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Earnings Yield and Expected Stock Returns: a Meta-Analysis

Master's thesis

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Declaration of Authorship

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Prague, July 31, 2024

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Abstract

This thesis conducts a meta-analysis to investigate the relationship between earnings yield and expected stock returns. By compiling and analysing data from numerous empirical studies, we aim to determine the extent to which earnings yield can serve as a reliable predictor of stock returns. Several statistical tests indicate the existence of publication selection bias and imply a reduced effect size in relation to earlier findings. Additionally, we employ Bayesian Model Averaging to account for heterogeneity across different studies. Our findings suggest that while earnings yield significantly affects stock returns, this effect is often overstated due to publication bias. The results underscore the importance of considering publication bias in financial meta-analyses and provide a more nuanced understanding of the earnings yield-stock return relationship.

JEL Classification	D53 , G12 , G14 , G15
Keywords	stock returns, earnings yield, meta-analysis, publication bias
Title	Earnings Yield and Expected Stock Returns: a Meta-Analysis

Abstrakt

Táto diplomová práca vykonáva metaanalýzu s cieľom preskúmať vzťah medzi výnosom zo ziskov a očakávanými výnosmi akcií. Kompiláciou a analýzou dát z mnohých empirických štúdií sa snažíme určiť, do akej miery môže výnos zo ziskov slúžiť ako spoľahlivý prediktor výnosov akcií. Niekoľko štatistických testov naznačuje existenciu výberového publikačného skreslenia a implikuje zníženie veľkosti efektu v porovnaní so skoršími zisteniami. Navyše používame Bayesovské modelové spriemerovanie na zohľadnenie heterogenity medzi rôznymi štúdiami. Naše zistenia naznačujú, že zatiaľ čo výnos zo ziskov má významný vplyv na výnosy akcií, tento efekt je často nadhodnotený kvôli publikačnému skresleniu. Výsledky zdôrazňujú dôležitosť zohľadnenia publikačného skreslenia vo finančných metaanalýzach a poskytujú komplexnejšie pochopenie vzťahu medzi výnosom zo ziskov a výnosmi akcií.

Klasifikácia JEL	D53 , G12 , G14 , G15
Kľúčové slová	výnosy akcií, výnos zo ziskov, meta-analýza, publikačné skreslenie
Názov práce	Profitabilita Spoločností a Očakávaný Výnos Akcií: Meta analýza

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Acronyms

AMEX American Stock Exchange

BMA Bayesian Model Averageing

BE Between Effects

BMA Bayesian Model Averageing

CAPM Capital Asset Pricing Model

CRSP Center for Research in Security Prices

EP Earnings-Price

FAT Funnel Asymmetry Test

FE Fixed Effects

IV Instrumental Variable

NASDAQ National Association of Securities Dealers Automated Quotations

NYSE New York Stock Exchange

OLS Ordinary Least Squares

PET Precision Effect Test

PIP Posterior Inclusion probability

PMP Posterior Model Probability

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

SE Standard Error

SUR Seemingly Unrelated Regression

VIF Variance Inflation Factor

WAAP Weighted Average of Adequately Powered

WLS Weighted Least Squares

Master's Thesis Proposal

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Proposed topic	Earnings Yield and Expected Stock Returns: a Meta-Analysis

Motivation The topic of stock returns has been popular among researchers for a long time. Several theories on stock selection were developed. One of the oldest and most prominent is a portfolio selection by Markowitz (1952), who relied on return-variance optimization of investors. He is the author of the so-called capital allocation line, which is a linear combination of an investment into an optimal risky portfolio and a risk-free asset that creates the best trade-off between return and risk. Based on the work of Markowitz (1952), Sharpe (1964), under a strict set of assumptions developed a capital asset pricing model. The capital asset pricing model states that the only source of the systemic risk of a stock is a correlation of its return with the return of the market. The idea is that a stock with a higher correlation with the market inflates more the variance of the overall portfolio that consists of stocks available on the market and investors as return-variance optimizers want to be rewarded. As a result, "market beta", which is a measure of the relationship between returns of the stock/portfolio and returns of the market is the only factor affecting stock returns. However, several studies analyzed the power of "market beta" in explaining a variation of stock returns in cross-sections. Relatively poor results lead to the discovery of several factors that might explain the variability of cross-sectional stock returns. The most prominent factors are the size of the firm (Banz, 1981), book-to-market ratio (Fama and French, 1992) and momentum (Carhart, 1997). As the number of available factors was rising, their multivariate explanatory power was difficult to assess and interpret, because the industry-wide conduct was to create portfolios selected by cutoffs in quantiles of factors. This portfolio sort was appropriate for univariate or bivariate analysis, but the limited number of stocks and required minimum number of stocks in each portfolio to diversify away firm-specific risks made the portfolio sort analysis not feasible. An answer to this issue is Fama-MacBeth regression (Fama and MacBeth, 1973), which consists of regressing stock returns on factors at each timeframe (cross-sectional regression) and then computing the means of time series of estimated coefficients. Because of the expected presence of heteroskedasticity and autocorrelation in the time series of estimated coefficients, Newey-West standard errors are computed (Newey and West, 1987). My diploma thesis will focus on the earnings-price ratio factor discovered by Basu (1983). The existing literature failed to deliver a holistic picture of the impact of the earning-price ratio on stock returns. Bali (2008) showed a significant explanatory power of the earnings-price factor on cross-sectional variations of stock returns. On the other hand, Chan et al. (1991) showed that the explanatory power of the earning-price ratio is statistically significant only for some model specifications and in presence of the book-to-market ratio in the model, the earning-price ratio becomes statistically insignificant.

Hypotheses

Hypothesis #1: The literature estimating the impact of the earning-price ratio on stock returns is affected by publication selection bias.

Hypothesis #2: The publication bias increases the mean of reported impact.

Hypothesis #3: The heterogeneity of collected estimates is driven by a period of time and geographic region.

Methodology The most important task is the collection of the data. Soundness and accuracy will play a crucial role in further analysis. The effect of earnings-price ratios on expected returns can be represented in various forms. The studies may present expected earnings in percentage points or in relative terms. Moreover, several studies take a logarithmic transformation of the earnings-price ratio to better fit the regression line or the distribution of the independent variable. If the data issues specified above were ignored and not corrected for, both publication selection bias analysis and heterogeneity analysis would not be valid.

The publication selection bias arises when researchers prefer to report some results in favour of the others. Researchers may choose to publish only results that may be easier to interpret and defend, based on the theoretical background of the area of interest. Another source of publication selection bias may be a preference to report statistically significant results. However, the results that are not reported may critically change the overall picture the previous research gives us on the problem. In my diploma thesis, I expect to encounter a positive publication selection bias, because of the combination of relatively low significance levels of estimated coefficients of earnings yield in previous research and, based on the theory, an expectation of the estimated coefficients to be positive (higher earnings yield $->$ higher expected returns). I will firstly unfold publication selection bias more informally by funnel plot (Egger et al., 1997) that plots the relationship between estimated effect (x-axis) and the precision of estimated effect (y-axis). If the publication selection bias is not present, the plot is symmetric and funnel-shaped. However, just observing the shape of the plot is not statistically interpretable. Hence, I will apply different specifications of the test of funnel plot asymmetry defined by (Stanley, 2005), which measures the correlation between the estimate and standard error. However, these tests assume the relationship to be linear which may not be valid. Therefore, I will apply more robust approaches, such as: "a kinked Meta-Regression model" by Bom & Rachinger (2019), "a p-hacking" by Ellliot et al. (2022), "a simple weighted average" by Ioannidis et al. (2017), etc.

The heterogeneity of collected estimates is expected due to the different model specifications, various geographic locations, the development level of the stock exchange where stocks are traded, length of the study period, publication characteristics etc. As a source of potential factors affecting the variability of estimated coefficients, I take the research of Asthakov et al. (2019), who conducted a meta-analysis on the effect of the size of companies on expected stock returns. However, we do not know in advance which factors are important. Due to the great number of potentially statistically significant explanatory variables, the OLS method is not feasible, as the inclusion of all factors inflates variances of estimated parameters. Therefore, we will employ Bayesian Model Averaging (Steel, 2017) that effectively deals with model uncertainty and plenty of factors as a benchmark analysis of heterogeneity.

Expected Contribution I will conduct a quantitative survey of research articles estimating the impact of the earnings-price ratio on stock returns. As far as I know, no meta-analysis of this factor has been done so far. I expect the publication selection bias to drive the effect of the earnings-price ratio on stock returns upwards. The estimates corrected for publication selection bias may be used in decision making during portfolio selection.

Outline

1. Introduction: Motivation, contribution and findings.
2. Related literature: Introduction to Markowitz portfolio theory, Capital asset pricing model and Fama-MacBeth regression.
3. The dataset: The process of collection of the data. Summary statistics of the data methods, including the funnel asymmetry test, precision effect test, and multilevel variants of these regressions.
4. Inspection of publication selection bias: Potential causes of publication selection bias. Visual inspection of publication selection bias (funnel plot). Linear and non-linear tests for publication selection bias.
5. Heterogeneity of estimates: I will analyze the heterogeneity of collected estimates across studies and try to find causes if present.
6. Conclusion: I will summarize the results and state implications for future research and decision making.

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Chapter 1

Introduction

Investing in stock markets has always been a pivotal area of financial research. Individual and institutional investors continuously strive to identify optimal strategies that maximise returns while minimising risk. The quest for such strategies has led to the development and refinement of various financial theories and models over the decades. Among these, the relationship between earnings yield and stock returns has emerged as a critical area of interest for academics and practitioners. The earnings yield, defined as the inverse of the price-earnings ratio, is a fundamental metric used by investors to evaluate the profitability and attractiveness of a stock. A higher earnings yield indicates that a company is generating significant earnings relative to its market price, suggesting that the stock might be undervalued and potentially offer higher returns. Despite its apparent simplicity and widespread use, the empirical relationship between earnings yield and stock returns has been the subject of extensive debate and research, with mixed findings reported across different studies and market conditions. The foundational theories in finance, such as Markowitz's (Markowitz 1952) portfolio theory and the Capital Asset Pricing Model (CAPM) (Sharpe 1964), have laid the groundwork for understanding how different factors influence stock returns. Markowitz's portfolio theory introduced the concept of optimising the return-variance trade-off in investment portfolios, while the CAPM posited that the expected return of a security is directly related to its systematic risk, measured by its market beta. However, subsequent empirical studies, such as those by Fama & French (1992), have shown that the CAPM's market beta alone does not fully explain the cross-sectional variation in stock returns, prompting the exploration of additional factors, including size, book-to-market ratio, and earnings yield. The pioneering work of Basu (1977) challenged the efficient market hypothesis by demonstrating that stocks with lower price-earnings ratios tend to yield higher returns, suggesting that the market might not fully incorporate earnings information into stock prices. This finding sparked a plethora of subsequent research aimed at understanding the robustness and underlying mechanisms of the earnings yield effect across different markets, periods, and economic conditions. However, these studies have produced heterogeneous results, with some confirming the predictive power of earnings yield on stock returns. In contrast, others attribute the observed effects to other confounding factors or question their statistical significance.

Given the mixed evidence and the potential for publication bias in financial research, a comprehensive meta-analysis is conducted to synthesise the existing literature and provide a more definitive assessment of the relationship between earnings yield and stock returns. By aggregating results from multiple studies, a meta-analysis offers a robust approach to addressing inconsistencies and identifying patterns that may not be apparent in individual studies. Moreover, it allows for the examination of potential moderators and the evaluation of publication bias, thereby enhancing the reliability of the findings. This thesis aims to conduct a rigorous meta-analysis of the empirical literature on the relationship between earnings yield and expected stock returns. Specifically, we will compile data from numerous studies, apply statistical techniques to address publication bias and employ Bayesian and Frequentist model averaging to account for heterogeneity across studies. Our objectives are threefold: first, to quantify the overall effect of earnings yield on stock returns; second, to identify and control for potential sources of publication bias; and third, to explore the economic significance of the earnings yield effect in different market contexts. We find the evidence for publication bias that significantly reduces the effect of earnings yield on expected stock returns. Moreover, this effect seems to be positively affected by survivorship bias and utilisation specific estimation technique. On the other hand, earnings yield effect is reduced in developed countries.

The structure of this thesis is as follows: Chapter 2 reviews the relevant literature, providing a theoretical and empirical backdrop for our analysis. Chapter 3 details the data collection process, including the literature search and the criteria for study inclusion. Chapter 4 discusses the methods used to detect and adjust for publication bias. Chapter 5 presents the results of our meta-analysis, including the application of model averaging and the interpretation of our findings. Finally, Chapter 6 concludes with a summary of our key findings and their implications for financial theory and practice. By addressing the gaps and inconsistencies in the existing literature, this thesis aims to contribute to a deeper understanding of the earnings yield-stock return relationship and to provide valuable insights for both academic researchers and practitioners in the field of finance.

Chapter 2

Literature Review

Research has long focused on investments. Specifically, wealth managers and the general public allocate resources to find an optimal strategy for their specific cases. Moreover, countless theories have been developed to understand how the market functions. In this chapter, we will move from Markowitz's portfolio theory and capital asset pricing model (CAPM) to factor models that are closely related to our thesis's topic.

2.1 Capital asset pricing model and market beta

According to Markowitz (1952), investors try to optimise the return-variance of their portfolios. Under several assumptions, such as the rationality of investors, unlimited access to information and risk aversion, he developed the capital allocation line, a linear combination of an investment into an optimal risky portfolio and a risk-free asset that creates the best trade-off between return and risk. Sharpe (1964) used the work of Harry Markowitz as a starting point for developing the CAPM, which states that the stock's systematic risk is related to the correlation between its returns and the market portfolio's returns. A higher correlation among stocks generally leads to a higher total variation of the portfolio's returns, under the assumption of investors' risk aversion, should be compensated by a higher expected return. As a result, the expected return of an asset shall be positively correlated with the asset's systematic risk. Systematic risk is usually approximated by market beta. Market beta measures individual assets' volatility compared to the stock market index. It is measured on past returns of securities. The decision about the length of the time interval and frequency of measurement is still a matter of research and a trade-off between accuracy, noisiness and relevancy of the data. A market beta of more than 1 implies that the security is more volatile than that of a relevant stock market index. Because of that, an investor shall require a higher expected return compared to a security with a lower market beta. According to the CAPM, there should be no other factors that would help to explain the variation in stock returns.

2.2 Size and other factors

Nevertheless, the market beta itself did not explain much of the return variation. Additionally, Lakonishok & Shapiro (1986) and Fama & French (1992) found that market beta was statistically insignificant in explaining variation in the cross-section of return in more recent periods. Specifically, Fama & French (1992) analysed market beta in the period spanning from 1963 to 1990. Moreover, further research showed that other factors have the power to explain a variation in the cross-section of returns. The most prominent factor is market capitalisation, discovered by Banz (1981). Due to the specific right-skewed distribution of market capitalisation of publicly traded companies, the logarithmic transformation of market equity is usually used in research. Banz (1981) examined the period spanning from 1938 to 1976 and found that a stock of small companies yields, on average, higher risk-adjusted returns compared to companies with large market capitalisation. However, he does not answer whether the "size effect", as he refers to it, is the main factor affecting stock returns or it is only a proxy for other true factors correlated with the company's market capitalisation. He also admits that there is no theoretical background for such an effect. Astakhov *et al.* (2019) conducted a meta-analysis focusing on the size effect and found that after correcting for publication bias, the size effect is, on average, almost three times smaller as is reported in the relevant literature.

As other important factors are considered price-earnings ratio (Basu 1977), debt-to-equity ratio (Bhandari 1988), book-to-market ratio (Fama & French 1992), return momentum (Carhart 1997) and market liquidity (Pástor & Stambaugh 2003). Harvey *et al.* (2016) collected 316 factors that had been analysed in an attempt to explain the cross-section of expected stock returns. He argued that given the fact that there are a lot of potential factors and data mining techniques, many are statistically significant purely by chance.

2.3 Earnings-price ratio

In his pioneering work, Basu (1977) questioned the efficient market hypothesis by analysing the performance of stock returns of groups of securities divided based on the price-earnings ratio. As the majority of stock market researchers, Basu (1977) used the Center for Research in Security Prices (CRSP) and COMPUSTAT as a source of information about both listed and delisted companies on the New York Stock Exchange (NYSE). He grouped securities by their respective price-earnings ratio into five groups. However, companies with negative earnings (the issue that offers multiple ways to be treated) were included in the highest price-earnings ratio quantile or discarded entirely. The analysis covered 14 years (April 1957 - March 1971), and the recreation process of 5 groups of portfolios was based on published earnings up until March of the respective year. Finally, Basu (1977) compared the annual returns of their artificial portfolios with surprising results. On average, two portfolios with the lowest price-earnings ratio offered higher returns (16.3 percent and 13.5 percent on annual returns) than the portfolios with the highest price-earnings ratios (9.3 percent). It can be argued that the return of this portfolio was affected by the inclusion of companies with negative earnings. However, results were unaffected by the withdrawal of such companies from the analysed subset.

