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Variance decomposition analysis: What is it and how to perform it – A complete guide for B2B researchers

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ABSTRACT

Variance decomposition analysis allows partitioning the total variance in an outcome variable, e.g., firm performance, into several components. Such partitioning allows identifying groups of factors (e.g., firm-, industry-, and country-specific) that explain a significant portion of the variation in firm performance, thus helping researchers, managers, and policymakers better understand the sources of competitive advantage. The present study aims to inform scholars, particularly those in business-to-business (B2B) marketing, about the benefits of utilizing variance decomposition analysis and draw scholarly attention to the relevant statistical techniques needed to produce accurate estimates. We specifically point to multilevel modeling techniques due to their significant advantages over other approaches to decompose the variance in a given outcome variable. We provide a detailed step-by-step guide as well as the related Stata codes on conducting variance decomposition analysis with multilevel modeling techniques. Using a 10-year (2009–2018) dataset comprising 7281 distinct European B2B firms operating in 348 industries and 29 countries, we empirically examine the relative importance of firm, industry, country, year, and residual effects in driving firm performance for B2B firms. Our analysis shows that firm-specific factors have the highest relative importance for B2B firms' performance, followed by home country and industry effects.

1. Introduction

Variance decomposition analysis is a statistical technique that allows partitioning the total variance in an outcome variable, for example, firm financial performance, into several components (groups of factors), such as firm, industry, and country (e.g., Guo, 2017; Makino, Isobe, & Chan, 2004; McGahan & Porter, 1997; Rumelt, 1991). Being able to identify effects that explain a significant portion of the variation in firm behavior and performance, variance decomposition analysis helps shed light on areas researchers should focus their attention to explain the phenomena. Such analysis can provide managers and policymakers with guidance regarding the most important sources of competitive advantage. Variance decomposition techniques have been widely utilized in social science disciplines, including strategic management (e.g., Guo, 2017; McGahan & Porter, 1997; Misangyi, Elms, Greckhamer, & Lepine, 2006), international business (e.g., Ma, Tong, & Fitza, 2013; McGahan & Victer, 2010), and economics (e.g., Schmalensee, 1985; Tarziján & Ramirez, 2010), enabling researchers to study the relative importance of various effects for behavior and outcomes of economic actors.

Rumelt (1991) and McGahan and Porter (1997) were some of the first to apply the variance decomposition approach to examine the relative importance of different groups of effects, such as business segment, corporate parent, and industry, on firm financial performance. Since then, researchers have increasingly been applying this methodology, adding new factors, such as country (Chan, Isobe, & Makino, 2008; Makino et al., 2004; McGahan & Victer, 2010) or strategic groups (Chang & Hong, 2002), to explain variation in firm performance. In parallel, there has been an advancement in methodological approaches from more basic ones, such as analysis of variance (ANOVA) (McGahan & Porter, 1997, 2002), to multilevel modeling with maximum likelihood estimation (Hough, 2006; Karniouchina, Carson, Short, & Ketchen, 2013; Misangyi et al., 2006) or more complex estimation methods involving Bayesian Markov chain Monte Carlo (MCMC) algorithms (Castellaneta & Gottschalg, 2016; Guo, 2017).

While being widely used in strategic management and other management subfields, variance decomposition analysis has remained overlooked in marketing. Among the few applications in marketing is a study by Zhang, Hult, Ketchen, and Calantone (2020). The authors argue

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that innovation as a strategic resource exists within (firm-level innovation) and beyond organizational boundaries (industry- and country-level innovation). Their variance decomposition analysis accounts for firm-, industry- and country-level factors to explain innovation-related variance in firm performance. Their analysis revealed that industry- and country-level innovations are far more important than firm-level innovation in explaining firm performance, suggesting scholars and managers to be more attentive to the former.

This paper is an attempt to (re)introduce the variance decomposition analysis as an effective technique to marketing scholars. We provide a step-by-step guide as well as the related Stata codes for (marketing) scholars that explains how to estimate the relative contribution of different types of effects on firm performance in Stata using multilevel modeling techniques. We illustrate the process by implementing the technique in an exemplative study that examines the relative importance of firm, industry, country, year, and residual effects on firm performance for B2B firms. Our study also shows how one can model data structures that are not perfectly hierarchical but rather cross-nested (e.g., firms are simultaneously nested within counties and industries). Such data structures are common in management and marketing research (Andersson, Cuervo-Cazurra, & Nielsen, 2014).

Examining the relative importance of firm, industry, country, and year on the financial performance of B2B firms, the present study relies on a 10-year (2009–2018) dataset comprising 7281 distinct European B2B firms operating in 348 industries and 29 countries. We decompose the variance in firm return on assets (ROA) accounting for a cross-nested data structure: repeated observations of ROA are nested within firms, which are cross-nested within both industries and countries. We utilize two of the most recent methodological approaches in variance decomposition research, namely, multilevel modeling with maximum likelihood estimation (e.g., Hough, 2006; Misangyi et al., 2006) and multilevel modeling with MCMC estimation in a Bayesian framework (e.g., Castellaneta & Gottschalg, 2016; Guo, 2017). We find that for B2B firms, firm-specific effects account for around 56.88% of the variation in ROA, while industry and country effects constitute only 2.76% and 3.98%, respectively. Similar to other variance decomposition studies, the proportion of residual variation constitutes 36.26%, with year effects remaining negligible (0.12%).

