixed effects (columns 1, 4, and 7), firm fixed effects (columns 2, 5, and 8), and median OLS quantile regressions (columns 3, 6, and 9). Since the FE specification is our main identification strategy, the discussion focuses on its estimates for profitability, growth, and risk.

We start with profitability. For P/B, ROE is positive and highly significant (FE: $\beta = 0.0037$, $p < 0.01$), and hence, within a given firm, a one-percentage-point expansion of ROE yields a 0.37%[6] premium in the multiple. Contrary to our theoretical prediction, the relationship between P/E and ROE is negative (FE: $\beta = -0.0546$, $p < 0.01$), indicating a 5.31% compression of the multiple per one-percentage-point

[6] Marginal effects are interpreted as exact semi-elasticities, calculated as $(e^{\wedge}(\beta_i \cdot \Delta x_i) - 1) \times 100$, since the dependent variable is in natural logarithm, where Δx_i denotes the change considered in the explanatory variable (one percentage point for variables measured in percent; 0.1 for ratios). The reported values represent the expected percentage change in the multiple, on average and *ceteris paribus*. The exception is firm size (in natural logarithm), for which the coefficient is interpreted directly as an elasticity ($\beta_i \times 100$)

increase in ROE. This effect could come either from a penalty on profitability or from an expansion of the denominator of the multiple that outpaces the market's adjustment of the numerator, with Muradova (2026) documenting a similar result. Penman (1996) has also noted that the relationship between P/E and current profitability is ambiguous, and that ROE driven by non-recurring items or cyclical peaks can cause the market to discount the multiple. However, it is unlikely that this explains the systematic pattern observed in our broad-market sample. Another departure from the theoretical model of Chapter 2 happens in EV/EBITDA, where ROIC enters negative and significant (FE: $\beta = -0.0121$, $p < 0.01$), with a one-percentage-point increase in ROIC compressing the EV/EBITDA multiple by 1.20%. The negative profitability coefficients in P/E and EV/EBITDA constitute an empirical puzzle that motivate further investigation, specifically through the decompositions of the valuation ratios, given that an economic penalty on trailing profitability is unlikely.

Growth, proxied by the one-year trailing revenue growth, is the only proxy used across all three valuation multiples. For P/B, the empirical evidence aligns with the theoretical expectation: trailing growth is positive and highly significant (FE: $\beta = 0.0016$, $p < 0.01$). Within a given firm, a one-percentage-point increase in realized revenue growth commands a 0.16% premium in the P/B multiple. For P/E, the coefficient entered the model as statistically indistinguishable from zero (FE: $\beta = 0.0000$). For EV/EBITDA, the relationship is technically negative (FE: $\beta = -0.0006$, $p < 0.05$), albeit economically negligible, resulting in a 0.06% compression for a one-percentage-point increase in trailing growth. In this case, the misalignment of P/E and EV/EBITDA with theory is more economically intuitive. As Zarowin (1990) shows, the P/E multiple is better predicted by forward growth, since investors price in future cash flow-generating potential rather than realized commercial growth. In contrast, P/B rewards trailing growth because equity book value is a cumulative measure, rather than a flow variable. This leads the market to assign a premium to past top-line growth as an indication of the productivity and scalability of the net assets already on the books. Therefore, the fact that trailing growth does not drive P/E and EV/EBITDA supports testing whether the forward growth channel is a better predictor, which we explore in Chapter 7.

Finally, the risk proxies also show mixed alignment with our expected signs. The P/B model remains aligned with theory, as Beta is negative and significant (FE: $\beta = -0.0602$, $p < 0.01$), implying a 0.60% compression in the multiple for every 0.1-unit increase in Beta. Economically, this indicates that a higher cost of equity via the Beta channel discounts the current market price relative to the stable book equity base. P/E and EV/EBITDA show economically counterintuitive responses with Beta ($\beta = 0.0400$, $p < 0.10$) and WACC (FE: $\beta = 0.0111$, $p < 0.01$) being marginally and highly significant, respectively. A one-percentage-point higher WACC is associated with a 1.12% higher EV/EBITDA. The literature shows that risk proxies exhibit ambiguous signs (Bhojraj & Lee, 2002), attributed to riskier firms holding embedded growth options (Golubov & Konstantinidi, 2019). However, an alternative explanation is that these effects may arise from the numerator-denominator relationship between the ratios. While market prices reflect strongly shocks to the discount rate, the accounting denominators are unresponsive to the cost of capital channel. Section 6.3 investigates this empirical puzzle.

Beyond fundamental value drivers, the control variables provide insights into how different firm characteristics interact with valuation multiples. Size is the most consistent control, being negative and significant across all three FE specifications (FE: P/B: −0.4057, P/E: −0.3188, EV/EBITDA: −0.1347; all $p < 0.01$) and driving compressions of 0.41%, 0.32%, and 0.13%, respectively, for every 1% increase in Total Assets. This size penalty has been identified by other authors (Alford, 1992; Gupta, 2018). Within firms, as total assets grow over time, the valuation multiple tends to compress, as a lower growth profile in a mature firm leads investors to assign lower multiples. Leverage enters the model with a positive sign for both equity multiples (FE: P/B: 0.2427, P/E: 0.2231; $p < 0.01$). Conditional on all other variables, a 0.1 unit increase in D/E delivers a premium of 2.46% for P/B and 2.26% for P/E. Trade-off theory states that, until a recognized level of bankruptcy risk is reached, incremental leverage can increase value, especially if a firm has significant opportunities for value creation (Koller et al., 2020). Hence, given the firms' moderate leverage in our sample, this premium can be economically justified. Intangibility is negative and significant for P/B under FE (FE: $\beta = -0.0070$, $p < 0.01$), compressing P/B by 0.70% for every one-percentage-point increase in the intangible asset ratio. Since our proxy already reflects capitalized intangibles (Mauboussin & Callahan, 2024), a higher intangible ratio leads to higher book equity directly. The negative coefficient indicates that the market does not fully reward these capitalized intangibles relative to their carrying value, so the denominator expands faster than the price component and the multiple compresses. For P/E and EV/EBITDA, the coefficients are insignificant ($\beta = -0.0015$ and $\beta = -0.0009$, both $p > 0.10$), indicating that intangible intensity does not drive within-firm variation in these multiples.

The FE estimator shows that the within R^2 is highest for P/E (0.409), followed by P/B (0.243) and EV/EBITDA (0.131).

We conclude that H1 is partially supported, with P/B aligning with the predicted directional effects across all driver categories. However, P/E and EV/EBITDA show unexpected signs in profitability and risk, while the growth channel was practically insignificant in these models. The theoretical framework is verified empirically in multiples that have a more stable denominator, which evolves more gradually than earnings-based multiples, such as the P/B multiple. To test whether the counterintuitive coefficients reflect a spurious correlation due to variable construction or a true economic effect, we further investigate by decomposing the valuation multiples in Section 6.3.

Table 7: Baseline Model Results for the P/B, P/E, and EV/EBITDA models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P/B OLS	P/B FE	P/B OLS Q50	P/E OLS	P/E FE	P/E OLS Q50	EV/EBITDA OLS	EV/EBITDA FE	EV/EBITDA OLS Q50
ROE	0.0085***	0.0037***	0.0137***	-0.0325***	-0.0546***	-0.0260***			
	(0.0007)	(0.0004)	(0.0003)	(0.0015)	(0.0011)	(0.0007)			
ROIC							-0.0066***	-0.0121***	-0.0032***
							(0.0010)	(0.0007)	(0.0004)
Revenue Growth	0.0024***	0.0016***	0.0022***	0.0012***	0.0000	0.0012***	0.0013***	-0.0006**	0.0012***
	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Beta	-0.0150	-0.0602***	-0.0387***	0.0222	0.0400*	-0.0219			
	(0.0280)	(0.0164)	(0.0131)	(0.0290)	(0.0218)	(0.0153)			
WACC							0.0057	0.0111***	0.0035
							(0.0048)	(0.0030)	(0.0024)
Controls									
Size	-0.0204**	-0.4057***	-0.0024	-0.0363***	-0.3188***	-0.0217***	-0.0082	-0.1347***	0.0043
	(0.0080)	(0.0229)	(0.0030)	(0.0076)	(0.0316)	(0.0033)	(0.0065)	(0.0255)	(0.0027)
Leverage	0.1965***	0.2427***	0.1908***	0.1023***	0.2231***	0.0850***			
	(0.0141)	(0.0114)	(0.0077)	(0.0152)	(0.0162)	(0.0095)			
Intangibility	0.0125***	-0.0070***	0.0112***	0.0157***	-0.0015	0.0148***	0.0106***	-0.0009	0.0092***
	(0.0018)	(0.0016)	(0.0007)	(0.0019)	(0.0025)	(0.0009)	(0.0018)	(0.0019)	(0.0006)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No	Yes	No	No	Yes	No
Sector FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Observations	23,751	23,751	23,751	19,212	19,212	19,212	19,089	19,089	19,089
R^2	0.185			0.207			0.230		
Within R^2		0.243			0.409			0.131	

Standard errors in parentheses - * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Author Elaboration, test run in Stata

6.3 How Does the Market Price Fundamentals?

To separate the market´s true economic response from the accounting denominator, we regress the price and accounting components on the fundamental value drivers. This decomposition follows from the logarithmic identity: ln (Multiple) = ln (Price Component) – ln (Accounting Component). We can hence distinguish whether the directional effects come from genuine market pricing of fundamentals or from the accounting denominator used to construct the multiple. We present two specifications on the ratio components. The first one is our main model, but on the valuation ratio components. The second decomposes our profitability drivers - ROE into its DuPont identity and ROIC into operating margin and capital turnover – to get some granularity on the operational factors driving market pricing (Nissim & Penman, 2001). Results are reported in Table 8 and Tables A.8 and A.9 help follow the discussion.