Nonetheless, even this difference in returns may have been explained by higher systematic risk posed by low price-earnings ratio companies. On the contrary, a low price-earnings ratio portfolio indicated a lower market beta (0.99) compared to a market beta of high price-earnings portfolios (1.11). Moreover, low price-earnings stock exhibited a superior Sharpe ratio (Sharpe 1966):

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}\ . \tag{2.1}$$

Where R_p states the return of the portfolio, R_f is a risk-free rate (usually approximated by United States treasury bills). The high Sharpe ratio signals that the portfolio exhibits high returns subject to the volatility of its returns. Based on his paper, Basu (1977) stressed that the price-earnings ratio should attract investors' attention while forming a portfolio.

Based on the potentially groundbreaking scientific work of Basu (1977), hundreds of research papers were trying to analyse the impact of price-earnings ratio on stock returns in different stock exchanges, history periods and continents using multiple analysing tools ranging from quartile analysis to complex machine learning algorithms. However, the most common analysis, which is relatively simple to implement and interpret, became Fama-MacBeth regression (Fama & MacBeth 1973) that is explained in Section 2.4. Contrary to Basu (1977), most researchers proxy earnings yield by an earnings-price ratio, which is an inverse of the price-earnings ratio. Consequently, in our thesis, we declare the earnings-price ratio as a variable of interest.

Compared to Basu (1977), who opted to view his findings as a manifestation of market inefficiency, Ball (1978) pointed out that market efficiency tests frequently involve assessing both the efficient market hypothesis and a specific equilibrium relationship simultaneously. Therefore, certain anomalies previously attributed to market inefficiency could be caused by the incorrect pricing model specification. Moreover, Reinganum (1981) concludes that CAPM misspecification should not be viewed as a market inefficiency but as an omission of risk factors in the model. Moreover, after controlling for size, the effect of earning-price ratio disappeared. He states that these two anomalies appear to be correlated with a common set of missing factors, which appear to have a stronger association with company size than the earnings-price ratio.

2.4 Fama-Macbeth regression

In univariate and bivariate analysis, portfolio sorting was a common practise in research. The stocks were sorted according to the factor, and historical averages were analysed. However, as the number of potential factors was rising, so was the need for another procedure because there was a requirement for a minimum number of stocks in one sorted group to minimise the impact of stock-specific factors and noise. To answer this issue, a two-step procedure developed by Fama & MacBeth (1973) is commonly used. The procedure (or its variations) is as follows. A set of T cross-sectional regressions are estimated:

$$R_{it} = \beta_{0t} + \beta_{1t} \cdot X_{1,it} + \beta_{2t} \cdot X_{2,it} + ... + \beta_{nt} \cdot X_{n,it} + \epsilon_{it} \ ; \ i = 1, ..., N \ . \quad (2.2)$$

Where R_{it} is a return of stock i during time t, β_{0t} is a constant, $X_{1,it}$ up to $X_{n,it}$ are factors 1 to n for firm i at time t and betas are coefficients for specific factors estimated at time t. As a result, we have a time series of estimated coefficient for a constant and each risk factor. Finally, we compute average and standard errors on a time series of estimated coefficients.

Chapter 3

Creating the data set

3.1 Literature search

To collect the studies, we apply a Google Scholar search, a common practice among researchers. We construct a query to find relevant studies: "earnings-price OR e/p) AND (cross-section OR cross OR returns)". We restrict the search according to the relevancy and look through the first 1500 results. We acknowledge that it is a higher number than is a common practice in meta-analysis. The frequency of relevant studies related to the earnings-price ratio is low because of the fact that the earnings-price ratio is only a supportive factor and is very often mentioned only in the related literature section but lacks further analysis.

Another method of gathering primary research is known as "snowballing". Generally speaking, snowballing involves identifying additional sources to incorporate into the meta-analysis by looking through a study's list of references (Wohlin 2014).

We reviewed meta-analyses on how the earnings-price ratio affects future stock returns and found 48 additional studies based on abstracts. Out of 1548 studies, 190 contained an analysis of the earnings-price ratio. As mentioned, most studies deal with the earnings-price ratio only in the related literature section and lack further analysis.

Moreover, a great deal of research analyses the impact of various factors on stock returns by presorting equities according to specific business attributes and comparing the returns of the largest and smallest quintiles of equities. In our thesis, we consider only studies that analyse the earnings-price effect on returns employing some regression technique, producing the coefficient estimate and standard error.

We did not keep studies dealing with the logarithmic transformation of the earnings-price ratio or its inverse (price-earnings ratio). Opposing Astakhov *et al.* (2019), we did not restrict our sample to studies that analyse monthly returns. We also included annual returns to increase the sample size. However, we transformed both annual estimates and respective standard errors (to retain statistical significance) to monthly by the following formula:

$$\begin{aligned} \textit{Earnings-price ratio}' &= \frac{\textit{Earnings-price ratio}}{\textit{Return duration}}, \\ \textit{Standard error}' &= \frac{\textit{Standard error}}{\textit{Return duration}}. \end{aligned} \tag{3.1}$$

We understand that this transformation introduces some level of endogeneity into estimates. Hence, we include the dummy variable indicating annual return in consequent heterogeneity analysis. Moreover, we conduct publication bias tests on two samples (all estimates and monthly estimates only). We consider higher frequencies (i.e., weekly, and daily) as too noisy for this task. On the other hand, for longer periods, the information carried by the factor may not be up to date and hereby not relevant, making analysis inconsistent with monthly/annual returns.

We also include working papers in our analysis. According to Rusnák *et al.* (2013), there is no disparity observed in the extent of selective reporting between economic studies that have been published and those that remain unpublished. The authors contend that this is because both types of research have the same goal of publishing the article, so getting rid of counter-intuitive outcomes is the ultimate goal.

Although the Fama-Macbeth methodology is the most prominent procedure for analysing the effect of factors on the cross-section of stock returns, we do not limit our analysis to this particular approach. Aside from Fama-Macbeth, our dataset includes studies employing pooled regression, various types of panel regressions, or maximum likelihood estimators.

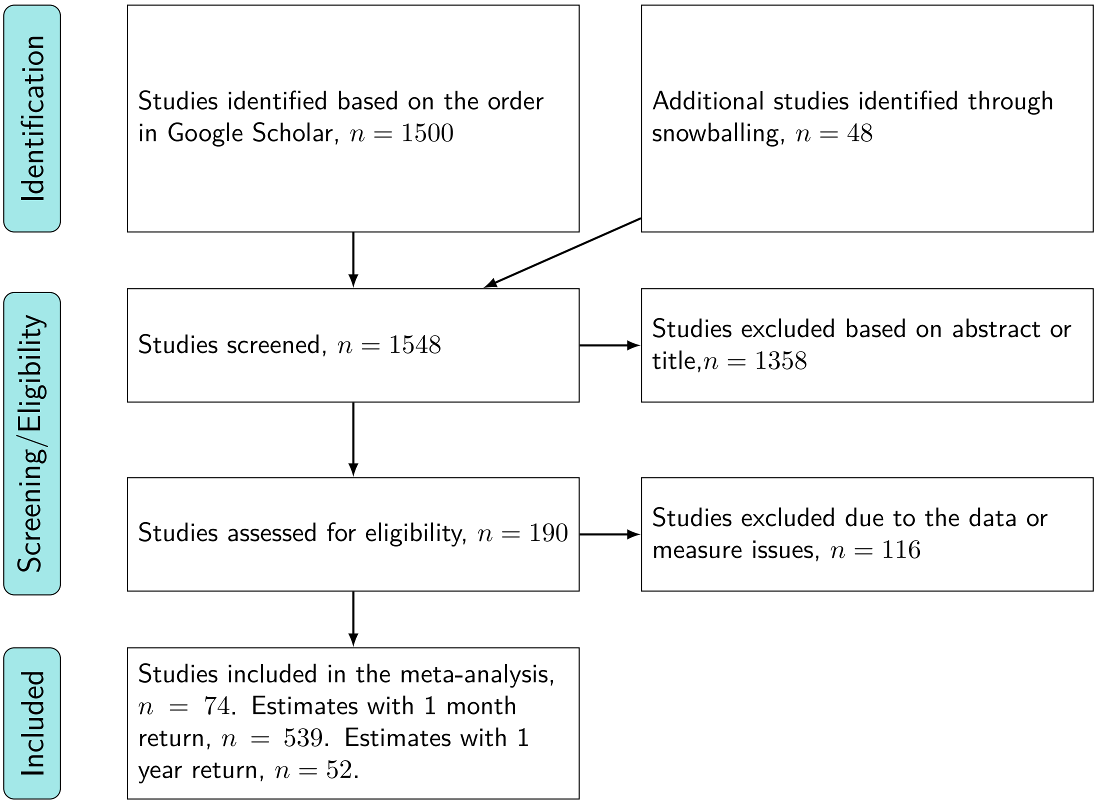
Considering the subsequent methodologies employed in this thesis, studies failing to disclose an effect along with its standard errors were excluded. Moreover, returns and earnings-price ratios may be measured in percentages or relative terms. We chose percentages (for returns) and decimals (for earnings-price ratios) as a benchmark measure for the analysis. Therefore, we needed to transform collected estimates and respective standard errors into a common measure: For example, we multiply both earnings-price coefficients and respective standard errors by 100 when they originate from studies analysing returns in decimals. Table 3.1 shows the transformation of coefficients depending on a measure of earnings-price coefficients and returns. In case we cannot find the measure of either the earnings-price ratio or returns in the study or deduce it from the author's interpretation, we discard the whole study as an incorrect transformation may bias the whole thesis.

Table 3.1: Transformation of collected coefficients

	Returns (Decimal)	Returns (Percentage)
Earnings-Price Ratio (Decimal)	Multiplied by 100	Multiplied by 1
Earnings-Price Ratio (Percentage)	Multiplied by 100000	Multiplied by 100

After applying all filters, we are left with 74 studies and 591 coefficient estimates. We present a thorough synopsis of our sample-gathering process by the PRISMA diagram in Figure 3.1 and a list of included studies in Table 3.2. In addition to the earnings-price ratios and standard errors, we gathered information on estimation methodology, the country's development indicators, the length of the data sample, various stock and publication characteristics and other relevant control variables. Estimates totalling 591 were gathered from 74 studies. More than 70,920 data points were gathered.

Figure 3.1: PRISMA flow diagram



Notes: A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram built in accordance with the identification of studies.

3.2 Data Description

We cautiously reviewed each study to determine which factors best fit our needs. Chapter 5 comprehensively lists all the variables and thoroughly explains the factors that led to selecting the more technical ones. This section will only touch on a few of the common variables' structures. We divided up the explanation of our variable selection in this way to fully support the methods used in subsequent analyses. We shall discuss a handful of the approximately thirty research characterisations gathered for the time being. Table 3.3 shows the summary statistics for the earnings-price ratio, standard error and various publication characteristics. Figures for the earnings-price ratio, t-statistics and standard error are presented after winsorization at a 2 percent level. The mean value of the earnings-price ratio after winsorization is 1.991 (pre-winsorization: 3.881). For comparison, coefficients for the earnings-price ratio estimated by

Table 3.2: Studies included in the analysis

Authors (year)	
Akdeniz *et al.* (2000)	Kim *et al.* (2020)
Andrade & Chhaochharia (2014)	Kish & Myers (2007)
Artmann *et al.* (2012)	La Porta (1996)
Asgharian & Hansson (2002)	Lakonishok *et al.* (1994)
Ashour & Hao (2019)	Lam & Spyrou (2003)
Bai (2011)	Lau *et al.* (2002)
Baik & Park (2003)	Lee *et al.* (2017)
Bali & Cakici (2010)	Leledakis *et al.* (2003)
Bartholdy (1998)	Lev & Sougiannis (1999)
Basiewicz & Auret (2009)	Lin *et al.* (2017)
Brouwer *et al.* (1997)	Liu & Mantecon (2017)
Cai (1997)	Liu *et al.* (2019)
Cakici & Zaremba (2020)	Lyle *et al.* (2013)
Çeliker (2004)	Lyn & Zychowicz (2004)
Cen *et al.* (2006)	Mashruwala *et al.* (2006)
Cen *et al.* (2008)	Miles & Timmermann (1996)
Cen *et al.* (2017)	Mohanty (2002)
Chan *et al.* (1991)	Nittayagasetwat & Vesarach (2005)
Chen *et al.* (2008)	de Peña & Gil-Alaña (2003)
Chen *et al.* (2010)	Penman & Zhu (2014)
Civelekoğlu (1993)	Remmits, D. and Knittel, V. (2015)
Clare *et al.* (1998)	Samarakoon (1997)
Conover *et al.* (2000)	So & Tang (2010)
Dasgupta & Glen (1999)	Soares & Stark (2011)
Davis (1994)	Soud & Konnestad (2018)
Davis (1996)	Strong & Xu (1997)
Desai *et al.* (2004)	Sun (2004)
Doeswijk (1997)	Trigeorgis & Lambertides (2014)
Emin (2018)	Umutlu *et al.* (2021)
Fama & French (1992)	Varga & Brito (2016)
Hahn & Yoon (2016)	Wang & Di Iorio (2007a)
Hou *et al.* (2011)	Wang & Di Iorio (2007b)
Howton & Peterson (1998)	Yang *et al.* (2022)
Howton & Peterson (1999)	Zaremba (2019)
Hu *et al.* (2015)	Zaremba *et al.* (2020)
Lin *et al.* (2020)	Zaremba *et al.* (2021)
Kim (1997)	Zou & Chen (2017)

Notes: This table presents a list of the 74 studies, from which we collect 591 estimates of the relationship between the earnings-price ratio and stock returns that constitute our sample.

Table 3.3: Summary statistics

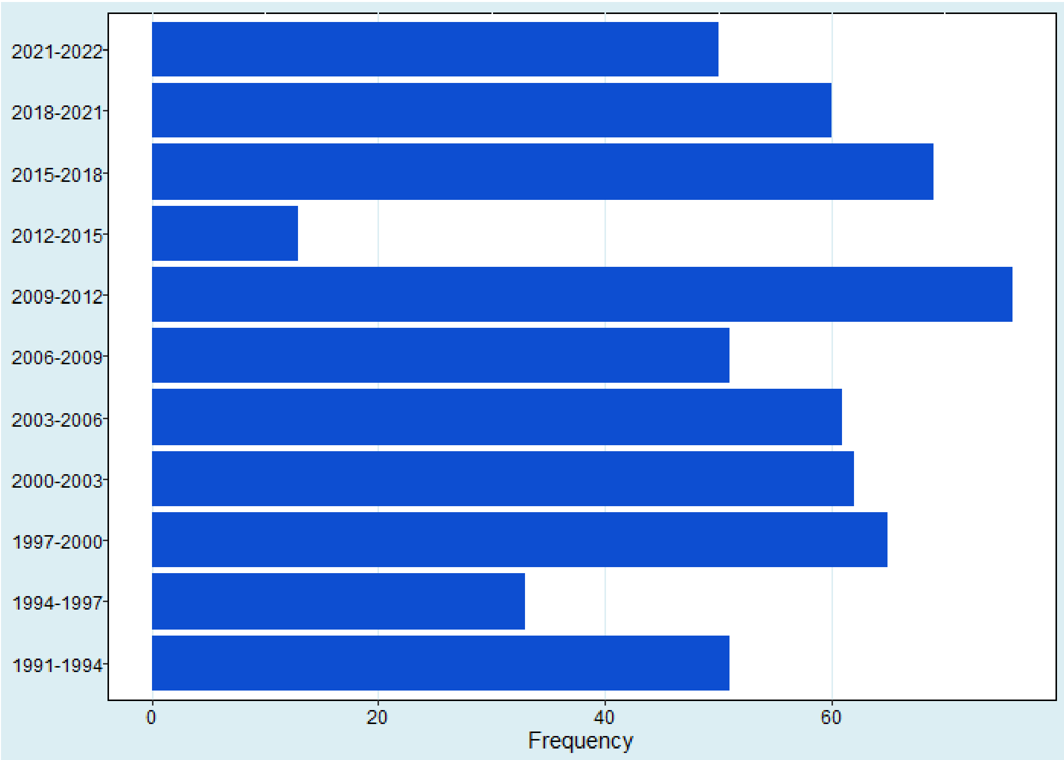
	Mean	**St.Dev**	**Min**	**Max**
Earnings-Price	1.991	4.013	-7.136	15.276
t-Statistic	1.232	1.959	-3.601	4.899
Standard Error	2.249	3.15	0.034	14.790
Start Year	1983.751	12.149	1940	2020
End Year	2002.228	10.672	1962	2021
Nbr.of Observations	188.609	152.097	8	714
Publication Year	2007.074	9.431	1991	2022
Google Scholar	474.098	2177.736	0	24797
Impact Factor	0.3373	0.76	0	3.142
N	591			

Notes: The table above shows the summary statistics of the final dataset. Measures for the earnings-price ratio, t-statistic and standard error are based on winsorised data at 2 percent level.

