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Abstract: This article analyzes persistence and the drivers of profitability in US and EU food processing using GMM estimations. Due to different firm size structures first comparable samples of US and EU food processors are derived using Propensity Score Matching. The GMM results indicate that profit persistence in food processing is lower than in other manufacturing sectors. Firm-specific drivers of profitability are size, growth and financial risk. Regarding industry characteristics the growth rate significantly influences profitability. The findings provide insights for the management of food processing firms as well as for policy decisions aiming to counter power imbalances in the food sector.

Keywords: Firm profit, persistence, food industry, GMM panel estimation, propensity score matching.

JEL codes: L12, L66, M21

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Non-technical summary

The present project analyses what drives profitability in the food sector and compares the results with the manufacturing industry in general but also between the European Union and the United States.

One of the main findings is that competition is stronger and profitability is lower within the food sector as compared with the manufacturing sector in general. This is mainly attributable to a high market saturation and to the fierce competition between the big retail companies. While the competition profits the consumer, it puts strong bargaining pressure on the producers. Therefore, one of the main drivers of profitability and profit persistence within the food sector is firm size. Larger producers seem to be in a better bargaining position against the retail sector and this seems to be both the case in the EU and in the US.

A determinant where the food sector seems to differ between the two regions is firm's growth. While the impact of firm's growth on profitability is positive in the US, it is insignificant in the EU. This may be because while growing firms have to take into consideration higher costs and this may decrease profitability.

And this may explain yet another difference between the determinants of profitability in the food sector in the US and in the EU. While the impact of (long-term) debt is positive in the US, it is negative in the EU. By having easier access to debt, US firms are presumably able to better counteract this potentially negative effect of growth. Long-term debt can enable firms to make the necessary investments that help to ensure competitiveness in times of crisis. In the EU firms indebted in the long run seem to find it more difficult to cope with risk.

The results have not only purely descriptive value but can also be useful when designing policies aimed at supporting food sector firms or the food sector as a whole. This is important as today firms are facing economic circumstances characterized by reduced entry barriers and possibilities to operate in previously hardly accessible foreign markets. Those developments are a consequence of intensified globalization represented by trade agreements such as the NAFTA or the formation of a single market for goods and services within the EU. However, these deregulations of borders and international trade have led to a significant intensification of competition among firms across many sectors. Pressure on the margins and competitiveness of food processors is further intensified by increasing uncertainty in raw material markets and strong concentration in retail sectors. A high and constantly growing share of private labels further increases power imbalances between processors and retailers. In the EU the food sector has already drawn attention of competition authorities with a focus of retailer's buyer power vis-à-vis the producers. The present results confirm the need for policy interventions at the downstream level. Moreover, the positive impact of firm size and growth on profitability indicates that small firms and firms with low growth are in a disadvantageous position. Thus, policy measures which address the industry could focus on a decrease of administrative burdens particularly for the large number of small enterprises. Furthermore, policy actions that decrease unfavourable financial risk factors -particularly short term risk in the US and long term risk in the EU- might strengthen processors and help to counter power imbalances. Finally, the US results indicate that in times of economic crisis measures that facilitate access to long term debt can counter the negative impact of the crisis.

1. Introduction

The analysis of firm profits that diverge from the competitive profit rate is one of the pivotal fields of study within economic research (e.g. Porter 1980; Barney 1991; McGahan and Porter 2003; Hirsch and Gschwandtner 2013).

From a theoretical point of view the neoclassical model of perfect competition postulates that firm profits above or below the competitive norm cannot persist in the long run as such ‘abnormal’ profits are immediately driven back to the norm by competitive forces (e.g. Carlton and Perloff 2005). Nevertheless, in the real world, profits that diverge from the competitive norm are, despite declining trade barriers, a rather usual phenomenon for many industrial markets.

Starting with the contributions of Mueller (1986, 1990) many empirical studies have shown that industries are in general characterized by a large number of firms generating profits that diverge from the competitive norm in the long run -a phenomenon usually referred to as profit persistence. The majority of those studies either considers entire economies or is restricted to firms operating in manufacturing sectors of specific countries. Some important studies on profit persistence include: Waring (1996), Wiggins and Ruefli (2002), Chacar and Vissa (2005), and Gschwandtner (2005), for the US manufacturing sector; Glen *et al.* (2001) for 7 developing countries; Goddard *et al.*, (2005), Bou and Satorra (2007), Pattitoni *et al.* (2014), and Gallizo *et al.* (2014) for the EU manufacturing and service sector.

