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Meta-analysis in Finance Research: Opportunities, Challenges, and Contemporary Applications

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Abstract

The number of empirical research studies in finance exhibits a strong upward trajectory, producing large differences in empirical results, which often impedes the drawing of consistent conclusions in relation to the phenomenon under examination. This creates demand for methods like meta-analysis that objectively consolidate and evaluate previous empirical findings. Meta-analysis is a group of statistical methods to aggregate prior empirical studies, to discover and explain consistencies as well as inconsistencies within reported results, and to detect and filter out distorting effects like publication bias or model misspecification bias. While meta-analysis is a standard tool for research synthesis and evidence-based decisions in many related research disciplines, like management, marketing, or economics, it has been rarely applied in finance. The goal of this article is to provide a comprehensive overview and discussion of the opportunities of meta-analytical research in finance, to present its recent applications, as well as to discuss related challenges and limitations. Thereby, we aim at increasing the awareness and acceptance of meta-analysis in finance and stimulating its future application in the field.

Keywords: meta-analysis, reviews, synthesis, publication bias, financial economics

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1 Introduction

'Thus, the foundation of science is the cumulation of knowledge from the results of many studies.'

(Hunter and Schmidt, 2004: xxvii)

We are living in the age of big data. Next to the bytes that we produce every day by sending emails, using social media or taking photos, we are also surrounded by huge data volumes in scientific research both in terms of the data input we are using for empirical analyses and the output we create as a result of our research. Adopting the characteristics of big data from computer science (McAfee and Brynjolfsson, 2012) suggests three key features of big data related to empirical research output: the abundance of published research (*volume*), the time it takes to produce new empirical output (*velocity*), and the diversity of results (*variety*).

<< INSERT FIGURE 1 HERE>>

Figure 1 captures the volume and velocity aspect. The graph illustrates the amount of annual Scopus-listed publications including different keywords for 'finance' and 'empirical analysis'. The number of articles increased from only one publication in the year 1965 to 11,120 documents in the year 2019.[1] In the last seven years, finance researchers produced more empirical studies as compared to the entire time before. This trend is underlined by the record number of paper submissions that are often reported by journal editors and conference organizers.[2] Volume and velocity are not only observable in the finance field as a whole, but also its specific topic areas. For example, Harvey et al. (2016) identify 316 papers on cross-sectional return patterns, Hang et al. (2018) find 591 studies on the determinants of corporate capital structure, and Veld et al. (2020) analyze 199 studies on the wealth effects of seasoned equity offerings. Extrapolating this growth, we could soon have research topics in finance with more than a thousand empirical studies.

The growth in research output offers many opportunities to expand our scientific knowledge on a broad and solid empirical foundation, but also comes with challenges. One of these challenges is the variety (also called heterogeneity) of empirical findings. In most of the major topic areas in finance, we

[1] It should be noted that Scopus also added more journals over time.
[2] For example, the American Finance Association received more than 2,000 paper submissions for its 2020 annual meeting (according to an email of the conference organizers sent to all submitters on May 31, 2019).

see substantial differences in what researchers report about a specific phenomenon (e.g., Astakhov et al., 2019; Feld et al., 2013; Holderness, 2018). We often find studies on the same research question providing evidence for a significant positive, negative, or no effect for the variable of choice (while controlling for a set of other variables). In addition to the variation in reported effects, finance studies testing the same hypotheses often vary widely in terms of their variable definitions (selection of dependent and independent variables, data transformations, etc.), data samples (countries, time period, industries, etc.), and applied methods (statistical estimator, outlier treatment, endogeneity correction, etc.). Mitton (2019) recently investigated the consequences of methodological choices by gathering data from 495 corporate finance papers. As one of his findings, he documents wide variation in the empirical methodology, especially the definition of key variables, the included set of control variables, and the methods of outlier treatment. Although the variety of results and applied methods reflects a critical discourse and, thus, progress in science, it is becoming increasingly difficult to find out what is really known in a particular research field and to what extent the observable variety of empirical results correlates with differences in study design, applied methods, and data samples.

Allied to the challenge of heterogeneity is the dwindling credibility of empirical research. In many fields of science, we see growing skepticism towards single approach findings and less confidence in the reliability of statistical test results produced under the pressure of reporting significant outcomes (among many others, Aguinis et al., 2017; Brodeur et al., 2016; Chordia et al., 2017; Christensen and Miguel, 2018; Harrison et al., 2017; Harvey et al., 2016; Ioannidis, 2005; Kim and Ji, 2015; Leamer, 1983; Morey and Yadav, 2018; Sterck, 2019; Wasserstein and Lazar, 2016). In his presidential address to the American Finance Association in 2017, Campbell Harvey criticized the misinterpretation of p-values and the fact that empirical research is prone to publish articles with positive findings, which creates strong incentives for researchers to engage in data mining and p-hacking (Harvey, 2017). Hence, if a data set is large enough and consists of many variables, statistically significant relations among these variables can be detected by sheer coincidence or active searching. For example, Chordia et al. (2017) implement a data mining approach to generate more than two million trading strategies and test their performance. Applying traditional statistics reveals a large number of rejections of the null hypothesis of no profitability. In contrast, when they correct for p-hacking, outperforming trading strategies are rare. In a similar vein, Kim and Ji (2015) review the top four journals in financial economics and find that only 2% of previous empirical studies present non-significant results. Mitton (2019) finds that statistically significant results can be achieved just by varying the methodology on different dimensions. His findings suggest that the variety in methods is not only a consequence of progress but may also be misused to deliberately produce preferred study outcomes.

Taken together, we observe an ever-growing amount of empirical literature that is evolving at a high velocity, often with diverse and sample-specific findings. At the same time, scholars and the public have less confidence in the credibility of empirical research output due to biases and questionable research methods. Hence, it is increasingly challenging to find out what we really know about a particular phenomenon, what drives the variability of empirical findings, and whether we can rely on the knowledge gained from empirical research. Searching for answers to these questions is not only relevant for academics, but also for decision- makers in politics and business and, thus, for the practical relevance of empirical research. To deal with these challenges, we need *'some objective and critical methodology to integrate conflicting research findings and to reveal the nuggets of "truth" that have settled to the bottom'* (Stanley and Doucouliagos, 2012: 2). A method that comes with these features is meta-analysis. It is a quantitative review technique that uses statistical methods to combine empirical results on the same research question across several studies and to draw conclusions about whether and to what extent an effect has received empirical support. In other words, meta-analysis is a method of big data analysis, which allows the piecemeal findings reported in several individual studies to be summarized and integrated into a big picture (Gurevitch et al., 2018). Meta-analysis also provides methods to detect and filter out empirical biases, such as model misspecification and preferential reporting of statistically significant results. Thus, meta-analysis also plays an essential role for transparency and integrity of empirical research.

Due to its distinct features, meta-analysis has become a frequently employed and established instrument for research synthesis and evidence-based decisions in many research fields (among others, Combs et al., 2019; Eisend, 2017; Geyskens et al., 2009; Grewal et al., 2018; Gurevitch et al., 2018; Khilf and Chalmers, 2015). There are more than 50,000 meta-analytical studies in medicine (Ioannidis, 2016), more than 400 published meta-analyses in management (Buckley et al., 2013), and more than

600 meta-analyses in economics (Poot, 2012). Meta-analyses in these areas are often highly acknowledged and frequently published in leading field journals like the Academy of Management Journal (e.g., Carney et al., 2011; Duran et al., 2015; Joshi et al., 2015), American Economic Review (e.g., Card and Krueger, 1995), Journal of Management (e.g., Lee et al., 2017; Marano et al., 2016; Shao et al., 2013), Management Science (e.g., Capon et al., 1990; VanderWerf and Mahon, 1992), or The Economic Journal (e.g., Card et al., 2010; Görg and Strobel, 2001). Despite its popularity and mainstream acceptance in many academic disciplines, meta-analysis is still rarely used in finance research. However, some recent examples successfully demonstrate its value for the field (among others, Feld et al., 2013; Holderness, 2018; Kysucky and Norden, 2016; van Ewijk et al., 2012).

Given the critical role of meta-analysis in advancing scientific knowledge and its increasing adoption many research fields, the central objective of this paper is to provide an introduction to its application in finance, to review existing meta-studies in the field, as well as to discuss opportunities and challenges associated with meta-analysis in finance. Although similar studies are available in other domains such as management, marketing, or economics (among others, Anderson and Kichkha, 2017; Eisend, 2017; Geyskens et al., 2009), to the best of our knowledge, there has not yet been an attempt to conceptually introduce the meta-analysis approach and its methods to the finance field.

The remainder of this paper is organized as follows. Section 2 describes the concept of meta-analysis and explains the three main meta-methods. Section 3 provides a snapshot of finance research that has been meta-analyzed. Section 4 reviews the opportunities of meta-analysis for finance research, and Section 5 discusses related challenges. Section 6 concludes.

