The relative importance of group-level effects on the performance of German companies*

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Abstract

We examine the impact of performance groups on the estimation of the relative importance of firm, industry and other effects on corporate performance. Performance groups comprise firms from the same industry with a similar performance over a longer period of time. We present a statistical method which improves the procedure of variance decomposition by allowing firm effects and the interacting effects of firms and time to be unified into the group effects. Applied to a German data set of 219 companies observed over a period of eleven years (1987-1997) it appears that the majority of the firms can be ascribed to performance groups. The variance proportion of the group effects is about one half of the non-grouped firm effects. They explain about 17.9 percent of the total variance of the returns.

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1 Introduction

This article builds upon the recent literature on the relative importance of firm, industry and other effects on corporate performance. The debate which provides the motivation for this line of research was initiated by the paper of Schmalensee (1985). His study is descriptive and does not aim at discriminating between theories. Rather, it addresses the question of which paradigm is potentially the most fruitful to deliver a consistent theory of corporate performance. Mainly, the prevalent paradigms of the following disciplines were considered to be competing in this arena: the traditional Industrial Organization (IO), the modern theoretical Industrial Organization, and the Strategic Management. The traditional IO emphasizes the structural characteristics of industries like growth and the degree of concentration as determinants of corporate performance. The modern theoretical IO, however, focuses on market shares and other partially firm-related concepts while the Strategic Management scholars consider the specific resources of a firm to be important performance predictors.

In order to assess the relative importance of the several research agendas it was analyzed how much of the variance of firm performance could be attributed to industry effects, to the market share, and to firm specific effects.[1] Using a cross-section of the 1975 FTC LB data on the manufacturing sector Schmalensee showed that with about 20 percent of the total variance of the firm performance the industry effects explained more than firm and market share effects. This was interpreted as supporting the view that industry is important but not the only influence on corporate performance.

The article provoked much criticism towards the choice of the data set and the estimation procedure. Rumelt (1991) extended Schmalensee's sample for another three years of data (1974-1977) which allowed him to distinguish not only between industry and corporate-parent effects but also between the error term and the effects of the business units. Further, he allowed business units to enter his data set which

[1]If data on business units are available, the firm effects are divided into corporate parent and business unit effects.

did not meet the size criterion of Schmalensee. In this case, the effects of the lines of businesses explaining about 45 percent of the firm performance variance dominated clearly the transient and intransient industry effects which accounted for about nine to sixteen percent. The corporate parent effects were shown to be small in comparison.

Subsequent studies were based on much larger data sets, more sophisticated estimation methods, and a greater variety of performance measures (Hansen and Wernerfelt 1989, Roquebert, Phillips, and Westfall 1996, McGahan and Porter 1997, McGahan 1999, Brush and Bromiley, and Hendrickx 1999, Bunke, Droge, and Schwalbach 2000). If we take stock of the estimation results of those studies the following stylized facts can be put forward: Industry matters, but to a much larger extent business units do. Temporal effects are consistently found to be rather small. With respect to corporate parent effects the results are equivocal. Another approach was used by Cubbin and Geroski (1987) who considered the dynamics of firm's profitability. They found a large degree of heterogeneity within the industries in the sense that about fifty percent of the companies profitability changes could not be attributed to industry-wide dynamic factors.

Schmalensee and his successors may be criticized for assessing two rather extreme views on economic firm behavior for their ability to predict profit rates: One which ignores firm-specific sources of profit variation versus a view which neglects performance determinants on the industry level. Intermediate concepts introducing some homogeneity between firms and some heterogeneity within an industry, respectively, were not considered.

The most popular concept in IO and Strategic Management of this kind is the concept of strategic groups. Strategic groups are defined as collections of firms whose performance is influenced by group characteristics after controlling for firm and industry effects (Dranove, Peteraf, and Shanley 1998).[2] In the literature, the relationship between strategic group membership and firm performance is a central

[2]Previous studies on strategic groups (Hunt 1972, Porter 1979) focussed on clusterings along the relevant strategic dimensions of an industry. However, Dranove, Peteraf, and Shanley (1998) argue that by doing so one is not able to distinguish between firm and group effects of performance.

issue. From the twenty papers surveyed by Thomas and Venkatraman (1988) fifteen are committed to the analysis of this relationship. Thus, one might be well advised to discuss the strategic group concept within the debate on the relative importance of firm and industry effects on firm performance.

Considering group effects could make a big difference for the estimation of the relative importance of the various effects. Assuming that the relationship exists between strategic group membership and performance at least for some industries, it might turn out that industry effects disappear when allowing for group effects because high performing industries consist of some well protected high performing groups. On the other side, it might be the case that within industries heterogeneity is attributable to some differently performing groups and thus, firm effects are upward biased if groups are neglected.

