Received: 12 December 2022 | Revised: 18 April 2023 | Accepted: 24 April 2023

DOI: 10.1002/agr.21822

RESEARCH ARTICLE

Agribusiness WILEY

Profit and viability persistence: Evidence from the Spanish agricultural sector

José A. Gómez-Limón[1] | Sandra Sánchez-Cañizares[2] | Amalia Hidalgo-Fernández[1] | Ana M. Castillo-Canalejo[2]

[1]WEARE: Water, Environmental and Agricultural Resources Economics Research Group, Universidad de Córdoba, Córdoba, Spain

[2]Department of Business Organization, Universidad de Córdoba, Córdoba, Spain

Correspondence
Sandra Sánchez-Cañizares, Faculty of Law, Economic and Business Sciences, Universidad de Córdoba, Puerta Nueva s/n, E-14071 Córdoba, Spain.
Email: sandra.sanchez@uco.es

Abstract

The literature focused on analyzing profit persistence in the agricultural sector is scarce. This paper contributes to reducing this gap by carrying out an empirical study of 10 types of farming in Spain based on a dynamic panel model with microeconomic data from a large sample of farms provided by the Spanish Farm Accountancy Data Network. The generalized method of moments system estimator is used to assess profit persistence, including all significant lagged profit rates explaining the adjustment of abnormal profits over time. Moreover, the dynamic of farms' economic performance is analyzed considering the return on assets as a dependent variable (i.e., measuring farms' profitability), as well as an alternative indicator that also accounts for opportunity costs (i.e., measuring farms' viability). The results show that profit and viability persistence in the farming sector are complex dynamic processes that depend on several lags of the aforementioned dependent variables (between 2 and 5 years), with high abnormal profit and viability persistence being widespread. In any case, heterogeneous persistence results are achieved

Abbreviations: BACON, blocked adaptive computationally efficient outlier nominators; CAP, common agriculture policy; COP, cereals, oilseeds, and protein crops; EBIT, earnings before interest and taxes; EU, European Union; FADN, farm accountancy data network; GMM, generalized method of moments; IV, instrumental variables; NROA, normalized return on assets; NVR, normalized viability ratio; OLS, ordinary least squares; PoP, persistence of profits; RBV, resource-based view; RECAN, red contable agraria nacional; ROA, return on assets; SGM, standard gross margin; TF, type of farming; VR, viability ratio.

depending on the type of farming. The differences found can be explained by disparities in several explanatory variables contributing to above- or below-average performance. The conclusions reached could lead to sounder decision-making regarding agricultural policy (i.e., farm subsidies) and competition policy (i.e., exceptions to competition law). [EconLit Citations: D41; L13; L22; L25; Q12; C23].

KEYWORDS
dynamic panel model, farming sector, GMM-system estimator, persistence of profit, Spain

1 | INTRODUCTION

The analysis of the competitive dynamics of industries is an important area of research in economics, as it provides insights into how companies interact with each other within a given market. According to economic theory, the existence of competitive markets leads to an efficient allocation of all resources in the economy. Under this optimal state of the economy, where prices are equal to marginal social costs of production and every firm obtains a "normal" profit (i.e., it makes just enough profit to cover the cost of capital), social welfare is maximized (Jehle & Reny, 2011, p. 179). This explains why policymakers worldwide seek to ensure a competition-based economic system to promote consumer welfare and economic growth. Understanding the competitive dynamics of an industry can help them design policies that facilitate economic growth and innovation (Davis & Garcés, 2010). More specifically, the intensity of competition in the agricultural sector is a particularly important field of interest, given the critical role agriculture plays in providing food security and the need to identify new technologies and practices that can improve productivity and foster sustainable agriculture (Latruffe, 2010).

To support sound policymaking, competition authorities and other policymakers need reliable measurements of the competitive intensity of the markets. The most common way to assess the intensity of market competition has been by analyzing firms' profitability, as profits indicate the deviation of prices from the marginal costs of production (Eklund & Lappi, 2019). According to this approach, the commonly occurring "abnormal" profits (i.e., above or below the norm) are explained by dynamic and complex rivalry processes between firms (Mathews, 2002). Successful entrepreneurs introduce innovations in products, production processes, marketing techniques, or organizational structures that create temporary monopolistic advantages over their competitors, which consumers reward with profits above the norm. Conversely, less innovative entrepreneurial firms are penalized by consumers (profits below the norm), and are then prompted to imitate successful market initiatives, or are replaced by more efficient market entrants. As a result, monopolistic advantages tend to disappear over time as other firms imitate and improve on the innovations that have been introduced, driving profits back to the norm. Considering this dynamic process, the competitive process can be seen as a constant succession of disequilibria (deviations from the equilibrium where firms obtain "abnormal"—above or below the norm—profits) evolving over time, although market competition prevents substantial and permanent welfare losses from price–cost deviations. Thus, differential profit performance by firms is mainly determined by their internal resources and capabilities, which allow them to achieve competitive advantages. These advantages leading to profit above the norm can only persist over time while firms' internal resources and capabilities remain scarce (i.e., irreproducible or inimitable) and nonsubstitutable. In this sense, a market is considered competitive if profits above the norm are successfully and quickly eroded, with all economic rents generated by internal resources tending toward zero in the long run.

There is a large and growing literature focused on the persistence of profits (PoP), with analyses conducted at both the sector and country levels (for recent reviews of the literature, see Eklund & Lappi, 2019; Hirsch, 2018). However, studies focused on the agricultural sector are almost entirely lacking. Therefore, the first objective of this paper is to bridge the existing knowledge gap regarding the PoP and the intensity of competition in the agricultural sector. The proposed analyses will yield valuable and necessary results, pointing to relevant policy implications for the agricultural sector. In fact, they could play a key role in supporting more efficient decision-making regarding agricultural policy (e.g., designing agricultural subsidies and incentives) and competition policy (e.g., establishing agricultural exceptions to competition law).

However, while profitability is an essential aspect of farms' economic performance and a key indicator of market competition, other economic performance indicators, such as productivity, efficiency, viability, or resilience, are also pertinent for agricultural policymakers. This is particularly true for the case of the European Common Agriculture Policy (CAP), which specifically establishes the objective of supporting viable farm income in its guidelines for the period 2023–2027. Hence, the second objective of this paper and its main contribution is the proposal to analyze an alternative economic performance indicator measuring farm viability dynamics that complements the traditional assessment of the PoP based on profit dynamics. Therefore, this paper explores the persistence of farms' viability, considering their ability to obtain enough income to cover both their fixed and variable costs as well as to remunerate the factors provided by the farmer (mainly labor and capital inputs) for agricultural production. This analysis of viability persistence will provide information related to farms' potential for long-term survival.

In addition to the main contribution noted above, this paper also contributes to the existing literature with two methodological innovations in the empirical analyses performed. First, it is worth noting the heterogeneity of national agricultural sectors, which include a wide variety of subsectors facing different competitive conditions, where we would expect to find varying degrees of profit or viability persistence. As such, it makes little sense to assess the PoP for the whole agricultural sector, as has been done in the past (e.g., Eklund & Lappi, 2019). The same applies equally to the analysis of viability persistence. Therefore, the empirical analysis conducted here explores the heterogeneity in the profit and viability persistence within the farming sector. For this purpose, the Spanish agricultural sector has been taken as a case study, and this paper estimates the degree of profit and viability persistence for different types of farming, each one considered as a distinct agricultural subsector. These analyses rely on dynamic panel modeling with microeconomic data from a large representative sample of Spanish farms over a 12-year period, using the generalized method of moments (GMM) estimator developed by Blundell and Bond (1998).

Second, almost all studies that have empirically analyzed the PoP examine the variation of firm-level profit rates over time, modeling profit dynamics by regressing individual profit rates in one period ($\pi_{i,t}$) on the profit rates in the previous period ($\pi_{i,t-1}$). However, there is evidence that profit dynamics can be better described by adding further profit lags ($\pi_{i,t-j}$) to the analysis (Gschwandtner, 2005, 2012). Thus, the second methodological contribution of this paper is to systematically consider all significant lags as the best way to model farms' profitability and viability dynamics and obtain more accurate estimates for both economic performance measures.

Our findings show that profit and viability persistence in the farming sector are complex dynamic processes in which abnormal results are highly dependent on farm performance over the preceding 2–5 years. Furthermore, heterogeneous results are achieved depending on the type of farming (TF). The differences found can be explained by disparities in several explanatory variables contributing to above- or below-average profit or viability measures. The conclusions reached could lead to sounder decision-making regarding agricultural policy (i.e., changes in the subsidies and incentives granted to farmers) and competition policy (i.e., exceptions to competition law and removal of barriers to entry).

2 | RESEARCH BACKGROUND

2.1 | PoP in the food and agricultural sectors

The PoP literature includes a wide range of empirical studies that have provided strong evidence for rejecting the hypothesis of fully competitive markets. However, most of these studies have focused on the manufacturing and service sectors (Eklund & Lappi, 2019; Hirsch, 2018), and some have analyzed the dynamic of profits within the food sector. Schumacher and Boland (2005) analyzed the four major industries in the US food sector (food processing, wholesale grocery, retail supermarket, and restaurant), evidencing the persistence of abnormal profits in all of them. Hirsch and Gschwandtner (2013) focused on the food industry in five European countries (Belgium, France, Italy, Spain, and the UK), finding that the PoP varies significantly across countries (i.e., differences in market competition), with Belgium registering the lowest value (0.110) and the UK the highest (0.304). Alarcón and Sánchez (2013) examined the PoP in the Spanish food industry, reporting that profits remain more stable in SMEs than in larger food firms. Hirsch and Hartmann (2014) studied the dairy processing industry in the European Union (EU), considering firms from Belgium, France, Italy, Spain, and the UK, and the results pointed to a high level of competition as profit persistence is low (0.173). Gschwandtner and Hirsch (2018) compared the food processing firms in the EU and the United States and found that profit persistence is similar in both cases and is lower than in other manufacturing sectors, indicating highly competitive food markets. Moreover, they reported that the food industry is a fairly crisis-proof sector since profit persistence remained stable despite the economic crisis. Hirsch et al. (2021) investigated the PoP in EU food retailing, considering firms from France, Spain, and Sweden. They found a high degree of profit persistence, presumably caused by the imbalance in bargaining power in the food value chains. Finally, Opstad et al. (2022) focused on the dynamics of profits in the Norwegian restaurant industry, finding significant profit persistence (around 0.25), which they explained as being due to isolation mechanisms preventing competitors from replicating a product.

From a theoretical point of view, there are conflicting reasons for the assumptions that the agricultural sector can operate under both intense and moderate levels of market competitiveness. On the one hand, some characteristics of this sector suggest that generalized intense competition (i.e., low profit persistence) should be expected: first, increasing free international trade in a globalized economy, which leads to lower market entry barriers (Josling et al., 2010); second, agricultural production is based on biological processes that are highly dependent on the weather, leading to a price-inelastic supply in the short-run and high price volatility (Assefa et al., 2015); and third, farmers face high concentration in the food industry and retail sectors, reducing their market and bargaining power (Bonanno et al., 2018). On the other hand, other characteristic features of the agricultural sector might lead us to expect that farms face a weak competitive environment (i.e., high profit persistence): first, government policies providing subsidies and economic incentives to farmers, which contribute to improved and steady levels of profitability (Guyomard et al., 2004); second, the heterogeneous quality of agricultural resources (mainly land and water), which creates differentiated permanent rents for the landowners (Eklund & Lappi, 2019); third, entry barriers for new domestic farmers, especially those related to the high capital requirements to start a farm business (Hartarska et al., 2022); and fourth, the use of multiple risk management instruments, such as insurance or future contracts, which stabilize agricultural profits (Sánchez-Cañizares et al., 2021).

In sum, profit persistence in the agricultural sector is determined by a complex interplay of various factors, many of which are local and time specific. Under these circumstances, it is difficult to foresee the level of competition faced by the farming sector. Thus, any valid assessment needs to rely on specific data analysis, as is done in this paper.

Moreover, as pointed out in Section 1, studies focused on the PoP in the agricultural sector are scarce, providing little guidance about the actual strength of the competition within the sector. To the best of our knowledge, there are only three papers in the literature that empirically assess the PoP in the farming sector. First, Eklund and Lappi (2019) analyzed the PoP across countries and industries in the EU, including agriculture as a separate industry. They found that European agriculture is one of the industries with the lowest profit persistence (0.217 vs. an average across sectors of 0.271). Nevertheless, the analysis was based on only 37 firms included in the Compustat Global Database, which only contains large corporate farms. Thus, the sample cannot be considered representative of the agricultural sector in the EU. Another shortcoming of the estimation is that the PoP was assessed at the industry level (i.e., agriculture), without accounting for the fact that the farming sector is made up of a wide range of heterogeneous farms with different types of farming (i.e., assets required for production) or labor and land ownership structures (i.e., opportunity costs).

The second paper is by Tamirat et al. (2018), who analyzed the PoP in four types of farming in the Netherlands (dairy, livestock, field crop, and horticulture farms) using data from the Dutch Farm Accountancy Data Network (FADN) (1796 farms). Accounting for single farms' characteristics, they reported significant profit persistence (0.304) in the dairy farms, very low values in horticulture and field crop types of farming (0.071 and 0.039, respectively), and zero abnormal profits in the case of livestock farming. The third and last study focused on the PoP within the agricultural sector is by Vigani and Dwyer (2020). On the basis of the microdata provided by the Farm Business Survey (the former English branch of the FADN), these authors focused their analysis on hill and upland farms, evidencing a very high profit persistence (0.768) in this case study. However, in these two research papers, the measures used to estimate the PoP are based only on the profit rates in the previous period ($\pi_{i,t-1}$). Moreover, farm profitability is just measured through the return on assets (ROA), as is standard when analyzing large firms. This paper aims to overcome both limitations by including further profit lags ($\pi_{i,t-j}$) in the analysis when examining the profit persistence, and complementing the assessment with an alternative indicator which measures viability persistence.

2.2 | Assessing the PoP

Considering the dynamic view of competition mentioned above, Mueller (1977, 1986) was the first to propose an empirical model to estimate the PoP based on a simple first-order autoregressive (AR(1)) equation:

$$\pi_{i,t} = \alpha + \lambda\pi_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where $\pi_{i,t}$ is the abnormal profit rate of firm i at a given point in time (year) t, $\pi_{i,t-1}$ is the abnormal profit rate in the previous period, λ is the short-run profit persistence parameter, and $\varepsilon_{i,t}$ is the error term. This coefficient λ quantifies the average degree of profit persistence across firms in the sample considered (i.e., for all i), indicating the speed of convergence to the normal level of profit rate in the industry or sector analyzed (McMillan & Wohar, 2011). Its value usually varies between 0 and 1. A value of λ close to zero (i.e., low degree of persistence) implies that the competition process reduces abnormal profits from period to period, indicating strong market competition (i.e., homogeneous products, good market information, and ease of entry/exit). On the contrary, a value of λ close to 1 (i.e., high degree of persistence) implies a slow adjustment to the competitive profit over time and, thus, a low level of market competition. According to the resource-based view of the firm, the latter situation is mainly caused by “isolation mechanisms” (i.e., knowledge, physical, or legal barriers) preventing competitors from replicating a product (Mazur & Kulczyk, 2013).

