A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from *Nova School of Business and Economics*

Understanding the Implied Market Risk Premium in Analysts' Forecasts

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A Directed Research carried out for the Masters in Finance Program, under the supervision of:

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04-01-2021

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Abstract

Analysts play a preponderant role in asset price formation. Although there is abundant literature on analysts' outputs, such as price targets, few robust analyses are performed on valuation inputs. This paper explores a large sample of analysts' market risk premium estimates, evaluating whether specific characteristics/incentives influence the parameter used when performing valuation exercises. We use publicly available I/B/E/S price targets to derive the implied market risk premium, obtaining an average of 5.15% for 2010-2019. We then employ a multivariate regression analysis and document that analysts providing optimistic earnings forecasts use heftier risk premium estimates, possibly to maintain predetermined price targets.

Keywords: Equity analysts, Market risk premium, Cost of equity, Price target, Earnings forecast, Analysts' characteristics, Analysts' incentives

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* I would like to thank Professor Fernando Anjos for the guidance, support and valuable suggestions provided throughout the development of the work project.

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1. Introduction

The market risk premium (MRP) - the excess expected return of a diversified market portfolio over the risk-free rate - has remained at the core of finance theory and literature over several decades. The parameter is of critical importance for investors' portfolio allocation decisions. Additionally, it is an essential input in the computation of the discount rates used in valuation exercises, and more specifically, in the estimation of price targets and recommendations provided by analysts.

Equity analysts play a preponderant role in asset price formation, with recommendations and price targets representing a primary source of information on which investors and other market participants base decisions (Baker, Nofsinger, and Weaver 2002; Mikhail, Walther, and Willis 2007). There is quite an extensive body of studies assessing analysts' outputs, such as price targets, earnings, and cash flows (Clement 1999; Mikhail, Walther, and Willis 1999; Hilary and Hsu 2013). However, there is a limited number of robust analyses that evaluate estimates of discount rates and MRP.

In contrast to earnings and cash flows, the market risk premium is not observable, restricting analysts' ability to refine it in future exercises. This has led authors to believe that little effort is exercised to estimate such a parameter (Green *et al.* 2014; Mukhlynina and Nyborg 2016) and that it may be arbitrarily adjusted to justify predefined price targets. Still, most of the evidence found is established on the ground of survey responses that do not analyse sufficiently large samples and, most of the time, are very susceptible to selection bias.

More recently, an additional topic that has gained relevance in finance is the relationship between uncertainty and return. The well documented positive correlation between ambiguity and market returns (Abel 2002; Chen and Epstein 2002) was challenged by Diether, Malloy, and Scherbina (2002), who found that companies exhibiting a higher degree of disagreement in analysts' earnings forecasts tend to perform worse. Notwithstanding, it is still unclear whether earnings disagreement adequately represents market ambiguity, and no consensus is reached regarding which measure should be used as a proxy for the latter.

In this paper, we first provide supporting evidence on the size of the market risk premium in the US between 2010 and 2019, calculating the implicit parameter on analysts' price targets.

Secondly, we analyse the cross-sectional variation found in the sample, testing the hypothesis that overly optimistic analysts may use heftier estimates of the premium to maintain pre-established price targets. We present an alternative approach to previous literature, which is mostly based on surveys. By using publicly available price targets to calculate the implicit MRP used by analysts, we are able to analyse firm and analyst-specific characteristics across a sufficiently large sample (153,555 observations). This approach overcomes some of the limitations associated with survey responses (*e.g.*, selection bias), enabling more profound and robust results.

Finally, we present a complementary analysis that proposes a new proxy for market ambiguity, the systematic disagreement between analysts, measured by MRP estimates' dispersion.

The remaining of the paper proceeds as follows: Section 2 summarizes previous literature on market risk premium and analysts' estimates. Section 3 describes the dataset and the methodology used. Section 4 documents the results regarding the size of the premium and the cross-sectional variation of estimates. Section 5 addresses the results of the complementary analysis on market ambiguity. Section 6 concludes the paper.

2. Literature Review

2.1. Market Risk Premium

The market risk premium has been one of the most studied subjects in finance literature for several decades. Historically, it was assumed that the premium required by investors was simply the compensation for the substantially higher inherent risk. However, the size of historical excess returns does not seem to be explained purely by the additional systematic risk incurred.

Mehra and Prescott (1985) initiated a string of theoretical literature on the equity premium puzzle. The authors developed a model, using plausible risk aversion assumptions, that implied an equity premium estimate of less than 1%. Furthermore, to obtain the commonly cited Ibbotson estimates of 7-9% (Ibbotson 1999), it was necessary to assume an unreasonably high degree of risk aversion. This result suggested that the additional systematic risk incurred when holding equities did not fully explain the excess return, as implied by standard asset pricing theory. "Stocks are not sufficiently riskier than Treasury Bills to explain the spread in their return" (Kocherlakota 1996).

There is a vast body of literature suggesting many possible explanations to the puzzle, such as market liquidity and borrowing constraints, transaction costs, imperfect information, taxation, survivorship bias, among others (Bansal and Coleman 1996; Constantinides, Donaldson and Mehra 2002). Moreover, several authors argue that historical realized returns are not necessarily reasonable estimates of expected returns (Elton 2002), which would invalidate the Ibbotson estimates as an appropriate proxy for MRP. Therefore, new methods were developed to estimate the premium, and results point out to substantially lower estimates.

Claus and Thomas (2001) used I/B/E/S earnings forecasts coupled with market prices to calculate the implied equity premium (through the residual income model). This represents a "forward-looking" approach (*ex-ante*) that does not rely on historical returns (*ex-post*). For the 1985-1998 period, the authors obtained an average cost of equity of 11% and an implied market risk premium of 3.4%[1]. Moreover, the results exhibited a declining trend of the equity premium throughout the period. Gebhardt, Lee, and Swaminathan (2001), McGrattan, Jagannathan, and Scherbina (2001), F. Fama and K. French (2004) have also used *ex-ante* methods (residual income, dividend growth, and Ohlson and Juettner[2] models) to estimate the market risk

[1] 10-year Government T-Bond yields as risk-free rate (Claus and Thomas, 2001)
[2] Ohlson and Juettner-Nauroth (2005)

premium and obtained similar results to those of Claus and Thomas (2001) (2-4%).

At the same time, other authors, such as Harris and Marston (2001), Easton *et al.* (2002), Daske, Gebhardt, and Klein (2004), using similar approaches, obtained estimations for the market risk premium of around 5-7%. Specifically, Easton *et al.* (2002) used a variation of the residual income model to simultaneously calculate the cost of capital and the long-term growth rate. The authors argue that previous literature obtained lower risk premium values due to the excessively conservative long-term growth rate assumed.

It appears that there is still disagreement in what concerns the actual value of the premium and what is the best way to estimate it. Such a parameter is a critical input for analysts to calculate the discount rate when performing price valuation estimates. Furthermore, these estimates "play an important role in capital markets" (Pinto, Robinson, and Stowe 2019), with analysts' price targets and recommendations representing a primary source of information for investors (Baker, Nofsinger, and Weaver 2002; Mikhail, Walther, and Willis 2007). Thus, it is also essential to understand how analysts derive and adjust their estimates of market risk premium and cost of capital.