6.3.1 Main Model on the Ratio Components

The decomposition resolves the empirical puzzle identified in Section 6.2. Table 8 (columns 1, 3, and 5) shows that the market rewards trailing profitability across all valuation multiples. ROE positively and significantly predicts market capitalization on a within-firm basis (P/B sample: $\beta = 0.0046$, $p < 0.01$; P/E sample: $\beta = 0.0119$, $p < 0.01$), while ROIC positively predicts enterprise value ($\beta = 0.0053$, $p < 0.01$). Within firms, a one-percentage-point increase in profitability expands the price component by 0.46% (P/B), 1.20% (P/E), and 0.53% (EV/EBITDA). Therefore, we confirm that the negative profitability coefficients identified in section 6.2 are driven by the denominator. Decomposing this effect explicitly (Table A.8), we note that the numerator and denominator respond positively to profitability shocks, but at different magnitudes. For P/B, market capitalization is about 5.1x more responsive to ROE than book value of equity, and hence the multiple expands. For P/E, net income is 5.6x more responsive than the price component, mechanically inducing the multiple to contract. For EV/EBITDA, EBITDA is 3.3x more responsive to ROIC shocks than EV. The profitability "penalty" is explained by the arithmetic construction of the ratios and asymmetric responses to profitability shocks, rather than an economic penalty on trailing profitability. The market did not penalize profitability, but the multiple construction did.

Regarding growth, one-year trailing revenue growth positively predicts the price components within firms across samples (P/B: $\beta = 0.0013$; P/E: $\beta = 0.0008$; EV/EBITDA: $\beta = 0.0007$; all $p < 0.01$). However, this expansion of the price components, while statistically significant, is not substantial from an economic perspective. The fact that the market barely prices trailing top-line growth reinforces the premise that investors price based on forward-looking expectations and provides a natural motivation to replace trailing with forward-looking expectations in Chapter 7.

Finally, for risk, the decomposition resolves the baseline findings. Beta negatively predicts market capitalization (P/B: $\beta = -0.0620$, $p < 0.01$; P/E: $\beta = -0.0457$, $p < 0.01$). A 0.1 unit increase in Beta compresses market capitalization by 0.62% (P/B) and 0.46% (P/E). The market penalizes systematic risk within firms, in line with economic logic. On the ratio level, the marginally positive Beta coefficient on the P/E multiple becomes informed by our decomposition in Table A.8 as well, with the ratio components contracting at different magnitudes. Beta is negative for both ln (Market Cap) and ln (Net Income), but earnings are more responsive ($\beta = -0.0857$, $p < 0.01$) than price ($\beta = -0.0457$, $p < 0.01$) to beta shocks, creating an expansionary effect on the P/E multiple. For EV/EBITDA, WACC predicts enterprise value positively ($\beta = 0.0093$, $p < 0.01$), while leaving EBITDA unaffected. We identify an economic and a mechanical explanation for the result. Economically, we note that EV is determined by the market as the present value of expected future cash flows, meaning investors directly price the discount rate into the numerator, which explains why EBITDA, as a purely operational metric, is unresponsive. Regarding the positive coefficient, we attribute it to built-in endogeneity: when investors price a stock higher, EV rises, and because equity carries (generally) a higher cost than debt, the equity weight lifts WACC as EV rises. EV/EBITDA may expand because the numerator drives both firm value and the cost of capital. Interestingly, as we have seen, this contrasts with net income´s responsiveness to Beta, which responds to the systematic swings Beta measures.

Table 8: Main Model Results Regressed on the Price Components

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(MktCap)	ln(MktCap)	ln(MktCap)	ln(MktCap)	ln(EV)	ln(EV)
ROE (%)	0.0046***		0.0119***			
	(0.0003)		(0.0006)			
Net Profit Margin (%)		0.0011***		0.0025***		
		(0.0001)		(0.0002)		
Asset Turnover		0.2534***		0.3186***		
		(0.0350)		(0.0327)		
Equity Multiplier		-0.0541***		-0.0587***		
		(0.0048)		(0.0060)		
ROIC (%)					0.0053***	
					(0.0005)	
Operating Margin (%)						0.0052***
						(0.0007)
Capital Turnover						-0.0101**
						(0.0046)
Revenue Growth (%)	0.0013***	0.0014**	0.0008***	0.0011***	0.0007***	0.0009***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Beta	-0.0620***	-0.0662***	-0.0457***	-0.0495***		
	(0.0161)	(0.0163)	(0.0159)	(0.0165)		
WACC (%)					0.0093***	0.0104***
					(0.0025)	(0.0026)
Controls						
Size (ln assets)	0.5669***	0.6203***	0.6639***	0.6940***	0.7598***	0.7317***
	(0.0228)	(0.0234)	(0.0226)	(0.0241)	(0.0230)	(0.0229)
Leverage (D/E)	-0.0723***		-0.1553***			
	(0.0088)		(0.0100)			
Intangibility (%)	-0.0071***	-0.0078***	-0.0055***	-0.0076***	-0.0023	-0.0045***
	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0016)
Observations	23,751	23,751	19,212	19,212	19,089	19,089
Within R^2	0.289	0.272	0.340	0.306	0.387	0.380

Columns 1-2: P/B estimation sample. Columns 3-4: P/E estimation sample. Columns 5-6: EV/EBITDA estimation sample. Odd columns: composite profitability (ROE or ROIC). Even columns: DuPont decomposition. FE with firm-clustered SE. Year FE included. Standard errors in parentheses - * $p<0.10$ ** $p<0.05$ *** $p<0.01$
Source: Author Elaboration, tests run in Stata

6.3.2 Profitability Deep Dive: ROE and ROIC Decompositions

Table 8 (columns 2, 4, and 6) also decomposes the drivers of profitability into their DuPont and ROIC channels.

At the equity-value level and within firms, the market prices operational efficiency more strongly than margin expansion. Asset Turnover exhibits the largest marginal effect on market capitalization (P/B sample: $\beta = 0.2534$, $p < 0.01$; P/E sample: $\beta = 0.3186$, $p < 0.01$), with a 0.1 unit increase in Asset

Turnover driving a 2.6% to 3.2% expansion in market value. Net Profit Margin is positive and significant, but smaller in magnitude (P/B sample: $\beta = 0.0011$; P/E sample: $\beta = 0.0025$, $p < 0.01$), with a one-percentage-point increase in NPM associated with a 0.11% to 0.25% increase in market capitalization. The Equity Multiplier coefficients show that the market penalizes leverage-boosted profitability (P/B sample: $\beta = -0.0541$, $p < 0.01$; P/E sample: $\beta = -0.0587$, $p < 0.01$) in quite similar magnitude between samples (compressions of 0.54% and 0.59%, respectively, for a 0.1-point increase in EM). These results are notable given that the DuPont specification of the P/B multiple (Table A.9) includes the Equity Multiplier with a positive coefficient ($\beta = 0.1277$, $p < 0.01$). While increases in financial risk depress the numerator, debt issuance creates a thinner book equity base, and the denominator contracts more than the price component, mechanically expanding the P/B multiple. Furthermore, the previously identified denominator distortions are present in this specification as well (Table A.8). For instance, Net Profit Margin and Asset Turnover both flip sign between the market value specification (Table 8) and the P/E multiple specification (Table A.9), confirming that the denominator effect distorts almost every profitability channel.

At the enterprise value level, Operating Margin positively predicts Enterprise Value ($\beta = 0.0052$, $p < 0.01$) with a one-percentage-point increase in Operating Margin being associated with a modest 0.52% increase in Enterprise Value. Capital Turnover enters with a negative and significant coefficient ($\beta = -0.0101$, $p < 0.05$), suggesting that, within firms, generating more revenue per euro of invested capital modestly lowers enterprise valuations. A possible interpretation is that a firm generating high revenues per unit of invested capital requires a smaller operating base, resulting in lower enterprise valuations, despite superior operating efficiency. This explanation seems more consistent with the data than one based on partial collinearity (Table A.7).

Interestingly, the decomposed version also improves the explanatory power of the model for the P/B multiple (from 0.140 to 0.268 in R^2) but reduces the explanatory power of the P/E and EV/EBITDA models (Table A.9).

Taken together, this section showed that the market prices profitability and risk in the direction predicted by valuation theory. The economically counterintuitive coefficients identified in 6.2 arise because accounting denominators respond differently to economic shocks than market prices do (Golubov & Konstantinidi, 2019), rather than because investors penalize less profitable firms or reward riskier ones.

6.4 Sector Heterogeneity

In this section, we test H3 by running cross-sector FE regressions of our main model to examine heterogeneity across the 10 industries. The results are reported in Figure A.2 of the Appendix section, which presents sector-level regressions of valuation multiples and price components across all industries.

Starting with the multiple-level results, we note that for P/B, ROE is positive in 9 of the 10 sectors (except for Health Care), where it is not significant. Coefficient magnitudes range from +0.0022 (Communication Services) to +0.0056 (Information Technology), suggesting that technology firms command a higher trailing profitability premium. For P/E, the negative ROE coefficient is universal across the 10 sectors, ranging from −0.0495 (Information Technology) to −0.0820 (Real Estate), confirming that the negative sign is structural across industries. Conversely, for the EV/EBITDA model, ROIC is negative across all 10 sectors ranging from -0.0099 (Consumer Staples) to -0.0368 (Real Estate). This is a direct reflection of the EBITDA denominator consistently outpacing the numerator (EV) in response to ROIC shocks (Table A.8), regardless of industry. The risk proxies show the greatest dispersion across sectors, with Beta significant in 2-3 sectors and WACC in only 3, suggesting that the risk channel (through the cost of capital) is highly industry specific. Revenue Growth on the multiple is positive and significant in 8 out of 10 sectors for P/B (Energy and Real Estate as exceptions), while the coefficient is negligible in the P/E and EV/EBITDA models (significant in only 2 sectors for each multiple) on a cross-sector basis. The strongest response of P/B to trailing profitability growth comes from the Consumer Staples and the Information Technology sectors (+0.0025). Size is negative and significant across all 10 sectors, making the Size penalty on valuation multiples one of the most robust findings. The size penalty is consistently strongest in Communication Services across all three multiples (P/B −0.5908; P/E −0.5552; EV/EBITDA −0.3511), with Health Care also among the largest for the equity multiples (P/B −0.5062; P/E −0.3652), while it is weakest, and occasionally insignificant, in Materials.