Up to now it is still not clear which relative impact strategic groups have on the performance of a firm. The literature on the performance effects of strategic groups cannot provide an answer to this question. Those studies are inherently limited in their ability to deliver such a decomposition of the profit rate variance because to accomplish that large scale data sets are necessary.[3]

The present paper aims at filling this research gap by extending the study of Bunke, Droge, and Schwalbach (2001) who neglected group phenomena. However, because of several reasons which are discussed in the following section we do not assess the relative importance of strategic groups directly. Instead, we use the concept of "performance groups" introduced by Wiggins and Ruefli (1995). Besides strategic groups, they comprise every clustering of equally performing firms within an industry. The data set consists of 219 German companies observed over a period of eleven years (1987-1997). The companies cover a wide range of industries from non-financial sectors. The performance measure is returns on sales. Applying a vari-

[3]The majority of the empirical studies testing theories of strategic groups are industry specific, i.e. particular industries were considered where background knowledge was used to extract the relevant strategic dimensions of the industry. Then clusters of firms were detected by different methods. Finally, it was tested if the average profitability differed significantly between or within groups (for surveys see Barney and Hoskisson 1990, Thomas and Venkatraman 1988, McGee and Thomas 1986).

ety of methods, we find that a large fraction of the firms have a similar performance after controlling for other effects. Hence, they can be grouped into performance groups. This supports the hypotheses that there may be concepts between the level of firms and the level of the industry which are able to explain a considerable share of the firm performance.

The study proceeds as follows. The next section gives a short overview over the literature on strategic groups and introduces the concept of performance groups. Then, we present the statistical method in Section 5.3. The data set and the empirical results are reported in Section 5.4 before the paper is concluded.

2 Performance groups

In the literature, there are several explanations for the appearance of strategic groups. The first one refers to the existence of mobility barriers within an industry (Caves and Porter 1977). This concept is an extension of the entry barriers of Bain (1956). Essentially, mobility barriers prevent firms from freely changing group membership, thus protecting higher performing groups from potential competition. The second, more recent concept, focuses on the perceptions of the managers whose cognition tend to simplify industries by mapping it into groups of firms (Porac and Baden-Fuller 1989, Fombrun and Zajac 1987, Reger and Huff 1993, Lant and Baum 1995, Hodgkinson 1997, Osborne, Stubbart, and Ramaprasad 2001).[4] A third concept combines the level of strategic interaction between firms with the mobility barriers concept (Cool and Dierickx 1993, Peteraf 1993, Dranove, Peteraf, and Shanley 1998).

From models of the first stream of research it can directly be deduced that performance consequences exist for group membership (Porter 1980). In the latter class of models, group membership may have consequences on intermediate outcomes such as the level of rivalry (Smith, Grimm, and Wally 1997, Cool and Dierickx 1993), the group's reputation (Ferguson, Deephouse, and Ferguson 2000), and the groups's identity (Peteraf and Shanley 1997) which may result in performance differentials

[4] Bogner and Thomas (1993) integrate both views into one theoretical framework.

between groups.

However, there is only weak empirical evidence suggesting the group membership-performance relationship holds (Barney and Hoskisson 1990, Thomas and Venkatraman 1988, Cool and Dierickx, 1993). Furthermore, Barney and Hoskisson conjectured that due to methodological problems both basic assertions of strategic group research are untested: first, that strategic groups exist, and second, that strategic group membership has performance implications. This made obvious the critical state of strategic group research. The main points of concern are the lack of theory about when strategic groups will emerge, the application of clustering algorithms which virtually always produce groups of firms whatever data set is explored, and the misleading interpretation of performance differences between groups as a result of mobility barriers (Barney and Hoskisson 1990). Hence, if studies detect group effects of performance it remains unclear if those effects are due to the existence of mobility barriers between strategic groups, cognitive mapping mechanisms, or if they are just statistical artifacts.[5]

Wiggins and Ruefli (1995, p. 1636) circumvent these problems by not selecting strategic groups *ex ante* as usual but by referring to "performance groups" which are defined as "set[s] of firms whose performance levels are statistically indistinguishable from those of other firms in the group but are distinguishable from the performance levels of firms in other performance groups." If performance groups are detected in a short period, then it is tested if those groups are stable over a longer time period. This reflects the idea that group membership requires temporal stability. When stable performance groups are discovered, further research is required to explore the reasons for their existence. Of course, performance groups and strategic groups are not necessarily congruent. However, the existence of performance groups is a necessary condition for the existence of differently performing strategic groups.[6] If performance groups are not detected, this can be interpreted as a case against the

[5] Nonetheless, there have been efforts to develop cluster analysis further as a reliable method in Strategic Management (Ketchen and Shook 1996).

[6] Note that we concentrate on horizontal groups of firms from the same industry. Vertical interindustry groups are neglected in this study.

existence of strategic groups. Indeed, Wiggins and Ruefli did not find evidence for the existence of strategic groups in their analysis of five industries.