Glen et al. (2001) and Callen and Morel (2001) showed that AR(2) regressions (i.e., considering two lags of profit —$\pi_{i,t-1}$ and $\pi_{i,t-2}$—as independent variables) are more suitable for modeling the PoP. Biagini et al. (2020) reached the same conclusion when modeling Italian farms' profit dynamics. Gschwandtner (2005, 2012) extended the standard approach mentioned above by estimating autoregressive processes of higher orders:

$$\pi_{i,t} = \alpha + \sum_{j=1}^{L} \lambda_j \pi_{i,t-j} + \varepsilon_{i,t}, \tag{2}$$

where L indicates the number of lags of the autoregressive process and $\Lambda = \sum_{j=1}^{L} \lambda_j$ is the parameter measuring the overall profit persistence (Gschwandtner, 2012). This extension is appropriate as the adjustment of abnormal profits over time is likely more complex than AR(1) and can be better characterized by higher-order autoregressive processes.

Although this standard approach based on autoregressions has been widely used in the past to model the PoP (e.g., Crespo Cuaresma & Gschwandtner, 2008; Schumacher & Boland, 2005), it has a serious shortcoming (Hirsch & Gschwandtner, 2013). Due to the presence of the lagged dependent variables, there are critical endogeneity issues (i.e., endogenous variables are correlated with the error term), meaning that the ordinary least squares estimator implemented on Equation (1) or (2) results in biased and inconsistent estimates (Baltagi, 2021). More recent studies use GMM estimators to avoid this drawback, as alternatives specifically created for dynamic panel modeling that ensures consistent and unbiased estimates of the autoregressive parameters (λ_j). Moreover, it is worth noting that GMM estimators are particularly suitable for analyzing dynamic data panels with relatively short time series (T) and a large number of firms (N) (Arellano & Bond, 1991; Blundell & Bond, 1998).

Arellano and Bond (1991) proposed the GMM-difference estimator, which transforms Equation (1) or (2) through its first difference, thus eliminating the error component that caused the correlations with the dependent variable. Goddard et al. (2005) were the first to use this estimator to assess the PoP. Notwithstanding, several studies (Blundell & Bond, 1998; Moral-Benito et al., 2019) have pointed out that the GMM-difference estimator can lead to inconsistent estimates, especially when the autoregressive parameters approach unity. To avoid this source of bias, Arellano and Bover (1995) and Blundell and Bond (1998) developed the GMM-system estimator, which combines the lagged level instruments for the differenced equation of the GMM-difference estimator with differenced instruments for the level equation. Liu and Wilson (2010) were the first to implement the GMM system to assess the PoP, with this econometric approach subsequently becoming the most used method for this purpose to date. Therefore, most recent studies use this improved version of the dynamic panel data GMM estimator (e.g., Hirsch et al., 2021); in this study, its use is justified by the fact that it is the one that provides the most accurate estimates of the autoregressive parameters measuring the PoP.

2.3 | Farm profitability and farm viability

Most of the previous profit persistence literature (e.g., Goddard et al., 2005; Hirsch, 2018) measures firms' profitability by the ROA, calculated as the ratio of earnings before interest and taxes (EBIT) to total assets. This measure of economic performance is widely used in the farm management literature, as it allows the comparison of farms regardless of their size or capital structure (Mishra et al., 2009). This justifies the suitability of using ROA to assess profit persistence in the farming sector.

However, the use of accounting measures to assess firms' profitability has been widely criticized because, despite the regulatory reporting framework, accounting statements are not a fair portrayal of firms' financial position and performance. Hirsch et al. (2021) summarize the various reasons for inaccurate accounting data, which potentially jeopardize the reliability of any analysis based on them. That said, it is worth noting that the fraud, systematic errors, and biases found elsewhere in accounting records are minimized when using the data provided by the FADN. There are a number of facts that support this statement (Bradley & Hill, 2015). First, the firms analyzed are farms (i.e., micro firms) whose accounting records are not biased by profit-smoothing and cross-subsidization, as may be the case when considering large firms and the related holding companies. Second, the procedures established by the EU for collecting and processing farms' data have been designed specifically for agricultural holdings, and as such are based on sound accounting and technical criteria that minimize systematic errors (e.g., valuation of fixed assets and the corresponding depreciations). And third, the correct implementation of these procedures is supervised by the national liaison agencies and the European Commission, which implement stringent data quality controls. All of this suggests that the ROA used in our study, calculated based on the FADN data, is a sufficiently accurate indicator to assess farming profitability across the agricultural subsectors.

In any case, it is worth pointing out that profitability is just one of the multiple dimensions of farms' economic performance. Profitability is one of the most extensively studied dimensions of economic performance since it enables the assessment of whether farms generate higher or lower profits than alternative businesses (Coppola et al., 2020). Furthermore, as explained above, it is a key indicator for assessing the strength of market competition. However, other dimensions of farms' economic performance, such as productivity, efficiency, viability, or resilience, are also relevant to support sound policymaking.

According to the Treaty on the Functioning of the EU, one objective of the CAP is to ensure a fair standard of living for the agricultural community (see article 39), which is the basis for policy measures aiming at supporting farm income (EC, 2018). This objective has been reinforced by Regulation (EU) 2021/2115, establishing the guidelines for the CAP during the programming period 2023–2027, where it is pointed out that the first out of the nine specific objectives of the CAP is "to support viable farm income and resilience of the agricultural sector across the Union." This focus is justified as farm viability is a requisite for the agricultural sector to provide a wide range of desired services, including the provision of food as well as ecosystem and cultural goods and services (Finger & El Benni, 2021).

Although farm income support has always been an objective of the CAP, the EU has never specified what should be understood as a "viable" income (Hill & Bradley, 2015). This lack of specificity means there is no normative reference level with which to compare the income actually obtained by farms, leading to multiple academic debates about the concept of farm viability, as evidenced by O'Donoghue et al. (2016) and Loughrey et al. (2022). However, most authors (e.g., Argilés, 2001; Coppola et al., 2022; Spicka et al., 2019; Vrolijk et al., 2010) conceptualize this term as the farms' capacity to generate sufficient income to cover all fixed and variable costs, as well as to remunerate the factors of production provided by the farmer. According to this approach, the only farms that have the potential to maintain their production activity over time are those whose income can cover all accounting costs and properly remunerate all the opportunity costs incurred by the farmers due to the use of internal resources (i.e., factors of production owned by the farmer) in his/her farming activities.

This paper aims to be the first to explore the persistence of farms' viability, mimicking the econometric approach proposed for assessing profit persistence, but with the model focusing on the dynamics of a viability indicator $v_{i,t}$ denoting abnormal viability performance (i.e., above or below the norm) of farm i at a given point in time (year) t:

$$v_{i,t} = \alpha + \sum_{j=1}^{L} \lambda_j v_{i,t-j} + \varepsilon_{i,t}. \tag{3}$$

Thus, while the analysis of profit persistence is suitable for assessing farms' ability to consistently generate abnormal profits over time and the degree of competitiveness faced by these agricultural holdings, the proposed analysis of viability persistence is useful for assessing farms' ability to maintain their income consistently above/below their opportunity costs over time. In other words, the analysis of viability persistence provides information related to their potential for long-term survival. Viability persistence is therefore a broader measure than profit persistence, as it encompasses not only market competition but also factors related to other structural features (e.g., capital and labor structure) that may impact farms' ability to survive and adapt to changing circumstances. This is especially relevant for those national agricultural sectors that are mainly composed of small or family farms whose legal form is a sole proprietorship (i.e., the farmers themselves provide a large share of the labor and capital inputs). Indeed, this is the case in Spain,[1] where the assessment of viability persistence would provide a useful complementary perspective to traditional PoP evaluations. In fact, the assessment of the persistence of farms' viability would indicate which agricultural subsectors and farms face problems in surviving and thriving over time (i.e., those whose viability indicator is consistently below the average). This information would help policymakers to assess the achievement of CAP objectives related to farm viability.

[1]According to the Spanish Agrarian Census 2020, 94% of farms have sole proprietorship as the legal form, and together they manage 77% of the country's utilized agricultural area. The EU's agricultural sector has a similar share of family farms, although there are large differences among member states (Klikocka et al., 2021).

3 | DATA, VARIABLES, AND ECONOMETRIC APPROACH

3.1 | Data

The FADN is the best source of farm-level microeconomic data for EU countries. For the case of Spain, these microdata are provided by the *Red Contable Agraria Nacional* (RECAN), the Spanish branch of the FADN. The RECAN annually collects structural, production, economic, and financial information on a representative sample of Spanish commercial farms.[2] The sample size of the RECAN annually exceeds 9000 farms. This large sample size and the quota sampling from the farm census guarantee that the information collected by this accounting network is representative of the population of commercial farms in Spain, adequately reflecting their heterogeneity both at the level of the sector as a whole and at the subsector level (i.e., TF) (RECAN, 2022). For illustrative purposes, Table 1 shows the population of farms represented by the RECAN and the sample drawn for 2020 broken down by TF. Although the total population of farms is split into 14 different TFs, the analysis implemented here focuses only on the 10 most important TFs (i.e., agricultural subsectors) in terms of the percentage of farms and the agricultural area covered. Only these TFs are included in Table 1.

We use the longitudinal dataset built from the farms participating in the RECAN sampling from 2009 to 2020. This dataset included data from 14,577 farms, which stayed in the sample for an average of 7.1 years, accounting for 102,994 observations (i.e., farm *i*–year *t*). Data regarding the farms included in the aggregate RECAN sample 2009–2020 and the number of available observations (farm-year) split into the TFs analyzed are also shown in Table 1. In any case, the original database was cleaned up to remove outliers (i.e., erroneous observations or implausible values). For this purpose, we used the blocked adaptive computationally efficient outlier nominators (BACON) algorithm developed by Billor et al. (2000). This algorithm allows the identification of multivariate outliers on the basis of Mahalanobis distances (Weber, 2010).[3] The observations identified as multivariate outliers and removed from the sample are shown by TF in the last column of Table 1.

Finally, it is worth noting that the sampling and data-gathering procedures feeding the RECAN have remained fairly stable over the last decade, since the basic regulation governing the network for collecting accountancy data on the incomes and business operations of agricultural holdings in the EU (Council Regulation (EC) No. 1217/2009) has not changed since 2009. Thus, data from the aggregate RECAN sample 2009–2020 are suitable as inputs for our econometric models, as the variables measuring farm profits and characteristics are perfectly homogeneous across the entire period.

3.2 | Variables

As explained above, farm profitability is measured by the ROA (EBIT/total assets). Departing from the RECAN data, EBIT has been calculated as the farm net income plus interest and tax payments:

$$\mathrm{ROA}_{i,t} = \frac{\text{Farm net income}_{i,t} + \text{Interest paid}_{i,t} + \text{Taxes}_{i,t}}{\text{Total assets}_{i,t}}. \quad (4)$$

[2]According to the last farm census (2020), there are 914,871 farms in Spain. However, the population of farms considered by the RECAN only includes those with an annual standard gross margin (SGM) greater than 8000 Euros (about 438,000 farms). Nevertheless, it should be pointed out that the latter population of farms manages 90% of the farmland in Spain and accounts for 96% of national agricultural output (RECAN, 2022). For this reason, the data and results obtained using this source are useful for policy analysis.

[3]The observations for which the deviation in the distance from the median of a variable lies within a certain limit determined by the $1 - \alpha$ percentile of the χ^2 distribution are kept in the sample, while observations beyond this limit are rejected (Billor et al., 2000). In our case study, we use the generally recommended limit of $\alpha = 0.15$ for this purpose.

TABLE 1 RECAN database feeding the econometric models.

Type of farming	RECAN 2020: population and sample: Population represented	RECAN 2020: population and sample: Farms sampled	RECAN 2009–2020: aggregate sample: Farms sampled	RECAN 2009–2020: aggregate sample: Observations (farm-year)	RECAN 2009–2020: aggregate sample: Number of outliers
TF15. Cereals, oilseeds, and protein crops (COP)	77,967	1255	1924	15,128	73
TF16. Other field crops	31,332	837	1052	8228	40
TF20. Horticulture	25,255	762	1700	9111	18
TF35. Wine	39,583	764	1019	7778	40
TF36. Orchards-fruits	61,430	919	1419	9188	59
TF37. Olives	55,863	435	611	4019	84
TF45. Dairy	14,042	843	1592	11,047	40
TF48. Sheep and goats	38,293	935	1404	11,113	57
TF49. Cattle	33,113	799	1143	8243	41
TF50. Granivores	17,261	722	1093	6974	11
All TFs	438,094	9215	14,577	102,994	463

Note: This table presents information about the number of farms and farm-year observations available in the RECAN dataset and the observations removed as outliers. However, a smaller number of farms and observations are actually used in the econometric models, as reported in Tables 4 and 5, because we include only the data that allow us to calculate the lagged profits required in each model (see the section explaining the econometric approach implemented).

Abbreviations: RECAN, red contable agraria nacional; TF, type of farming.

Source: RECAN microdataset.

To account for the opportunity costs for the use of the labor and capital factors provided by the farmer, we have also considered the following viability ratio (VR) as an alternative farm economic performance measure:

$$\mathrm{VR}_{i,t} = \frac{\text{Farm net income}_{i,t}}{\mathrm{OC}_{\mathrm{labor}i,t} + \mathrm{OC}_{\mathrm{capital}_{i,t}}}, \tag{5}$$

where $\mathrm{OC}_{\mathrm{labor}i,t}$ and $\mathrm{OC}_{\mathrm{capital}_{i,t}}$ are the farmer's opportunity costs of labor and capital, respectively. $\mathrm{OC}_{\mathrm{labor}i,t}$ is computed by multiplying the average cost of paid labor in the region where the farm is located by the agricultural work units provided by the farmer and his/her family, while $\mathrm{OC}_{\mathrm{capital}_{i,t}}$ is computed by multiplying the value of the farm equity by the tax-free yield of 10-year government bonds (data published by the Spanish Ministry of Finance). Both estimations are considered to be rather conservative since the wages used are mostly related to nonqualified personnel and the alternative investment opportunity taken has a very low risk (Vrolijk et al., 2010).[4]

[4]In expression (3), $\mathrm{OC}_{\mathrm{labor}i,t}$ or $\mathrm{OC}_{\mathrm{capital}_{i,t}}$ can take zero values in cases where farms do not use any of their own labor or own capital. However, such cases are likely to be uncommon considering farmers' role in managing their farms. In fact, out of all the observations in the initial database, only 1.29% have zero opportunity costs of capital and 0.18% have zero opportunity costs of labor (less than 0.05% of the observations have zero total opportunity costs). However, these extreme cases registering anomalously high values that could lead to biased estimations were detected as outliers using the BACON algorithm explained above. Thus, the observations with anomalous values in the VR indicator were removed from the database, and in the data feeding the econometric models the values of VR ranged from −1.01 to 6.42.

