Industry, firm, year, and country effects on profitability: Evidence from a large sample of EU food processing firms

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2009

AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin, July 26-29, 2009

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This paper analyzes the variance in accounting profitability within the European food industry. Based on a large panel data set, the variance in return on assets (ROA) is decomposed into year, country, industry, and firm effects. Further on, we include all possible interactions between year, country, and industry and discuss the theoretical foundations for these effects. After singling out the significant effect classes in a nested ANOVA with a thoroughly designed rotation regarding the order of effect introduction, we determine effect magnitude using components of variance (COV). Our results show that firm characteristics seem to be far more important than industry structure in determining the level of economic return within the food industry. Year and country effects, as well as their interactions were weak or insignificant, indicating that macroeconomics and trade theory offer little potential to serve as a basis for the explanation of performance differentials. While neither national nor industry-specific cycles were significant, EU-wide fluctuations significantly contributed to explaining differences in performance, suggesting that economic cycles in the EU are by and large synchronized.

Key words: variance components, abnormal profit, EU-27, MBV, RBV, comparative advantage.

"There are many theories because each is based on different assumptions about the world; it is their relevance rather than their logic which is in dispute." Cook, P. L. 1958. Effects of Mergers, London: George Allen & Unwin, p. 17.

According to the model of perfect competition, firm performance that deviates from average values should not exist. However, such deviations are not an exemption to the rule but the normal case. While the so-called 'market-based view', which draws heavily on Industrial Organization (IO) theory, mainly attributes such 'abnormal' profits to industry characteristics, proponents of the 'resource-based view' assume that performance differentials can better be explained by firm properties. In order to resolve this debate, a series of contributions following Schmalensee's (1985) seminal paper, has used components-of variance analysis (COV) and nested (i.e., hierarchical) analysis of variance (ANOVA) techniques to decompose the variation in firm profitability into firm and industry specific effects. Subsequent papers have also looked at the impact of year, and more recently, country effects on firm profitability. While the influence of country and country-industry interaction on the variation in profitability can be explained by models developed in trade theory, in the literature, so far little attention has been given to the theoretical foundations of year effects, and the year-country, year-industry and year-country-industry interactions. Likewise, research has either tried to quantify effects within the general economy, or looked at specific sectors or parts thereof. Within the agribusiness, a few attempts have been made (e.g., Schumacher and Boland 2005; Szymański et al. 2007), but evidence for the sector is as yet sparse. In addition, the majority of studies either focused on the US, or, in order to estimate country effects, had a worldwide scope. However, the increasing relevance of supranational economic areas, such as the EU or NAFTA, provides an interesting, but yet neglected perspective for analyzing the effects of country versus trade area-wide economic fluctuations on performance.

In order to fill these gaps, this study aims to quantify firm, industry, year, and country effects on profitability in the EU food industry. It is the first, to also include all possible interactions between industry, year, and country in a thorough methodological design.

The paper is structured as follows. After providing a brief overview of the different theoretical approaches that explain performance differentials, the methodology used to estimate the relevance of the different types of effects is introduced. Here, we try to identify and duplicate best-practices used by previous papers in order to be able to compare our results to earlier work. This is followed by the presentation of our empirical result based on the nested ANOVA and COV analysis. In the final section of the article, we discuss our findings conclude.

Theoretical explanations for performance differentials

In perfect competition (1) goods are homogeneous, (2) suppliers have identical cost curves, and (3) there exists a single market price, not subject to manipulation by individual market participants. Since, all firms produce equal amounts of output, intra-industry variation in profits does not exist. With the additional assumption of general equilibrium conditions across markets, and costless market entry and exit, inter-industry variation in profitability is not possible either. This is the case since investors will switch markets if their capital can be used more productively, which will (gradually) lead to the leveling of profitability across industries. Since this neo-classical model offers no explanations for the phenomenon of variation in profitability (i.e., for economic as opposed to accounting profit), numerous other theoretical models have been developed to deal with this issue.

Industrial organization (IO) and some of its neoclassical antecedents, focus on the characteristics of industries as the main source of performance differentials. Here, the structure-conduct-performance model can be seen as a summary of the IO perspective. Within this paradigm it is believed that performance depends on the conduct of suppliers (e.g., their inclination to invest, to innovate, and to collude) which in turn is determined by industry structure (e.g., concentration, product differentiation, and vertical integration). Structure, conduct and performance, in addition, are influenced by a set of basic industry condition (e.g., demand elasticity and the possibilities for economies of scale). Thus, it can be subsumed that IO theory predicts a rather deterministic link between industry membership and economic return[2]. Usually, this notion is referred to as the ‘industry view’ (IV).