We follow Wiggins and Ruefli by considering performance groups instead of strategic groups in our analysis. Our statistical procedure is different. In search for performance groups, Wiggins and Ruefli discriminate between firm clusters of different profit distributions by applying iteratively Kolmogorov-Smirnov tests. The drawback of this procedure is that nothing can be said about its reliability. The error of the grouping is the result from the errors made at each single step of the procedure. Hence, it is not clear how large the error is that was made during the whole procedure, since the significance level ($\alpha = .05$) used for the tests at each step can only be regarded as some tuning parameter. Significance tests testing the equality of average returns also seem to be inadequate statistical methods from the point of view that firms forming a performance group should not necessarily have exactly identical average performances, the performance differences having to be small in some not well-defined sense. Furthermore, the considered tests are non-parametric in nature but rely on rather few observations for each firm. Moreover, these observations, although obtained for consecutive years, are treated as independent replications, which does not seem to be always reasonable. Finally, as in any procedure based on iterative testing it remains unclear how the obtained grouping takes into account the objective of the analysis. Confirming the resulting groups by some discriminant function analysis may not be sufficient to completely overcome these drawbacks. In contrast, our method considers simultaneously (almost) every possible grouping of firms within each industry. Then, the grouping of firms with similar performance is chosen which is optimal with respect to some criterion presented later. This criterion reflects clearly the objective of the analysis and, hence, the procedure provides a result which is optimal (in a certain way). The next section describes our method in more detail.

3 Methods

As performance measure we observe the returns on sales r_{ikt} of firm k's activity in industry i at time t. Throughout this paper we will assume that the returns are uncorrelated and have variances which may depend on the firm and industry, but not on time. Hence, the expectation and variances of the returns may be denoted by

$$E(r_{ikt}) = \mu_{ikt} \quad \text{and} \quad Var(r_{ikt}) = \sigma^2_{ik} \ , \tag{1}$$

respectively, with $i = 1, \ldots, m;\ \ k = 1, \ldots, n_i;\ \ t = 1, \ldots, T;\ \ \sum_i n_i = n$ and $N = nT$.

If the impact of certain effects on the performance is investigated, one uses typically analysis of variance models which decompose the expected returns as follows:

$$\mu_{ikt} = \mu + \alpha_i + \phi_{ik} + \gamma_t + \delta_{it} + \nu_{ikt} \ , \tag{2}$$

where μ is the average return of firms of all industries over the whole time period, the terms α_i, ϕ_{ik} and γ_t denote the effects of industry i, of firm k within industry i and of year t, respectively, and δ_{it} and ν_{ikt} represent time-dependent effects, i.e., the interaction between industry i and year t as well as the interaction between firm k and year t. The identification of the parameters in (2) requires certain parameter constraints such as

$$\begin{aligned} \sum_i w_{i.}\alpha_i &= \sum_k w_{ik}\phi_{ik} = \gamma_. = \sum_i w_{i.}\delta_{it} = \delta_{i.} = \nu_{ik.} = \sum_k w_{.k}\nu_{ikt} = 0 \\ i &= 1, \ldots, m;\ \ k = 1, \ldots, n_i;\ \ t = 1, \ldots, T \ , \end{aligned} \tag{3}$$

where $w_{ik} \geq 0$ are some time-independent weights. Taking $w_{ik} \equiv 1$ in (3) provides the "usual" parameter constraints. Here, and in the remaining part of the paper we use the usual ANOVA notation. That is, if a suffix is replaced by a dot, variables are summed over the values of that suffix, e.g. $\gamma_. = \sum_i \gamma_i$. The average over the values of a suffix is denoted by an additional upper bar, e.g. $\bar{\gamma}_. = \frac{1}{T} \sum_i \gamma_i$.

Without any additional model assumptions, (2) describes a saturated model. Most analyses are based on smaller models, that is, on models with fewer "effective" parameters than the number of observations N. Such models may be obtained by deleting some effects, compare Bunke, Droge, and Schwalbach (2001) where, for example, a model without interactions ν_{ikt} was considered:

$$\mu_{ikt} = \mu + \alpha_i + \phi_{ik} + \gamma_t + \delta_{it} \ . \tag{4}$$

However, the analyses differ not only in their assumptions on the expected returns. There are also several models for the variances σ^2_{ik} in (1) imaginable. Very popular is, for example, the homogeneous variance model assuming a common variance for the returns of all firms over the whole time period:

$$\sigma^2_{ikt} \equiv \sigma^2 \ . \tag{5}$$

Alternatively, one could use a homogeneous variance model within each industry allowing the returns' variances to depend on the industries, but not on the specific firm:

$$\sigma^2_{ikt} = \sigma^2_i \ . \tag{6}$$

The objective of our analysis is to find groups of firms within each industry with a similar performance over the whole time period. Let $M_i = \{1, \ldots, n_i\}$ denote the firms of industry i. Then a grouping of firms within the industries may be described by a partitioning of M_i into g_i disjoint groups M_{il} $(l = 1, \ldots, g_i \ , \ 1 \leq g_i \leq n_i)$:

$$M_i = M_{i1} \cup \ldots \cup M_{ig_i} \ , \quad i = 1, \ldots, m \ . \tag{7}$$