2 The Concept of Meta-Analysis

According to Glass (1976: 3), a meta-analysis is the '*statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings*'. It originates from medical research, where studies are often based on small samples because large clinical trials are both costly and time-consuming. Due to small sample sizes, which induce low statistical power, clinical studies might fail to find statistically significant relations due to high standard errors of their estimates. In the traditional medical applications, the use of meta-analysis to synthesize small-sample results increases the precision of the estimated effects and thus has the power to uncover important findings that could not been found in a single study based on a few subjects.

Different research areas adopted meta-analysis in different ways and adjusted its methods and concepts to their discipline. For example, the management literature is largely focused on the aggregation of correlational data reported in previous empirical studies and the test of structural models at the meta-level (Geyskens et al., 2009). In contrast, economic literature focuses on explaining the large variability of earlier regression results and the identification/correction of biases (Stanley and Doucouliagos, 2012). Meta-analysis in finance research is a fairly young discipline. It is mainly inspired by meta-analytic applications in management and economics.

2.1 Contemporary Methods of Meta-Analysis

Before starting a meta-analysis, the first step is the collection of the population or a representative sample of the body of literature on a particular phenomenon. The required data must be extracted by manual coding of the studies. This step is typically the most time-consuming element of a meta-analysis and usually demands several months of reading and coding. For the data collection, it is essential to stick to high-quality standards to avoid any systematic bias or errors in the data. The steps of data search and coding are well documented in many handbooks and guidelines (among others, Borenstein et al., 2009; Havranek et al., 2020; Stanley et al., 2013; Stanley and Doucouliagos, 2012) and, thus, will not be further discussed in this study.

There are three main methodological approaches used in business and economics to meta-analyze primary results: (i) traditional meta-analysis, (ii) meta-regression analysis (MRA), and (iii) meta-analytic structural equation modeling (MASEM). The three approaches, which are summarized in Table 2, are not mutually exclusive, but meta-analysts often apply several methods in the same study.

<< INSERT TABLE 1 HERE>>

2.1.1 Traditional Meta-Analysis

Traditional meta-analysis methods focus on the aggregation of statistical effect sizes reported in a set of prior studies. An effect size is a quantitative measure of the magnitude of a phenomenon that is used to address a research question of interest (Kelley and Preacher, 2012: 140). Effect sizes are either statistical measures (like correlations) or economic effects (like elasticities). There are several methodological approaches for traditional meta-analysis. One of the most popular methods is the Hedges-Olkin meta-analysis (Hedges and Olkin, 1985), which is discussed here.[3]

We assume a set of $i = 1, \ldots, k$ empirical primary studies investigating the same phenomenon, e.g., the abnormal return effects after announcements of equity issuances by publicly traded firms. Each study reports one[4] effect size estimate α_i, and the corresponding standard error of the effect size $SE(\alpha_i)$ or statistics to re-calculate the standard error (e.g., t-statistics and number of observations). Traditional meta-analysis aims at deriving the best estimate for the unknown population effect size θ by calculating the weighted mean $\hat{\theta}$ over all effect size estimates collected from the primary studies in the meta-sample.

A key parameter is the weight assigned to each effect size estimate α_i. The fixed-effects model (FEM) assumes that each study reports an estimate for the same underlying population effect, i.e., the true effect is the same in all studies (Borenstein et al., 2009). Accordingly, the variation of the effect size estimates across studies is attributed purely to random sampling error and, thus, assumes that there is no additional variation beyond (no heterogeneity). Hedges and Olkin (1985) show that the optimal study weight w_i for the FEM is the inverse of the effect size estimate's squared standard error $SE(\alpha_i)^2$:

$$w_i^{\text{FEM}} = \frac{1}{SE(\alpha_i)^2} \tag{1}$$

This weighting scheme indicates that more precise studies, i.e., those with lower standard errors, receive larger weights and hence have a greater impact on the weighted average effect.

Genuine heterogeneity in the sample of primary studies causes another source of variation (beyond sampling error) that must be considered in the weights (Borenstein et al., 2009). In the case of real differences between studies, the effect size estimates will be different even if all studies would have an infinitely large sample (Riley et al., 2011). For example, regional differences in governance structures could lead to fundamentally different reactions of shareholders to equity issuance announcements in different countries. In this case, the FEM would be an unsuitable model for combining heterogeneous effect sizes. In contrast to the FEM, the random-effects model (REM) assumes that effect size estimates

[3] There are alternative approaches to summarize effect size estimates across studies, e.g., the artifact-corrected meta-analysis by Hunter et al. (1982) is widely used in psychology and management sciences.

[4] Model extensions of the traditional approach exist that account for multiple estimates reported in the same study (Card, 2012).

are drawn from study-specific populations. The REM-weights take heterogeneity into account by splitting the variation of effect sizes into two components: within-study variation $SE(\alpha_i)^2$ (capturing sampling error) and between-study variation $T_i{}^2$ (capturing the variance of the effect size parameters across study-specific populations). Study weights are assigned to minimize both sources of variance:

$$w_i^{\text{REM}} = \frac{1}{SE(\alpha_i)^2 + T_i^2} \tag{2}$$

The between-study variation $T_i{}^2$ is usually unknown, but can be estimated by a method of moments (DerSimonian and Laird, 1986) or (restricted) maximum likelihood estimator (Viechtenbauer, 2005).

Beyond inverse variance weighting as shown in Equations (1) and (2), traditional meta-analysis also applies alternative weights. For example, Stanley and Doucouliagos (2015) show that, in the case of publication bias, an unrestricted weighted least squares (WLS) estimator is superior to the conventional REM and better than FEM if there is heterogeneity. Moreover, standard errors are sometimes not reported in the primary studies and re-calculations from other reported statistics are unreliable. In this case, meta-analysts also use the primary studies' sample sizes, journal impact factors, or citations as quality indicators to give larger weights to 'better' studies (Stanley and Doucouliagos, 2012).

After selecting and calculating appropriate weights, the estimated value for the population effect size $\hat{\theta}$ is given by the weighted average of the effect size estimates α_i observed from each study:

$$\hat{\theta} = \frac{\sum_{i=1}^{k} w_i \alpha_i}{\sum_{i=1}^{k} \alpha_i} \tag{3}$$

The estimate $\hat{\theta}$ and corresponding confidence intervals provide an estimate for the overall effect implied by the literature.

Traditional meta-analysis is also used to analyze the combined effect sizes of different subgroups of studies. In the subgroup analysis, the sample is divided into two or more separate groups. For example, all studies that examine US firm data compared to all studies that examine data from other countries. After splitting the sample of studies, the average effect for each subgroup can be calculated as in Eq. (1) – (3). The variance of the difference between the subgroup effects is used to compute confidence intervals and significance tests to find out whether differences between subgroups, and hence heterogeneity, are significant (see, e.g., Borenstein et al., 2009). If heterogeneity exists, the variation within the subgroups should decrease while there is a significant variation between subgroups

(Rosenbusch et al., 2013). Accordingly, the analysis of the significance of the subgroup differences is a test of whether the criterion used to split the subgroups is a moderator (Shadish and Sweeney, 1991).

A disadvantage of subgroup analysis is that it cannot reveal the simultaneous effect of different heterogeneity drivers. In business and economics research, however, empirical results are not only driven by a single study feature, but rather by a number of different observable and unobservable aspects of study design. In the next section, we proceed with meta-regression analysis, which explicitly models the joint impact of many study characteristics and sources of biases in a regression-based framework.

2.1.2 Meta-Regression Analysis

Meta-regression is defined as '*the regression analysis of regression analyses*' (Stanley and Jarrell, 1989: 161). In an empirical research environment where studies routinely report regression parameters, it provides a method for integrating and explaining diverse findings from a number of prior regressions. It is a tool that explicitly accounts for heterogeneity and determines the sources of variability of study outcomes and frequent biases, such as selective reporting of statistically significant results.

We assume a set of $i = 1, \dots, k$ empirical primary studies investigating the same phenomenon. Each study reports estimates for $j = 1, \dots, m$ regression models like:

$$Y = X\beta + \varepsilon, \tag{4}$$

where Y is a dependent variable in the primary study that measures the economic phenomenon under examination (e.g., the corporate debt level), $X\beta$ is a set of explanatory variables in the primary study (e.g., the determinants of corporate debt level), and ε represents the random error term. Eq. (4) shows the simplest form of a primary regression that can be extended by fixed effects, instrumental variables, or other advanced regression methods. β measures the magnitude and statistical significance of a certain effect under examination (e.g., the impact of tax rates on corporate debt financing). From a collection of primary studies, we obtain a sample of estimates for β, which are denoted b_{ij}. The index j accounts for the fact that empirical studies in economics and business routinely report more than one regression parameter, e.g., for different robustness analyses and subsample tests. As regression coefficients are not always comparable across studies, e.g., due to different scaling of variables or functional forms, b_{ij} can also represent transformations of regression parameters, such as elasticities, semi-elasticities, or partial correlation coefficients.[5] In addition, we assume that the standard errors of the regression coefficient $SE(b_{ij})$ are given in the primary studies or, alternatively, we can obtain other statistics to re-calculate standard errors. Besides the effect sizes and their standard errors, we also assume that the set of $i = 1, \dots, k$ primary studies differs in study design and sample characteristics. These study differences are covered by a set of dummy variables (denoted Y and Z). Next to dummy variables, study characteristics might also be captured by continuous variables.