Considering VR as a farm economic performance indicator ($v_{i,t}$), only farms with a value of VR greater than or equal to one can be considered viable (i.e., farm incomes are enough to remunerate all the opportunity costs, allowing the generation of an economic surplus). Accounting for this indicator enables the comparison of farms with different labor and land ownership structures, and also provides a complete picture of entrepreneurial farm profitability and viability.

According to the existing literature, average industry profit can be considered the industry competitive norm. Thus, the abnormal profit of farm *i* at time *t* is defined as the deviation of the profit of farm *i* at time *t* from the average profit of all other farms in the same agricultural subsector or TF at time *t*. Following this approach for the two economic performance indicators mentioned above, the two dependent variables considered in the empirical analysis are

$$\pi_{i,t} = \mathrm{NROA}_{i,t} = \mathrm{ROA}_{i,t} - \overline{\mathrm{ROA}}_{TF,t}, \tag{6}$$

$$v_{i,t} = \mathrm{NVR}_{i,t} = \mathrm{VR}_{i,t} - \overline{\mathrm{VR}}_{TF,t}, \tag{7}$$

where $\mathrm{NROA}_{i,t}$ and $\mathrm{NVR}_{i,t}$ are the normalized values of ROA and VR indicators for farm *i* at time *t*. This way of normalizing farm profitability/viability assessment removes the impact of macroeconomic cycles.

The econometric models used also include farm characteristics as variables that can potentially explain the profit and viability persistence. These variables, together with their descriptions and the descriptive statistics for the aggregate sample, are included in Table 2. Table A1 shows the descriptive statistics for the different subsamples by TF.

Moreover, we calculated correlation coefficients (Table A2 includes a table with Spearman correlation coefficients between all pairs of variables)[5] and variance inflation factors (VIFs) among all the abovementioned explanatory variables to check for potential multicollinearity problems in estimating the econometric models. This analysis, as expected, confirmed that the pairs of variables TOUTPUT and TASSEST (proxies of farm size) and LEVERAGE and GEAR (proxies of financial risk exposure) are highly correlated. A similar case was detected regarding FAMLAB and OUTSOUR, although in this case indicating that family labor and outsourcing are substitutive inputs in farming management. For this reason, we did not include the variables TASSEST, GEAR, and OUTSOUR in our models. Following these omissions, it has been confirmed that multicollinearity is not present in any of the models run (the set of explanatory variables considered had a VIF lower than 3, below the cut-off value suggested by Hair et al., 2019).

3.3 | Econometric approach

Our empirical analysis is based on the following autoregressive models of order *L* (AR(*L*)):

$$\pi_{i,t} = \alpha + \sum_{j=1}^{L} \lambda_j \pi_{i,t-j} + \sum_{k} \alpha_k X_{k,i,t-1} + \varepsilon_{i,t}, \tag{8}$$

$$v_{i,t} = \alpha + \sum_{j=1}^{L} \lambda_j v_{i,t-j} + \sum_{k} \alpha_k X_{k,i,t-1} + \varepsilon_{i,t}, \tag{9}$$

where $\pi_{i,t}$ and $v_{i,t}$ are the abnormal farm profit and farm viability indicators, respectively, measured as $\mathrm{NROA}_{i,t}$ and $\mathrm{NVR}_{i,t}$, $\pi_{i,t-j}$ and $v_{i,t-j}$ are the abnormal profit and viability indicators lagged *j* periods, λ_j are the autoregressive parameters measuring the adjustment of abnormal normalized return on assets (NROA) or normalized viability ratio

[5]Given the nonnormality of the variables, we use Spearman's rank correlation coefficient instead of Pearson's.

TABLE 2 Variables included in the econometric models: Definition and descriptive statistics (farms from all types of farming).

Variable	Description	Unit	Average	St. Dev.
ROA	Return on assets (farm net income plus interest payment/total assets)	Ratio × 100	12.30	12.28
VR	Viability ratio (farm net income/farmer's total opportunity cost)	Ratio	1.10	1.17
TOUTPUT	Total farm output	,000 Euros	119.61	274.62
TASSEST	Total farm assets	,000 Euros	434.61	706.40
GROWTHTA	% Of increase in total farm assets	Ratio × 100	2.73	44.96
LEVERAGE	Total debt/total assets	Ratio × 100	3.93	12.50
GEAR	Total liability/owner's equity	Ratio × 100	7.64	244.27
AGE	Farmer's age	Years	54.31	11.83
SEX	Farmer's sex	0 = male; 1 = female	0.07	0.25
AGTRAIN	Farmer's practical experience or formal training	0 = practical experience; 1 = training or degree	0.12	0.33
FAMLAB	Family labor/total farm labor	Ratio × 100	79.98	27.18
LANDOWN	Owned land/total farmland	Ratio × 100	61.28	41.09
IRRIG	Irrigated area/total farmland	Ratio × 100	26.84	39.96
ALTITUDE	Farm altitude location	0 = less than 300 m; 1 = more than 300 m	0.65	0.48
LFA	Farm location in less favored area	0 = not located in LFA; 1 = located in LFA	0.69	0.46
CAPINT	Total assets/total output	Ratio	6.92	38.47
LABINT	Total labor in working hours/total output	Ratio	0.07	0.64
ICINT	Intermediate consumption/total output	Ratio	0.61	1.48
OUTSOUR	Cost of practices subcontracted/total costs	Ratio × 100	15.80	16.40
ORGANIC	Implementation of organic production	0 = no organic production; 1 = organic production	0.07	0.25
SUBSID	Subsidy payments/total farm income	Ratio × 100	20.40	1003.0
DIVERS	Other farm output/total farm output	Ratio × 100	5.89	17.58

Source: Authors' calculations based on RECAN microdataset.

(NVR) over time, $X_{k,i,t-1}$ is the vector of variables capturing the influence of farms' characteristics explaining the persistence of abnormal NROA or NVR, α_k are the parameters reflecting their impact on profitability or viability, and $\varepsilon_{i,t}$ is the error term. This modeling approach was implemented for each TF to obtain separate results for each farming subsector.

It is worth explaining here that the profit/viability dynamics of individual farms were modeled considering all significant profit/viability lags to allow for a more comprehensive adjustment process (Geroski & Jacquemin, 1988). Once the number of significant lags was determined in each TF, the parameter $\Lambda = \sum_{j=1}^{L} \lambda_{i,j}$ was calculated as a measurement of the profit/viability persistence at the TF level (Gschwandtner, 2012). In this way, we aim to add new insights to the existing literature, most of which relies on AR(1) processes, by assessing the number of periods that influence the PoP in each TF analyzed.

As explained in Section 2, the Blundell and Bond (1998) GMM-system estimator was used to estimate our dynamic panel models as it is the most efficient estimator available to date. However, the validation of the GMM-system estimations requires meeting a series of assumptions about dynamic endogeneity issues and the use of the instrumental variables (IV) approach to cope with them. In this sense, we adopt an IV strategy to account for potential endogeneity, including both lagged dependent and independent variables as instruments, as valid external instruments were difficult to construct. More specifically, as explained above, we included up to L lagged profit and viability indicators ($\pi_{i,t-j}$ and $v_{i,t-j}$) as explanatory factors of profit/viability dynamics. Moreover, as suggested in Hirsch et al. (2021), an IV strategy was adopted to consider the potential endogeneity of farms' specific drivers of profitability and viability which could initially be treated as exogenous. Thus, we lagged all these independent variables by 1 year ($X_{k,i,t-1}$) to reduce the risk that our results are driven by reverse causation (Kingsley & Graham, 2017). The lagged values of all these variables satisfy the relevance and exogeneity conditions and, therefore, can be assumed to be valid IV (Abdallah et al., 2015; Wintoki et al., 2012).

In any case, the following three tests were implemented to check the validity of the chosen IV (Li et al., 2021). First, the validity of the instruments used requires that the error term $\varepsilon_{i,t}$ is not serially correlated. Then, first-order differenced residuals $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-1}$ are correlated by construction and the AR(1) test statistic shows a statistically significant p value. However, second-order differenced residuals (i.e., between $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-2}$) should not be correlated, and thus the AR(2) test statistic is expected to show no second-order serial correlation ($p > 0.05$). Second, the Hansen J overidentification test (Hansen, 1982) was applied to test the validity of instruments. The null hypothesis for this test is that the instruments used are exogenous. Consequently, the p value of the Hansen test is not expected to reject this null hypothesis. Finally, the difference-in-Hansen J test (Eichenbaum et al., 1988) was implemented, as system GMM requires the assumption of additional exogeneity; that is, any potential correlation between endogenous variables and possible unobserved fixed effects in the models should remain constant over time. The null hypothesis in this test is that the subsets of instruments in the level equation are exogenous and, consequently, the p value should be large enough that this null hypothesis cannot be rejected.

4 | PROFITABILITY AND VIABILITY OF THE SPANISH FARMS

Spain has a long history of agriculture, dating back to prehistoric times. Today, agriculture is still an important sector in the Spanish economy, contributing around 3% of the country's gross domestic product and employing around 5% of the workforce. However, it is not only because of its economic weight that the agricultural sector is strategically important for Spain; it also plays a crucial social and environmental role in rural areas, being the backbone of the Spanish territory and a cohesive element of Spanish society.

Spain is a major producer of a variety of agricultural products, including cereals and livestock products (dairy, swine, and cattle) in the north and west of the country (the Atlantic area), and fruits, vegetables, wine, and olive oil in the south and east (the Mediterranean area). Thanks to the location and the competitive advantages offered by the climate, the latter products are the most profitable and viable (see sectoral ROA and VR indicator for 2020 in Table 3). Indeed, these high-quality products represent the lion's share of Spanish agricultural exports, which all together make Spain the eighth largest exporter of food in the world. In 2021, total food exports exceeded 60 billion euros, with a positive food trade balance of 19 billion euros (MAPA, 2022).

Table 3 provides general information about the current farm economic performance (ROA and VR indicators) in the various TFs considered, accounting for average farm data in 2020. Moreover, this table also describes recent trends across the different subsectors, showing the average annual percentage change for the period 2009–2020. To properly understand these data, it is worth explaining that ROA values cannot be directly compared between TFs since this indicator is shaped by the asset requirements in each type of agricultural production (i.e., to obtain one

TABLE 3 Average economic performance by TF: current situation (2020) and recent trends (2009–2020).

Type of farming	Area (ha)	Total output (€)	Total subsidies (€)	Farm net income (€)	ROA (×100)	VR
Average for the current situation (2020)						
TF15. COP crops	76.9	52,277	16,174	25,008	7.56	0.84
TF16. Other field crops	45.8	77,329	17,138	30,179	8.16	1.14
TF20. Horticulture	8.3	224,398	2992	74,942	12.58	2.21
TF35. Wine	25.4	49,821	6355	24,604	8.84	1.01
TF36. Orchards-fruits	19.7	88,732	7598	42,008	11.33	1.66
TF37. Olives	25.9	49,083	11,280	27,510	8.07	1.37
TF45. Dairy	37.2	248,531	22,201	68,298	12.61	1.39
TF48. Sheep and goats	89.7	98,097	18,951	42,800	12.30	1.14
TF49. Cattle	70.3	60,586	17,108	27,636	8.54	0.99
TF50. Granivores	29.2	451,902	6702	148,624	19.03	3.38
All TFs	47.0	96,756	12,582	39,706	10.40	1.49
Average annual percentage change (2009–2020)						
TF15. COP crops	0.08	6.13	0.24	5.30	0.28	2.94
TF16. Other field crops	−1.52	7.38	−2.10	2.85	0.17	3.88
TF20. Horticulture	0.10	10.64	4.54	10.70	0.00	0.11
TF35. Wine	−0.03	5.20	12.11	6.24	0.28	4.14
TF36. Orchards-fruits	2.19	9.82	6.13	9.80	0.45	8.11
TF37. Olives	0.16	3.68	2.52	3.95	0.16	6.07
TF45. Dairy	3.68	9.86	4.80	4.35	0.34	4.86
TF48. Sheep and goats	3.31	3.64	1.86	0.60	0.07	−0.69
TF49. Cattle	0.22	2.61	−0.13	0.69	0.19	3.33
TF50. Granivores	1.13	11.06	1.56	14.28	0.52	17.05
All TFs	0.55	6.25	1.15	4.84	0.29	6.08

Abbreviations: COP, cereals, oilseeds, and protein; RECAN, red contable agraria nacional; ROA, return on assets; TF, type of farming; VR, viability ratio.

Source: Authors' calculations based on RECAN microdataset.

monetary unit of EBIT, different amounts of assets may be needed, depending on the technical characteristics of the production). However, this is not the case with the VR indicator; since this is a relative measure of the economic surplus obtained by the farm, it allows the comparison of farms with different asset and labor requirements.

Accounting for the VR indicator, the data confirm that the economic performance of average farms in Horticulture (TF20) and Orchards-fruits (TF36) is better than the sector average (1.49). Granivores (TF50) shows the best economic performance in terms of VR, indicating the competitiveness of Spanish swine production. The rest of the TFs have average VR values lower than the national average, although only cereals, oilseeds, and protein

(COP) crops (TF15) and Cattle (TF49) have averages lower than one, denoting nonviability. Considering the VR average annual percentage change during the period 2009–2020, it can be seen that Granivores (TF50) and Orchards-fruits (TF36) are not only the most profitable and viable subsectors in the Spanish agricultural sector, but are also those that register the greatest improvement in economic performance. Horticulture (TF20), however, has simply maintained its high economic performance levels over the last decade. On the other hand, the average Sheep and goats farm (TF48) shows a decreasing trend in VR, despite the increase in its average area and total output over the last decade.

The farming sector in the EU is supported by the CAP in an effort to narrow the gap between farm incomes and incomes in the rest of the economy and to reduce their volatility over time (EC, 2018). This support is recorded in Table 3, showing how subsidies received by different average farms shape their profitability and viability. In Spain, the average subsidy rate (variable *SUBSID* measuring total subsidy payments divided by total farm income) is lower (11.1%) than in the EU (13.4%) (data from FADN, 2022 for the year 2020). Nevertheless, the role of CAP payments is notably heterogeneous among Spanish TFs, with the average values of SUBSID ranging from 4.6% to 28.7% (see Table A1). In this sense, it can be seen that CAP support is mainly targeted at less viable subsectors (e.g., COP crops–TF15, Other field crops–TF16, Sheep and goats–TF48, or Cattle–TF49, all with average values of SUBSID higher than 20%), while payments received by Horticulture (TF20), Orchards-fruits (TF36), and Granivores (TF50) are much lower (average values of SUBSID below 10).

