WHAT DRIVES FIRM PROFITABILITY? A MULTILEVEL APPROACH TO THE SPANISH AGRI-FOOD SECTOR

(Rentabilität von Firmen in der Spanischen Agrar- und Lebensmittelindustrie)

Ferdaous Zouaghi, Stefan Hirsch, Mercedes Sanchez Garcia

stehirsch@ethz.ch

ETH Zürich, AECP Group, Sonneggstr. 33, 8092 Zurich

2016

Vortrag anlässlich der 56. Jahrestagung der GEWISOLA
„Agrar- und Ernährungswirtschaft: Regional vernetzt und global erfolgreich“
Bonn, 28. bis 30. September 2016

WHAT DRIVES FIRM PROFITABILITY? A MULTILEVEL APPROACH TO THE SPANISH AGRI-FOOD SECTOR

(Rentabilität von Firmen in der Spanischen Agrar- und Lebensmittelindustrie)

Abstract

Strategic management research has demonstrated the importance of firm resources and industry structure as drivers of profitability. However, less is known about how factors related to firms´ geographical locations affect profitability. In this article, we estimate firm-, industry-, year-, and region-specific effects on agri-food firm profitability in Spain. We apply the multilevel approach of Hierarchical Linear Modeling to a sample of 3,273 agri-food firms operating in different geographical districts during the time span 2006-2013. The results reveal the dominance of firm-specific effects which contribute up to 48.8% to variance in profitability. Moreover, firm size, growth, financial risk as well as innovation activity turn out as significant profit drivers. Although firm-effects have a stronger impact than industry affiliation and location, the results indicate that structural industry factors such as concentration and size as well as territorial factors such as regional education and unemployment influence profitability. Moreover, location in rural districts is not necessarily a handicap for firm profitability.

Keywords: agri-food profits, hierarchical linear model, firm-, industry-, and location effects

1 Introduction

The agri-food chain is one of the most important economic branches in the European Union (EU) (Food Drink Europe 2013). An increase in agri-food companies' competitiveness is therefore decisive for continuous economic growth (Alarcón and Sánchez 2013). Individual components of the agri-food chain are also of high economic importance. The food processing industry is the largest manufacturing sector in the EU in terms of turnover (14.9%) and constitutes the top manufacturing activity in several member states (Food Drink Europe 2013). In Spain, the country under investigation in this article, the food processing industry contributes 21.6% to total manufacturing turnover. The upstream sector to the processing industry –i.e. primary agricultural production– is mainly of high economic importance in developing countries where contribution to total GDP commonly exceeds 20%. Still, the 2.5% share that the Spanish agricultural sector adds to national GDP is higher than in most western EU countries such as Germany and the UK where the share is below 1.0% (World Bank 2015). In addition, Spanish agriculture provides employment for more than 2 million individuals which highlights its social importance (Eurostat 2015b).

Hence, due to its high economic and social relevance the Spanish agri-food sector deserves investigation concerning the factors that influence its profitability. Previous studies that analyze the drivers of firm profits mainly focus on whole economies or entire manufacturing sectors (Elango and Wieland 2014). The few existing studies with a food sector focus have so far neglected to analyze the agricultural sector (Schumacher and Boland 2005; Chaddad and Mondelli 2013; Hirsch *et al*. 2014). Thus, the present study contributes to previous literature by analyzing the food processing industry as well as primary agricultural production and revealing differences between both sectors regarding the drivers of firm profitability.

More specifically, we explore the influence of firm-, industry-, region- and year-specific factors on firm profitability by studying performance differences within the Spanish Communities of Valencia and Navarre based on a sample of 3,273 agri-food firms. These firms operate in 60 agri-food subsectors[1] and 97 different regional districts during the period 2006–2013. We apply the multilevel approach of Hierarchical Linear Modeling (HLM) which is an improved methodology for the decomposition of variance in profitability into different effect levels (i.e. firm, industry, region, year). Simultaneously, structural variables that influence profitability at each level (e.g. firm size, industry concentration, unemployment within a region) can be incorporated (Short *et al*. 2006). The main advancement of HLM in comparison to classical decomposition methods such as analysis of variance (ANOVA) or components of variance (COV) is that it allows for varying error structures at each level of the analysis and is therefore better suited to capture nested data structures (Elango and Wieland 2014).

Previous research has focused on a diversity of different aspects of firm profitability in various economic sectors and countries (e.g. Claver, *et al.* 2002; Goddard *et al.* 2005; Gallizo *et al.* 2014; Pattitoni *et al.* 2014). However, little is known about the regional factors that influence firm performance. This comes from limitations in the conceptualization of the relationship between regions and firm profitability as well as data availability (Raspe and van Oort 2011). García-Alvarez-Coque *et al*. (2013) point out that specific locations can provide advantages for agri-food firms in form of local resources, such as favorable natural and labor conditions or access to technological inputs. Moreover, Hoffmann and Hirsch (2015) find that strategic location, such as producing or processing agricultural products obtained in the territory where they are located, is a source of competitive advantage. In addition, regional organization is an important economic factor, particularly in systems characterized by many small and medium sized enterprises (SMEs) such as the EU food industry, where the share of SMEs is 99% (Giusti and Grassini 2007).[2]

While mainly focusing on the importance of firm- and industry effects the existing HLM literature analyzes the impact of regional effects on firm profits mainly by focusing on the country-level (e.g. Goldszmidt *et al*. 2011). Our data allows to extend the empirical evidence on more disaggregated regional determinants of profitability. We focus on local resources as well as different regional macro-level variables such as education level and unemployment rate as drivers of firm profitability. These variables reflect the state of a region's economy and are fundamental in explaining firm profitability through their effect on aggregated demand and supply.

Valencia and Navarre contribute 12% to national GDP (INE 2011a) and provide interesting settings to study the effect of location as they represent different regional environments. While Navarre primarily consists of larger, rural districts (12 out of 14), Valencia is mainly comprised of smaller districts of which a high fraction (48 out of 83) is urban (Boix and Galletto 2005). In addition the two regions have different agricultural systems regarding product specialization. In Navarre, cereal, vegetable, ovine, bovine and pork production are dominant, whereas, in Valencia, citrus, fruits and

---

[1] These subsectors are defined based on the 4-digit NACE classification of economic activity of the European Commission.

[2] Based on the SME classification of the European Commission (2005) which defines SME's as firm with <250 employees and total assets <EUR 43m. (Eurostat 2015a).

vineyards prevail, leaving a smaller share to poultry and pork production.[3] Moreover, the agri-food sector is of high economic relevance in both regions as it takes second and fourth place in contribution to regional GDP in Navarre and Valencia, respectively (Valencia Generalitat 2015; GdN 2015).

The remainder of the paper has the following structure. Section 2 provides background information on the theoretical and empirical literature of profit variance decomposition. Section 3 describes the data, while the applied methodology is described in section 4. Results are presented in section 5 and conclusions are drawn in section 6.

2 Theoretical and empirical background

From a theoretical perspective the effect of industry- and firm-effects on profitability can be substantiated by strategic management (SM) approaches. SM research focuses on managerial skills that best utilize a firm's resources based on its external environment. The industry in which a firm operates is usually assumed as the most relevant external factor (Grant and Nippa 2006). The market-based view (MBV) which is a dynamic extension of the classical structure-conduct-performance (SCP) paradigm[4] postulates that structural characteristics of the industry are the main driver of firm profits although firms can favorably influence those characteristics and thus the degree of competition through strategic behavior (Grant and Nippa 2006; Hirsch 2014). Given its primary focus on the industry and the strategic positioning of firms within this industry, according to the MBV industry-effects and their underlying structural variables should have a major impact on firm profitability (Welge and Al-Laham 2008). As the simple relationship between industry structure and performance cannot account for the vast heterogeneity across industries in the 1980's the 'New Empirical Industrial Organization' literature (NEIO) has emerged (e.g. Bresnahan 1981). Based on game theory, NEIO studies model the strategic and competitive behavior of firms using structural econometric approaches which comprise more detailed industry- and firm-specific factors. NEIO models decompose the drivers of profitability into factors related to demand structures, cost advantages and cooperative conduct that decreases competition. While NEIO approaches are useful for case studies as they enable a detailed modelling of a specific industry, we aim to provide generalizable insights of profitability across industries. (Kadiyali *et al*. 2001) Our focus will therefore be on the MBV as the theoretical underpinning of industry effects. As shown in Table 1, previous HLM studies on firm profitability have found a diverse range of results regarding industry effects depending on the analyzed industry and country. Those vary from a negligible impact of below 1% (Hirsch *et al*. 2014) in the EU food industry to a significant contribution of around 18% in Central American countries (Ketelhöhn and Quintanilla 2012). Regarding structural industry characteristics according to Bain (1956) and Porter (1980), the focus should be on those factors which determine the degree of entry barriers and competition. Besides the estimation of the aggregate industry effect, we include concentration ratios as well as industry size and growth as

[3] Agri-food output in Navarre is composed of 49.7% vegetal production and 50.3% animal orientated production while the region of Valencia has mainly a vegetal focus, which represents 75.3% of the total agribusiness production (Spanish Ministry of Agricultural, Food and Environment 2015).

[4] In contrast to the MBV the classical SCP paradigm assumes that structural industry characteristics such as concentration or entry barriers directly determine firm profitability. Tirole (1988) postulates that the focus should be on the MBV as the SCP is based on rather poor theories that neglect the strategic decisions of firms.

industry-specific drivers of firm profits (Bhuyan and McCafferty 2013; Chaddad and Mondelli 2013).