In the meta-regression model, the estimates b_{ij} are regressed on a set of explanatory variables that quantify study characteristics and biases. This goes much further than averaging effect sizes in the traditional meta-analysis, as meta-regression analysis simultaneously models the impact of different variables in a multiple regression framework. The general meta-regression model is defined as:

$$b_{ij} = \gamma_0 + \gamma_1 SE(b_{ij}) + \sum_{l=1}^{L} \lambda_l Y_{ijl} + \sum_{k=1}^{K} \varphi_k Z_{ijk} + u_{ij} \tag{5}$$

Eq. (5) accounts for publication bias by including $SE\left(b_{ij}\right)$ as an explanatory factor. In the absence of publication bias, the observed effect sizes b_{ij} and their standard errors $SE(b_{ij})$ should be independent quantities. If authors actively change their model specification or data sets until they find that estimates are large enough to offset high standard errors (Stanley et al., 2008), and thus to be statistically significant, correlation between the effect size estimates and their standard errors occurs. The relation between the primary studies' regression estimates and their (inverse) standard errors is often depicted in a scatter diagram, the so-called funnel plot. Without bias, this graph should resemble a symmetrical distribution around the most precise estimates (those with the lowest standard errors), forming an inverted funnel. In the case of publication bias, the graph will be truncated.[6] Figure 2 presents an exemplary funnel plot reported by Astakhov et al. (2019) examining 102 studies reporting effects for the impact of firm size as a predictor for stock returns. The funnel plot appears asymmetric, with many estimates concentrated in the left-tail, suggesting publication bias towards negative firm size effects.

<< INSERT FIGURE 2 HERE>>

[5] See Stanley and Doucouliagos (2012), Chapter 2.3, for a detailed overview of commonly applied effect sizes in meta-regression analysis.
[6] Asymmetry in the funnel graph might also be driven by methodological or structural heterogeneity as explained in the subsequent paragraphs.

The rejection of the null hypothesis, H$_0$: $\gamma_1 = 0$, tests the presence of publication bias, i.e., the truncation in the funnel plot (Egger et al., 1997). The corresponding regression parameter γ_1 measures the direction and magnitude of the bias. The estimated value for the intercept, γ_0, is the mean effect size across all studies assuming that $SE(b_{ij})$ is close to zero ($SE(b_{ij}) \to 0, E(b_{ij}) \to \gamma_0$) and the values of vectors Y_{ijl} and Z_{ijk} are zero. Thus, rejecting the null hypothesis, H$_0$: $\gamma_0 = 0$, is a test for the existence of a genuine effect beyond publication bias conditional on the values for Y_{ijl} and Z_{ijk} (Stanley, 2008).[7]

Meta-regression also provides a means to quantify the sensitivity of primary study results to variations in the model specification. Thus, meta-regression studies typically include a set of dummy variables (vector Y in Eq. 5) that indicate whether a specific control variable is present/absent in the original regression model (Eq. 4) or which functional form was used (e.g., level-level, log-log or log-level). The estimated meta-regression coefficients $\hat{\lambda}_l$ measure the sensitivity of the examined effect to changes in the control variables or functional form of the primary regression model.

Finally, vector Z_{ijk} represents a collection of meta-independent variables that quantify relevant study characteristics and explain variation across the collected results related to differences in data and methods. The meta-coefficients φ_k reflect the average effect of a given study characteristic on the effect sizes. Accordingly, the explanatory variables Z_{ijk} can be interpreted as moderators of effect sizes b_{ij}.

The error variance in Eq. (5) is usually non-constant due to the differences in the effect size variance. To address this heteroscedasticity, the meta-regression model is commonly estimated via WLS using the inverse of the squared standard errors $1/SE(b_{ij})^2$ as weights (Stanley and Doucouliagos, 2012). Additional weights are the sample size of the study or the inverse of the number of effect sizes extracted from each study. The latter is used to consider the unbalancedness of the meta-data set arising from the extraction of multiple reported effect sizes per each study (Zigraiova and Havranek, 2016).

2.1.3 Meta-Analytical Structural Equation Modeling

Beyond traditional meta-analysis and meta-regression, the adoption of structural equation modeling for meta-analysis allows simultaneous testing of the relationships between several variables (Cheung,

[7] Meta-analysts usually estimate Eq. (5) without Y and Z in a first stage to identify publication bias and to estimate the corrected mean effect beyond bias γ_0 (Stanley and Doucouliagos, 2012). Then, in a second stage, other meta-explanatory variables are added to the model.

2015; Cheung and Chan, 2005; Viswesvaran and Ones, 1995). This group of methods is referred to as meta-analytic structural equation modeling (MASEM). While the traditional meta-analysis approach examines a single bivariate relationship, MASEM takes into account the interactions with other variables, allows the evaluation of mediating effects among these variables, and tests entire structural models. In this way, MASEM enables the meta-researcher to compare the explanatory power of competing theory frameworks and to contribute to the identification of boundaries, structures, and shortcomings of theoretical models (Bergh et al., 2016).

MASEM begins with the definition of a theoretical model for the relations among a set of variables. To judge whether the model is supported by empirical evidence, the theoretical model is fitted on the pooled data from the primary studies. In this way, MASEM benefits from the data reported in all studies, even if the studies in the sample do not investigate all relations between the variables featured in the structural model to be tested.

We assume a set of $i = 1, \ldots, k$ empirical primary studies investigating one or more bivariate relations among a set of $x = 1, \ldots, n$ variables. After defining the structural model, the meta-data is collected from the primary studies. We also assume that each study in the sample reports Pearson correlations coefficients for one or more relations among the set of variables. Moreover, the sample size can be obtained from each study. The information from the primary studies is arranged in a correlation matrix R_j per study. After the structural model is defined and correlation coefficients are collected from the set of primary studies, MASEM is typically conducted in two stages (Viswesvaran and Ones, 1995). In stage one, the Pearson correlation coefficients are combined into a meta-analytic pooled correlation matrix. In stage two, the structural model is fitted on the pooled correlation matrix.

Stage one. In contrast to classical structural equation modeling methods, MASEM typically fits the model to the meta-analyzed correlation matrix rather than a covariance matrix (Cheung and Chan, 2009). Several methods exist to receive the pooled correlation matrix (Jak, 2015). The simplest approach takes the correlation coefficients from the primary studies and pools them into one overall effect by calculating weighted mean correlations (equivalent to the traditional meta-analysis methods, Eq. (1) – (3)). The weighted means are calculated separately for each bivariate relation. Advanced multivariate pooling methods, such as the generalized least squares (GLS) approach (Becker, 1992, 2009) or the two-stage structural equation modeling (TSSEM) method (Cheung and Chan, 2005), take into account that correlation coefficients from the same study might not be independent. Beyond non-independent effects, a second issue might arise if the correlation coefficients are not homogenous across studies, i.e., if heterogeneity exists. Similar as to the traditional meta-analysis, fixed and random effects models can be applied to pool the correlation matrix (Cheung, 2015).

Stage two. To fit the structural model to the meta-analyzed correlation matrix, the model parameters are presented as matrices (Cheung, 2015; Jak, 2015). Matrix **B** captures the path coefficients, matrix **P** represents variances and covariances, and matrix **I** is an identify matrix. The general hypothesis to be tested by fitting the structural model to the meta-data is that the population covariance matrix $\boldsymbol{\Sigma}$ is equal to the model implied covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Model}}$. The three matrices $\mathbf{B}$, $\mathbf{P}$, and **I** serve as input to formulate the model implied covariance matrix:

$$\boldsymbol{\Sigma}_{\mathbf{Model}} = (\mathbf{I} - \mathbf{B})^{-1}\mathbf{P}(\mathbf{I} - \mathbf{A})^{-1'} \tag{6}$$

Since the population covariance matrix $\boldsymbol{\Sigma}$ is unavailable to the meta-researcher, MASEM makes use of the sample covariance matrix **S**.

To estimate the model parameters in **B** and **P**, the difference between the model implied covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Model}}$ and the observed covariance matrix **S** is minimized. This leads to the following discrepancy function that can be estimated by maximum likelihood:

$$F_{ML} = log|\boldsymbol{\Sigma}_{\mathbf{Model}}| - log\left|\mathbf{S} + \mathrm{trace}\left(\mathbf{S}\boldsymbol{\Sigma}_{\mathbf{Model}}^{-1}\right) - p\right|, \tag{7}$$

where p represents the number of variables in the model. If the model perfectly fits to the data, F_{ML} would be zero and $\boldsymbol{\Sigma}_{\mathbf{Model}} = \mathbf{S}$.