2.2. Analysts' Estimates of Market Risk Premium

Pablo Fernandez, Corporate Finance professor at IESE, conducts yearly surveys to infer the MRP used by analysts and other finance professionals. Between 2010 and 2019, the average premium reported in the U.S. was 5.5%, with an average yearly standard deviation of 1.5%, not exhibiting any particular declining trend, as suggested by Claus and Thomas (2001) and McGrattan, Jagannathan, and Scherbina (2001). Nonetheless, the surveys highlight significant cross-analyst dispersion in the same year, suggesting that analysts take different approaches to estimate the risk premium.

Balakrishnan, Shivakumar, and Taori (2020) evaluated cost of equity (R_e) estimates revealed in analysts' reports. The study is mainly focused on which company characteristics are associated with higher R_e values, and results point out to strong association with the firm's beta, low market value, and book-to-market ratio. Additionally, the authors find that analysts tend to adjust R_e estimates following company financial announcements, which suggests that measures such as the risk premium and the cost of equity might be "strategically used to justify predetermined target prices or stock recommendations"[3] (Balakrishnan, Shivakumar, and Taori 2020).

There is an extensive body of literature that aims to understand whether analysts' estimations of cost of capital are made on the basis of financial theory, most of which through analyst surveys (Richardson, Teoh and Wysocki 1999; Bradshaw 2004; Guay, Kothari and Shu 2011; Green *et al.* 2014; Brown *et al.* 2015). Notably, Pinto, Robison, and Stowe (2019) conducted a scientific survey on 13,500 CFA valuation practitioners (1,980 valid responses). Among the obtained results, the authors report that most respondents tend to estimate the MRP when performing valuation exercises. However, there is still a significant number of professionals (24.5% of respondents) who do not calculate the risk premium. Although no evidence is provided, the authors propose that analysts might use a standard value predefined by their brokerage firm.

Bancel and Mittoo (2014) surveyed 365 finance practitioners about valuation methodologies and inputs used in discount rates. Responses exhibit substantial cross-individual dispersion in the MRP used and lack of significant adjustment across time. The latter finding is fascinating given that the time-period surveyed (2006-2012) includes the 2008 financial crisis, which would imply an upward adjustment of the market risk premium, according to finance literature (Harvey 1989; Li 2001; Paoli and Zabczyk 2009; Gourio 2012).

Similarly, Mukhlynina and Nyborg (2016), Green *et al.* (2014) argue that analysts exercise little effort when estimating the market premium and the discount rate, providing evidence that

[3] See Appendix 1 for real episode that illustrates this possibility

such estimates suffer from significant execution error. Green *et al.* (2014) analysed 120 analyst reports and found unusually variable and high market risk premia (7-8%), compared to theoretically motivated assumptions. Along the same lines, Mukhlynina and Nyborg (2016) gathered 272 responses and reported significant variability in both the estimation method and the risk premium used.

2.3. Ambiguity and Analysts' Disagreement

A parallel theme that has gained substantial relevance in the finance community is dispersion and disagreement between analysts' forecasts.

Diether, Malloy, and Scherbina (2002) documented an anomaly in capital markets that challenged standard asset pricing theory. The authors found that companies with higher dispersion in analysts' earnings forecasts produce lower future returns. This was considered puzzling since disagreement is accepted as a good proxy for uncertainty (Zarnowitz and Lambros 1987), which is usually associated with higher required returns.

Johnson (2004) attempted to justify the previous puzzle by drawing a clear distinction between fundamental and parameter risk. The author defines the former as the random evolution of the underlying parameter, independent from the informational environment, while the latter represents uncertainty generated by the degree of information available about a company. Johnson argued that dispersion in analysts' earnings forecasts should be considered a proxy for parameter risk, which is specific to each company (idiosyncratic). In this case, the results obtained by Diether, Malloy, and Scherbina (2002) do not necessarily conflict with the established relationship between systematic risk and required return.

Although Johnson (2004) and subsequent literature (Barinov 2013) have provided reasonable explanations for the puzzle observed, uncertainty and analyst disagreement remain active topics. Most papers tend to focus on earnings and cash flow disagreement. In contrast, little to no analyses are performed on analysts' disaccord about systematic risk (measured by the dispersion of MRP estimates used by analysts) and how it correlates with the size of the premium. This is particularly interesting if we consider systematic disagreement a reasonable proxy for uncertainty and ambiguity.

Ambiguity aversion has been documented by several studies, where the majority provide abundant evidence on the positive correlation with required returns (Abel 2002; Chen and Epstein 2002).

More recently, Ngo, Rieger, and Yuan (2018) estimated the implicit cost of equity for a total of 28,256 companies (from 54 countries) and tested the relationship with ambiguity (measured by country-specific risk preferences inferred through the INFRA survey[4]). The authors found significant and robust evidence that ambiguity aversion contributes to higher required returns (cost of equity). Similar results were reported by Ju and Miao (2012) and Zhang (2019). Provided that dispersion in MRP estimates represents a proxy for ambiguity, we should expect inflated market premia in periods exhibiting a higher degree of systematic disagreement.

Literature on the market risk premium and analysts' estimates is still an area with several unanswered questions. We fill some of the gaps of previously published work by analysing a large sample of price targets. Although surveys allow to individualize analysts while not requiring any estimation method to infer the MRP used (analysts provide the answer), most of the time, the samples gathered are not sufficiently large to perform robust testing. Simultaneously, it is unreasonable to assume that analysts who do not follow finance theory to produce estimates would report it in survey responses (selection bias).

[4] Tests decision making of individuals when faced with alternative lottery scenarios over unknow risks (Ngo, Rieger, and Yuan 2018)

3. Data and Methodology

3.1. Analysts' Implied Market Risk Premium

There are several methods available to extract the cost of equity implicit in analysts' forecasts. Amongst the models exhibited in previous literature, the most commonly used are the dividend growth and the residual income models (Gebhardt, Lee, and Swaminathan 2001; Claus and Thomas 2001; Easton *et al.* 2002). In this paper, we use a variation of the residual income model, similar to the approach developed by Daske, Gebhardt, and Klein (2004). Afterward, the Capital Asset Pricing Model (CAPM) is employed to calculate the MRP.

The residual income model (also known as abnormal returns) is an accounting-based stock valuation method, representing an alternative to models that are too dependent on long-term assumptions. It is a specification of the dividend growth model (1), assuming that changes in the book value of equity are driven by either earnings or transactions with shareholders (clean surplus rule).

$$p_0 = \frac{div_1}{(1+r_{ed})} + \frac{div_2}{(1+r_{ed})^2} + \frac{div_3}{(1+r_{ed})^3} + \cdots + \frac{div_t}{(1+r_{ed})^t} \tag{1}$$

$$eps_t = div_t + (bps_t - bps_{t-1}) \Leftrightarrow div_t = eps_t - (bps_t - bps_{t-1}) \tag{2}$$

where:
p_0: current stock price
div_t: expected dividends per share at year *t*
eps_t: expected earnings per share at year *t*
bps_t: expected book value of equity per share at the end of year *t*
r_{ed}: cost of equity derived from the dividend growth model

Equation (2), the clean surplus rule, is the residual income model's main assumption. It disregards some captions that are usually less relevant in companies' financial statements, such as foreign currency translation gains and losses.