Fama & French (1992), the most cited study in our sample, range between 0.87 and 4.72. Another well-cited paper by Chan *et al.* (1991) reviewed the relationship between fundamentals and stock returns in Japan with a mean value of the estimated coefficient for the earnings-price ratio of 0.92. Judging by the standard deviation of the earnings-price coefficient in our sample, the literature is quite diverse, and there is no even agreement on the expected sign of the effect. Analysis of the source of such diversity will be subject to heterogeneity analysis. The publication years range from 1991 to 2022, and the average number of Google Scholars citations is 474.098 (observation-level weighting) with a maximum value of 24797 held by Fama & French (1992), which in combination with Basu (1977) is a benchmark study for the majority of studies in our sample. Studies included in our sample cover an interval of 81 years, with Davis (1994) analysing New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) equities from 1940 to 1962 using Moody's Industrial Manuals and CRSP database.

On the other hand, Yang *et al.* (2022) analysed the relationship between the company's fundamentals and stock returns in emerging countries during the pandemic period (2020-2021). Regarding the length of the analysed period, Cakici & Zaremba (2020) investigated the equity index returns of 69 countries during almost six decades. Figure 3.2 shows the number of published estimates in our sample in different periods. It is clear that interest in the fundamental

Figure 3.2: Interest in the empirical relationship of the earnings-price ratio and stock returns is stable over time

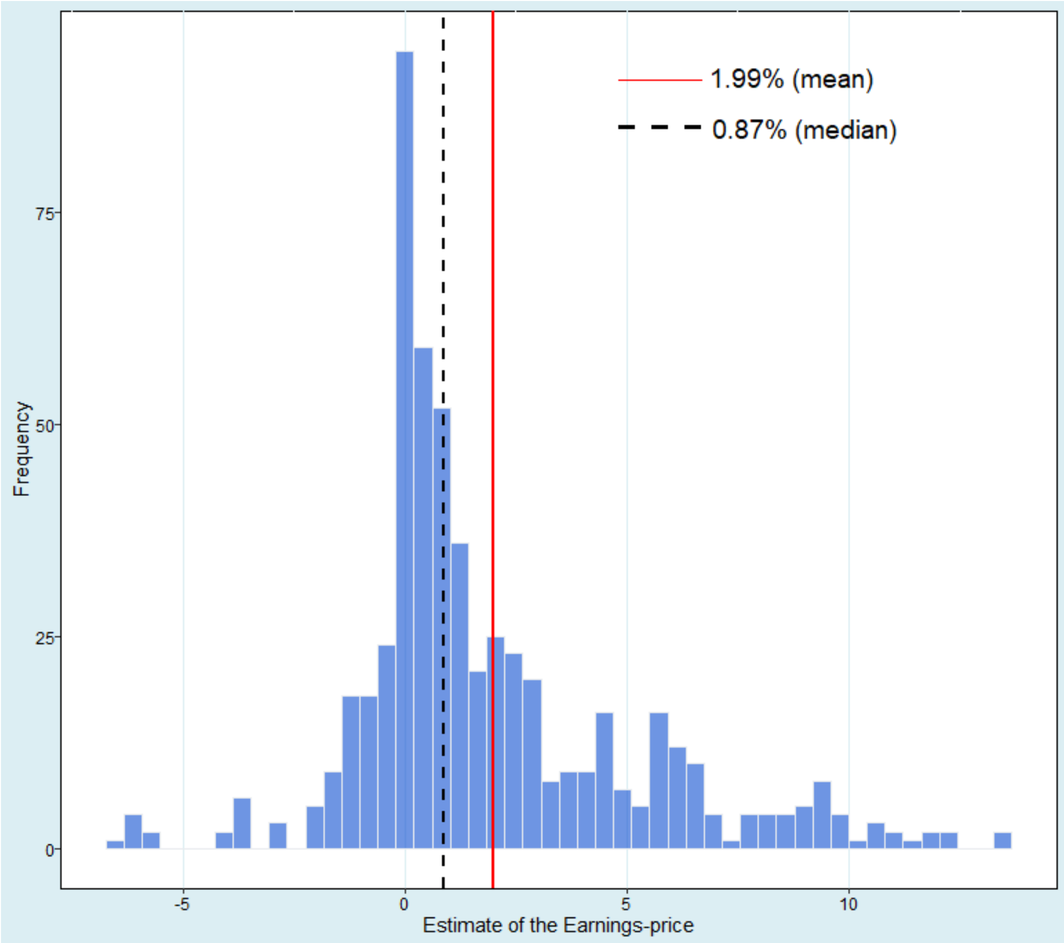


Notes: The figure shows the number of estimates of the relationship between the earnings-price ratio and stock returns published in different periods.

relationship between the earnings-price ratio and stock returns is stable and has not worn out since the discovery of Basu (1977). Moreover, interest in recent years may be undervalued due to the usage of advanced machine learning techniques that do not produce interpretable results and, hence, are not included in our sample.

As can be seen in Figure 3.3, there is a slight deviation from the normal distribution in the earnings-price ratio estimate distribution (excess kurtosis: 2.174). This suggests that the coefficients we gather from the primary research have a significant heterogeneity. The distribution is positively skewed, with a mean value of 1.99 percent above the sample median of 0.87 percent (skewness: 1.025). Hence, our data set has more positive observations than

Figure 3.3: Earnings-price effect distribution

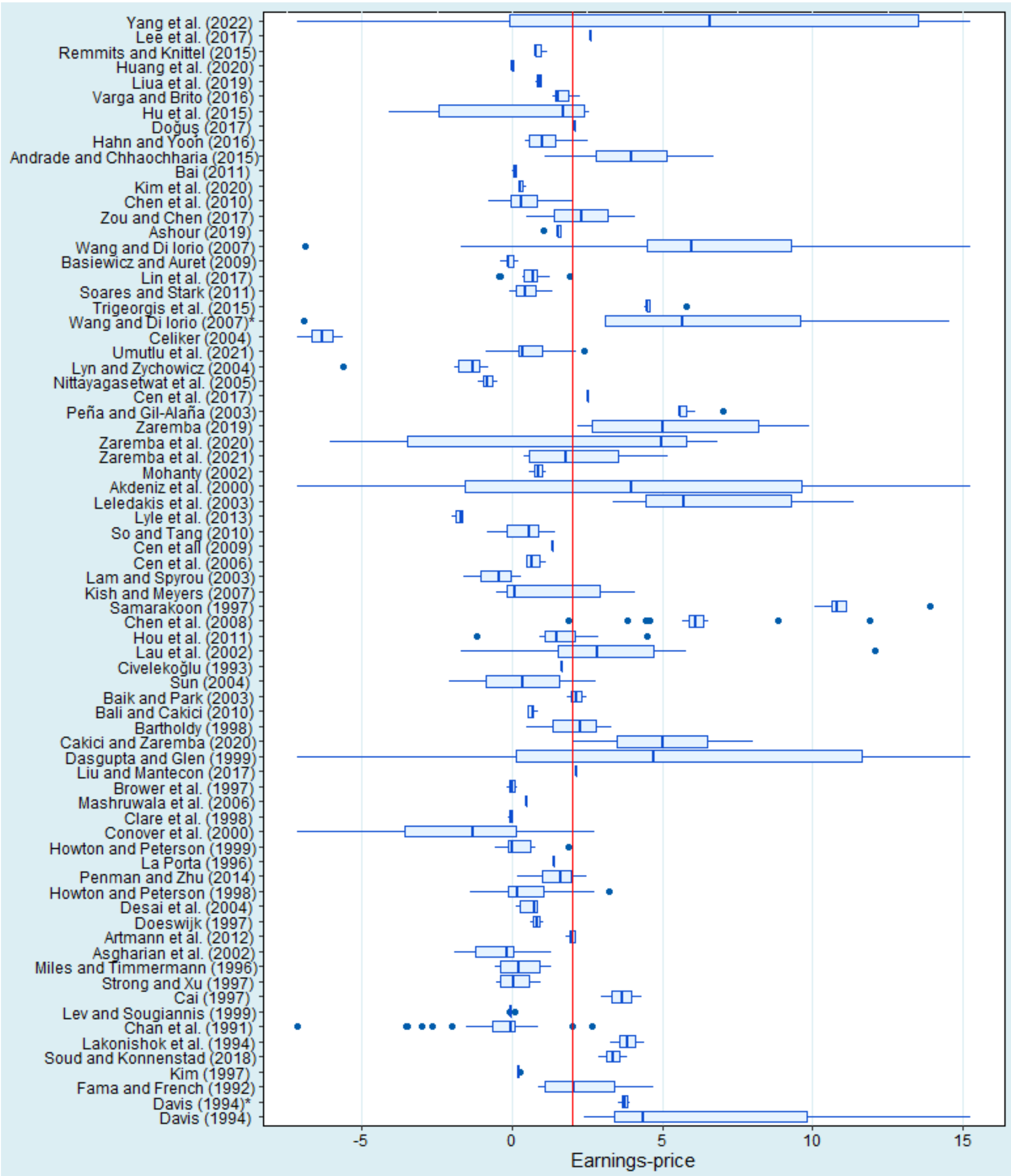


Notes: The figure shows the distribution of the earnings-price ratio by its magnitude. The effect is winsorized at a 2 percent level, and outliers are excluded from the figure. However, they are included in all calculations. The red solid and black dashed lines represent the sample mean and median, respectively.

we would have predicted. Negative observations are less frequent, which is in line with a tendency to discard negative estimates that contradict previous research by Basu (1977) and the researcher's ex-ante expectations. Additionally, a weighted mean is below a simple mean (1.84 percent), suggesting that studies with greater estimates on average report a higher number of observations in our dataset.

The forest plot in Figure 3.4 portrays the earnings-price ratio estimates. Each row constitutes the individual study included in our sample. The box plot is drawn for each study. Boxes represent an interquartile range, and dots are outliers. There is high heterogeneity not only between but also within studies. Heterogeneity within studies is probably caused by estimating the relationship on different periods, modifying the studies dataset, or including other factors that affect earnings and are correlated with the earnings-price ratio. We explore the heterogeneity of estimates in a separate chapter.

Figure 3.4: Estimates of the earnings-price ratio from individual studies.



Notes: The figure displays a box plot illustrating the coefficient estimates of the earnings-price ratio across individual studies.

We compute the mean of the underlying relationship and the associated confidence intervals across different data sub-samples to assess the effect's behaviour in our data in more detail. Table 3.4 displays the summary of results. Firstly, published and not published studies seem not to differ in the average effect. On the other hand, studies estimating the relationship on annual returns report, on average, lower effect of the earnings-price on stock returns. However, these coefficients were transformed by dividing the original coefficient by 12. Hence, before transformation, the estimates on annual returns were six times larger than the ones on monthly returns. It seems plausible, as stock returns are (on average) higher for longer horizons. Moreover, even if we accept a positive effect of the earnings-price ratio on stock returns, the effect should not increase linearly if we increase the duration of returns because the information about the firm's earnings per share is temporal (e.g. updates of quarterly returns). Moreover, investors make decisions based on the most current info and update their portfolios as soon as new information is available.

On the other hand, the stock's geographic region does not seem to affect the average earnings-price coefficient estimates. Although North America depicts lower estimates, this is caused mainly by estimates for the USA, which covers the majority (almost 99 percent) of observations for North America. Region "Other" covers South American and African countries, combined with estimates of multiple regions.

Our sample does not have enough observations for the split by country, so we cover only the USA and China. As mentioned above, the average reported estimates are lower for the USA. It might be caused by a better availability of information in the most developed stock market or a different reaction of investors to the firm's fundamentals. On the other hand, coefficients reported from China are higher than the average, which might be caused by the specific responsiveness of Chinese investors to a firm's financial performance, as discussed by Liu *et al.* (2019).

As mentioned by Astakhov *et al.* (2019), most studies researching the cross-section of returns employ Fama-MacBeth regression. It can be viewed as an evolution from sorting portfolios and comparing the returns of different quantiles in time, overcoming the multidimensionality problem of a high number of factors combined with a limited number of stocks. In our sample, the Fama-Macbeth approach exhibits, on average, higher coefficient estimates than other estimation techniques. As shown in the publication bias section, it is partly caused by the over-reporting of positive estimates. However, even after correction for the publication bias, reported coefficients estimated by Fama-MacBeth are higher.

Developed countries have a lower average estimate of the effect. The reason might be that stock markets in developed countries are structurally different from those in emerging countries, with a different reaction to firms' fundamentals. Interestingly, adjusting returns by a risk-free rate in regression seems to decrease the average coefficient of the earnings-price ratio. On the other hand, if another methodology is applied, e.g. adjusting the return, the four-factor model by Carhart (1997), the average estimate is lower. Moreover, the winsorization of the earnings-price ratio (and other variables included in the regression of the underlying study) nearly doubles the average effect. Last but not least, the incorporation of delisted stock increases, on average, the effect in our sample.

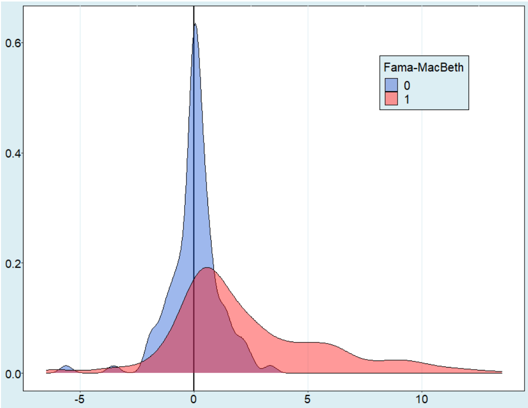
However, we can not conclude due to the low number of observations in particular sub-samples combined with possible collinearity, as is the case for the extreme example of the USA and North America. A thorough explanation of the variables can be found in Chapter 5.

Figure 3.5 documents a great dispersion of the effect visually. It can be seen in the Fama-MacBeth subplot that the distribution is slightly shifted to the right, skewed and much more dispersed. There is an observable under-reporting of negative coefficients in studies using the Fama-Macbeth procedure. On the other hand, the distribution seems to be more symmetric for studies employing other estimation techniques. A similar set of distributions can be seen in the sample construction subplot, where the distribution of the earning-price ratio on sub-samples that include delisted companies is far from normal. However, the conclusion cannot be drawn decisively due to a low number of observations in specific sub-samples, and a more informative analysis of heterogeneity can be found in Chapter 5.