Within strategic management another perspective, usually referred to as the ‘market-based view’ (MBV), has been developed during the 1980ies and early 1990ies. According to Porter (1980), who laid the cornerstones of the concept, firms can achieve above average profits if they manage to position themselves in an attractive industry. While this assumption is consistent with the IV perspective, Porter (1980) also assumed that choice of the strategy within a given market can lead to cost and/or differentiation

[2] However, it is often neglected that IO literature also comprises models that allow for performance differential within the same industry. This includes, e.g., locational models of product differentiation as well as models with Stackelberg competition. Nevertheless, the emphasis in IO is certainly on the explanation of industry-wide abnormal profits.

advantage and thus, influence firm profitability[3]. Therefore, although industry attractiveness is perceived to be an important element, the MBV also recognizes the strategic position within a given market as a cause of persistent firm-specific deviations from average industry profitability.

While the MBV has long been the leading paradigm in the management literature, during the 1990ies, the attention turned to a competing school of thought known as the 'resource-based view' (RBV)[4]. Here, it is expected that industry membership has little explanatory value for performance differentials but that the factors responsible for superior profits rather adhere to the firm and its resources. Based on the general assumption of heterogeneity in the endowment with resources, superior profits are believed to result from utilizing tangible and intangible resources that are rare, and costly to copy or imitate (Barney 1991)[5]. Due to the difficulty to copy such differential

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[3] Similar to the notion of entry barriers in IO, strategy-related advantages that lead to superior profitability can persist due to so-called mobility barriers, which make the switch from one strategic group to another costly (Tremblay 1985, S. 184).

[4] Usually, Barney (1991) is credited as the intellectual father of the RBV. Other important theoretical contributions to the RBV include Day und Wensley (1988) as well as Hunt & Morgan (1995).

[5] Drawing on similar ideas, Prahalad & Hamel (1990) introduced the terms 'capabilities', which are defined as complex combinations of resources. Since, due to complexity, such capabilities are difficult to imitate, above-average profits is believed to persist in the long-run.

advantages, the RBV primarily predicts firm-specific deviations from the average profitability levels.

Although IV, MBV, and RBV, each have a different perspective on inter vs. intra-industrial variation in profits, none of them provides justification for systematic differences in profitability between countries. Generally, under the condition of free trade, factor mobility, and general equilibrium, differences in profitability across countries should vanish, if capital is used in its most productive way. However, national borders can act as barriers to commodity trade and capital mobility, which can prevent the leveling of profitability. Therefore, in order to explain industry-specific as well as country-wide differences in profitability, trade theory offers a useful perspective. One example for a model that predicts country-wide differences in performance is the technological gap theory, which assumes that countries differ with respect to their level of technological sophistication. Consequently, some countries are able to constantly produce innovation and persistently earn monopoly rents. In turn, industry-specific differences in national profitability can arise from absolute cost advantages in certain industries[6].

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[6] In turn, these can result if countries with a large domestic market realize external economies of scale.

Besides variation across countries, profitability can also systematically vary over time[7] Economic fluctuations that do not equally affect all actors in an economy but are limited to a certain subsets of firms are referred to as asymmetric shocks or cycles (Buti & Sapir 1998, S. 24). While industry-specific changes in aggregated supply or demand (e.g., due to the imposition of a consumption tax or a sudden shortage in an input supply) can cause shocks that are limited to specific industries, asymmetry may also relate to the geographic spread. Here, a stream of research that deals with the synchronization of business cycles has analyzed the relative importance of common, country, and industry-specific shocks (e.g., Clark & Wincoop 2001, Ramos et al. 2003, and Artis et al. 2004). With regard to the EU as a frame of reference, four possible macroeconomic effects on profitability can be distinguished: (1) EU-wide fluctuations, (2) national fluctuations, (3) EU-wide industry–specific fluctuations, and (4) national industry–specific fluctuations.

[7] Numerous earlier studies have therefore incorporated a 'year' effect and/or an industry-specific year effect in their modelling approaches and referred to it as a component capturing the economic cycle (e.g., Rumelt 1991, McGahan & Porter 1997, Makino et. al 2004; Roquebert et al. 1996, Schumacher & Boland 2005). However, the theoretical underpinnings for these inclusions have not been laid out in detail.

Model, estimation, and data

From the above discussion, nine types of effects on performance differentials can be induced. We use the following model as a basis to test the significance and estimate the size of these effects:

$$(1) \qquad r_{tjik} = \mu + \alpha_t + \beta_j + \gamma_i + \delta_k + \varphi_{tj} + \chi_{ti} + \psi_{ji} + \omega_{tji} + \varepsilon_{tjik},$$

where r_{tjik} is year t's accounting ROA of corporation k that operates in industry i of country j, μ is the grand mean, α_t are year effects, β_j are country effects, γ_i are industry effects, δ_k are firm effects, φ_{tj}, χ_{ti}, ψ_{ji} as well as ω_{tji} are all possible two and three-way interactions between year, country, and industry, and ε_{tjik} is the error term.

With regard to relevance of the effects in the specified model, proponents of the IV and MBV would expect relatively large γ_i, while according to the RBV, the δ_k should dominate. In addition, the α_t (representing EU-wide economic fluctuations) can be seen as an indicator for the relevance of macroeconomic theory while the β_j are connected to the relevance of trade theory in explaining differences in ROA. Finally, ε_{tjik} corresponds to the unexplained variance that remains within the firm (over time).