Our findings shed light on significant sources of variability in B2B firm performance. While the results point to a substantial role of firm-specific effects (i.e., firm resources and capabilities have been claimed instrumental for B2B firm performance), the impact of the external environment (especially industry) remains rather limited. The findings imply that scholars and practitioners should focus on firm-specific factors as the main driver of competitive advantage. The sources of the substantial amount of residual variation could be further explored by introducing other levels of analysis. More generally, utilizing variance decomposition study in marketing provides ramifications for marketing theory and practice: it highlights crucial yet less researched areas in extant marketing literature and provides practitioners with guidance regarding which factors affect performance (of different kinds) the most. Finally, our study adds to a series of methodological papers in Industrial Marketing Management (e.g., Davvetas, Diamantopoulos, Zaefarian, & Sichtmann, 2020; Ullah, Zaefarian, Ahmed, & Kimani, 2021; Ullah, Zaefarian, & Ullah, 2021) by enhancing marketing scholars' understanding of the exact procedures to implement variance decomposition analysis using common statistical packages.

2. Variance decomposition analysis

2.1. Overview, development over the years, and theoretical value

Variance decomposition analysis is a widely used methodology in strategic management, international business, and economics. The methodology implies splitting the total variance in an outcome variable, such as firm performance, into various components or groups of factors, such as country factors that explain differences in institutions and cultures, industry factors characterizing the competitive landscape in the industry, and firm factors capturing unique firm resources and capabilities. The methodology implies computing the relative importance of different groups of factors and understanding which ones drive firm performance the most.

Rumelt (1991) was among the first to conduct a variance decomposition study to understand the sources of variation in the rate of return on assets of business units of American manufacturing corporations observed over 1974–1977. Rumelt was particularly interested in comparing industry and business-unit effects to challenge the then-dominant view that industry structure is a central determinant of firm performance instead of unique resources and capabilities. Rumelt disaggregated business-unit profitability into components associated with the industry, corporate parent, and business unit effects. While substantial industry effects would support industrial organization tradition, sizeable business-unit effects would instead favor the propositions of the resource-based view. Rumelt (1991) found relatively minor industry and corporate parent effects, yet significant business unit effects. Specifically, while industry effects accounted for 4% of the variance in business-unit profitability, business unit effects were equal to 44%. These results confirmed firms' resources and capabilities to be important determinants of heterogeneity in firm performance. Rumelt's study gave rise to fruitful research in strategic management, further refining his original findings.

Building on Rumelt's (1991) work, McGahan and Porter (1997) examined the contribution of industry, year, corporate parent, and business unit effects in the variation of U.S. public corporations' profitability. Using data from Compustat's Business Segment Reports, which covered corporate parents and their business units in numerous industries during 1981–1994, McGahan and Porter found that industry, corporate parent, and business unit effects accounted for 19%, 4%, and 32% in variation of business unit profitability. They also found that the contribution of each type of effects varied significantly across economic sectors. For example, industry effects accounted for a smaller portion of variation in profitability in manufacturing sectors, while a more significant portion was observed in services, wholesale and retail trade, transportation, and entertainment sectors.

Both Rumelt (1991) and McGahan and Porter (1997) suggested that time-varying effects need to be distinguished from time-invariant ones when explaining firm performance. The majority of studies investigating the relative importance of business unit, corporate parent, and industry effects also introduced so-called "year effects," or, in other words, the effects of "macroeconomic fluctuations that affect all business segments to the same degree in a particular year" (McGahan & Porter, 1997: 24). These effects stem from a reduction in residual variation when year fixed-effects are incorporated in a model (Misangyi et al., 2006).

Since McGahan and Porter's (1997) work, there has been a surge in variance decomposition research in strategic management and other fields. For example, Chang and Hong (2002) extended Rumelt (1991) and McGahan and Porter (1997) to the Korean context. They decomposed the variance in the profitability of companies associated with Korean business groups into the business group-, industry-, and company-specific factors, which roughly matched corporate parent-, industry-, and business unit-specific factors in Rumelt and McGahan and Porter's studies, respectively. Chang and Hong (2002) found substantial business group effects (around 9%), controlling for industry and company effects. The findings indicated that business groups could play an essential role in developing countries with higher market inefficiencies.

Makino et al. (2004) significantly extended prior variance decomposition studies that focused on a single country by adding a new level, namely the host country. Specifically, the authors focused on multinational corporations and examined the relative importance of host country effects in explaining variation in foreign affiliates' performance. They relied on a database consisting of a panel of foreign affiliates of Japanese multinational corporations observed over 1996–2001. Makino and colleagues found that country factors (equal to nearly 6%) were as vital as industry factors (7%), following affiliate (31%) and corporate parent (11%) factors. The results also suggested that corporate parent and affiliate factors explained the most variance in the foreign affiliates' performance in the developed countries, equating to 13% and 28%, respectively. In contrast, host country (4%) and industry (5%) factors were more critical in the subsample of developing countries. Makino et al. (2004) concluded that internal (affiliate and corporate) effects tend to play a relatively more salient role than external (industry and country) effects in the developed country context because "countries with advanced economies are more integrated in terms of market transactions, infrastructure, institutional rules and enforcement mechanisms" (p. 1038).

In a more recent study, Bamiatzi, Bozos, Cavusgil, and Hult (2016) attempted to reconcile institutional theory with the resource-based view and industrial organization economics by decomposing variation in firm performance in recessionary and expansionary economic periods. Utilizing a sample of more than 15,000 firms from ten emerging and ten developed economies and operating in 779 industries, Bamiatzi and colleagues found that the relative importance of firm effects on firm performance is higher during periods of economic recession as opposed to economic expansion. This result helped solve the existing contention about whether firm heterogeneity should become more pronounced during recessionary periods when the rules of the game are fluid, and there are imperfections in strategic factor markets (Oliver, 1997).