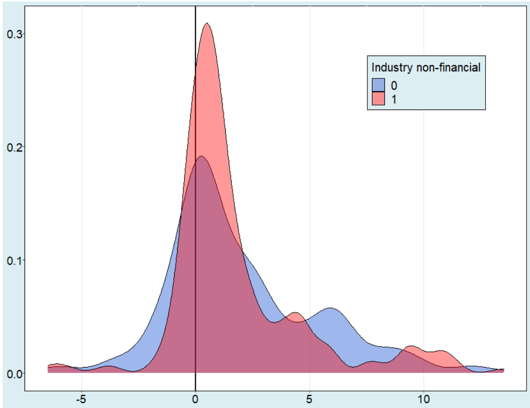
Table 3.4: Mean statistics for various data subsets

	n	**Mean**	**95% CI, lower bound**	**95% CI, upper bound**
All estimates	591	1.991	1.666	2.315
Publication status				
Published	473	2.014	1.657	2.372
Not Published	118	1.895	1.120	2.670
Return duration				
Monthly return	539	2.090	1.739	2.442
Annual return	52	0.955	0.508	1.402
Region				
Asia	234	2.169	1.557	2.781
North America	147	0.770	0.338	1.202
Europe	104	2.524	1.781	3.267
Other	106	2.765	2.063	3.466
Country				
USA	145	0.744	0.308	1.181
China	39	3.403	1.585	5.222
Country other	407	2.299	1.896	2.702
Methodology				
Fama-MacBeth	483	2.434	2.051	2.817
Pooled regression	39	-0.050	-0.357	0.256
Panel regression	69	0.041	-0.262	0.343
Development status				
Developed	310	1.230	0.906	1.554
Emerging	222	2.370	1.720	3.019
Merged	69	3.980	3.008	4.952
Returns adjustment				
Raw returns	422	2.298	1.906	2.691
Excess returns	127	0.833	0.163	1.502
Risk-adjusted returns	42	2.300	1.456	3.337
Industry				
Non-financial	233	1.800	1.350	2.249
Other	358	2.115	1.665	2.564
Winsorization				
Windsorized	87	3.251	2.633	3.869
Not winsorized	504	1.773	1.411	2.135
Sample construction				
With delisted stock	132	2.948	2.335	3.560
Without delisted stock	459	1.715	1.340	2.091

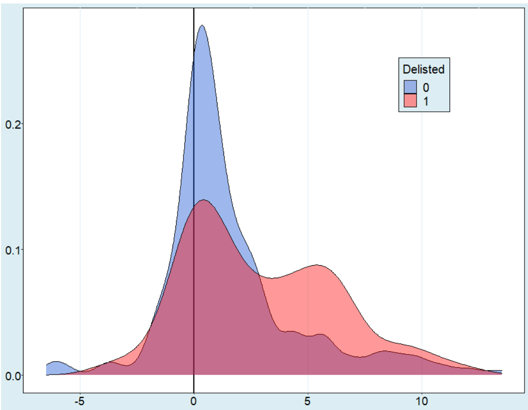
Figure 3.5: Distribution of the earnings-price ratio in sub-samples



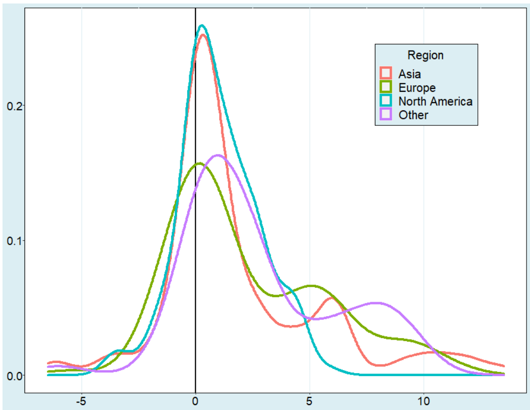
(a) Methodology



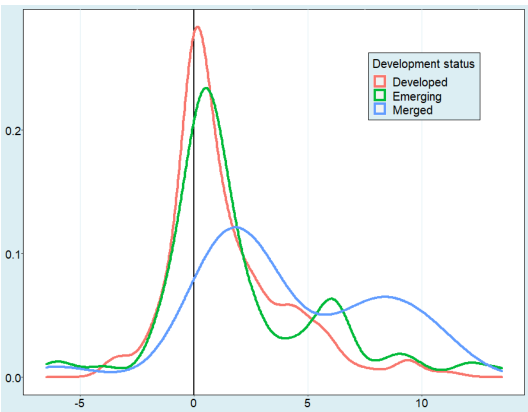
(b) Industry



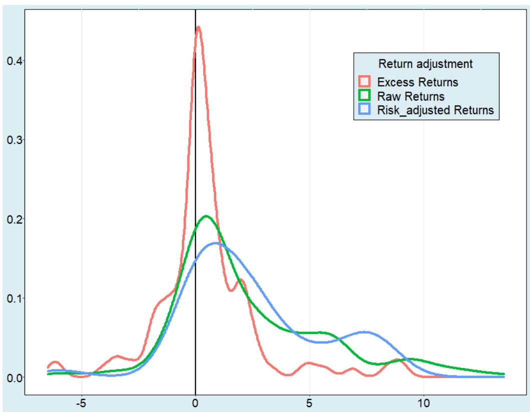
(c) Sample construction



(d) Region



(e) Development status



(f) Returns adjustment

Notes: The figure depicts the distribution of the earnings-price ratio in sub-samples. More detailed information on the construction of variables can be found in Chapter 5.

Chapter 4

Publication bias

In order to identify the fundamental patterns influencing the behaviour of the effect, this chapter will center on identifying publication bias within the literature sample. In summary, this bias signifies a specific inclination among researchers towards statistical significance, as examined by Ioannidis *et al.* (2017), Stanley (2005) or Thornton & Lee (2000). Previous research has identified instances of selective reporting of research findings across various research contexts in the fields of economics and finance. This phenomenon has been documented in research conducted by Brown *et al.* (2024), Astakhov *et al.* (2019) or Havránek (2015). Ioannidis *et al.* (2017) concluded that the findings reported in academic journals within the field of economics often indicate a reported effect that is, on average, double the actual effect. Astakhov *et al.* (2019) conducted a meta-analysis on the relationship between stock earnings and a firm's size. He found that the effect corrected from the publication bias is almost three times smaller than the mean value reported in the analysed literature. The sheer number of studies that exist, of which we have only mentioned a few, should emphasize to the reader the importance of exploring this effect in our thesis. To elaborate, publication selection bias occurs when authors and editors are inclined to publish findings that align with their ex-ante expectations of the relationship under study or with previously reported results. In our specific case, the most prominent studies conducted by Basu (1977) and Fama

& French (1992) reported a positive relationship between the earnings-price ratio and stock returns. It may be deemed justifiable to reject results that appear improbable based on the assumed relationship or in consideration of previous findings. However, doing so can lead to a distortion of the collective estimates presented in the empirical research literature. This problem is more visible in small studies that estimate the effect on short periods or a low number of firms. In our sample, most of the studies' primary goal is to study the effect of other factor than the earnings-price ratio. Hence, if the analysis yields unintuitive results for a specific factor, they might be tempted to remove it or change it to another one, causing under-reporting of negative estimates. Harvey *et al.* (2016) pointed out that hundreds of factors were discovered, most of which are most likely significant purely by chance on specific samples or periods. Another source of publication bias is p-hacking (Brodeur *et al.* 2018). According to Gerber & Malhotra (2008), there is the tendency for research papers to be more likely published if their results are statistically significant, resulting in researchers being less inclined to submit papers with non-significant findings. Consequently, insignificant estimates may be under-reported, or researchers may be deliberately manipulating data sets or creating sub-samples to attain statistical significance. Furthermore, researchers may be inclined to employ various specifications, leading to misspecified models and biased results. These practices may bias the whole literature, resulting in the wrong understanding of the underlying relationship. Our meta-analysis enables us to evaluate the potential impact of selective reporting on the published empirical findings and to make appropriate adjustments to the coefficients in order to account for any bias present.

In the pursuit of identifying publication bias, our study is informed by and adheres closely to the methodologies utilised by Astakhov *et al.* (2019), Havránek (2015), and Gechert *et al.* (2022), among other researchers. Drawing inspiration from their approaches to meta-analyses, we have implemented a range of established and innovative techniques, all detailed in this thesis's subsequent sections.

4.1 Funnel plot

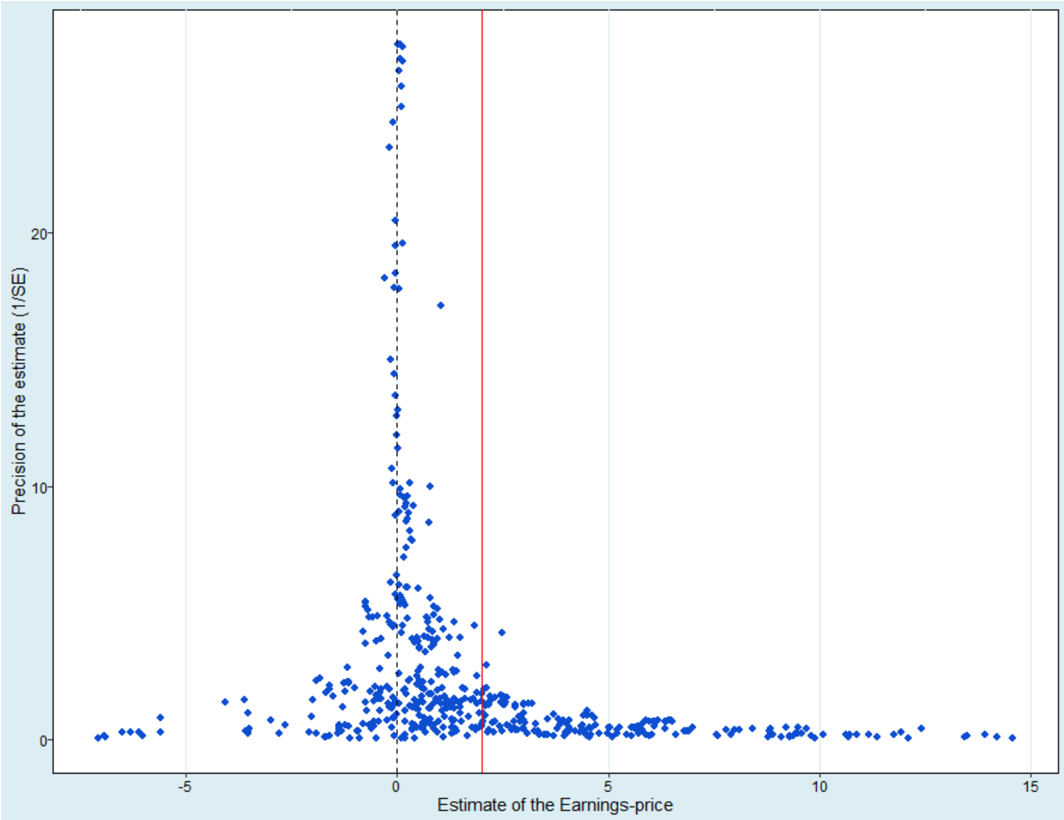
One of the most commonly utilised meta-analytic technique for identifying publication bias is the funnel plot. The x-axis displays the magnitude of the estimates. The y-axis displays the precision of the estimates, defined as the reciprocal of their standard errors. Estimates with greater precision are more likely to be in closer proximity to the true value of the risk. Conversely, estimates with lower precision will result in a wider distribution of values. In case of no presence of publication bias, the funnel plot should be symmetric.

Estimates that are less precise and deviate from the sample mean should have an equal likelihood of being published, irrespective of whether they are high, low, or negative. On the other hand, in the presence of the publication bias, some unintuitive are discarded, causing asymmetry.

Upon visual inspection of Figure 4.1, it is apparent that the funnel plot exhibits a positive skew. This observation suggests that imprecise estimates are more prone to being disclosed when they are positive as opposed to negative ones. The sample mean of 1.99 and median 0.86 support the evidence for skewness. Outliers are excluded from the figure but included in calculations. These findings offer preliminary suggestive evidence that aligns with the notion that researchers may be inclined to disregard imprecise negative estimates due to their preconceived expectations set by prominent studies of Basu (1977) and Fama & French (1992). The mean value of estimates may inaccurately exaggerate the actual influence of the earnings-price ratio on stock returns.

To further investigate plot asymmetry, we split our dataset into sub-samples. Panel a) of Figure 4.2 depicts the funnel plot split by monthly and annual returns. It seems that our transformation of estimates and respective standard errors to a common scale did not distort the distribution of estimates based on annual returns as they are not of higher precision or centered closer around zero. On the other hand, split by estimation methodology yields different results. It

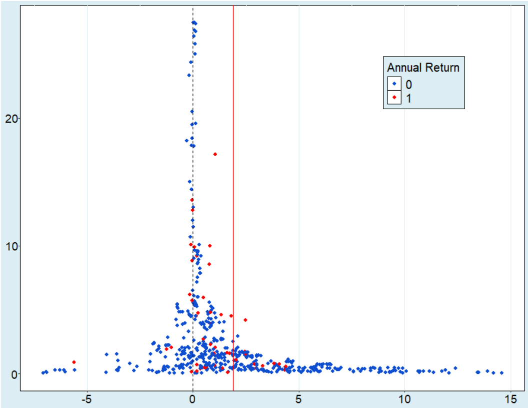
Figure 4.1: Funnel plot on all available estimates



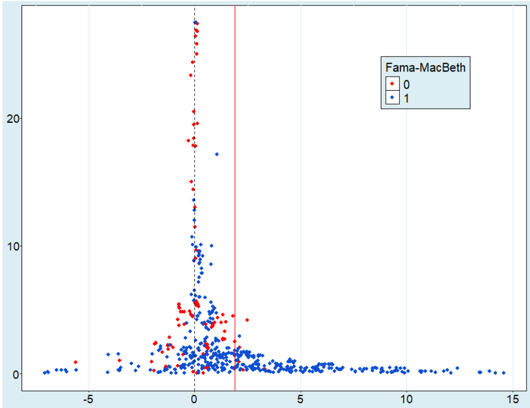
Notes: Outliers are excluded from the figure but included in all calculations. The sample mean is indicated by a red line, while a dashed vertical line represents the zero effect.

may occur that the Fama-MacBeth methodology is generally less precise than others. It seems logical because the Fama-MacBeth procedure operates with fewer degrees of freedom than panel regression, as the effect is computed as a mean of a time series of estimated coefficients in cross-sections of the data. Moreover, asymmetry of distribution is apparent only for estimates based on the Fama-MacBeth procedure. The distribution for other estimation methodologies looks symmetrical. However, due to a low number of observations for methodologies other than Fama-MacBeth, we cannot draw a decisive conclusion as the symmetry could be only by chance, nor are we going to analyse why (if they are) studies based on the Fama-MacBeth methodology are structurally different when facing publication bias. Nevertheless, it might be a source of endogeneity in consequent linear publication bias tests.

Figure 4.2: Distribution of the earnings-price ratio in sub-samples



(a) Annual split



(b) Fama-MacBeth split

Notes: Figure (a) depicts a funnel plot of estimates based on annual and monthly returns. Figure (b) depicts a funnel plot of estimates based on the Fama-MacBeth methodology and other methodologies (more detail in Table 3.4). Outliers are excluded from the figures.

4.2 Linear methods

In addition to the Funnel plot, more accurate tests are available for detecting publication bias. We have utilised the Funnel Asymmetry Test (FAT) and Precision Effect Test (PET), adhering to the approaches outlined by Stanley & Doucouliagos (2012) and Egger *et al.* (1997).

As mentioned by Stanley (2005), in the absence of evidence for publication bias in the gathered estimates, the potential association between the earnings-price ratio and stock returns should not show a correlation with the standard errors of the risk estimates. This relationship may be influenced by studies with less precise estimates adjusting their methodologies or sample sizes to attain statistically significant findings. Moreover, over-reporting of high or low estimates also leads to a relationship between the reported estimates and their corresponding standard errors. If inaccurate estimates, especially those with negative values, are more prone to being omitted, it is probable that positive estimates will exhibit a greater standard error compared to negative estimates. The relationship between the earnings-price ratios and their standard errors can be mathematically outlined by the equation:

$$EP_{ij} = \beta_0 + \beta_1 \cdot (SE_{EP})_{ij} + u_{ij} \ , \tag{4.1}$$

where EP_{ij} represents the i-th estimate of the earnings-price ratio from the j-th study. The over-reporting of positive estimates suggests a positive slope coefficient β_1 in Equation 4.1. In contrast, the intercept term β_0 reflects the "actual" effect adjusted for publication bias. Conversely, the term β_1 signifies the estimated "size" of the publication bias, while u_{ij} denotes the error term in the analysis.

