**RESEARCH ARTICLE**

# What drives firm profitability? A multilevel approach to the Spanish agri-food sector

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## Abstract

Strategic management research has demonstrated the importance of firm- and industry structure as drivers of firm profitability. However, less is known about how firms´ geographical locations affect profitability. Applying a multi-level approach of hierarchical linear modeling we estimated firm-, industry-, and region-specific effects on profitability of 3,273 agri-food firms operating in different Spanish districts over the time span 2006-2013. The results reveal the dominance of firm-specific effects which contribute up to 48.8% to variance in firm profitability while the contribution of industry effects (0.8-4.2%), geographical location (0.1-1.8%), and year effects (0.1-2.5%) is rather small. Moreover, firm size, risk, and innovative activity turn out as significant profit drivers at the firm level. Although firm-effects outweigh industry- and region-specific factors, the results indicate that industry concentration as well as regional education and unemployment influence profitability. In addition, proximity to technological institutes as well as the degree of urbanization of the region in which a firm operates can be drivers of profitability. Hence, despite the superiority of firm effects the results indicate that agri-food managers should also consider possible advantages from location-based resources in order to ensure competitiveness.

**Additional keywords:** agri-food profits; firm-, industry-, and location effects; hierarchical linear model.

**Abbreviations used:** ANOVA (Analysis of variance); COV (components of variance); EU (European Union); EVA (economic value added); GDP (gross domestic product); HLM (hierarchical linear model); LLS (local labor system); MBV (market-based view); RBV (resource-based view); ROA (return on assets); SCP (structure-conduct-performance); SM (strategic management).

# Introduction

The agri-food chain is one of the most important 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 & Sánchez, 2013). Individual components of the agri-food chain are also of high economic importance. In Spain, the country under investigation in this article, the food industry is one of the largest economic sectors with a contribution of 21.6% to total manufacturing turnover. The upstream sector –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). Additionally, Spanish agriculture provides employment for more than 2 million individuals which highlights its social importance (Eurostat, 2015).

Despite its relevance previous studies that analyze the drivers of firm profits mainly focus on whole economies or entire manufacturing sectors while evidence for agri-food firms is as yet scarce

(Elango & Wieland, 2014)[1]. Thus, the present study contributes by exploring the influence of firm-, industry-, region- and year-specific factors on firm profitability within the autonomous Spanish Communities of Valencia and Navarre based on a sample of 3,273 agri-food firms. These firms operate in 60 agri-food subsectors 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 & Wieland, 2014).

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). Nevertheless, the new urban economics and economic geography research (*e.g.* Brakman *et al.*, 2009; Duranton *et al.*, 2015) has pointed out the importance intra-regional differences for profitability (Tamminen, 2016). García-Alvarez-Coque *et al.* (2013) show 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. In addition, Giusti & Grassini (2007) show that 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.

Our data allows to extend the empirical evidence on the regional determinants of profitability. We focused on local resources as well as 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.

## Material and methods

The majority of previous research on firm profitability has focused on industry- and firms-specific factors (*e.g.* Chaddad & Mondelli, 2013). 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 & Nippa, 2006). The market-based view (MBV) which is a dynamic extension of the classical structure-conduct-performance (SCP) paradigm 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 & 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 & Al-Laham, 2008). As shown in Table 1, previous HLM studies on firm profitability have found a diverse range of results regarding industry effects which vary from a negligible impact of below 1% in the EU food industry (Hirsch *et al.*, 2014) to a significant contribution of around 18% in Central American countries (Ketelhöhn & 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. Thus, besides the estimation of the aggregate industry effect, we include concentration ratios as well as industry size and growth as industry-specific drivers of firm profits in our empirical implementation.

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 resources. Based on the assumption of heterogeneity in resource endowment, profitability is 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

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[1] Exceptions are Schumacher & Boland (2005) as well as Chaddad & Mondelli (2013). However, those studies focus on the US food sector.

between 20.8% and 82.3% to variance in profits. Besides the aggregate impact that firm-effects have on profitability we estimated 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 included as drivers of profitability (Chaddad & Mondelli, 2013; Hirsch *et al.*, 2014).