Hence, variance decomposition analysis has proven helpful in refining our knowledge of the drivers of firm performance heterogeneity and better understanding the boundaries of existing theories of competitive advantage.

2.2. Key analytical techniques to conduct variance decomposition study

2.2.1. Overview of earlier techniques

Earlier studies utilizing variance decomposition analysis to estimate components of firm performance relied on two approaches: variance components analysis (VCA) or analysis of variance (ANOVA) (e.g., McGahan & Porter, 1997, 2002; Rumelt, 1991). Although these studies provided a step forward in enhancing our understanding of the "general importance of industry, corporate, and business effects on firm performance" (McGahan & Porter, 2002: 835), VCA and ANOVA have been found to have several critical limitations (Bowman & Helfat, 2001; Brush & Bromiley, 1997).

The advantage of VCA is that it allows decomposing variance for calculating the relative importance of different effects. However, this technique requires certain assumptions to be met (Garson, 2012): (1) effects of different components must be independent and identically distributed, (2) residuals must be uncorrelated and normally distributed, and (3) residuals must have constant variance. If these assumptions are violated, estimates will be biased and unreliable. VCA also does not allow modeling interaction effects. Thus, estimates may be biased when cross-level interactions exist.

In turn, ANOVA progressively adds components into the model allowing calculating incremental R^2. Respective incremental changes to R^2 show the relative importance of various components. ANOVA requires the following assumptions to be met (Hedeker & Gibbons, 2006): (1) sphericity of variance-covariance, and (2) the residuals are independent and normally distributed. Compared to VCA, ANOVA is more robust to deviations from these assumptions, producing more consistent and reliable empirical findings (Garson, 2012). At the same time, the main limitations of ANOVA are that it provides no explicit variance decomposition (i.e., the result differs depending on how the effects enter the model) and does not allow to capture interaction effects adequately (Hoffman, 2015). Hence, if interactions exist, the unmodeled effects may be confounded with other effects, resulting in potentially biased results.

Since both ANOVA and VCA assume independence between effects (Bowman & Helfat, 2001; Brush & Bromiley, 1997), both methods present difficulties in calculating the correct size of the effects. Due to the inability of the methods to incorporate the relationships that could exist between effects, McGahan and Porter (2002: 850) have concluded that "while there are ways to continue to learn from this research, its limits suggest that the time has come to explore whole new approaches." VCA and ANOVA have subsequently been replaced by multilevel modeling.

2.2.2. Cross-nested data structures and the limitations of earlier variance decomposition techniques

A traditional stream in variance decomposition research studies the performance of business units that are nested, or "embedded," within both corporate parents and industries (McGahan & Porter, 1997, 2002; Rumelt, 1991). Rumelt (1991: 171) acknowledged that "both industries and corporations are considered to be sets of business units." Although economics often views business units as atomistic actors, they are still interrelated with industries, as firm conduct is reciprocally related to industry conditions (Henderson & Mitchell, 1997; Porter, 1980). Corporations are not strictly nested within industries as they often have multibusiness operations, and industries are not nested within corporations. At the same time, corporations and industries are interrelated (McGahan & Porter, 2002: 838) because "the covariance between industry and corporate-parent effects is potentially important because, for example, a diversified firm may be more likely to expand into particular types of industries." Therefore, business units, corporate parent, and industry effects are not independent, producing biased results in ANOVA and VCA techniques (Misangyi et al., 2006). Similarly, international business research has acknowledged that it is critical to account for the simultaneous embeddedness of firms in industry and country contexts when exploring drivers of firm performance (Andersson et al., 2014).

To conclude, firm performance varies across levels that are not characterized by perfect hierarchical nesting (Andersson et al., 2014; Guo, 2017; Misangyi et al., 2006). As mentioned above, business unit performance over time is nested within business units, and business units may be cross-nested within corporate parents, industries, and countries. To appropriately model such complex structures, scholars have advocated for *multilevel modeling* that provides a number of advantages over other techniques to partition the variation in firm performance or other outcome variables.

2.2.3. Multilevel modeling (MLM) approaches to variance decomposition

Multilevel modeling (MLM), also known as hierarchical linear modeling, allows addressing the discussed limitations of both VCA and ANOVA (Hoffman, 2015). First, MLM directly decomposes variance in the outcome variance into each level (Hoffman, 2015), relaxing the assumption of independence of lower-level units nested in higher-level units. Second, MLM ensures efficient estimation of unbalanced data, preventing the loss of information (Raudenbush & Bryk, 2002). Third, MLM permits modeling complex data structures, such as interactions, cross-nesting, and multiple-membership (Browne, Goldstein, & Rasbash, 2001), thus addressing the issue of collinearity among different types of the effects, such as business units, corporate parents, and industries (Guo, 2017; Hough, 2006; Misangyi et al., 2006). Fourth, while VCA and ANOVA employ only categorical independent variables (Brush & Bromiley, 1997; McGahan & Porter, 1997, 2002), MLM allows explaining variance in a more nuanced way, including both categorical and continuous independent variables that could be either time-invariant or time-varying (Guo, 2017; Misangyi et al., 2006). Finally, MLM can account for autocorrelation in longitudinal data (Guo, 2017). Therefore, MLM is a significant step forward in the variance decomposition research that allows moving away from descriptive models toward inferential models to examine relationships and test multiple theories (Andersson et al., 2014; Guo, 2017; Hough, 2006; Mathieu & Chen, 2011; Misangyi et al., 2006).