Table 1: Previous studies decomposing firm profits using HLM

Authors	Country	Effect class (%)			
		Firm[a]	Industry	Year	Country/ Region
Hough (2006)	US	40.1	5.3	< 1.0	n.a.
Misangyi *et al*. (2006)	US	36.6	7.6	0.8	n.a.
Short *et al*. (2006)	US	45.0	8.3	n.a.	n.a.
Chan *et al*. (2010)	US	19.2	13.6	0.2	1.4
	China	20.8	10.5	2.2	6.7
Molina-Azorin *et al*. (2010)	Spanish services firms	82.3	n.a.	n.a.	17.7
Goldszmidt *et al*. (2011)	37 countries	32.7	2.5	n.a.	3.2
Ketelhöhn and Quintanilla (2012)	Central American countries	44.7	17.5	n.a.	5.1
Chaddad and Mondelli (2013)	US food economy / processing	36.1 36.7	7.0 7.5	0.5 1.0	n.a. n.a.
Hirsch *et al*. (2014)	EU food processing	40.2	0.4	0.9	1.8

Source: Authors´ own literature review
[a] In the U.S. studies (with the exception of Short *et al*., 2006) the firm effect is split into a business-unit and a corporate effect whereat the business unit effects are reported as firm effects.

Another strand of SM literature emphasizes the role of business-specific resources as determinants of profitability (Goddard *et al.* 2005). Penrose (1959) interprets firms as bundles of physical and intangible resources where differences between firms, emerge due to differences in endowment with those resources. Based on the assumption of heterogeneity in resource endowment, profits above the competitive norm are assumed to result from the utilization of tangible (financial and physical factors of production) or intangible (technology, innovation or reputation) resources (Claver *et al.* 2002; Goddard *et al.* 2005). According to the resource based view (RBV), firms endowed with specific valuable, rare, and inimitable resources are more competitive, enabling these firms to outperform the market (Barney 1991). Therefore, according to the RBV firm effects and the underlying firm-specific variables should have a major impact on firm profitability. Table 1 indicates that there is consensus across previous HLM studies regarding the dominance of firm effects which contribute between 20.8 and 82.3% to variance in profits. Besides the aggregate impact that firm-effects have on profitability in accordance with the RBV we estimate the impact of physical, financial, human, and organizational firm-specific resources. In this respect, firm size, growth, age, financial risk, and innovativeness have been identified by previous literature and are therefore included as drivers of profitability (Chaddad and Mondelli 2013; Hirsch *et al*. 2014).

The effect of macroeconomic fluctuations can be incorporated by means of year effects. The contribution of macroeconomic cycles on profits is consistently below 1% in previous studies (e.g. Hough 2006) (cf. Table 1). However, as the present dataset includes the years 2008/09 besides the aggregate impact of macroeconomic cycles, we evaluate how far agri-food firm profitability has been impacted by the financial crisis.

Regarding regional effects, previous studies have mainly focused on the country level. Thereby, the influence of country effects is based on trade theory models (Ricardo

1817). If capital can flow freely between countries or regions, it will be moved where it generates the highest return. This implies that profitability will converge across countries and that country effects are close to zero. As the elimination of trade barriers and the formation of a single market is one of the main motives of the EU formation (Goddard et al. 2009), studies that focus on the EU only detect weak country effects with a contribution below 2.0% (Hirsch *et al*. 2014) (cf. Table 1). In contrast, if estimated for regions outside the EU country effects are generally larger (Ketelhöhn and Quintanilla 2012; Goldszmidt *et al*. 2011).

Studies that focus on interregional comparisons within countries find evidence of significant relationships between location specific resources and firm performance (Chan *et al.* 2010; Molina-Azorin *et al.* 2010). Molina-Azorin *et al*. (2010) analyze Spanish service firms operating in 14 provinces using HLM and provide evidence for the importance of location effects (17.7%) in explaining firm profitability. Chan *et al*. (2010) focus on performance differences in a two country setting (US and China) with subnational regions (34 states in the US and 21 cities and provinces in China). Their results indicate that corporate effects are stronger determinants of profitability than region effects both in the US and in China. Analyzing 4,000 Italian firms localized in various provinces Lasagni *et al.* (2015) provide evidence supporting the importance of macroeconomic factors of regions such as institutional quality and geographical conditions as determinants of firm productivity. Thus, besides the aggregate impact that geographical location has on profits we include regional macroeconomic factors as drivers of profitability. Okun's law states that the unemployment rate is the main indicator for economic growth and profitability (Lee 2000). Faggian and McCann (2009) verify the importance of regional endowment with human capital. Regional education levels, and the share of foreign population are therefore also included as region-specific drivers of profitability. Moreover, proxies for regional resource endowment such as presence of scientific/research institutions or airports as well as the degree of urbanization are incorporated. While the latter can provide a competitive advantage by faster access to downstream markets and lower transportation costs proximity to universities or research centers is related to knowledge generation within a region (Giuliani *et al*. 2010).

As regards HLM results for agribusiness firms Chaddad and Mondelli (2013) are the first to apply this approach to US food processor and retailer accounting data. Besides dominant firm effects, they find a significant impact of factors related to firm structure such as size, capital intensity and R&D expenditure on profitability. Hirsch *et al*. (2014) present similar results for EU food processing firms where in particular firm size and industry concentration turn out as important drivers of performance. We add to this literature by providing a detailed investigation regarding the influence of firm-, industry-, region- and year-specific drivers of firm profitability in the Spanish agribusiness sector.

3 Data

Firm data are drawn from the SABI balance sheet database, generated by INFORMA and Bureau van Dijk. Initially, all firms operating in primary agricultural production (NACE 01) and processing of food and drinks (NACE 10, 11) located in the Communities of Valencia and Navarre during are selected. Data is available for the period 2006 to 2013. As the dependent variable, we use Return on Assets (ROA) to proxy firm profitability. ROA measures the degree of efficiency by which a firm uses its assets and is calculated as Earnings Before Interest and Taxes (EBIT) divided by Total

Assets (Bae and Gargiulo, 2004; Russo and Fouts, 1997). Although commonly used (e.g. Gaganis *et al.* 2015; Hirsch *et al.* 2014; Rassier and Earnhart 2011; Reynaud and Thomas 2013), accounting measures such as ROA have often been referred to as biased proxies for profitability due to profit smoothing arrangements or cross subsidization of less successful business units (Fisher and McGowan 1983; Long and Ravenscraft 1984). Nevertheless, alternative measures such as economic value added (EVA) do not necessarily represent superior proxies for real economic profit. For example, Biddle *et al*. (1997) show that ROA outperforms EVA as a measure for profitability. Therefore, due to data availability and to allow comparability with previous HLM literature we employ ROA as the profitability measure. To assess the impact of physical, financial, human, and organizational, firm-specific resources in accordance with the RBV the following explanatory variables are added at the firm level: firm size measured by the logarithm of total assets, yearly sales growth, and age. We also introduce two proxies to assess the impact of firms' financial risk. Short-run risk (1/Curr) is defined as the ratio of current liabilities to current assets (i.e. the reciprocal of a firms current ratio). The second risk proxy is debt leverage (Lev_debt) calculated as the ratio of total debt to total assets. Moreover, the dummy variable 'innovative' indicates whether or not a firm conducts innovation activities. This variable is not directly available from SABI but can be proxied by the growth in intangible assets. This rests on the fact that innovation results from the implementation of intangible assets such as R&D, intellectual property, organizational structures or core competencies[5] (OECD 2010; Stone *et al.* 2008). Firms with growth in intangible assets in year *t* are considered as innovative in this year.

To estimate the impact of structural characteristics that, according to the MBV, determine the degree of entry barriers and competition in each 4-digit NACE industry, the following variables were added using Eurostat's structural business statistics (Eurostat 2015b): industry concentration measured by the Herfindahl-Hirschman index (HHI), industry growth measured by the yearly growth rate of the number of firms in an industry, and industry size proxied by the logarithm of sales. Eurostat only provides industry data for the processing of food and drinks while data for primary agricultural production is not available.