The residual income formula can be derived from the two previous equations.

$$p_0 = bps_0 + \frac{ri_1}{(1+r_{er})} + \frac{ri_2}{(1+r_{er})^2} + \frac{ri_3}{(1+r_{er})^3} + \cdots + \frac{ri_t}{(1+r_{er})^t} \quad (3)$$

where:

p_0: current share price

$ri_t = eps_t - r_{er}\,(bps_{t-1})$: expected residual income at year *t*

bps_0: book value of equity recorded at the end of the last fiscal year

bps_t: expected book value of equity per share at the end of year *t*

r_{er}: cost of equity derived from the residual income model

Equation (3) demonstrates how the price of a stock can be computed through the sum of the current book value of equity and the present value of residual income.

Several authors have used the model exhibited in Equation (3). However, this formula only allows for the estimation of the cost of equity at a specific date in the year, which is predefined by the disclosure of financial statements (at the time book value is reported). We use a revised version of the residual income model, similar to the one developed by Daske, Gebhardt, and Klein (2004), to extract the implicit cost of equity at any given estimation date. This way, we use price targets (instead of the current stock price) of individual analysts at different dates to calculate the implicit cost of capital in each estimate. Equation (4) presents the modified version of the residual income model:

$$\begin{aligned} p_a = bps_a &+ \frac{eps_{1a} - r_e\,(bps_a)}{(1+r_e)^{1-a}} + \frac{eps_2 - r_e\,(bps_1)}{(1+r_e)^{2-a}} + \frac{eps_3 - r_e\,(bps_2)}{(1+r_e)^{3-a}} \\ &+ \frac{eps_4 - r_e\,(bps_3)}{(1+r_e)^{4-a}} + \cdots + \frac{eps_t - r_e\,(bps_{t-1})}{(1+r_e)^{t-a}} \end{aligned} \quad (4)$$

$$bps_a = bps_0 \times (1 + \frac{eps_1}{bps_0})^a \quad (5)$$

$$eps_{1a} = eps_1 - (bps_a - bps_0) \quad (6)$$

where:

a : period between the beginning of the fiscal year and the estimation date (in years)

p_a: price target

bps_0: book value per share at the end of the fiscal year preceding the estimation date
bps_a: expected book value per share at estimation date
bps_t: expected book value per share at the end of fiscal year *t*
eps_{1a}: expected *eps* for the period between the estimation date and the end of the 1st fiscal year
eps_t: expected earnings per share at year *t*
r_e: cost of equity derived from the modified residual income model

Equation (3) (initial residual income formula) uses the book value of the previous fiscal year (bps_0), whereas in (4), the book value is adjusted to the earnings that have been generated between the beginning of the fiscal year and the estimation date, through formula (5). The latter equation uses the return on equity implied by the first fiscal year earnings forecast ($\frac{eps_1}{bps_0}$) to calculate the expected book value at the estimation date. Simultaneously, the earnings used in the first fraction term of Equation (4) (eps_{1a}) are also adjusted to the previous point, using formula (6)[5].

All components of model (4) were retrieved from I/B/E/S. The I/B/E/S Detail History database provides analysts' earnings, book value, and price target estimations throughout the year. Our sample includes forecasts/price targets announced between 2010 and 2019 for companies incorporated in S&P500 with fiscal-year end between September and December.

We only considered forecasts that contained earnings and book value estimations for (at least) the first two fiscal years and a price target (eps_1, eps_2, bps_1, bps_2, p_a), discarding all observations for which one of these variables was not provided. For forecasts where earnings per share were not available from the third year onwards ($eps_{3\text{-}5}$), we used the 5-year eps growth best estimate[6] to calculate it[7]. The same procedure was applied to the estimates of the book value of equity.

Given that the database does not provide analysts' forecasts of earnings after the fifth fiscal

[5] For more information on this model, please see Daske, Gebhardt, and Klein (2004)
[6] Median of analysts' company-specific 5-year eps growth forecasts for each I/B/E/S statistical period, $g_{3\text{-}5}$
[7] $eps_3 = eps_2 \times (1 + g_{3\text{-}5})$; $eps_4 = eps_3 \times (1 + g_{3\text{-}5})$; $eps_5 = eps_4 \times (1 + g_{3\text{-}5})$; $bps_3 = bps_2 \times (1 + g'_{3\text{-}5})$; $bps_4 = bps_3 \times (1 + g'_{3\text{-}5})$

year, it was assumed that the residual income increases at a constant rate g_{lt} (long term growth) after year 5, following the same approach as Claus and Thomas, 2001.

$$p_a = bps_a + \frac{eps_{1a} - r_e\,(bps_a)}{(1+r_e)^{t-a}} + \frac{eps_2 - r_e\,(bps_1)}{(1+r_e)^{2-a}} + \cdots$$
$$+ \frac{eps_5 - r_e\,(bps_4)}{(1+r_e)^{5-a}} + \left[\frac{(eps_5 - r_e\,bps_4)(1+g_{lt})}{(r_e - g_{lt}) \times (1+r_e)^{5-a}}\right] \tag{7}$$

The book value recorded at the end of the fiscal year preceding the estimation date (bps_0) was retrieved from the I/B/E/S Actuals database. The long-term growth rate (g_{lt}) used was the historical expected long-term inflation in the United States, provided by FRED[8]. The latter assumption is not as critical in the residual income model as in other valuation methods (Claus and Thomas 2001). The proportion of the price target explained by the terminal value is reduced when the book value of equity is introduced as a determinant of the share price.

Equation (7) is a 5-degree polynomial in r_e with many possible solutions. Using a GRG non-linear optimization method (replicating MS excel Solver), r_e was calculated (similar to the IRR calculation process).

After extracting the implicit cost of equity for each forecast, the market risk premium (*mrp*) was calculated using the CAPM model.

$$r_e = r_f + \beta_{5y} \times mrp \Leftrightarrow mrp = \frac{(r_e - r_f)}{\beta_{5y}} \tag{8}$$

The risk-free rate (r_f) used was the prevailing yield of the 10-year[9] U.S. government bond at the beginning of the month of the estimation date[10] (Eikon Thomson Reuters). β_{5y} was calculated for each company and forecast date using "Beta Suite by WRDS." In the main sample, the beta was calculated using 5-year historical price data with daily frequency. Implicitly, we assume that all analysts under all scenarios and companies use this method to

[8] Expected long-term inflation is amongst the most commonly proxies for g_{lt} (Mukhlynina and Nyborg 2016)
[9] Most commonly used risk-free proxy by finance practitioners (Bancel and Mittoo 2014)
[10] *E.g.*: a forecast announced January 2010, was attributed the yield that prevailed on the 1st of January 2010

calculate β. In reality, different techniques may be employed, such as 10-year historical price data (β_{10y}), or the Bloomberg adjusted beta (β_{blm}). This assumption is tested further ahead by simulating a sample where the beta for each firm at a specific date is calculated using the three previously mentioned methods and randomly assigning them to the forecasts.

The final sample includes a total of 153,555 price targets for the 10-year period under study. Appendix 2 portrays detailed information about the sample on a yearly basis.

3.2. Cross-sectional Analysis of Implied Market Risk Premium

The MRP estimated for each observation is the primary focus of study. To understand this parameter's cross-section variation, we regressed it on a set of analyst/firm-specific characteristics. The central hypothesis tested with the multivariate regression is whether earnings forecast error is associated with greater MRP estimates. Should analysts lack motivation to exercise effort in the MRP and discount rate estimation process, then the actual value used might the result of some characteristics and incentives that are not related to theoretical concepts and literature.

$$\begin{aligned} mrp_i = \alpha_0 + \beta_1 \times ferror_i + \beta_2 \times bold_i + \beta_3 \times blg_i + \beta_4 \times Ln(exp_i) \\ + \sum_{j=5}^{6} \beta_j \times cpl_i + \sum_{k=7}^{9} \beta_k \times X_i + \sum_{t=10}^{18} \beta_t \times T_i + \beta \times E_i + \varepsilon_i \end{aligned} \tag{9}$$

Equation (9) is the main regression estimated through the Ordinary Least Square method. The sample is in a cross-sectional setup, where each observation corresponds to an individual forecast made by an analyst about a company at a given estimation date.

mrp_i is the risk premium resulting from the estimation process explained in Section 3.1.