The regressions on market value (P/B sample employed) provide additional insights. ROE on ln (Market Capitalization) enters the model with positive coefficients across all sectors, ranging from +0.0022 (Communication Services) to +0.0071 (Information Technology), with Consumer Staples (+0.0053) and Utilities (+0.0060) showing strong market responses. Since market capitalization is the numerator common to both equity multiples, this positive sector-level pricing of ROE indicates that the negative P/E coefficients across sectors reflect the earnings denominator mechanism documented in Section 6.3.1, rather than a sector-specific penalty on profitability. ROIC on ln (Enterprise Value) is positive in 7 out of 10 sectors, significant in 6 out of 10 sectors, with Consumer Discretionary showing the strongest enterprise-level response ($\beta = 0.0075$, $p < 0.01$), followed by Consumer Staples ($\beta = 0.0070$, $p < 0.01$) and Industrials ($\beta = 0.0061$, $p < 0.01$). The sectors that show insignificance share structural features - highly regulated, cyclical commodities and NAV-based pricing - where enterprise valuations are less meaningful relative to industry-specific operating efficiency. Revenue growth relative to market capitalization is positive and significant in 7 of the 10 sectors. Beta is negative and significant in only 4 sectors (Consumer Discretionary, Materials, and marginally Industrials and Utilities), confirming that risk effects remain the most industry-specific channel. The same conclusion applies to WACC.

Hence, we find that H3 is strongly supported. Profitability, growth, and risk drivers exhibit significant cross-industry heterogeneity, both in the magnitude of coefficients and in the explanatory power of fundamental value drivers across the GICS non-financial industries. We also find that our results are only close to universal, on a cross-sector basis, in the profitability drivers.

6.5 Robustness Tests

We subjected the main model from section 6.2 to ten alternative specifications organized into three categories: specification robustness (where both the model and samples can vary), sample robustness (same model, different sample), and distributional robustness (through quantile estimation). Results can be found in Tables A.10 to A.14 in the Appendix section.

Regarding specification robustness, we tested four alternative specifications. Substituting Net Profit Margin for ROE and EBITDA Margin for ROIC preserves all directional findings across P/E, P/B and EV/EBITDA, but with weakening associations. Replacing the "current" profitability proxy with the one-year lagged version of profitability preserves the signs but reduces substantially model fit for P/E and EV/EBITDA (R^2 P/E from 0.409 to 0.077; R^2 EV/EBITDA from 0.131 to 0.086) Interestingly, the R^2 for the P/B model under this specification decreases only slightly (0.243 vs 0.220) which shows that the P/B multiple prices persistence in profitability, as found by Penman (1996), albeit with a lower coefficient. For EV/EBITDA and P/E, the contemporaneous nature of the denominator channel (Section 6.3.1) dictates that the relationship breaks down when profitability is lagged. Conversely, regressing the one-year-ahead multiple on current profitability shows that 92% of the P/E compression and 79% of the EV/EBITDA profitability compressions reverse (Table A.14). Since a future multiple cannot be mechanically compressed by today's denominator, the effect is confirmed as contemporaneous. The P/B coefficient drops from 0.0037 to 0.0007 but remains positive, with the pricing effect of persistent profitability collapsing when measured one year ahead. WACC drops from +0.0111*** to −0.0032 (insignificant), confirming that the cost-of-capital channel is contemporaneous and carries no forward predictive power. Finally, our last specification robustness test re-estimated the three models with Driscoll-Kraay standard errors. This specification corrects for heteroskedasticity, serial autocorrelation, and cross-sectional dependence simultaneously. We found that this specification does not change our profitability findings, but beta loses significance, and WACC moves from 1% to the 5% significance threshold, meaning the risk channels are the least robust ones.

Regarding sample robustness, we tested three new samples on the main model from section 6.2. We first removed the largest sector (GICS: Industrials) to test for a potential sample composition effect, since this sector accounts for roughly 27% of the sample across the three samples employed in this study. The primary findings remained intact under this new sample (P/E ROE: −0.0565, $p < 0.01$; EV/EBITDA ROIC: −0.0145, $p < 0.01$). To test the impact of the COVID-19 pandemic on the samples, we have also excluded the years 2020 and 2021 from the sample. Changes in profitability and growth coefficients are negligible, and the most important finding is that WACC is not significant in the non-COVID-impacted sample ($\beta = 0.0054$, $p > 0.10$). Restricting the sample to firms with at least five firm-year observations does not change our primary findings as well.

To test distributional robustness, we estimate FE quantile regressions (Canay, 2011) at Q10, Q50, and Q90 percentiles to confirm the findings across the distribution. For P/B, ROE is positive across all quantiles (Q10: 0.0043; Q50: 0.0037; Q90: 0.0032; all $p < 0.01$), with the premium slightly higher for lower-valued firms. For P/E, the negative sign concentrates at Q90 (−0.0596***), meaning the denominator effect is stronger for expensive stocks. In this sample, the quantile estimates are less precise at the lower and median quantiles, so the distributional evidence for the profitability channel is clearest at the upper quantiles, where the denominator effect is strongest. For EV/EBITDA, the ROIC coefficient remains uniform across the distribution (although stronger for cheaper stocks), while the positive WACC effect strengthens at Q90 ($\beta = 0.0150$, $p < 0.01$), being stronger for expensive stocks.

While the risk and growth proxies exhibit variation between models, with the risk findings being the least robust and generalizable, the most consistent finding is that the market´s pricing of profitability for P/E and EV/EBITDA - positive through the price component and inverted by the accounting denominator – is robust across specifications, samples, and the upper quantiles of the distribution.

7 – Additional Analysis: Forward Expectations

The objective of this chapter is to extend the trailing specification used in Chapter 6 and to replace the profitability and growth proxies with consensus analyst forecasts, allowing us to test H2. We require a new sample for these tests (P/B: 16,328; P/E: 13,466; EV: 13,786) that comprises systematically larger firms. For instance, in this new P/B sample, the median firm holds €1.4 billion in total assets, compared with €775 million in the original P/B sample. Since analyst coverage is more concentrated among larger, more liquid equities, results should be interpreted with this sample composition effect in mind. From our descriptive tests, Trailing Revenue Growth and forward NI Growth are essentially uncorrelated ($r = 0.009$), indicating that this new model adds new information. The results are available in Tables A.15-A.17 in the Appendix section, with each multiple being analyzed across three columns: (1) is the trailing baseline on the new sample, (2) is forward one-year growth employed in the model with everything else unchanged, and (3) specifies forward one-year profitability substituted into the model with everything else unchanged.

For P/B, one-year forward growth slightly reduces explanatory power ($R^2 = 0.270$ vs 0.278), with the coefficient being technically significant but economically meaningless ($\beta = 0.0000$, $p<0.05$). On the other hand, the addition of one-year forward ROE nearly doubles the coefficient ($\beta = 0.0082$ versus 0.0042, both $p < 0.01$), with R^2 rising to 0.323 (from the 0.278 baseline). A one-percentage-point increase in forward ROE is associated with a 0.82% premium on the P/B multiple, compared with 0.42% for trailing ROE. This confirms that the market prices expected returns stronger than realized ones.

For P/E, the one-year forward growth addition shows a great improvement in model fit, with R^2 increasing from 0.431 to 0.645 (21 percentage-point gain). A one-percentage-point increase in forward NI Growth commands a 0.10% premium on the P/E multiple ($\beta = 0.0010$, $p < 0.01$), and this forward growth variable explains nearly two-thirds of within-firm P/E variation. This confirms previous findings by Zarowin (1990) and Liu, Nissim, & Thomas (2002) in that the P/E multiple is fundamentally a growth-expectations multiple. On the other hand, forward ROE shows a coefficient that is statistically indistinguishable from zero ($\beta = -0.0008$, $p > 0.10$), with model fit deteriorating significantly. When profitability is measured forward, the link between current ROE and the earnings denominator identified in Section 6.3 ceases to exist.

For EV/EBITDA, forward EBITDA growth substantially improves model fit (R^2 of 0.392 vs 0.153 in the baseline, a 24 percentage-point gain), with the growth coefficient ($\beta = 0.0010$, $p < 0.01$) driving a 0.10% premium on the multiple. Forward EBITDA margin enters the model with a positive coefficient ($\beta = 0.0046$, $p < 0.01$), and although R^2 stays roughly the same, it drives a premium of 0.46% for every percentage-point increase in forward EBITDA margin. WACC remains positive across all specifications, reinforcing our previous conclusions about this result. Controls remain stable across specifications.

Hence, we conclude that H2 is strongly supported. Forward variables clearly improve model fit, with stronger structural associations than trailing metrics, yielding R^2 improvements of 21 percentage points for P/E and 24 percentage points for EV/EBITDA through the growth channel. Nevertheless, certain forward channels are more relevant than others. We find that the forward profitability channel is more relevant to the P/B multiple, whereas the forward growth channel is more relevant to P/E and EV/EBITDA, with the forward profitability channel being also relevant in this multiple. Each multiple captures a different economic dimension of value. This analysis extends the US evidence of Liu et al. (2002) and Kim & Ritter (1999) for European equity markets. We further discuss these findings in Chapter 8.