The ideal assumption of identical performance of the firms within the groups leads thus to a submodel of (1) by setting

$$\mu_{ikt} = \mu_{ik't} \quad \text{if} \quad k, k' \in M_{il} \quad (l = 1, \ldots, g_i; i = 1, \ldots, m) \ . \tag{8}$$

The return of a firm would then be predicted by a weighted average of the returns of all firms which belong to the same group:

$$\hat{\mu}^g_{ikt} = \sum_{j \in M_{il}} \frac{w_{ij}}{\sum_{j \in M_{il}} w_{ij}} r_{ijt} \quad \text{for all} \ \ k \in M_{il} \ . \tag{9}$$

Note that (8) may also be described as submodel of (2) by

$$\phi_{ik} = \phi_{ik'} \ \text{and} \ \nu_{ikt} = \nu_{ik't} \quad \text{if} \quad k, k' \in M_{il} \quad (l = 1, \ldots, g_i; i = 1, \ldots, m) \ . \tag{10}$$

Now, if we more realistically assume that the firms belonging to the same group have similar but not necessarily identical average returns, we still may use the weighted group mean (9) as a prediction and be more accurate than using the returns as predictions of the average returns. The latter predictions correspond to the trivial partition into groups each containing a single firm. It seems sensible to form performance groups, grouping firms together in such a way that the prediction of the average return using the model determined by the grouping (that is using (9)) is as accurate as possible. Equivalently, the estimation of the dependence of the return on the industry, the firm and time will be as accurate as possible. The performance of a model such as a grouping of the firms may therefore be assessed by the weighted mean squared error of prediction (MSEP)

$$R_g = \sum_{i,k,t} \frac{w_{ik}}{Tw_{..}} E(\hat{\mu}^g_{ikt} - \mu_{ikt})^2 + \sum_{i,k} \frac{w_{ik}}{w_{..}} \sigma^2_{ik} \quad , \tag{11}$$

where $\hat{\mu}^g_{ikt}$ denotes the estimate of the expected returns under the model associated with the grouping g, cp. (9). Assuming a specific model for the variances σ^2_{ik}, we would always use the inverse of these variances as weights, i.e.:

$$w_{ik} = \sigma^{-2}_{ik} \quad , \tag{12}$$

since this leads to generalized least squares estimators of the expected returns, which possess certain optimality properties.

To select an appropriate grouping of the firms, one would ideally try to minimize the MSEP over all possible groupings. Unfortunately, this is impossible since the MSEP depends on the unknown expected returns and variances. Therefore one resorts in practice to data-driven methods such as minimizing some convenient estimator of the MSEP. Now, for given variances σ^2_{ik} and a given grouping g, an unbiased "estimate" of the MSEP (11) could be calculated which depends, however, on the unknown variances. Replacing in this formula the variances by some estimates $\tilde{\sigma}^2_{ik}$ based on the assumed variance model, we finally obtain the following criterion for comparing the competing groupings of firms:

$$\hat{R}_g = RSS^w_g + \frac{2\sum_i g_i}{\sum_{i,k} \tilde{\sigma}^{-2}_{ik}} \quad , \tag{13}$$

where

$$RSS_g^w = \sum_{i,k,t} \frac{w_{ik}}{Tw_{..}} (r_{ikt} - \hat{\mu}_{ikt}^g)^2$$

denotes the weighted residual sum of squares for the grouping g using the weights $w_{ik}/Tw_{..} = \tilde{\sigma}_{ik}^{-2}/(T \sum_{i,k} \tilde{\sigma}_{ik}^{-2})$. Note that we have also to replace the unknown weights in (9) in the same way to arrive at "reasonable" estimates (weighted least squares estimates, WLSE) of the expected returns. To reduce bias effects due to an inadequate modelling of the expected returns, we will use the following model-independent variance estimates:

$$\hat{\sigma}_{ik}^2 = \frac{1}{2(T-1)} \sum_{t=2}^{T} (r_{ikt} - r_{ik,t-1})^2 \ . \tag{14}$$

Consequently, the variance estimates under the submodels (5) and (6) are given by

$$\tilde{\sigma}_{ik}^2 = \frac{1}{n} \sum_{i,k} \hat{\sigma}_{ik}^2 := \hat{\sigma}^2 \quad \text{and} \quad \tilde{\sigma}_{ik}^2 = \frac{1}{n_i} \sum_{k} \hat{\sigma}_{ik}^2 := \hat{\sigma}_i^2 \ , \ \text{respectively.} \tag{15}$$

4 Data and empirical results

4.1 Data set and exploratory data analysis

The empirical analysis is based on a panel data set of German companies provided by the Kienbaum Consultants International GmbH. The sample consists of $n = 219$ firms and covers a wide range of $m = 26$ industries from non-financial sectors. Originally, it includes more than 1700 large companies. However, eliminating the firms whose profits or sales are not observed over the whole period of time and excluding all the financial companies reduces the set enormously. No information is available about whether the companies are diversified or not. Each company is assigned to a single industry. The performance measure is returns on sales, defined as the ratio of accounting profits to sales. For each firm, the returns on sales are available over a period of $T = 11$ years (1987-1997). The distribution of the firms over the industries is shown in Table 1.