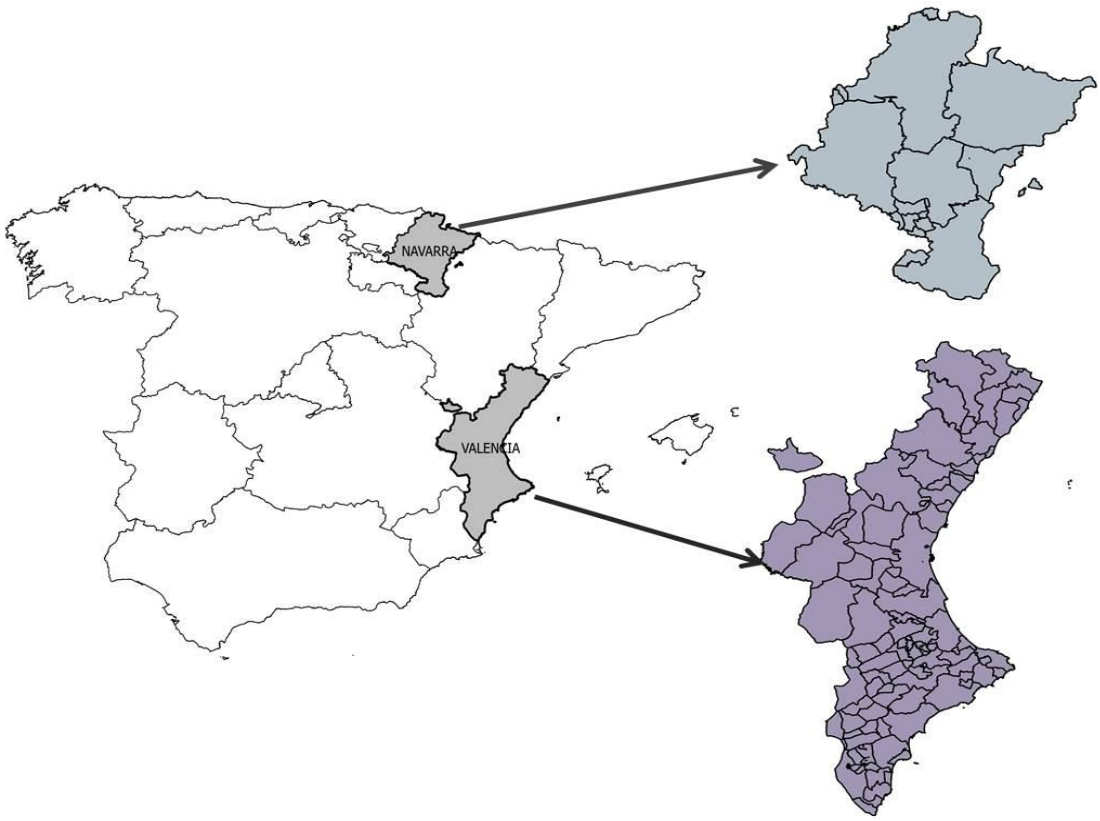
We define regions by means of geographical units called Local Labor Systems (LLS) proposed by the Italian National Statistical Institute (ISTAT 1991). A LLS is an area characterized by internal commuting patterns that produce a self-contained labor market. LLS are delimited by applying the Sforzi algorithm to information regarding enterprises and commuters, i.e. data on daily commuting to work contained in the population census. This can be summarized in two steps: first, agglomeration points that attract flows of workers from neighborhoods are identified. Subsequently, neighboring municipalities from which work flows originate are aggregated to the agglomeration points (Ciccone and Cingano 2003). Boix and Galletto (2005) have used this methodology to delimit LLS in Spain using data from the 2001 population census and the Central Directory of Firms. The result is a categorization of Spain into 806 LLS, 83 of them located in Valencia and 14 located in Navarre (Figure 1).

The LLS-specific variables used to capture regional macroeconomic conditions and resource endowment have been generated from two databases: the Spanish Census of Population and Houses (INE 1991; 2001; 2011) and the statistical yearbook of La Caixa (Caixa 2013). We include the following LLS related variables: the unemployment rate, education level, distance to the nearest airport and technological institute as well as the ratio of foreign-born migrants to total population. Based on the OECD classification

[5] However, it has to be kept in mind that generally accepted accounting principles only include intangible assets that are acquired and have a measurable value.

(OECD 1994) we classify LLS according to their degree of urbanization to determine possible relations between firm performance and rural/urban location. A LLS is considered urban if its population density is higher than 150 inhabitants per square kilometer (García-Alvarez-Coque *et al.* 2013).

Figure 1: LLS of Valencia and Navarre in Spain



For each variable, anomalous observations lying outside an interval of +/- 3 standard deviations from the mean were removed. The final sample includes 2,582 and 691 agri-food firms operating in Valencia and Navarre, respectively. This sample accounts for 14.1% of the population of Spanish agri-food firms (Eurostat 2015b).

Table 2 provides definitions and descriptive statistics for ROA and the independent variables related to firm, industry and region. Moreover, matrices displaying correlations among independent variables can be found in the appendix. For both Navarre and Valencia, mean ROA is 0.016. Firms in Navarre are somewhat larger than firms in Valencia, although companies in Valencia are characterized by higher growth. Furthermore, firms in Valencia are on average older and prone to taking higher financial risk than firms in Navarre. In both regions, an average of 16% of firms conduct innovative activity. In both regions industries are characterized by a decrease in the number of firms. Industry concentration measured by the Herfindahl Index is on average slightly higher in Valencia but overall on a moderate level. More than 80% of the firms in the Valencian sample are located in urban LLS, whereas in Navarre, 97% of firms are located in rural LLS. Firms located in Valencia are better connected to airports and technological institutes. The foreign population and unemployment rate is higher in Valencia than in Navarre (16.9% and 11.1% compared to 12.7% and 9%), while education is on a comparable level.

Table 2: Variable definitions and descriptive statistics (2006-2013)

Variable	Definition	Valencia n=20,652		Navarre n=5,528	
		Mean	SD	Mean	SD
Dependent variable					
ROA	Return on Assets = Earnings before interest and taxes/total assets	0.016	0.118	0.016	0.129
Firm-level					
Ln TA	Firm size: natural logarithm of total assets	6.469	1.707	6.934	2.669
Age	Number of years since incorporation	20.302	10.676	19.161	13.005
Gr. sales	Yearly sales growth	13.953	87.876	11.796	72.160
1/Curr	current liabilities / current assets	1.439	3.398	1.251	2.168
Lev_debt	total debt/total assets	0.846	2.063	0.609	0.396
Innovative	Dummy with value 1 if the companies perform innovation with innovation proxied by growth in intangible assets.	0.158	0.365	0.155	0.362
Industry-level[a] (4-digit NACE)					
HHI	Herfindahl-Hirschman index. Sum of the squared market shares of firms operating in an industry	0.020	0.758	0.002	0.007
Ln sales	Natural logarithm of industry sales.	8.255	1.228	8.369	0.800
Gr. NF	Yearly growth rate of the number of firms in an industry.	-1.263	8.506	-0.449	9.267
Territory-Level (LLS)					
Unemployment rate	LLS unemployment rate	11.098	4.777	8.969	3.152
Dist_port	Driving minutes to nearest airport	71.072	41.201	175.005	12.41
Dist_tec	Driving minutes to nearest technological institute	34.460	23.607	42.939	15.662
Edu_level	Education level of LLS population between 30 and 39 years old. Ranging from 0 (uneducated) to 4.5 (PhD)	2.765	0.192	2.994	0.139
Urban	Dummy with value 1 if the LLS is considered urban (>150 inhabitants/km²)	0.803	0.398	0.030	0.172
Foreign_pop	Proportion of foreign born population in total LLS population.	16.915	10.878	12.655	3.248

Source: Authors´own calculations based on SABI and Eurostat (2015b).

[a] Industry-level data is only available for the processing of food and drinks (NACE 10, 11).

4 Hierarchical Linear Model (HLM)

Most previous studies employ ANOVA or COV to decompose the variation in firm profitability into different effect classes (McGahan and Porter 1997; McNamara *et al.* 2005; Rumelt 1991; Schmalensee 1985). However, both techniques have limitations, sometimes generating inconsistent and unreliable results (Misangyi *et al.* 2006). The main disadvantages of those approaches result from their underlying assumptions. ANOVA assumes that each effect class is composed of specific effect levels, which are all present in the analyzed sample. COV is based on the assumption that the effect levels in the analyzed sample are randomly chosen from the population of levels (Searle *et al*. 2006; Hirsch *et al.* 2014). In addition, ANOVA results are highly sensitive to the chosen pattern of effect introduction (Hirsch and Schiefer 2016). Finally, both ANOVA and COV do not account for possible correlations between individual effects (Misangyi *et al*. 2006).

The methododological framework to capture adequately the nested structure in the dataset is Hierarchical Linear Modeling (HLM) (Erkan et al. 2015). HLM is an approach, recently used in studies on firm performance, which allows to simultaneously determine entire effect classes and the underlying structural covariates that drive performance (Hough 2006; Gaganis *et al*. 2015). HLM predicts values of the dependent variable as a function of predictor variables at more than one level (Luke 2004), thus taking into account the nested, non-independent nature of the data both within and between groups (Sahaym and Nam 2013). We employ HLM with random intercepts, using an iterative restricted maximum likelihood estimation (REML) (Gaganis *et al.* 2015). We estimate separate models for Valencia and Navarre as well as for the agricultural sector and the processing industry in order to control for differences between regions and sectors.

It has to be noted that while HLM is particularly suited to capture the nested structure in the data it does not allow to model dynamics in firm profits. Dynamics in firm profits refer to the interrelation of profits from year to year and thus competition in a Schumpeterian way.[6]

4.1 Null model

For each region and sector we first estimate a three-level hierarchical null-model without structural independent variables (Raudenbush and Bryk 2002). The effect levels are incorporated into the model by means of nested regressions that can be iteratively estimated.[7] Level 1 represents the repeated measures of each firm over the analyzed time span and is therefore considered as the time-level:

$$ROA_{tij} = \pi_{0ij} + e_{tij} \quad (1)$$

where *t* denotes time with *t*= 2006, …, 2013. Individual firms are indexed by *i* and introduced at level 2. For both regions we consider -from the LLS or industry level- the level with more manifestations as level 3 while the remaining level is introduced via dummy variables (Chaddad and Mondelli 2013). Thus, depending on which case applies to the analyzed region, *j* indicates either the LLS or the industry in which firms operate. In (1) π_{0ij} is mean ROA over time of firm *i* in LLS/industry *j* and e_{tij} is the random

[6] For studies that focus on the dynamics of firm profits by means of panel estimation techniques such as the GMM estimator (e.g. Arellano and Bond 1991; Baltagi 2008) we refer to Goddard et al. (2005) and Hirsch and Gschwandtner (2013).