8 -Discussion & Conclusion

This study examined the structural relationship between fundamental value drivers – profitability, growth, and risk – and relative valuation multiples (P/B, P/E, and EV/EBITDA), across European non-financial equities over 2016-2025. The central contribution of this work is that valuation multiples can distort the market´s economic signals through asymmetric responses of the price and accounting components of the ratio, when valuation multiples and fundamental value drivers are measured on a trailing basis. All remaining findings flow through this mechanism.

The European equity market consistently rewards trailing profitability within firms, a finding confirmed across industries. The negative association between trailing profitability and P/E and EV/EBITDA does not reflect an economic penalty – it is justified by the accounting denominator being more responsive than the price numerator. Quantile regressions show that this denominator effect is stronger in the top decile, for the most expensive stocks. Robustness tests showed that this effect is predominantly current: most of the P/E and EV/EBITDA compression reverses within one year. In tests that employ lagged profitability, only P/B retains a structural relationship with profitability, confirming Penman's (1996) findings that P/B prices persistence in profitability. For equity analysts, this finding cautions against interpreting a low P/E or EV/EBITDA multiple, in the presence of a high ROE or ROIC, as a sign of undervaluation – the compression in the multiple may not be the best reflection of pure market pricing. Conversely, screening for low P/B and high ROE can better help identify "cheap" opportunities that reflect genuine market pricing.

Our analysis of forward expectations revealed that each multiple captures a distinct angle on firm value (Koller et al., 2020; Mauboussin & Callahan, 2024). P/B is fundamentally a profitability multiple – forward profitability nearly doubles the coefficient relative to the trailing version – while forward growth adds no explanatory power. P/E is a growth expectations multiple – the model with forward earnings growth captures two-thirds of within-firm variation – consistent with Zarowin (1990). EV/EBITDA responds more strongly to forward operating growth, though forward profitability also predicts it positively (contrary to P/E). This brings direct implications for M&A advisors on which multiple to rely on, depending on the value proposition of the firm being valued: P/B for profitability-driven valuations, where a competitive advantage creates a ROE premium; P/E with forward consensus when the value proposition relies on earnings growth and accretive transactions; EV/EBITDA where accretion relies on operating growth. Portfolio managers should also be aware that value and growth factors defined with trailing metrics may be misclassifying firms relative to how the market actually prices them.

Not all findings are equally robust across the ten industries under study. The market´s positive pricing of profitability is observed in most industries, with stronger responses in the Consumer Staples and Information Technology sectors. Trailing revenue growth is significant for most P/B specifications but largely insignificant for the P/E and EV/EBITDA multiples – justifying our additional analysis using forward growth metrics. Risk shows the greatest cross-sector heterogeneity and is the least robust result, with CAPM proxies being significant only in a minority of industries, suggesting other proxies for risk in European equity markets. Size is the most consistent control variable across the three multiples. The consistency of the profitability results suggests that the decomposition framework we have applied is broadly applicable across European non-financial industries for this specific driver.

The differential-responsiveness mechanism shapes the remaining results. The market penalizes systematic risk within firms, but earnings fall more than market capitalization in response to beta shocks, expanding the P/E multiple. Beta's loss of significance under Driscoll-Kraay marks it as a market-wide rather than a firm-specific channel. In EV/EBITDA, WACC predicts EV but not EBITDA, and this relationship is not robust to excluding the COVID-19 period, suggesting simultaneous determination rather than a risk channel. The DuPont decomposition shows leverage commands a premium in the P/B multiple, yet the market penalizes leverage through price, a signal corporate managers should read with caution. It also shows that the market prices profitability's components unequally: Asset Turnover dominates Net Profit Margin in pricing market capitalization, while Operating Margin drives enterprise value – providing a blueprint for corporate managers on which operational components to focus, to maximize market-perceived value.

The ratio decomposition framework can be used as a replicable framework to assess whether other financial ratios reflect genuine market pricing or are distorted by mechanical effects. By unveiling the mechanism responsible for distorting the relationship between fundamentals and valuation multiples, we contribute to the integrity of the no-arbitrage pricing principle and for more accurate relative valuations (Berk & DeMarzo, 2023**).**

Several limitations are inherent to this work. The WACC endogeneity, identified through the decomposition of EV/EBITDA into its components and temporal tests, could be formally resolved using instrumental variables or system GMM (Roberts & Whited, 2013), thereby strengthening the causal interpretation. The forward analysis sample reflects analyst-covered firms, and this sample composition effect means that the results in this section cannot be directly compared to our main model. The linear functional form may not fully capture the non-linear interactions among profitability, growth, and risk, as suggested by the derivations in Chapter 2. Furthermore, the IFRS-focused European sample limits direct generalizability to the US GAAP market. This limitation is mitigated by one of this study's purposes: to provide a counterpoint to the heavy US-focused relative valuation literature. A clear limitation of this work is that the breadth of studying three valuation multiples naturally limits the analytical depth of the analysis. Studying a single valuation multiple would have allowed us to run deeper tests.

Many natural extensions arising from the limitations discussed can be explored in future studies. The denominator effects on valuation multiples could be studied in a US or emerging-market sample to provide a point of comparison with our findings, and with other multiples. WACC endogeneity could be addressed by using instrumental variables or system GMM. Non-linear specifications that test the conditional interactions of the implied derivations of the valuation multiples could also be included in further studies. To make the forward and trailing samples more comparable, one could try correcting the forward samples using, for example, the Heckman procedure and assessing the impact on the results. Future research could also extend this framework by including macroeconomic variables in the model and test in which industries the numerator-denominator adjustment mechanism is stronger.

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Appendix

Table A.1: Variables Used in Chapter 2 Derivations of the Valuation Multiples

Variable	Explanation
P **(0)**	Current market value of equity (price per share)
DPS **(1)**	Expected dividends per share in the next period
Ke	Risk-adjusted required rate of return for equity holders (i.e., cost of equity)
g	Stable growth rate of dividends, earnings and/or FCFF into perpetuity
EPS **(0)**	Current trailing earnings per share
Payout Ratio	Proportion of earnings distributed to shareholders as dividends
EV **(0)**	Enterprise value: current market value of equity plus net debt
FCFF **(1)**	Expected free cash flow to the firm in the next period
WACC	Weighted average cost of capital, reflecting the risk of debt and equity financing
NOPAT	Net operating profit after tax
IC	Invested capital: operating assets less operating liabilities (capital employed in operations)
Reinvestment Rate	The share of NOPAT reinvested into operating assets to sustain future growth
ROIC	Return on invested capital (*NOPAT / IC*)
ROE	Return on equity (Net Income / Book Value of Equity)
BVPS(0)	Current book value of equity per share
EBITDA **(0)**	Current earnings before interest, taxes, depreciation and amortization
RR(Retention Rate)	Proportion of earnings retained rather than paid as dividends
t	The effective corporate tax rate
Depreciation Rate	Depreciation and amortization divided by EBITDA

Source: Author Elaboration, based on Bhojraj & Lee (2002); Damodaran (2007); Knudsen, Kold, & Plenborg (2017); Koller et al. (2020)

Table A.2: Derivations of the P/E, EV/EBITDA, and P/B valuation multiples

Multiple	Derivation Equation	Fundamental Value Drivers
Price-to-Earnings (P/E)	$\frac{P(0)}{EPS(0)} = \frac{P}{E} = \frac{\left(1 - \frac{g}{ROE}\right) \times (1+g)}{Ke - g}$	Expected Growth, Risk (Cost of Equity, Ke), and Return on Equity (ROE)
EV/EBITDA	$\frac{EV(0)}{EBITDA(0)} = \frac{EV}{EBITDA} = \frac{ROIC - g}{WACC - g} \times \frac{(1+g)\times(1-t)\times(1-Depreciation\ Rate)}{ROIC}$	Expected Growth, Risk (WACC), Return on Invested Capital (ROIC), Tax Rate, and Depreciation Rate
Price-to-Book (P/B)	$\frac{P(0)}{BVPS(0)} = \frac{P}{B} = \frac{ROE - g}{Ke - g}$	Return on Equity (ROE), Expected Growth, and Risk (Cost of Equity, Ke)