Finally, it should be mentioned that farm profitability and viability are also shaped by entry barriers making it difficult for new farmers to start and operate successful farming businesses. Although these barriers take many forms and vary depending on the specific type of agriculture being considered, the most relevant ones for the Spanish case are: (a) high capital requirements to start a farm business and limited access to credit; (b) policy regulations (e.g., decoupled direct payments in Spain are only received by those farmers who own payment entitlements; thus, any new farmer that does not have an entitlement is at a competitive disadvantage); and (c) market concentration in the food industry and retail sectors and limited access to markets, especially for more perishable agricultural products such as fruits and vegetable or those produced for the export market.

5 | EMPIRICAL RESULTS AND DISCUSSION

5.1 | Profit persistence

Table 4 shows the estimates of modeling NROA dynamics by TF. As commented in Section 4, all the tests describing the model validity (see lower panel in Table 4) confirm the overall adequacy of the outcomes for every TF. Although the Blundell and Bond GMM-system estimator does not provide R^2 values, AR(2), Hansen, and difference-in-Hansen test p values, respectively, demonstrate the absence of second-order correlation, the overidentification of models, and exogeneity of instruments. Therefore, the results obtained are reliable enough to be analyzed.

Regarding the results, the number of significant lagged profits ($\pi_{i,t-j}$) explaining the PoP ranged from two, in the case of TF15 (COP) and TF37 (Olives), to five, in the case of TF48 (Sheep and goats). Furthermore, the coefficients obtained for these autoregressive variables followed the expected rationale, displaying positive values in every TF (i.e., current abnormal profits are positively related to abnormal profits in the past) and generally showing that the higher the order of the lagged profit, the lower the coefficient (i.e., more recent profits have a higher impact on current profit).[6]

[6]There are only occasional exceptions (e.g., the coefficient for $NROA_{t-3}$ is higher than for $NROA_{t-2}$ in TF20 and TF49, and the coefficient for $NROA_{t-5}$ is higher than for $NROA_{t-4}$ in TF48). However, the differences between these coefficients are almost negligible in these cases. At any rate, in all the subsectors, the first lag is clearly higher than the rest, underscoring the idea that the more recent past has a greater influence.

TABLE 4 Dynamic panel model estimation results for NROA by types of farming.

Variable	TF15. COP Coef. (S.E.)	TF16. Other field crops Coef. (S.E.)	TF20. Horticulture Coef. (S.E.)	TF35. Wine Coef. (S.E.)	TF36. Orchards-fruits Coef. (S.E.)	TF37. Olives Coef. (S.E.)	TF45. Dairy Coef. (S.E.)	TF48. Sheep and goats Coef. (S.E.)	TF49. Cattle Coef. (S.E.)	TF50. Granivores Coef. (S.E.)
$NROA_{t-1}$	0.562*** (0.05)	0.332*** (0.07)	0.370*** (0.04)	0.450*** (0.03)	0.450*** (0.03)	0.470** (0.18)	0.482*** (0.04)	0.478*** (0.04)	0.339*** (0.04)	0.393*** (0.04)
$NROA_{t-2}$	0.074* (0.04)	0.233*** (0.05)	0.079** (0.03)	0.119*** (0.04)	0.120*** (0.04)	0.322*** (0.10)	0.152*** (0.03)	0.098** (0.03)	0.120*** (0.03)	0.194*** (0.04)
$NROA_{t-3}$		0.191*** (0.04)	0.113*** (0.03)	0.063** (0.02)	0.070*** (0.02)		0.090*** (0.02)	0.090*** (0.03)	0.139*** (0.02)	0.091* (0.04)
$NROA_{t-4}$								0.062** (0.02)		
$NROA_{t-5}$								0.067** (0.02)		
Intercept	−3.388 (2.72)	−6.487 (3.44)	0.048 (0.21)	4.256* (1.80)	4.086* (1.85)	4.066 (2.26)	−3.709* (1.86)	−2.858 (2.08)	1.682 (2.05)	−4.562 (2.36)
$TOUTPUT_{t-1}$	−4.5E−3 (0.01)	−6.0E−3 (0.01)	7.0E−7* (0.00)	−5.2E−3 (0.00)	−5.2E−3 (0.00)	3.6E−3 (0.01)	−3.9E−5 (0.00)	−3.1E−3 (0.01)	−3.3E−3 (0.00)	−8.8E−4 (0.00)
$GROWTHTA_{t-1}$	−0.032** (0.01)	−0.069** (0.03)	−0.002 (0.00)	−0.012 (0.01)	−0.012 (0.01)	−0.046 (0.04)	−0.011 (0.01)	−0.059*** (0.02)	−0.028*** (0.01)	−0.029* (0.01)
$LEVERAGE_{t-1}$	0.060 (0.05)	−0.044 (0.06)	0.004 (0.00)	−0.057 (0.06)	−0.069 (0.06)	0.213 (0.25)	−0.012 (0.03)	0.134* (0.05)	−0.018 (0.04)	0.061 (0.04)
AGE_{t-1}	−0.020 (0.03)	0.028 (0.02)	−0.001 (0.00)	−0.008 (0.01)	−0.010 (0.01)	−0.050 (0.05)	0.015 (0.01)	0.033* (0.02)	−0.004 (0.01)	−0.006 (0.02)
SEX_{t-1}	0.055 (0.56)	2.571** (0.92)	−0.180** (0.07)	−0.001 (0.57)	0.015 (0.57)	0.053 (0.50)	0.420 (0.35)	−1.266 (0.69)	−0.324 (0.40)	−1.326 (1.10)
$AGTRAIN_{t-1}$	3.240 (1.83)	−0.574 (1.08)	0.005 (0.07)	−0.463 (1.04)	−0.385 (1.03)	−0.981 (0.52)	0.450 (0.36)	0.455 (0.73)	0.450 (0.51)	1.058 (0.65)
$FAMLAB_{t-1}$	−0.002 (0.02)	0.047 (0.03)	0.000 (0.00)	−0.028** (0.01)	−0.023* (0.01)	−0.026* (0.01)	0.002 (0.01)	−0.003 (0.01)	−0.018 (0.02)	0.023 (0.02)
$LANDOWN_{t-1}$	0.013 (0.01)	−0.027 (0.02)	−0.002 (0.00)	−0.025 (0.02)	−0.024 (0.02)	−0.014 (0.01)	0.004 (0.01)	−0.014 (0.01)	0.000 (0.01)	0.012 (0.02)
$IRRIG_{t-1}$	−0.003 (0.00)	0.005 (0.01)	−0.001 (0.00)	0.006 (0.01)	0.006 (0.01)	0.013 (0.01)	−0.024 (0.03)	0.010 (0.02)	−0.005 (0.01)	−0.008 (0.01)
LFA_{t-1}	−0.321 (0.96)	0.777 (0.88)	0.085 (0.05)	−0.587 (0.49)	−0.592 (0.48)	0.550 (0.79)	0.598* (0.27)	0.559 (0.47)	−0.226 (0.32)	−1.660** (0.64)
$ALTITUDE_{t-1}$	0.571 (0.60)	0.804 (0.91)	0.144** (0.05)	0.352 (0.30)	0.417 (0.30)	1.391 (0.81)	−0.678* (0.34)	0.506 (0.48)	0.239 (0.54)	0.258*** (0.08)
$CAPINT_{t-1}$	−0.153*** (0.04)	−0.437*** (0.11)	−0.004 (0.01)	−0.170** (0.06)	−0.158** (0.06)	−0.099 (0.14)	−0.296*** (0.09)	−0.204** (0.08)	−0.136*** (0.04)	−0.606*** (0.17)
$LABINT_{t-1}$	0.569 (4.38)	−1.138 (6.70)	−1.214 (0.87)	13.967* (6.14)	13.041* (5.84)	10.334 (5.90)	28.854* (11.37)	9.585 (6.32)	6.395 (3.75)	37.952*** (10.72)
$ICINT_{t-1}$	4.707*** (1.05)	3.843 (2.07)	0.002 (0.21)	5.745** (2.13)	5.291* (2.09)	2.335 (2.84)	5.298*** (1.46)	1.933 (1.18)	1.145 (0.60)	5.500** (1.91)

TABLE 4 (Continued)

Variable	TF15. COP Coef. (S.E.)	TF16. Other field crops Coef. (S.E.)	TF20. Horticulture Coef. (S.E.)	TF35. Wine Coef. (S.E.)	TF36. Orchards-fruits Coef. (S.E.)	TF37. Olives Coef. (S.E.)	TF45. Dairy Coef. (S.E.)	TF48. Sheep and goats Coef. (S.E.)	TF49. Cattle Coef. (S.E.)	TF50. Granivores Coef. (S.E.)
$ORGANIC_{t-1}$	0.931 (1.27)	−0.860 (1.63)	−0.243** (0.08)	1.513* (0.77)	1.607* (0.77)	−0.375 (0.76)	1.826* (0.75)	0.630 (1.08)	0.249 (0.39)	1.317 (1.56)
$SUBSID_{t-1}$	0.044 (0.02)	0.119** (0.04)	0.000 (0.00)	−0.051** (0.02)	−0.058* (0.02)	−0.022 (0.07)	−0.047 (0.04)	0.042 (0.02)	0.000 (0.01)	0.144** (0.05)
$DIVERS_{t-1}$	0.080* (0.03)	−0.050 (0.05)	0.019 (0.01)	0.036 (0.05)	0.033 (0.05)	−0.897 (2.60)		−0.081*** (0.02)	−0.063** (0.02)	−0.001 (0.01)
−0.008 (0.02)										

Model diagnostics	TF15. COP	TF16. Other field crops	TF20. Horticulture	TF35. Wine	TF36. Orchards-fruits	TF37. Olives	TF45. Dairy	TF48. Sheep and goats	TF49. Cattle	TF50. Granivores
Number of observations	8477	2742	3572	4174	4385	2425	5955	3997	4288	4288
Number of farms	1546	735	844	789	980	427	1044	808	762	762
Wald χ^2 (*p* value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(1) test (*p* value)	0.000	0.001	0.000	0.000	0.000	0.028	0.000	0.000	0.000	0.000
AR(2) test (*p* value)	0.529	0.751	0.795	0.646	0.670	0.081	0.962	0.905	0.699	0.699
Hansen test of overidentification (*p* value)	0.105	0.830	0.489	0.516	0.564	0.507	0.474	0.178	0.320	0.320
Difference-in-Hansen test of exogeneity (*p* value)	0.999	0.975	0.633	0.953	0.972	0.822	0.676	0.893	0.988	0.988

Note: Numbers in parentheses are robust standard errors (i.e., unbiased standard errors under heteroskedasticity). The Hansen test of overidentification tests the null hypothesis that all of the instruments are valid. The difference-in-Hansen test of exogeneity tests the null hypothesis that the instruments used for the equations in levels are exogenous.

Abbreviations: AGE, farmer's age; AGTRAIN, farmer's practical experience or formal training; ALTITUDE, farm altitude location; AR, autoregressive; CAPINT, total assets/total output; COP, cereals, oilseeds, and protein; DIVERS, other farm output/total farm output; FAMLAB, family labor/total farm labor; GROWTHTA, % of increase in total farm assets; ICINT, intermediate consumption/total output; IRRIG, irrigated area/total farmland; LABINT, total labor in working hours/total output; LANDOWN, owned land/total farmland; LEVERAGE, total debt/total assets; LFA, less favored area; NROA, normalized return on assets; ORGANIC, implementation of organic production; SEX, farmer's sex; SUBSID, subsidy payments/total farm income; TF, type of farming; TOUTPUT, total farm output.

*, **, and *** significant at 5%, 1%, and 0.1% level, respectively.

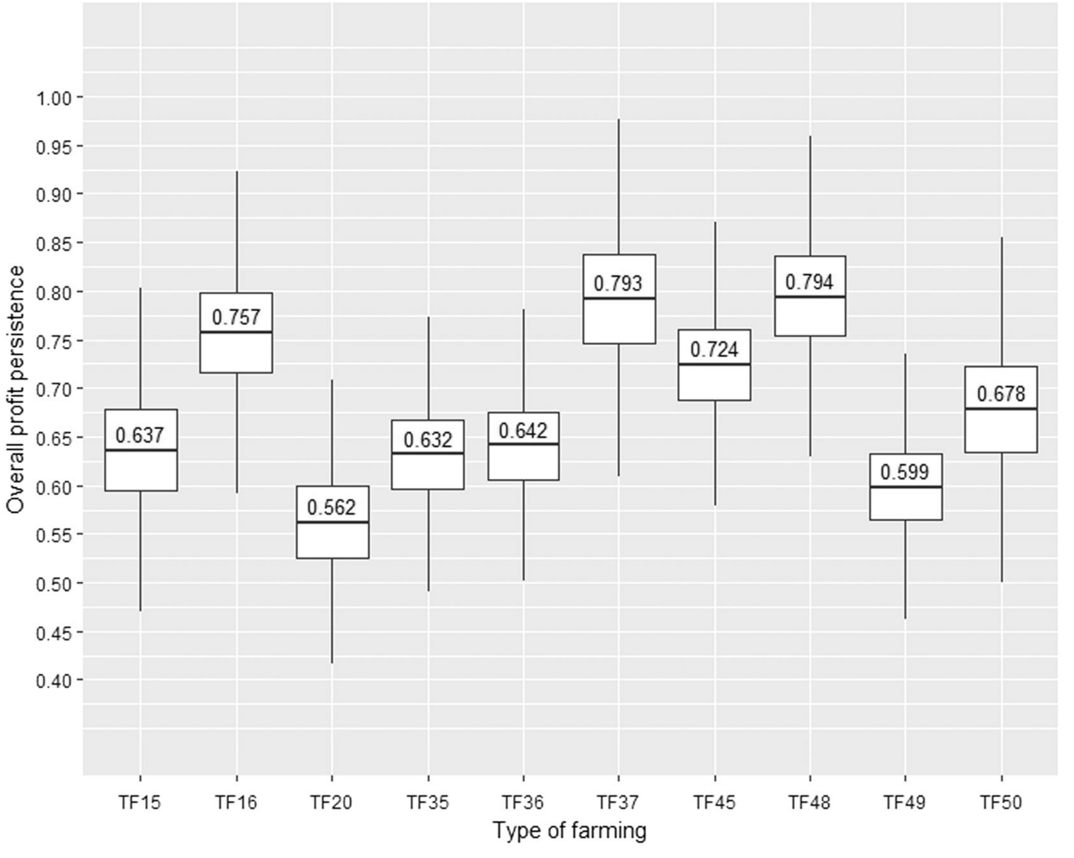

FIGURE 1 Distributions of the overall measures of profit persistence (Λ) by type of farming.