$ferror_i$ represents the earnings forecast error for the first fiscal year ($\frac{F(eps_1)}{eps_1} - 1$). Data on earnings reported by each company was retrieved from the I/B/E/S Actuals database.

$bold_i$ is the absolute value of the percentage difference between an analyst's earnings forecast and the consensus forecast ($|\frac{F(eps_1)}{Avg(eps_{1})} - 1|$) (Hilary and Hsu 2013). The I/B/E/S average earnings forecast for each period and company was retrieved from the I/B/E/S Summary History database.

blg_i is a dummy variable set to 1 if the analyst providing the forecast is employed by a top size decile brokerage firm. Size is calculated based on the number of analysts providing estimates under the same brokerage firm ID (Clement 1999) (I/B/E/S database).

exp_i replicates analyst experience, and it is measured by the number of price target estimates announced by the analyst providing the observation in the two years preceding the estimation date (I/B/E/S database).

cpl_i , portfolio complexity, is a set of two variables representing the number of companies and industries followed by the analyst performing the estimate ($cmpfwl_i$ and $indfwl_i$, respectively) (I/B/E/S database).

X_i is a set of company-specific control variables (market capitalization, market-to-book ratio and industry classification). The first two variables were calculated using the share price observed at the beginning of the year of the estimation date (retrieved from the CRPS database). Furthermore, observations were assigned to different sector groups based on the SIC code of the company for which the forecast was performed (Hutira 2016) (See Appendix 3).

T_i is a set of time dummy variables representing each year of the 2010-2019 period, in an attempt to eliminate year-specific events that could disrupt other coefficients.

E_i is a set of dummy variables identifying the analyst and the brokerage firm that provided the price target. The latter variables are used since there may be unobserved characteristics specific to each analyst and brokerage firm that are correlated to both the dependent and the independent variables, which would create biased coefficients. This is an attempt to control fixed effects at the analyst and brokerage firm level, reducing endogeneity issues.

Additionally, since the sample contains different observations (forecasts) that may have been produced by the same analyst, standard errors were clustered at the analyst level.

Appendix 4 presents descriptive statistics of the dependent and independent variables.

4. Results and Discussion

4.1. Implied Cost of Equity

Table 1 illustrates the average implied cost of equity obtained through the adjusted residual income model (Equation 7) and the respective standard deviation on a yearly basis.

Year	R_e	St. Dev.
2010	8.73%	2.53%
2011	8.89%	2.23%
2012	9.11%	2.68%
2013	8.63%	2.47%
2014	8.37%	2.48%
2015	8.49%	3.75%
2016	8.73%	3.99%
2017	8.42%	3.72%
2018	9.36%	3.74%
2019	8.72%	3.33%
Average	8.74%	3.09%

Table 1: Average cost of equity (R_e) derived from the residual income model and respective standard deviation on a yearly basis

The average cost of equity throughout the 2010-2019 period was 8.7%, ranging from 8.4% to 9.4% and exhibiting a high degree of variability each year. By itself, this result is not very meaningful as the sample includes forecasts for different companies, which are entitled to distinct sizes of cost of equity. Thus, we performed a quick analysis to gain confidence in the R_e results obtained. We observed the correlation between the cost of equity, the market capitalization and the market-to-book ratio. Appendix 5 documents this experiment's results, exhibiting negative correlation between the cost of equity and the other two variables, corroborating the 3-factor model proposed by F. Fama and K. French (1993).

An important question that may also arise is whether the model employed to estimate the cost of equity for each observation is the most appropriate. By introducing a company's reported book value as a component to evaluate its share price, theoretically, the fraction explained by the terminal value is lower than in other commonly used methods, such as the dividend growth model (DMG). Appendix 6 presents the average proportion of the price target (every year) that is explained by each of the components of the residual income formula. In our sample, we find that, on average, the terminal value explains 48% of the price target compared to *c.* 85% obtained by Claus and Thomas (2001) when using the dividend growth model. This experiment illustrates the main advantage of the residual income method, the lower relevance given to the terminal value, which is mostly based on uncertain long-term assumptions.

4.2. Implied Market Risk Premium

Using the CAPM model, the MRP for each observation was retrieved. Table 2 presents a summary of the estimates obtained and the respective st. deviation, on a yearly basis.

Year	MRP	St. Dev.
2010	4.37%	2.71%
2011	4.57%	2.59%
2012	5.62%	2.93%
2013	4.82%	2.61%
2014	4.62%	2.38%
2015	5.19%	3.03%
2016	5.53%	3.05%
2017	5.04%	2.81%
2018	5.73%	3.02%
2019	5.96%	2.97%
Average	5.15%	2.81%

Table 2: Average market risk premium and respective standard deviation on a yearly basis

For the period observed (2010-2019), the average MRP fluctuated between 4.4% and 6.0%, with no particular trend. We also find a high degree of volatility within each year. As expected, most of this dispersion is driven by cross-analyst variation. However, there is still some dispersion for observations/forecasts provided by the same analyst (st. dev. decomposition can be found in Appendix 7). One possible explanation for this dispersion may be that analysts perform estimations for different companies and dates, meaning they might adjust MRP parameters throughout the year.

The approach employed in this paper uses price targets, which allows to retrieve the implicit MRP under a specific estimation date. This differs from the standard procedure followed by previous literature on this topic, which uses companies' market prices (Claus and Thomas 2001;

McGrattan, Jagannathan, and Scherbina 2001; E. F. Fama and K. French 2004). Furthermore, these authors provide estimates for periods before 2000 and, consequently, our results are not necessarily comparable with the 2-3% estimates obtained.

Year	MRP	St. Dev.	PMRP	PSt. Dev.
2010	4.37%	2.71%	5.10%	1.10%
2011	4.57%	2.59%	5.50%	1.70%
2012	5.62%	2.93%	5.50%	1.60%
2013	4.82%	2.61%	5.70%	1.60%
2014	4.62%	2.38%	5.40%	1.40%
2015	5.19%	3.03%	5.50%	1.40%
2016	5.53%	3.05%	5.30%	1.30%
2017	5.04%	2.81%	5.70%	1.50%
2018	5.73%	3.02%	5.40%	1.70%
2019	5.96%	2.97%	5.60%	1.80%
Average	5.15%	2.81%	5.47%	1.51%

Notes: MRP is the year average implicit market risk premium obtained through the residual income and CAPM model. PMRP corresponds to estimates from Pablo Fernandez's surveys, conducted each year to analysts and finance professionals

Table 3: Side-by-side comparison with Pablo Hernandez' survey results

Table 3 exhibits a side-by-side comparison between our estimates and those of Pablo Hernandez's surveys. The magnitude of the premium estimates is quite similar, with period (2010-2019) averages differing by *c.* 0.3 p.p., while displaying a comparable trend throughout time. Given that the surveys' estimates are based on individual analyst responses, it represents a better comparison than studies that use consensus forecasts of earnings and the share price observed in the market to backout the market risk premium.