Source: Author Elaboration, reflecting the work in Chapter 2

Table A.3: Variable definition and construction

Variable	Construction	Units	Data Type	Role	Expected Sign	Theoretical Basis	Key Literature
DEPENDENT VARIABLES							
Price-to-Earnings	ln (Company Market Capitalization / Net Income After Minority Interests).	Natural log	Mixed	Dependent Variable	N/A	Equation 4 (Chapter 2).	Muradova (2026); Bhojraj & Lee (2002)
Price-to-Book	ln (Company Market Capitalization / Book Value of Equity).	Natural log	Mixed	Dependent Variable	N/A	Equation 14 (Chapter 2).	Bhojraj & Lee (2002); Barros & Gonçalves (2025)
EV/EBITDA	ln (Enterprise Value / EBITDA). EV = Market Cap + Total Debt - Cash.	Natural log	Mixed	Dependent Variable	N/A	Equation 9 (Chapter 2).	Lie & Lie (2002); Koller et al. (2020)
FUNDAMENTAL DRIVERS							
Net Profit Margin	(Net Income / Revenue) x 100.	Percent (%)	Accounting Data	DuPont Component /Alternative Profitability Proxy	+ in P/B and P/E	Captures the earnings/margin quality dimension of ROE.	Bhojraj & Lee (2002); Geertsema & Lu (2023)
Asset Turnover	Revenue / Total Assets.	Ratio	Accounting Data	DuPont Component	+ in P/B and P/E	Captures operational efficiency in ROE: revenue generated per euro of assets deployed.	Geertsema & Lu (2023)
Equity Multiplier	Total Assets / Book Value of Equity.	Ratio	Accounting Data	DuPont Component	+/- for P/B and P/E	Captures financial leverage contribution to ROE.	Geertsema & Lu (2023)
Return on Equity	Net Profit Margin x Asset Turnover x Equity Multiplier	Percent (%)	Accounting Data	Fundamental Driver	+ for P/B and P/E	Equations 4 and 14 (Chapter 2).	Penman (1996); Bhojraj & Lee (2002)
EBITDA Margin	(EBITDA/Revenue) x 100	Percent (%)	Accounting Data	Alternative Profitability Proxy	+ for EV/EBITDA	Used as an alternative profitability proxy for robustness purposes of the main model.	Koller et al. (2020); Geertsema & Lu (2023)
Operating Margin	NOPAT / Revenue x 100. NOPAT = EBIT x (1 - effective tax rate).	Percent (%)	Accounting Data	ROIC Component	+ for EV/EBITDA	Captures after-tax operating profitability leg of ROIC.	Koller et al. (2020)
Capital Turnover	Revenue / Invested Capital | Invested Capital = Total Debt + Book Equity - Cash.	Ratio	Accounting Data	ROIC Component	+ for EV/EBITDA	Captures capital deployment efficiency leg of ROIC: revenue generated per euro of invested capital.	Koller et al. (2020)
Return on Invested Capital	Operating Margin x Capital Turnover	Percent (%)	Accounting Data	Fundamental Driver	+ for EV/EBITDA	Equation 9 (Chapter 2).	Koller et al. (2020); Geertsema & Lu (2023)
1-Y Trailing Revenue Growth	(Revenue(t) – Revenue(t-1)) / Revenue(t-1).	Percent(%)	Accounting Data	Fundamental Driver	+ for P/E, P/B and EV/EBITDA	Growth (g) enters all three multiples. We use trailing rather than forward growth, even though Chapter 2 prescribes forward growth for P/E and EV/EBITDA.	Barros & Gonçalves (2025);Geertsema & Lu (2023)
MARKET DATA VARIABLES							

Variable	Construction	Units	Data Type	Role	Expected Sign	Theoretical Basis	Key Literature
WACC	Extracted directly from Refinitiv. Blended cost of debt and equity weighted by capital structure.	Percent (%)	Market Data	Fundamental Driver	- for EV/EBITDA	Equation 9 (Chapter 2).	Koller et al. (2020); Damodaran (2007); Knudsen et al. (2017)
Market Beta	Extracted directly from Refinitiv. Sensitivity of firm equity returns to market returns.	Ratio	Market Data	Fundamental Driver	- for P/B and P/E	Beta proxies for cost of equity Ke in P/B and P/E derivations (Equations 4 and 14 – Chapter 2).	Gupta (2018); Damodaran (2007); Geertsema & Lu (2023)
CONTROL VARIABLES							
Intangibility	(Intangible Assets / Total Assets) x 100.	Percent (%)	Accounting Data	Control Variable	+ for P/B; ambiguous for P/E and EV/EBITDA	Controls for accounting-driven distortion in book value comparability.	Gracia (2019); Lie & Lie (2002); Schreiner & Spremann (2007);
Leverage	Total Debt / Book Equity	Ratio	Accounting Data	Control Variable	Ambiguous; excluded from EV/EBITDA and DuPont decomposition specifications	Leverage affects equity multiples through financial risk and tax shields. Excluded from EV/EBITDA (capital structure neutral).	Barros & Gonçalves (2025); Binoy (2025); Muradova (2026)
Size	Natural logarithm of Total Assets.	Natural log	Accounting Data	Control Variable	- (larger firms trade at lower multiples)	Larger firms exhibit more stable earnings, lower growth optionality and reduced idiosyncratic risk.	Alford (1992); Plenborg & Pimentel (2016); Golubov & Konstantinidi (2019)
FORWARD AND CONSENSUS VARIABLES							
Forward ROE (1Y)	Consensus analyst forecast of Net Income / Book Value of Equity x 100.	Percent (%)	Mixed	Forward Measure	+ for P/B and P/E	Forward profitability proxy for P/E and P/B.	Liu et al. (2002); Damodaran (2007)
Forward EBITDA Margin (1Y)	Consensus analyst forecast of EBITDA / Revenue x 100.	Percent (%)	Mixed	Forward Measure	+ for EV/EBITDA	Forward profitability proxy for EV/EBITDA.	Koller et al. (2020); Schreiner & Spremann (2007)
Forward Net Income Growth (1Y)	Consensus analyst forecast of (Net Income$_{t+1}$ − Net Income$_t$) / |Net Income$_t$| × 100.	Percent (%)	Mixed	Forward Measure	+ for P/B and P/E	Forward growth proxy for P/B and P/E. Better alignment with Chapter 2 derivations.	Liu et al. (2002); Harbula (2009)
Forward EBITDA Growth (1Y)	Consensus analyst forecast of (EBITDA$_{t+1}$ − EBITDA$_t$) / |EBITDA$_t$| × 100.	Percent (%)	Mixed	Forward Measure	+ for EV/EBITDA	Forward growth proxy for EV/EBITDA. Better alignment with Chapter 2 derivations.	Koller et al. (2020); Harbula (2009)

Source: Author Elaboration, with supporting literature in the "Key Literature" column. Definitions for the Market Data Variables supported by Refinitiv Eikon

Table A.4: Key Descriptives of the Samples Employed in the Main Model

Variable	Mean	Std. Dev.	p25	Median	p75
Panel A: Price-to-Book Sample (N = 23,751)					
P/B (ln)	0.618	1.076	-0.077	0.519	1.208
Return on Equity (%)	6.664	25.103	2.256	9.079	16.074
Net Profit Margin (%)	4.443	57.102	1.145	4.963	11.098
Asset Turnover	0.834	0.634	0.400	0.736	1.112
Equity Multiplier	2.942	2.376	1.721	2.258	3.191
Revenue Growth (%)	12.388	36.406	-1.836	6.562	17.610
Beta	0.845	0.500	0.507	0.817	1.130
Size (ln assets)	20.698	2.071	19.111	20.469	22.091
Leverage (D/E)	0.886	1.198	0.227	0.549	1.059
Intangibility (%)	7.387	10.436	0.482	3.107	10.041
Panel B: Price-to-Earnings Estimation Sample (N = 19,212)					
P/E (ln)	2.982	1.101	2.367	2.874	3.433
Return on Equity (%)	14.359	12.453	6.484	11.393	18.149
Net Profit Margin (%)	16.212	32.499	3.271	6.728	13.397
Asset Turnover	0.871	0.630	0.458	0.774	1.145
Equity Multiplier	2.759	1.999	1.712	2.210	3.055
Revenue Growth (%)	13.078	31.690	0.057	7.375	17.740
Beta	0.818	0.473	0.497	0.794	1.103
Size (ln assets)	20.832	2.069	19.238	20.610	22.257
Leverage (D/E)	0.784	0.998	0.217	0.519	0.979
Intangibility (%)	7.038	9.892	0.498	3.036	9.571
Panel C: EV/EBITDA Estimation Sample (N = 19,089)					
EV/EBITDA (ln)	2.465	0.983	1.890	2.367	2.930
ROIC (%)	13.247	16.012	5.086	9.272	15.776
Operating Margin (%)	12.148	15.985	3.995	7.607	13.847
Capital Turnover	2.060	2.663	0.750	1.355	2.290
Revenue Growth (%)	12.875	30.470	0.066	7.317	17.548
WACC (%)	6.378	2.903	4.409	6.057	7.916
Size (ln assets)	20.867	2.075	19.273	20.647	22.293
Intangibility (%)	7.144	9.876	0.575	3.174	9.748

Notes: All accounting variables are measured at fiscal year-end (December 31 Year N-1). Market Variables are measured as of June 30 of each year N (or closest trading date). Continuous variables were winsorized at the 1st and 99th percentiles.
Source: Author Elaboration, run in Stata

Table A.5: Correlation Matrix – P/B sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) P/B Ratio (log)	1.000									
(2) Return on Equity (%)	0.136*	1.000								
(3) Net Profit Margin (%)	-0.010	0.442*	1.000							
(4) Asset Turnover	0.176*	0.162*	-0.004	1.000						
(5) Equity Multiplier	0.194*	-0.221*	-0.062*	0.105*	1.000					
(6) Revenue Growth (%)	0.086*	0.075*	0.035*	-0.027*	-0.007	1.000				
(7) Beta	0.012	-0.071*	-0.111*	0.060*	0.099*	-0.018*	1.000			
(8) Size (ln assets)	-0.023*	0.129*	0.106*	-0.150*	0.140*	-0.059*	0.184*	1.000		
(9) Leverage (D/E)	0.140*	-0.242*	-0.050*	-0.080*	0.859*	-0.009	0.084*	0.142*	1.000	
(10) Intangibility (%)	0.186*	-0.066*	-0.085*	-0.100*	0.010	0.038*	0.039*	0.031*	0.011	1.000

**** Significant at the 5% level (two-tailed).***

Source: Author Elaboration, run in Stata

Table A.6: Correlation Matrix – P/E sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) P/E Ratio (log)	1.000									
(2) Return on Equity (%)	-0.329*	1.000								
(3) Net Profit Margin (%)	-0.240*	0.154*	1.000							
(4) Asset Turnover	-0.052*	0.249*	-0.385*	1.000						
(5) Equity Multiplier	-0.029*	0.303*	-0.140*	0.114*	1.000					
(6) Revenue Growth (%)	-0.011	0.096*	0.071*	-0.022*	0.024*	1.000				
(7) Beta	-0.008	0.063*	-0.136*	0.091*	0.093*	0.003	1.000			
(8) Size (ln assets)	-0.077*	0.039*	0.034*	-0.174*	0.188*	-0.067*	0.200*	1.000		
(9) Leverage (D/E)	-0.015*	0.218*	-0.038*	-0.093*	0.829*	0.025*	0.059*	0.186*	1.000	
(10) Intangibility (%)	0.183*	0.013	-0.126*	-0.107*	0.012	0.025*	0.039*	0.080*	0.024*	1.000