In order to formally examine the presence of publication bias, regression analyses were conducted as outlined in Equation 4.1. The findings of these analyses can be found in Table 4.1. Specification (1) displays the initial OLS regression results showing the estimated slope coefficients of the earnings-price ratio regressed against their standard errors. The significantly positive β_1 coefficient indicates the presence of selective reporting bias. The estimated intercept of 1.071 reflects the underlying average earnings-price ratio effect adjusted for the selective reporting bias. Furthermore, in line with the concept of selective reporting, it is observed that the intercept value is significantly lower than the unadjusted mean slope coefficient that was presented in the descriptive statistics outlined in Table 3.3. The initial result offers evidence for the presence of a positive earnings-price ratio effect while also indicating that the effect may not be as significant as commonly believed. In specifications (2) and (3), the outcomes of panel data regressions with fixed and between effects are showcased. In both models, there is evidence suggesting the existence of selective reporting bias. The between effects model explained the variance between studies. On the other hand, study-level fixed effects absorb idiosyncratic variation in research methodologies and data samples at the study level. Specifications (4) and (5) present weighted least squares, where in the former one, observations are weighted by an inverse of the number of observations reported per the study, so each study obtains an equal weight in the regression. In the latter, we weigh

Table 4.1: Linear tests for publication bias

	(1) OLS	(2) FE	(3) BE	(4) Study	(5) Precision
Constant	1.071***	1.548***	1.35***	1.117***	0.125
Effect beyond bias	(0.357) [0.449,1.728]	(0.456)	(0.333)	(0.298) [0.572,1.654]	(0.088) [-0.010,0.362]
Standard Error	0.409***	0.197***	0.237***	0.338**	0.829***
Publication bias	(0.145) [0.062,0.645]	(0.061)	(0.055)	(0.163) [0.027,0.668]	(0.192) [0.483,1,174]
Studies	74	74	74	74	74
Observations	591	591	591	591	591

Notes: The table presents the findings of regression analysis using the equation $EP_{ij} = \beta_0 + \beta_1 * (SE_{EP})_{ij} + u_{ij}$, where EP_{ij} represents the i-th estimated earnings-price ratio effect from study j and $SE_{EP})_{ij}$ is respective standard error. Specification (1) was estimated by Ordinary Least Squares (OLS) with clustered standard errors by study. Specifications (2) and (3) are panel data regressions with fixed and between effects, respectively. Specifications (4) and (5) utilized Weighted Least Squares (WLS) with the precision (1/standard error) and inverse of the number of size effect estimates reported per study as a weight. Standard errors are presented in parentheses, with significance levels denoted by *, **, and *** indicating significance at the 10, 5, and 1 percent levels, respectively. Values in square brackets represent a 90 percent confidence interval using wild-bootstrap (Roodman *et al.* 2019).

observations by the inverse of their standard error, as suggested by Ioannidis *et al.* (2017). This method emphasises more accurate estimates, aiding in the mitigation of potential heteroskedasticity within our sample. Specification (4) displays similar results as specification (1), suggesting that our results are not driven by studies that report more estimates than the general average. Upon examination of Table 4.1, it is evident that all five methods indicate a notable presence of publication bias. On the other hand, four of them suggest a statistically significant effect of the earnings-price ratio on stock returns even after correction for publication bias. However, the magnitude of the β_0 coefficient is lower than the values typically reported in the existing research literature, ranging from 0.125 to 1.548. Additionally, we repeated linear tests for publication bias on studies estimating the relationship on month return, yielding consistent results. Details can be found in Table A.1 in the appendix.

4.3 Non-linear methods

All the tests discussed up to this point operate under the assumption that selective reporting results in a linear relationship between the earnings-price ratio and standard error. In this section, non-linear methods are utilised to investigate publication bias. These methods allow for the presence of a non-linear relationship between effect sizes and standard errors. We have implemented several techniques for estimating the effect beyond bias. The first one, TOP 10, developed by Stanley *et al.* (2010), proposes that by exclusively incorporating the most precise 10 percent of observations, statistical estimation can be enhanced and potential publication selection bias can be mitigated, even though this approach may appear to oppose established statistical principles. This is due to the non-representativeness of 90 percent of the data resulting from publication bias. Consequently, the remaining 10 percent of data is posited to serve as a more effective foundation for accurately estimating the true effect. Not surprisingly, the effect beyond bias estimated by this technique yields an estimate close to zero, as the most precise estimates are concentrated around zero in Figure 4.1. However, the reliability of the estimate is brought into question due to the limited number of observations (n = 59). The second method chosen for implementation in this study is the Weighted Average of Adequately Powered (WAAP) introduced by Ioannidis *et al.* (2017). They recommend applying unrestricted WLS solely to the estimates of studies that are sufficiently powered. The method examines this condition by evaluating the calculated standard errors in relation to a power threshold established using statistical significance and sufficient power. Within our dataset, 64 estimates that meet the criteria for possessing sufficient statistical power have been identified. As can be seen in Figure 4.2, the WAAP test yields similar results as the TOP 10 method, bringing the effect beyond bias close to zero (0.072), although statistically significant.

As outlined by Bom & Rachinger (2019), the endogenous kink model employs a meta-regression approach for addressing publication bias, which identifies a discontinuity in the standard errors distribution. This non-linear method is characterised by a horizontal section and a sloped line, which are combined to produce a kink. The location of the kink in the distribution of standard errors is selected to ensure that publication bias is unlikely below a specific threshold value. Contradictory to other non-linear techniques, the model suggests a negative value of the effect corrected from publication bias, although not statistically significant at a 5 percent level.

Furukawa (2019) adopts a methodology similar to the Top 10 method, recommending the use of the most precise estimates from the sample. These observations can be identified by minimising the mean squared error:

$$MSE(n) = Bias^2(n) + Var(n) \ . \tag{4.2}$$

As described by Furukawa (2019), as n increases, the squared bias increases due to the inclusion of estimates with greater bias. At the same time, the variance decreases due to the inclusion of more studies in the sample. His algorithm aims to implement this trade-off by utilising non-parametric techniques to estimate the empirical equivalent of the bias squared term. In our meta-analysis, the estimation of mean effect utilised the most accurate 118 estimates. Figure 4.3 depicts the outcomes of applying this approach to our sample.

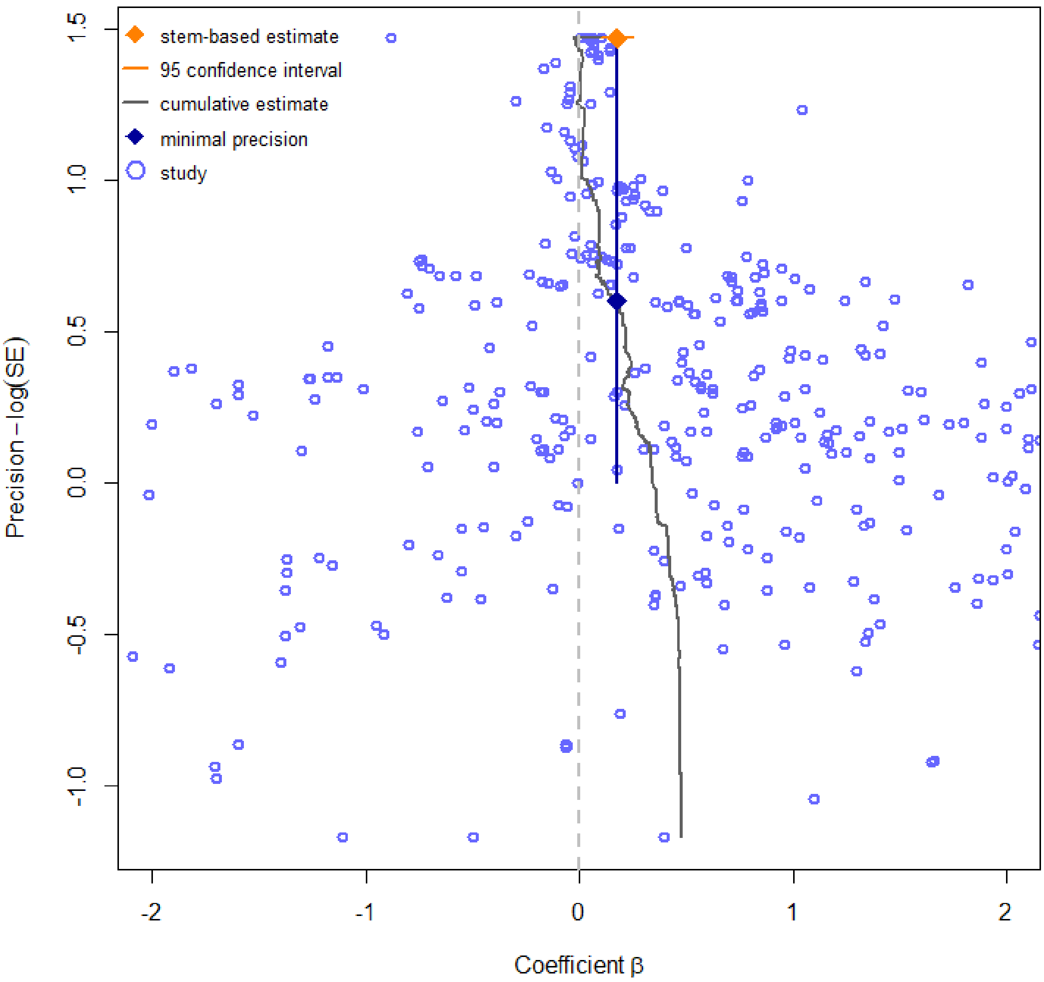
Table 4.2: Non-linear tests for publication bias

	Effect beyond bias
TOP 10	0.071**
(Stanley el al. 2010)	(0.031)
WAAP	0.072***
(Ioannidis et al. 2017)	(0.004)
Endogenous Kink	-0.031*
(Bom Rachinger 2019)	(-0.017)
Stem-based method	0.179***
(Furukawa 2019)	(0.039)
Selection model	0.988
(Andrew Kasy 2019)	(0.912)

Notes: The table illustrates non-linear approaches for detecting publication bias. The unadjusted mean value of the earnings-price ratio effect is 1.99. Standard errors are presented in parentheses, with significance levels denoted by *, **, and *** indicating significance at the 10, 5, and 1 percent levels, respectively.

The final model utilised in our analysis to examine potential non-linear relationships within the data is the Selection model proposed by Andrews & Kasy (2019). As per the authors' findings, a study's publication probability is determined non-parametrically and is dependent on its results. This probability can be utilised to address publication bias. We opted for a significance level of 5 percent was utilised in conjunction with the symmetrical distribution. Out of all non-linear tests used, the Selection model places the effect of earnings-price ratio beyond publication bias closest to linear methods applied in Section 4.2, although not statistically significant. Detail can be found in Table 4.2. It is clear that non-linear methods yield an effect beyond bias of much lower magnitude compared to linear methods. They put much more weight on the most precise estimates that are very close to zero in our sample, as can be seen in Figure 4.1.

Figure 4.3: Stem-based method



Notes: This figure illustrates a non-linear estimation of the effect, as described by Furukawa (2019). The orange diamond symbolizes the stem-based estimate of the partial correlation coefficient, with the orange line indicating the 95 percent confidence interval. The black line represents estimates at different levels, and the black diamond signifies the minimum precision required for the model to calculate the stem.

4.4 Addressing endogeneity in the tests for publication bias

In order to enhance the reliability of our results, we will now address the assumption of exogeneity that has been maintained thus far. This assumption suggests that the standard errors were not associated with the original effect in the absence of publication bias. However, the standard errors and effects may exhibit a relationship not only due to publication bias but also as a consequence of unobserved heterogeneity or measurement errors. Due to the varying methodological approaches employed in the primary studies, it is anticipated that certain methods may result in consistently higher standard errors.

The initial two techniques that will be implemented are the Instrumental Variable (IV) regression, as well as a method known as p-uniform (van Aert & van Assen 2018), as referenced in Table 4.3. During constructing the in-

Table 4.3: Tests accounting for endogeneity

	IV	p-uniform
Effect beyond bias	1.018***	0.923***
	(0.287)	(<0.001)
Publication bias	0.455***	YES
	(0.142)	(<0.001)
Studies	74	74
Observations	577	591

Notes: IV = Instrumental variable regression. As an instrument for standard errors, we used the square root of the inverse of a number of observations. Standard errors are presented in parentheses, with significance levels denoted by *, **, and *** indicating significance at the 10, 5, and 1 percent levels, respectively. For p-uniform, p-values are presented in parentheses. We employed maximum likelihood estimation in this test.

strumental variable regression model, the reciprocal of the square root of the number of studies (Gechert *et al.* 2022) is selected. The method referred to as "p-uniform" is based on the concept of a uniform distribution of p-values around the true effect value. This method assesses the validity of this assumption by examining the distribution of p-values in the dataset at different intervals and analysing their distribution pattern. Nevertheless, the distribution of significant estimates is being influenced by publication bias. This bias results in an over-representation of significant estimates just below the specific thresholds while simultaneously leading to an under-representation of estimates with p-values slightly above the thresholds. If publication bias is present in the sample, the distribution may appear uneven or often clustered around specific statistically significant values (van Aert & van Assen 2018).

The results obtained from applying these two methods are consistent with the linear tests for publication bias, indicating a significant publication bias and the "true" effect corrected from publication bias almost half of the mean reported value of our sample.

To further examine the presence of publication bias, we employ the methodology used by Havranek & Irsova (2012). Specifically, we examine the relationship between the reported standard error and proxies of the study's quality (impact factor of journal and number of citations in Google Scholar normalised to yearly value to avoid putting more weight on older studies). Moreover, we include the test for the Fama-Macbeth procedure, where we include both level and interaction with standard error, to distinguish whether the higher average coefficient reported in Table 3.4 is attributable to the Fama-Macbeth approach itself or the presence of publication bias in studies using this approach. As can be seen in Figures 4.2 and 3.5, the asymmetry of the funnel plot seems to be caused by studies using the Fama-Macbeth procedure. Hence, we include Fama-Macbeth interaction with standard errors in our analysis.

Table 4.4: Factors affecting publication bias

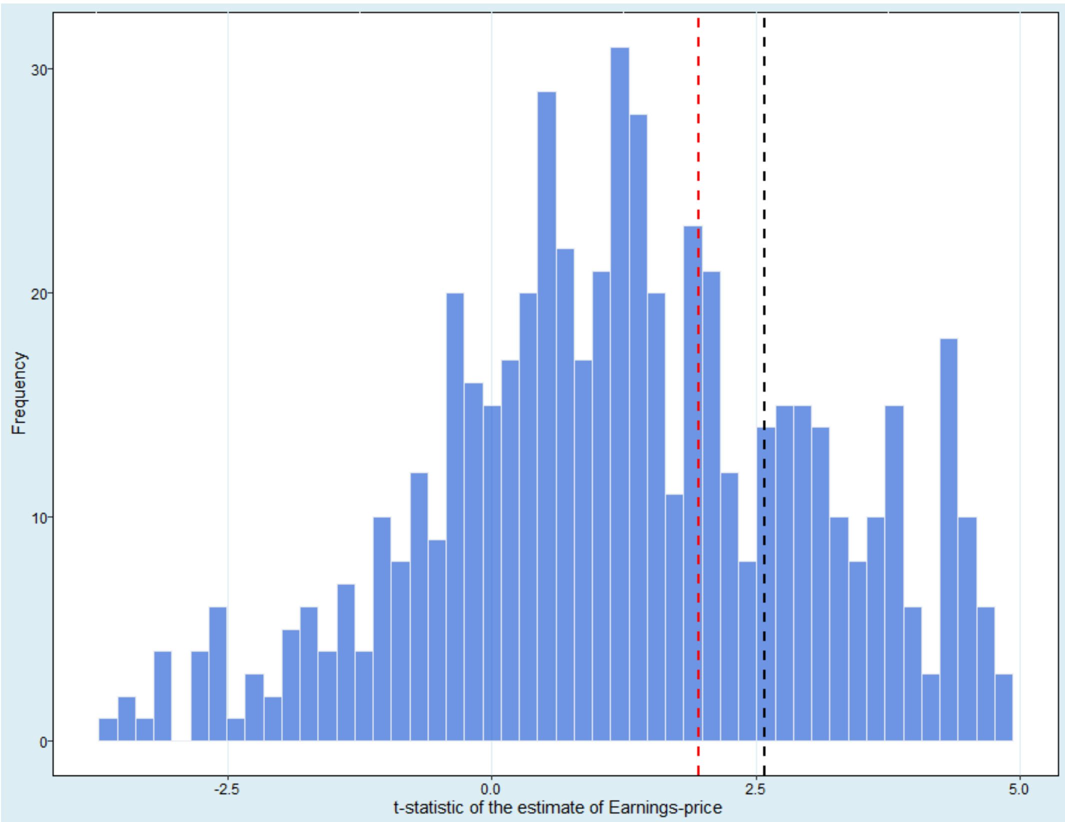
	(1) OLS	(2) OLS	(3) OLS
Constant	1.069*** (0.355)	1.103*** (0.359)	0.001 (0.228)
SE	0.480** (0.221)	0.435*** (0.143)	0.010 (0.049)
SE*Citations	-0.054 (0.093)		
SE*Impact		-0.237* (0.142)	
Fama-Macbeth			1.436*** (0.161)
Fama-Macbeth*SE			0.377** (0.161)
Studies	74	74	74
Observations	591	591	591

Notes: The table presents the results of regression equation $EP_{ij} = \beta_0 + \beta_1 * (SE_{EP})_{ij} + u_{ij}$ with inclusion of interaction term capturing publication characteristics. Standard errors are presented in parentheses, with significance levels denoted by *, **, and *** indicating significance at the 10, 5, and 1 percent levels, respectively.

The conclusions concerning the impact of journal quality on selective reporting bias are indecisive. Only for journal impact is the interaction term marginally statistically significant. On the other hand, using the Fama-Macbeth procedure has a positive, statistically significant impact on the earnings-price ratio. However, the interaction term of Fama-Macbeth and standard error is statistically significant. After the modification, the standard error of non-Fama-Macbeth studies is not statistically significant, which is in line with Figure 4.2. Hence, in the heterogeneity analysis in Chapter 5, we split the standard error term into Fama-Macbeth studies and others to test our findings.