These results confirm the suggestion made by Gschwandtner (2005, 2012), who pointed out that the adjustment of abnormal profits over time can be better modeled using autoregressive processes of orders higher than one, unlike most studies in the literature, which use first-order autoregressive processes. In fact, by including several lags of the dependent variable we show that the PoP is a complex dynamic process, with farms' current economic performance highly dependent on the profits obtained over the last 2–5 years.

As explained above, the overall profit persistence can be proxied at the TF level by the parameter $\Lambda = \sum_{j=1}^{L} \lambda_j$ (Gschwandtner, 2012). In any case, it must be pointed out that these parameters Λ are the averages of stochastic variables distributed according to the sum of the distributions followed by the corresponding parameters λ_j. The distributions of the parameters measuring the overall profit persistence were empirically shaped using a bootstrapping procedure. The results obtained are shown graphically in Figure 1.

The differences in means of Λ shown in Figure 1 prove that the PoP is heterogeneous within the agricultural sector, varying depending on the TF considered. In the Spanish case study, the TFs with the lowest profit persistence ($\Lambda < 0.6$) were Horticulture (TF20) and Cattle (TF49). On the other hand, the subsectors showing the highest degree of profit persistence ($\Lambda > 0.7$) were Sheep and goats (TF48), Olives (TF37), Other field crops (TF16), and Dairy (TF45). The remaining subsectors (COP–TF15, Wine–TF35, Orchards-fruits–TF36, and Granivores–TF50) had overall measures of profit persistence ranging from 0.6 to 0.7.

The value estimates of Λ for the different TFs ranging from 0.562 to 0.794 (i.e., between 0 and 1) mean that abnormal profits within the agricultural sector converge to the TF-specific norm (i.e., the average profitability in each agricultural subsector) over time. However, the speed of convergence (1 − Λ) is relatively slow, ranging from

43.8% to 20.6% per year, respectively. All these figures suggest a relatively low intensity of competition in the Spanish agricultural sector.

On the other hand, in addition to assessing the strength of market competition, the analysis of the PoP can also be considered as a way to measure farms' robustness, indicating their capacity to absorb the consequences of shocks caused by changing markets, climate, and policy conditions by minimizing variations in farm profits (Vigani & Dwyer, 2020). Thus, the higher the profit persistence, the lower the intensity of competition, but the higher the resilience of the farms. This point, however, can be better assessed by considering the viability persistence, as explained in Section 5.2.

Persistence measures are not directly comparable across the estimation methods (Hirsch & Gschwandtner, 2013). Thus, the abovementioned measures of overall profit persistence can only be compared with those from studies that also use GMM estimators. In this sense, the estimates of Λ for the Spanish TFs are in line with the figures reported by Vigani and Dwyer (2020) for the English hill and upland farms (0.768). However, they are much higher than those estimated by Tamirat et al. (2018) for different Dutch TFs, which varied from 0.304 for dairy farms to null values for livestock farming. In any case, the profit persistence in these two studies could be underestimated since they modeled the PoP using only first-order autoregressive processes, ignoring the impact of other past profits on farms' current profitability.

It is also interesting to compare the average profit persistence for agricultural holdings to the persistence estimates found for other sectors within the food value chain. For example, Hirsch and Gschwandtner (2013) showed relatively low profit persistence estimates for the European food industry, ranging between 0.110 and 0.304, depending on the countries. Similarly, Hirsch and Hartmann (2014) reported a persistence equal to 0.173 for the specific case of the European dairy processing industry. Notwithstanding, Hirsch et al. (2021) found a higher profit persistence for the food retail sector in different European countries, with estimations ranging from 0.451 to 0.636.[7] These authors explain differences in the PoP across sectors as being due to power imbalances within the food value chain (Hirsch et al., 2021). Thus, the higher degree of profit persistence in food retailing (i.e., lower intensity of competition) is assumed to be caused by both the higher bargaining power and the higher market power in comparison with suppliers (i.e., food industry) and final customers.

The estimates found here for the PoP in the Spanish agricultural subsectors are similar to those reported for the food retail sector by Hirsch et al. (2021). However, the explanation for the apparently low intensity of market competition cannot be the same since it has been consistently proven that the agricultural sector has low bargaining and market power in both the upstream (i.e., input suppliers) and downstream (i.e., food industry firms) sectors (for a review, see Bonanno et al., 2018). Among the reasons for the high degree of profit persistence in the agricultural sector, the specific characteristic of natural resources needed for farming and the role of public support presumably stand out. Regarding the first reason, it is worth noting that the heterogeneous quality of agricultural land (i.e., diverse agroclimatic characteristics affecting land productivity) and the availability of irrigation water create differentiated permanent rents for the landowners, allowing a significant share of abnormal farm profits to persist over time. This is especially relevant in the Spanish case study since the percentage of land owned by the farmers (58%) is much higher than the EU average (43%) (data from FADN, 2022 for the year 2020). In this sense, it is expected that the more extensive the agricultural production (i.e., farming systems needing higher land inputs) and the higher the share of owned land, the higher the farm's profit persistence.

CAP support for farming activity is mainly provided through direct payments to farmers, both decoupled and coupled. Under CAP arrangements, subsidy payments strongly influence farms' profitability and agricultural profit dynamics, and represent another key factor explaining the PoP within the European agricultural sector (Kryszak et al., 2021). The reason is that these payments create quasi-permanent rents for farmers, especially because of decoupled payments that are granted for long periods with only minor changes required, regardless of the farms'

[7]These two studies assessed the PoP accounting only for first-lagged values of firms' profit. Thus, the values reported could also be underestimated.

production levels. It is thus to be expected that the larger the share of decoupled payments in total farm income, the higher the farm's profit persistence.

The reasons set out above could explain why the TFs with the highest (lowest) profit persistence in Spain were those that had a prevalence of farms combining an extensive (intensive) production system, a high (low) share of owned land, and a high (low) share of decoupled payments in total income. The TFs Other field crops (TF16) and Horticulture (TF20) are good examples of this, representing agricultural subsectors with higher and lower overall profit persistence, respectively.

Table 4 also shows the estimates for the variables capturing the influence of farms' characteristics explaining the persistence of abnormal profits. Positive (negative) and significant coefficients point to variables positively (negatively) affecting farm profitability, leading to farm profits higher (lower) than the average for the TF. Thus, these results could be discussed in comparison with the vast existing literature focused on the factors influencing farm profitability (see Tey & Brindal, 2015 for a review). As can be seen, the results obtained are fairly heterogeneous depending on the TF considered.

Some of the farm characteristic variables that can potentially explain the PoP are worth noting. On the one hand, only TF20 shows a higher average profit in larger farms (only statistically significant coefficient for TOUTPUT, the variable used as a proxy for farm size) despite the fact that many studies (including Tamirat et al., 2018; Vigani & Dwyer, 2020) have reported evidence that larger farms can achieve economies of scale and thus above-average profits. On the other hand, significant negative coefficients were generally found across TFs for farm investments (i.e., increase in total farm assets, GROWTHTA). Hirsch and Gschwandtner (2013) reported similar results for the European food industry, even when we might expect to see a positive relation between investments and profit; a possible explanation lies in the fact that investments take time to generate profits (Nilsson & Wixe, 2021). In fact, NROA usually decreases just after an investment is made.

With respect to the personal characteristics of the farmers, practically no TFs showed significant coefficients for AGE (except a positive coefficient for TF48) and AGTRAIN, even though farmers with more experience or a degree in agriculture (a proxy for farm management knowledge and skills) could be expected to be in a better position to make higher profits (Mishra et al., 2009).

The CAPINT and ICINT ratios showed, as expected, opposite results. While farms that need more assets to obtain the same output have persistent profits below the average (negative and significant CAPINT coefficient for almost all TFs considered, as in the study by Tamirat et al., 2018), a higher ratio of intermediate consumption boosts farm profitability (positive and significant coefficients for ICINT, as reported by Kryszak et al., 2021).

Finally, the variable SUBSID was included to test whether CAP payments were properly granted to those farms needing such support (i.e., less profitable farms) (Piet & Desjeux, 2021). If the coefficient of this variable is positive, it means that CAP payments make farmers (unnecessarily) richer; if the coefficient is negative, payments are not enough to cover the profitability gaps. We found positive and significant coefficients for Other field crops and Granivores, while the coefficients for Wine and Orchards-fruits are negative and significant.

5.2 | Viability persistence

Table 5 shows the results obtained by regressing the NVR indicator using the Blundell and Bond GMM-system estimator, as a way to assess the "persistence of farm viability." Similar to the NROA modeling, all parameters describing the model fit evidence the overall adequacy of the estimates for every TF (see lower panel in Table 5).

Results showed that the persistence of farm viability is also a complex dynamic process that should be modeled considering several lagged values of the independent variable. In our case study, most of the TFs had three significant lags, except TF16 (Other field crops), TF20 (Horticulture), TF48 (Sheep and goats), and TF50 (Granivores), which had only two. As expected, the significant coefficient of the autoregressive variables also followed a

TABLE 5 Dynamic panel model estimation results for NVR by types of farming.

Variable	TF15. COP Coef. (S.E.)	TF16. Other field crops Coef. (S.E.)	TF20. Horticulture Coef. (S.E.)	TF35. Wine Coef. (S.E.)	TF36. Orchards-fruits Coef. (S.E.)	TF37. Olives Coef. (S.E.)	TF45. Dairy Coef.	TF48. Sheep and goats Coef. (S.E.)	TF49. Cattle Coef. (S.E.)	TF50. Granivores Coef. (S.E.)
NVR_{t-1}	0.427*** (0.05)	0.316*** (0.07)	0.386*** (0.04)	0.433*** (0.03)	0.435*** (0.03)	0.459*** (0.18)	0.576*** (0.04)	0.413*** (0.04)	0.314*** (0.04)	0.329*** (0.04)
NVR_{t-2}	0.132*** (0.04)	0.038 (0.05)	0.052* (0.03)	0.094** (0.04)	0.094** (0.04)	0.124** (0.10)	0.143*** (0.03)	0.111** (0.03)	0.114*** (0.03)	0.161*** (0.04)
NVR_{t-3}	0.065*** (0.03)	0.112*** (0.04)		0.107*** (0.02)	0.104*** (0.02)	0.188* (0.00)	0.117*** (0.02)		0.117*** (0.02)	
Intercept	−0.082 (2.72)	0.104 (3.44)	0.041 (0.21)	−0.003 (1.80)	−0.026 (1.85)	−0.419 (2.26)	−0.265 (1.86)	−0.015 (2.08)	0.015 (2.05)	0.150 (2.36)
$TOUTPUT_{t-1}$	9.2E−4 (0.01)	−8.6E−4 (0.01)	1.1E−3*** (0.00)	−8.2E−5 (0.00)	−2.2E−5 (0.00)	1.3E−3* (0.01)	1.2E−4 (0.00)	1.2E−3* (0.01)	8.1E−4 (0.00)	2.5E−4 (0.00)
$GROWTHTA_{t-1}$	0.000 (0.01)	0.000 (0.03)	−0.001 (0.00)	0.000 (0.01)	0.000 (0.01)	0.000 (0.04)	0.000 (0.01)	−0.001 (0.02)	0.000 (0.01)	0.000 (0.01)
$LEVERAGE_{t-1}$	0.003 (0.05)	−0.006 (0.06)	−0.003 (0.00)	−0.008 (0.06)	−0.009 (0.06)	0.068** (0.25)	−0.005* (0.03)	0.000 (0.05)	−0.005 (0.04)	0.014 (0.04)
AGE_{t-1}	0.000 (0.03)	0.001 (0.02)	−0.001 (0.00)	−0.001 (0.01)	−0.002 (0.01)	0.006 (0.05)	0.002 (0.01)	0.000 (0.02)	−0.002 (0.01)	0.004 (0.02)
SEX_{t-1}	0.005 (0.56)	0.136* (0.92)	−0.249*** (0.07)	−0.034 (0.57)	−0.035 (0.57)	0.083 (0.50)	0.046 (0.35)	−0.069 (0.69)	−0.001 (0.40)	−0.187 (1.10)
$AGTRAIN_{t-1}$	0.007 (1.83)	0.112 (1.08)	0.045 (0.07)	−0.163 (1.04)	−0.172 (1.03)	0.015 (0.52)	0.001 (0.36)	0.078 (0.73)	0.005 (0.51)	0.089 (0.65)
$FAMLAB_{t-1}$	−0.003 (0.02)	−0.002 (0.03)	−0.001 (0.00)	−0.001 (0.01)	−0.001 (0.01)	−0.005*** (0.01)	−0.002 (0.01)	−0.002 (0.01)	−0.002 (0.02)	−0.003 (0.02)
$LANDOWN_{t-1}$	0.001 (0.01)	−0.001 (0.02)	−0.004* (0.00)	−0.001 (0.02)	0.000 (0.02)	0.001 (0.01)	0.000 (0.01)	−0.001 (0.01)	0.000 (0.01)	−0.006* (0.02)

(Continues)

TABLE 5 (Continued)

Variable	TF15. COP Coef. (S.E.)	TF16. Other field crops Coef. (S.E.)	TF20. Horticulture Coef. (S.E.)	TF35. Wine Coef. (S.E.)	TF36. Orchards-fruits Coef. (S.E.)	TF37. Olives Coef. (S.E.)	TF45. Dairy Coef.	TF48. Sheep and goats Coef. (S.E.)	TF49. Cattle Coef. (S.E.)	TF50. Granivores Coef. (S.E.)
$IRRIG_{t-1}$	0.000 (0.00)	0.000 (0.01)	−0.002 (0.00)	−0.003** (0.01)	−0.003** (0.01)	0.002 (0.01)	−0.001 (0.03)	0.000 (0.02)	0.000 (0.01)	0.001 (0.01)
LFA_{t-1}	−0.041 (0.96)	0.126 (0.88)	0.061 (0.05)	0.031 (0.49)	0.029 (0.48)	−0.189* (0.79)	0.059* (0.27)	0.023 (0.47)	0.044 (0.32)	−0.337*** (0.64)
$ALTITUDE_{t-1}$	−0.065 (0.60)	−0.060 (0.91)	0.202*** (0.05)	0.008 (0.30)	0.005 (0.30)	0.223* (0.81)	−0.013 (0.34)	0.057 (0.48)	0.036 (0.54)	0.258*** (0.08)
$CAPINT_{t-1}$	−0.004 (0.04)	−0.033*** (0.11)	0.002 (0.01)	−0.012 (0.06)	−0.013* (0.06)	−0.019 (0.14)	−0.011 (0.09)	−0.001 (0.08)	−0.007*** (0.04)	−0.034 (0.17)
$LABINT_{t-1}$	−1.299*** (4.38)	−3.698*** (6.70)	0.495 (0.87)	−0.989 (6.14)	−0.948 (5.84)	1.261 (5.90)	1.649 (11.37)	−1.363*** (6.32)	−0.397* (3.75)	−1.351 (10.72)
$ICINT_{t-1}$	0.331*** (1.05)	0.220 (2.07)	0.184 (0.21)	0.887*** (2.13)	0.927*** (2.09)	0.140 (2.84)	0.681*** (1.46)	0.171 (1.18)	0.136** (0.60)	−0.302 (1.91)
$ORGANIC_{t-1}$	0.105 (1.27)	0.083 (1.63)	−0.306*** (0.08)	0.062 (0.77)	0.078 (0.77)	0.105 (0.76)	0.233 (0.75)	0.137 (1.08)	0.065 (0.39)	0.162 (1.56)
$SUBSID_{t-1}$	0.005** (0.02)	0.012*** (0.04)	−0.001 (0.00)	−0.004 (0.02)	−0.005 (0.02)	0.001 (0.07)	−0.008 (0.04)	0.002 (0.02)	0.003 (0.01)	0.012** (0.05)
$DIVERS_{t-1}$	0.003 (0.03)	−0.007 (0.05)	0.009 (0.01)	0.007 (0.05)	0.005 (0.05)	−0.054 (2.60)	−0.011*** (0.02)	−0.001 (0.02)	0.001 (0.01)	0.001 (0.02)