While the interpretation of the model's main effects is relatively straightforward, there are several possibilities to interpret the various model interactions (a fact that has been largely neglected in previous papers). So far, industry-country interactions have been treated as comparative advantages and were thus assumed to support the importance of trade theory in explaining performance differences (e.g., Hawawini et al. 2004).

However, under the condition that borders isolate the nations from international competition to a certain degree, large industry-country interactions may also originate from substantial differences in (national) industry structure. Likewise, one can interpret year-country and year-industry interactions as national and industry-specific business cycles and consider them to be indicators for the relevance of macroeconomic theory in explaining ROA variation. In turn, assuming that comparative advantages and industry structure (e.g., concentration) are at least to a certain degree volatile, these effects can be explained by trade theory and IO as well. Finally, three-way interactions can be interpreted as business cycles in industries that are rather isolated from international competition, but there are other possibilities as well. Due to these ambivalences, sufficient care must be given to the interpretation of the model results.

Previous papers have used ANOVA and/or components of variance analysis (COV) to partition the observed variance in ROA into effect-specific components. Since both, COV and ANOVA have certain advantages, none of these methods is superior to the other on conceptual grounds. A main advantage of COV over ANOVA is that the latter relies on the assumption that each factor contains a certain amount of factor levels, which are all present in the data, while COV assumes that the factor levels in the data set are a subset of factor levels, randomly drawn from a finite population of effects. Due to this underlying random-effects assumption, COV results allow for a generalization of the sample results to a larger group of effects, not necessarily present in the data (Searle et al. 2006, p. 3). For the given case, this is beneficial as we aim to infer from a sample of firms to the size of firm effects in general, from a selection of accounting periods to all year effects, from a subset of industries to every industry within food processing, and from an incomplete list of member states (17 countries) to the EU as a whole. However, the main disadvantage of COV is that (unlike for an ANOVA) there exists no test for the significance of effects. Therefore, we follow most previous papers (e.g., Schmalensee 1985; Rumelt 1991; McGahan & Porter 1997; Hawawini et al. 2004; Schu-macher & Boland 2005; Szymański et al. 2007) by singling out significant effect classes using ANOVA and estimating their size with COV.

For the significance testing, we use a nested ANOVA that relies on the following iterative procedure. Starting with a „null model", which contains the ROA observations (r_{tjik}) as the dependent variable, and the grand mean as a single explanatory variable, we estimate the model and store the residuals (i.e., the part of ROA not explained by the intercept). Then, with these residuals as dependent and a first effect class (e.g., year effects) on the explanatory side, we estimate a second one-way ANOVA, store the residuals and run an F-test. Since the model contains one effect class only, the results of this F-test can be used to determine whether the newly introduced effect class significantly increases explanatory power. Next, we use the residuals of the latter model as dependent, introduce a further effect class, and test its significance with another F-test. This procedure continues until all effect classes have subsequently been introduced.

The appeal of this method lies in the possibility to test for the significance of an effect while simultaneously controlling for all previously introduced effects. However, its main drawback is that it is unclear, which effects should be introduced first, and which should follow. Despite the fact that this can severely influence the results, most of the previous papers that employ nested ANOVA approaches lack a solid design in the order of effect introduction. Therefore, we use Schmalensee (1985) as a benchmark and extend his approach (designed for three effect classes), into a tailored rotation scheme for the nine effect classes contained in the model.

In total, 60 individual ANOVA models were computed. Due to the considerable computing time and the large number of models in the design, for the nested ANOVA approach, we reduced the size of our samples (presented below) by random draw to 20,000 observations. For the estimation, we used a General Linear Model with Type III Sums of Squares since we deal with an unbalanced data set.

Before we estimate effect sizes, we eliminate effects and interactions from model (1), whose contribution was not significant in the nested ANOVA. For the COV approach, it is assumed that the remaining effects are random with expected values of 0 and constant variances $\sigma_r^2, \sigma_\alpha^2, \sigma_\beta^2, \sigma_\gamma^2, \sigma_\delta^2, \sigma_\varphi^2, \sigma_\chi^2, \sigma_\psi^2,$ as well as σ_ω^2. Residuals are assumed to be uncorrelated, with expected values of 0 and constant variances. Further on, we assume all effect classes to be uncorrelated with each other and with the residuals. Under these conditions, we can decompose the total variance in r_{tjik} into the following variance components (Norusis 2008, S. 192):

$$(2) \qquad \sigma_r^2 = \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma_\delta^2 + \sigma_\varphi^2 + \sigma_\chi^2 + \sigma_\psi^2 + \sigma_\omega^2 + \sigma_\varepsilon^2$$

As estimation method, the majority of contributions in the literature has either used MINQUE (e.g., Vasconcelos 2006) or (restricted) maximum likelihood (REML/ML) techniques (e.g., Makino et al. 2004). Like Roquebert et al. (1996), we employ both, ML and MINQUE and interpret differences in the results as an indicator of estimator robustness (cf. Rao 1973 and Searle et al. 1992 for in-depth treatments of COV and its estimation methods).