**** Significant at the 5% level (two-tailed).***

Source: Author Elaboration, run in Stata

Table A.7: Correlation Matrix – EV/EBITDA sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) EV/EBITDA (log)	1.000							
(2) ROIC (%)	-0.119*	1.000						
(3) Operating Margin (%)	0.137*	0.135*	1.000					
(4) Capital Turnover	-0.167*	0.562*	-0.265*	1.000				
(5) Revenue Growth (%)	0.042*	0.090*	0.087*	0.012	1.000			
(6) WACC (%)	-0.054*	0.158*	-0.113*	0.096*	0.096*	1.000		
(7) Size (ln assets)	-0.036*	-0.106*	0.048*	-0.116*	-0.072*	0.080*	1.000	
(8) Intangibility (%)	0.064*	-0.017*	-0.075*	-0.117*	0.035*	0.060*	0.075*	1.000

**** Significant at the 5% level (two-tailed).***

Source: Author Elaboration, run in Stata

FIGURE A.1: ESTIMATOR SELECTION PROCESS – BREUSCH-PAGAN LM TEST AND HAUSMAN SPECIFICATION TEST

Estimator Selection Process - Base Model: Pooled OLS

Breusch-Pagan LM Test
Ho = Var(u) = 0 (no unobserved firm level heterogeneity)

P/B	P/E	EV/EBITDA
$\chi^2(1) = 49,973$	$\chi^2(1) = 18,547$	$\chi^2(1) = 29,511$
P< 0.001	p< 0.001	p< 0.001

Ho rejected – Unobserved firm heterogeneity present in the data

Hausman specification test

P/B	P/E	EV/EBITDA
$\chi^2(15) = 1,283$	$\chi^2(15) = 740$	$\chi^2(14) = 157$
p< 0.001	P< 0.001	P< 0.001

Ho rejected – RE estimates are inconsistent
Since firm FE correlated with regressors, fixed effects were deemed required

Firm fixed effects + year fixed effects
Given the diagnostics, this is our main model applied for the 3 multiples across specifications

Source: Author Elaboration, tests ran in Stata

Table A.8: Main Model on Valuation Ratio Components

	(1) ln(MktCap)	(2) ln(BookEq)	(3) ln(MktCap)	(4) ln(NI)	(5) ln(EV)	(6) ln(EBITDA)
ROE (%)	0.0046***	0.0009***	0.0119***	0.0665***		
	(0.0003)	(0.0002)	(0.0006)	(0.0011)		
ROIC (%)					0.0053***	0.0174***
					(0.0005)	(0.0007)
Revenue Growth (%)	0.0013***	-0.0003***	0.0008***	0.0008***	0.0007***	0.0013***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Beta	-0.0620***	-0.0018	-0.0457***	-0.0857***		
	(0.0161)	(0.0059)	(0.0159)	(0.0182)		
WACC (%)					0.0093***	-0.0021
					(0.0025)	(0.0026)
Size (ln assets)	0.5669***	0.9727***	0.6639***	0.9827***	0.7598***	0.8946***
	(0.0228)	(0.0094)	(0.0226)	(0.0269)	(0.0230)	(0.0200)
Leverage (D/E)	-0.0723***	-0.3150***	-0.1553***	-0.3784***		
	(0.0088)	(0.0079)	(0.0100)	(0.0164)		
Intangibility (%)	-0.0071***	-0.0001	-0.0055***	-0.0040*	-0.0023	-0.0014
	(0.0015)	(0.0007)	(0.0015)	(0.0021)	(0.0016)	(0.0015)
Observations	23,751	23,751	19,212	19,212	19,089	19,089
Within R²	0.289	0.863	0.340	0.597	0.387	0.465

Notes: P/B: columns 1-2|P/E: columns 3-4|EV/EBITDA: columns 5-6 | Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Author Elaboration, run in Stata

Table A.9: Models with Decomposed Profitability Proxies

	(1) P/B Composite	(2) P/B DuPont	(3) P/E Composite	(4) P/E DuPont	(5) EV/EBITDA Composite	(6) EV/EBITDA Decomposition
ROE (%)	0.0005		-0.0530***			
	(0.0004)		(0.0012)			
Net Profit Margin (%)		0.0008***		-0.0170***		
		(0.0001)		(0.0007)		
Asset Turnover		0.2697***		-0.6418***		
		(0.0345)		(0.0512)		
Equity Multiplier		0.1277***		0.0412***		
		(0.0055)		(0.0092)		
ROIC (%)					-0.0121***	
					(0.0007)	
Operating Margin (%)						-0.0131***
						(0.0013)
Capital Turnover						-0.0527***
						(0.0059)
Revenue Growth (%)	0.0018***	0.0014***	0.0000	-0.0018***	-0.0006**	-0.0008***
	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Beta	-0.0320*	-0.0562***	0.0664***	0.0434*		
	(0.0177)	(0.0164)	(0.0221)	(0.0235)		
WACC (%)					0.0111***	0.0104***
					(0.0030)	(0.0031)
Controls						
Size	-0.3358***	-0.3302***	-0.2441***	-0.3257***	-0.1347***	-0.1162***
	(0.0252)	(0.0233)	(0.0321)	(0.0362)	(0.0255)	(0.0259)
Intangibility	-0.0082***	-0.0069***	-0.0014	0.0093***	-0.0009	0.0013
	(0.0018)	(0.0016)	(0.0026)	(0.0023)	(0.0019)	(0.0019)
Observations	23,751	23,751	19,212	19,212	19,089	19,089
Within R²	0.140	0.268	0.388	0.227	0.131	0.125

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Author Elaboration, run in Stata

FIGURE A.2: SECTOR HETEROGENEITY MAP: CROSS-SECTOR REGRESSIONS ON VALUATION MULTIPLES AND RATIO COMPONENTS

Panel A - Price-to-Book (P/B)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROE	+0.0022***	+0.0048***	+0.0037**	+0.0024*	+0.0011	+0.0027***	+0.0056***	+0.0051***	+0.0041***	+0.0037***
Rev Growth	+0.0023***	+0.0020***	+0.0025***	+0.0003	+0.0015***	+0.0020***	+0.0025***	+0.0012**	+0.0003	+0.0012**
Beta	+0.0002	-0.0813**	-0.0778	+0.0159	+0.0209	-0.0500	-0.0197	-0.1696***	+0.0033	-0.1316
Size	-0.5908***	-0.4064***	-0.2812***	-0.4566***	-0.5062***	-0.4020***	-0.4450***	-0.2658***	-0.3400***	-0.2895***
Intangibility	+0.0009	-0.0113***	-0.0166***	+0.0084	-0.0107***	-0.0020	-0.0060	-0.0205***	+0.0237	-0.0107
Leverage	+0.2840***	+0.2459***	+0.1343***	+0.2034***	+0.2909***	+0.2297***	+0.3536***	+0.2533***	+0.0418	+0.2859***
N	1,573	3,552	1,914	771	1,787	6,287	2,684	1,798	2,465	920
Within R^2	0.400	0.337	0.199	0.268	0.360	0.214	0.277	0.301	0.317	0.196

Panel B - Price-to-Earnings (P/E)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROE	-0.0547***	-0.0502***	-0.0551***	-0.0651***	-0.0551***	-0.0504***	-0.0495***	-0.0597***	-0.0820***	-0.0557***
Rev Growth	+0.0005	+0.0012*	-0.0013	-0.0011	+0.0029***	-0.0002	+0.0007	-0.0011	-0.0004	-0.0006
Beta	+0.1922**	+0.0231	+0.0751	-0.0380	+0.2362***	+0.0172	+0.0420	-0.1230*	+0.1904***	-0.2591*
Size	-0.5552***	-0.2918***	-0.1437	-0.3755**	-0.3652***	-0.2854***	-0.2493***	-0.1792	-0.4232***	-0.3712***
Intangibility	+0.0041	+0.0016	-0.0203*	+0.0263	-0.0031	-0.0027	-0.0010	-0.0070	+0.0295	-0.0039
Leverage	+0.2913***	+0.1961***	+0.1674**	+0.2800***	+0.2068**	+0.1944***	+0.3345***	+0.2983***	+0.1124	+0.1929***
N	1,211	2,824	1,628	534	1,339	5,242	2,146	1,514	1,971	803
Within R^2	0.419	0.414	0.386	0.518	0.419	0.421	0.366	0.502	0.530	0.433

Panel C - EV/EBITDA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROIC	-0.0139***	-0.0194***	-0.0099***	-0.0161***	-0.0109***	-0.0073***	-0.0083***	-0.0268***	-0.0368***	-0.0152***
Rev Growth	-0.0013	+0.0003	-0.0001	-0.0017***	-0.0003	-0.0001	+0.0009	-0.0006	-0.0013**	-0.0007
WACC	+0.0253**	-0.0042	+0.0063	+0.0221	+0.0388***	+0.0041	+0.0206**	+0.0023	+0.0108	+0.0256
Size	-0.3511***	-0.1618*	-0.1154	-0.2248**	-0.2387***	-0.1467***	-0.0996*	+0.0010	-0.1060	-0.1214
Intangibility	-0.0017	+0.0045	-0.0014	+0.0209**	-0.0020	+0.0076**	-0.0071	-0.0043	-0.0023	-0.0053
N	1,211	2,793	1,664	528	1,335	5,268	2,130	1,632	1,736	792
Within R^2	0.268	0.148	0.173	0.366	0.237	0.139	0.134	0.426	0.162	0.172