Besides this general approach, there are alternative procedures for the two steps described above. A common method is the TSSEM (Cheung and Chan, 2005), where multigroup structural modeling is applied to pool the correlation coefficients in stage one and WLS estimation is used to fit the model to the pooled data in stage two. For a detailed description and applied examples of the different MASEM calculations, see Cheung (2015) and Jak (2015). Up to now, the MASEM methods are mainly applied in management research (Bergh et al., 2016) and very rarely in finance-related topics (e.g., Hang et al., 2019; van Essen et al., 2015b).

3 Review of Previous Meta-Research in Finance

The previously presented methods are independent of the specific research field and can be applied in all areas of business and economics. The remainder of this paper will focus on the application and advances of meta-analysis in finance research.

3.1 Identification of Studies

To identify existing meta-analyses in finance, we conduct a comprehensive literature search. In the first step, we used keywords to search in the following electronic databases: Business Source Premier, EconLit, ABI/INFORM Complete, and Google Scholar. Our search term combines two groups of keywords: the meta-analytic nature of the study (meta-analysis, meta-regression, quantitative review), and the focus on the finance research field (finance, asset pricing, financial intermediation, financial markets, investment, capital markets). In a second step, we additionally screened all articles published in the 35 top journals in the finance field with a ranking of 4*, 4, or 3 in the 2018 Academic Journal Guide (AJG) by the Chartered Association of Business Schools.[8] In the third step, the references in all relevant articles identified in the first two steps were investigated to find further research publications.

During the literature search process, we excluded several studies from the sample due to the following reasons. (i) The unit of analysis are not the results reported in primary studies, but rather the performance measures of funds (Coggin et al., 1993; Coggin and Hunter, 1993), forecasts of analysts (Coggin and Hunter, 1983), or the effects of cloud cover on stock returns across several stock exchanges (Keef and Roush, 2007). (ii) The authors call their approach meta-analysis, although it is not a quantitative integration of the literature using one of three methodological frameworks introduced in the previous sections. For example, Harvey et al. (2016) and Harvey (2017) use the term 'meta-analysis' to compare factors for the cross-section of expected returns across different studies, but they do not present a synthesis of previous research with meta-analytical methods. (iii) The study presents a real meta-analysis, but the examined research question cannot be assigned to finance research. However, it should be noted that there is no clear cutoff. This holds especially for topic areas that lie in-between finance and other research fields (especially economics and management). For example, the examination of the

[8] https://charteredabs.org/academic-journal-guide-2018-view/

relation between ownership structure and firm performance covers aspects from both management and finance research. We decided to include all meta-studies examining such cross-disciplinary topics if their list of primary studies covers a substantial amount of research papers published in traditional finance journals. Nevertheless, this approach is subjective and, thus, the true list of all finance meta-studies depends on the author's judgement.

After applying the selection criteria on the sample of collected search results, we end up with a final sample of 61 studies (s as of December 2019) using meta-analysis to aggregate and compare empirical results in finance. A full list of the studies is reported in Appendix A.

3.2 Descriptive Statistics

Figure 3 breaks down the number of meta-studies in finance per publication year. The earliest published study is by Coggin and Hunter (1987), who aggregate the results of two studies reporting estimates for the impact of risk factors in asset pricing. Despite this early application of meta-analysis, there are only a few studies published until 2014. However, we observe an increasing trend in the recent years. After 10 studies published in 2018, there are 15 meta-analysis papers published in 2019.[9] The rather low number of prior meta-analyses and the fact that half of the existing studies have been published in the past three years illustrate that meta-analysis is a rather young discipline in finance.

<< INSERT FIGURE 3 HERE>>

We see three main reasons for the growing interest in meta-analysis research in finance. First, the amount of empirical research output in finance has increased significantly over the past decade. This provides a reasonable basis of empirical results for aggregation. Second, the rising demand for transparency in empirical research calls for methods like meta-analysis to detect and correct distortions like publication bias or *p*-hacking. Third, meta-analysis has been successfully applied in various related areas like economics, management, accounting, or marketing. This might generate a 'spill-over' effect into finance research.

To break down the topics addressed in prior finance meta-analyses, we group them into three topic fields: (1) asset pricing, (2) corporate finance, and (3) financial intermediation. Within the topic fields,

[9] This increase is also driven by a special call for meta-analysis in the *International Review of Financial Analysis in* 2019 and the corresponding *Symposium on Meta-Analysis, Scientometrics and Systematic Reviews in International Finance* (2018 in Poznan).

we further classify studies into topic areas.[10] As a result of this classification, we find that the majority of meta-analyses examines research questions in corporate finance (42 studies), followed by asset pricing (14 studies), and financial intermediation (5 studies). In corporate finance, four topic areas are dominant: corporate governance (13 studies), raising capital (7 studies), risk management (6 studies), and capital structure (6 studies). A reason for the predominant use of meta-analysis in corporate finance might be that there are various fundamental theories and hypotheses, often with ambiguous empirical evidence from a large body of literature. This may create demand for aggregation and comparison. Also, the examined effects are often similar in terms of the applied statistical models producing comparable quantities, which builds the foundation for a meaningful synthesis via meta-analysis.

Regarding the publication outlet, we observe that 49 studies are published in referred journals, while 12 studies are unpublished working papers and book chapters. Among the published papers, several articles appeared in leading journals like the Journal of Financial Economics (Holderness, 2018), Management Science (Kysucky and Norden, 2016), Journal of Banking and Finance (Feld et al., 2013), or Journal of Empirical Finance (van Ewijk et al., 2012). The high recognition of these journals accepting meta-analyses for publication and the recent increase in the number of studies might indicate a near-term breakthrough and broader acceptance of meta-analysis in finance research.

A breakdown of the journals shows that 34% are management journals, 25% are original finance journals, 20% are economics journals, 2% are accounting journals, and 20% are working papers and book chapters. Accordingly, the majority of finance-related meta-analyses are published in management journals. The dominance of management journals may be due the fact that there are various meta-analyses on corporate governance topics, which cover elements of both finance and management. Another factor could be that editors and reviewers of management journals are more receptive to accept meta-analysis papers because the method is widely used and accepted in their discipline.

Table 2 provides summary statistics for several dimensions characterizing the study design and applied methodology in the 61 studies. Based on a systematic review, we derive opportunities and challenges of meta-analysis in finance, which are discussed in the subsequent Sections 4 and 5.

[10] These topic areas are the same as for list area assignments of the Annual Meeting of the American Finance Association (AFA).

<< INSERT TABLE 2 HERE>>

4 Opportunities of meta-analysis in finance

Knowledge accumulation. By combining evidence from many seemingly conflicting primary studies, meta-analysis draws a statistical summary of the research field under examination. The estimation of an overall population-level effect size, which is the main objective of meta-analyses in finance (see Table 2), builds on previous empirical findings produced by many different researchers using a range of different methodologies and data sources over various time periods and countries. Due to this variety of research setups used as input, meta-analysis comes with a level of independence and rigor over traditional primary studies in order to develop an overall understanding of the answers to important research questions. Meta-analysis creates a '*store of accumulated knowledge*' (Grewal et al., 2018: 9), which is important for scientific progress. The demand for this knowledge accumulation even increases with the growing volume of empirical finance research papers, which are difficult to aggregate without statistical methods like meta-analysis.

Especially corporate finance research might benefit from the aggregation of statistical effects. Here, we routinely find empirical studies focusing on firms from a specific country or world region. A reason why it is difficult for corporate finance authors to analyze large and cross-country samples is that it often requires to manually gather corporate data from annual reports or other documents. Moreover, corporate reports are often in the local language, which creates another barrier to code their information correctly. Meta-analysis benefits from the single country data that individual (domestic) study authors gathered and integrates them into a global effect while accounting for country-level differences. Accordingly, meta-analysis can create international samples in research fields without international evidence at primary study level. In contrast to local firms, capital markets are global and integrated. Accordingly, in capital markets research meta-analysis can contribute especially by disaggregating and finding sources of differences and biases.

Precision. An important advantage of meta-analysis comes from the way it handles sampling error. Sampling error is the random deviation from the overall population, which arises when researchers draw samples, e.g., by selecting a set of firms. The larger the study, the smaller the sampling error and the more precise are the effect estimates (Combs, 2010; Hackshaw, 2008). As meta-analysis combines the power of many studies, positive and negative sampling errors average out and the overall sampling error becomes smaller than in any of the individual studies, especially those with small samples (Hunter and Schmidt, 2004).