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) (Table 1). In contrast, if estimated for regions outside the EU country effects are generally larger (Goldszmidt *et al.*, 2011; Ketelhöhn & Quintanilla, 2012).

Studies that focus on interregional comparisons within countries find evidence of significant relationships between location specific resources and firm performance (Chan *et al.*, 2010; Lasagni *et al.*, 2015; Tamminen, 2016). Molina-Azorin *et al.* (2010) analyzed Spanish service firms operating in 14 provinces using HLM and provide evidence

for the importance of location effects (17.7%) in explaining firm profitability. 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). Moreover, high regional unemployment levels can trigger entry of new firms, which increases competition and hence lowers profitability (Fairlie, 2013). Faggian & McCann (2009) verify the importance of regional endowment with human capital. Regional education levels, the presence of research institutions, and the share of foreign population are therefore also included as region-specific drivers of profitability. Moreover, the degree of urbanization as well as proximity to airports are incorporated as region specific factors. While location in urban districts can provide a competitive advantage by faster access to downstream markets and lower transportation costs it can also be the case that profitability is lower in such districts due to higher competition levels (Melitz & Ottaviano, 2008; Lu *et al.*, 2012; Tamminen, 2016).

Finally, 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) (Table 1). However, as the present dataset includes the years 2008/09 we evaluated how far agri-food firm profitability has been impacted by the financial crisis.

**Table 1.** Previous studies decomposing firm profits using hierarchical linear model (HLM).

| Authors | Country | Effect class contribution (%) | | | |
|---|---|---|---|---|---|
| | | **Firm** | **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.[a] | n.a. | 17.7 |
| Goldszmidt *et al.* (2011) | 37 countries | 32.7 | 2.5 | n.a. | 3.2 |
| Ketelhöhn & Quintanilla (2012) | Central American countries | 44.7 | 17.5 | n.a. | 5.1 |
| Chaddad & Mondelli (2013) | US food economy / processing | 36.1 | 7.0 | 0.5 | n.a. |
| | | 36.7 | 7.5 | 1.0 | n.a. |
| Hirsch *et al.* (2014) | EU food processing | 40.2 | 0.4 | 0.9 | 1.8 |

Source: Authors' literature review. [a]n.a.: not available

## Data

Firm data are drawn from the SABI balance sheet database, generated by Bureau van Dijk[2]. 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 the period 2006 to 2013 are selected. Return on Assets (ROA) calculated as Earnings Before Interest and Taxes (EBIT) divided by Total Assets is used to proxy firm profitability. Although commonly used (*e.g.* Hirsch *et al.*, 2014; Gaganis *et al.*, 2015), 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 & McGowan, 1983; Long & Ravenscraft, 1984). Nevertheless, alternative measures such as economic value added (EVA) do not necessarily represent superior proxies for economic profit. For example, Biddle *et al.* (1997) showed that ROA outperforms EVA as a measure for profitability. Therefore, due to data availability and to allow comparability with previous HLM literature we employed 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 were added at the firm level: firm size measured by the logarithm of total assets, yearly sales growth, and age. We also introduced 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 a firm conducts innovation activities. This variable takes the value one if a firm is characterized by growth in intangible assets in year t. 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[3] (Stone *et al.*, 2008; OECD, 2010).

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, 2015): concentration measured by the Herfindahl-Hirschman index (HHI), growth measured by the yearly growth rate of the number of firms in an industry, size proxied by the logarithm of total industry sales. Eurostat only provides industry data for the processing of food and drinks while data for primary agricultural production is not available.

To analyze the impact of regional factors we focus on the communities of Navarre and Valencia which together contribute 12% to national GDP (INE, 2011a). In both communities, the agri-food sector is of high economic relevance taking second and fourth place in contribution to regional GDP, respectively (GdN, 2015; Valencia Generalitat, 2015). We define regions by means of Local Labor Systems (LLS) (ISTAT, 1991). A LLS is an area characterized by internal commuting patterns that produce a self-contained labor market. LLS are defined using information regarding enterprises and commuters, *i.e.* data on daily commuting to work contained in the population census (Ciccone & Cingano, 2003). Boix & Galletto (2005) have categorized Spain into 806 LLS, 83 of them located in Valencia and 14 located in Navarre (Fig. 1).