Recent variance decomposition studies (e.g., Castellaneta & Gottschalg, 2016; Guo, 2017; Karniouchina et al., 2013; Meyer-Doyle, Lee, &

Helfat, 2019; Misangyi et al., 2006) have shown the advantages of using MLM as opposed to VCA and ANOVA. In particular, scholars have modeled the cross-nested structure of corporate parent and industry and obtained a more nuanced picture compared to studies utilizing earlier techniques (e.g., McGahan & Porter, 1997, 2002; Rumelt, 1991).

2.3. Use of the variance decomposition analysis in marketing

Despite being common in strategic management and other related disciplines, marketing scholars have only recently started to employ variance decomposition analysis to examine the relative role of different factors in driving firm behavior and outcomes. One of the few examples is Zhang et al. (2020) who applied the variance decomposition approach to study the contribution of the firm-, industry- and country-level innovation in explaining variance in firm performance. Zhang et al. (2020) compiled a dataset comprising 4530 firms operating in 794 industries with headquarters in 39 countries. They utilized hierarchical linear multilevel modeling techniques to test the effects of innovation at the three levels on performance. The technique was appropriate due to the hierarchical nature of the study's data and the possibility of simultaneously partitioning the variance-covariance components. Specifically, firms were nested within industries, which were nested within countries. Having decomposed variance in firm performance, the authors found that industry- and country-level innovations were the most important drivers of firm performance by explaining 34% and 40% of the variance in firm performance, respectively, contrary to firm-level innovation explaining only 26% of the total variance.

In the following section, we provide a step-by-step procedure to conduct variance decomposition analysis. We examine the relative importance of firm, industry, country, year, and residual effects in explaining the performance of B2B firms. We utilize multilevel modeling to estimate the effects at each level of analysis. Specifically, we utilize two existing MLM approaches to decompose the variance in firm performance: a more common approach relying on multilevel modeling with maximum likelihood estimation (e.g., Hough, 2006; Misangyi et al., 2006) and a more recent approach involving multilevel modeling with MCMC estimation in a Bayesian framework (e.g., Castellaneta & Gottschalg, 2016; Guo, 2017). We demonstrate how a variance decomposition analysis could be done in common statistical software packages, such as Stata.

3. Step-by-step procedure for the variance decomposition analysis

3.1. Step 1: Defining categories of explanatory variables

The steps follow several guidelines established in the previous variance decomposition studies (Guo, 2017; McGahan & Porter, 1997; McGahan & Victer, 2010; Misangyi et al., 2006). First, we have to clearly define categories of explanatory variables. The aim of variance decomposition studies is mainly to capture categorical effects, e.g., industry, country, corporate parent, and business unit as a whole (McGahan & Porter, 1997, 2002). We define a *firm* as an independent entity as indicated in the Orbis database (i.e., no shareholder with more than 25% direct or total ownership). Such firms are not prone to external interference in their decision-making, having more freedom in their strategy development and implementation. The firm's *industry* membership is based on its primary 4-digit NACE Rev. 2 code.[1] The *home country* is defined as the country of the firm's headquarters.

3.2. Step 2: Initial data selection

We then continue by constructing a dataset. Variance decomposition studies normally require a sizeable amount of lower-level observations (e.g., firms nested in industries or countries). Also, to separate residual effects from firm effects, the data should have a panel structure (Guo, 2017; Misangyi et al., 2006). In variance decomposition studies, residual effects can also be referred to as "error" or "unexplained variance," i.e., "the performance variance potentially attributable to transient factors" (Misangyi et al., 2006: 580). We obtained all data for the analyses from the Orbis Europe database, which identifies both listed and nonlisted European firms (both within and outside of the European Union), the core industry in which they operate, and their home country. The period considered for this study is 2009–2018.

3.3. Step 3: Identifying possible subsamples

As discussed above, we investigate the relative importance of firm, industry, home country, and year effects on firm performance for B2B firms. A B2B firm is defined in line with Delgado and Mills (2020). The authors classify all industries into two broad categories: those selling primarily to businesses or government (i.e., business-to-business industries) and those selling primarily to consumers (i.e., business-to-consumer industries). If a firm's primary activity is in the former type of industry, it is classified as a B2B firm and is of interest to our study.[1 and 2] More specifically, Delgado and Mills' classification is based on the percentage of output sold to Personal Consumption Expenditure (PCE). "The PCE is a final use item in the [Input-Output] IO Accounts that captures the value of the goods and services that are purchased by households, such as food, cars, and college education" (Delgado & Mills, 2020, p. 4). Delgado and Mills classify an industry as B2B if it sells less than 35% of its output to PCE, with the rest being classified as B2C. To date, this is one of the most systematic and comprehensive classifications of industries into B2B and B2C.