According to Table 2, the median meta-analysis in finance includes 35 primary studies and 183 effect sizes estimates. Some studies even cover more than 1,000 effect sizes estimates (sample maximum is 6,312) collected from hundreds of primary studies (sample maximum is 411). This underpins the power of meta-analysis to bring together and to compare the large body of literature on a particular phenomenon while minimizing sampling error. However, the gain in precision in finance might be lower than in other research fields. In contrast to empirical research in economics, which is often based on data with lower frequency (e.g., quarterly data on economic growth), many data sets in empirical finance, especially in capital markets research, are often available with higher frequency (e.g., daily or intra-day stock prices). This increases sample sizes within primary studies and, thus, also precision. Nevertheless, also in finance, the aggregation within a meta-analysis has the power to further decrease sampling error by pooling large and small sample studies.

Identification and correction of publication bias. Publication bias has been widely regarded as a serious threat for the validity of empirical research (Andrews and Kasy, 2018; Begg and Berlin, 1988; Ferguson and Brannick, 2012; Harrison et al., 2017; Hunter and Schmidt, 2004; Roberts and Stanley, 2005; Rothstein et al., 2005; Stanley, 2005; Stanley and Doucouliagos, 2014; Thornton and Lee, 2000). As shown by Doucouliagos and Stanley (2013) in a review of 87 meta-studies covering 3,599 prior studies, most fields of economics research (including financial economics) are affected by publication bias. In finance, Harvey (2017) detects strong selective reporting of significant research results in factor studies explaining the cross-section of expected returns. Figure 10 shows the distribution of the *t*-statistics reported in 313 factor studies. The number of studies reporting *t*-values between 2.0 and 2.57 is almost identical to the number of studies reporting *t*-values within the interval of 2.57 to 3.14. This makes only sense in the presence of publication bias (Harvey, 2017). Accordingly, it appears that authors in this field systematically neglect insignificant results and discard them from being published.

<< INSERT FIGURE 4 HERE>>

When the 'consumers' of finance research are not aware of the alternative results that end up in the file drawer due to *p*-hacking or publication bias and, thus, remain unpublished, their conclusions about the importance and robustness of the results can be highly distorted (Mitton, 2019). If publication bias exists, also averaging across studies in a meta-analysis creates biased mean effects. However, meta-analysis, and especially meta-regression, allows to identify and even to filter out publication bias using statistical methods. Thereby, meta-analysis contributes to transparency and increased credibility of empirical research results. This is a clear advantage over primary research as several biases cannot be controlled at the level of individual studies; this particularly holds for publication bias, which *'is caused by the process of conducting empirical research itself'* (Stanley and Doucouliagos, 2012: 4).

According to Table 2, there are 31 meta-studies in finance that explicitly detect and control for the impact of publication bias via graphical analysis or statistical testing. Most of these studies discover medium to strong impact of publication bias. For example, Astakhov et al. (2019) conduct a meta-analysis of the firm size effect on stock returns. On average across 102 prior studies, smaller firms outperform larger stocks by 5.08% in annualized terms. However, after correcting for selective reporting, the mean size premium is only 1.72%.[11] Accordingly, due to publication bias, the literature as a whole exaggerates the size effect by a factor of three.

Correction for model misspecification bias. Primary studies in finance use a variety of model specifications (Mitton, 2019). Changes in research design are often regarded as innovation over prior work. An important decision for model specification is the set of control variables to be added to the model. Some of these variables are used consistently across the literature (e.g., controls for firm size); other control variables are study specific. Data constraints and the desire to be 'different' often lead to varying sets of control variables (Koetse et al., 2005). Bias occurs when important variables are omitted from the primary study model (omitted variable bias). If the empirical literature is a mix of correctly and incorrectly specified models, this might also induce bias on the meta-level.

Meta-analysis, and especially meta-regression, is designed to detect and control for misspecification bias (Stanley and Jarrell, 1989). In the meta-regression model in Eq. (5), the vector Y accounts for biases arising from the exclusion of relevant control variables from the original regression model in Eq. (4).

[11] This refers to the implied difference between the 10^{th} and the 90^{th} percentile of NYSE stocks.

Meta-regression reveals the sensitivity of empirical effects against omitted variables or changes in other model specifications. We can even compute a synthetic overall effect assuming a perfect model setup.

Seventeen prior meta-studies in finance explicitly test for misspecification bias by coding the control variables included in the primary regression model. For example, Feld et al. (2013) find that six control variables in the primary study regression model significantly determine the reported marginal effect of tax on the corporate debt level. As finance studies often include a fixed standard set of several control variables, meta-studies can also include a dummy variable indicating whether this standard set of control variables is included or not.

Exploration of heterogeneity. Regarding the primary purpose of meta-analysis, Table 2 suggests that the analysis of methodological heterogeneity is a major goal of the previous meta-studies in finance. Heterogeneity is inherently present in empirical finance research, which is mostly a non-experimental field of science, where study design and data selection are widely different across different studies and authors. With the rapid increase of empirical research and the progress in data availability and statistical methods, heterogeneity even grows over time, producing a wide distribution of estimates for a specific effect. With meta-analysis, researchers can leverage the study-level differences to find an explanation for the variation in effect sizes and to understand the relationship between those effects and the study design characteristics. This can resolve conflicts in the literature and determine important moderating factors.

In Eq. (5), the vector Z represents the moderator variables for heterogeneity. The estimated meta-regression coefficients capture the impact of the moderators on the examined effect. As many moderators are dummy or categorical variables indicating the presence of a certain study characteristic (e.g., whether a model controls for endogeneity or not), the estimated coefficients commonly reflect the average impact on the reported effect if the study design deviates from the base group in that aspect, all other factors being equal. Thus, significant meta-regression coefficients can be interpreted as an indication that a specific study feature changes the focal relationship, i.e., it increases or decreases the effect collected from models with this attribute (Lipsey and Wilson, 2001). For example, van Ewijk et al. (2012) find in their meta-regression that the equity premium gathered from 24 studies is on average

1.31% larger when using ex-post as compared to ex-ante methods and 3.54% smaller before 1910 as compared to more recent time periods.

Based on the evaluation of the previous 61 meta-analyses, we derive the following best groups of moderator variables for meta-analysis in finance (beyond including controls for publication bias and misspecification as described above):

- Measurement of the focus variables (e.g., variations in the definition of the dependent and independent variables)
- Data characteristics (e.g., number of observations/degrees of freedom, average sample year, or data frequency)
- Method choices (e.g., control for endogeneity, type of estimator, fixed effects included, or robust estimation of standard errors)
- Publication characteristics (e.g., number of citations, journal impact factor, or type of publication)

As in finance data is often derived from similar databases (like Bloomberg, Thomson, etc.), we also recommend including the data source as a moderator variable. Moreover, real economic differences across countries, industries, or company size can be explained via meta-regression. In finance, we often see that the majority of studies refer to US data. Hence, we recommend adding a binary variable for studies focusing on US data (and other countries or world regions). However, the final selection of the moderators depends on the specific research question and the data observable from the respective studies.

Theory advancement. Meta-analysis can be helpful in testing different or alternative competing theories on an aggregated level. MASEM even allows comparing complex theoretical models and their empirical support. Moreover, the meta-analyst can also add previously unexamined data from external sources to test new theory-driven hypotheses about moderating effects. For example, meta-analysis can be employed for testing cross-country boundary conditions that drive the direction and size of a certain relationship, which would otherwise demand an expensive collection of data over many different countries and time periods.

For example, Kysucky and Norden (2016) collect a sample of 101 studies on the benefits of relationship lending and collect additional data for bank competition from the World Bank. Based on the country and time period in the original studies, bank competition information can be assigned to each study. The study finds that the level of bank competition is an essential moderator for the realization of benefits from relationship lending.

Predictions and benchmarks. The results from meta-analysis, especially from meta-regression, can be used to make predictions and to derive better practical implications. The meta-analyst can use the coefficients from Eq. (5) to estimate the underlying true effect conditional on the examined moderator variables. By inserting 'best practice' values for the moderators, meta-analysis creates a synthetic study.

For example, Feld et al. (2013) predict the marginal tax impact on debt for a synthetic benchmark study by setting all significant dummy meta-regressors to a value of one (i.e., the study is in line with the benchmark) and all insignificant as well as continuous moderators are set to the sample mean (i.e., referring to the 'average study'). This benchmark study predicts a marginal tax effect on the debt ratio of 0.27.

Future enhancements in primary studies can be evaluated against the benchmark given by meta-analysis. Moreover, Bayesian approaches, which often rely on theoretical distributions of priors, can refer to the empirical distribution of previous results gathered in a meta-analysis to generate alternative priors (Moral-Benito, 2012). Meta-analysis results are also helpful for reviewers, editors, and readers of scientific work to have a reference point of previous literature when evaluating the findings of a new study, but also to discover new research questions and the demand for further research.