LLS-specific variables used to capture regional macroeconomic conditions and resource endowment have been generated from the Spanish Census of Population and Houses (INE, 1991; 2001; 2011b) and the statistical yearbook of La Caixa (2013). We included 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. 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
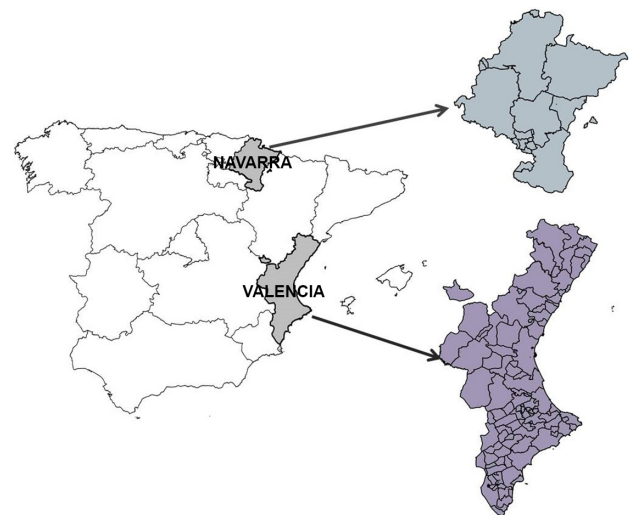


**Figure 1.** Local labor system (LLS) of Valencia and Navarre.

kilometer (OECD, 1994; García-Alvarez-Coque *et al.*, 2013). 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 & Galletto, 2005).

For each variable, anomalous observations 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, 2015). Definitions and descriptive statistics for ROA and the independent variables related to firm, industry and region are provided in Table 2.

## Methods

Most previous studies employ ANOVA or COV to decompose the variation in firm profitability into different effect classes (Rumelt, 1991; McGahan & Porter, 1997; McNamara *et al.*, 2005). However, both techniques have limitations resulting from their underlying assumptions, sometimes generating inconsistent and unreliable results (Misangyi *et al.*, 2006). 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 & 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 HLM (Erkan *et al.*, 2015). HLM allows to simultaneously determine entire effect classes and the underlying structural covariates that drive profitability (Hough,

**Table 2.** Variable definitions and descriptive statistics

| 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´ calculations based on SABI and Eurostat (2015). [a] Industry-level data is only available for the processing of food and drinks (NACE 10, 11).

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 & Nam, 2013). We employ HLM with random intercepts, using an iterative restricted maximum likelihood estimation (REML) (Gaganis *et al.*, 2015). Separate models for Valencia and Navarre as well as for the agricultural sector and the processing industry are estimated 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 (*i.e.* interrelation over time) in firm profits[4].

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

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

where t denotes time with $t = 2006, \ldots, 2013$. 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 & 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) $\pi_{0ij}$ is mean ROA over time of firm $i$ in LLS/industry $j$. $e_{tij}$ is the random time-level error which is normally distributed with mean zero and variance $\sigma^2$. Consequently, $e_{tij}$ reflects the model's error term. Its variance $\sigma^2$ 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 $\pi_{0ij}$ is simultaneously modeled as the result of random variation around the LLS/industry mean $\beta_{00j}$:

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

$r_{0ij}$ is the random firm-level error which is normally distributed with mean zero and variance $\tau_\pi$. Hence $\tau_\pi$,

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[5] $j$ ($\beta_{00j}$) simultaneously as the result of random variation around the grand mean ($\gamma_{000}$):

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

The random LLS/industry-level error ($\pi_{0ij}$) is normally distributed with mean zero and between LLS/industry variance     .