3.4. Step 4: Data cleaning

Our total initial sample consisted of 1,322,458 observations of yearly firm performance for the years 2009–2018. This dataset is further screened following the steps initially reported in McGahan and Porter (1997) and then adopted by subsequent variance decomposition studies (e.g., Guo, 2017; Karniouchina et al., 2013; Misangyi et al., 2006). From our original total, we drop: (a) 62,102 observations of firms conducting financial and insurance activities and (b) 30,024 observations of firms with activities in public administration and defense, compulsory social security, and not elsewhere classified. Variance decomposition research often excludes firms from these industries as their returns are not comparable with those of other industries according (McGahan & Porter, 1997). We further proceed to eliminate (c) 1,161,740 observations of small firms with sales or assets less than €10 million and (d) 1390 observations of firms that have been in this dataset for only one year. Single-year appearances may have anomalous performance and are normally excluded from the analysis (McGahan & Porter, 1997, 2002; Misangyi et al., 2006). Unless small firms are of interest to a researcher, they are also often excluded from the analysis for a reason similar (McGahan & Porter, 1997, 2002). We also drop (e) 787 observations of firms that are the only ones in an industry in a given year, as these entities may be analogous to monopolies (McGahan & Porter, 1997). In addition, (f) 619 firm observations are removed due to a limited number of them in a given country as opposed to other countries. Keeping these observations in the analysis can affect the power of

[1] NACE is the Statistical Classification of Economic Activities in the European Community. The current version is revision 2. It is the European implementation of the United Nations International Standard Industrial Classification of All Economic Activities (ISIC), revision 4.

[2] Delgado and Mills' classification is provided with respect to the North American Industry Classification System (NAICS). We use conversion tables to translate it to NACE Rev. 2.

higher-level effects (Hofmann, 1997; Peterson, Arregle, & Martin, 2012), such as home country effects. Finally, we remove (g) 14,272 observations from our sample as they do not fall under our definition of a B2B firm. Our final sample consists of 51,524 firm-year observations. This screened 10-year dataset represents 7281 different firms operating in 348 industries and 29 countries. This sample's mean return on assets (ROA) is 5.45%, with a variance of 10.88%.

3.5. Step 5: Model specification and estimation

The next step is to specify and estimate a model. We proceed by decomposing variance in firm ROA by fitting multilevel models to the dataset. In the dataset, repeated observations of ROA (Level 1) are nested within firms (Level 2), which are cross-nested within both industries (Level 3) and countries (Level 3). There are certain specifics in modeling such data structures as they are not characterized by perfect hierarchical nesting. Industries and countries represent imperfect hierarchies because lower-level units (firms) simultaneously belong to multiple higher-level units (industries and home countries). In other words, industries and home countries are not hierarchically nested, as not all firms from a particular home country compete in the same industry, nor do all firms competing in a particular industry originate from the same home country. Cross-nested data structures like this are common to marketing and management research and need to be appropriately modeled (Andersson et al., 2014).

We utilize two existing approaches to performance variance decomposition: multilevel modeling with maximum likelihood estimation (e.g., Hough, 2006; Misangyi et al., 2006) and multilevel modeling with MCMC estimation in a Bayesian framework (e.g., Castellaneta & Gottschalg, 2016; Guo, 2017). The former approach has been more standard in the variance decomposition research, and it can be easily implemented using standard statistical software, such as using the "mixed" command in Stata. The latter approach has been introduced to the management literature relatively recently; one of its benefits is that it allows obtaining reference statistics, such as standard error, for both the absolute effects (variances) and relative effects (percentages) of different variance components (Browne, 2017).

3.5.1. Multilevel modeling with maximum likelihood estimation

We start by following Misangyi et al. (2006) to perform *multilevel modeling with maximum likelihood estimation*. It involves estimating a series of equations that nest repeated observations of firm ROA within firms and cross-nest firms within both industries and countries. In line with prior research, our models also attempt to capture so-called year effects or the general impact of macroeconomic fluctuations in business activity (McGahan & Porter, 1997, 2002). First, an unconditional three-level model (i.e., a model with no predictors) is estimated (Model 1). The model separates the variation in firm ROA into three components. At Level 1, firm ROA is modeled as the following:

$$ROA_{tij} = \alpha_{0ij} + e_{tij}, \tag{1.1}$$

where ROA_{tij} is firm ROA at time t in firm i in industry j; α_{0ij} is the over-time mean ROA of firm i in industry j; e_{tij} is the time-level random error. The model assumes $e_{tij} \sim N(0, \sigma_e^2)$. σ_e^2 is therefore denoted as *residual* (also referred to as "across-time") *variance*.

At Level 2, the over-time mean ROA, α_{0ij}, is simultaneously modeled as an outcome varying randomly around the industry mean:

$$\alpha_{0ij} = \beta_{00j} + u_{ij,} \tag{1.2}$$

where β_{00j} is the mean ROA of all firms in industry j and u_{ij} is the between-firm residual that is distributed as $u_{ij} \sim N(0, \sigma_u^2)$. σ_u^2 thus denotes *between-firm variance*.

At Level 3, the mean ROA of all firms in industry j, β_{00j}, is simultaneously modeled as an outcome varying randomly around the grand mean:

$$\beta_{00j} = \gamma_{000} + v_j, \tag{1.3}$$

where γ_{000} is the grand-mean ROA of all firms in the dataset and v_j is the between-industry residual distributed as $v_j \sim N(0, \sigma_v^2)$. σ_v^2 is *between-industry variance*.