Evidence-based decision making. To make a practical impact, empirical research must be approachable for practitioners, politicians, and other decision makers like corporate managers. However, the growing body of literature, distorting biases, and the variation within empirical results constitute challenges for the practical usage of research findings. Meta-analysis summarizes the state-of-the-art in a research domain, explains differences in its results, detects and corrects biases. This makes research findings more accessible for practitioners, as it allows them to integrate scientific outcomes in their decision making and to rely on the evidence provided by the literature as a whole instead of a selected individual study.

5 Challenges of meta-analysis in finance and how to address them

Choice of effect size. The choice of the effect size, which is the central unit to define the outcomes of different studies on the same scale (and thus to make them comparable), is crucial for an impactful meta-study. In our sample, several meta-studies analyze economic effects, such as abnormal returns or elasticities. For example, Feld et al. (2013) show that the average marginal tax effect on the corporate debt ratio is 0.27, i.e., leverage-to-equity ratio increases by 2.7 percentage points if the marginal tax rate increases by 10 percentage points. Moreover, Rahim et al. (2014) find that the mean cumulative abnormal return across 35 event studies is -1.14% for the announcement of convertible debt offerings and -0.02% for warrant-bond offerings. In contrast, 37 studies examine partial or zero-order correlations, which are unitless measures for the association between two variables and thus are suitable for aggregation over studies. Nevertheless, the aggregated findings do not reveal the economic magnitude of the effect under examination, but only the direction and size of the statistical relation.

Statistical measures, such as partial correlation coefficients or Pearson correlations, do not allow interpreting the economic magnitude of the accumulated effects. Thus, we recommend that the meta-analyst should prefer economic measures, like abnormal returns or elasticities, as effect sizes. They provide a more powerful interpretation of the findings and increase the contribution of meta-analysis to practical decision making (e.g., Holderness, 2018; van Ewijk et al., 2012; Veld et al., 2020). Sometimes economic measures can be re-calculated from the information provided in the primary studies. Purely statistical quantities can serve as a second-best option, especially if economic effects cannot be computed, e.g., due to missing data.

Sample composition. As with any empirical study, the quality of the input data determines the reliability of the results. Garbage-in-garbage-out is an issue that is often discussed in connection with meta-analysis (Borenstein et al., 2009). This problem has multiple levels, which affect the best practices to solve it. First, if results are obviously incorrect (e.g., a t-value does not correspond to the statistical significance level indicated by the asterisks), such observations should be omitted from the analysis or corrected if possible. Second, meta-samples often include observations from both studies published in top journals and studies, which are published in low-ranked journals or remain unpublished. This is quite common, especially in well-elaborated fields where the first seminal papers are often published in top journals and follow-up work examining the same research questions based on different data, time horizons, or with another methodology are spread across other journals or working papers. Following Stanley and Doucouliagos (2012: 19), we recommend to rather '*err on the side of inclusion*' of all studies available than being selective, as selection requires an obvious criterion on what a 'good' study is. Also from a statistical perspective, we should aim at including all available data points to increase the sample size and only drop obvious errors.

Essential for the inclusion of all available studies is that meta-regression can explicitly control for both paper quality characteristics (e.g., by including the number of citations or the journal rank as a moderator variable) and methodological quality (e.g., by including a dummy indicating whether a study controls for endogeneity). If there are measurable differences among highly published papers and studies in lower-ranked journals, meta-regression can detect and control for their impact. In all cases, the meta-analysts should clearly inform the reader how he addressed quality differences in his sample.

Econometric issues. According to Table 2, meta-analysts in finance typically code more than one effect size estimate per study. The median is 176 observations from 28 studies, i.e., about 6 effects per study. Sampling multiple estimates per study leads to *within-study* correlation among the collected effect sizes. Moreover, in contrast to experimental research, studies in empirical economics are usually non-independent and commonly rely on similar and overlapping data sets. Consequently, samples from different studies and authors are often related, e.g., because they examine data from the same/similar companies (e.g., S&P 500). This introduces *between-study* correlation, but also comes with other types of dependencies like between-author or between-database correlation.

The sources and consequences of dependencies in a meta-study are similar to a primary study. For example, a global panel data set causes interdependencies due to the clustering of observations taken from the same country, identical time period, or multiple observations of the same firm across several years. To handle potential dependencies, meta-regression analysis can apply the same remedies as a primary study, especially panel regression models, robust standard errors, or multi-level models (Hedges et al., 2010; Stanley and Doucouliagos, 2012). We recommend that meta-analysis in finance should explicitly account for the different levels of dependencies, at least by using clustered standard errors.

Quality. The total amount of meta-studies across all disciplines rapidly increased in recent years. At the same time, criticisms evolved that challenges the quality and correct application of meta-analysis methods. For example, Ioannidis (2016) criticizes the mass production of redundant and misleading meta-analysis in medicine. Nelson and Kennedy (2009) discuss the use and abuse of meta-analysis in environmental and natural resource economics. The bottom line of these critiques is that it takes a rigorous and high-quality meta-study to realize the benefits outlined in the previous section.

Many 'how to' guides and best practices on conducting and reporting meta-analyses have been offered in different research domains that help authors to achieve high standards and rigor. However, also reviewers and consumers of meta-studies need to do their part to ensure quality (as in any of field of research). Related guidelines for meta-regression in economics have been published by the Meta-Analysis in Economics Research Network (MAER-Net) (Havranek et al., 2020; Stanley et al., 2013). We recommend that meta-analysts in finance should refer to these guidelines during all steps of their meta-work. Making data and codes available to the public is another essential aspect of transparency and replicability of meta-research.[12]

Data retrieval. Another issue that often occurs with meta-analysis is the limited availability of required data reported in the primary studies (e.g., to calculate elasticities as effect sizes). Sometimes missing information can be gathered from web appendices, earlier working paper versions, by email requests from the authors, or by re-calculating missing values from the reported data. We see this as an important challenge, which can be overcome when finance journals routinely require that authors of empirical work must report all information required for replications and meta-analysis in the paper or a technical appendix, a routine that is already common in other research fields such as the management literature.

Clear contribution. The statistical aggregation of empirical studies, including the exploration of the factors determining the previous results in the literature and the analysis of publication or misspecification bias, is a unique advantage of meta-analysis that comes with an inherent value for a research field. However, to be impactful, a meta-analysis has to clearly elaborate its contribution, also

[12] See, for example, the data repository of the Deakin Lab for Meta-Analysis of Research: http://www.deakin.edu.au/business/research/delmar/databases

against large-sample and cross-country primary studies. It is important to illustrate how the meta-results encode dissidence of previous findings and have theoretical implications. The dedicated examination of specific moderator variables that are subject to ongoing discussions, e.g., related to specific methodological choices or variable measurement, supports the progress in a field. Moreover, if there is a lack of cross-country studies due to data collection problems for large international samples, meta-analysis can help to create insights into country-level moderators by integrating the findings of many single-country studies (e.g., Holderness, 2018; Kysucky and Norden, 2016). Also the inclusion of international variables collected from additional databases (e.g., macroeconomic data matched to the studies based on the time period and country examined) can reveal new insights in a research field. In a similar vein, meta-analysis can aggregate data from very early studies and from recent studies, which allows to derive long-run estimates across the entire time period analyzed in the previous literature. We recommend that meta-analysts in finance clearly communicate the contribution made by their analysis. This contribution should be more than a statistical integration of previous findings.

6 Concluding remarks

Over the last two decades, we have observed a massive increase in the volume of empirical research in finance, with results being spread across many journals, unpublished working papers, and book chapters. Despite or even because of the large empirical output, the findings from finance research have not always been conclusive and often depend on certain sample characteristics and method choices. Allied to this, we observe growing concerns about the replicability and reliability of reported empirical results. The inconclusiveness and skepticism of single-approach findings call for more powerful and generalized hypothesis testing, which is offered by review techniques such as meta-analysis.

This review of 61 prior meta-analyses in finance illustrates its ability to bring coherence in a pool of inconsistent findings and to explore why studies produce different results. With meta-analysis, we can also learn about the impact that method choices in finance have on a certain empirical result. Biases in empirical research, especially the preferential publication of significant and strong results (publication bias) and the incorrect specification of econometric models (misspecification bias), might produce literature illustrating a false impression regarding the underlying effect in question. Meta-analysis provides methods for finance researchers to identify, assess, and correct such biases. At the same time, econometric issues in the meta-model, questions about data composition, as well as a clear message of the contribution through the meta-analysis have to be addressed to make meta-research impactful. Taken together, meta-analysis, if applied carefully, can be a powerful tool that facilitates progress in financial research.

There are several promising topic areas in corporate finance, asset pricing, and banking, where such a systematic aggregation could be fruitful. Especially in those research fields with controversy in theory and a rich set of empirical studies with mixed evidence using similar but differently specified methods, the application of meta-analysis has the potential to provide valuable insights. Also for event-study based approaches that are frequently applied in empirical finance, meta-analysis can be valuable to calculate overall abnormal return effects across several country-level studies and to test new moderating factors (e.g. Holderness, 2018; Rahim et al., 2014; Veld et al., 2018).