While most previous studies on food industry performance, focus on more specific aspects such as the impact of retailer concentration on industry innovation (Weiss and Wittkopp 2005) or the influence of diversification strategies on profit (Dorsey and Boland 2009) as yet, only a few studies have explicitly analyzed the persistence and drivers of ‘abnormal’ profits in the food sector. For the US food economy Schumacher and Boland (2005) using variance decomposition methods find that industry effects are more important for profit persistence than corporate effects. Nevertheless, Schumacher and Boland do not quantify the firm and industry characteristics (such as firm size or industry concentration) which determine the extent of ‘abnormal’ profits. Chaddad and Mondelli (2013) apply hierarchical linear modeling (HLM) to the US food economy to determine the impact of industry and firm effects as well as those structural factors that affect the performance of firms in this sector. They find that firm effects outweigh industry effects and that structural firm- and industry variables such as corporate R&D intensity and industry capital intensity are significant drivers of firm profits. In a similar study Hirsch *et al.* (2014) apply HLM to the EU food processing industry. Their results also provide evidence for dominant firm effects. Furthermore, firm size and industry concentration

are identified as the main drivers of performance. However, the HLM approach is of static nature and not suitable to capture the dynamics of firm profits over time. Nevertheless, it can be assumed that the conditional probability that a firm will achieve a specific degree of ‘abnormal’ profits in the future is a dynamic function of ‘abnormal’ profits in the past (e.g. Hsiao 2007; Baltagi 2008). Due to this reason Hirsch and Gschwandtner (2013) implement a dynamic panel model to a large panel of EU food processors. They show that due to high market saturation and strong bargaining pressure from the retail sector the persistence of ‘abnormal’ firm profits in the EU food industry is significantly lower compared to other manufacturing sectors. As the main profit driver they identify firm size as besides economies of scale larger firms are in a better bargaining position against the retail sector.

In summary as yet no study exists that estimates the degree of profit persistence as well as the structural drivers of ‘abnormal’ firm profits in the US food sector using a dynamic approach. Our primary objective is therefore to provide evidence on the drivers and persistence of ‘abnormal’ firm profits in the US food processing industry by analyzing a sample of 125 publicly quoted US food processors over the time span 1990-2008. Moreover, we aim to compare the US results to a matched sample of EU food processing firms. We advance the literature by first applying propensity score matching (PSM) in order to derive a sample of EU firms which is comparable to the US sample. This is necessary due to significant structural differences between the US and EU food processing industry -in particular regarding firm size. Subsequently, we apply the GMM dynamic panel estimator to the US and the matched EU panel to determine the extent of profit persistence as well as those factors that have an impact on the degree of ‘abnormal’ firm profits. The US results are the first of this kind and we identify significant differences to the results of the matched EU panel.

In the next section we present the theoretical background based on which the drivers of firm profitability are identified. Subsequently the econometrics used to match the US and EU panel and to estimate the persistence and drivers of ‘abnormal’ firm profits are described. We then provide an overview of US and EU food processing and a description of the data. This is followed by the discussion of the empirical results. Finally, conclusions are drawn and implications derived.

2. Theoretical background

Classical industrial organization theory and in particular the structure-conduct-performance (SCP) paradigm assumes that industry characteristics which determine the extent of entry

barriers and competition are the main determinant of firm performance. Among those characteristics are the degree of concentration as well as the size and growth rate of an industry (Bain 1956, 1968; Porter 1980). While the SCP has been heavily criticized for its assumption of a direct impact of industry structure on profitability (e.g. Tirole 1988) the Market-Based View (MBV), as a dynamic extension of the SCP, additionally considers the strategic positioning of firms within the industry (Welge and Al-Laham 2008). Consequently, besides industry structure strategic management literature stresses the importance of business-specific resources as determinants of profitability (Goddard *et al.* 2005). According to Penrose (1959) firms are to be interpreted as bundles of physical and intangible resources. Divergence of performance between firms, emerges due to differences in endowment with those resources. According to the resource based view (RBV), firms endowed with specific valuable, rare and inimitable resources are more competitive and hence outperform the market (Barney 1991; Peteraf 1993). Those resources include tangible i.e. financial and physical factors of production as well as intangible factors such as technology and reputation (Claver *et al.* 2002; Goddard *et al.* 2005). When estimating the impact of firm specific resources in particular firm size, market share, growth, age, advertising, R&D, patents and financial risk have been identified as empirical proxies by previous literature (e.g. Yurtoglu 2004; Chaddad and Mondelli, 2013).

In the 1980's a supplementary strand of research known as the 'New Empirical Industrial Organization' literature (NEIO) has emerged (e.g. Bresnahan, 1981). NEIO studies model the strategic and competitive behavior of firms on the basis of game theory and structural econometric approaches. Those models enable to consider more detailed industry- and firm-specific factors than what modeling based on the MBV and the RBV can capture. Among those factors are demand structures, cost advantages and collusive behavior that decreases competition. However, while NEIO provides a useful background for case studies, as it allows for a detailed modeling of specific sub-industries (e.g. dairy processing or meat processing), we aim to provide generalizable insights of profitability across industries of the food sector based on the structural relationships suggested by the MBV and the RBV. (Kadiyali *et al.*, 2001)

3. Methodology

We first employ PSM, a method commonly applied in observational studies to eliminate selection biases, to construct an EU sample that matches the 125 publicly quoted US firms (Huang *et al.* 2013). Afterwards, we quantify the persistence of 'abnormal' firm profits as well as the factors that have an influence on the degree of 'abnormal' firm profits for both samples.