Even though our results seem reasonable and in line with similar literature, one critical assumption was made. To calculate the premium, we assumed that all analysts use the same method to calculate the company beta (5-year historical data, β_{5y}). Appendix 8 documents the results of a sensitivity test performed on this assumption. First, each company's beta (at each estimation date) was calculated through three different methods (Bloomberg adjusted beta[11], 5-year and 10-year historical data), and afterward, we randomly assigned them to each observation. The exercise was repeated three times, and results were quite similar to those of

[11] Bloomberg adjusted beta = $\frac{2}{3} \times \beta_{5y} + \frac{1}{3} \times 1$

Table 3 (using exclusively β_{5y}), confirming the robustness of our initial estimates.

4.3. Cross-sectional Analysis of Implied Market Risk Premium

Once the implicit MRP was obtained for each observation, we regressed (OLS) it on a set of variables representing analyst characteristics. Table 4 reports the results of the regression analysis performed.

	(1)	(2)	(3)	(4)	(5)
ferror (normalized)	0.0720***	0.0724***	0.0570***	0.0511***	0.0405***
	(-4.92)	(-4.96)	(-4.00)	-(3.67)	(-3.16)
bold (normalized)		-0.0338***	-0.0240**	-0.0219**	-0.0058
		(-2.89)	(-2.41)	(-2.37)	(-0.63)
blg		0.2137*	0.1901*	0.0791	-0.0706
		(-1.66)	(-1.73)	(-0.74)	(-0.45)
ln(exper)		0.0208	0.0466**	0.0233	0.0252
		(-0.86)	(-2.25)	(-1.2)	(-1.14)
cmpflw		-0.0004	0.0061	0.0054	0.002
		(-0.04)	(-0.93)	(-0.89)	(-0.29)
indflw		-0.0528	-0.1150***	-0.1640***	-0.029
		(-1.61)	(-4.04)	(-5.94)	(-0.74)
Company controls	No	No	Yes	Yes	Yes
Year dummies	No	No	No	Yes	Yes
Analyst and Broker ID dummies	No	No	No	No	Yes
Observations	153,555	153,555	153,555	153,555	153,555
Adjusted R-squared	0.0006	0.0018	0.057	0.0926	0.28
F	24.2004	6.2738	45.018	80.9588	.
p	0	0	0	0	.

Notes: t-stats are in parenthesis. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***). Standard errors are clustered at the analyst level.

Table 4: Baseline results of regression analysis performed with implicit market risk premium as dependent variable

Column (1) presents the OLS coefficients that resulted from regressing the implicit market risk premium (dependent variable) on the standardized forecast error ($\frac{ferror_i - Avg(ferror_i)}{Std(ferror_i)}$). Column (2) adds analyst characteristics (experience, boldness, and portfolio complexity). We further control company-specific features (market cap., M/B ratio, and industry classification) (Column 3). Column (4) adds time dummies to the regression to control for year specific events. Finally, column (5) includes analyst and employer brokerage firm ID dummies in an attempt to control for fixed effects. All standard errors obtained from the regressions are robust to heteroskedasticity and are clustered at the analyst level.

Across all OLS regression specifications (column 1 through 5), the coefficient for *ferror* is consistently positive and statistically significant at 1% level. According to column (1), on average, a one standard deviation change in the forecast error is associated with a 0.07 p.p. increase in the implicit market risk premium. The coefficient decreases to 0.04 when controlling for time effects, analyst and employer brokerage firm fixed effects (column 5).

The significant association between the forecast error and the premium size suggests that analysts may adjust MRP and, consequently, discount rate estimates to compensate for overly optimistic earnings/cash-flow forecasts. Additionally, the magnitude of the coefficient seems reasonable, since a change in the market risk premium (through the discount rate) causes a substantially larger effect on the price target than the impact caused by a change in first-year earnings (see Appendix 9 for comparison between effects).

Bold, the percentage deviation from the I/B/E/S consensus earnings forecast, exhibits a negative and significant relationship with the implicit MRP. As reported in column (2), a one standard deviation change in boldness (distance from consensus forecast) is associated with a 0.03 p.p. decrease in the estimate of market risk premium. Moreover, we find that analysts employed by bulge bracket brokerage firms (*blg*) tend to use larger MRP estimates (columns 2 and 3).

Portfolio complexity, measured by the number of companies (*cmpflw*) and industries (*indflw*) followed by the analyst providing the forecast, also exhibits a significant association with the dependent variable. When controlling for company characteristics and time-effects (column 4), an increase (by 1) in the number of industries covered by the analyst providing the price target estimate is associated with a 0.16 p.p. decrease in the implicit MRP.

When controlling for analyst and brokerage firm fixed effects (column 5), the coefficients regarding analyst characteristics lose significance, as expected. Nevertheless, the main independent variable (forecast error) remains significant at 1% level. Although causality cannot be inferred from the analysis performed, it seems that estimation error may be compensated by the use of a larger market risk premium (and discount rate), to maintain a pre-established price target, as suggested by Balakrishnan, Shivakumar, and Taori (2020).

Results presented in Table 4 derive from a regression analysis where we measure *ferror* through the percentage difference between the earnings forecast and the actual value reported at the end of the fiscal period. To consolidate the hypothesis that analysts providing overly confident earnings forecasts also use heftier MRP estimates, we redefined the variable *ferror*.

Table 5 reports the results obtained when *ferror* (now *dferror*) is set as a dummy variable equal to 1 if the forecast error is positive (overestimation).

	(1)	(2)	(3)	(4)	(5)
dferror	0.1245***	0.1287***	0.0898***	0.0606**	0.1013***
	(-4.39)	(-4.62)	(-3.47)	(-2.46)	(-4.9)
bold		-0.0345***	-0.0244**	-0.0223**	-0.0059
		(-2.96)	(-2.46)	(-2.42)	(-0.64)
blg		0.2167*	0.1920*	0.0803	-0.0709
		(-1.68)	(-1.74)	(-0.76)	(-0.45)
ln(exper)		0.0207	0.0466**	0.0234	0.0258
		(-0.85)	(-2.25)	(-1.21)	(-1.17)
cmpflw		-0.0004	0.0061	0.0054	0.002
		(-0.05)	(-0.93)	(-0.89)	(-0.29)
indflw		-0.0529	-0.1152***	-0.1640***	-0.029
		(-1.62)	(-4.04)	(-5.94)	(-0.73)
Company controls	No	No	Yes	Yes	Yes
Year dummies	No	No	No	Yes	Yes
Analyst and Broker ID dummies	No	No	No	No	Yes
Observations	153,555	153,555	153,555	153,555	153,555
Adjusted R-squared	0.0004	0.0017	0.0568	0.0924	0.2801
F	19.2874	6.2402	46.4507	82.1597	.
p	0	0	0	0	.

Notes: t-stats are in parenthesis. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***). Standard errors are clustered at the analyst level.

Table 5: Baseline results of regression analysis performed with implicit market risk premium as dependent variable and forecast error set as a dummy variable

The evidence found is quite similar to the results documented previously. The forecast error coefficient remains positive and significant across all specifications of the regression. Interestingly, the coefficient illustrates a stronger association between the forecast error and the size of the premium. On average, observations where analysts overestimate earnings are associated with 0.1 p.p. larger market risk premium estimates (column 5), which can constitute evidence on the use of the premium to attenuate the effect of earnings overestimations on the price target.