We hope that this study will make meta-analysis methods more accessible to finance researchers, stimulate its future application in the field, and let meta-analysis become a companion to conventional primary research and replication studies. This study is also a call for editors, reviewers, and conference organizers in finance to be open towards meta-analytical work, as it can integrate summarize and explain the often conflicting reported findings in finance.

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Table 1. Comparison of contemporary approaches to meta-analysis in business and economics

	Traditional meta-analysis	Meta-regression analysis (MRA)	Meta-analytic structural equation modeling (MASEM)
Approach	Uses weighted averages to combine empirical results obtained from a set of individual studies.	Uses weighted regressions to explore a set of moderator variables as drivers of heterogeneity (independent variables) in the effect sizes obtained from a set of individual studies (dependent variable).	Uses structural models and path analysis to explain the simultaneous relation among a group of variables obtained from a set of individual studies.
Main purpose	Integrates effect sizes from multiple studies in one pooled effect to draw overall conclusions.	Quantifies the impact of factors moderating variation across studies as well as biases from publication selection and model misspecification.	Tests simultaneous theoretical relationships/models including mediating factors.
Common effect sizes	Correlations, mean differences, elasticities	Regression coefficients, partial correlations, elasticities	Correlations
Main opportunity	Provides an estimate for the population effect across the literature.	Reveals why empirical results vary and detects biases affecting credibility of empirical research results.	Allows testing complex structural models based on the results of many studies.
Main challenge	Accounting for (complex) heterogeneity and publication bias.	Accounting for non-independent samples in the meta-analysis.	Accounting for results from heterogeneous primary studies.
Guidelines	Borenstein et al. (2010); Hunter and Schmidt (2004)	Stanley et al. (2013); Havranek et al. (2020)	Bergh et al. (2016); Jak (2015)

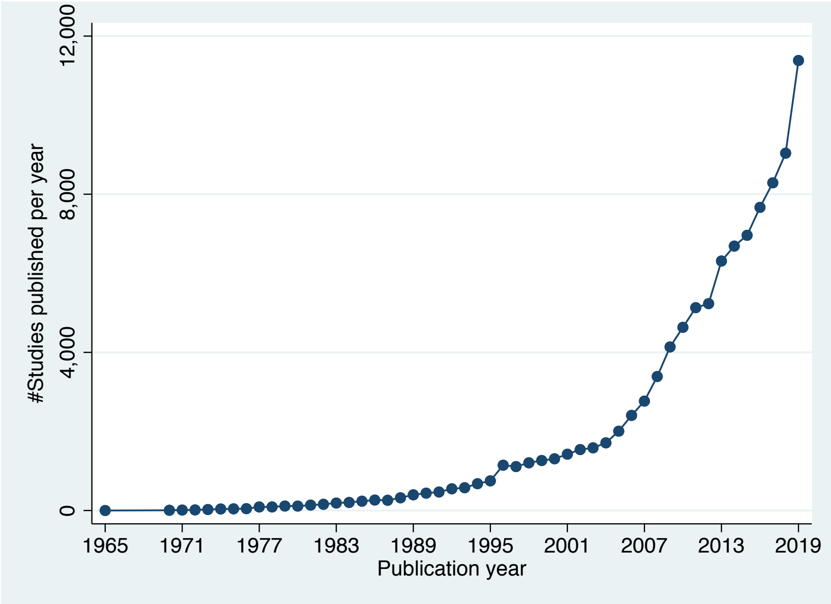
Notes: This table provides an overview of the three main meta-methods applied in business and economics research.

Table 2. Quantitative summary of 29 meta-analyses in finance

Study attribute	**Statistic / No. of studies**	**Study attribute**	**No. of studies**
Publication year		*Analysis of publication bias*	
Mean	2013	No analysis of publication bias	31
Median	2017	Analytically and graphically	16
Min.	1987	Analytically	9
Max.	2019	Graphically	5
No. of studies included[*]		*Analysis of misspecification bias*	
Mean	54	No analysis of misspecification bias	44
Median	35	Control variables in meta-regression	17
Min.	2		
Max.	411	*Analysis of heterogeneity*	
		Control variables in meta-regression	45
No. of observations in meta-sample[*]		Subgroups	20
Mean	420	No analysis of heterogeneity	5
Medians	183		
Min.	3	*Method*[†]	
Max.	6,312	Meta-regression analysis	45
		Hedges and Olkin meta-analysis	14
Primary goal of analysis[†]		Hunter and Schmidt meta-analysis	10
Estimation of summary effects	55	Meta-analytic structural equation model	3
Analysis of methodological heterogeneity	50	Lipsey and Wilson meta-analysis	2
Analysis of structural heterogeneity	35	ANOVA/ANCOVA	1
Analysis of publication bias	24	Multivariate meta-analysis	1
Statistical effects size[†]			
Pearson correlations	19		
Partial correlations	18		
Abnormal returns	10		
Regression coefficients	5		
Elasticities	4		
Others	14		

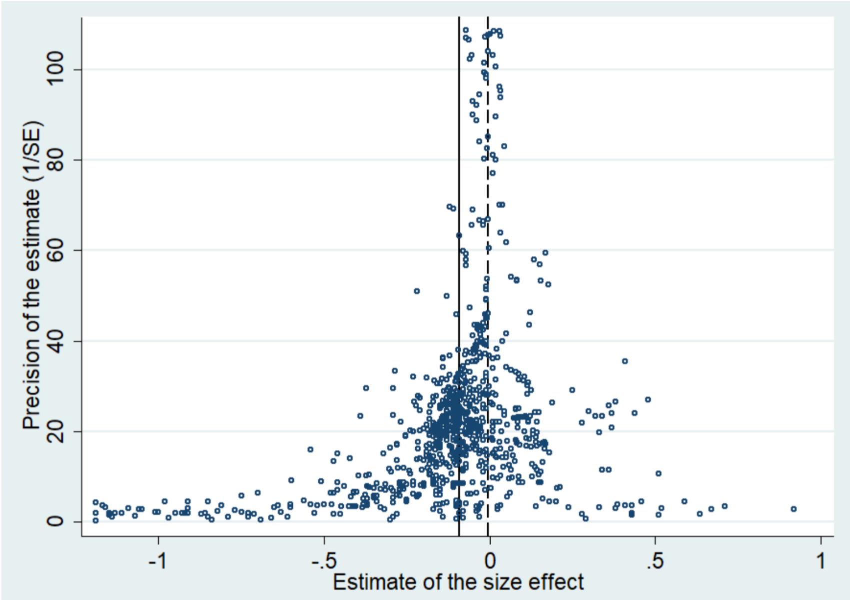
[*] Some studies report several distinct meta-analyses in the same study (e.g., for the different determinants of the corporate debt-equity ratio). The number of studies and the number of observations consider that a study reports different samples for multiple meta-analyses reported in the same study. [†] Multiple counts possible

Figure 1. Annual number of empirical studies in finance



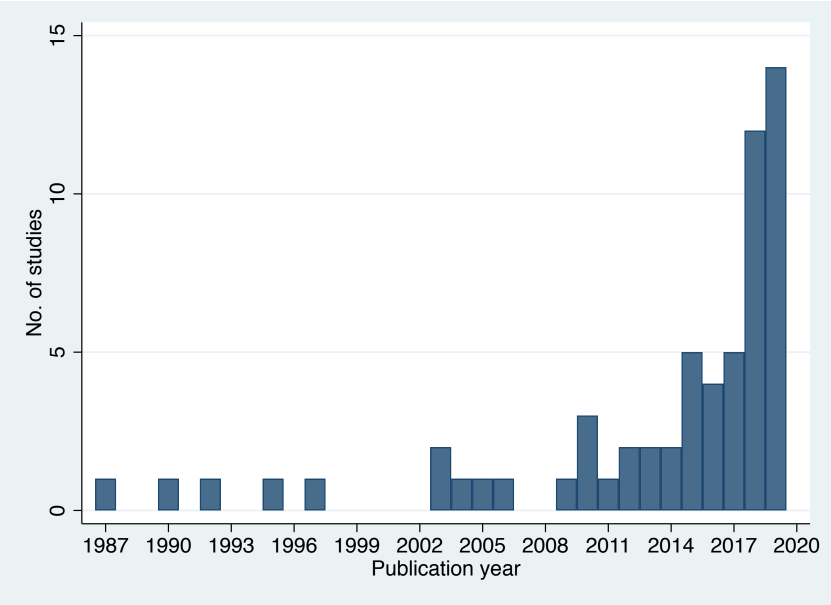
Notes: This graph shows the annual number of Scopus search results between 1965 and 2019 for the document type 'articles' in the subject area 'Economics, Econometrics and Finance' for the following search term: (corporate finance OR asset pricing OR financial intermediation OR banking) AND (empiric* OR data OR sample).