To model the cross-nesting of country effects on firm ROA, we incorporate these effects at the firm level (Misangyi et al., 2006). Year effects are incorporated at the time level of analysis (Guo, 2017; Misangyi et al., 2006). To calculate year effects, we need to estimate Model 2 below:

$$ROA_{tij} = \alpha_{0ij} + \alpha_{1ij} Year_{tij} + e_{tij}, \tag{2.1}$$

$$\alpha_{0ij} = \beta_{00j} + u_{ij}, \tag{2.2}$$

$$\beta_{00j} = \gamma_{000} + v_j. \tag{2.3}$$

In turn, Model 3 is used to derive home country effects:

$$ROA_{tij} = \alpha_{0ij} + \alpha_{1ij} Year_{tij} + e_{tij}, \tag{3.1}$$

$$\alpha_{0ij} = \beta_{00j} + \beta_{01j} Home\ country_{ij} + u_{ij}, \tag{3.2}$$

$$\beta_{00j} = \gamma_{000} + v_j. \tag{3.3}$$

In Models 2 and 3, α_{1ij} denotes year effects (the impact of macroeconomic fluctuations in business activity); *Year* is a matrix of dummy variables coded for each of the years for each firm *i* in industry *j*. α_{0ij} now stands for across-time mean ROA for firm *i* in industry *j* adjusted for year effects. In Model 3, β_{01j} represents (stable) home country effects, i.e., the effect home country affiliation on mean firm ROA; *Country* is a matrix of dummy variables capturing home country affiliation of firm *i* in industry *j*. β_{00j} is now the mean ROA of firms nested in industry *j* adjusted for country effects.

Having specified Models 1, 2, and 3 above, we can now calculate the relative importance of firm, industry, country, and year effects on firm ROA, as well as the residual variation. Estimating the unconditional model comprising Eqs. (1.1), (1.2), and (1.3), the percentage of total variance attributable to each level is calculated as: $\sigma_e^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)$ is the proportion of residual variance, $\sigma_u^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)$ is the proportion of variance between firms, and $\sigma_v^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)$ is the proportion of variance between industries.

The percentage of total variance explained by *year effects* can be obtained by comparing the change in residual variance between Model 1 (unconditional model) and Model 2 comprising Eqs. (2.1)–(2.3) where year effects enter at the time level (Guo, 2017; Misangyi et al., 2006). Formally, year effects are calculated as follows: $(\sigma^2_{e,\ Model\ 1} - \sigma^2_{e,\ Model\ 2})/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)_{Model\ 1}$.

As follows from Model 3, Eqs. (3.1)–(3.3), the cross-nesting of home country effects involves their introduction at the firm level and may account for both between-firm and between-industry variance (recall that intercept β_{00j} represents the mean ROA of firms nested in industry *j* adjusted for country effects, and it is also modeled as the outcome at the industry level). In line with Misangyi et al. (2006), we can calculate home country effects by observing the decrease in the variance at the firm and industry levels as a proportion of total variance when home country effects are included, i.e., by comparing the Model 2 and Model 3 estimates of σ_u^2 and σ_v^2. Formally: $(\sigma^2_{u,\ Model\ 2} - \sigma^2_{u,\ Model\ 3})/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)_{Model\ 2} + (\sigma^2_{v,\ Model\ 2} - \sigma^2_{v,\ Model\ 3})/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2)_{Model\ 2}$.

To obtain the final results, we need to adjust residual, firm, and industry effects estimated in Model 1 (unconditional model) by year effects and the respective parts of home country effects. Table 1. below specified the Stata commands that can be used to estimate Models 1, 2, and 3 to obtain the variance components and calculate the relative importance of the effects.

Note that in Stata there are workarounds to decompose variance in a cross-classified model with maximum likelihood estimation in one step

Table 1
Stata commands to fit Models 1, 2, and 3 using maximum likelihood estimation.

Code	Explanation
mixed ROA || industry: || firm:	This command fits Model 1—a simple variance-components model. Note that we have two specifications for the random part, one at the industry level (Level 3), and one at the firm (Level 2). The lowest level (residual variance at Level 1) is not specified. These specifications are both null (intercept-only) models, so we are simply estimating an error term at each level. The levels need to be specified going down the hierarchy. By default, the *-mixed-* command in Stata 16 performs maximum likelihood estimation (MLE). To estimate models with restricted maximum likelihood estimation (REML), the *-reml-* option needs to be specified. Both REML and MLE estimations give almost identical result in our case.
mixed ROA i.year || industry: || firm:	This command fits Model 2. Year fixed-effects are entered in the fixed part of the model. As previously, the random part of the model estimates three variance components: residual, between-firm, and between-industry variance.
mixed ROA i.year i.country || industry: || firm:	This command fits Model 3. Year and country fixed-effects are entered in the fixed part of the model. The random part stay the same.

(Rabe-Hesketh & Skrondal, 2012). Table 2 reports Stata codes and the respective explanations for these workarounds.

Because the procedure in Table 2 is now allowing to fit a cross-classified model directly, the model specification can be rewritten as follows (e.g., Guo, 2017):

$$ROA_{tijk} = \alpha_{0ijk} + e_{tijk}, \tag{4.1}$$

$$\alpha_{0ijk} = \beta_{00jk} + u_{ijk}, \tag{4.2}$$

$$\beta_{00jk} = \gamma_{000} + v_j + \delta_k, \tag{4.3}$$

where $e_{tijk} \sim N(0, \sigma_e^2)$, $u_{ijk} \sim N(0, \sigma_u^2)$, $v_j \sim N(0, \sigma_v^2)$, and $\delta_k \sim N(0, \sigma_k^2)$. All terms except for δ_k and σ_k^2 are defined as above. δ_k is between-home country residual normally distributed with a mean of zero and variance of σ_k^2. The percentage of total variance attributable to a given type of effect is therefore calculated as: $\sigma_k^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_k^2)$ for home country effects, $\sigma_v^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_k^2)$ for industry effects, $\sigma_u^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_k^2)$ for firm effects, and $\sigma_e^2/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_k^2)$ for residual effects.