Like any statistical method, our procedure depends on certain assumptions. Therefore we carried out some exploratory data analysis to reveal the features of the data set under study. In particular, we tried to answer the following questions:

Do the data contain errors or outliers? Since the data were collected over time, is there any evidence of serial correlation? Do the data have a nearly constant variance? Can the analysis be improved by some convenient data transformation?

A first impression of the data is provided by the box plots of the returns for all firms. A detailed inspection of extreme or outlying values led to the conclusion that the raw data set contained errors probably introduced at the point of data collection. In most cases it was not possible to reconstruct the correct values, so that we eventually omitted the data of 18 firms from the original data set of 237 firms.

The distribution of the observational errors $\varepsilon_{ikt} = r_{ikt} - \mu_{ikt}$ is roughly described by the distribution of the residuals $\hat{\varepsilon}_{ikt} = r_{ikt} - \hat{\mu}_{ikt}$, where $\hat{\mu}_{ikt}$ is obtained by fitting some model for the expected returns μ_{ikt}. But the residuals are not independent nor do they have constant variance, even if both conditions are fulfilled by the errors.

To examine possible serial correlations, or dependencies, we tested for each firm ik, whether the autocorrelation function ρ_{ik} of the errors ε_{ikt} at time lag 1 vanishes. The tests are based on estimates of the autocorrelations ρ_{ik} calculated under model (4) as well as under the simple model,

$$\mu_{ikt} = \mu_{ik} \quad , \tag{16}$$

which considers the returns of a firm over the years as replicated observations. It turned out that, among the 219 firms, only 28 (under (4)) and 32 (under (16)), respectively, possess coefficients ρ_{ik} which differ significantly from 0 at level $\alpha = 0.05$. Consequently, it seems plausible to assume uncorrelated returns or observational errors.

Box plots as well as plots of standardized residuals under (4) against fitted values indicate that the variances of the returns depend on the firms. In case of replicated observations (16) heteroscedasticity is easy to detect and there exist simple formal tests such as the Cochran and the Bartlett tests under the assumption of normally distributed errors. Thus, as a formal quantity for checking (5), i.e., the homogeneity of the error variances, we use, in analogy to Cochran's test, the statistic

$$G = \max_{i,k} \frac{\hat{\sigma}^2_{ik}}{\sum_{i,k} \hat{\sigma}^2_{ik}} \quad , \tag{17}$$

where $\hat{\sigma}_{ik}^2$ is given by (14), and compare it with the related critical value for Cochran's test. Cochran's test is based on a statistic, $\tilde{G}$ say, which in (17) replaces the variance estimates $\hat{\sigma}_{ik}^2$ by $s_{ik}^2 = (T-1)^{-1} \sum_t (r_{ikt} - \bar{r}_{ik\cdot})^2$, and the corresponding critical value is calculated under (16) assuming normally distributed errors. Naturally, this critical value is not the correct one when using G, since the variance estimates (14) are not χ^2-distributed as in the "Cochran"-case of replicated observations; but it turns out to be a reasonable approximation and so the resulting test may serve as exploratory data analysis tool. For our data set, the hypothesis of homogeneous variances was rejected at significance level $\alpha = 0.01$ based on both statistics G and $\tilde{G}$.

Similarly, we have performed tests for checking (6), i.e. the variance homogeneity within each industry, using statistics G_i defined as G in (17) but with the summation and maximization over k only. At significance level $\alpha = 0.05$ the hypothesis of a homogeneous variance of the firms within an industry was always rejected except for five industries. Under the replication model (16), one would use the variance estimates s_{ik}^2 instead of $\hat{\sigma}_{ik}^2$, leading to Cochran-statistics $\tilde{G}_i$. On the basis of these statistics, the homogeneity hypotheses would always be rejected except for two industries.

If heteroscedasticity is detected, then ordinary least squares (OLS) methods cannot be used. Points for which the variance is comparatively large should be downweighted when models for the expected returns are fitted to the data. This may be accomplished by using WLSE with weights depending on the variances instead of OLS estimates. However, in general this requires estimation of the variances since these variances will be unknown. Therefore it is *not* clear whether WLS with estimated variances is superior to OLS or not! Nevertheless, our analysis will be based on WLS with weights

$$w_{ik} = \hat{\sigma}_{ik}^{-2} \quad , \tag{18}$$

since the variances differ significantly such that neither (5) nor (6) can be assumed. Naturally, improvements of the procedure are imaginable by searching for an appropriate variance model with less than n parameters, which is different from (5) and (6); but this is beyond the scope of this paper.