AMADEUS, a commercial pan European balance sheet database provided by Bureau van Dijk Electronic Publishing will be used as a data source. Since it is most established, we employ the (pre-tax, pre-interest) ROA as an indicator of profitability. Since asset values are snapshots of points in time, but profits are realized during periods of time, we relate profits in accounting period t to average assets over t and t-1. Here, our analysis is based on the 2001 through 2006 financial statement, since the data availability in AMADEUS is best for this period[8]. Like Makino et al. (2004, p. 1033) we consider only firms with complete ROA data across the full period under study.

The industry classification systems used by the preceding papers were 4-digit SIC (e.g., Rumelt 1991, McGahan & Porter 1997), 3-digit SIC (Hawawini et al. 2004), and 3-digit NACE (Szymański et al. 2007). As AMADEUS provides information at the NACE-4 level, we define industry membership along this categorization, which is broader than SIC-4, but less broad than SIC-3 and NACE-3. Generally, we considered all firms with main activities in any official NACE-4 food processing industry (32 categories between NACE-1511 and NACE-1599). However, as in Schmalensee (1985) and Rumelt (1991),

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[8] Previous panel studies on this topic were based on four to seven years of data (Roquebert et al. 1996: seven years; Makino et al. 2004 six years; Szymański et al. 2007: five years; Rumelt 1991, Hawawini et al. 2004, Brito & Vasconcelos 2006: four years).

we eliminated one ‘miscellaneous’ category (NACE 1589: manufacture of other food products not elsewhere classified). In addition, since AMADEUS does not provide data at the level of individual business units, but on corporations as a whole, we also removed firms active in more than one NACE-4 industry from the database. This was necessary, since we use corporate ROA to estimate industry effects and therefore, secondary activities would bias the results.

With regard to firm size, some previous studies have either used a minimum size criterion (McGahan &Porter 1997; Brito & Vasconcelos 2006; Schmalensee 1985; Rumelt 1991) or considered all firms regardless of size. Such a restriction can be justified by the fact that by considering all firms, the estimation results will mainly depend on a large number of small firms, whose economic relevance is, however, comparatively small[9]. Further on, considering small corporations can bias the sample composition, since there are substantial international differences in small firm obligations to disclose annual accounts. In order to identify the bias connected to the inclusion of small firms, we followed Rumelt (1991) in constructing two samples, one with and one without a size restriction. Therefore, for the sample referred to as ‘sample A’ we eliminated micro-sized enterprises, while ‘sample B’ considers all size classes. For the definition of micro-sized enterprises, we adhere to the European Commission’s threshold (less than two million

[9] When considering the EU food industry as an example, micro enterprises represent 79% of all food industry ventures, while they contribute only 16% to industry employment and 7% to industry turnover (Eurostat 2008)

Euros in assets)[10]. Due to the size restriction, only 25% of all firms in sample B were contained in sample A. However, 96% of all corporate assets in sample B remain in sample A[11].

In order to estimate three-way interactions, it is necessary to assure a minimum amount of observations in every category. Therefore, like Schumacher and Boland (2005, p. 101), we first eliminated industries within countries that contained less than three corporations. Second, in order to be able to separate country, and industry effects from their interactions, we iteratively eliminated (1) countries with data on less than three industries and (2) industries occupied in less than three countries. Therefore, only 16 (sample A) and 17 (sample B) out of the 27 EU member states could be considered in the analysis. Moreover, this included the elimination of four NACE-4 categories from sample A (1562, 1594, 1595, and 1597). Since these industries and countries are relatively small, the loss in sample size caused by the procedure was moderate (about 8% for each sample).

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[10] As a cut off, McGahan & Porter (1997) as well as Brito & Vasconcelos (2006) used 10 million US$ in assets. Schmalensee (1985) and Rumelt (1991) eliminated observations with less than 1% in industry turnover.

[11] Since the AMADEUS data is rounded to the nearest thousand, integer-related problems force us to impose a minor size restriction (ten thousand Euros in average assets) on the full sample as well. At low values, the rounding can cause artificial leaps in ROA over time (and thus increase intra-firm volatility), although the changes in assets or profits may have been marginal.

With a final number of 6,282 enterprises in sample A (31,410 observations across the five years of data) and 24,960 enterprises in sample B (124,800 observations), to our knowledge, we use the largest sample among the preceding papers.

To assess whether these samples are good representations of the population of EU food processing firms, we compare the distribution of country and industry shares in the population and with the shares in the samples.