Model diagnostics	TF15.COP	TF16. Other field crops	TF20. Horticulture	TF35. Wine	TF36. Orchards-fruits	TF37. Olives	TF45. Dairy	TF48. Sheep and goats	TF49. Cattle	TF50. Granivores
Number of observations	6763	2742	4572	4174	4385	1991	5955	7039	4288	4172
Number of farms	1371	728	982	789	980	387	1044	1113	762	705
Wald χ^2 (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 5 (Continued)

Model diagnostics	TF15.COP	TF16. Other field crops	TF20. Horticulture	TF35. Wine	TF36. Orchards-fruits	TF37. Olives	TF45. Dairy	TF48. Sheep and goats	TF49. Cattle	TF50. Granivores
AR(1) test (*p* value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (*p* value)	0.630	0.630	0.205	0.276	0.302	0.942	0.911	0.469	0.958	0.843
Hansen test of overidentification (*p* value)	0.772	0.772	0.124	0.870	0.766	0.846	0.490	0.180	0.225	0.065
Difference-in-Hansen test of exogeneity (*p* value)	0.875	0.875	0.964	1.000	0.994	0.979	0.959	0.969	0.966	0.306

Note: Numbers in parentheses are robust standard errors (i.e., unbiased standard errors under heteroskedasticity). The Hansen test of overidentification tests the null hypothesis that all of the instruments are valid. The difference-in-Hansen test of exogeneity tests the null hypothesis that the instruments used for the equations in levels are exogenous.

Abbreviations: AGE, farmer's age; AGTRAIN, farmer's practical experience or formal training; AR, autoregressive; COP, cereals, oilseeds, and protein; DIVERS, other farm output/total farm output; FAMLAB, family labor/total farm labor; GROWTHTA, % of increase in total farm assets; ICINT, intermediate consumption/total output; IRRIG, irrigated area/total farmland; LABINT, total labor in working hours/total output; LANDOWN, owned land/total farmland; LEVERAGE, total debt/total assets; LFA, less favored area; NVR, normalized viability ratio; ORGANIC, implementation of organic production; SEX, farmer's sex; SUBSID, subsidy payments/total farm income; TF, type of farming; TOUTPUT, total farm output.

*,**, and *** significant at 5%, 1%, and 0.1% level, respectively.

generalized economic rationale (i.e., positive values in every TF and more recent values of NVR having a higher impact on current NVR).

Compared with the results obtained for NROA, it is worth pointing out that when modeling NVR, two TFs show more significant lags (TF15-COP and TF37-Olives) and three TFs show fewer significant lags (TF20-Horticulture, TF48-Sheep and goats, and TF50-Granivores). These differences can be explained by the different levels of opportunity costs in each TF. In fact, what the two TFs showing more significant lags have in common is significantly higher opportunity costs (TF15-COP because of a high share of family labor and TF37-Olives because of a high share of owned land), while those showing fewer significant lags are characterized by significantly lower opportunity costs (TF20-Horticulture because of a low share of family labor, and TF48-Sheep and goats and TF50-Granivores because of a low share of owned land) (see the average values of FAMLAB and LANDOWN variables in Table A1). Thus, these results suggest that the higher the opportunity costs, the more lasting the momentum in terms of farm viability (i.e., more significant lagged values of the independent variable).

The average measure of the overall viability persistence (Λ, see Figure 2) ranges from 0.428 (TF16-Other field crops) to 0.836 (TF45-Dairy). These differences in viability persistence also indicate heterogeneity within the agricultural sector, with viability persistence depending on the TF considered.

Again, comparing with the results obtained for NROA, it can be seen that overall profit and viability persistence are quite similar for most TFs. However, there are significant differences for TF16 (Other field crops), TF20 (Horticulture), TF48 (Sheep and goats), and TF50 (Granivores), for which the average values of overall viability persistence are much lower than the average values of overall profit persistence. These differences can also be

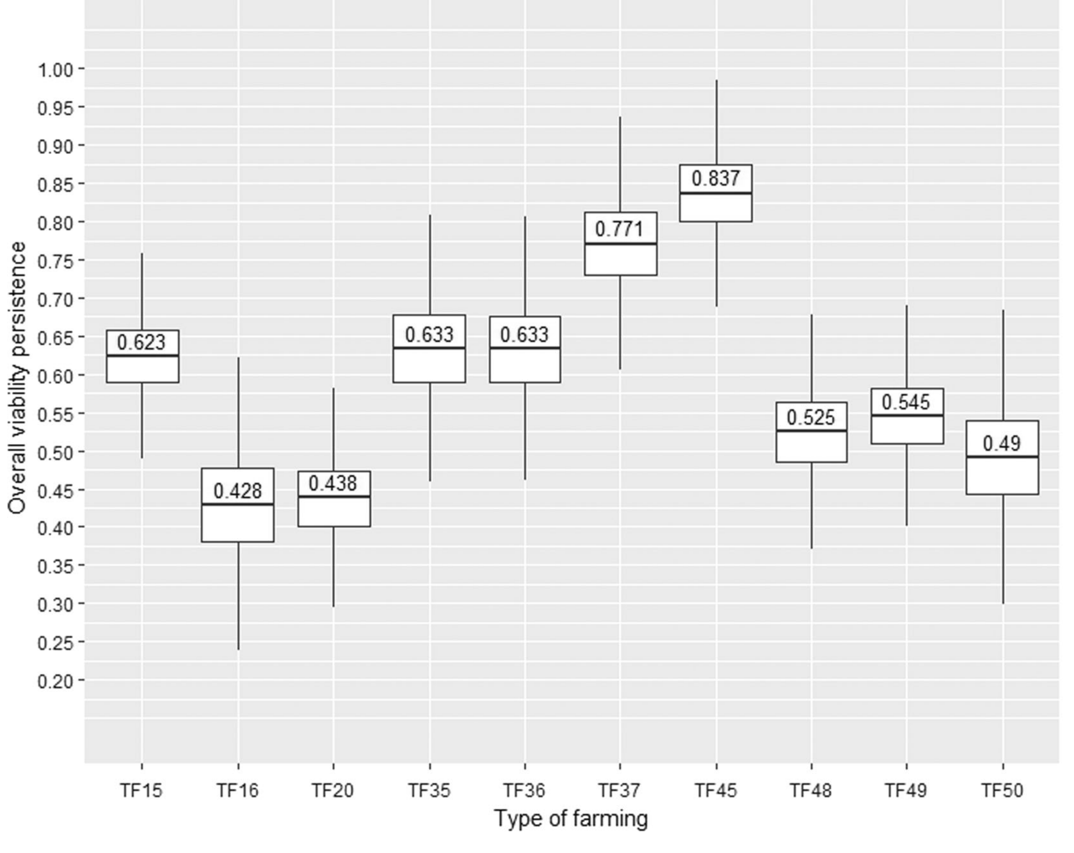

FIGURE 2 Distributions of the overall measures of viability persistence (Λ) by type of farming.

explained by the differences in labor and land ownership structures characterizing each TF in Spain. These results show that the higher the opportunity costs, the lower the overall viability persistence, suggesting that subsectors and farms with large shares of family labor and owned land are less likely to thrive over time.

For the reasons mentioned above, the different TFs analyzed are not ranked the same based on overall profitability criteria as they are based on viability persistence criteria, since these two concepts assess farms differently. However, by conducting a Wilcoxon signed ranks test, we can conclude that there was no significant difference between the rankings, demonstrating that profitability and viability are closely related concepts. In any case, assessing the viability persistence as proposed is a sounder way to measure farms' robustness and resilience (Vigani & Dwyer, 2020). Thus, the higher the viability persistence, the higher the resilience of the farms.

As shown in Table 5, the results also provide information about the farm variables that explain values of NVR persistently above the average for the TF. We can see changes in the significance of the coefficients compared to the results reported for the NROA. An explanation for this is that the same variables do not necessarily explain farms' profitability and viability, particularly when analyzing farms with heterogeneous labor and land ownership structures.

6 | CONCLUDING REMARKS

The first contribution of this study is the empirical analysis of the intensity of competition in the agricultural sector in Spain. The present paper has aimed to fill the gap in the literature on the PoP, which has so far focused on other economic sectors and countries. The results have revealed some aspects worth emphasizing because of their novelty compared to other studies.

First, we should highlight the inclusion of several lagged profit variables as explanatory variables in the dynamic panel model assessing the PoP. In models considering NROA as the dependent variable, statistically significant autoregressive coefficients were found in all the TFs analyzed, where current profitability is explained by profits lagged by between 2 and 5 years. Similar results were obtained from GMM-system models accounting for farm viability (i.e., considering NVR as the dependent variable). Consequently, it is confirmed that both profit and viability persistence in the farming sector are dynamic and complex processes in which abnormal performances are highly dependent on the farm profitability and viability over the preceding 2–5 years.

Furthermore, a significantly high overall abnormal profit persistence has been found in all Spanish TFs analyzed, much higher than that previously found in the food industry but similar in value to the food retailing sector. Consequently, this indicates weak market competition in Spanish agriculture, which conversely points to the high resilience of farms. However, the persistence of abnormal profits is highly heterogeneous across TFs, with lower PoP parameters in Horticulture and Cattle (which implies stronger competition) and higher values in the cases of Sheep and goats, Other field crops, Olives, and Dairy (TFs with a weaker level of competition).

The second contribution of the empirical analysis performed is the assessment of the persistence of farm viability by modeling the dynamics of the VR indicator. This indicator makes it possible to consider the farmers' opportunity costs due to the use of owned resources (mainly land and labor) in their farm, an element ignored by the ROA indicator. Therefore, this analysis is a valuable complement to the traditional assessment of farms' profit persistence. The results obtained show common elements in the estimates for the ROA and VR indicators in the different TFs analyzed, mainly in the structure of significant lags, which mostly reach three periods. This implies an evident relationship between profitability and viability. However, there are differences in the significant independent variables explaining the dynamics of these two indicators of farms' economic performance. The differences found are mainly explained by the heterogeneity in farms' land ownership and labor structures, which mean the explanatory factors of profitability and viability cannot be the same.

The analysis performed provides valuable results for policy decision-making. In this sense, the results provide useful insights on which to base changes to the subsidies and incentives granted by the agricultural policy. Since we have detected farms whose CAP payments are above or below the appropriate level to guarantee average profitability and viability, the reported evidence could be used to better tailor CAP payments. The results can also support decisions regarding competition policy, especially with respect to agricultural exceptions to competition law. For instance, for those TFs that have registered weaker market competition, it would be helpful to check whether reasons such as reducing asymmetries in the market and bargaining powers (e.g., Dairy) or increasing farmers' income (e.g., Sheep and goat) actually justify current exceptions to competition law. This is clearly a fruitful avenue for further research, as Velázquez and Buffaria (2017) pointed out. Similarly, these results can be useful for policymakers in pointing out the agricultural subsectors where government programs should be implemented to overcome barriers to entry, providing another way to promote competition.

This study is not without limitations, derived from the data and estimation methods. On the one hand, it is worth noting the potential shortcomings related to the farm sample considered for data gathering. The RECAN ignores microfarms (annual SGM lower than 8000 euros), which may result in a bias leading to the overestimation of the PoP (Hirsch, 2018; Tamirat et al., 2018). Moreover, given that most of the farms sampled stayed in the RECAN sample for long periods (an average of 7.1 years), estimations could be affected by survivorship bias (Linnainmaa, 2013), which again could lead to an overestimation of the PoP. It should also be pointed out that the GMM-system estimator used relies on several key assumptions, some of which are unlikely to be met in the case of the agricultural sector. The most notable is the assumption of the stationarity of the mean of the cross-sectional data (i.e., each farm should have reached its natural profit rate and be in a steady state at the beginning of the sample period). To overcome this type of limitation, authors such as Allison et al. (2017) and Williams et al. (2018) propose the implementation of the maximum likelihood structural equation modeling approach as an alternative to the GMM estimators. Under less restrictive conditions, it is expected to obtain more accurate and unbiased results. Therefore, this represents another future line of research in the analysis of profit and viability persistence, which can provide more robust results.

ACKNOWLEDGMENTS

This work was supported by the Andalusian Department of Economy and Knowledge and the European Regional Development Fund through the research project TRANSECOag (Grant PROYEXCEL_00459). The authors thank the Spanish Ministry of Agriculture, Fisheries, and Food (MAPA) for providing the microdata files from the Spanish Farm Accountancy Data Network (RECAN) used for the research. Funding for open access was provided Universidad de Córdoba/CBUA.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

Not applicable.

ORCID

José A. Gómez-Limón http://orcid.org/0000-0002-6364-0027
Sandra Sánchez-Cañizares http://orcid.org/0000-0003-0705-3327
Amalia Hidalgo-Fernández http://orcid.org/0000-0002-2764-6624
Ana M. Castillo-Canalejo http://orcid.org/0000-0002-5193-2989

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/agr.21822.