[7] Our model is based on the methodological frameworks implemented by Chaddad and Mondelli (2013) and Hirsch *et al.* (2014).

time-level error which is normally distributed with mean zero and variance σ^2. Consequently, e_{tij} reflects the model's error term. Its variance σ^2 reflects variability in ROA within the firms over time and is assumed to be uniform only among the observation within each of the *i* firms.

At level 2 (firm-level), mean firm profitability over time π_{0ij} is simultaneously modeled as the result of random variation around the LLS/industry mean β_{00j}:

$$\pi_{0ij} = \beta_{00j} + r_{0ij} \qquad (2).$$

r_{0ij} is the random firm-level error which is normally distributed with mean zero and variance τ_π. Hence τ_π, which is assumed to be uniform only for firms within the same industry, reflects variance across firms.

The third level (LLS/industry-level) models mean profitability of the LLS/industry[8] *j* (β_{00j}) simultaneously as the result of random variation around the grand mean (γ_{000}):

$$\beta_{00j} = \gamma_{000} + \mu_{00j} \qquad (3).$$

The random LLS/industry-level error (μ_{00j}) is normally distributed with mean zero and between LLS/industry variance τ_β.

Based on the null model defined by equations (1) – (3) the percentage contribution of each effect can be calculated as $\sigma^2/(\sigma^2 + \tau_\pi + \tau_\beta)$ for the time effect, $\tau_\pi/(\sigma^2 + \tau_\pi + \tau_\beta)$ for the firm effect and $\tau_\beta/(\sigma^2 + \tau_\pi + \tau_\beta)$ for the LLS/industry effect.

Effects with less than 20 manifestations have generally to be introduced as dummy variables at the respective level (Hox 2008). Therefore, as our sample only covers 8 years we incorporate dummy variables at the time-level to capture year effects.[9] Equation (1) then becomes:

$$ROA_{tij} = \pi_{0ij} + \pi_{1ij}(year_1)_{tij} + \pi_{2ij}(year_2)_{tij} + ... + \pi_{8ij}(year_8)_{tij} + e_{tij} \qquad (1a)$$

where $year_1$, $year_2$, . . ., $year_8$ are dummy variables for the 8 years. π_{0ij} now represents mean firm profitability across time for firm *i* in LLS/industry *j* adjusted for year effects. The coefficients π_{1ij}, π_{2ij}, …, π_{8ij} capture the year effects. The percentage contribution of year effects can be calculated as the reduction in time-level variance (σ^2) in comparison to the null model.

[8] For Valencia, the number of LLS (83) exceeds the number of industries (60) which means that LLS is introduced as an effect at level 3 while industry effects are captured via dummy variables at level 2 (eq. (2b)). For Navarre however, the number of industries (58) exceeds the number of LLS (14). In this case LLS dummies enter at level 2 (eq. (2a)) while the industry affiliation is captured as the level 3 effect.

[9] The year effect has to be distinguished from the time effect (level 1). While the time effect considers the repeated measures of each firm over time and can therefore constitutes an error term the year effect captures yearly macroeconomic fluctuations that influence all firms simultaneously.

Similarly, LLS/industry effects can be incorporated by means of dummy variables at the firm-level (Equation (2)):

$$\pi_{0ij} = \beta_{00j} + \beta_{01j}(LLS_1)_{ij} + \beta_{02j}(LLS_2)_{ij} + ... + \beta_{0nj}(LLS_n)_{ij} + r_{0ij} \quad (2a)$$

if the number of LLS is smaller than the number of industries as in the case of Navarre. LLS_1, LLS_2, ..., LLS_n are LLS dummies and β_{01j}, β_{02j}, …, β_{0nj}, capture LLS effects. In turn, if the number of industries is smaller than the number of LLS –as in the case of Valencia– industry dummies are added (Ind_1, Ind_2, …, Ind_n) and β_{01j}, β_{02j}, …, β_{0nj} reflect industry effects:

$$\pi_{0ij} = \beta_{00j} + \beta_{01j}(Ind_1)_{ij} + \beta_{02j}(Ind_2)_{ij} + ... + \beta_{0nj}(Ind_n)_{ij} + r_{0ij} \quad (2b).$$

β_{00j} has then to be interpreted as mean ROA of firms in industry/LLS *j* adjusted for LLS/industry effects. When introduced via dummies, the percentage contribution of LLS/industry effects can be calculated as the share of the reduction in variance at the firm-level that occurs when LLS/industry dummies are introduced in relation to total variance of the model including only year effects. For the final effect class results, time, firm and LLS/industry effects have to be adjusted for those effects introduced via dummy variables (i.e. year and industry/LLS)[10].

4.2 Incorporation of structural independent variables

When introducing explanatory variables to the null model (eq. (1) – (3)) it is important to determine their adequate introduction level. Two approaches exist, which differ in whether explanatory variables are treated as stable or transient. The stable approach (e.g. Chaddad and Mondelli 2013) suggests that explanatory variables are introduced at their respective level, i.e. firm specific variables at level 2 (between firms) and industry/LLS specific variables at level 3 (between industries/LLS). However, this approach has the disadvantage that variables are incorporated by taking their average values over time, implying that only cross sectional variance in profitability between firms or industries/LLS is captured, while variance over time remains unexplained (Misangyi *et al.* 2006). In contrast treating variables as transient implies introduction at level 1 (across time) (e.g. Hirsch *et al*. 2014). Hence, for each variable all observations across time are taken into account, with the effect that the variable's impact on profitability over time is also considered. To identify whether variables should be treated as stable or transient similar to Hirsch *et al*. (2014) and Misangyi *et al.* (2006) we conducted COV analyses that estimate the extent of variance in each variable that occurs across time, between firms, and industries/LLS. For the majority of variables the results show that the bigger part of variance occurs across time[11]. Therefore, to adequately capture the information present in the data we incorporate all explanatory variables at the time level, extending (1) to:

$$ROA_{tij} = \pi_{0ij} + \pi_{1ij}(X_1)_{tij} + \pi_{2ij}(X_2)_{tij} + ... + \pi_{nij}(X_n)_{tij} + e_{tij} \quad (1b).$$

[10] E.g. firm effects are adjusted by relating firm level variance of the model with year and LLS/industry dummies to total variance estimated by the null model:
$\tau_{\pi\ \text{model with year and LLS/industry dummies}} / (\sigma^2 + \tau_\pi + \tau_\beta)_{\text{null model}}$.

[11] Results of the COV analyses are available from the authors upon request.

X_1, X_2, ..., X_n are firm, industry and LLS specific variables as specified in Table 2. We assume that those variables are fixed with a similar impact on all firms:

$$\pi_{1ij} = \gamma_{100} \quad (2c),$$

$$\pi_{2ij} = \gamma_{200} \quad (2d),$$

$$\ldots,$$

$$\pi_{nij} = \gamma_{n00} \quad (2q).$$

The coefficients γ_{100}, γ_{200}, ..., γ_{n00} capture the fixed effect of each independent variable on ROA, while π_{0ij} now represents mean firm profitability across time for firm *i* in LLS/industry *j* adjusted for explanatory factors specific to the firm, industry and region.

5 Results and discussion

5.1 Null model

Tables 3 and 4 show the effect class estimation results for Valencia and Navarre. According to the null model results (upper panels) firm effects have a significant impact on ROA across regions and sectors. The corrected final results (bottom panels) indicate that firm effects have a stronger impact in Navarre, where the contribution is between 33.9 and 48.8% as compared to Valencia with 26.3 to 26.6%. Moreover, there is a tendency that firm effects have a stronger impact in the food industry than in the agricultural sector. These results highlight the importance for firm-specific factors as drivers of profitability and thus support the RBV as a theoretical foundation.

Although mainly significant[12], with the exception of the agricultural sector in Navarre, year effects only account for 0.1-2.5% and 0.0-0.9% of the variance in ROA in Valencia and Navarre, respectively[13]. This implies that similar to previous HLM studies an impact of macro-level shocks on ROA cannot be detected. The impact of the financial crisis in 2009 can be assessed by inspecting the respective year-dummies[14]. For both regions and sectors the 2009 year-dummy shows no abnormalities compared to preceding years which indicates that the food sector is a rather crisis proof sector due to static demand for food products (Lienhardt 2004).

Consistent with previous HLM research (Table 1), industry effects in our study are notably smaller compared to firm effects. The contribution is up to 4.2% and turns out to be slightly higher in Navarre than in Valencia[15]. The effect of the industry also varies by economic sector. For both Valencia and Navarre, the results show a stronger influence of this effect class in the food processing industry than in the agricultural sector where the impact is insignificant. This outcome can be explained by the fact that the sub sectors of agricultural production are more homogeneous than processing

[12] The significance of those effects introduced via dummy variables can be determined by a Wald test which reveals whether the inclusion of explanatory variables leads to a significant improvement in comparison to the null model.

[13] The magnitude of year-effect is calculated as:

$(\sigma^2_{\text{null model}} - \sigma^2_{\text{model with year dummies at time-level}}) / (\sigma^2 + \tau_\pi + \tau_\beta)_{\text{null model}}$

[14] Due to space considerations individual coefficients for year-, industry-, or LLS-dummies are not presented in Tables 3 and 4 but are available upon request.

[15] The magnitude of LLS/industry effects -when introduced via dummies- is calculated as:

$(\tau_{\pi\,\text{model with year dummies}} - \tau_{\pi\,\text{model with year and LLS/industry dummies}}) / (\sigma^2 + \tau_\pi + \tau_\beta)_{\text{model with year dummies}}$

industry sub sectors leading to less distinct industry effects. Compared to internal firm-specific resources external industry characteristics are hence less important drivers of firm profitability.