Panel D - ln (Market Capitalization)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROE	+0.0022***	+0.0049***	+0.0053***	+0.0028***	+0.0027***	+0.0040***	+0.0071***	+0.0057***	+0.0045***	+0.0060***
Rev Growth	+0.0018***	+0.0018***	+0.0019**	+0.0004	+0.0013***	+0.0017***	+0.0018***	+0.0008*	+0.0003	+0.0003
Beta	-0.0322	-0.0924***	-0.0772	-0.0061	+0.0141	-0.0606*	-0.0098	-0.1645***	+0.0187	-0.1836*
Size	+0.4187***	+0.5707***	+0.6493***	+0.4228***	+0.4644**	+0.5615***	+0.5979***	+0.6597***	+0.6289***	+0.5701***
Leverage	-0.0386*	-0.0486***	-0.1542***	-0.0939***	-0.0261	-0.0767***	-0.0471	-0.1160***	-0.2521***	+0.0057
Intangibility	-0.0010	-0.0130***	-0.0142***	+0.0122	-0.0120***	-0.0011	-0.0052	-0.0191***	+0.0162	-0.0046
N	1,573	3,552	1,914	771	1,787	6,287	2,684	1,798	2,465	920
Within R^2	0.195	0.286	0.379	0.326	0.293	0.308	0.404	0.323	0.401	0.375

Panel E - ln(Enterprise Value)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROIC	-0.0018	+0.0075***	+0.0070***	+0.0019	+0.0048***	+0.0061***	+0.0056***	+0.0039*	-0.0038	+0.0041
Rev Growth	-0.0002	+0.0013***	+0.0008	+0.0003	+0.0015**	+0.0011***	+0.0025***	+0.0012**	+0.0000	-0.0004

WACC	+0.0167	+0.0016	-0.0017	+0.0192*	+0.0292***	+0.0089*	+0.0249***	+0.0072	-0.0055	+0.0045
Size	+0.5613***	+0.7563***	+0.7990***	+0.7731***	+0.5703***	+0.8107***	+0.7584***	+0.7999***	+0.8883***	+0.6339***
Intangibility	+0.0012	-0.0115***	-0.0096*	+0.0132	-0.0058	+0.0080**	-0.0039	-0.0099*	+0.0015	+0.0004
N	1,211	2,792	1,664	528	1,334	5,267	2,130	1,632	1,736	792
Within R²	0.294	0.346	0.358	0.415	0.454	0.415	0.473	0.354	0.634	0.433

Notes: Green: positive significant. Red: negative significant. Grey: not significant.
**** p<0.01, ** p<0.05, * p<0.10. Fixed Effects with firm-clustered standard errors*

1: Communication Services; 2: Consumer Discretionary; 3: Consumer Staples; 4: Energy; 5: Health Care; 6: Industrials; 7: Information Technology; 8: Materials; 9: Real Estate; 10: Utilities
Source: Author Elaboration, run in Stata. Edited in Power Point

Table A.10: P/B Model – Robustness Analysis

	(1) Baseline	(2) Alt.Prof	(3) Lagged	(4) ex-COVID	(5) Min 5	(6) ex-Ind	(7) Q10	(8) Q50	(9) Q90
ROE (%)	0.0037***			0.0039***	0.0038***	0.0040***	0.0043***	0.0037***	0.0032***
	(0.0004)			(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0003)	(0.0007)
NPM (%)		0.0008***							
		(0.0001)							
ROE (t-1)			0.0018***						
			(0.0003)						
Revenue Growth (%)	0.0016***	0.0018***	0.0020***	0.0015***	0.0016***	0.0015***	0.0011***	0.0016***	0.0022***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Beta	-0.0602***	-0.0638***	-0.0620***	-0.1000***	-0.0591***	-0.0650***	-0.0249	-0.0602***	-0.0963***
	(0.0164)	(0.0167)	(0.0167)	(0.0194)	(0.0166)	(0.0190)	(0.0248)	(0.0139)	(0.0273)
Size (ln assets)	-0.4057***	-0.3899***	-0.3913***	-0.3449***	-0.4049***	-0.4075***	-0.3331***	-0.4058***	-0.4802***
	(0.0229)	(0.0229)	(0.0230)	(0.0227)	(0.0231)	(0.0258)	(0.0356)	(0.0200)	(0.0391)
Leverage (D/E)	0.2427***	0.2083***	0.2028***	0.2372***	0.2428***	0.2469***	0.1991***	0.2427***	0.2873***
	(0.0114)	(0.0108)	(0.0104)	(0.0121)	(0.0114)	(0.0131)	(0.0169)	(0.0095)	(0.0186)
Intangibility (%)	-0.0070***	-0.0082***	-0.0077***	-0.0073***	-0.0068***	-0.0080***	-0.0078***	-0.0070***	-0.0062**
	(0.0016)	(0.0016)	(0.0015)	(0.0017)	(0.0016)	(0.0017)	(0.0024)	(0.0014)	(0.0027)
Observations	23,751	23,751	23,673	18,991	23,183	17,464	23,751	23,751	23,751
Within R²	0.243	0.229	0.220	0.212	0.244	0.260			

Columns: (1) Baseline FE; (2) alternative profitability proxy (Net Profit Margin for ROE); (3) one-year lagged ROE; (4) excluding 2020-2021; (5) firms with ≥5 firm-year observations; (6) excluding Industrials; (7)-(9) FE quantile regressions (Canay, 2011) at Q10, Q50, and Q90. Columns 1-6 use within-firm FE + year FE with firm-clustered SE; (7)-(9) use asymptotic SE. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses
Source: Author Elaboration, run in Stata.

Table A.11: P/E Model – Robustness Analysis

	(1) Baseline	(2) Alt.Prof	(3) Lagged	(4) ex-COVID	(5) Min 5	(6) ex-Ind	(7) Q10	(8) Q50	(9) Q90
ROE (%)	-0.0546***			-0.0544***	-0.0546***	-0.0565***	-0.0503	-0.0541*	-0.0596***
	(0.0011)			(0.0012)	(0.0011)	(0.0013)	(0.0554)	(0.0276)	(0.0135)
NPM (%)		-0.0166***							
		(0.0007)							
ROE (t-1)			-0.0035***						
			(0.0007)						
Revenue Growth (%)	0.0000	-0.0023***	-0.0025***	0.0000	0.0001	0.0001	0.0005	0.0001	-0.0005
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0166)	(0.0083)	(0.0041)
Beta	0.0400*	0.0555**	0.0852***	0.0053	0.0400*	0.0514**	-0.0019	0.0352	0.0898
	(0.0218)	(0.0236)	(0.0247)	(0.0251)	(0.0219)	(0.0261)	(1.3895)	(0.6929)	(0.3392)
Size (ln assets)	-0.3188***	-0.1944***	-0.2294***	-0.2970***	-0.3164***	-0.3338***	-0.2365	-0.3093	-0.4166
	(0.0316)	(0.0342)	(0.0348)	(0.0338)	(0.0317)	(0.0352)	(1.8508)	(0.9230)	(0.4519)
Leverage (D/E)	0.2231***	0.0804***	0.1411***	0.2193***	0.2224***	0.2379***	0.1578	0.2155	0.3008
	(0.0162)	(0.0166)	(0.0184)	(0.0174)	(0.0163)	(0.0200)	(0.9362)	(0.4669)	(0.2286)
Intangibility (%)	-0.0015	0.0118***	0.0163***	-0.0012	-0.0014	-0.0013	-0.0011	-0.0014	-0.0019
	(0.0025)	(0.0023)	(0.0027)	(0.0027)	(0.0025)	(0.0029)	(0.1360)	(0.0678)	(0.0332)
Observations	19,212	19,212	19,144	15,508	18,826	13,970	19,212	19,212	19,212
Within R^2	0.409	0.211	0.077	0.391	0.410	0.408			

Columns: (1) Baseline FE; (2) alternative profitability proxy (Net Profit Margin for ROE); (3) one-year lagged ROE; (4) excluding 2020-2021; (5) firms with ≥5 firm-year observations; (6) excluding Industrials; (7)-(9) FE quantile regressions (Canay, 2011) at Q10, Q50, and Q90. Columns 1-6 use within-firm FE + year FE with firm-clustered SE; (7)-(9) use asymptotic SE. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses
Source: Author Elaboration, run in Stata.

Table A.12: EV/EBITDA Model – Robustness Analysis

	(1) Baseline	(2) Alt.Prof	(3) Lagged	(4) ex-COVID	(5) Min 5	(6) ex-Ind	(7) Q10	(8) Q50	(9) Q90
ROIC (%)	-0.0121***			-0.0121***	-0.0120***	-0.0145***	-0.0128***	-0.0121***	-0.0114***
	(0.0007)			(0.0008)	(0.0007)	(0.0009)	(0.0010)	(0.0006)	(0.0010)
EBITDA Margin (%)		-0.0308***							
		(0.0019)							
ROIC (t-1)			-0.0023***						
			(0.0006)						
Revenue Growth (%)	-0.0006**	-0.0010***	-0.0019***	-0.0002	-0.0006**	-0.0007***	-0.0008**	-0.0006***	-0.0003
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0004)
WACC (%)	0.0111***	0.0072**	0.0071**	0.0054	0.0111***	0.0155***	0.0075	0.0110***	0.0150***
	(0.0030)	(0.0030)	(0.0032)	(0.0035)	(0.0030)	(0.0037)	(0.0048)	(0.0027)	(0.0050)
Size (ln assets)	-0.1347***	-0.0357	-0.0839***	-0.1154***	-0.1330***	-0.1372***	-0.1088***	-0.1340***	-0.1625***
	(0.0255)	(0.0284)	(0.0279)	(0.0283)	(0.0255)	(0.0301)	(0.0366)	(0.0201)	(0.0380)
Intangibility (%)	-0.0009	0.0025	0.0035*	0.0000	-0.0007	-0.0032	-0.0023	-0.0009	0.0006
	(0.0019)	(0.0019)	(0.0019)	(0.0022)	(0.0019)	(0.0021)	(0.0027)	(0.0015)	(0.0028)
Observations	19,089	19,089	17,387	15,397	18,713	13,821	19,089	19,089	19,089
Within R^2	0.131	0.197	0.086	0.102	0.131	0.140			

Columns: (1) Baseline FE; (2) alternative profitability proxy (EBITDA Margin for ROIC); (3) one-year lagged ROIC; (4) excluding 2020-2021; (5) firms with ≥5 firm-year observations; (6) excluding Industrials; (7)-(9) FE quantile regressions (Canay, 2011) at Q10, Q50, and Q90. Columns 1-6 use within-firm FE + year FE with firm-clustered SE; (7)-(9) use asymptotic SE. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses.
Source: Author Elaboration, run in Stata.