3.1 Propensity Score Matching

PSM is commonly applied in observational studies to eliminate selection biases that arise if observations are not randomly assigned to receive a specific treatment (Heinrich *et al.* 2010). The main objective of PSM is to match an untreated group to a group that receives a specific treatment such that the observations of the untreated group can be compared to those of the treated group regarding all attributes except for the treatment (Huang *et al.* 2013).

PSM has been employed in diverse fields of study such as the evaluation of labor market policies (e.g. Dehejia and Wahba 1999), or medical and pharmacoepidemiological research (e.g. Perkins *et al.* 2000; Austin 2008) (Caliendo and Kopeining 2005). Regarding the agribusiness sector Cavatassi *et al.* (2011) examine the effect of an agricultural program to increase potato production in Ecuador. They show that participants in the program generate enhanced yields compared to a matched sample of non-participants. Bontemps *et al.* (2013) derive matched samples of French cheese industry firms and estimate the impact of adopting quality labels on firm survival. The results indicate that quality label effects reduce the risk of non-survival for smaller firms. In order to estimate the effect of a ban on antibiotics on U.S. hog farmers Key and McBride (2014) use PSM to derive matched samples of antibiotic users and non-users. They find that the output of users is 1.0 to 1.3% higher compared to the matched sample of non-users.

In general, PSM can be applied to settings where a treatment (e.g. medication, labor market policy, agricultural policy intervention) is given to a specific group of individuals. The majority of research focuses on the outcome of the treatment, referred to as the ‘average treatment effect on the treated (ATT)’, by comparing the treated sample with a constructed matched sample of untreated observations. Algebraically the ATT can be defined as:

$$ATT = E[Y(1) | D = 1] - E[Y(0) | D = 1], \quad (1)$$

where $Y(D)$ is either the outcome of an observation that has been treated (if $D = 1$) or of an observation that has not been exposed to treatment (if $D = 0$). Thus, the first conditional expectation in (1) refers to the mean outcome of the treatment across observations in the treated group while the second one indicates the mean outcome of observations in the treated group assuming that they did not receive treatment. However as $E[Y(0) | D = 1]$ is not observable a suitable substitute has to be constructed. Simply using the mean outcome value across all untreated observations $E[Y(0) | D = 0]$ leads to biased results as observations are not randomly assigned to treated and untreated groups. Thus, those factors (X) which have an impact on the likelihood of receiving treatment also have an impact on the treatment outcome (Caliendo and Kopeining 2005; Briggeman *et al.* 2009). One possible approach to construct a suitable proxy

for $E[Y(0)|D=1]$ is to use a balancing score $P(D=1|X) = P(X)$ which indicates the probability that an observation receives treatment, given the covariates X (Heckman *et al.* 1997; Caliendo and Kopeining 2005). $P(X)$ is usually referred to as an observation's Propensity Score (PS) (Rosenbaum and Rubin 1983; Becker and Ichino 2002). PS's are calculated using a probit regression where the binary dependent variable takes a value of 1 for observations in the treated group and a value of 0 for non-treated observations. As independent variables (X) those factors are included which have an impact on receiving the treatment and on the treatment-outcome (Rubin and Thomas 1996; Heckman *et al.* 1997; Smith and Todd 2005). The estimated values of the dependent variable of this regression constitute the observations' PS's. Using the PS's the ATT can be calculated as:

$$ATT(P(X)) = E_{P(X)|D=1} \{E[Y(1)|D=1, P(X)] - E[Y(0)|D=0, P(X)]\}, \quad (2)$$

where $E_{P(X)|D=1}$ denotes the mean over the area of overlapping PS's for the treated and untreated group (Briggeman *et al.* 2009). The overlapping area of PS's is referred to as the area of 'common support' (Becker and Ichino 2002; Caliendo and Kopeining 2005). Thus, the ATT defined by (2) is the average difference in the treatment-outcome variable between the treated and the untreated group over the area of common support. While equation (2) is defined over the common support area some problems regarding the goodness of the matching can arise when solely relying on the common support criterion. First, intervals within the area of common support which are characterized by minor overlap between PS's of both groups are not considered (Caliendo and Kopeining 2005). Second, observations with PS's marginally outside the area of common support might still be adequate matches for observations of the opposing group slightly inside the area of common support (Smith and Todd 2005). In order to eliminate this 'common support problem' several matching algorithms can be applied in addition to the precondition of common support. The method we apply is referred to as radius matching where only those untreated observations are included that lie within a specific radius (e.g. 0.05 or 0.1) of the PS's of observations in the treated group (Becker and Ichino 2002; Caliendo and Kopeining 2005). Radius matching accounts for areas with only minor PS overlap within the common support interval and considers suitable observations marginally outside this interval (Smith and Todd 2005).