Based on the null model defined by equations (1), (2) and (3) the percentage contribution of each effect can be calculated as $\sigma^2 / (\sigma^2 + \tau_\pi + \tau_\beta)$ fot 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[6]. Equation (1) then becomes:

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

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

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

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

if the number of LLS is smaller than the number of industries as in the case of Navarre. $LLS_1, LLS_2, \ldots, LLS_n$ are LLS dummies and $\beta_{01j}, \beta_{02j}, \ldots, \beta_{0nj}$, 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 ($Ind_1, Ind_2, \ldots, Ind_n$) and $\beta_{01j}, \beta_{02j}, \ldots, \beta_{0nj}$ reflect industry effects:

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[4] For a study that focus on the dynamics of firm profits in the EU food industry we refer to Hirsch & Gschwandtner (2013).

[5] 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 in turn, 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.

[6] 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.

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

$\beta_{00j}$ 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)[7].

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 & 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 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[8]. Therefore, to adequately capture the information present in the data we incorporate all explanatory variables at the time level, extending (1) to:

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

$X_1$, $X_2$, ..., $X_n$ 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:

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

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

$$...,$$

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

The coefficients $\gamma_{100}, \gamma_{200}, ..., \gamma_{n00}$ capture the fixed effect of each independent variable on ROA, while $\pi_{0ij}$ 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.

## Results

Table 3 shows the effect class estimation results for Valencia and Navarre. The results indicate the dominance of firm-specific factors as drivers of profitability. 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.

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[9]. The findings suggest that the impact of LLS effects is relatively small with a maximum contribution of 1.8% to ROA variance of agricultural firms in Navarre. Although mainly significant[10], year effects only account for 0.1-2.5% and 0.0-0.9% of the variance in ROA in Valencia and Navarre, respectively[11].

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[7] 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: model with year and LLS/industry dummies/ $(\sigma^2 + \tau_\pi + \tau_\beta)$ null model.

[8] Results of the COV analyses are available upon request.

[9] The magnitude of LLS/industry effects -when introduced via dummies- is calculated as: ( $\tau_\pi$ model with year dummies - $\tau_\pi$ model with year and LLS/industry dummies)/ $\sigma^2$ /($\sigma^2 + \tau_\pi + \tau_\beta$) model with year dummies.

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

[11] The magnitude of year-effect is calculated as: ( $\sigma^2$ null model - $\sigma^2$ model with year dummies at time-level)/ $\sigma^2$ /($\sigma^2 + \tau_\pi + \tau_\beta$) null model.

**Table 3.** Hierarchical linear model (HLM) effect class estimates Valencia and Navarra.

| | All firms | | Agriculture | | Food industry | |
|---|---|---|---|---|---|---|
| | **Variance components** | **%** | **Variance components** | **%** | **Variance components** | **%** |
| | | | **Valencia** | | | |
| *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 $\chi^2$ | 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 $\chi^2$ | | 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 | | 0.5 | | 2.5 |
| LLS | | 0.4 | | 0.5 | | 0.1 |
| | | | **Navarre** | | | |
| *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 $\chi^2$ | | 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 $\chi^2$ | | 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 |

*, **, *** significance at the 10%, 5% and 1% level.

The final results indicate that 70.6-73.2% of the ROA variance in Valencia and 46.9-63.0% in Navarre is attributed to the time-level –*i.e.* the error component of the model– and can hence not be explained by firm-, industry-, region- and year-effects.

The results of the models incorporating the explanatory variables specified in Table 2 are reported in Table 4. It can be detected that firm size and growth (Gr. sales) as well as innovative activity are significant drivers of profitability at the firm-level while financial risk has a significant negative impact. At the industry-level concentration measured by the HHI impacts positively and significant on food industry profitability in both regions while industry size (ln sales), impacts negatively and significant on firm profitability in Valencia. Finally, at the LLS-level our results show a negative impact of LLS related unemployment rates. Higher regional education levels increase profitability of industry firms in Navarre while profitability of Valencian agricultural firms is in contrast negatively influenced. As regards distance to the nearest airport (Dis_port) or technological centers (Dis_tec) we find that proximity to such facilities decreases profitability of agricultural firms in Navarre. In contrast, profits of food industry firms in Navarre are positively influenced by proximity to technology centers or universities. In addition, operation in urbanized LLS has a positive and significant impact for food industry firms in Valencia.