Figure 2. Funnel plot of 102 studies reporting firm size effect on stock returns



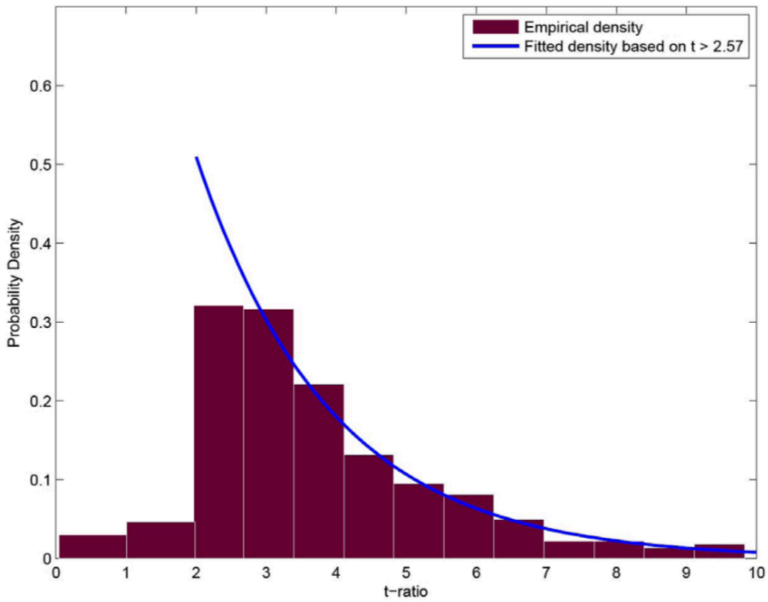
Notes: Scatter plot of estimates for the firm size effect on stock returns by Astakhov et al. (2019).

Figure 3. Number of meta-analysis studies in finance over time



Notes: This graph shows the number of studies using meta-analysis in finance per publication year (as of 31/12/2019).

Figure 4. Histogram of *t*-statistics from 313 factor studies in asset pricing showing publication bias



Notes: Distribution of *t*-statistics from factor studies reported in Harvey et al. (2016). The low proportion of reported values below a *t*-value of 2.0 (indicating statistical significance at the 5% level) suggests publication bias.

Appendix A. Overview of existing meta-analytics research in finance

Topic field	Authors	Topic area	Publication outlet	AJG 2018 ranking
Asset Pricing	Astakhov et al. (2019)	Cross-Section of Returns	Journal of Economic Surveys	2
	Bialkowski and Perera (2019)	Derivatives, Market Mispricing	International Review of Financial Analysis	3
	Coggin and Hunter (1987)	Market Risk Factors	Journal of Portfolio Management	2
	Frooman (1997)	Analysts, News, Media and Market Sentiment	Business and Society	3
	García-Meca and Sánchez-Ballesta (2006)	Analysts, News, Media and Market Sentiment	International Business Review	3
	Geyer-Klingeberg et al. (2018b)	Analysts, News, Media and Market Sentiment	Applied Economics	2
	Hubler et al. (2019)	Analysts, News, Media and Market Sentiment	Journal of Economic Surveys	2
	Kim et al. (2019)	Frictions and Market Efficiency	Working Paper	–
	Reilly et al. (2010)	Return Dynamics	Working Paper	–
	Revelli and Viviani (2015)	Mutual funds	Business Ethics: A European Review	2
	Seidens (2019)	Market Risk Factors, Volatility and Tail Risk	Working Paper	–
	Tanda and Manzi (2019)	Raising Capital (incl. IPOs/SEOs)	Economics of Innovation and New Technology	2
	van Ewijk et al. (2012)	Market Risk Factors	Journal of Empirical Finance	3
	Wimmer et al. (2019)	Market Mispricing	Working Paper	–
Corporate Finance	Arnold et al. (2014)	Risk Management	Quarterly Review of Economics and Finance	2
	Bachiller (2017)	Corporate Governance	Management Decision	2
	Bessler et al. (2019)	Risk Management	International Review of Financial Analysis	3
	Burkhard et al. (2018)	Behavioral, CEOs/CFOs	Working Paper	–
	Cambrea et al. (2017)	Liquidity and Cash Management†	Working Paper	–
	Capon et al. (1990)	Financial performance†	Management Science	4*
	Daily et al. (2003)	Raising Capital (incl. IPOs/SEOs)	Entrepreneurship, Theory and Practice	4
	Dalton et al. (2003)	Corporate Governance	Academy of Management Journal	4*
	Datta et al. (1992)	Mergers and Acquisitions	Strategic Management Journal	4*
	de Mooij (2011)	Capital Structure	Working Paper	–
	Feld et al. (2013)	Capital Structure	Journal of Banking and Finance	3
	Fernau and Hirsch (2019)	Dividend and Payout Policy	International Review of Financial Analysis	3
	Geyer-Klingeberg et al. (2019b)	Risk Management	International Review of Financial Analysis	3
	Geyer-Klingeberg et al. (2019a)	Risk Management	Working Paper	–
	Geyer-Klingeberg et al. (2018a)	Risk Management	Business Research	–
	Hang et al. (2019)	Capital Structure, Risk Management	Working Paper	–
	Hang et al. (2018)	Capital Structure	The Quarterly Review of Economics and Finance	2
	Heugens et al. (2009)	Corporate Governance	Asia Pacific Journal of Management	3
	Holderness (2018)	Corporate Governance, Raising Capital (incl. IPOs/SEOs)	Journal of Financial Economics	4*

Topic field	Authors	Topic area	Publication outlet	AJG 2018 ranking
	Iwasaki and Mizobata (2018)	Corporate Governance	Annals of Public and Cooperative Economics	2
	Iwasaki et al. (2018)	Corporate Governance	Post-Communist Economies	1
	Kim (2019)	Corporate Culture or Social Responsibility	Asia-Pacific Journal of Financial Studies	–
	King et al. (2004)	Mergers and Acquisitions	Strategic Management Journal	4*
	Klein (2017)	Raising Capital (incl. IPOs/SEOs)	Working Paper	–
	La Rocca et al. (2017)	Corporate Governance	Economics Bulletin	–
	Lee and Madhavan (2010)	Mergers and Acquisitions	Journal of Management	4*
	Lindner et al. (2018)	Capital Structure	International Business Review	3
	Nehrebecka and Dzik-Walczak (2018)	Capital Structure	Working Paper	–
	Post and Byron (2015)	Corporate Governance	Academy of Management Journal	4*
	Rahim et al. (2014)	Raising Capital (incl. IPOs/SEOs)	European Journal of Finance	3
	Ratcliffe and Dimovsdki (2012)	Mergers and Acquisitions	Journal of Property Investment and Finance	1
	Rosenbusch et al. (2013)	Raising Capital (incl. IPOs/SEOs)	Journal of Business Venturing	4
	Schommer et al. (2019)	Corporate strategy†	Journal of Management Studies	4
	Siddiqui (2015)	Corporate Governance	International Journal of Accounting and Information Management	2
	Singh et al. (2017)	Liquidity and Cash Management†	Quantitative Research in Financial Markets	–
	Sundaramurthy et al. (2005)	Corporate Governance	Journal of Managerial Issues	–
	van Essen et al. (2012)	Corporate Governance	Asia Pacific Journal of Management	3
	van Essen et al. (2015a)	CEOs/CFOs, Compensation and Agency	Journal of Management	4*
	Veld et al. (2020)	Raising Capital (incl. IPOs/SEOs)	International Review of Finance	3
	Wang and Shailer (2015)	Corporate Governance	Journal of Economic Surveys	2
	Wang and Shailer (2018)	Corporate Governance	Abacus	3
	Weidemann (2016)	Liquidity and Cash Management†	Working Paper	–
	Aiello and Bonanno (2016)	Financial Intermediation: Banking	International Review of Applied Economics	1
	Aiello and Bonanno (2018)	Financial Intermediation: Banking	Journal of Economic Surveys	2
Financial intermediation	Irsova and Havranek (2012)	Financial Intermediation: Banking	Prague Economic Papers	–
	Kysucky and Norden (2016)	Bank Lending Behavior	Management Science	4*
	Zigraiova and Havranek (2016)	Banking	Journal of Economic Surveys	2

Notes: This table presents an overview of existing meta-analytical studies in finance research [as from 31/12/2019]. Topic fields and topic areas are the same as in the list area assignments of the Annual Meeting of the American Finance Association (AFA). ABS is the ranking in the Academic Journal Guide published by the Chartered Association of Business Schools (https://charteredabs.org/academic-journal-guide-2018-view/): 4* is the top category, followed by 4, 3, 2, and 1 (lowest ranking).

† Marks additional topic areas not listed in the AFA list area assignments.