To summarize, the regression analyses performed provide evidence that incentives and analyst-specific characteristics influence the MRP estimates used when performing valuation exercises. The forecast error coefficient exhibits a positive and significant relation with the implicit market risk premium, corroborating the hypothesis that sell-side analysts, who provide overly confident earnings forecasts (possibly to entice to establish stable relationships with companies), may compensate it with a bulkier discount rate to maintain reasonable price targets.

Simultaneously, analysts-specific characteristics exhibit robust association with the implicit MRP (except when using ID dummies). It may be unreasonable to assume that analysts who exhibit the characteristics tested deliberately and arbitrarily provide larger MRP estimates. Alternatively, it can be the case that these characteristics influence the analyst's estimation method, which consequently creates estimates that are significantly different[12].

5. Additional Analysis - Ambiguity and Disagreement

To complement our findings of the size and cross-sectional variation of the market risk premium, we further analyse ambiguity and analyst disagreement.

As mentioned in Section 2, previous literature documents that investors tend to require a higher premium when faced with considerable uncertainty. Under such a scenario, low yield

[12] *E.g.*, analysts with more experience use forward-looking methods which, historically, have resulted in lower MRP estimates (Claus and Thomas, 2001).

bonds are considered safe havens and, thus, the market risk premium tends to expand. At the same time, Diether, Malloy, and Scherbina (2002) found that companies with high dispersion in analysts' earnings forecasts tend to generate lower future returns. We analyse this relation hypothesizing that earnings forecast dispersion also captures firm-specific characteristics that are not associated with systematic and long-term uncertainty (as suggested by Johnson, 2004). Instead, analyst disagreement in MRP estimates would represent a better proxy for market ambiguity and would better explain the size of the premium.

To analyse the hypothesis explained above, we aggregated the initial sample (153,555 observations) into 15,998 firm-quarter observations[13]. MRP_i is the average market risk premium used in price targets of a particular company during a given quarter. $Dsgmrp_i$, systematic disagreement, is the standard deviation of the implicit market risk premium used in price targets performed by analysts for a specific company in a given quarter. $Dsgeps_i$ is measured through the standard deviation of earnings forecasts made for a given company in a particular quarter.

	Coeficient	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
dsgmrp	0.809***	0.051	15.94	0	0.709	0.908
dsgeps	-0.004***	0.001	-4.58	0	-0.006	-0.002
Time dummies	Yes					
Company ID dummies	Yes					
Observations	15,598					
R-squared	0.724					
Root MSE	0.014					

Notes: Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***). Standard errors are clustered at the firm level

Table 6: Baseline results of regression analysis performed, with average firm-quarter implicit market risk premium as dependent variable

Table 6 documents the OLS regression results when using MRP as the dependent variable and both disagreement measures as independent variables. The regression performed includes time-dummies to control for year-specific events and company ID dummies in an attempt to

[13] *E.g.*, Observation number 1 corresponds to aggregated estimates made by analysts regarding Apple in the 1st quarter of 2010

remove company fixed effects. Additionally, all standard errors are robust to heteroskedasticity and clustered at the firm level.

Systematic disagreement, measured by the standard deviation of the market risk premium estimates, is strongly and significantly associated with the size of the premium (dependent variable). This result follows the widely documented association between uncertainty and required returns (ambiguity aversion). Even though proxies for ambiguity are usually derived from practical experiments that evaluate how individuals behave when faced with uncertainty (Ngo, Rieger, and Yuan 2018), we suggest that analysts' systematic disagreement might also be used as a proxy for uncertainty and ambiguity.

Focusing on the disagreement in earnings forecasts, although significant, the coefficient is relatively small and negative. As suggested by previous literature, conflict in earnings forecasts might capture company-specific characteristics (Diether, Malloy, and Scherbina 2002; Johnson 2004; Barinov 2013). Thus, it might not represent an adequate proxy for overall market uncertainty. As illustrated in the table above, disagreement in earnings forecasts does not explain much of the variation of the MRP.

This analysis provides statistical evidence that systematic disagreement is strongly associated with the risk premium. Furthermore, dispersion in MRP estimates appears to better explain the size of the premium, compared to disagreement in earnings forecasts. The latter can be considered a measure of short-term uncertainty, which is influenced by companies' characteristics and informational environment. On the other hand, systematic disagreement captures long-term disagreement/uncertainty, which is more meaningful for asset pricing. We thus suggest that dispersion in analysts' MRP estimates represents a better proxy for ambiguity.

Notwithstanding, caution is necessary when arguing that systematic disagreement is a good proxy for ambiguity. Knight (1921) highlights the distinction between ambiguity and risk. The author refers to the former as a situation where investors are uncertain about the probability of outcomes. In contrast, the latter refers to a situation where the probability distribution of the result is known. In Appendix 10, we document the correlation between systematic disagreement and the VIX, a widely used proxy of aggregate market risk, to test this distinction.

6. Conclusion and Final Remarks

The market risk premium is one of the core concepts of finance theory. It is an essential component of the CAPM model, and thus, is of extreme importance for portfolio asset allocation decisions. Additionally, it is a critical input in the calculation of the discount rate used by analysts when performing price target estimations.

Most literature evaluating cost of capital estimates reports that analysts might be exposed to incentives that result in little effort exercised in the discount rate estimation process. However, most evidence is based on surveys with low number of respondents, which does not allow for robust testing.

This paper explores a sample of 153,555 analysts' implicit market risk premium estimates, derived from publicly available price targets (I/B/E/S). We use the residual income and the CAPM model to backout the implicit market risk premium, obtaining an average of 5.15% between 2010 and 2019, matching other authors' findings (Fernandez, P. 2010-2019).

We further find strong evidence that analysts who provide earnings overestimations tend to use a significantly larger market risk premium (+0.1 p.p.). Our approach overcomes some of the drawbacks associated with previously published work (survey responses), which does not analyse a sufficiently large number of analysts' estimates and, most of the time, suffer from selection bias. Although not inferring causality, we contribute with robust evidence on the hypothesis that analysts may attenuate the impact of overly confident earnings forecasts on the price target by using heftier discount rates.

Informal discussions tend to point out that analysts might produce aggressive earnings forecasts to establish and maintain stable and long-lasting relationships with the companies for which the estimates are performed. These relationships can contribute to future partnerships, providing increased deal flow for the brokerage firm where the analyst is employed. Simultaneously, the MRP and the discount rate are fairly technical concepts that are not very transparent, which would allow analysts to manipulate them and offset the impact of aggressive forecasts on the price target. The evidence found in this paper supports the previous hypothesis, which, proven right, raises concerns on whether analysts' estimates constitute reliable sources of information for investors.

Finally, we take advantage of having calculated a large sample of analysts' market risk premium estimates and address market ambiguity and disagreement. We provide solid evidence that dispersion in analysts' MRP estimates is strongly associated with the size of the premium (coefficient of 0.8). Furthermore, we document that previously used uncertainty measures (disaccord in earnings forecasts) explain little to no variation of the MRP. As such, we propose that systematic disagreement represents a better proxy for ambiguity.

Future work may employ other methods to estimate the market risk premium and observe whether similar results are obtained. Although accepted by most literature, the residual income is not amongst the most commonly used valuation models, and consequently, some error might be present in the overall size of the estimates obtained. Nevertheless, it is essential to remark that the conclusions drawn in this paper are based on the variation between MRP estimates and not on their actual value. Moreover, subsequent work can build on the evidence found on cross-sectional variation and analyse specific analysts across time, observing cost of capital and market risk premium adjustments.