In line with Guo (2017), year effects can be calculated by entering these effects at the time level, as indicated in Model 5 below, and then comparing the changes in residual variance between this and the unconditional model. Model 5 is therefore specified as:

$$ROA_{tijk} = \alpha_{0ijk} + \alpha_{1ijk} Year_{tijk} + e_{tijk}, \tag{5.1}$$

Table 2
A Stata workaround to fit the cross-classified model with maximum likelihood estimation.

Code	Explanation
mixed ROA || _all: R.country || industry: || firm:	To estimate a cross-nested model in Stata, it is possible to use a work-around solution that creates a "fake" four-level model in which repeated observations are nested in firms, which nested in industries, which are then nested in an entire set but with random effects for dummy variables for countries. That effectively can give us variances for each level. Therefore, for countries, we use the following additional specification in the random part of the model: *-_all: R.country-.*
mixed ROA i.year || _all: R. country || industry: || firm:	Year effects are entered in the fixed part of the model, while the random part stays as above.

$$\alpha_{0ijk} = \beta_{00jk} + u_{ijk}, \tag{5.2}$$

$$\beta_{00jk} = \gamma_{000} + v_j + \delta_k. \tag{5.3}$$

Year effects are calculated as before, i.e., $(\sigma^2_{e,\ Model\ 4} - \sigma^2_{e,\ Model\ 5})/(\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_k^2)_{Model\ 4}$. Residual effects have to be subsequently adjusted on this value.

3.5.2. *Multilevel modeling with MCMC estimation in a Bayesian framework*

We now shift our attention to an alternative estimation approach that has been recently adopted in variance decomposition research, namely, *multilevel modeling with MCMC estimation in a Bayesian framework*. This approach has the same advantages as multilevel modeling with maximum likelihood estimation (Hough, 2006; Karniouchina et al., 2013; Misangyi et al., 2006) since both build on the assumptions of the normal joint distribution of residuals and independence of random effects (Guo, 2017). Both approaches allow modeling cross-classified structures and explicit variance decomposition, resulting in their recent application in variance decomposition research (Castellaneta & Gottschalg, 2016; Guo, 2017; Meyer-Doyle et al., 2019). The additional advantage of a Bayesian MCMC estimation approach is that it reports the means and standard deviations of the parameter monitoring chains (Browne, 2017; Goldstein, 2011), thus providing inference statistics for estimated absolute (variances) and relative (percentages) effects. Importantly, this approach can provide more precise estimates in the presence of cross-classified structures (Rasbash & Goldstein, 1994). Finally, it is possible to implement in Stata quickly, yet it requires the MLwiN software (Rasbash, Charlton, Browne, Healy, & Cameron, 2009) to be additionally installed.

We fit Models 4 and 5 using the MCMC estimation procedure with a Bayesian estimation (Browne, 2017) by running the MLwiN software (Rasbash et al., 2009) in Stata using the "runmlwin" command (Leckie & Charlton, 2012) with the cross-classification option. Because the software requires us to specify starting values for the model parameters, we first estimate a naive hierarchical linear model by iterative generalized least squares (IGLS). Even though the resulting IGLS estimates are not substantively interpretable because the effects are not perfectly nested, they typically provide good starting values for correctly fitting a cross-nested model. The procedure to estimate variances and their percentages, therefore, replicates Guo (2017). Table 3 below specified the Stata commands that can be used to estimate Models 4 and 5 to obtain the variance components.

4. Discussion of the results

We first discuss the maximum likelihood estimation results obtained by using Stata codes in Table 1 (e.g., Misangyi et al., 2006). The results of the estimation of the unconditional model, i.e., Eqs. (1.1), (1.2), and (1.3), are reported in the top panel of Table 4. The percentage of total variance attributable to each level are: 36.45% is the proportion of residual variance (σ_e^2), 60.35% is the proportion of variance between firms (σ_u^2), and 3.20% is the proportion of variance between industries (σ_v^2). We can additionally conduct likelihood-ratio tests to determine whether the random intercepts at Level 2 (versus linear model) and Level 3 (versus two-level model) improve model fit. We find that there is significant variance across firms (p = 0.000) and across industries (p = 0.000).

As noted above, the percentage of total variance explained by year effects can be obtained by comparing the change in residual variance between Model 1 and Model 2 (Guo, 2017; Misangyi et al., 2006). We find that year effects account for 0.12% of the total variance in firm ROA (as reported in the top middle panel of Table 4). Home country effects result from a decrease in the variance at the firm and industry levels as a proportion of total variance when home country effects are included. Using the results in the two middle panels of Table 3, home country effects constitute 4.18% of the total variance in firm ROA.

Table 3
Stata commands to fit Models 4 and 5 using MCMC estimation in a Bayesian framework.