Figure 4.4 depicts the t-statistics distribution. Estimates seem to be concentrated at values 1.96 and 2.65, which correspond to a level of statistical significance of 5 percent and 1 percent, respectively. However, there are relatively few observations to determine p-hacking from the figure. Considering

Figure 4.4: T-statistics distribution



Notes: The figure depicts the distribution of t-statistics, with red and black dashed vertical lines indicating thresholds at 1.96 and 2.58, respectively. Outliers have been excluded from the figure.

that, we proceed to check this finding empirically by following Gerber & Malhotra (2008). The Caliper test compares the proportion of results with p-values in intervals of the same width below and above specific levels (in our specific case: 1.645, 1.96 and 2.56). If p-hacking is present, the frequency of estimates with a p-value below the threshold should be higher than above the threshold. On the other hand, if publication bias is not present, the ratio of estimates below and above the threshold is expected to be 1:1 (0.5). We present the results of the Caliper test in Table 4.5. We chose thresholds 1.645, 1.96 and 2.56, representing statistical significance at 10, 5 and 1 percent levels, respectively. Additionally, we opted for interval widths of 0.05, 0.1 and 0.2. We can see that only for t-statistic of 2.58 and caliper size of 0.1, the Caliper ratio's 10 percent lower bound is above 0.5. To recapitulate, we did not find enough evidence for the presence of p-hacking.

Table 4.5: Caliper test at different thresholds

t-statistic	Caliper size	n	Caliber ratio	10% CI LB	10% CI UB
1.645	0.05	22	0.409	0.224	0.594
1.645	0.1	40	0.425	0.292	0.558
1.645	0.2	100	0.440	0.357	0.523
1.96	0.05	35	0.406	0.313	0.602
1.96	0.1	53	0.460	0.374	0.607
1.96	0.2	97	0.436	0.369	0.538
2.58	0.05	23	0.591	0.430	0.787
2.58	0.1	47	0.630	0.519	0.757
2.58	0.2	94	0.538	0.457	0.628

Notes: Caliper size indicates length of interval at the t-statistic value. Caliper ratio denotes a ratio of estimates above the t-statistic value in the interval and 10 percent CI LB and UB indicating 10 percent confidence interval lower and upper bound, respectively.

Chapter 5

Heterogeneity

We will now examine variations within our data and studies to gain a deeper understanding of the possible factors driving the size of the earnings-price ratio effect. Specifically, we examine the variables included in our data set, considering how their inclusion may impact the reported outcome. Moreover, we utilise these variables in the application of Bayesian and frequentist model averaging techniques to address model uncertainty and conduct thorough robustness checks.

5.1 Construction of variables

First, we begin by examining and contrasting the diverse attributes present in the studies. In order to accomplish this task, we carefully analyse the specific parameters outlined in the primary studies and select the appropriate variables for our dataset to effectively capture the underlying effect economically. Moreover, we split the following estimation into two parts. In the first, we include key economic factors (market capitalisation, book-to-market ratio, etc.) that were included in studies' estimations to study their impact on the size of the earnings-price ratio effect. On the other hand, in the second specification, we restrict variables to specific study characteristics without variables included in the estimation. The variables were categorised into distinct groups: Main variables, publication characteristics, sample characteristics, industry and region, structural variation, estimation technique, sample adjustments and supportive factors.

Main variables: This group contains the main variables of interest: the earnings-price ratio and respective standard errors. The mean value of the earnings-price ratio is 1.991 with a rather high standard deviation of 4.012, demonstrating a great disperse of collected estimates seen in Figure 3.3. Moreover, the mean value of collected standard errors is 2.249.

Publication characteristics: Our sample consists of 473 estimates (more than 80 percent) originating from 56 studies that were published in an economic journal. The most prominent studies are: Fama & French (1992), exploring the effect of the earnings-price ratio, market capitalisation of a company and three specifications of a company's leverage (book value to market equity, total assets to market equity and assets to book value) in the US stock market during the period from July 1963 to December 1990. The study employed the Fama-Macbeth procedure, which might have affected researchers for decades.

Another prominent study conducted by Chan *et al.* (1991), which received over 2700 citations (collected in May 2024), investigated the effect of fundamental firms' characteristics on stock returns in the Japanese stock market using seemingly unrelated regression (SUR). On the top of variables mentioned in Fama & French (1992), this study included cash flow to price ratio in the regressions. As one might suspect, the cash flow-to-price ratio is generally correlated with the earning-price ratio and might have a significant effect on the estimated coefficients. In the specific case of Chan *et al.* (1991), including a cash flow-to-price ratio in the regression decreased an estimated effect of the earnings-price ratio and made him statistically insignificant.

The other two characteristics are connected to the quality of publication.

The number of citations in Google Scholar (collected in May 2024) was divided by the number of years since publication and transformed by logarithm to decrease the weight of older publications. The other characteristic, the impact factor of a journal according to RePEc, measures the quality of a journal.

Sample characteristics: We collected nine characteristics concerning the sample structure. "Delisted" marks estimates based on samples including delisted stock. The inclusion of delisted companies mitigates the survivorship bias according to Penman & Zhu (2014). Survivorship bias may significantly affect the relationship between stock returns and fundamental characteristics, as stated by Banz & Breen (1986).

As negative earnings produce a negative earnings-price ratio that might affect the analysis, researchers came up with several procedures to mitigate this issue. One of them is to restrict the sample to companies with positive earnings. The other one is to include a dummy variable for stock with a negative earnings-price ratio. According to our sample, including the "earnings-price ratio dummy" is more prevalent among researchers as almost 45 percent of coefficients are estimated in combination with the negative earnings-price ratio dummy compared to 10 percent of coefficients estimated on companies with positive earnings only. A common practice among researchers is to inspect the so-called "January effect" by splitting samples into January and non-January. As inspected by Keim & Stambaugh (1984), the January effect has an impact on the relationship between size and stock returns. According to the authors, more than 50 percent of the size effect is related to January's abnormal returns.

More than 80 percent of collected coefficients were estimated on samples consisting of "local" companies. As "local", we mark studies analysing companies from one country. On the contrary, earnings-price ratios originating from studies inspecting pooled data from several countries we mark as "across countries pooled". Moreover, researchers tend to gather stock into indexes and consequently estimate the relationship on these indexes across countries. For example, Bali & Cakici (2010) estimated regression on a sample of 37 country-level indices.

Researchers also tend to restrict the sample to companies with a share price or market capitalisation above a specific limit. Davis (1994)) limited the sample to companies in the first half of the market capitalisation ranking to limit the impact of illiquidity and high transactional costs on investors' behaviour. As there are many possibilities for defining "large stock" (e.g., specific value or cumulative market capitalisation coverage of included companies), we merge them into one indicator. On the other hand, Chen *et al.* (2010) excluded companies with a stock price below 1 Yen to address the issue of measuring returns and market microstructures.

Industry and region: Collected estimates can be split into two samples: Ones estimated on all eligible companies for researchers or ones where financial companies are restricted from the sample. Fama & French (1992) argue that financial ratios such as leverage have a different interpretation for non-financial companies than for financial companies. There is also one study inspecting real estate investment trusts, although there is not enough observation to constitute a reliable indicator in further analysis. Regarding geographic location, the biggest share of collected estimates originated from Asia and North America. Almost a quarter of observations are connected to the United States stock exchanges (NYSE and NASDAQ). With regard to the development status, a majority of the sample is represented by developed countries.

Structural variation: As can be seen in Figure 3.2, our sample covers the period from 1991 to 2022 when it comes to publication year and a period of almost 70 years (1951 - 2020.5) with respect to the median year of collected data.

Estimation technique: As in a meta-analysis conducted by Astakhov *et al.* (2019), the most frequent estimation procedure is Fama-Macbeth regression described in Section 2.4. Moreover, similarly to Astakhov *et al.* (2019), who analysed the size factor, we observe a more substantial effect on studies that select Fama-Macbeth as an estimation technique. As a "panel", we merge various modifications of the panel and pooled regressions together as there are not enough observations to consider all of them separately.

Sample adjustments: To limit the impact of outliers, authors chose to winsorize the data at various levels. Moreover, several methodologies were applied to adjust returns. Apart from unadjusted raw returns that constitute a majority of collected estimates, our sample consists of excess returns and risk-adjusted returns. Excess returns are a difference of raw returns and a risk-free rate. On the contrary, risk-adjusted returns are constructed by employing a more complex methodology: capital asset pricing model (Sharpe 1964), Fama-French three-factor model (Fama & French 1993) or Carhart four-factor model (Carhart 1997). Lastly, "return annual" indicates coefficients, where a variable of interest is a yearly return instead of a monthly return, although we divided both coefficients and standard errors by 12 to adjust for the duration.

Supportive factors: To investigate whether including another factor in the estimation systematically affects the coefficient estimate of the earnings-price ratio, we create dummy variables for the most frequent ones. As expected, size, book-to-market ratio, and beta are the most frequent ones, representing 65.5, 53.4, and 38.7 percent of our sample, respectively.

Table 5.1: Description of variables

Variable	Description	Mean	SD
Main variables			
Earnings-Price	Earnings-price ratio (Response variable)	1.991	4.013
Standard error	The Standard error of the Earnings-Price ratio	2.249	3.150
Publication characteristics			
Published	Equals 1 if the study was published in the journal	0.800	0.400
Working paper	Equals 1 if the study was published in the working paper	0.108	0.311
Study citations	The logarithm of number of citations study received in the Google Scholar	1.490	1.362
Journal impact	The journal impact factor (RePEc)	0.337	0.760
Sample characteristics			
Positive earnings	Equals 1 if the study covers only companies with positive earnings	0.102	0.302
Large stock	Equals 1 if the study excludes companies with a low market capitalisation	0.061	0.239
Stock price more than 1	Equals 1 if the study covers only companies with a share price more than 1	0.061	0.239
Local	Equals 1 if the study if the study uses companies from one country	0.829	0.377
Across countries pooled	Equals 1 if the study if the study pools companies from multiple countries	0.080	0.271
Country firm	Equals 1 if the study if the study uses country level data	0.085	0.279
January	Equals 1 if the study is restricted to January returns	0.063	0.242
Non-January	Equals 1 if the study excludes January returns	0.063	0.242
Delisted	Equals 1 if the study includes delisted stock	0.223	0.417
Industry and region			
Industry non-financial	Equals 1 if the study covers only non-financial companies	0.394	0.489
USA	Equals 1 if the study covers only the United States	0.245	0.431
China	Equals 1 if the study covers only China	0.066	0.248
Emerging	Equals 1 if the study covers only emerging countries	0.376	0.485
Developed	Equals 1 if the study covers only developed countries	0.525	0.500
Structural variation			
Publication year	The logarithm of the year study was published	7.604	0.005
Median year	The logarithm of the median year of study's dataset	7.597	0.005
Estimation technique			
Fama-MacBeth	Equals 1 if the authors employ Fama-MacBeth procedure	0.817	0.387
Panel	Equals 1 if the equation employ variations of panel regression	0.117	0.321
Sample adjustments			
Winsorized	Equals 1 if the variables were winsorized	0.147	0.355
Excess returns	Equals 1 if the response variable is an excess return	0.215	0.411
Raw returns	Equals 1 if the response variable is a raw return	0.714	0.452
Risk-adjusted returns	Equals 1 if the response variable is a risk-adjusted return	0.071	0.257
Supportive factors			
Market cap	Equals 1 if the equation includes a variable market capitalisation	0.655	0.476
Book to market	Equals 1 if the equation includes a variable book to market ratio	0.535	0.499
EP dummy	Equals 1 if the equation includes earnings price dummy variable	0.447	0.498
Beta	Equals 1 if the equation includes beta	0.387	0.488
Earnings estimate	Equals 1 if the equation includes earnings estimate	0.037	0.189
Momentum	Equals 1 if the equation includes momentum	0.201	0.401
Dividend yield	Equals 1 if the equation includes dividend yield	0.085	0.279
Liquidity	Equals 1 if the equation includes liquidity	0.063	0.242
Growth	Equals 1 if the equation includes growth of the company	0.052	0.223
Reversal	Equals 1 if the equation includes reversal	0.110	0.313
Return on assets	Equals 1 if the equation includes return of assets of the company	0.037	0.189
Cash flow	Equals 1 if the equation includes cash flow of the company	0.073	0.260
Turnover	Equals 1 if the equation includes turnover of the company	0.076	0.265
Leverage	Equals 1 if the equation includes leverage of the company	0.098	0.298

5.2 Model averaging

After identifying the potential factors contributing to the variability in effects, we proceed with the estimation process. Due to the correlation among the collected variables, it was necessary to exclude certain variables from the analysis in order to prevent the presence of multicollinearity in the models. Initially, we split standard errors into Fama-Macbeth and non-Fama-MacBeth standard errors. We removed specific variables to avoid a dummy variable trap. Then, we removed a number of citations due to a high correlation (over 0.81) with an impact factor of a journal. Moreover, the year of publication was highly correlated with the median year of a dataset. We chose to remove a former one. We computed the Variance Inflation Factor (VIF) scores for each variable. Due to high VIF values, we removed two additional variables: Asia and emerging countries. We chose to exclude key supportive factors in BMA from our benchmark model specification. However, we included them in the model specification presented in the appendix to find whether the inclusion of an additional economic factor in the regression systematically affects the size of the earnings-price ratio. The chosen variables, along with their VIF scores, are listed in Table B.1 in the appendix. Table B.2 in the appendix depicts VIF scores for the sample that includes supportive factors.

In order to assess the impact of the selected variables on the magnitude of the earnings-price ratio, we employ the following equation:

$$EP_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{k,ij} + \gamma SE(FM_{ij}) + \delta SE(Non\text{-}FM_{ij}) + \mu_{ij} \; . \qquad (5.1)$$

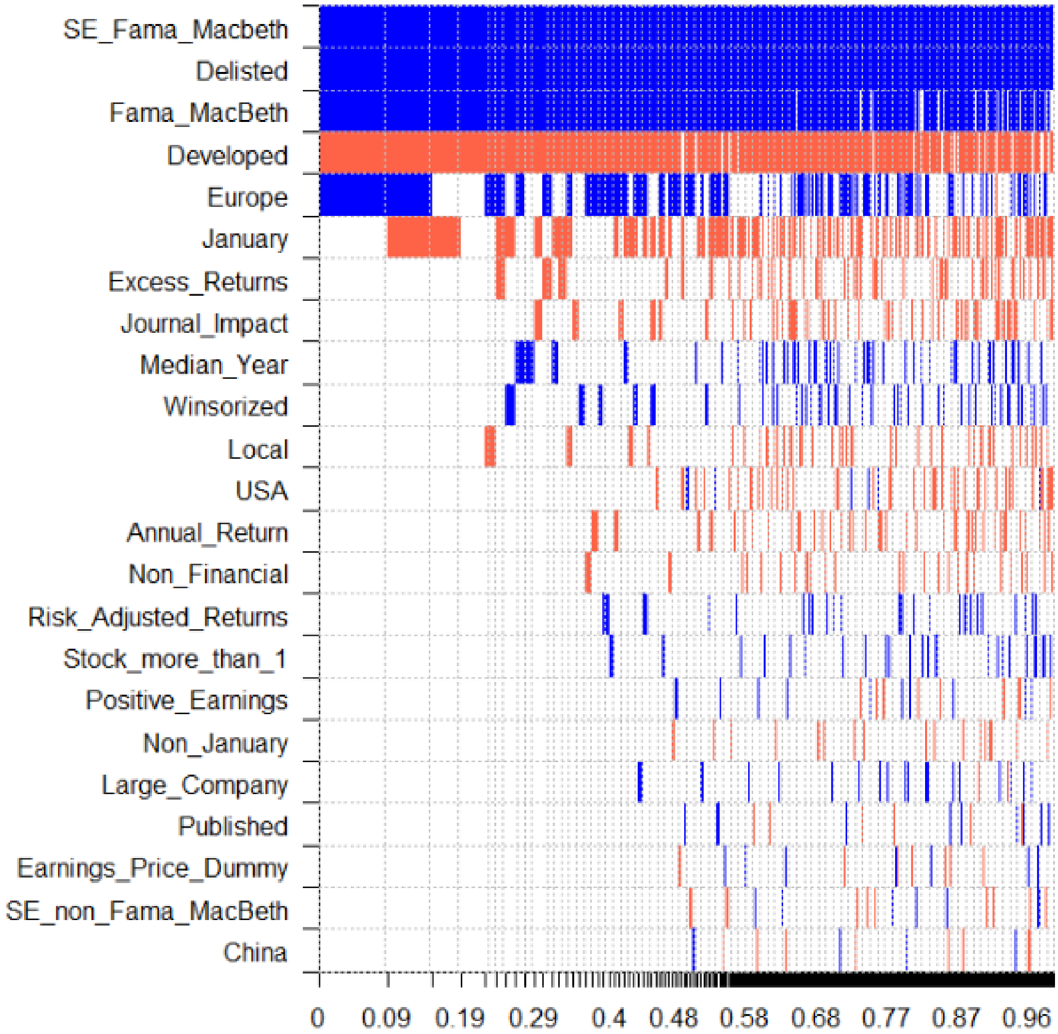
The variable EP_{ij} denotes the i-th estimation of the earnings-price ratio derived from the j-th study. The parameter β_0 signifies the effect beyond bias given X. However, the interpretation of β_0 should not be considered in isolation from other factors. $X_{k,ij}$ pertains to the matrix of control variables as outlined in Table 5.1. Where n denotes the number of variables (apart from standard errors) selected into the final model. There are 28 variables in the full model and 21 in the restricted model. γ and δ denote estimates of publication bias for studies employing Fama-Macbeth and non-Fama-Macbeth procedures, respectively, while μ_{ij} signifies the error term. However, estimating Equation (5.1) utilising OLS regression would pose a challenge. It is plausible that incorporating all variables into one model could result in over-specification. Conversely, opting to select only a subset of the variables may not be prudent due to the inherent model uncertainty. Furthermore, the outcomes of such an estimation are prone to bias and lack precision. If models were to be estimated with all possible combinations of variables, the total number of such models would be 2^{28} (2^{21} in the restricted model). Consequently, we have chosen to utilise Bayesian Model Averaging (BMA), following Cazachevici *et al.* (2020). As implied by its name, the BMA approach involves the averaging of multiple statistically plausible models, addressing the uncertainty surrounding the selection of the most appropriate model for estimation. Subsequently, each model is allocated a weight known as the posterior model probability. The method computes the probability of each variable being included in the model (referred to as posterior inclusion probability), thereby emphasising the significance of each of these variables (more details in (Raftery *et al.* 1997)). Similar to the approach taken by Cazachevici *et al.* (2020), our analysis was conducted utilising the bms package in R (Zeugner & Feldkircher 2015) with the implementation of the Monte Carlo algorithm. Utilising this algorithm, we are able to select models for which posterior model probability would be significant.