REFERENCES

Abdallah, W., Goergen, M., & O'Sullivan, N. (2015). Endogeneity: How failure to correct for it can cause wrong inferences and some remedies. *British Journal of Management*, *26*(4), 791–804. https://doi.org/10.1111/1467-8551.12113

Alarcón, S., & Sánchez, M. (2013). External and internal R&D, capital investment and business performance in the Spanish agri-food industry. *Journal of Agricultural Economics*, *64*(3), 654–675. https://doi.org/10.1111/1477-9552.12015

Allison, P. D., Williams, R., & Moral-Benito, E. (2017). Maximum likelihood for cross-lagged panel models with fixed effects. *Socius: Sociological Research for a Dynamic World*, *3*, 237802311771057. https://doi.org/10.1177/2378023117710578

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Argilés, J. M. (2001). Accounting information and the prediction of farm non-viability. *European Accounting Review*, *10*(1), 73–105. https://doi.org/10.1080/713764592

Assefa, T. T., Meuwissen, M. P. M., & Oude Lansink, A. G. J. M. (2015). Price volatility transmission in food supply chains: A literature review. *Agribusiness*, *31*(1), 3–13. https://doi.org/10.1002/agr.21380

Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Springer. https://doi.org/10.1007/978-3-030-53953-5

Biagini, L., Antonioli, F., & Severini, S. (2020). The role of the common agricultural policy in enhancing farm income: A dynamic panel analysis accounting for farm size in Italy. *Journal of Agricultural Economics*, *71*(3), 652–675. https://doi.org/10.1111/1477-9552.12383

Billor, N., Hadi, A. S., & Velleman, P. F. (2000). BACON: Blocked adaptive computationally efficient outlier nominators. *Computational Statistics & Data Analysis*, *34*(3), 279–298. https://doi.org/10.1016/S0167-9473(99)00101-2

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bonanno, A., Russo, C., & Menapace, L. (2018). Market power and bargaining in agrifood markets: A review of emerging topics and tools. *Agribusiness*, *34*(1), 6–23. https://doi.org/10.1002/agr.21542

Bradley, D., & Hill, B. (2015). *Cost of and good practices for FADN data collection*. European Commission. https://doi.org/10.2762/294831

Callen, J. L., & Morel, M. (2001). Linear accounting valuation when abnormal earnings are AR(2). *Review of Quantitative Finance and Accounting*, *16*(3), 191–204. https://doi.org/10.1023/A:1011255602608

Coppola, A., Amato, M., Vistocco, D., & Verneau, F. (2022). Measuring the economic sustainability of Italian farms using FADN data. *Agricultural Economics (Czech Republic)*, *68*(9), 327–337. https://doi.org/10.17221/169/2022-AGRICECON

Coppola, A., Scardera, A., Amato, M., & Verneau, F. (2020). Income levels and farm economic viability in Italian farms: An analysis of FADN data. *Sustainability*, *12*(12), 4898. https://doi.org/10.3390/su12124898

Crespo Cuaresma, J., & Gschwandtner, A. (2008). Tracing the dynamics of competition: Evidence from company profits. *Economic Inquiry*, *46*(2), 208–213. https://doi.org/10.1111/j.1465-7295.2007.00062.x

Davis, P., & Garcés, E. (2010). *Quantitative techniques for competition and antitrust analysis*. Princeton University Press. https://doi.org/10.1515/9781400831869

Eichenbaum, M. S., Hansen, L. P., & Singleton, K. J. (1988). A time series analysis of representative agent models of consumption and leisure choice under uncertainty. *The Quarterly Journal of Economics*, *103*(1), 51–78. https://doi.org/10.2307/1882642

Eklund, J. E., & Lappi, E. (2019). Persistence of profits in the EU: How competitive are EU member countries. *Empirica*, *46*(2), 327–351. https://doi.org/10.1007/s10663-018-9399-5

European Commission (EC). (2018). CAP specific objectives explained. Ensuring viable farm income. DG AGRI, European Commission.

Farm Accounting Data Network (FADN). (2022). FADN database. Directorate-General for Agriculture and Rural Development, European Commission. https://agridata.ec.europa.eu/extensions/FarmEconomyFocus/FADNDatabase.html

Finger, R., & El Benni, N. (2021). Farm income in European agriculture: New perspectives on measurement and implications for policy evaluation. *European Review of Agricultural Economics*, *48*(2), 253–265. https://doi.org/10.1093/erae/jbab011

Geroski, P. A., & Jacquemin, A. (1988). The persistence of profits: A European comparison. *The Economic Journal*, *98*(391), 375–389. https://doi.org/10.2307/2233373

Glen, J., Lee, K., & Singh, A. (2001). Persistence of profitability and competition in emerging markets. *Economics Letters*, *72*(2), 247–253. https://doi.org/10.1016/S0165-1765(01)00425-6

Goddard, J., Tavakoli, M., & 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. https://doi.org/10.1080/09603100500387139

Gschwandtner, A. (2005). Profit persistence in the 'very' long run: Evidence from survivors and exiters. *Applied Economics*, *37*(7), 793–806. https://doi.org/10.1080/0003684042000337406

Gschwandtner, A. (2012). Evolution of profit persistence in the USA: Evidence from three periods. *The Manchester School*, *80*(2), 172–209. https://doi.org/10.1111/j.1467-9957.2011.02277.x

Gschwandtner, A., & Hirsch, S. (2018). What drives firm profitability? A comparison of the US and EU food processing industry: Profitability in US and EU food processing. *The Manchester School*, *86*(3), 390–416. https://doi.org/10.1111/manc.12201

Guyomard, H. (2004). Impacts of alternative agricultural income support schemes on multiple policy goals. *European Review of Agriculture Economics*, *31*(2), 125–148. https://doi.org/10.1093/erae/31.2.125

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis*. Cengage Learning EMEA.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029–1054. https://doi.org/10.2307/1912775

Hartarska, V., Nadolnyak, D., & Sehrawat, N. (2022). Beginning farmers' entry and exit: Evidence from county level data. *Agricultural Finance Review*, *82*(3), 577–596. https://doi.org/10.1108/AFR-05-2021-0057

Hill, B., & Bradley, B. D. (2015). *Comparison of farmers' incomes in the EU Member States*. Policy Department B: Structural and Cohesion Policies, European Parliament. https://doi.org/10.2861/892960

Hirsch, S. (2018). Successful in the long run: A meta-regression analysis of persistent firm profits. *Journal of Economic Surveys*, *32*(1), 23–49. https://doi.org/10.1111/joes.12188

Hirsch, S., & Gschwandtner, A. (2013). Profit persistence in the food industry: Evidence from five European countries. *European Review of Agricultural Economics*, *40*(5), 741–759. https://doi.org/10.1093/erae/jbt007

Hirsch, S., & Hartmann, M. (2014). Persistence of firm-level profitability in the European dairy processing industry. *Agricultural Economics*, *45*(S1), 53–63. https://doi.org/10.1111/agec.12129

Hirsch, S., Lanter, D., & Finger, R. (2021). Profitability and profit persistence in EU food retailing: Differences between top competitors and fringe firms. *Agribusiness*, *37*(2), 235–263. https://doi.org/10.1002/agr.21654

Jehle, G. A., & Reny, P. J. (2011). *Advanced microeconomic theory*. Pearson Education Limited.

Josling, T., Anderson, K., Schmitz, A., & Tangermann, S. (2010). Understanding international trade in agricultural products: One hundred years of contributions by agricultural economists. *American Journal of Agricultural Economics*, *92*(2), 424–446. https://doi.org/10.1093/ajae/aaq011

Kingsley, A. F., & Graham, B. A. T. (2017). The effects of information voids on capital flows in emerging markets. *Journal of International Business Studies*, *48*(3), 324–343. https://doi.org/10.1057/s41267-016-0056-6

Klikocka, H., Zakrzewska, A., & Chojnacki, P. (2021). Characteristics of models of farms in the European Union. *Sustainability*, *13*(9), 4772. https://doi.org/10.3390/su13094772

Kryszak, Ł., Guth, M., & Czyżewski, B. (2021). Determinants of farm profitability in the EU regions. Does farm size matter? *Agricultural Economics (Czech Republic)*, *67*, 90–100. https://doi.org/10.17221/415/2020-AGRICECON

Latruffe, L. (2010). Competitiveness, productivity and efficiency in the agricultural and agri-food sectors. *OECD Food, Agriculture and Fisheries Papers*, *30*, 1–63. https://doi.org/10.1787/5km91nkdt6d6-en

Li, J., Ding, H., Hu, Y., & Wan, G. (2021). Dealing with dynamic endogeneity in international business research. *Journal of International Business Studies*, *52*(3), 339–362. https://doi.org/10.1057/s41267-020-00398-8

Linnainmaa, J. T. (2013). Reverse survivorship bias. *The Journal of Finance*, *68*(3), 789–813. https://doi.org/10.1111/jofi.12030

Liu, H., & Wilson, J. O. S. (2010). The profitability of banks in Japan. *Applied Financial Economics*, *20*(24), 1851–1866. https://doi.org/10.1080/09603107.2010.526577

Loughrey, J., O'Donoghue, C., & Conneely, R. (2022). Alternative measures of family farm viability—Incorporating gap measures. *Journal of Rural Studies*, *89*, 257–274. https://doi.org/10.1016/j.jrurstud.2021.11.022

Mathews, J. A. (2002). A resource-based view of Schumpeterian economic dynamics. *Journal of Evolutionary Economics*, *12*(1), 29–54. https://doi.org/10.1007/s00191-002-0106-z

Mazur, K. (2013). Isolating mechanisms as sustainability factors of resource-based competitive advantage. *Management*, *17*(2), 31–46. https://doi.org/10.2478/manment-2013-0053

McMillan, D. G., & Wohar, M. E. (2011). Profit persistence revisited: The case of the UK. *The Manchester School*, *79*(3), 510–527. https://doi.org/10.1111/j.1467-9957.2010.02177.x

Ministerio de Agricultura Pesca y Alimentación (MAPA). (2022). *Anuario de estadísitica*. Ministerio de Agricultura, Pesca y Alimentación.

Mishra, A., Wilson, C., & Williams, R. (2009). Factors affecting financial performance of new and beginning farmers. *Agricultural Finance Review*, *69*(2), 160–179. https://doi.org/10.1108/00021460910978661

Moral-Benito, E., Allison, P., & Williams, R. (2019). Dynamic panel data modelling using maximum likelihood: An alternative to Arellano–Bond. *Applied Economics*, *51*(20), 2221–2232. https://doi.org/10.1080/00036846.2018.1540854

Mueller, D. C. (1977). The persistence of profits above the norm. *Economica*, *44*(176), 369–380. https://doi.org/10.2307/2553570

Mueller, D. C. (1986). *Profits in the long run*. Cambridge University Press. https://doi.org/10.1017/CBO9780511664731

Nilsson, P., & Wixe, S. (2021). Assessing long-term effects of CAP investment support on indicators of farm performance. *European Review of Agricultural Economics*, *49*(4), 760–795. https://doi.org/10.1093/erae/jbab038

O'Donoghue, C., Devisme, S., Ryan, M., Conneely, R., Gillespie, P., & Vrolijk, H. (2016). Farm economic sustainability in the European Union: A pilot study. *Studies in Agricultural Economics*, *118*(3), 163–171. https://doi.org/10.7896/j.1631

Opstad, L., Idsø, J., & Valenta, R. (2022). The dynamics of the profitability and growth of restaurants; The case of Norway. *Economies*, *10*(2), 53. https://doi.org/10.3390/economies10020053

Piet, L., & Desjeux, Y. (2021). New perspectives on the distribution of farm incomes and the redistributive impact of CAP payments. *European Review of Agricultural Economics*, *48*(2), 385–414. https://doi.org/10.1093/erae/jbab005

Red Contable Agraria Nacional (RECAN). (2022). *Red contable agraria nacional (RECAN). Metodología y resultados empresariales provisionales 2020*. Ministerio de Agricultura, Pesca y Alimentación.

Sánchez-Cañizares, S. M., Guerrero-Baena, M. D., & Gómez-Limón, J. A. (2021). Factors influencing the simultaneous adoption of risk management instruments in Mediterranean irrigated agriculture. *Journal of Environmental Planning and Management*, *65*(6), 1088–1109. https://doi.org/10.1080/09640568.2021.1922364

Schumacher, S. K., & Boland, M. A. (2005). The persistence of profitability among firms in the food economy. *American Journal of Agricultural Economics*, *87*(1), 103–115. https://doi.org/10.1111/j.0002-9092.2005.00705.x

Spicka, J., Hlavsa, T., Soukupova, K., & Stolbova, M. (2019). Approaches to estimation the farm-level economic viability and sustainability in agriculture: A literature review. *Agricultural Economics (Czech Republic)*, *65*(6), 289–297. https://doi.org/10.17221/269/2018-AGRICECON

Tamirat, A. S., Trujillo-Barrera, A., & Pennings, J. M. E. (2018). *Do profit rates converge? Evidence on the persistence of farm profit in the long-run*. Paper presented at the Agricultural & Applied Economics Association 2018 AAEA Annual Meeting, Washington, DC, August 5–7, 2018.

Tey, Y. S., & Brindal, M. (2015). Factors influencing farm profitability. In E. Lichtfouse (Ed.), *Sustainable agriculture reviews* (pp. 235–255). Springer. https://doi.org/10.1007/978-3-319-09132-7-5

Velázquez, B., & Buffaria, B. (2017). About farmers' bargaining power within the new CAP. *Agricultural and Food Economics*, *5*(1), 16. https://doi.org/10.1186/s40100-017-0084-y

Vigani, M., & Dwyer, J. (2020). Profitability and efficiency of high nature value marginal farming in England. *Journal of Agricultural Economics*, *71*(2), 439–464. https://doi.org/10.1111/1477-9552.12351

Vrolijk, H. C. J., De Bont, C. J. A. M., Blokland, P. W., & Soboh, R. A. M. E. (2010). *Farm viability in the European Union: Assessment of the impact of changes in farm payment*. LEI.

Weber, S. (2010). Bacon: An effective way to detect outliers in multivariate data using Stata (and Mata). *The Stata Journal: Promoting Communications on Statistics and Stata*, *10*(3), 331–338. https://doi.org/10.1177/1536867x1001000302

Williams, R., Allison, P. D., & Moral-Benito, E. (2018). Linear dynamic panel-data estimation using maximum likelihood and structural equation modeling. *The Stata Journal: Promoting Communications on Statistics and Stata*, *18*(2), 293–326. https://doi.org/10.1177/1536867X1801800201

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of Financial Economics*, *105*(3), 581–606. https://doi.org/10.1016/j.jfineco.2012.03.005

How to cite this article: Gómez-Limón, J. A., Sánchez-Cañizares, S., Hidalgo-Fernández, A., & Castillo-Canalejo, A. M. (2023). Profit and viability persistence: Evidence from the Spanish agricultural sector. *Agribusiness*, *39*, 1300–1332. https://doi.org/10.1002/agr.21822

APPENDIX A

TABLE A1 Descriptive statistics of the variables included in the models by types of farming.