Finally, future research may explore and consolidate systematic disagreement, measured by the dispersion in MRP estimates, as an adequate proxy for market ambiguity, through the comparison with other commonly used metrics.

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Appendix

Appendix 1

"On March 27th, 2017, nearly a month after helping Snap Inc. raise $3.4 billion in an IPO, Morgan Stanley published its first equity research report on the firm and gave it a target price of $28.00. A day later, the bank issued a revised report correcting tax calculation errors, which reduced the projected cash flows by a total of nearly $5 billion. In spite of this correction, the bank did not change its target price, preferring instead to reduce its CoE from 9.9% to 8.1%. While the change in CoE could have been innocuous, there were clear incentives for Morgan Stanley to change its discount rate, as otherwise the bank would not have been able to justify a buy recommendation or issue a target price comparable to peers" (Balakrishnan, Shivakumar, and Taori 2020).

Appendix 2

Even though the I/B/E/S Actuals database contains more than 100,000 yearly price target forecasts, given that observations were only considered if the analyst provided a price target and earnings and book value forecasts for (at least) fiscal years 1 and 2, the sample was severely reduced to a total of 153,555 observations. Table 7 portrays detailed information about the sample on a yearly basis.

Year	Observations	Nr. Analysts	Nr. Companies
2010	11,232	1,408	423
2011	14,565	1,741	435
2012	14,335	1,698	446
2013	15,152	1,708	461
2014	14,948	1,644	490
2015	16,654	1,690	497
2016	17,063	1,594	479
2017	16,075	1,561	466
2018	17,476	1,504	457
2019	16,055	1,455	426
Total	153,555	-	-

Table 7: Yearly information about sample used

Appendix 3

Companies were allocated to 8 different industry groups based on SIC codes. This variable was used as a company control variable, replicating the approach followed by Hutira (2016).

Group	SIC code	Description
1	0100-1799	Agriculture, Forestry and Fishing, Mining and Construction
2	2000-3999	Manufacturing
3	4000-4999	Transportation, Communications, Electric, Gas and Sanitary service
4	5000-5199	Wholesale Trade
5	5200-5999	Retail Trade
6	6000-6799	Finance, Insurance and Real Estate
7	7000-8999	Services
8	Other	Other

Table 8: Industry classification used as a company-control variable

Appendix 4

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
Market Risk Premium *(mrp)*	153,555	0.0518	0.0288	0.0105	0.1869
Main independent variable					
Forecast error *(ferror)*	153,555	-0.0016	0.2254	-0.5451	0.6667
Analyst Controls					
Boldness *(bold)*	153,555	0.1343	0.1106	0.0000	0.4687
Top decile broker *(blg)*	153,555	0.1045	0.3059	0	1
Experience *(lnexper)*	153,555	4.7779	1.3355	0.0000	5.5215
Companies followed *(cmpflw)*	153,555	19.1229	8.1772	1	82
Industries followed *(indflw)*	153,555	2.9627	1.3607	1	8
Company Controls					
Market Capitalization	153,555	10.2932	0.5017	8.3244	11.9292
Market-to-Book ratio	153,555	6.5963	28.2472	0.0007	1,257.5830

Notes: The values illustrated correspond to statistics of the entire sample, instead of yearly averages and st. dev., as presented in previous tables.

Table 9: Descriptive statistics of dependent, independent, and control variables

The market risk premium is measured in percentage points; The forecast error is measured in percentage points; Boldness is measured in percentage points; Top decile brokerage firm is a dummy variable; Experience was retrieved in integer units and, afterward the natural logarithm was applied; Companies and Industries followed are measured in integer units; Market capitalization was retrieved in dollars, and after that, the natural logarithm was applied; Market-to-Book ratio has no particular measurement scale.

Appendix 5

Table 10 illustrates the correlation between the cost of equity (R_e), the market capitalization, and the market-to-book ratio (M/B) using all 153,555 observations.

Pearson Corr.	R_e	*Mkt Cap*	*M/B*
R_e	1.000		
Mrk Cap	-0.029	1.000	
M/B	-0.046	0.070	1.000
Observations	153,555		

Table 10: Pearson correlation matrix for variables cost of equity (R_e), market capitalization (Mkt Cap), and market-to-book ratio (M/B)

According to the Fama-French 3-factor model, the expected return of a stock (cost of equity) is negatively correlated to both the size of the firm (small-cap firms tend to overperform) and the M/B ratio (value stocks tend to overperform) (F. Fama and K. French 1993). We find negative correlation between the cost of equity and the firm's market value (-0.03). The same happens for the market-to-book ratio, with a correlation coefficient of -0.05. Our results seem to follow the 3-factor model proposed by Fama-French (F. Fama and K. French 1993).

Appendix 6

Table 11 documents the average proportion of the price target (every year) explained by each of the residual income formula components (Equation 4).

Year	**BPS_a**	**5y explicit forecast**	**Terminal value**
2010	43.82%	10.72%	45.46%
2011	46.48%	7.49%	46.03%
2012	45.19%	7.06%	47.75%
2013	43.76%	5.32%	50.92%
2014	41.48%	7.85%	50.67%
2015	46.25%	10.36%	43.39%
2016	50.51%	6.01%	43.48%
2017	38.28%	6.91%	54.82%
2018	41.29%	7.32%	51.38%
2019	46.61%	7.84%	45.55%
Average	44.37%	7.69%	47.94%

Table 11: Average proportion of price target explained by each of the components of the residual income model, on a yearly basis

As illustrated above, on average, the terminal value represents *c.* 48% of the price target. Although still a significant fraction, it is substantially lower than the typical results obtained through the dividend growth model. Claus and Thomas (2001) used both models and found that the terminal value explains *c.* 85% of the price when using the dividend growth model, compared to *c.* 42% when using the residual income model.

The experiment illustrates the main advantage of using the residual income method. By introducing the reported book value of equity, we attribute less relevance to the terminal value, which is mostly based on uncertain long-term assumptions.

Appendix 7

Table 12 presents the decomposition of the standard deviation found in each year's MRP estimates.

Year	St. Dev_{mrp}	St. Dev_{ca}	St. Dev_{wa}
2010	2.71%	2.34%	0.74%
2011	2.59%	2.13%	0.87%
2012	2.93%	2.49%	0.78%
2013	2.61%	2.07%	0.83%
2014	2.38%	1.85%	0.78%
2015	3.03%	2.09%	0.82%
2016	3.05%	2.12%	0.84%
2017	2.81%	2.10%	0.83%
2018	3.02%	2.33%	0.87%
2019	2.97%	2.44%	0.80%
Average	2.81%	2.20%	0.82%

Notes: The two components (St. Dev_{ca}, St. Dev_{wa}) estimated do not have to sum up to the total standard deviation (St. Dev_{mrp}) as this does not represent a mathematical decomposition.

Table 12: Market risk premium standard deviation decomposition on a yearly basis

St. Dev_{mrp} is the standard deviation of the market risk premium estimates measured each year. St. Dev_{ca} (cross-analyst dispersion) is the standard deviation found between analysts' average market risk premium estimates. St. Dev_{wa} (within-analyst dispersion) is the yearly average standard deviation found between observations from the same analyst.

The high variability found in our sample is mostly driven by cross-analyst dispersion (differences in estimates provided by different analysts). However, we also observe some dispersion in observations entitled to the same analyst. One possible explanation for this dispersion may be that analysts perform estimations for different companies and dates, meaning they might adjust MRP parameters throughout the year.