Finally, Box-Cox transformations may be seen as another approach to correct for both nonnormality and heteroscedasticity. We tried the seven (modified) Box-Cox transformations described in Bunke, Droge, and Schwalbach (2001) and found that the identical transformation is optimal for both models (4) and (16). All investigations in the remaining part of this paper will therefore deal with the original, untransformed data.

4.2 Performance groups under heteroscedasticity

As explained in the previous subsection, we allow different variances for the returns of different firms, i.e., we assume (1). Consequently, we use the WLSE based on weights (18) for estimating the effects and expected returns. The optimal model or performance group, $\hat{g}$ say, is then defined as the minimizer of the criterion $\hat{R}_g$ over all possible groupings g of firms, where $\hat{R}_g$ is defined by (13) with $\tilde{\sigma}^2_{ik} = \hat{\sigma}^2_{ik}$, cp. (14).[7] It turns out that the optimal grouping of the 219 firms within the 26 industries consists of 113 groups. The number of groups within the different industries is presented in Table 1. Note that 56 of these groups contain only one firm.

Table 1: *For each industry, number of firms and number of groups under the optimal model $\hat{g}$.*

Industry (i)	1	2	3	4	5	6	7	8	9	10	11	12	13
No. of firms (n_i)	10	5	9	15	7	4	3	5	4	9	10	3	3
No. of groups under $\hat{g}$	5	2	4	9	6	4	2	2	3	3	4	2	3

Industry (i)	14	15	16	17	18	19	20	21	22	23	24	25	26
No. of firms (n_i)	12	4	7	16	5	4	3	9	6	5	49	8	4
No. of groups under $\hat{g}$	7	2	3	6	3	4	2	5	4	2	19	4	3

[7] Actually, the implemented procedure does not examine all possible partitionings of firms within the industries. Instead, because of numerical feasability, it proceeds stepwise, starting by taking each of the n firms as a group. Then, among all possible pairs of groups within any industry, we join that pair to a single group, which leads to the largest reduction of the estimated risk (13). This process is continued until no further decrease of the estimated risk can be achieved and leads to a suboptimal grouping.

Table 2 summarizes some additional results. It shows also how the weighted variance proportions of some effects is influenced by the optimal grouping. Here, $\tilde{r}_1$, $\tilde{r}_2$, $\tilde{r}_3$, $\tilde{r}_{13}$ and $\tilde{r}_{23}$ denote the empirical weighted variance proportions of the industries, firms, years, industry-year interactions and firm-year interactions, respectively. Their definition as measure for the impact of the different factors or effects on the performance may be found in Bunke, Droge, and Schwalbach (2001).[8]

Table 2: *Some results of optimal grouping under (1) using WLS.*

Model g	Dimension of g	MSEP $10^4 \cdot \hat{R}_g$	Weighted variance proportions $\tilde{r}_2$	$\tilde{r}_{23}$	$\tilde{r}_2 + \tilde{r}_{23}$
Saturated model (2)	$N = 2409$	0.335819	0.449305	0.117614	0.566919
Optimal model $\hat{g}$	1243	0.258688	0.443392	0.086713	0.530105
Reduction (in %)	48.40	22.97	1.32	26.27	6.49

A grouping of firms leads to a replacement of the firm effects and the firm-year interactions by firm group effects and firm group-year interactions, respectively, when modelling the expected returns. Hence, the grouping of firms has only an influence on the variance proportions of the firms and the firm-year interactions. The other empirical weighted variance proportions remain unchanged, and for our data set we obtain:

$$\tilde{r}_1 = 0.396843 \ , \quad \tilde{r}_3 = 0.006797 \ , \quad \tilde{r}_{13} = 0.029440 \ .$$

Similarly to Bunke, Droge, and Schwalbach (2001), we could conclude that the industry effects are dominated by the firm effects. This holds for both the permanent effects ($\tilde{r}_1 < \tilde{r}_2$) and when adding the time-dependent effects to the permanent effects ($\tilde{r}_1 + \tilde{r}_{13} < \tilde{r}_2 + \tilde{r}_{23}$), and it remains also true after an optimal grouping of the firms. Despite optimal grouping the percentage of performance variance explained

[8]For example, the weighted variance proportion of the industry effects is defined by $\tilde{r}_1 = \tilde{s}_1^2/\tilde{s}^2$, where $\tilde{s}^2 = (Tw_{..})^{-1}\sum_{i,k,t} w_{ik}(r_{ikt} - \hat{\mu})^2$ and $\tilde{s}_1^2 = w_{..}^{-1}\sum_i w_{ik}\hat{\alpha}_i^2$ are the weighted empirical variances of the returns and the industry effects, respectively, and $\hat{\mu}$, $\hat{\alpha}_i$ denote the WLSE of the effects μ, α_i.

by the permanent and time-dependent firm effects remains nearly unchanged (53.0% instead of 56.7% before the grouping), although the corresponding model dimension is drastically reduced by 48.8 % . Note that about 35.1 % of the performance variance is explained by the 53 "single-firm-groups", whereas the remaining 60 groups with 163 firms in all explain 17.9 % of that variance.