In the context of BMA, it is necessary to designate the importance of the prior probabilities for each coefficient. We adhere to a widely accepted approach in meta-analyses by selecting the unit information g-prior (Havranek *et al.* 2018) as our benchmark specification. We utilise the unit information prior methodology, wherein the weights are adjusted to assign equal importance to the prior information as to each individual observation (Eicher *et al.* 2011). This setting implicitly presumes a lack of prior knowledge regarding the significance of individual characteristics.

Furthermore, in order to proceed, it is necessary to select an appropriate prior for the model probability. We chose two specifications: dilution and uniform. The former one is more appropriate for addressing potential collinearity, which might be present in our relatively small sample. The dilution prior effectively addresses the multicollinearity by assigning lesser weight to models that experience high levels of collinearity, as demonstrated by George (2010). The appendices contain robustness checks utilising varying g-priors and model priors. Moreover, we conducted a frequentist check through an Ordinary Least Squares (OLS) regression model, which incorporated six explanatory variables identified by BMA as significant for elucidating the variability in the dependent variable with a PIP greater than 0.5.

The graphical representation of the model averaging results can be observed in Figure 5.1, alongside the numerical data and a robustness check using OLS displayed in Table 5.2.

Figure 5.1: Bayesian model averaging results - uniform prior



Notes: The figure depicts the results of the BMA analysis, employing the uniform g-prior and uniform prior methodologies. The dependent variable in this analysis is represented by the earnings-price ratio, which is quantified on the x-axis in relation to cumulative posterior model probabilities. The explanatory variables have been prioritised based on their posterior inclusion probability, with the ranking displayed in descending order along the y-axis. The blue colour (dark in grayscale) signifies that the variable is incorporated in the model with a positive coefficient. Conversely, the red colour (light in grayscale) indicates the variable included in the model with a negative coefficient. The variables excluded from the model are represented without any visual differentiation. For a comprehensive description of the variables, please refer to Table 5.1.

In addition to providing information on each variable's direction, size, and significance, we also include the Posterior Inclusion Probability (PIP), as briefly mentioned in the theoretical framework above. Figure 5.1 illustrates the visual representation of BMA. The different regression specifications in the columns are arranged according to their Probability model probability (PMP) as depicted by the width of each column. The individual explanatory variables in each row are organised according to their PIP, with the most significant variables appearing at the top of the figure. The blue cells indicate a positive relationship between a specific explanatory variable and the earnings-price ratio, while the red cells signify a negative relationship.

Figure 5.1 illustrates that a relatively small number of factors are included in regression models displaying a high goodness of fit. There are four variables included in a majority of regression specifications.

It is reassuring to note that the relationships between these four variables and the earnings-price ratio remain consistent in all models analysed using the BMA. Table 5.2 displays the results of BMA numerically. In assessing the significance of each variable according to its Posterior Inclusion Probability (PIP), we adhere to the methodology outlined by Kass & Raftery (1995). They suggest that PIP values falling within the range of 0.5 to 0.75 denote marginal evidence of an effect, values between 0.75 and 0.9 denote a probable effect, values between 0.9 and 0.99 denote a substantial effect and values surpassing 0.99 denote a conclusive effect. Moreover, Table 5.2 shows posterior mean and posterior standard deviation of variables that are derived from the distribution of slope coefficients resulting from different regression specifications analysed within the BMA. The posterior mean indicates the average value of a specific coefficient, while its standard deviation signifies the degree of variability of the estimated coefficients across various combinations of factors.

There are five variables with PIP above 0.5. Consistent with Table 4.4, the standard error of studies employing the Fama-Macbeth methodology has a positive impact on the size of the earnings-price ratio with a posterior mean of 0.353, comparable to the size of the publication bias estimated with OLS specification presented in Table 4.1. According to PIP, the second most significant variable is "delisted" with a positive posterior mean. There seems to be some level of survivorship bias, and the impact of the earnings-price ratio is higher in studies that include delisted stock in analyses. Even after correcting for publication bias, employing the Fama-Macbeth methodology results in, on average, a higher coefficient estimate. Some firm-specific factors may be correlated with stock returns and earnings-price ratios that are accounted for in more complex panel models. On the other hand, the magnitude of the earnings-price ratio is smaller in developed countries. This might be explained by better access to information in developed countries or a different attitude toward a company's financial fundamentals in emerging countries. Although Europe's PIP is over 0.5 (0.526), in Figure 5.1, we can see that even the direction of its effect is not consistent across all model specifications. Moreover, a frequentist check that consists of OLS regression employing all variables with PIP above 0.5 rejects a statistical significance at a 10 percent level. On the other hand, a frequentist check supports the statistical significance (at a 5 percent level) of the other four variables with PIP above 0.5.

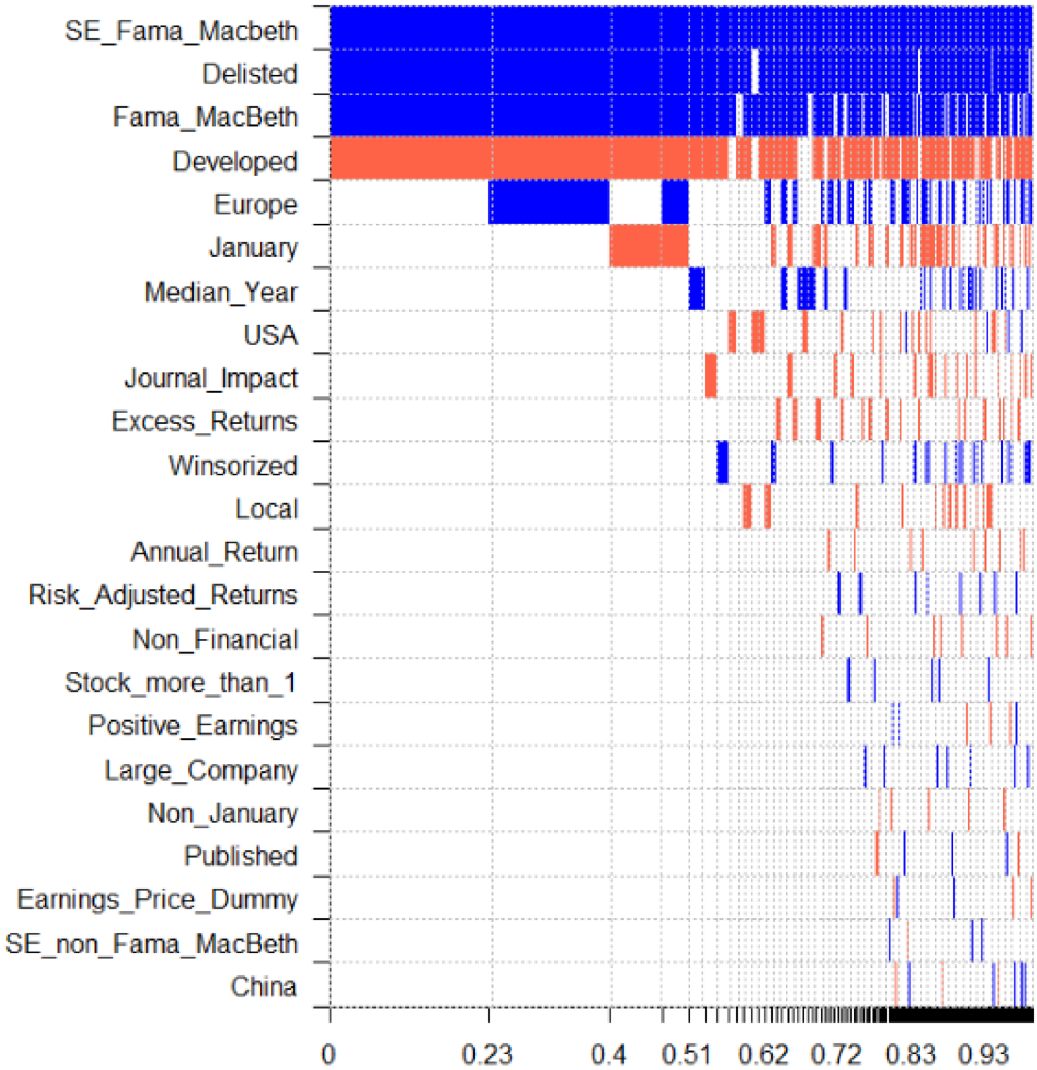
Moreover, a BMA analysis was carried out with consideration given to the dilution prior, in order to address the correlation among factors. A visualization is presented in Figure 5.2. It supports the presented results of a significance of 4 factors. However, the impact of Europe is diminished.

Table 5.2: The results of BMA

	BMA			**Freq. Ch. (OLS)**		
	P.Mean	P.SD	PIP	Coef.	SE	p-value
Constant	-0.422	NA	**1.000**	0.287	0.444	0.520
SE Fama-Macbeth	0.353	0.059	**1.000**	0.322	0.148	0.033
SE non Fama-Macbeth	0.001	0.035	0.034	-0.010	0.135	0.941
Publication characteristics						
Published	0.002	0.082	0.037			
Journal Impact	0.065	0.180	0.156			
Sample characteristics						
Positive earnings	-0.009	0.163	0.043			
Large company	0.016	0.161	0.042			
Local	-0.081	0.26	0.121			
Stock price more than 1	0.039	0.22	0.058			
January	-0.824	0.960	0.492			
Non January	-0.017	0.155	0.042			
Delisted	1.872	0.427	**0.997**	1.917	0.802	0.019
Industry and region						
Industry non-financial	-0.021	0.117	0.062			
USA	-0.089	0.369	0.104			
China	-0.001	0.119	0.034			
Europe	0.606	0.659	**0.526**	1.222	0.809	0.135
Developed	-1.536	0.574	**0.940**	-1.962	0.831	0.021
Structural variation						
Median year	0.234	0.695	0.140			
Estimation technique						
Fama-Macbeth	1.536	0.543	**0.957**	1.727	0.432	0.000
EP dummy	-0.001	0.072	0.036			
Sample adjustments						
Winsorized	0.107	0.327	0.132			
Excess returns	-0.118	0.326	0.156			
Risk adjusted returns	0.040	0.214	0.061			
Annual return	-0.066	0.275	0.086			

Overally, we considered 4 specifications of BMA using different g-priors and model priors. Figure 5.3 pictures PIPs of variables of all models. Furthermore, we inspected whether the inclusion of a supportive factor in the underlying analysis has a systematic impact on the size of the earnings-price ratio or affects the significance of other factors. Figure B.1 and Table B.3 in the appendix present the results. It seems that only the inclusion of cash flow, on average,

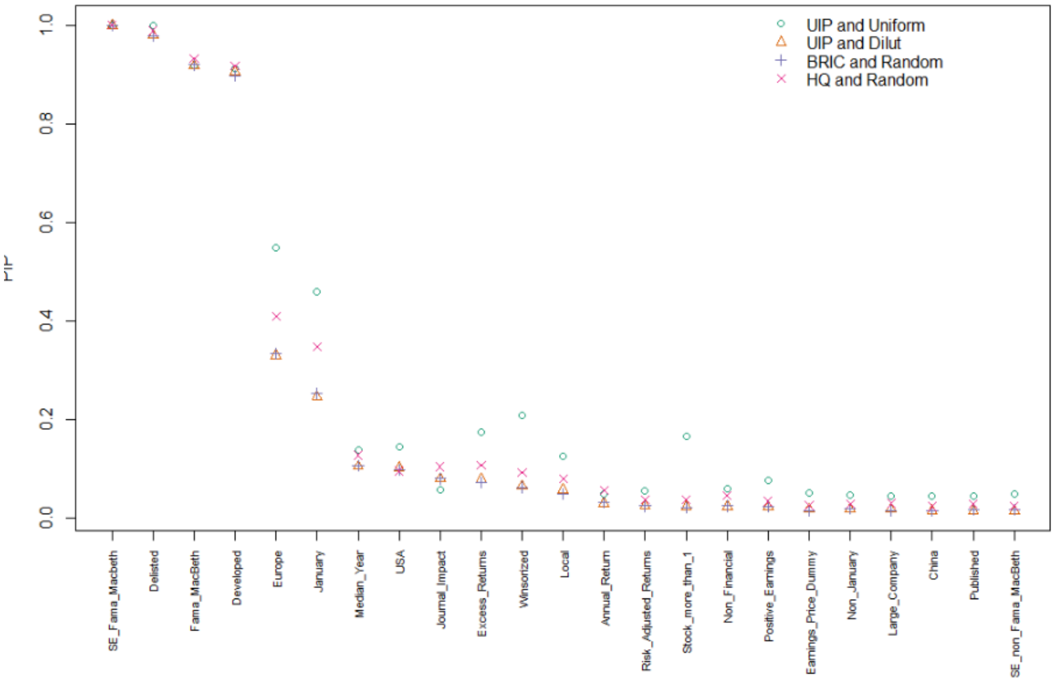
Figure 5.2: Bayesian model averaging results - dilution prior



Notes: The figure depicts the results of the BMA analysis, employing the uniform g-prior and dilution prior methodologies.The dependent variable in this analysis is represented by the earnings-price ratio, which is quantified on the x-axis in relation to cumulative posterior model probabilities. The explanatory variables have been prioritized based on their posterior inclusion probability, with the ranking displayed in descending order along the y-axis. Blue color (dark in grayscale) signifies that the variable is incorporated in the model with a positive coefficient. Conversely, red color (light in grayscale) is indicative of the variable being included in the model with a negative coefficient. The variables excluded from the model are represented without any visual differentiation. For a comprehensive description of the variables, please refer to tTable 5.1.

affected the size of the earnings-price ratio. It seems logical because these two factors are highly correlated. On the other hand, previous analysis results are robust to the inclusion of supportive factors as all variables retained statistical significance (both in PIP and p-value in frequentist check).

Figure 5.3: The summary of Posterior Inclusion Probabilities for various BMA models



Notes: This figure presents a visualisation of all variables plotted against their corresponding posterior inclusion probabilities in various BMA specifications. The abbreviations used are PIP for Posterior Inclusion Probability, UIP for Uniform g-prior, Dilut for Dilution Prior, Uniform for Uniform Model Prior, BRIC for Benchmark g-prior, Random for Random Model Prior, and HQ for Hannan-Quinn Criterion. For a comprehensive description of the variables, please refer to Table 5.1.