Table 3: HLM effect class estimates for Valencia

	All firms (n = 20,652)		Agriculture (n = 9,172)		Food industry (n = 11,480)	
	Variance components	%	Variance components	%	Variance components	%
Null model						
Time-level	0.010372	73.0	0.010935	73.4	0.009933	73.0
Firm-level	0.003758***	26.4	0.003899***	26.2	0.003653***	26.8
LLS-level	0.000079*	0.6	0.000066*	0.4	0.000025*	0.2
Model with year dummies at time-level						
Time-level	0.010209		0.010913		0.009597	
Firm-level	0.003842***		0.003916***		0.003809***	
LLS-level	0.000081*		0.000072*		0.000024*	
Year-effects		1.1		0.1		2.5
Wald χ^2		168.87***		14.49***		212.24***
Model with year dummies at time-level and industry dummies at the firm-level						
Time-level	0.010212		0.010907		0.009603	
Firm-level	0.003731***		0.003924***		0.003616***	
LLS-level	0.000057*		0.000074*		0.000013*	
Industry-effects		0.8		no effect		1.4
Wald χ^2		107.09***		31.57		71.18***
Final results						
Time		71.9		73.2		70.6
Firm		26.3		26.3		26.6
Industry		0.8		no effect		1.4
Year		1.1		0.1		2.5
LLS		0.4		0.5		0.1

Notes: *, **, *** significance at the 10%, 5% and 1% level.
Wald χ^2 for industry effects is derived from a model including industry dummies at the firm-level only.

The predominantly small relevance of LLS effects in our study supports the view that resources flow indeed freely to where returns are greatest (Hirsch *et al.* 2014). The findings suggest that location matters most in the agricultural sector in Navarre, where the effect accounts for 1.8% of ROA variance. Accordingly, Goldszmidt *et al.* (2011) find that territory effects are higher for nonmanufacturing sectors (i.e., agriculture, mining and construction) than for manufacturing firms.

The final results indicate that 70.6-73.2% of the ROA variance in Valencia and 46.9-63.0% in Navarre can be attributed to the time-level which corresponds to the error components of e.g. regression analysis and thus indicates variance in ROA that cannot be captured by firm-, industry-, region- and year-effects.

Table 4: HLM effect class estimates for Navarre

	All firms (n = 5,528)		Agriculture (n = 2,424)		Food industry (n = 3,104)	
	Variance components	%	Variance components	%	Variance components	%
Null model						
Time-level	0.010009	54.5	0.012712	62.7	0.008183	47.9
Firm-level	0.007818***	42.6	0.007234***	35.7	0.008249***	48.2
Industry-level	0.000527**	2.9	0.000334	1.6	0.000667*	3.9
Model with year dummies at time-level						
Time-level	0.009974		0.012742		0.008035	
Firm-level	0.007778***		0.007243***		0.008189***	
Industry-level	0.000524**		0.000331		0.000635*	
Year-effects		0.2		no effect		0.9
Wald χ^2		22.11***		3.46		47.36***
Model with year dummies at time-level and LLS dummies at the firm-level						
Time-level	0.009971		0.012779		0.008026	
Firm-level	0.007873***		0.006883***		0.008352***	
Industry-level	0.000531**		0.000448		0.000711*	
LLS-effects		no effect		1.8		no effect
Wald χ^2		7.35		17.81		8.03
Final results						
Time		54.3		63.0		46.9
Firm		42.9		33.9		48.8
Industry		2.9		2.2		4.2
Year		0.2		no effect		0.9
LLS		no effect		1.8		no effect

Notes: *, **, *** significance at the 10%, 5% and 1% level.
Wald χ^2 for LLS effects is derived from a model including LLS dummies at the firm-level only.

5.2 The impact of structural variables on ROA

The results of the models incorporating the explanatory variables specified in Table 2 are reported in Table 5. Firm size, measured by the logarithm of total assets, has a positive effect on profitability in all models with the exception of the food industry in Navarre. Previous empirical evidence generally detects a positive relationship between firm size and profitability (e.g. Misangyi *et al*. 2006). For the EU food processing sector Hirsch *et al*. (2014) show that firm size is a decisive factor to overcome downstream market power and administrative barriers associated with pre-market approval procedures (Wijnands *et al.* 2007). Pindado and Alarcon (2015) show for the Spanish meat industry that investment in fixed assets is positively related to profitability as such investments reflect efforts to remain competitive through modernization and innovation.

Regarding firm age (Age) Yazdanfar and Öhman (2014) verify based on the life cycle model that performance is higher for younger firms compared to their older counterparts. Loderer and Waelchli (2010) and Hirsch *et al*. (2014) explain the negative impact of age found in their studies by the fact that ageing leads to organizational rigidities, slower growth and outdated assets which are not replaced. In accordance, we also find a mostly negative –but insignificant– impact of firm age.

Table 5: HLM results for the drivers of firm profitability

	Valencia			Navarre		
	All firms (n = 20,652)	Agriculture (n = 9,172)	Food industry (n = 11,480)	All firms (n = 5,528)	Agriculture (n = 2,424)	Food industry (n = 3,104)
Intercept	0.0876	0.1687**	0.0867	-0.0027**	-0.1960	-0.3715**
	(0.0531)	(0.0752)	(0.0694)	(0.0012)	(0.2120)	(0.1828)
Firm-level						
Ln TA	0.0081***	0.0039**	0.0099***	0.0019**	0.0031**	0.0009
	(0.0098)	(0.0017)	(0.0012)	(0.0039)	(0.0013)	(0.0008)
Age	-0.0000	-0.0004	0.0000	-0.0005	-0.0009	-0.0005
	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0006)	(0.0004)
Gr. sales	0.0001***	0.0001***	0.0001***	0.0001***	0.0002***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1/Curr	-0.0058***	-0.0043***	-0.0077***	-0.0027**	-0.0014	-0.0048**
	(0.0005)	(0.0006)	(0.0007)	(0.0012)	(0.0016)	(0.0021)
Lev_debt	-0.0009	-0.0022*	0.0001	-0.0996***	-0.1280***	-0.072***
	(0.0008)	(0.0012)	(0.0011)	(0.0085)	(0.0130)	(0.0111)
Innovative	0.0055**	0.0009	0.0084***	0.0102**	0.0066	0.0111**
	(0.0021)	(0.0034)	(0.0027)	(0.0040)	(0.0068)	(0.0047)
Industry-level[a]						
HHI	n.a.	n.a.	0.2124*	n.a.	n.a.	1.018*
			(0.1251)			(0.5731)
Ln sales	n.a.	n.a.	-0.0054*	n.a.	n.a.	0.0022
			(0.0028)			(0.0066)
Gr. NF	n.a.	n.a.	-0.0001	n.a.	n.a.	-0.0004
			(0.0002)			(0.0066)
Territory-level						
Unemployment	-0.0024***	-0.0011***	-0.0032***	-0.0016***	0.0022	-0.0038***
	(0.0002)	(0.0003)	(0.0003)	(0.0006)	(0.0011)	(0.0008)
Dis_port	-0.0001	-0.0001	0.0000	0.0010**	0.0015**	0.0004
	(0.0007)	(0.0001)	(0.0001)	(0.0004)	(0.0006)	(0.0005)
Dis_tec	-0.0001	0.0000	-0.0002	-0.0002	0.0009*	-0.0008**
	(0.0001)	(0.0002)	(0.0018)	(0.0003)	(0.0005)	(0.0003)
Level_edu	-0.0344	-0.0544**	-0.0032	0.0608*	-0.0186	0.1341***
	(0.0184)	(0.0257)	(0.0228)	(0.031)	(0.0477)	(0.0408)
Foreign_pop	0.0002	-0.0001	0.0005	0.0007	0.0015	0.0004
	(0.0002)	(0.0003)	(0.0003)	(0.0012)	(0.0019)	(0.0017)
Urban	0.0066	0.0011	0.0124*	0.0235	0.0667	0.0246
	(0.0051)	(0.0075)	(0.0065)	(0.023)	(0.0582)	(0.0265)
Variance components						
Time level	0.00858	0.00921	0.00809	0.00817	0.00983	0.00694
Firm level	0.00334	0.00324	0.00319	0.00039	0.00561	0.00583
Territory level	0.00009	0.00013	0.00011	-	-	-
Industry level	-	-	-	0.00598	0.00040	0.00047
Wald $\chi 2$	517.89***	138.03***	466.08***	236.05***	174.83***	136.53***
Explanatory power (%)	12.59	11.58	13.48	10.02	14.17	7.24

Notes: Significant at ***p<0.01; **p<0.05; * p<0.1; Robust standard errors are shown in parentheses
All variables as defined in Table 2.
[a] Industry-level data is only available for the processing of food and drinks (NACE 10, 11).

Sales growth (Gr. sales), is an indicator of a firm's ability to compete and protect itself from cyclical market variations (Rassier and Earnhart 2015). Delmar *et al*. (2013) find a positive relationship between profitability and sales growth, suggesting that growth is associated with an increase in the likelihood of survival. Pattitoni *et al*. (2014) also find a positive impact explained by the fact that growth motivates employees and thus leads to higher profitability. Similarly, the effect in our study is positive and significant in all models with exception of the food industry in Navarre.