Table 1. Distribution of observations within sample A and B and in the population (by country)

	Share in sample and population (%)		
Country	*Sample A (N = 6,282)*	*Sample B (N = 24,960)*	*Population*[a] *(N = 309,209*[b]*)*
Italy	30.5	10.6	24,7
Spain	22.3	19.1	10,2
France	21.1	38.6	23,7
United Kingdom	6.6	2.2	2,5
Poland	4.8	1.6	5,9
Belgium	3.6	5.0	2,7
Romania	2.9	14.9	3,8
Greece	2.5	1.2	5,3
Portugal	2.0	1.5	3,6
Finland	1.0	1.4	0,6
Sweden	0.8	2.3	1,2
Netherlands	0.6	0.2	1,6
Slovenia	0.4	0.2	0,3
Estonia	0.3	0.8	0,1
Germany	0.3	0.1	11,4
Ireland	0.2	0.1	0,2
Bulgaria	-	0.2	2,0

Note: “Population” refers to all EU-27 firms active in the manufacturing of food products and beverages (according to Eurostat 2008).
[a] Share in the countries listed below
[b] EU-27

Table 1 reveals that German firms are significantly underrepresented in both samples. This is caused by the fact that during the time considered in our analysis, the obligation to disclose annual accounts applied to few German enterprises and, in addition, noncompliance to these obligations was rarely penalized[12]. Spanish firms are overrepresented both samples while Italian firms are overrepresented in sample A and underrepresented in sample B. France and Romania are overrepresented only in sample B. Here, this is due to a relative good availability of small business annual accounts. All in all, country shares in the population seem to better be reflected by the size-restricted sample (sample A).

On the contrary, within the distribution of industry shares, sample B better represents the population (cf. table 2). Largely, this is due to the fact that enterprises active in NACE 158 (manufacture of 'other' food products)[13] are severely underrepresented in sample A, while the opposite holds for all other industries (mainly NACE 151, 155, and 159) except NACE 154. In sample B, the underrepresentation of NACE 158 is moderate, and NACE 151, and 159 are overrepresented.

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[12] For the same reason, the Austrian sample was too small to be considered in the analysis.

[13] In this category, we find the largest deviation within NACE 1581 (manufacture of bread; manufacture fresh pastry goods and cakes). This activity is dominated by many small retail or artisan bakeries, as well as franchisees, many of them are not included in the size-restricted sample.

Table 2. Distribution of observations within sample A and B and in the population (by industry)[a]

(NACE Code), Industry description [a]	Share in sample and population (%) *Sample A (N = 6,282)*	*Sample B (N = 24,960)*	*Population (N = 309,209)*
(151) Production, proc. & pres. of meat & meat prod.	22.2	20.2	15.0
(159) Manuf. of beverages	20.0	11.1	7.4
(158) Manuf. of other food prod.	17.7	45.1	60.9
(155) Manuf. of dairy prod.	13.2	7.3	4.3
(153) Proc. & pres. of fruit & vegetables	8.6	4.5	3.4
(157) Manuf. of prepared animal feeds	5.9	2.8	1.7
(156) Manuf. of grain mill prod., starches & starch prod.	5.4	4.8	2.8
(152) Proc. & pres. of fish & fish prod.	4.9	2.6	1.3
(154) Manuf. of vegetable & animal oils & fats	2.0	1.6	3.1

Note: "Population" refers to all EU-27 firms active in the manufacturing of food products and beverages (according to Eurostat 2008). Proc. & pres. = processing and preserving; Manuf. = manufacturing; Prod. = products

[a] For the purpose of clarity, population and sample shares are compared at NACE-3, instead of NACE-4 level (nested ANOVA and COV relied on NACE4 classifications).

Since none of the samples clearly represents the population better than the other, the results for both samples will be given equal attention in the discussion and similarity in these results will be used as indicator for their robustness.

Nested ANOVA results

Table 3 shows the first step results of the nested ANOVA approach. For each model, differences between the grand mean and individual firm profitability were used as the dependent variable. F-test results show that the introduction of every individual effect class (as first effect) leads to a highly significant increase in explanatory power over the null model. R^2 and adjusted R^2, which can be used as a first indicator of effect size, are by far largest in the model with firm effects, where one half and two thirds of the variation in the null model residuals are explained. In general, results for sample A and B are very similar, but explanatory power is higher for the sample with size restriction (sample A).

Table 3. First step ANOVA results for sample A and B

	Sample A			Sample B		
Model with	*Sign.*[a]	R^2	*adj.* R^2	*Sign.*[a]	R^2	*adj.* R^2
year effects α_t	***	0.005	0.005	***	0.004	0.004
country effects β_j	***	0.024	0.024	***	0.015	0.014
industry effects γ_i	***	0.033	0.032	***	0.014	0.012
firm effects δ_k	***	0.670	0.587	***	0.536	0.419
year-country interactions φ_{tj}	***	0.032	0.028	***	0.023	0.019
year-industry interactions χ_{ti}	***	0.045	0.038	***	0.024	0.017
Industry-country interactions ψ_{ji}	***	0.107	0.097	***	0.052	0.040
three-way interactions ω_{tji}	***	0.152	0.102	***	0.092	0.031

Note: Models contain the null model residuals as dependent and single effect as independent variables.
[a] F-test significance. Triple asterisk (***) denotes significance at the 0.1% level

Figure 1 and 2 depict the further ANOVA steps, i.e., the stepwise introduction of effects beginning from models with an intercept and a main effect (year, country, or industry). The design in the rotation is subject to some logical constraints. Two-way interaction effects (e.g. industry-country effect) cannot be introduced before the introduction of their respective main effects (industry effect and country effect) in order to produce meaningful results. The same holds for three-way interactions (e.g. year-country-industry effect) that have to be sequenced after two-way interactions (e.g. year-country). If e.g. industry-country interactions were introduced first, the model residuals correspond to differences from average ROA in each industry-country combination and thus, the mean of all residuals in any industry-country combination will be zero. Since this is the case, each industry's (and country's) mean will also be zero. Therefore, industry (and country) effects can not be significantly different from zero after the introduction of their interaction.