Recall that our procedure for finding performance groups does not rely on the assumption of normally distributed observations. However, some formal tests such as those described in Section 3 for checking variance homogeneity would require such an assumption (at least approximately). To check whether the observational errors are normally distributed, one should use the standardized residuals,

$$e_{ikt} = \frac{\hat{\varepsilon}_{ikt}}{\tilde{\sigma}_{ik}\sqrt{1 - h_{ikt}}} \quad . \tag{19}$$

Here, h_{ikt} denotes the diagonal element ikt of the hat matrix associated with the model under consideration. Several diagnostic plots (plots of standardized residuals against fitted values, normal QQplots and histograms for standardized residuals) as well as estimated skewness (0.005) and kurtosis (5.787) of the standardized residuals after optimal grouping suggest that a normal approximation to the error distribution would work.

4.3 Firm groups under alternative aims and short summary

Here we consider two additional approaches for the definition of performance groups which correspond to different models for the expected returns. That is, the competing models are no longer given by (8). We continue to assume heteroscedastic variances as in (1).

First we aim at finding groups of firms within each industry, which show a similar behavior of their returns over the time, but which have possibly different levels of performance, i.e., possibly different averages of returns. For this, we start with model (4) and introduce additionally firm-year interactions ν_{ikt} as in (2). If two firms, (ik) and (ik') say, interact with the years in a similar way, then they will enter the same group. Hence, the model for the expected returns will assume the same interactions with the years for both firms, but not the same firm effects! That is, the competing models for the expected returns may be described by the set of all possible partitions (7) such that additionally to (2) the following constraints hold:

$$\nu_{ikt} = \nu_{ik't} \quad \text{if} \quad k, k' \in M_{il} \quad (l = 1, \ldots, g_i; i = 1, \ldots, m) \ . \tag{20}$$

As before, a model selection criterion may be derived as an appropriate estimate of the risk (11). With the notations of the previous section and $\hat{\mu}^g_{ikt}$ being the WLSE of the expected returns calculated under the assumption (20), this leads to

$$\tilde{R}_g = RSS^w_g + \frac{2[n + (T-1)\sum_i g_i]}{T \sum_{i,k} \tilde{\sigma}^{-2}_{ik}} \ . \tag{21}$$

The minimizer of (21) with respect to the possible groupings g will be denoted by $\tilde{g}$. For our data set, the optimal grouping $\tilde{g}$ classifies the 219 firms into 80 groups. It is not surprising that this number is smaller than that of $\hat{g}$, because it is now more likely that firms are considered to behave similarly.

Another aim could be the search for groups of firms with approximately the same time-independent firm effects, neglecting completely the year-firm interactions. That is, the competing models for the expected returns are given by (16) and assuming additionally

$$\mu_{ik} = \mu_{ik'} \quad \text{if} \quad k, k' \in M_{il} \quad (l = 1, \ldots, g_i; i = 1, \ldots, m) \ . \tag{22}$$

In this case, the competing models (partitions g) can be compared by the following criterion:

$$\bar{R}_g = RSS^w_g + \frac{2\sum_i g_i}{T \sum_{i,k} \tilde{\sigma}^{-2}_{ik}} \ , \tag{23}$$

whose minimizer over g will be denoted by $\bar{g}$. Here, $\hat{\mu}^g_{ikt}$ is the WLSE of the expected returns assuming (22). Note that the optimal grouping (model) would remain unchanged by assuming any submodel of (2), which contains at least firm effects ϕ_{ik} ($i = 1, \ldots, m;\ \ k = 1, \ldots, n_i$), and selecting among the partitions (7) with

$$\phi_{ik} = \phi_{ik'} \quad \text{if} \quad k, k' \in M_{il} \quad (l = 1, \ldots, g_i; i = 1, \ldots, m) \ . \tag{24}$$

For our data set, the optimal grouping $\bar{g}$ classifies the 219 firms into 117 groups.

Obviously, the obtained optimal groupings depend on the different aims of the analysis. Table 3 summarizes some results. For the sake of completeness, it contains also the results of subsection 4.2 as well as those for some models for the expected returns such as

$$\mu_{ikt} := \mu + \alpha_i + \phi_{ik} + \gamma_t \;\; , \tag{25}$$

which have not been considered until now.