Code	Explanation
runmlwin ROA cons, level4(country: cons) level3(industry: cons) level2(firm: cons) level1(year: cons)	In Stata 16, the following syntax is first employed to estimate a naive unconditional hierarchical linear model using IGLS, i.e., a naive Model 4. *cons* is a variable that is equal to 1 for all observations. It is generated as *-gen cons = 1-*. For information, this *-runmlwin-* command produces results identical to: *-mixed ROA || country: || industry: || firm:-*
runmlwin ROA cons, level4(country: cons) level3(industry: cons) level2(firm: cons) level1(year: cons) mcmc(cc on) initsprevious	We then fit Model 4—the unconditional cross-classified model—with a Bayesian MCMC estimation using the IGLS estimates from the previous command. *-initsprevious-* specifies that the parameter estimates from the previous model are used as the initial values. *-mcmc(cc on)-* specifies a cross-classified model and fits it using default MCMC options. It is important to note that *-level4-* is used for country effects because the *-runmlwin-* command does not allow indicating two Level 3s. Switching cross-classification option on allows accounting for the actual data structure. In general, while one can put the levels in any order, it is recommended putting them in the partly nested way as MLwiN will run IGLS first for starting values and this assumes nesting (Browne, 2017; Leckie & Charlton, 2012; Rasbash et al., 2009).
runmlwin ROA cons year_dummies, level4 (country: cons) level3(industry: cons) level2(firm: cons) level1(year: cons)	A command to fit Model 5 using a naive unconditional hierarchical linear model. *-year_dummies-* includes all year dummy variables from the sample (need to be manually generated).
runmlwin ROA cons year_dummies, level4 (country: cons) level3(industry: cons) level2(firm: cons) level1(year: cons) mcmc(cc on) initsprevious	A command to fit Model 5 with a Bayesian MCMC estimation using the IGLS estimates from the previous command.

To obtain the final results, we need to adjust residual, firm, and industry effects estimated in Model 1 by year effects and the respective parts of home country effects. As indicated in the bottom panel of Table 3, residual effects constitute 36.33%, firm effects are equal to 56.63%, and industry effects are 2.74%. Firm effects align with prior variance decomposition research (Guo, 2017; McGahan & Porter, 1997; Misangyi et al., 2006; Sharapov, Kattuman, Rodriguez, & Velazquez, 2021), explaining the largest proportion of total variance in B2B firm ROA. Some scholars interpret this finding to support the resource-based perspective (McGahan & Porter, 1997, 2002), emphasizing that idiosyncratic historical factors give rise to firm performance differences (Barney, 1991; Peteraf, 1993; Peteraf & Barney, 2003; Wernerfelt, 1984). Under this view, firm resources and capabilities play a major role in gaining and sustaining competitive advantages, while industry structures are less important for competitive advantage. Indeed, industry and home country effects are 20.67 and 13.55 times smaller than firm effects.

We then fit Models 4 and 5 using a Bayesian MCMC estimation (Browne, 2017). Table 5 presents the results of fitting Models 4 and 5. The relative magnitudes of the effects in Table 5 are similar to Table 4. Standard errors for the parameter estimates are calculated by using post estimation commands of *"runmlwin"*: we first save the MCMC parameter chains from the "*runmlwin*" estimations using the *"mcmcsum, getchains"* command and then calculate MCMC summary statistics using the *"mcmcsum, variables"* command.

Table 4
Results from maximum likelihood estimation of Models 1, 2, and 3.

	Parameter estimate
Model 1, unconditional model	
Level 1 variance (residual), σ_e^2	48.95319
Level 2 variance (between firms), σ_u^2	81.05917
Level 3 variance (between industries), σ_v^2	4.298835
% of total residual variance	36.45
% of total variance explained by firm effects	60.35
% of total variance explained by industry effects	3.20
Model 2, incorporating year effects at Level 1	
Level 1 variance (residual), σ_e^2	48.78532
Level 2 variance (between firms), σ_u^2	81.22981
Level 3 variance (between industries), σ_v^2	4.318855
% of total variance explained by year effects	0.12
Model 3, incorporating year effects at Level 1 and home country effects at Level 2	
Level 1 variance (residual), σ_e^2	48.80061
Level 2 variance (between firms), σ_u^2	76.22929
Level 3 variance (between industries), σ_v^2	3.69721
% of total variance explained by home country effects	4.18
Final results	
% of total variance	
residual	36.33
explained by year effects	0.12
explained by firm effects	56.63
explained by industry effects	2.74
explained by home country effects	4.18

Table 5
Results from Bayesian MCMC estimation of Models 4 and 5.

	Parameter estimate	Standard error
Model 4, unconditional model		
Level 1 variance (residual), σ_e^2	48.96681	0.3302873
Level 2 variance (between firms), σ_u^2	76.56591	1.485538
Level 3 variance (between industries), σ_v^2	3.7189	0.7561023
Level 3 variance (between home countries), σ_k^2	5.352018	2.010238
% of total variance		
residual	36.38	0.71
explained by firm effects	56.88	1.05
explained by industry effects	2.76	0.55
explained by home country effects	3.98	1.41
Model 5, incorporating year effects at Level 1		
Level 1 variance (residual), σ_e^2	48.80599	0.3267018
% of total variance		
explained by year effects	0.12	0.34
Final results		
% of total variance		
residual	36.26	0.72
explained by year effects	0.12	0.34
explained by firm effects	56.88	1.05
explained by industry effects	2.76	0.55
explained by home country effects	3.98	1.41

5. Conclusion

The variance decomposition method is a step forward in enhancing our understanding of how much effects at various levels of analysis contribute to the variation in an outcome variable, like firm performance. However, it has not been widely used in marketing yet. This study aims to show the relevance of variance decomposition study for a marketing audience and equip researchers with a step-by-step guide on how to conduct variance decomposition analysis to study research questions relevant to marketing. We hope that the present study will help marketing scholars and practitioners better understand the importance of the variance decomposition approach in explaining the relative contribution of firm, industry, country, year, and residual effects on the variation of firm performance in the B2B context. The results of our study suggest which factors should be devoted the most attention to in future research and managerial practice.

Data availability

The data that has been used is confidential.

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