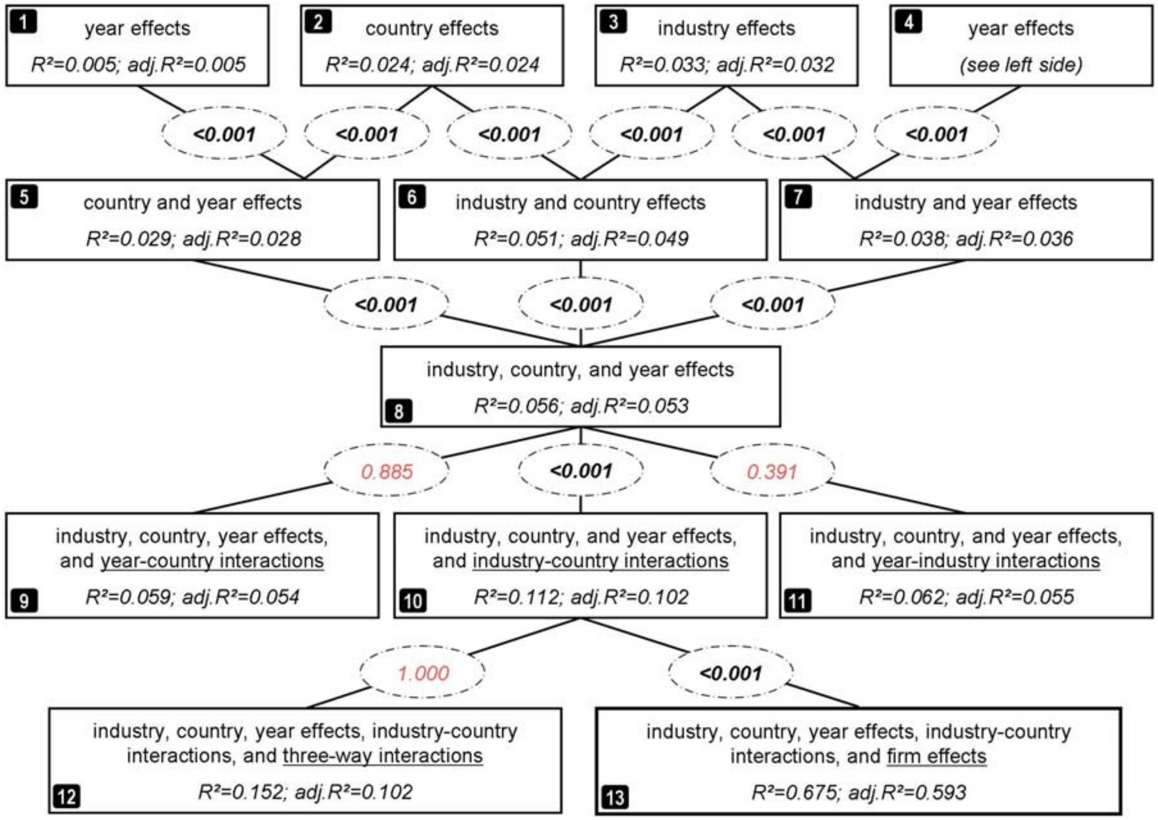

Figure 1. Nested ANOVA results for sample A

Numbers in oval shapes in Figures 1 and 2 correspond to F-test significance levels. They show that year, country, and industry effects still significantly enhance explanatory power even if the respective other main effects are introduced beforehand. With the exception of industry-country interactions, none of the two-way interactions remain significant when main effects are controlled for. Likewise, three-way interactions are not significant after the introduction of significant two-way interactions. Firm effects, in turn, stay significant after controlling for all other significant effect classes. Each of these results count for both, sample A and sample B.