The impact of both financial risk measures is mainly negative and significant. Those results contradict classical risk theory but are in line with several previous empirical studies (e.g. Enqvist *et al*. 2014; Gschwandtner 2005; Hirsch *et al*. 2014; Pattitoni *et al*. 2014). The negative effect of financial risk can be explained by the risk-return paradox which states that good management practices can increase ROA and at the same time reduce financial risk (Bowman 1980). Fiegenbaum and Thomas (1988) explain the negative risk-profit relationship based on prospect theory which assumes that firms below a specific target performance are risk seeking while firms exceeding their target are risk averse.

Innovation measured by growth in intangible assets is particularly important in the food industry where the impact is significant and positive in both regions. The food industry is a highly saturated market characterized by high competition for retailer shelf space (Hirsch and Gschwandtner 2013) implying that innovations play a major role for firms' to stay in the market.

We now turn our attention to the impact of industry specific characteristics. For each 4-digit NACE industry concentration is measured by the HHI. Concentration is associated with impediments to entry as well as lower competition and thus higher profitability (Bain 1956; Porter 1980). Previous empirical research confirms the positive relationship between the HHI and firm profitability (Bhuyan and McCafferty 2013; Delmar *et al.* 2013; Hirsch *et al.* 2014). Similarly, our results show that the HHI impacts positively and significant on food industry profitability in both regions.

Industry size (ln sales), measured by the natural logarithm of each 4-digit industry's sales, impacts negatively and significant on profitability in Valencia. High industry sales can be an indicator for strong demand and high profits. However, larger industries can also be characterized by strong dynamism which causes instability and higher volatility in their environment leading to a negative influence on profits (Misangyi *et al.* 2006).

Industry growth (Gr. NF) is calculated by the growth rate of the number of firms in each 4-digit industry. If an industry grows, competition for market shares increases (Hirsch and Hartmann 2014). Accordingly, the results point towards a negative impact on profits in both regions, which however is non-significant.

Regarding territorial variables, in accordance with Okun's law our results show a negative impact of LLS related unemployment rates for agri-food firms. Similarly, Bekeris (2012) found that increases in unemployment reduce profitability especially for smaller companies more proactive in the internal market.

Short distance to the nearest airport (Dis_port) can provide a competitive advantage by faster access to downstream markets and lower transportation costs. However, the impact is insignificant for the Valencian agri-food sector. In addition, we find that in the case of agricultural firms in Navarre profitability increases with the driving minutes to the closest airport implying that in regions close to airports specific disadvantages for agricultural firms prevail.

Proximity to technological centers (Dis_tec) such as universities or research centers is related to knowledge generation within a LLS. Giuliani *et al*. (2010) analyze university-industry linkages in the Chilean, Italian and South African wine industries and find that firms' knowledge as well as researchers' individual characteristics are the main drivers of successful linkages that can lead to higher performance. For food industry firms in Navarre we find that profitability increases when driving minutes to the nearest technology center or university decrease. However, the impact on food industry firms in Valencia is insignificant. Jacobs (1969) shows that knowledge spillovers increase with the diversity of industries in a region. As Navarre comprises a significantly smaller number of LLS compared to Valencia (14 vs. 83) but a similar number of 4-digit NACE industries diversification in each LLS is higher in Navarre leading to the significant impact of the Dis_tec variable. Similarly to airport proximity, technology center proximity decreases profitability of agricultural firms in Navarre implying that in regions close to such centers competitive disadvantages for agricultural firms are present.

We used the education level (Level_edu) of the population between 30 and 39 years in each LLS as a spatial knowledge indicator. It can be expected that firms located in regions with easy access to high levels of human capital are more productive and competitive (Raspe and van Oort 2011; Usai and Paci 2003). We find that higher education is related to higher profitability of industry firms in Navarre. Profitability of Valencian agricultural firms in contrast is negatively influenced. This is likely due to a higher demand for low qualified workers in the agricultural sector as compared to the industry (Ollinger *et al*. 2005; Schiefer 2011; Singer 2012).

In addition, we assess the impact of the share of foreign-born migrants within total population in each LLS (Foreign_pop). Foreign-born population is usually associated with low labor costs which can provide a competitive advantage particularly for agriculture companies. In turn, the propensity of micro and small firms to innovate is expected to decrease with the share of foreign population leading to a negative impact on ROA (García-Alvarez-Coque *et al*. 2013). This can be of relevance especially for food industry firms as innovation turned out to be an important driver of profitability in this sector. However, across our models, such effects cannot be substantiated.

Finally, operating in urbanized LLS (Urban) is found to have a positive and significant impact for food industry firms in Valencia. Moreover, rurality does not turn out as constraining for profitability of the food industry in Navarre. This is consistent with the results of García-Alvarez-Coque *et al*. (2013) and Fearne *et al*. (2013), who show –particularly for micro and small firms– that rurality is not perceived to be a significant constraint for performance. As regards the agricultural sector the importance of urban agriculture as a part of local food systems has significantly increased in the last years (Hendrickson and Porth 2012). However, consensus regarding the impact of urban farming on food security and economic performance has not been reached yet (Thebo *et al*. 2014). Our results show no significant impact of the urbanization variable on profitability in the agricultural sector.

As regards model diagnostics the Wald tests indicate a significant contribution of the joint set of independent variables in all models. The explanatory power of independent variables is derived as the reduction in time-level variance relative to total null-model variance.[16] The bottom row indicates that contribution of independent variables to ROA variance is between 7.2 and 14.2%.

[16] Explanatory power of explanatory variables is calculated as:
(σ^2 null model - σ^2 model with explanatory variables at time-level)/ $(\sigma^2 + \tau_\pi + \tau_\beta)$ null model

6 Discussions and Conclusions

Our findings provide evidence for henpecking firm effects across Spanish agri-food firms as this effect class adds between 26.3 and 48.8% to ROA variance. Similar to earlier research this indicates that firm resources and capabilities are the primary determinant of firm profitability in both regions (e.g. Hough 2006; Ketelhöhn and Quintanilla 2012). The predominance of firm effects does not seem to be influenced by structural differences between the two regions such as variation in product specialization or Navarre being more rural than Valencia.

In accordance with previous HLM studies on the food industry (Chaddad and Mondelli 2013; Hirsch *et al*. 2014) we identify firm size and growth as important drivers of agri-food performance in Spain. Thus, economics of scale as well as stronger bargaining power of larger firms towards up- and downstream sectors seem to be crucial for firm profitability. Furthermore, taking financial risks leads to competitive disadvantages likely caused by the fact that good management practices can increase returns and at the same time reduce risk (Bowman 1980). Moreover, the results provide evidence that innovative activities are important measures for firms to prevail in a competitive environment such as the food industry.

Although, our results are in line with previous research regarding the small contribution of industry effects (e.g. Hough 2006) several structural industry factors can be related to profitability. The positive effect of industry concentration on profitability suggests that firms in highly concentrated industries benefit from entry barriers and lower competitive forces. Moreover, larger industry size in Valencian food processing seems to cause strong dynamism which leads to instability in the industry environment and lower profitability (Misangyi *et al.* 2006).

While similar to (Chan *et al*. 2010) aggregate LLS effects only have a minor impact several location-specific factors drive profitability. Proximity to knowledge and skills turns out to be an important factor in Navarre's food industry. For agricultural firms in Valencia in contrast proximity to highly educated labor forces has a negative effect likely caused by a higher demand of low skilled labor. While operating in urban LLS is advantageous for firms in the Valencian food industry the insignificant impact of this variable for the food industry in Navarre indicates that operating in rural regions does not have to be a disadvantage. Finally, in line with Okun's law, unemployment, as a measure for the economic performance of LLSs, negatively influences ROA.

Comparing results for the primary sector and the industry reveals that innovative activity is primarily important for industrial firms. Moreover, while regional endowment with technological centers can positively influence profitability of food industry firms it can constitute a competitive disadvantage for agricultural firms. Finally, while the food industry benefits from availability of highly educated labor forces regional endowment with a less qualified work force tends to be an important profit driver for agricultural firms.

The main deficiency of the paper is that other variables which have previously been related to profitability such as advertising and capital intensity (Chaddad and Mondelli 2013), membership of specific strategic groups (Pindado and Alarcon 2015) or import and export activity (Yurtoglu 2004) cannot be included due to data availability. Especially within the food sector, advertising intensity can constitute an important competitive advantage that leads to higher profit margins (Chaddad and Mondelli 2013; Sutton 1991). For the agricultural sector it would be interesting to incorporate the impact of subsidies and the reduction of CAP measures and to assess whether regional endowment with natural resources determines profitability across LLS.

Implications from our findings are that given the predominance of firm effects agri-food managers should allocate effort and attention to accumulate and leverage firm internal resources to ensure competitive advantages. Although firm effects outweigh the effect of the environment in which firms operate the significant impact of several territorial factors indicates that managers should also consider possible advantages from location-based resources. Examples are a location of agricultural firms closer to less educated labor forces –as in the case of Valencia– or proximity to technological institutes and highly qualified labor forces as in the case of food industry firms in Navarre.