5.3 The best-practice estimate

Upon investigating publication bias and heterogeneity of the estimates, we intend to determine the optimal estimate representing best practices. This best-practice estimate can be viewed as the conclusive result of the meta-analysis. This approach entails substituting the coefficients of the aforementioned model with the characteristics that represent the most optimal result for each variable. However, it is imperative to highlight that determining the most optimal estimate is a subjective undertaking and should provide additional validation of the findings rather than introducing new results. This process is informed by the author's perspectives and expertise gained through an examination of the papers incorporated in this thesis and relevant literature.

When creating the optimal estimate through subjective methods, we assigned most variables a value equivalent to the sample mean. This prudent strategy was selected due to the underlying effect being ambiguous. Conversely, we have identified several variables where the relationship is clear and have established their values according to the guidelines provided below. The standard error should be set to zero as the presence of publication bias is deemed undesirable. Moreover, we prefer analyses of published articles with a maximum value of the journal's impact factor due to higher credibility. Finally, we do not want to restrict the estimate to a specific month. Hence, we set variables "January" and non-January to zero.

Furthermore, we analyze the estimates from the prominent study conducted by Fama & French (1992), considering adjustments for publication bias. Table 5.3 depicts the findings of this estimation, showcasing the best practice estimates alongside the corresponding confidence intervals. These intervals were computed utilizing OLS with clustered standard errors at the study level.

Table 5.3: Implied best-practice

Study	Best practise estimate	95% CI
Subjective	1.125	(0.649,1.601)
Fama and French (1992)	0.579	(-0.988,2.146)

5.4 Economical significance of publication bias

In this section, we follow the approach of Astakhov *et al.* (2019) and analyse the effects of publication bias on the perceived magnitude of the earnings-price risk premium indicated by the data. Hence, we downloaded a dataset[1] containing an earnings-price ratio breakdown of US companies into various percentiles. However, compared to Astakhov *et al.* (2019), who conducted a similar analysis on size effect, the distribution of the earnings-price ratio is relatively unstable in time. As opposed to selecting a specific period, we

[1] Available at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

averaged percentiles during the period spanning from 1951 to 2023. Earnings-price ratio breakpoints are calculated at the end of each June, with earnings taken from June of the preceding fiscal year and share price from December of the previous year.

Table 5.4: Percentiles of the earnings-price ratio of companies traded on NYSE and implied earnings-price risk premium

Percentile	Earnings-price ratio	Annualised difference with 5th percentile (earnings-price ratio) ,unadjusted	Annualised difference with 5th percentile (earnings-price ratio), accounting for selective reporting bias
5th	0.027	0.000%	0.000%
10th	0.037	0.251%	0.135%
20th	0.051	0.579%	0.311%
30th	0.061	0.820%	0.441%
40th	0.070	1.034%	0.556%
50th	0.078	1.240%	0.667%
60th	0.088	1.463%	0.787%
70th	0.099	1.732%	0.932%
80th	0.114	2.088%	1.123%
90th	0.140	2.718%	1.462%
95th	0.170	3.434%	1.847%

Notes: Percentile values are calculated as the mean of respective breakpoints on NYSE firms from 1951 to 2023.

Based on the presumption of a linear relationship between earnings-price ratio and returns, the premium for earnings-price risk premium can be determined by subtracting the product of the slope coefficient and the 5th percentile of earnings-price ratio from the product of the slope coefficient and the 95th percentile of earnings-price ratio.

The calculation of the unadjusted earnings-price risk premium, not correcting for selective reporting bias, is derived by using the simple mean reported value of 1.991, as outlined in Table 3.3. The difference in annualised returns is 3.434 percent. Further details are presented in Table 5.4.

To determine the earnings-price risk premium adjusted for selective reporting bias, we utilise the estimate of 1.071 derived from our baseline specification discussed in Table 4.1. The observed difference in percentage returns between the 5th and 95th percentiles of NYSE stocks is 1.847 percent on an annualised basis, representing almost a two-fold reduction from the unadjusted figure. The present findings, in conjunction with previous results, underscore the overarching issue of substantial overestimation of size risk premiums in academic studies, partly attributed to selective reporting bias. This has significant implications for professionals in the field.

Chapter 6

Conclusion

We conducted a meta-analysis on 591 estimates derived from 74 studies to examine the influence of earnings yield on expected stock returns. In our thesis, the earnings-price ratio is a proxy for earnings yield. The analysis reveals a notable publication selection bias within the existing literature, leading to an overestimation of the earnings-price risk premium in conventional estimates reported within the academic sphere. After accounting for bias, our calculation indicates a discrepancy in annual stock returns between the largest and smallest earnings-price ratio quintile of 1.85 percent, significantly diverging from the unadjusted mean reported size premium of approximately 3.43 percent.

Conventional methods are employed to assess the presence of publication selection bias in the literature: linear methods utilized for the detection of publication bias include a graphical approach known as the funnel plot, as proposed by Egger *et al.* (1997), as well as the numerical meta-regression method with varying weights. In the informal funnel-plot methodology, a visual diagnostic tool is utilized to assess the accuracy of estimates: The true mean earnings-price premium is expected to closely align with the most precise estimates of this effect. In contrast, estimates with lower precision should exhibit greater dispersion, resulting in the formation of an inverted funnel shape when graphically represented with the size of estimates on the x-axis and their precision on the y-axis in a scatter plot. Essentially, a symmetrical funnel plot is imperative in the context of no publication bias, which involves favouritism towards significant or negative estimates. On the other hand, meta-regression methods explore the linear association between the earnings-price ratio and respective standard errors. In the absence of publication bias, there should be no statistically significant relationship between these two measures. We also utilized non-linear methods, including TOP 10 (Stanley *et al.* 2010), WAAP (Ioannidis *et al.* 2017), endogenous kink model (Bom & Rachinger 2019) and more. The final category encompasses approaches that address endogeneity concerns, such as the meta-regression method utilizing instrumental variables or the p-uniform method (van Aert & van Assen 2018). All methods demonstrate notable publication selection bias. There is a positive, statistically significant relationship between reported estimates and respective standard errors, pointing at selective reporting in economic literature. After accounting for the publication selection bias, the estimates of the earnings-price ratio range from -0.031 (not statistically significant) to 1.548, depending on the linearity assumption and weight of the most precise estimates, compared to the uncorrected mean 1.991.

In the subsequent section of the thesis, our focus centered on model averaging in order to investigate the heterogeneity of estimates. Both Frequentist and Bayesian model averaging techniques were employed in this analysis. The objective of employing the averaging method is to determine the significant variables that impact the effect of the earnings-price ratio on expected stock returns. In total 21 (28 in extended specification including supportive factors) variables were included in the analysis. For model averaging, we split standard errors into one Fama-Macbeth and non-Fama-Macbeth because we observe a symmetric funnel plot in case of studies that do not utilize the Fama-Macbeth procedure. Apart from Fama-Macbeth standard errors, we have identified the following variables that exhibit a positive effect on the size of the earnings-price ratio: employment of the Fama-Macbeth procedure and including delisted companies in the dataset. Although Europe shows a positive effect in one specification of Bayesian model averaging, robustness checks do not support this evidence. On the other hand, the effect of the earnings-price ratio is smaller in developed countries, which can be explained by the development stage of the markets and investors' behaviour.

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Appendix A

Data sample restricted to one month return

Table A.1: Linear tests for publication bias - one month returns

	(1) OLS	(2) FE	(3) BE	(4) Study	(5) Precision
Constant	1.085**	1.541**	1.329***	1.129**	0.09
Effect beyond bias	(0.391)	(0.449)	(0.387)	(0.366)	(0.082)
	[0.407,1.821]			[0.456,1.791]	[-0.027,0.337]
Standard Error	0.454**	0.260***	0.293***	0.365*	0.877***
Publication bias	(0.151)	(0.069)	(0.061)	(0.163)	(0.201)
	[0.086,0.697]			[0.007,0.751]	[0.508,1,236]
Studies	61	61	61	61	61
Observations	539	539	539	539	539

Notes: The table presents the findings of regression analysis using the equation $EP_{ij} = \beta_0 + \beta_1 * (SE_{EP})_{ij} + u_{ij}$, where EP_{ij} represents the i th estimated earnings-price ratio effect from study j and $SE_{EP})_{ij}$ is respective standard error. Specification (1) was estimated by Ordinary Least Squares (OLS) with clustered standard errors by study. Specifications (2) and (3) are panel data regressions with fixed and between effects, respectively. Specifications (4) and (5) utilized Weighted Least Squares (WLS) with the precision (1/standard error) and inverse of the number of size effect estimates reported per study as a weight. Standard errors are presented in parentheses, with significance levels denoted by *, **, and *** indicating significance at the 10, 5, and 1 percent levels, respectively. Values in square brackets represent a 90 percent confidence interval using wild-bootstrap (Roodman *et al.* 2019).

Appendix B

BMA

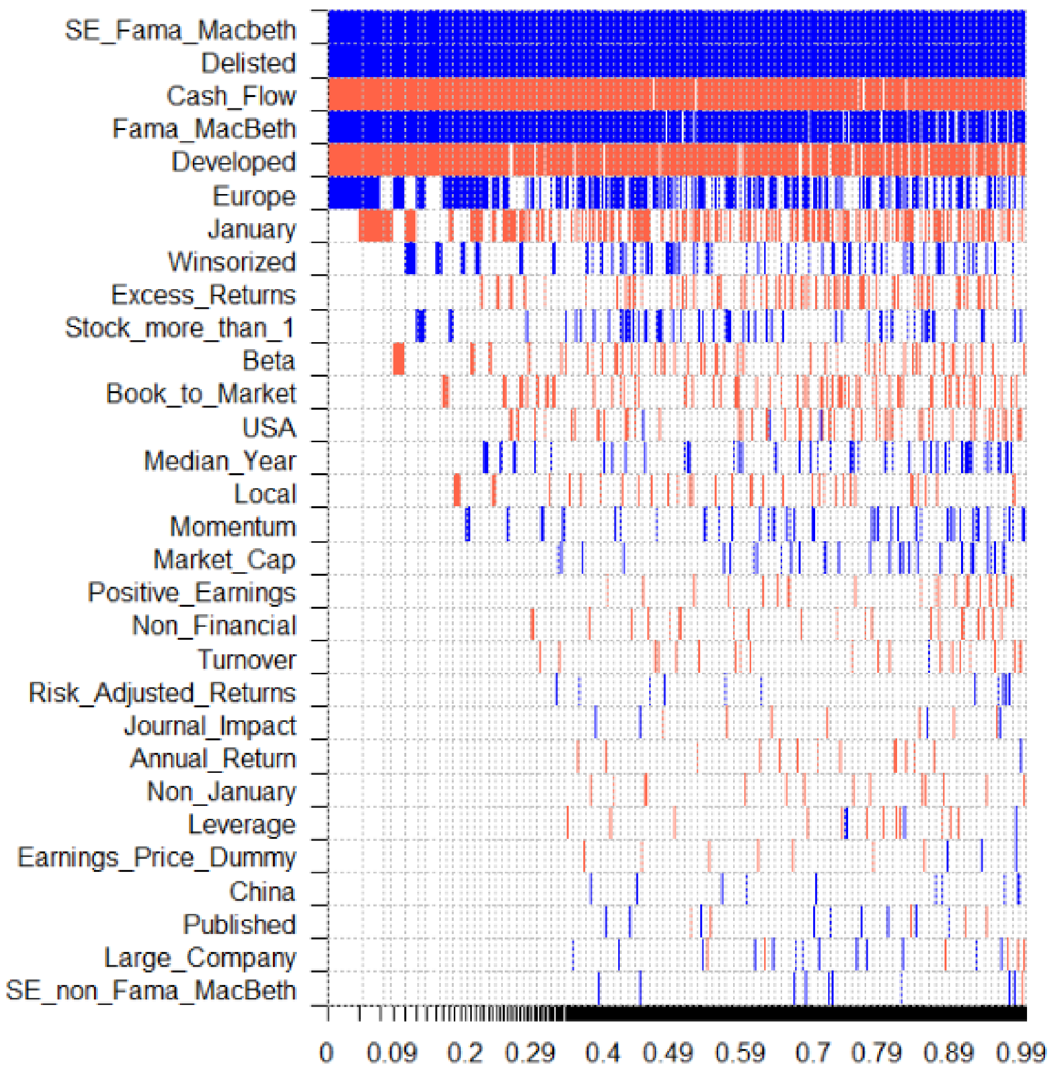
Table B.1: Variables and their value of VIF

Variable	VIF		
Fama-MacBeth SE	1.462	Fama-MacBeth	2.512
Non Fama-MacBeth SE	1.201	Excess returns	2.325
Journal impact	2.664	Risk-adjusted returns	1.229
Published	1560	Delisted	1.889
Median year	2.746	Positive earnings	2.056
China	1.438	January	1.376
USA	5.534	Non-January	1.234
Local	1.850	EP dummy	2.160
Developed	4.688	Winsorized	1.673
Non-financial	1.680	Annual return	1.798
Stock 1	1.577	Europe	3.090
Large stock	1.482		

Table B.2: Variables and their value of VIF - extended sample

Variable	VIF		
Fama-MacBeth SE	1.510	Fama-MacBeth	2.544
Non Fama-MacBeth SE	1.250	Excess returns	2.645
Journal impact	3.151	Risk-adjusted returns	1.417
Published	1.803	Delisted	1.971
Median year	3.002	Positive earnings	2.101
China	1.514	January	1.400
USA	5.952	Non-January	1.249
Local	2.268	Momentum	2.396
Developed	5.381	Market cap	1.497
Non-financial	1.734	Leverage	1.511
Stock 1	1.875	Book to market	1.685
Large stock	1.556	Beta	2.047
Winsorized	1.897	EP dummy	2.761
Annual return	2.094	Cash.flow	1.483
Europe	3.419	Turnover	1.482

Figure B.1: Bayesian model averaging results - extended sample



Notes: The figure depicts the results of the BMA analysis, employing the uniform g-prior and uniform prior methodologies. Compared to baseline model specification, extended model includes key supportive factors, to find whether their inclusion in underlying regression systematically affect the magnitude of the earnings-price ratio. The dependent variable in this analysis is represented by the earnings-price ratio, which is quantified on the x-axis in relation to cumulative posterior model probabilities. The explanatory variables have been prioritized based on their posterior inclusion probability, with the ranking displayed in descending order along the y-axis. Blue color (dark in grayscale) signifies that the variable is incorporated in the model with a positive coefficient. Conversely, red color (light in grayscale) is indicative of the variable being included in the model with a negative coefficient. The variables excluded from the model are represented without any visual differentiation. For a comprehensive description of the variables, please refer to table 5.1.

Table B.3: The results of BMA - extended sample

	BMA			**Freq. Ch. (OLS)**		
	P.Mean	P.SD	PIP	Coef.	SE	p-value
Constant	-0.005	NA	**1.000**	0.456	0.458	0.323
SE Fama-Macbeth	0.335	0.058	**1.000**	0.302	0.148	0.049
SE non Fama-Macbeth	0.002	0.033	0.029	0.048	0.095	0.615
Publication characteristics						
Published	0.001	0.071	0.030			
Journal Impact	-0.004	0.061	0.038			
Sample characteristics						
Positive earnings	-0.031	0.216	0.049			
Large company	0.007	0.126	0.030			
Local	-0.062	0.232	0.096			
Stock price more than 1	0.179	0.502	0.149			
January	-0.745	0.927	0.458			
Non January	-0.015	0.143	0.035			
Delisted	2.035	2.035	**1.000**	2.151	0.725	0.004
Industry and region						
Industry non-financial	-0.015	0.098	0.048			
USA	-0.143	0.462	0.126			
China	0.001	0.125	0.031			
Europe	0.660	0.670	**0.561**	1.215	0.771	0.112
Developed	-1.568	0.601	**0.929**	-1.918	0.818	0.019
Structural variation						
Median year	0.181	0.607	0.114			
Estimation technique						
Fama-Macbeth	1.479	0.545	**0.950**	1.699	0.441	0.000
EP dummy	-0.001	0.070	0.032			
Sample adjustments						
Winsorized	0.193	0.444	0.201			
Excess returns	-0.117	0.331	0.150			
Risk adjusted returns	0.020	0.155	0.041			
Annual return	-0.014	0.133	0.037			
Supportive factors						
Market cap	0.027	0.134	0.065			
Leverage	-0.009	0.113	0.033			
Book to market	-0.077	0.226	0.140			
Beta	-0.086	0.245	0.144			
Momentum	0.046	0.191	0.081			
Cash flow	0.986	-2.20	**0.647**	-2.151	0.725	0.004
Turnover	-0.023	0.167	0.044			