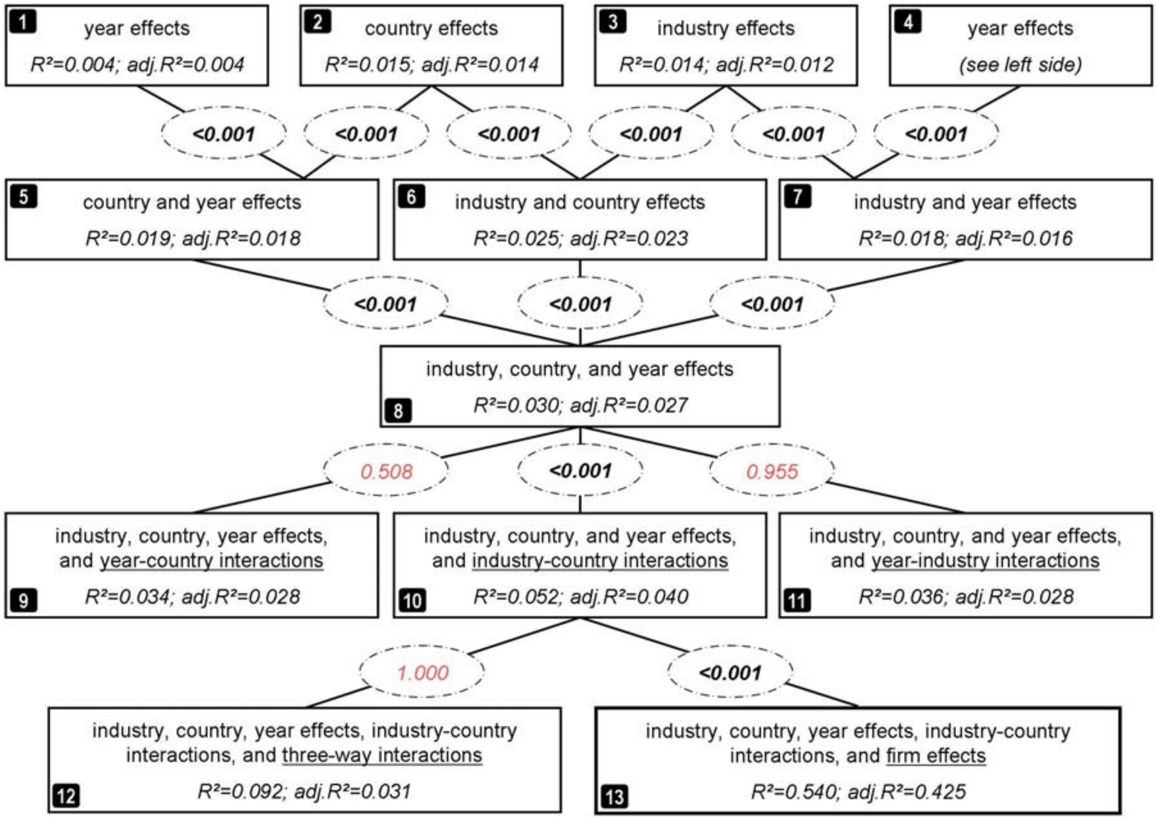

Figure 2. Nested ANOVA results for sample B

R^2 and adjusted R^2 values were calculated for models that contain the newly introduced effect classes as well as all other previously introduced effects. With an R^2 of 0.68 (adj. R^2 of 0.59) in model 13, all significant effects explain almost two thirds of the total ROA variation in sample A (cf. figure 1). With the size restriction not in place (sample B), total explanatory power drops to 54% (cf. figure 2).

Table 4. (Mean) increment to R^2 by type of effect and sample (A and B)

Effect class	From model … to model… [a]	Increment to R^2 A	Increment to R^2 B	Average [b] A	Average [b] B	Share in total [c] R^2 A	Share in total [c] R^2 B
year effects	0 to 1	0.005	0.004	0.005	0.004	0.7%	0.8%
	2 to 5	0.005	0.004				
	3 to 7	0.005	0.004				
	6 to 8	0.005	0.005				
country (C) effects	0 to 2	0.024	0.015	0.021	0.013	3.1%	2.5%
	1 to 5	0.024	0.015				
	3 to 6	0.018	0.011				
	7 to 8	0.018	0.012				
industry (I) effects	0 to 3	0.033	0.014	0.030	0.012	4.4%	2.3%
	2 to 6	0.027	0.010				
	1 to 7	0.033	0.014				
	5 to 8	0.027	0.011				
I-C interactions	8 to 10	0.056	0.022	0.056	0.022	8.3%	4.1%
firm effects	10 to 13	0.563	0.488	0.563	0.488	83.4%	90.4%

Note: [a] model numbers as depicted in figure 1 and 2. Zero denotes the null model.
[b] mean increment to R^2 across all models into which the effect was introduced.
[c] R^2 of model 13

Again, the increment in explanatory power from one model to another can be used as an indicator for the relevance of a newly introduced effect class. For each significant effect, table 4 lists the average change in R^2 caused by its introduction over all relevant models. With an average increase in explanatory power of 0.563 in sample A (0.488 in sample B) firm characteristics account for a share of 84% (90%) in the explained variation of firm profitability. Industry-country interactions, industry effects, and country effect follow in importance but are much smaller. Year effects are significant, but marginal in size.

COV results

All COV results are depicted in Table 5. In the case of the size restricted sample (A), about 60% of the total ROA variation is explained by the five remaining effect classes which were significant in the ANOVA. Without the size restriction (sample B), the error variance is larger and thus, the explanatory power of each effect class tended to fall. In addition, the relative relevance of some of the effect classes slightly varies depending on sample and estimation technique. However, the results seem to be rather robust to sample type and estimation method.