Compared to this standard matching procedure our approach is slightly different. We do not attempt to match US and EU firms based on propensity scores that are calculated by means of all structural firm characteristics and afterwards calculate the ATT (i.e. differences in 'abnormal' profits between US and matched EU firms) based on (2). In contrast we take the

treatment, which in the present case is either being an US or an EU firm, as exogenously given and solely match the firms based on the most important structural measure -firm size. Afterwards, for both the US and the matched EU panel we estimate the effect of several structural firm- and industry variables on the outcome variable, which in the present case is ‘abnormal’ firm profit. For this purpose we apply dynamic panel models based on the GMM estimator. We also check for significant differences between regression coefficients of both models. The advantage of our approach is that it first provides comparable samples regarding the structural characteristic of interest -firm size- and afterwards allows to implement the GMM estimator which is the suitable econometric approach to capture the dynamics present in the data. The standard matching process described above, however, does not adequately consider the dynamic time series behavior of ‘abnormal’ firm profits.

3.2 Dynamic panel model (GMM estimator)

Following the matching process we estimate the persistence as well as the drivers of ‘abnormal’ profits for the US and the matched EU panel. Earlier studies analyzing the dynamics of firm profits over time (e.g. Mueller 1990; Gschwandtner 2005) employ a simple autoregressive process of order one (AR1) estimated with OLS¹:

$$\pi_{i,t} = c + \lambda_i \pi_{i,t-1} + \eta_i + v_{i,t} , \quad (3)$$

where η_i is an unobserved firm-specific effect and $v_{i,t}$ is an observation specific error term (Baltagi 2008; Andres *et al.* 2009). In (3) $\pi_{i,t}$ is firm i 's ‘abnormal’ profitability in period t . $\pi_{i,t}$ is defined as the difference between firm i 's return on assets (ROA) in t and the competitive norm which is proxied by average industry ROA in t (e.g. Hirsch and Gschwandtner 2013). The estimated autoregressive coefficient $\hat{\lambda}_i$ can then be used for each firm as a measure of profit persistence as it indicates the percentage of ‘abnormal’ profits that sustains from period to period. Mean $\hat{\lambda}_i$ across firms in an industry can serve as an indicator for the competitive pressure within this sector as high competition decreases the likelihood that ‘abnormal’ profits persist. Some studies (e.g. Gschwandtner 2012) implement a second estimation step by regressing structural firm and industry variables such as firm size or industry concentration on $\hat{\lambda}_i$ in order to explain the latter.

¹ Some studies also implement a ‘best lag model’ which incorporates lags of higher order (Gschwandtner 2005).

However, the classical approach has the drawback that applying OLS to (3) leads to inconsistent and upward biased estimates of λ_i due to an endogeneity bias caused by $Cov(\pi_{i,t-1}; \eta_i) \neq 0$. Similarly, the fixed effects (within) estimator leads to biased estimates. This estimator performs OLS on the equation with each variable adjusted by its mean over time. However, fixed effects estimates are still inconsistent and biased as $Cov(\pi_{i,t-1}; v_i) \neq 0$, where $v_i = v_{it} - \bar{v}_i$ reflects the mean-adjusted error term (Baltagi 2008; Andres *et al.* 2009). Thus, to obtain consistent and unbiased estimates we apply the Arellano and Bond (1991) GMM estimator to an extended version of (3):

$$\pi_{i,t} = c + \lambda \pi_{i,t-1} + \sum_j \alpha_j (Z_{j,i,t}) + \eta_i + v_{i,t} \quad (4)$$

The autoregressive coefficient ($\hat{\lambda}$) can then be used as a measure for the degree of profit persistence across the analyzed panel of firms. Additionally, a vector of j time-variant structural firm and industry specific variables (Z) is added to the model in order to estimate the impact of these variables on ‘abnormal’ firm profits over time. The GMM estimator first-differentiates the equation eliminating the time invariant firm-specific effect (η_i). Afterwards, based on the assumption of no serial correlation in the error term (v_{it}) lags of the endogenous independent variable ($\pi_{i,t-1}$) can be used as valid instruments to estimate the first-differenced equation. Similar to Goddard *et al.* (2005) the independent variables included in Z are treated as exogenous implying that they can instrument themselves (Andres *et al.* 2009; Roodman 2009, Hirsch and Gschwandtner 2013). However, Arellano and Bover (1995) and Blundell and Bond (1998) show based on Monte Carlo simulations that in cases where the autoregressive parameter (λ) is large the difference GMM estimator behaves poorly as lagged values of the endogenous independent variable ($\pi_{i,t-1}$) constitute weak instruments. They extend the difference GMM estimator by focusing on a system of first-differenced and levels equations. Lagged differences of the endogenous independent variable ($\pi_{i,t-1}$) are then used as instruments for the levels equation in addition to the lagged values of the independent variable which are used as instruments for the first-differenced equation. This estimator is usually referred to as system GMM (Baltagi 2008; Andres *et al.* 2009).²

² Compared to the classical two-step AR(1) approach GMM has the disadvantage that we can only determine the impact of the independent variables (Z) on ‘abnormal’ profits but not on the profit persistence measure $\hat{\lambda}$.