Appendix 8

Tables 13 and 14 present the results from simulating samples using three different beta estimation methods (Bloomberg adjusted, 5-year and 10-year historic price data). The betas were calculated for all companies at each estimation date and randomly assigned to the observations. After that, we used the CAPM model to estimate the MRP.

Year	MRP	MRP_{R1}	MRP_{R2}	MRP_{R3}
2010	4.369%	4.433%	4.430%	4.428%
2011	4.575%	4.604%	4.605%	4.603%
2012	5.619%	5.648%	5.648%	5.650%
2013	4.823%	4.819%	4.821%	4.820%
2014	4.623%	4.603%	4.603%	4.605%
2015	5.189%	5.164%	5.168%	5.165%
2016	5.529%	5.533%	5.532%	5.528%
2017	5.036%	5.032%	5.029%	5.031%
2018	5.729%	5.669%	5.670%	5.667%
2019	5.963%	5.807%	5.808%	5.806%
Average	5.145%	5.131%	5.131%	5.130%

Table 13: Side-by-side comparison between main sample results (MRP) and randomized samples using three different estimation methods for the beta to include in CAPM

Year	St. Dev.	St. Dev_{R1}	St. Dev_{R2}	St. Dev_{R3}
2010	2.708%	2.717%	2.696%	2.693%
2011	2.590%	2.480%	2.484%	2.475%
2012	2.931%	2.780%	2.775%	2.780%
2013	2.611%	2.483%	2.488%	2.488%
2014	2.380%	2.267%	2.271%	2.267%
2015	3.035%	3.023%	3.023%	3.015%
2016	3.049%	3.122%	3.121%	3.112%
2017	2.815%	2.890%	2.879%	2.884%
2018	3.023%	3.020%	3.029%	3.013%
2019	2.967%	2.820%	2.816%	2.816%
Average	2.811%	2.760%	2.758%	2.754%

Table 14: Side-by-side comparison between main sample standard deviation (St. Dev.) and randomized samples using three different estimation methods for the beta to include in CAPM

As illustrated above (Table 13), the results obtained from repeating this exercise three times (MRP_{R1}, MRP_{R2}, MRP_{R3}) were quite similar to our main sample (using exclusively beta estimated through 5-year historical data). Furthermore, the overall variability of the MRP estimates is also comparable (Table 14), which confirms the robustness of our sample.

Appendix 9

Table 15 reports the average effect on the price target caused by changes in the market risk premium (through the discount rate) and the forecast error (through first-year earnings forecast). As expected, the price target is much more sensitive to changes in the market risk premium than to changes in the forecast error.

ΔMRP	0.10%	0.50%	1.00%
ΔPrice target	-1.54%	-6.91%	-12.39%
ΔForecast error	1.00%	5.00%	10.00%
ΔPrice target	0.06%	0.29%	0.58%

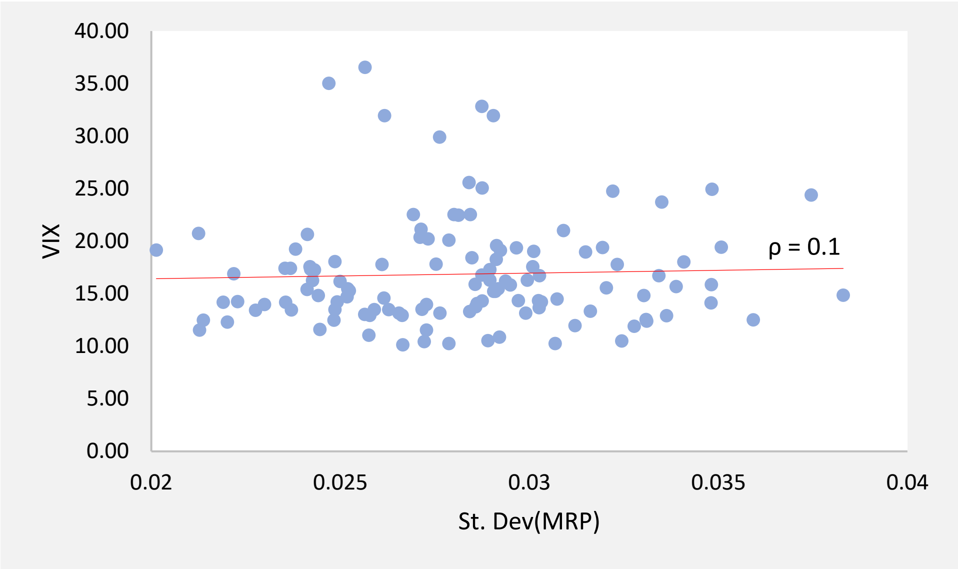
Table 15: Average effect on the price target caused by changes in the market risk premium (through the cost of equity) and the forecast error (through first-year eps forecast)

A 1.p.p change in the market risk premium has an absolute effect *c.* 200x larger than a 1 p.p. change in the forecast error. In other words, to compensate the impact on the price target caused by a 1 p.p. increase in the forecast error, it would be required to increase the market risk premium by *c.* 0.005% (1% * $\frac{0.06\%}{12.39\%}$). Hence, the forecast error coefficient obtained in the regression analysis seems reasonable.

Appendix 10

Graphic 1 (next page) documents the relationship between the monthly CBOE Volatility Index (VIX) and the monthly standard deviation of our sample's market risk premium estimates.

We find small positive correlation (0.1), suggesting that systematic disagreement does not fully capture aggregate volatility (risk). Should this result be confirmed for larger samples, it may be the case that systematic disagreement, measured by the dispersion in analysts MRP estimates, represents a good proxy for ambiguity. Future work should test this hypothesis by comparing this measure with other ambiguity proxies.



Graphic 1: Relationship between VIX (CBOE volatility index) and systematic disagreement, measure by the st. dev. in market risk premium estimates, on a monthly basis

Appendix 11

Table 16 outlines the correlation between the yearly average MRP obtained and the real GDP growth. Our sample exhibits positive correlation between MRP and real GDP growth (0.1).

Year	MRP	Real GDP growth
2010	4.37%	2.56%
2011	4.57%	1.55%
2012	5.62%	2.25%
2013	4.82%	1.84%
2014	4.62%	2.53%
2015	5.19%	3.08%
2016	5.53%	1.71%
2017	5.04%	2.33%
2018	5.73%	3.00%
2019	5.96%	2.16%
Average	5.15%	2.30%

Table 16: Estimated implicit market risk premium and real GDP growth on a yearly basis

This result conflicts with the hypothesis that investors require a substantially higher return on risky assets during recessions, translating into an increased market risk premium. The latter theory has been tested several times, resulting in exhausting evidence on the counter-cyclicality of the MRP (Harvey 1989; Li 2001; Paoli and Zabczyk 2009; Gourio 2012). Although the correlation found in our sample does not follow previous literature, the market risk premium estimate in this paper represents the value implied by individual analysts' forecasts. As Bancel and Mittoo (2014) documented, analysts and other finance professionals might abstain from making significant adjustments to their discount rate inputs even if, according to finance theory, this would be the right approach[14]. Furthermore, it is important to remark that the low number of periods under observation (10 years) does not allow for a robust analysis.

[14] Bancel and Mittoo (2014) reported that 54% of the analysts surveyed did not make any significant adjustments to discount rates used during the 2008 financial crisis