Variable	TF15. COP		TF16. Other field crops		TF20. Horticulture		TF35. Wine		TF36. Orchards-fruits	
	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.
ROA	9.04	9.81	11.67	12.55	16.93	17.04	11.97	10.07	12.95	13.81
VR	0.83	0.87	1.03	1.03	1.36	1.54	1.12	0.94	1.21	1.33
TOUTPUT	58.37	79.13	84.75	145.69	172.77	444.61	65.55	79.34	123.08	458.41
TASSEST	393.99	654.14	409.61	709.97	500.21	1456.24	361.48	409.35	426.65	955.73
GROWTHTA	1.52	17.43	3.11	19.36	6.92	134.51	3.01	16.30	4.17	34.55
LEVERAGE	3.74	10.60	3.76	9.39	4.16	17.53	1.93	6.43	3.05	17.08
GEAR	6.30	70.01	6.18	26.86	13.45	484.30	1.99	53.47	13.08	498.15
AGE	56.51	11.99	54.82	12.09	51.80	11.87	54.77	12.15	55.88	12.82
SEX	0.03	0.18	0.05	0.22	0.07	0.26	0.06	0.24	0.04	0.20
AGTRAIN	0.10	0.30	0.11	0.31	0.20	0.40	0.06	0.24	0.18	0.38
FAMLAB	91.07	19.36	86.54	22.81	59.77	29.52	69.24	23.06	65.40	30.29
LANDOWN	63.17	38.16	59.31	38.84	67.13	40.78	87.70	26.16	82.77	32.31
IRRIG	25.69	37.29	58.01	39.52	61.85	42.78	7.74	21.91	71.21	38.91
ALTITUDE	0.71	0.45	0.56	0.50	0.44	0.50	0.86	0.35	0.43	0.50
LFA	0.68	0.46	0.53	0.50	0.54	0.50	0.64	0.48	0.43	0.49
CAPINT	9.30	15.22	7.43	8.18	4.78	12.00	6.93	7.65	9.36	109.48
LABINT	0.07	0.83	0.06	0.07	0.08	1.08	0.08	0.06	0.10	1.31
ICINT	0.70	0.91	0.69	0.38	0.48	1.15	0.30	0.32	0.50	4.06
OUTSOUR	12.20	11.32	13.89	13.20	26.73	17.02	31.06	20.44	25.37	18.86
ORGANIC	0.04	0.20	0.02	0.15	0.11	0.31	0.08	0.28	0.11	0.31
SUBSID	26.64	14.11	23.91	17.68	4.91	10.50	8.96	10.72	10.50	15.85
DIVERS	2.35	15.36	1.69	7.83	0.38	3.85	0.85	5.67	0.00	16.72
	TF37. Olives		TF45. Dairy		TF48. Sheep and goats		TF49. Cattle		TF50. Granivores	
Variable	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.
ROA	12.18	11.60	10.88	8.78	15.09	12.33	9.49	8.53	15.05	14.89
VR	1.31	1.35	1.12	0.96	1.15	0.94	0.80	0.81	1.47	1.55
TOUTPUT	61.20	129.24	223.50	254.01	88.02	118.26	73.40	221.20	277.79	536.40
TASSEST	410.74	799.72	598.10	488.71	347.71	359.18	392.32	595.56	535.90	655.08
GROWTHTA	2.83	15.99	0.53	15.12	2.01	18.28	1.18	15.34	5.49	33.22
LEVERAGE	0.43	2.78	4.58	9.44	4.04	10.50	3.47	9.83	10.21	22.86

TABLE A1 (Continued)

Variable	TF37. Olives		TF45. Dairy		TF48. Sheep and goats		TF49. Cattle		TF50. Granivores	
	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.
GEAR	1.49	61.23	6.51	18.55	11.67	433.58	6.19	53.70	15.00	414.25
AGE	58.12	11.27	52.29	10.22	53.88	11.48	52.90	11.47	52.83	11.33
SEX	0.18	0.38	0.08	0.27	0.06	0.23	0.12	0.33	0.08	0.27
AGTRAIN	0.14	0.34	0.11	0.31	0.09	0.28	0.09	0.28	0.21	0.41
FAMLAB	62.70	26.40	87.04	23.86	85.96	23.36	91.26	20.80	80.13	30.17
LANDOWN	85.67	29.84	52.60	37.90	45.75	42.68	43.13	40.86	39.49	44.29
IRRIG	27.28	40.29	4.15	17.33	4.39	16.73	2.50	11.77	11.51	27.80
ALTITUDE	0.71	0.46	0.60	0.49	0.80	0.40	0.74	0.44	0.64	0.48
LFA	0.70	0.46	0.84	0.37	0.90	0.31	0.89	0.31	0.61	0.49
CAPINT	9.46	9.61	3.80	10.91	5.96	9.71	8.05	29.53	3.66	3.77
LABINT	0.09	0.08	0.03	0.11	0.06	0.07	0.08	1.13	0.03	0.04
ICINT	0.41	0.26	0.74	0.88	0.65	0.39	0.78	1.33	0.56	0.27
OUTSOUR	29.65	17.47	4.48	5.95	10.39	10.88	9.45	10.36	8.61	11.94
ORGANIC	0.27	0.45	0.02	0.14	0.07	0.26	0.07	0.26	0.03	0.17
SUBSID	24.08	14.99	11.90	7.83	20.76	15.80	28.82	22.47	4.56	7.81
DIVERS	0.14	2.06	7.37	12.86	13.72	22.75	15.85	20.26	13.89	22.04

Abbreviations: AGE, farmer's age; AGTRAIN, farmer's practical experience or formal training; ALTITUDE, farm altitude location; CAPINT, total assets/total output; COP, cereals, oilseeds, and protein; DIVERS, other farm output/total farm output; FAMLAB, family labor/total farm labor; GEAR, total liability/owner's equity; GROWTHTA, % of increase in total farm assets; ICINT, intermediate consumption/total output; IRRIG, irrigated area/total farmland; LABINT, total labor in working hours/total output; LANDOWN, owned land/total farmland; LEVERAGE, total debt/total assets; LFA, less favored area; ORGANIC, implementation of organic production; OUTSOUR, cost of practices subcontracted/total costs; RECAN, red contable agraria nacional; ROA, return on assets; SEX, farmer's sex; SUBSID, subsidy payments/total farm income; TASSEST, total farm assets; TF, type of farming; TOUTPUT, total farm output; VR, viability ratio.

TABLE A2 Spearman correlation coefficients between all pairs of variables.

Variable	TASSE-TS	GROWH-TTA	LEVER-AGE	GEAR	AGE	SEX	AG-TRAIN	FAML-AB	LANDO-WN	IRRIG	ALTITU-DE	LFA	CAPI-NT	LABINT	ICINT	OUTS-OUR	ORGA-NIC	SUBSID	DIVERS	ROA	VR
TOUTPUT	0.591**	0.134**	0.268**	0.267**	−0.125**	−0.071**	0.122**	−0.329**	−0.248**	−0.002	−0.049**	0.021**	−0.593**	−0.733**	−0.027**	0.146**	−0.054**	−0.333**	0.230**	0.270**	0.450**
TASSETS	1.000	0.084**	0.158**	0.158**	−0.080**	−0.066**	0.072**	−0.211**	0.041**	−0.024**	−0.056**	−0.040**	0.228**	−0.479**	0.072**	0.013**	0.034**	−0.002	0.183**	−0.269**	0.128**
GROWHTTA		1.000	0.032**	0.032**	0.013**	−0.024**	0.003	−0.028**	−0.056**	0.057**	−0.007	−0.014**	−0.073**	−0.173**	−0.246**	0.059**	0.005	−0.068**	−0.038**	0.259**	0.330**
LEVERAGE			1.000	0.997**	−0.144**	−0.045**	0.047**	0.004	−0.218**	0.005	0.037**	0.048**	−0.174**	−0.226**	0.159**	0.055**	−0.026**	−0.026**	0.192**	−0.052**	−0.020**
GEAR				1.000	−0.143**	−0.045**	0.046**	0.005	−0.215**	0.005	0.037**	0.048**	−0.173**	−0.226**	0.158**	0.054**	−0.026**	−0.025**	0.192**	−0.051**	−0.019**
AGE					1.000	−0.002	−0.126**	−0.018**	0.153**	0.028**	0.013**	−0.040**	0.079**	0.109**	−0.039**	−0.004	−0.020**	0.017**	−0.094**	0.011**	−0.001
SEX						1.000	0.086**	0.021**	0.041**	−0.055**	−0.049**	0.002	0.015**	0.087**	−0.026**	−0.037**	0.066**	0.004	−0.019**	0.005	−0.037**
AGTRAIN							1.000	−0.085**	−0.047**	0.122**	−0.146**	−0.096**	−0.079**	−0.072**	−0.017**	0.051**	0.038**	−0.040**	0.010**	0.013**	0.037**
FAMLAB								1.000	−0.121**	−0.206**	0.095**	0.142**	0.193**	−0.016**	0.287**	−0.740**	−0.104**	0.282**	0.162**	−0.011**	−0.145**
LANDOWN									1.000	0.116**	−0.026**	−0.100**	0.349**	0.295**	−0.248**	−0.095**	0.063**	−0.080**	−0.167**	−0.105**	−0.067**
IRRIG										1.000	−0.286**	−0.367**	−0.016**	0.009**	−0.148**	0.209**	−0.066**	−0.152**	−0.234**	0.016**	0.057**
ALTITUDE											1.000	0.405**	0.020**	0.023**	0.014**	−0.014**	0.008*	0.103**	0.107**	0.017**	−0.014**
LFA												1.000	−0.057**	0.017**	0.146**	−0.096**	0.038**	0.189**	0.158**	0.042**	−0.016**
CAPINT													1.000	0.403**	0.080**	−0.139**	0.098**	0.408**	−0.096**	−0.602**	−0.412**
LABINT														1.000	−0.056**	0.145**	0.087**	0.183**	−0.229**	−0.218**	−0.510**
ICINT															1.000	−0.333**	−0.078**	0.407**	0.234**	−0.466**	−0.490**
OUTSOUR																1.000	0.082**	−0.125**	−0.174**	0.035**	0.075**
ORGANIC																	1.000	0.074**	−0.020**	−0.018**	0.022**
SUBSID																		1.000	0.101**	−0.117**	−0.094**

TABLE A2 (Continued)

Variable	TASSE-TS	GROWH-TTA	LEVER-AGE	GEAR	AGE	SEX	AG-TRAIN	FAML-AB	LANDO-WN	IRRIG	ALTITU-DE	LFA	CAPI-NT	LABINT	ICINT	OUTS-OUR	ORGA-NIC	SUBSID	DIVERS	ROA	VR
DIVERS																			1.000	−0.029**	−0.004
ROA																				1.000	0.821**
VR																					1.000

Abbreviations: AGE, farmer's age; AGTRAIN, farmer's practical experience or formal training; ALTITUDE, farm altitude location; CAPINT, total assets/total output; DIVERS, other farm output/total farm output; FAMLAB, family labor/total farm labor; GEAR, total liability/owner's equity; GROWTHTA, % of increase in total farm assets; ICINT, intermediate consumption/total output; IRRIG, irrigated area/total farmland; LABINT, total labor in working hours/total output; LANDOWN, owned land/total farmland; LEVERAGE, total debt/total assets; LFA, less favored area; ORGANIC, implementation of organic production; OUTSOUR, cost of practices subcontracted/total costs; ROA, return on assets; SEX, farmer's sex; SUBSID, subsidy payments/total farm income; TASSEST, total farm assets; TOUTPUT, total farm output; VR, viability ratio.

* and ** indicate significant at 5% and 1% levels, respectively.

AUTHOR BIOGRAPHIES

José A. Gómez-Limón born in Cordoba (Spain) in 1968, I got my degrees of B. Agricultural Engineer (1993) and Agricultural Economics, PhD (1996), both in the University of Cordoba (Spain). From 1997 to the present, I have worked at the Universities of Valladolid and Cordoba (Spain) as an Associate and full Professor in the Departments of Agricultural Economics. In these professional posts, I have reached a wide experience in teaching (+25 academic courses in Agricultural Policy and Agricultural Business Administration) and research in agricultural policy and economics (+90 peer-reviewed papers in international journals and a full array of other scientific documents). Dealing with my expertise in research and consultancy work, I could point out that I have obtained 32 public-sector financed projects and contracts, and in 11 of these, I was the director. The purpose of most of them was public decision-making support, especially dealing with agricultural policy. Google Scholar: http://scholar.google.es/citations?user=uI-DdxUAAAAJ.

Sandra Sánchez-Cañizares, I am the Head of the Business Direction and Applied Economics Research Group and work as a Professor of the Department of Business Organization at the University of Cordoba (Spain). I hold two bachelor's degrees in business administration and in Market Research and Techniques. I hold a European Doctoral Degree in Economics (PhD) and I was the Vice-dean of International and Institutional Affairs at the Faculty of Law and Business Sciences for 5 years. I am the author of more than 80 papers published in different academic journals with impact factor. My main lines of research are Organizational Behavior, Tourism, Entrepreneurship, and Business Internationalization. I have been a visiting professor in different universities in the United States, Europe, Africa, and South America. I have been both IP and a participant in different UE and national research projects. Google Scholar: https://scholar.google.es/citations?user=P_zO2nYAAAAJ&hl=es&oi=ao.

Amalia Hidalgo-Fernández born in Cordoba (Spain) in 1963, I graduated in Economic and Business Sciences (1985), PhD (2011) both from the University of Córdoba (Spain). I am the author of more than 20 articles published in magazines from different countries. I am also the author of more than 10 book chapters and two books. I have participated in different congresses, seminars, and conferences. I have also participated in various $R + D + i$ projects. I have carried out part of his research period at the center of recognized international prestige in the town of Bologna (Italy), with a scholarship obtained in a competitive public tender. Regarding the line of research followed, the economic valuation of natural resources, the platform economy, tourism, corporate social responsibility, the social economy, and cooperatives stand out. Currently, this research focuses on analyzing tourist destinations, tourism and heritage, and corporate social responsibility. Google Scholar: https://scholar.google.es/citations?user=nSNNPL8AAAAJ&hl.

Ana M. Castillo-Canalejo, I hold a European PhD degree in Management Science from the University of Cordoba. I currently work as a lecturer in the Statistics and Business Administration Department at the University of Cordoba (Spain). I have conducted research projects in Africa and have published over 10 scientific articles related to community-based tourism and environment. I have written more than 30 papers that have been published in different academic journals related to Tourism. My main lines of research are tourism economics, environment, wine and gastronomy tourism, community-based tourism in developing countries, tourism demand, tourist satisfaction, and loyalty. I have participated in research projects financed by public funds and performed research stays in different European and African countries. I have worked as a consultant for Arthur Andersen. Google Scholar: https://scholar.google.es/citations?hl=es&user=pOmj64QAAAAJ.