Hirsch (2014) shows that average $\hat{\lambda}$ across manufacturing sectors is 0.45. Furthermore, according to Hirsch and Gschwandtner (2013) $\hat{\lambda}$'s for the EU food processing industry turn out to be even lower with values between 0.110 and 0.304 for the five EU countries analyzed in their study. Thus, as we can expect rather low $\hat{\lambda}$'s, system GMM will likely not be superior to the difference estimator. We therefore focus on the robustness parameters of each estimator (e.g. Hansen/Sargan test for the correct implementation of the instruments and the test for second order autocorrelation) in order to decide which of the estimators to present. Furthermore, we also estimate equation (4) using OLS in order to quantify the bias of this estimator.

4. US and EU food processing industry population and sample

In this section we first discuss structural characteristics of the US and EU food processing industry. We then present the construction, representativeness and descriptive statistics of our samples.

4.1 US and EU food processing industry

The first two columns of table 1 compare the US and EU-28 food processing industry based on key indicators. The EU-28 food industry is in general larger than the US food processing industry having both a higher value of overall sales and a much larger number of firms. The number of firms in the EU exceeds the respective US value by a factor of almost 10. In 2011 the US food processing industry contributes 14.7%, 14.2%, and 10.3%, to total manufacturing sales, employees and number of firms, respectively (USDoC 2014). The EU-28 food processing industry is characterized by a similarly high economic importance with shares of 14.8% of total manufacturing sales and 14.1% in manufacturing employees. However, the EU-28 food processing industries' share in the total number of manufacturing firms is with 13.8% higher than in the US (Eurostat 2014). Combined with the much larger number of food processors in the EU-28 this points towards significantly different size class structures between both industries.

This fact is also highlighted in the lower panel of table 1 which shows a significantly higher percentage of small firms in the EU-28 and a much higher percentage of larger firms in the US. While almost 80% of the firms in the EU-28 food sector have less than 10 employees³, in the US only around 50% of the firms are that small. At the same time the percentage of firms with

³ Although, the majority of EU firms are micro sized with less than 10 employees those firms only account for 8.6% of total EU-28 food processing industry turnover (Eurostat 2014).

more than 20 employees is more than three times as large in the US than in the EU-28. While the percentage of firms with more than 500 employees is 13.7 in the US, in the EU-28 less than 1% of the firms has more than 250 employees.

Insert table 1 here

4.2 US and EU dataset

The US sample was constructed using Standard and Poor's Compustat, a commercial database on financial information of US publicly quoted firms, and the US economic census (USDoC 2014). The EU sample is based on AMADEUS, a pan European balance sheet database including firms of all legal forms and size classes, and the Eurostat database (Eurostat 2014). While Compustat and AMADEUS provide firm-level data the US census and Eurostat serve for the construction of variables related to the subsectors of the food processing industry.

In order to construct the US sample we first selected all 409 firms active in any of the 6-digit NAICS⁴ codes between 311111 and 312140, i.e. firms that operate in food and beverage manufacturing. The time span available is 1990-2012. However, as data for the EU is only available till 2008 we first restrict the US sample to 1990-2008 in order to ensure comparability. Subsequently we consider the effect that the 2008/2009 economic crises, which is not covered by the EU sample, has on firms in the US sample by estimating a second model that includes the post 2008 observations. We deleted all firms with less than 10 years of ROA data available as this is the minimum time series dimension necessary to adequately capture the persistence of profits (Wiggins and Ruefli 2002). We identify all observations outside an interval of +/- 3 standard deviations around the mean as outliers leading to a final sample of 125 firms. On average 12.5 years of data are available for each firm. Besides ROA, data on firm size, firm growth, market share as well as firms' financial risk is available to capture the impact of physical, human and organizational firm specific resources in accordance with the RBV. Finally, in line with the MBV concentration as well as size and growth of 6-digit food processing subsectors are added to the sample from the US census (USDoC 2014) to capture the impact of entry barriers and competition.

The EU sample was constructed similarly by including all firms active in any 4-digit NACE industry between DA1511 and DA1598 (i.e. the manufacturing of food and beverages) with at least 10 ROA observations. The period covered is 1996 to 2008 as AMADEUS was initiated in 1996 and data availability post 2008 is poor.⁵ Due to data availability the EU sample is

⁴ NAICS and NACE are the statistical classifications of economic activities in the US and the EU, respectively.