Appendix

Table A1: Correlation matrix of independent variables Valencia

Variable	1	2	3	4	5	6	7	8	9	10	11
Firm											
(1) Ln TA	1.00										
(2) Age	0.21	1.00									
(3) Gr. sales	0.07	-0.01	1.00								
(4) 1/Curr	-0.02	-0.01	-0.01	1.00							
(5) Lev_debt	-0.09	-0.01	0.00	0.07	1.00						
Industry											
(6) Ln sales	-0.05	-0.02	-0.02	-0.02	-0.01	1.00					
(7) Gr. NF	0.09	0.00	0.01	-0.01	-0.01	-0.28	1.00				
Region											
(8) Unemployment	-0.01	-0.01	-0.03	0.02	0.01	0.01	0.16	1.00			
(9) Dist_port	-0.10	-0.01	-0.02	-0.02	0.00	-0.04	-0.01	0.09	1.00		
(10) Dist_tec	-0.08	-0.05	-0.01	-0.02	0.01	0.01	0.00	0.05	0.60	1.00	
(11) Edu_level	0.10	0.02	0.02	0.03	-0.02	0.04	0.01	-0.08	-0.75	-0.60	1.00
(12) Foreign_pop	-0.06	-0.06	0.00	0.00	0.03	-0.02	-0.01	0.08	0.41	0.57	-0.31

Source: Authors´own calculations based on SABI and Eurostat (2015b).
Note: Dummy variables not included

Table A2: Correlation matrix of independent variables Navarre

Variable	1	2	3	4	5	6	7	8	9	10	11
Firm											
(1) Ln TA	1.00										
(2) Age	0.10	1.00									
(3) Gr. sales	0.04	-0.06	1.00								
(4) 1/Curr	-0.01	-0.07	0.00	1.00							
(5) Lev_debt	-0.08	-0.07	0.02	0.10	1.00						
Industry											
(6) Ln sales	0.00	0.09	0.01	-0.02	0.02	1.00					
(7) Gr. NF	-0.05	-0.03	-0.01	-0.02	0.02	-0.22	1.00				
Region											
(8) Unemployment	-0.49	0.02	-0.04	0.00	0.00	0.01	0.21	1.00			
(9) Dist_port	0.01	-0.03	0.01	0.04	0.04	0.00	0.01	0.06	1.00		
(10) Dist_tec	-0.03	-0.03	0.01	0.04	0.03	0.04	-0.06	0.00	0.41	1.00	
(11) Edu_level	-0.02	0.06	-0.03	-0.01	-0.01	-0.03	-0.01	0.07	-0.48	0.08	1.00
(12) Foreign_pop	0.04	-0.01	0.03	0.03	0.00	0.02	0.00	0.07	0.47	0.26	-0.35

Source: Authors´own calculations based on SABI and Eurostat (2015b).
Note: Dummy variables not included

References

ALARCÓN, S. AND SÁNCHEZ, M. (2013): Business Strategies, Profitability and Efficiency of Production. Spanish Journal of Agricultural Research 11(1):19–31.

ARELLANO, M. AND BOND, S. (1991): Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58(2):277–297.

BAE, J. AND GARGIULO, M. (2004): Partner substitutability, alliance network structure, and firm profitability in the telecommunications industry. Academy of Management Journal 47(6):843–859.

BAIN, J. (1956): Barriers to New Competition. Harvard University Press, Cambridge, MA.

BALTAGI, B.H. (2008): Econometric Analysis of Panel Data. Chichester, UK: John Wiley & Sons.

BARNEY, J.B. (1991): Firm resources and sustained competitive advantage. Journal of Management 17(1):99–120.

BEKERIS, R. (2012): The impact of macroeconomic indicators upon SME's profitability. EKONOMIKA 91(3):117–128.

BHUYAN, S. AND MCCAFFERTY, M. (2013): U.S: Brewing Industry Profitability: A Simultaneous Determination of Structure, Conduct and Performance. Journal of Agricultural & Food Industrial Organization 11(1):139-150.

BIDDLE, G., BOWEN, R., AND WALLACE, J. (1997): Does EVA beat earnings? Evidence on associations with stock returns and firm values. Journal of Accounting & Economics 24(3):301–336.

BOIX, R. AND GALLETTO, V. (2005): Identificación de sistemas locales de trabajo y distritos industriale s en España. Dirección General de Política de la Pequeña y Mediana Empresa. http://www.ipyme.org/Publicaciones/IdentificacionSLT.pdf.

BOWMAN, E.H. (1980): A risk/return paradox of strategic management. Sloan Management Review 21(3):17–31.

BRESNAHAN, T.F. (1981): Departures from marginal-cost pricing in the american automobile industry. Journal of Econometrics 17:201-227.

CAIXA. (2013): Spanish Statistical Yearbook. http://www.anuarieco.lacaixa.comunicacions.com/java/X?

CHADDAD, F.R. AND MONDELLI, M.P. (2013): Sources of firm performance differences in the US food economy. Journal of Agricultural Economics 64:382–404.

CHAN, C.M., MAKINO, S., AND ISOBE, T. (2010): Does sub-national region matter? Foreign affiliate performance in the United States and China. Strategic Management Journal 31(11):1226–1243.

CICCONE, A. AND CINGANO, F. (2003): Skills and clusters, in Brocker J, Dohse D, Soltwedel R., eds., Innovation Clusters and Interregional Competition. Springer, Berlin.

CLAVER, E., MOLINA, J., AND TARÍ, J. (2002): Firm and Industry Effects on Firm Profitability : A Spanish Empirical Analysis. European Management 20(3):321–328.

DELMAR, F., MCKELVIE, A., AND WENNBERG, K. (2013): Untangling the relationships among growth, profitability and survival in new firms. Technovation 33(8-9):276–291.

ELANGO, B. AND WIELAND, R.J. (2014): How much does region affect performance? Multinational Business Review 22(1):4–14.

ERKAN, A., FAINSHMIDT, S., AND JUDGE, W.Q. (2015): Variance decomposition of the country, industry, firm, and firm-year effects on divided policy. International Business Review. doi:10.1016/j.ibusrev.2016.04.003.

ENQVIST, J., GRAHAM, M., AND NIKKINEN, J. (2014): The impact of working capital management on firm profitability in different business cycles: Evidence from Finland. Research in International Business and Finance 32:36–49.

EUROPEAN COMMISSION. (2005): The new SME definition. Enterprise and Industry Publications. Luxembourg: European Commission.

EUROSTAT. (2015a): Agricultural census in Spain. http://ec.europa.eu/eurostat/statistics-explained/index.php/Agricultural_census_in_Spain#Key_indicators.

EUROSTAT. (2015b): Structural Business Statistics. http://ec.europa.eu/eurostat/web/structural-business-statistics/data/database.

FAGGIAN, A. AND MCCANN, P. (2009): Human capital, graduation migration and innovation in British regions. Cambridge Journal of Economics 33(2):317-333.

FEARNE, A., GARCÍA ÁLVAREZ-COQUE, J.M., LÓPEZ GARCÍA USACH, T., AND SÁNCHEZ GARCÍA, M. (2013): Innovative firms and the urban/rural divide: the case of agro-food system in the Valencia region. Management Decision 51(6):1293–1310.

FIEGENBAUM, A. AND THOMAS, H. (1988): Attitudes toward risk and the risk return paradox: Prospect theory explanations. Academy of Management Journal 31(1):85–106.

FISHER, F.M. AND MCGOWAN, J.J. (1983): On the misuse of accounting rates of return to infer monopoly profits. American Economic Review 73:82–97.

FOOD DRINK EUROPE. (2013): Data & Trends of the European Food and Drink Industry 2012. Food Drink Europe: Brussels, Belgium. http://www.fooddrinkeurope.eu/uploads/publications_documents/Data__Trends_%28interactive%29.pdf.

GAGANIS, C., LIU, L., AND PASIOURAS, F. (2015): Regulations, profitability, and risk-adjusted returns of European insurers: An empirical investigation. Journal of Financial Stability 18:55–77.

GALLIZO, J.L., GARGALLO, P., SALADRIGUES, R., SALVADOR, M. (2014): The persistence of abnormal return on assets: an exploratory analysis of the performance of firms by country and sector. Applied Stochastic Models in Business and Industry 30:609-631.

GARCÍA-ALVAREZ-COQUE, J.M., LÓPEZ-GARCÍA, USACH, T., AND SANCHEZ-GARCÍA, M. (2013): Determinants of Agri-food Firms' Participation in Public Funded Research and Development. New Medit 12(3):2–10.

GdN. (2015): Gobierno de Navarra. Community Foral of Navarra. Available at: www.navarra.es.

GIULIANI, E., MORRISON, A., PIETROBELLI, C. AND RABELLOTTI, R. (2010): Who are the researchers that are collaborating with industry? An analysis of the wine sectors in Chile, South Africa and Italy. Research Policy 39:748–761.

GIUSTI, A. AND GRASSINI, L. (2007): Local labor systems and agricultural activities: The case of Tuscany. International Advances in Economic Research 13(4):475–487.

GODDARD, J., TAVAKOLI, M. AND WILSON, J.O.S. (2005): Determinants of profitability in European manufacturing and services: evidence from a dynamic panel model. Applied Financial Economics 15(18):1269–1282.

GODDARD, J., TAVAKOLI, M., AND WILSON, J.O.S. (2009): Sources of variation in firm profitability and growth. Journal of Business Research 62:495–508.

GOLDSZMIDT, R.G.B., BRITO, L.A.L., AND DE VASCONCELOS, F.C. (2011): Country effect on firm performance: A multilevel approach. Journal of Business Research 64(3):273–279.

GRANT, R.M. AND NIPPA, M. (2006): Strategisches Management. Analyse, Entwicklung und Implementierung von Unternehmensstrategien. Munich, Germany: Pearson Studium.

GSCHWANDTNER, A. (2005): Profit persistence in the 'very' long run: evidence from survivors and exiters. Applied Economics 37(7):793–806.

HENDRICKSON MK, PORTH M (2012): Urban Agriculture – Best Practices and Possibilities. Division of Applied Social Sciences, University of Missouri.

HIRSCH, S. (2014): Abnormal profits and profit persistence: evidence from the European food industry. Dissertation University of Bonn.