Table A.13: Driscoll-Kraay Standard Errors - Cross-Sectional Dependence

	(1) P/B FE	(2) P/B DK	(3) P/E FE	(4) P/E DK	(5) EV/EBITDA FE	(6) EV/EBITDA DK
ROE (%)	0.0037***	0.0037***	-0.0546***	-0.0546***		
	(0.0004)	(0.0006)	(0.0011)	(0.0011)		
ROIC (%)					-0.0121***	-0.0121***
					(0.0007)	(0.0015)
Revenue Growth (%)	0.0016***	0.0016***	0.0000	0.0000	-0.0006**	-0.0006*
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Beta	-0.0602***	-0.0602	0.0400*	0.0400		
	(0.0164)	(0.0383)	(0.0218)	(0.0306)		
WACC (%)					0.0111***	0.0111**
					(0.0030)	(0.0043)
Size (ln assets)	-0.4057***	-0.4057***	-0.3188***	-0.3188***	-0.1347***	-0.1347**
	(0.0229)	(0.0607)	(0.0316)	(0.0513)	(0.0255)	(0.0521)
Leverage (D/E)	0.2427***	0.2427***	0.2231***	0.2231***		
	(0.0114)	(0.0083)	(0.0162)	(0.0066)		
Intangibility (%)	-0.0070***	-0.0070***	-0.0015	-0.0015	-0.0009	-0.0009
	(0.0016)	(0.0010)	(0.0025)	(0.0010)	(0.0019)	(0.0008)
Observations	23,751	23,751	19,212	19,212	19,089	19,089
Within R^2	0.243	0.243	0.409	0.409	0.131	0.131

FE columns: clustered SE | DK columns: Driscoll-Kraay SE (lag=2). Standard errors in parentheses * p<0.10 ** p<0.05 *** p<0.01

Source: Author Elaboration, Run in Stata

Table A.14: Robustness Test: Current Proxies on Next-Year Multiple

	(1) F.ln(P/B)	(2) F.ln(P/E)	(3) F.ln(EV/EBITDA)
ROE (%)	0.0007**	-0.0041***	
	(0.0003)	(0.0010)	
ROIC (%)			-0.0025***
			(0.0007)
Revenue Growth (%)	0.0007***	-0.0008***	-0.0007***
	(0.0001)	(0.0003)	(0.0002)
Beta	-0.0525***	-0.0190	
	(0.0162)	(0.0256)	
WACC (%)			-0.0032
			(0.0033)
Size (ln assets)	-0.4160***	-0.1186***	-0.1718***
	(0.0217)	(0.0372)	(0.0271)
Leverage (D/E)	0.1174***	-0.0175	
	(0.0091)	(0.0149)	
Intangibility (%)	-0.0046***	0.0064**	-0.0012
	(0.0015)	(0.0026)	(0.0018)
Observations	20,550	15,076	16,165
Within R^2	0.175	0.073	0.088

Dependent variable is the one-year forward multiple. FE with clustered SE. Year FE included.
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author Elaboration, run in Stata

Table A.15: P/B Model – Forward vs Trailing Analysis

	(1)	(2)	(3)
	Trailing	Forward Growth	Forward Profitability
ROE (trailing)	0.0042***	0.0047***	
	(0.0004)	(0.0004)	
ROE (forward)			0.0082***
			(0.0006)
Revenue Growth (trailing)	0.0016***		0.0015***
	(0.0002)		(0.0002)
NI Growth (forward)		0.0000**	
		(0.0000)	
Beta	-0.0761***	-0.0808***	-0.0741***
	(0.0193)	(0.0193)	(0.0195)
Size	-0.4283***	-0.4181***	-0.3632***
	(0.0257)	(0.0260)	(0.0262)
Leverage	0.2353***	0.2383***	0.1669***
	(0.0127)	(0.0128)	(0.0122)
Intangibility	-0.0071***	-0.0071***	-0.0067***
	(0.0016)	(0.0017)	(0.0016)
Profitability	Trailing ROE	Trailing ROE	Forward ROE
Growth	Trailing	Forward NI	Trailing
Observations	16,328	16,328	16,328
Within R^2	0.278	0.270	0.323

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Author Elaboration, run in Stata

Table A.16: P/E Model – Forward vs Trailing Analysis

	(1)	(2)	(3)
	Trailing	Forward Growth	Forward Profitability
ROE (trailing)	-0.0530***	-0.0417***	
	(0.0013)	(0.0011)	
ROE (forward)			-0.0008
			(0.0007)
Revenue Growth (trailing)	0.0001		-0.0021***
	(0.0003)		(0.0004)
NI Growth (forward)		0.0010***	
		(0.0000)	
Beta	0.0137	0.0048	0.0709**
	(0.0242)	(0.0206)	(0.0288)
Size	-0.3521***	-0.2883***	-0.2082***
	(0.0355)	(0.0304)	(0.0416)
Leverage	0.2324***	0.1763***	0.1560***
	(0.0196)	(0.0154)	(0.0215)
Intangibility	0.0003	-0.0007	0.0180***
	(0.0027)	(0.0021)	(0.0031)
Profitability	Trailing ROE	Trailing ROE	Forward ROE
Growth	Trailing	Forward NI	Trailing
Observations	13,466	13,466	13,466
Within R^2	0.431	0.645	0.091

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Author Elaboration, run in Stata

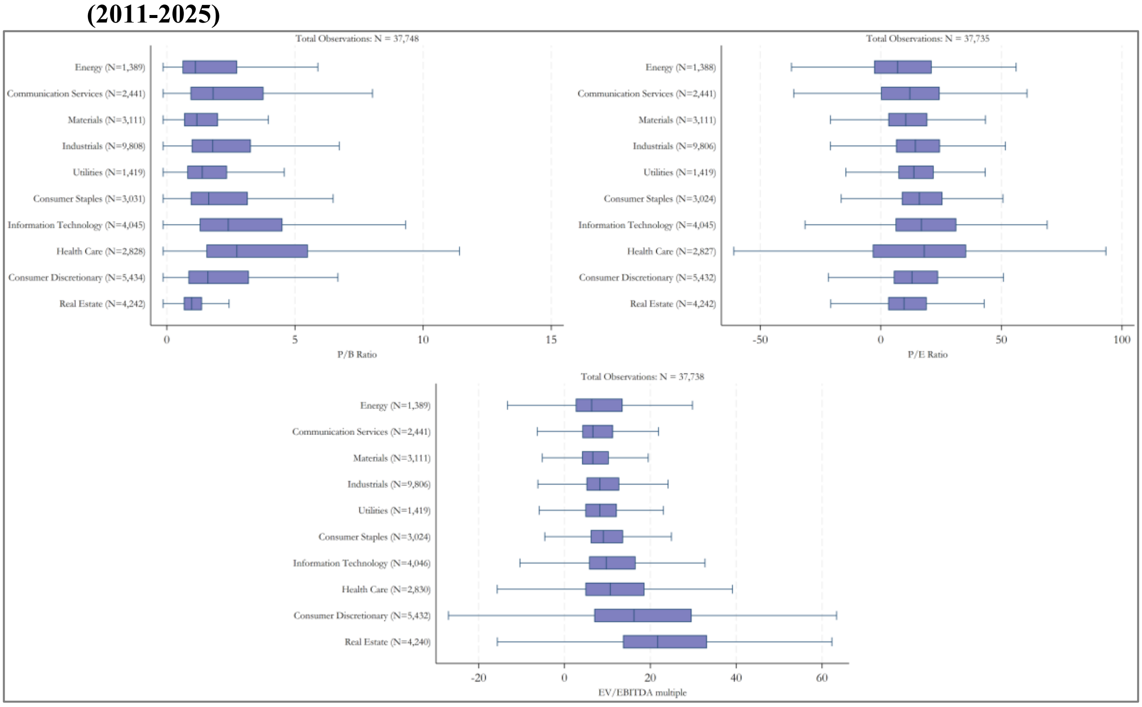
Table A.17: EV/EBITDA Model – Forward vs Trailing Analysis

	(1)	(2)	(3)
	Trailing	Forward Growth	Forward Profitability
ROIC (trailing)	-0.0106***	-0.0081***	
	(0.0008)	(0.0007)	
EBITDA Margin (forward)			0.0046***
			(0.0007)
Revenue Growth (trailing)	-0.0006**		-0.0011***
	(0.0003)		(0.0003)
EBITDA growth (forward)		0.0010***	
		(0.0001)	
WACC	0.0083**	0.0086***	0.0081**
	(0.0034)	(0.0028)	(0.0034)
Size	-0.1510***	-0.1074***	-0.0883***
	(0.0273)	(0.0252)	(0.0270)
Intangibility	0.0024	0.0009	0.0061***
	(0.0021)	(0.0018)	(0.0022)
Profitability	Trailing ROIC	Trailing ROIC	Fwd EBITDA Margin
Growth	Trailing	Fwd EBITDA	Trailing
Observations	13,786	13,786	13,786
Within R^2	0.153	0.392	0.125

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author Elaboration, run in Stata

FIGURE A.3: SECTOR LEVEL DISTRIBUTION OF VALUATION MULTIPLES BY GICS SECTOR (2011-2025)



Source: Author Elaboration, graphs elaborated in Stata