⁵ Although this time span is not totally equal to the time span covered by the US sample, reducing the US sample to 1996-2008 would significantly reduce the number of firms with at least 10 ROA observations and lead to an inadequate sample size.

restricted to the 5 countries Belgium, France, Italy, Spain and the UK. However, with contributions of 53.2%, 41.3% and 55.5% to total EU-28 food processing industry sales, employees and number of firms, respectively a significant share of the EU-28 food processing industry is covered by those 5 countries (cf. last column of table 1). Germany, the largest contributor to EU food processing industry turnover with 17.8 % (Eurostat 2014) could not be included due to a lack of data as non-publicly quoted firms had no legal obligations to publicize accounting data until the year 2007 (Hirsch and Schiefer 2016).

All observations outside +/- 3 standard deviations around the mean were dropped and industry data related to concentration as well as size and growth of 4-digit food processing subsectors from Eurostat's structural business statistics (Eurostat 2014) was added. As AMADEUS comprises firms of all legal forms (limited partnerships, private, publicly quoted, and cooperatives) and size classes the resulting sample comprises 5,494 firms and is significantly larger than the US sample. On average 13 years of data are available for each firm. This EU sample has previously been analyzed regarding profit persistence by Hirsch and Gschwandtner (2013). In the present article we use this sample as a basis to construct a sample that matches the 125 publicly quoted US firms.

Table 2 presents descriptive statistics of firm and industry characteristics in the US and the EU samples. We first describe the variables for the US sample and the initial EU sample. The results for the matched EU sample in the third column will be discussed below subsequent to the matching procedure.

ROA is calculated as the quotient of firms' profit/loss before taxation, plus interest⁶, and total assets. There has been a vast debate regarding the suitability of accounting profit measures such as ROA as those measures can suffer from biases due to profit smoothing or cross subsidization (e.g. Fisher and McGowan 1983; Long and Ravenscraft 1984). Some studies therefore use alternatives such as economic value added (EVA) developed by Stern Steward and Co., which measures the economic returns generated for shareholders or Tobins q. However, Biddle *et al.* (1997) illustrate that EVA is outperformed by balance sheet earnings as a performance proxy as returns and firm values are more strongly correlated with earnings than with EVA. Therefore, to assure comparability to previous literature we use ROA as the proxy for firm profitability. Moreover, correlation coefficients between ROA and the value added measure provided by AMADEUS exceed 0.8 and are significant at $p < 0.01$ for each year and country⁷. According to table 2 ROA is on average significantly lower in the US sample than in

⁶ To make ROA independent of the source of funds used, interest has to be included in the numerator.

⁷ This only holds for the 5 EU countries as VA is not available for the US.

the EU sample pointing towards higher competition in the US, maybe due to the lower concentration in the retail sector and less potential subsidies than in the EU.

Confirming the results for the population in table 1, the average firm size, measured by firms' total assets, is with \$2.5 bn. significantly higher in the US sample than in the EU sample where the respective value is only \$19.2 m. As can be seen from the size class distribution at the bottom of the table, similar to the population, we have mainly large firms in the US sample (72.8%) and mainly small and micro firms in the EU sample (85.8%). Nevertheless, the firm growth factor, calculated as the yearly growth rate of total assets, is similar in both samples with a value around 1.1.

Market share was calculated for each firm as the ratio of its sales to the overall sales in the NAICS/NACE sector in which the firm operates. Surprisingly, average market share of firms in the US sample is with 2.3% significantly lower than in the EU sample where the average firm has a market share of 7.5%. However, as will become apparent below in comparison to the EU sample the US sample is characterized by a larger share of firms that operate in subsectors that generate higher outputs and vice versa. Despite the much larger average firm size this leads to a lower average market share in the US sample.

Firms in the US sample engage on average significantly less in short-term and long-term financial risk than firms in the EU. Average short-term risk, measured by the reciprocal of a firm's current ratio, i.e. the quotient of current liabilities to current assets, is approximately twice as large in the EU. Long-term risk is measured by the firms gearing ratio, i.e. the quotient of non-current liabilities to shareholder funds. The average gearing ratio is about $\frac{2}{3}$ in the US than it is in the EU sample.

We now turn our attention to industry related variables. For the EU sample concentration is measured by the Herfindahl-Hirschman Index (HHI). The HHI is calculated as the sum of the squared market shares of the 50 largest firms in each 4-digit NACE subsector. Due to data availability concentration for each 6-digit NAICS sector in the US sample has to be measured by the four-firm concentration ratio (CR4) which corresponds to the market share of the four largest firms in each NAICS sector. While the HHI and the CR4 cannot be directly compared quantitatively, both measures indicate that the majority of firms in the samples operate in industries that are characterized by moderate concentration. While the mean CR4 of 0.489 in the US sample is just below the threshold for oligopolistic industry structures ($CR4 > 0.5$), the average HHI for the EU sample of 0.039 indicates that the majority of firms are active in industries with low concentration (Threshold for oligopolistic structure: $HHI > 0.1$).