HIRSCH, S. AND GSCHWANDTNER, A. (2013): Profit persistence in the food industry: evidence from five European countries. European Review of Agricultural Economics 40(5):741–759.

HIRSCH, S. AND HARTMANN, M. (2014): Persistence of firm-level profitability in the European dairy processing industry. Agricultural Economics 45(S1):53–63.

HIRSCH, S. AND SCHIEFER, J. (2016): What Causes Firm Profitability Variation in the EU Food Industry? A Redux of Classical Approaches of Variance Decomposition. Agribusiness 32(1):79-92
HIRSCH, S., SCHIEFER, J., GSCHWANDTNER, A., AND HARTMANN, M. (2014): The Determinants of Firm Profitability Differences in EU Food Processing. Journal OF AGRICULTURAL ECONOMICS 65(3):703–721.
HOFFMANN, J. AND HIRSCH, S. (2015): Identification of spatial agglomerations in the German food processing industry. Papers in Regional Science doi:10.1111/pirs.12171
HOUGH, J.R. (2006): Business Segment Performance Redux: A Multilevel Approach. Strategic Management Journal 27:45–61.
HOX, J. (2008): Multilevel Analysis, Techniques and Applications. Hove, UK: Psychology Press.
INE. (1991): Cifras de Población y Censos Demográficos. http://www.ine.es/jaxi/menu.do?type=pcaxis&path=%2Ft20%2Fe243&file=in ebase&L=0.
INE. (2001): Censos de Población y Viviendas de 2001. http://www.ine.es/censo2001. Accessed March 2015.
INE. (2011): Censos de Población y Viviendas 2011. http://www.ine.es/censos2011_datos/cen11_datos_inicio.htm.
INE. (2011a): Contabilidad Regional de Espana. http://www.ine.es/prensa/np695.pdf.
ISTAT. (1991): I sistemi locali del lavoro. Istituto nazionale di statistica, Rome.
JACOBS J. (1969): The Eeconomies of Ccities. Random House, New York.
KADIYALI, V., SUDHIR, K., AND VITHALA, R.R. (2001): Structural analysis of competitive behavior: New Empirical Industrial Organization methods in marketing. International Journal of Research in Marketing 18:161-186.
KETELHÖHN, N.W. AND QUINTANILLA, C. (2012): Country effects on profitability: A multilevel approach using a sample of Central American firms. Journal of Business Research 65(2):1767–1772.
LASAGNI, A., NIFO, A., AND VECCHIONE, G. (2015): Firm Productivity and Institutional Quality: Evidence From Italian Industry. Journal of Regional Science 00(0):1–27.
LEE, J. (2000): The Robustness of Okun’s Law: Evidence from OECD countries. Journal of Macroeconomics 22(2):331–356.
LIENHARDT, J. (2004): The food industry in Europe. Statistics in focus 39/2004. European Communities, Luxembourg.
LODERER, C. AND WAELCHLI, U. (2010): Firm age and performance. Working paper, University of Bern, Bern, Switzerland.
LONG, W.F. AND RAVENSCRAFT, D.J. (1984): The usefulness of accounting profit data: A comment on Fisher and McGowan. American Economic Review 74:494–500.
LUKE DA 2004 Multilevel Modeling. Thousand Oaks: Sage Publications.
MCGAHAN, A.M. AND PORTER, I.E. (1997): How much does industry matter, really? Strategic Management Journal 18:15–30.
MCNAMARA, G., AIME, F., AND VAALER, P.M. (2005): Is performance driven by industry- or firm-specific factors? A response to Hawawini, Subramanian, and Verdin. Strategic Management Journal 26(11):1075–1081.
MISANGYI, V.F., ELMS, H., GRECKHAMER, T., AND LEPINE, J.A. (2006): A new perspective on a funda- mental debate: A multilevel approach to industry, corporate and business unit effects. Strategic Management Journal 27:571–590.
MOLINA-AZORIN, J.F., PEREIRA-MOLINER, J., AND CLAVER-CORTÉS, E. (2010): The importance of the firm and destination effects to explain firm performance. Tourism Management 31(1):22–28.
OECD. (1994): Creating Rural Indicators for Shaping Territorial Policies. OECD Publishing, Paris.
OECD. (2010): Measuring Innovation: A new Perspective. OECD Innovation Strategy. OECD France, Paris.

OLLINGER, M., NGUYEN, S.V., BLAYNEY, D., CHAMBERS, W., AND NELSON, K. (2005): Effects of Food Industry Mergers and Acquisitions on Employment and Wages. USDA: Washington.

PATTITONI, P., PETRACCI B., SPISNI M. (2014): Determinants of profitability in the EU-15 area Determinants of profitability in the EU-15 area. Applied Financial Economics 24(11):763–775.

PENROSE, E.T. (1959): The theory of the growth of the firm. New York: John Wiley and Sons.

PINDADO, E. AND ALARCON, S. (2015): Quality strategies and profitability: a multilevel analysis in the meat industry, in C. Porter, ed., Business strategies. Types, benefits and effects on firm performance. Hauppauge, NY: Nova Publisher.

PORTER, M.E. (1980): Competitive Strategy. Techniques for Analyzing Industries and Competitors. New York: Free Press.

RASPE, O., AND VAN OORT, F. (2011): Firm heterogeneity, productivity and spatially bounded knowledge externalities. Socio-Economic Planning Sciences 45(1):38–47.

RASSIER, D.G. AND EARNHART, D. (2011): Short-run and long-run implications of environmental regulation on financial performance. Contemporary Economic Policy 29(3):357–373.

RASSIER, D.G. AND EARNHART, D. (2015): Effects of environmental regulation on actual and expected profitability. Ecological Economics 112:129–140.

RAUDENBUSH, S. AND BRYK, A.S. (2002): Hierarchical Linear Models: Applications and Data Analysis Methods (Advanced Quantitative Techniques in the Social Sciences), Thousand Oaks, CA: 2nd ed. Sage.

REYNAUD, A. AND THOMAS, A. (2013): Firm's profitability and regulation in water and network industries: An empirical analysis. Utilities Policy 24:48–58.

RICARDO, D. (1817): Principles of political economy and taxation. Amherst, NY: Prometheus Books,.

RUMELT, R.P. (1991): How much does industry matter? Strategic Management Journal 12(3):167–185.

RUSSO, M.V., AND FOUTS, P. (1997): A Resource-Based Perspective on Corporate Environmental Performance. Academy of Management Journal 40(3):534–559.

SAHAYM, A. AND NAM, D. (2013): International diversification of the emerging-market enterprises: A multi-level examination. International Business Review 22(2):421–436.

SEARLE, S.R., CASELLA, G., AND MCCULLOCH, C.E. (2006): Variance Components. New York, NY: John Wiley & Sons.

SCHIEFER, J. (2011): Was bestimmt die Rentabilität in der Lebensmittelindustrie? Eine empirische Analyse unternehmensinterner und -externer Effekte. Hamburg, Germany: Verlag Dr. Kovac.

SCHMALENSEE, R. (1985): Do Markets Differ Much? The American Economic Review 75(3):341–351.

SCHUMACHER, S. AND BOLAND, M. (2005): The effects of industry and firm resources on profitability in the food economy. Agribusiness 21(1):97–108.

SHORT, J.C., KETCHEN, J.D., BENNETT, N., AND DU TOIT, M. (2006): An Examination of Firm, Industry, and Time Effects on Performance Using Random Coefficients Modeling. Organizational Research Methods 9(3):259–284.

SINGER, A. (2012): Immigrant Workers in the U.S. Labor Force. Brookings: Washington D.C. http://www.brookings.edu/research/papers/2012/03/15-immigrant-workers-singer. Accessed July 2015.

SPANISH MINISTRY OF AGRICULTURAL, FOOD AND ENVIRONMENT (2015): Annual indicators: Agriculture, Food and Environment 2014.

STONE, A., ROSE, S., LAL, B., AND SHIPP, S. (2008): Measuring Innovation and Intangibles: A Business Perspective. Science and Technology Policy Institute, IDA Document D-3704.

SUTTON, J. (1991): Sunk costs and market structure: Price competition, advertising, and the evolution of concentration. Cambridge: MIT Press.

THEBO, A.L., DRECHSEL, P., AND LAMBIN, E.F. (2014): Global assessment of urban and peri-urban agriculture: irrigated and rainfed croplands. Environmental Research Letters 9(11):1–9.

TIROLE, J. (1988): The Theory of Industrial Organization. MIT Press, Cambridge.

USAI, S. AND PACI, R. (2003): Externalities and local economic growth in manufacturing industries, in B. Fingleton, ed., European Regional Growth. Springer, Berlin.

VALENCIA GENERALITAT (2015): Generalitat Valenciana Region. www.gva.es.

WELGE, M.K. AND AL-LAHAM, A. (2008): Strategisches Management. Gabler, Wiesbaden, Germany.

WIJNANDS, J.H.M., VAN DER MEULEN, J.B.M., AND POPPE, K.J. (2007): Competitiveness of the European Food Industry: An Economic and Legal Assessment 2007. European Commission, Luxembourg.

WORLD BANK. (2015): Agriculture, value added (% of GDP). http://data.worldbank.org/indicator/NV.AGR.TOTL.ZS.

YAZDANFAR, D. AND ÖHMAN, P. (2014): Life cycle and performance among SMEs: Swedish empirical evidence. The Journal of Risk Finance 15(5), 555–571.

YURTOGLU, B.B. (2004): Persistence of firm-level profitability in Turkey. Applied Econometrics 36:615–625.