As in the case of the nested ANOVA, firm effects account for the largest share (roughly 90%) in explained ROA variation, while all other effects were much weaker. With a share in the explained variation of 5% in sample A, and 1% in sample B, industry-country interactions were stronger in the size restricted sample. Shares for industry and country effects ranged between 2 and 4%, while year effects (1 to 1.5%) were the weakest effect class.

Table 5. Components of variance results for sample A and B

	Sample A		Sample B[a]	
Variance component	*ML*	*MINQUE (0)*	*ML*	*MINQUE (0)*
year effects	0.6%	0.6%	0.6%	0.6%
country effects	2.5%	1.1%	1.6%	1.7%
industry effects	2.3%	2.1%	0.9%	0.7%
I-C interactions	3.6%	2.7%	0.4%	0.5%
firm effects	51.9%	53.3%	38.1%	37.8%
error term	39.2%	40.1%	58.5%	58.6%

Note: [a] Average values across five subsamples: Due to computational constraints and the large number of observations (124,800), sample B could not be processed in a simultaneous run. As did Roquebert et al. (1996), we split the sample into equal-sized subsamples (random draw without replacement) and analyzed each subsample separately. Individual results (which can be obtained from the authors upon request) were robust across subsamples.

Discussion and Conclusions

Our results show that industry, firm, year, and country effects, as well as industry-country interactions significantly influence food industry ROA explaining about 40% of the variation in profitability. If micro-sized firms are excluded, explanatory power rises to 60%. All year interaction effects proved to be not significant. With a share of 85 to 90% in the explained variance, firm effects considerably outweigh all other effect classes. Country effects, industry effects, and industry-country interactions are small, but larger than year effects whose contribution was marginal. Generally, all of these results were robust to (1) method (COV vs. ANOVA increment to R^2), (2) estimation technique (MINQUE vs. ML), and (3) sample type (A vs. B) [14].

Our findings confirm the previous results with regard to the dominance of firm effects, as well as relatively small contributions of year effects (e.g., McGahan & Porter 1997, Schumacher & Boland 2005), country effects (e.g., Makino et al. 2004, Brito & Vasconcelos 2006), and the two-way interactions (e.g., Hawawini et al. 2004, Schumacher & Boland 2005)[15]. However, there is much less consensus regarding the relevance of industry effects. Similar to our results, a number of studies found that industry effects account for less than 5% in ROA variation (e.g., Hawawini et al 2004,.Brito & Vasconcelos 2006, Szymański et al. 2007), while others estimate this

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[14] Moreover, the COV results were stable across the five subsamples of sample B.

[15] Three-way interactions were not considered in any previous paper.

effects class to be larger than 18% (McGahan & Porter 1997, Schumacher & Boland 2005). In part, this may be due to differences in industry heterogeneity, since some authors focused on certain sectors, and others looked at the general economy[16]. Moreover, industry effects seem to be smaller if their estimation is based on a broader industry classification system, and on corporate-level rather than business-unit data.

While the comparison of the results for sample A and B suggests that small-firm bias was not an issue in this study, a main source of bias in papers that use accounting ROA as the dependent variable relates to the common practices and systems used in corporate financial reporting[17]. First, during profitable periods, firms tend to produce hidden reserves or realize hidden charges that were set up during less profitable times. Since such practices cause a smoothing effect on the ROA time series, they may lead to an underestimation of the error component, year effects, and year interactions while firm effects may be overestimated. Second, in an international context, differences in the national reporting regulations and practices can bias the estimation of country effects. For instance, countries which make extensive use of practices that lead to a contraction of balance sheet totals (such as sale-and-leaseback or third-party factoring), may systematically achieve higher ROA values. Moreover, firms in market-oriented financial systems (e.g., the United Kingdom), as opposed to, banking-oriented economies (e.g.,

[16] However, in spite of their restriction to the food economy, Schumacher & Boland (2005) also found large industry effects.

[17] Although several types of distortions are introduced, this issue has not been brought up by papers.

France) tend to positively appraise performance, which may lead to an overestimation of profitability in those countries. Although the size of the above mentioned distortions is unknown, the results of our analysis are clear with regard to the main question under investigation so that it is unlikely, that they are influenced by these sources of bias.

Regarding the contribution of the above discussed theoretical viewpoints on the driving forces of performance differentials, our results have the following implications. First, the effect classes representing economic fluctuations were weak, indicating that macroeconomic theory provides little potential to serve as a basis for explaining performance differentials in the food industry. Here, the fact that EU-wide fluctuations were small, but significant, while national fluctuations were not, suggests that within the EU-27, national business cycles are largely synchronized. Second, as most effect classes emphasized by IO and trade theory were weak or insignificant, while firm effects were strong, our results provide further evidence for the relevance of firm-specific characteristics as determinants of superior performance. In this respect, this article strongly supports a resource-based view on above-normal returns.

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