Regarding 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[12]. The bottom row indicates that contribution of independent variables to ROA variance is between 7.2 and 14.2%.

## Discussion

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 supports the RBV as a theoretical foundation indicating that firm resources and capabilities are the primary determinant of firm profitability in both regions (*e.g.* Hough, 2006; Ketelhöhn & Quintanilla, 2012). The predominance of firm effects does not seem to be influenced by structural differences between the two regions such as Navarre being more rural than Valencia.

The small contribution of industry effects with up to 4.2% is consistent with previous HLM research (Table 1). Nevertheless, variations across economic sectors can be detected. For both Valencia and Navarre, the results show a stronger influence of industry effects in the food processing industry than in the agricultural sector. This outcome can be explained by the fact that the 4-digit NACE sectors of agricultural production are more homogeneous than processing industry sectors leading to less distinct industry effects.

The predominantly small relevance of LLS effects confirms the results of Chan *et al.* (2010) and supports the view that resources are moved to where returns are greatest. 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 such as agriculture than for manufacturing firms.

The finding that year effects only account for up to 2.5% of variation in ROA implies that similar to previous HLM studies (*e.g.* Hough, 2006; Chaddad & Mondelli, 2013) an impact of macro-level shocks on ROA cannot be detected. Moreover, across regions and sectors the 2009 year-dummies show no significant impact of the financial crisis[13]. This indicates that the food sector is a rather crisis proof sector due to static demand for food products (Lienhardt, 2004).

As regards the impact of structural variables at the firm-level we find that firm size 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 Chaddad & Mondelli (2013) and Hirsch *et al.* (2014) show based on HLM 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). Along these lines Pindado & 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) it can be expected that organizational rigidities, slower growth and outdated assets of older firms usually lead to a negative impact on profitability (Loderer & Waelchli, 2010; Hirsch *et al.*, 2014). In accordance, we also find a mostly negative, but insignificant, impact of firm age.

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

[13]Due to space considerations coefficients for year-, industry-, and LLS-dummies are not reported in Table 3 but are available upon request.

**Table 4.** Hierarchical linear model (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) |
| 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 |

All variables as defined in Table 2. Significant at *** $p<0.01$; ** $p<0.05$; * $p<0.1$; Robust standard errors are shown in parentheses.
[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 & Earnhart, 2015). Delmar *et al.* (2013) show 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.* Gschwandtner, 2005; Enqvist *et al.*, 2014; 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).

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

We now turn our attention to the impact of industry specific characteristics. 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 & 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), 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). Moreover, if an industry grows (Gr. NF), competition for market shares increases (Hirsch & Hartmann, 2014). Accordingly, the results point towards a negative impact on profits in both regions, which however is non-significant.

Although aggregate LLS effects only have a minor impact several location-specific factors drive profitability. 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 regional unemployment reduce profitability especially for smaller companies.

Moreover, high unemployment can induce firm entry, hence leading to stronger competition and lower profitability (Fairlie, 2013).

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 likely 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 (Usai & 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).

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. Moreover, urban districts can also be characterized by higher competition and thus lower profits (Melitz & Ottaviano, 2008; Lu *et al.*, 2012).

The main deficiency of the paper is that other variables which have previously been related to profitability such as advertising and capital intensity (Chaddad & Mondelli, 2013), membership of specific strategic groups (Pindado & Alarcon, 2015), import and export activity (Yurtoglu, 2004), mergers and acquisitions (Melia *et al.*, 2010), vertical integration (Grau & Reig, 2015), or regional factors such as local fiscal policy and consumption power (Tamminen, 2016) cannot be included due to data availability. Especially within the food sector, advertising intensity can constitute an important competitive advantage (Sutton, 1991; Chaddad & Mondelli, 2013). For the agricultural sector it would be interesting to incorporate the impact of subsidies and the reduction of Common Agricultural Policy measures or 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.

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