Industry size and growth are measured by the sales of each 6-digit NAICS and 4-digit NACE food processing subsector, respectively. Despite the lower number of total food processing sales in the population average industry size is significantly larger in the US sample (\$22.4 billion vs. \$3.9 billion). This is due to the fact that in the EU sample a larger fraction of firms is active in subsectors that generate lower outputs (e.g. NACE DA1593 ‘Manufacture of wines’ or DA1561 ‘Manufacture of grain mill products’). Nevertheless, firms in the EU sample operate in industries that grow stronger as the average industry growth factor of 1.4 is significantly larger than in the US sample where growth stagnates.

Insert table 2 here

5. Estimation results

5.1 Propensity score matching results

Propensity scores are estimated using a probit model where the binary dependent variable takes a value of 1 for observations in the US sample and a value of 0 for observations in the EU sample. As independent variable we use firm size as the structural characteristic of interest. In order to avoid sample selection bias, for the matching process we use firm sales as an instrument for our prime firm size measure, total assets. This is necessary as we aim to afterwards include total assets as an independent variable to explain ‘abnormal’ profits. The probit-regression results indicate that firm size measured by sales has a significantly positive impact on the probability that a firm is in the US sample.

The third column of table 2 shows the firm size distributions after the matching process. From the initial EU sample which comprises 5,494 firms 1,911 are identified, based on the area of common support of PS’s and the radius matching algorithm, to match the 125 US firms.⁸ The fraction of micro firms is significantly reduced in the EU sample from 61.1% to 9.3%. However, the fraction of large firms remains significantly smaller in the EU sample than in the US sample.

The balancing property serves as a goodness measure for the matching process. In the present case it is fulfilled at $p < 0.01$ which indicates that the size of firms in the US and the matched EU sample is similar even within PS subsets (i.e. quantiles) over the common support area (Cavatassi *et al.* 2011). Additionally, the reduction in the standardized bias⁹ can be used as a measure for the success of the matching. Previous studies interpret a reduction of this bias by

⁸ Several estimation attempts with different radii (0.15, 0.1 and 0.05) led to identical results.

⁹ The standardized bias is calculated as: $SB = (\bar{x}_1 - \bar{x}_0) / \sqrt{0.5 * (V(x_1) + V(x_0))}$, where $\bar{x}_1, V(x_1)$ and $\bar{x}_0, V(x_0)$ are mean and variance of firm size in the US and the (matched) EU sample, respectively.

around 3% as sufficient (Caliendo and Kopeining 2005). Nevertheless, the matching process only leads to a reduction of the bias by 1.1% indicating that significant differences in size classes remain after the matching process. Those also become evident from table 2 which indicates that although average firm size in the EU sample increases from \$19.2 to \$52.6 m. in total assets this value remains significantly smaller than the US value of \$2.9 bn. Nevertheless, our intention to use PSM is to identify EU firms that are embedded in a similar competitive situation as the US firms. This implies however, that firms in both samples are not necessarily equal in terms of size. Nonetheless, the matched EU sample likely represents a similar part of the size class distribution of the EU food processing industry as the one represented by the 125 US firms. We suppose that this approach is more meaningful than simply focusing on EU firms that have exactly the same size as the US firms as firms would be less comparable regarding their competitive situation.¹⁰

5.2 Explaining 'abnormal' profits

The results of the GMM dynamic panel estimation are presented in table 3 in the first two columns. The OLS results in columns 4 and 5 are presented just as robustness checks. If the results of GMM shall be correct then the autoregressive coefficient shall be below the OLS results and we can observe that this is the case. We also calculated the significances of the differences between the US and EU-5 GMM coefficients.

We can observe that the short-run persistence parameter ($\hat{\lambda}$) is positive and significant in both samples, meaning that past year's profits have a significant impact on this year's profits and therefore profit persistence exists. However, there is no significant difference between the US and EU persistence coefficient which confirms that the matching process has generated US and EU firms that operate in comparable competitive situations in their respective industries. The $\hat{\lambda}$ values of 0.292 for the US and 0.236 for the EU food processing industry are lower compared to other manufacturing sectors. For the entire US manufacturing sector Gschwandtner (2012) using GMM with a similar set of explanatory variables finds $\hat{\lambda}$ values between 0.549 and 0.722. Goddard *et al.* (2005) find $\hat{\lambda}$ values between 0.323 and 0.452 for entire manufacturing sectors of the same five EU countries.