Table 3: *Estimated risk for some models for the expected returns assuming heteroscedastic variances.*

Model g	Dimension of g	$10^4\times$ Estimated risk
(2)	2409	0.335819
(4)	479	0.339645
(25)	229	0.373098
(16)	219	0.387474
Optimal under:		
(2), (10); i.e. $\hat{g}$	1243	0.258688
(2), (20); i.e. $\tilde{g}$	1019	0.238697
(4), (24)	377	0.327375
(25), (24)	127	0.360828
(16), (22); i.e. $\bar{g}$	117	0.375204

Recall that all considered models contain the same industry effects, so that they have the following associated empirical weighted variance proportion: $\tilde{r}_1 = 0.396843$. Moreover, the presented estimated risks were always calculated as almost unbiased estimates of the MSEP (11) under the condition that the variances are given by (14), that is, they were calculated according to (13), (21), (23) or a corresponding formula for other models. We observe that even some optimal models may be outperformed by the saturated model with respect to the estimated risk when this "largest model" doesn't belong to the class of competing models.

The optimal grouping model $\tilde{g}$ under (2) and (20) with 80 groups of firms appears most convenient for predicting future returns when we compare all candidates considered in Table 3. The second choice would be model $\hat{g}$, which was obtained in Subsection 4.2 as optimal solution under (2) and (10). This model provides a grouping of the firms into 113 groups with both a similar time-dependent and a similar permanent behavior of their returns. Note that another grouping could be preferred to the optimal one if its estimated risk is close to the optimal risk $\hat{R}_{\hat{g}}$ and if it provides fewer or easily interpretable groups. This is reasonable, since our procedure is based on *estimates* of the risk. Thus any appealing grouping in our stepwise search, g^* say, fulfilling a rule of thumb like

$$\hat{R}_{g^*} < (1+\delta)\hat{R}_{\hat{g}} \ , \quad \text{with some small } \delta > 0 \text{ such as } 0.1 \ ,$$

could be our first choice. But such an approach is not discussed in more detail, since the economic interpretation of specific groupings is not addressed in this paper.

Generally, time-dependent industry and firm effects seem to be important for describing the dependence of the returns on some effects. Models such as (16) neglect this fact by treating the data observed over time as independent replications and may thus not serve as an appropriate basis for statistical analysis. Naturally, there is some hope to improve the prediction quality of the models by considering some variations such as allowing an additional grouping of the years, which could drastically reduce the dimension of models containing, for example, interactions between industries (and/or firms) and years, without having a substantial effect on the fit.

Finally, one could also try to find optimal groups of firms with industries by a simultaneous selection of (grouping) models for the expected returns and of (again grouping) models for the variances by use of an appropriate criterion such as cross-validation, which can be defined without having some estimates of the variances. But this is beyond the scope of this paper. The most convenient way of analyzing the data in our setting is probably to assume just the rather general model (1) of heteroscedastic variances.

5 Conclusions

This chapter extends the literature on the relative importance of firm, industry, and other effects on firm performance by examining the effect of performance groups.

The concept of performance groups was introduced by Wiggins and Ruefli (1995) to investigate necessary conditions for the existence of strategic groups. Using a variety of methods, we found that, in contrast to Wiggins and Ruefli, performance groups exist in almost every industry of our data set. In particular, we found that the majority of firms can be grouped with respect to a criterion which measures the ability of a grouping and of the corresponding model to predict the returns of a firm. The performance groups explain about 17.9 percent of the performance variance. However, about 35.1 percent of this variance is explained by non-grouped firms. Because of the splitting of the firm effects into group and single-firm effects, now the largest impact is associated with the industry effects of about 39.7 percent. It is worth noting that the grouped model uses much less parameters than the saturated model (about one half) but does not explain much less of the firm effects (53.0 percent versus 56.7 percent).

How can these results be interpreted? Of course, the study is descriptive in nature and thus, no structural causalities can be uncovered. Nonetheless, the results suggest that firm-focussed concepts from Strategic Management and industry-focussed concepts from IO do not tell the whole story about corporate performance. Hence, the respective literature could be fertilized by considering intermediate group-level concepts. However, a note of caution seems to be appropriate as Dranove, Peteraf, and Shanley (1998) point out that real evidence of group effects can only be found if data on group characteristics are available. Possibly, our group effects are spurious in the sense that they just result from some aggregated firm specific characteristics and not from genuine group characteristics.

What other reasons are possible for firms having apparently similar levels of performance within an industry? First, our data set offers a segmentation of firms into industries which might be too coarse. Comparing with segmentations like the SIC-3 and SIC-4 code, our classification covers relatively large bundles of industry segments. On the other side, we only considered groups which lasted for the whole period of time. Peteraf and Shanley (1997) suggest that the periods of group membership vary and that groups may be more important in unstable industries. However, addressing these questions remains for further research.

In particular, it would be interesting to investigate if our results (which are to a certain extent opposing to Wiggins' and Ruefli's) can be reproduced with different sets of data and different measures of performance. Another possible research avenue would be to further elaborate on the constituent characteristics of strategic groups and other possible group concepts which are correlated with the performance groups. The empirical framework of Dranove, Peteraf, and Shanley (1998) is a possible starting point.

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