¹⁰ An alternative matching strategy would have been to first ensure homogeneity across EU firms by performing PSM for all 10 possible combinations between the 5 EU countries. However, this was neglected as similar to Hirsch and Gschwandtner (2013) we want to consider the EU food processing industry in its entirety as a single market of goods and services.

We now focus on firm-specific characteristics that in accordance with the RBV should affect profitability. Regarding firm size the results are significantly different between the EU and US. Even though the impact on ‘abnormal’ profitability is positive and significant in both samples it is significantly higher in the EU. This is likely the case because in the EU the number of small firms is much higher and size is more crucial in outperforming the market. Moreover, as argued by Hirsch and Gschwandtner (2013) firm size plays an important role in the EU food processing industry and this also seems to be the case in the US. Probably, larger size allows to better deal with pre-market approvals, advertising costs, to establish reputation and to counteract the market power of retailers.

Another variable where the EU and the US differ significantly is firm growth. While the impact on ‘abnormal’ profitability is positive and significant in the US, its impact in the EU is insignificant. Obviously it is more difficult for firms in the EU food sector to successfully grow than it is in the US which may also be the reason why most of the firms in the EU are smaller than in the US. It may also be that in the EU the positive effect of growth is counteracted by its potentially negative effects e.g. in form of costs associated with growth.

Market share is insignificant both in the EU and in the US. Usually a higher market share is expected to have a positive impact on ‘abnormal’ profits. However, firms with high market share may also have transparency problems and diseconomies of scope that may counteract the positive effect leading to an insignificant effect in the end. Moreover, Prescott *et al.* (1986) show that the impact of market share is influenced by the external environment in which firms operate and can therefore also be negative.

Short-term financial risk negatively impacts in both samples and the coefficients are not significantly different. However, the impact is only significant in the US sample. A negative impact has also been found by Hirsch and Gschwandtner (2013) for the EU. Short-term risk may put high pressure on the financial stress of firms and is expected to have a negative impact. Long-term financial risk (gearing) however, may help the firm to invest in R&D and recover from eventual financial distress. Thus, it may enable firms to make investments that help the company to grow and to reach a specific established market position or a critical firm size that ensures its competitiveness. Furthermore, Chaddad and Mondelli (2013) mention that financial pressure of debt reduces free cash flow, and may lead managers to invest more wisely and not to waste firm resources in perquisites and unprofitable growth. Therefore, a positive impact of long-term debt is expected. However, similar to our EU results the impact they found in their study is negative. Goddard *et al.* (2005) who also find a negative impact of gearing for EU

manufacturing firms conclude that ‘highly leveraged firms may suffer in increasingly competitive markets, as they need to use a higher proportion of gross profits to service debt’.

The focus shall now be on those structural industry factors which according to the MBV determine the degree of entry barriers and competition. The results show that the impact of industry concentration is insignificant in both samples. Since in the US sample we measure concentration by the CR4 and in the EU sample by the HHI the difference between the coefficients of both samples could not be estimated. It is usually assumed that high concentration prevents entry, leading to less competition and higher ‘abnormal’ profits. Nevertheless, strong concentration can also lead to intense rivalry between the dominant firms resulting in a negative impact. Moreover, it can also be the case that both effects neutralize each other leading to the insignificant impact of concentration in both the US and EU.

Industry size does not impact significantly on ‘abnormal’ profits and there is no significant difference between the two samples. However, there is a significant difference between the US and EU in the impact of industry growth on ‘abnormal’ profitability. While the impact is positive and significant in the EU, it is significantly negative in the US. This indicates that US firms engage in stronger non-profit competition such as advertising when the industry grows which in turn reduces ‘abnormal’ profitability. In contrast firms in growing EU industries behave more cooperatively which increases their profitability on average. The negative impact of industry growth in the US is not necessarily a contradiction to the positive impact of firm’s growth. The growth of an individual firm may confer it a stronger position towards its rival. If the whole industry grows however, more fierce competition may develop between the firms that can have a negative impact on ‘abnormal’ profitability.

As the $\hat{\lambda}$ ’s are rather small the system GMM estimator is not necessarily superior. However, for both samples we estimated system as well as difference GMM and decided to keep the model for which the goodness of fit parameters point towards higher robustness. For the US sample system GMM and for the matched EU panel difference GMM has been chosen as the best estimator according to the model diagnosis. For the final models the Wald statistic indicates their overall significance at the 1% level. Lags of second order or higher have been used as instruments for the endogenous independent variable in both models and the Hansen test does not reject the null hypothesis that this is the correct implementation of instruments. Finally, for none of the models the null hypothesis of no second-order autocorrelation is rejected indicating the consistency of the GMM estimator (Arellano and Bond 1991).

Insert table 3 here

In order to capture the effect that the inclusion of US observations that fall into the time span of the economic crisis and its aftermaths (2009-2013) has on the results we also estimate the US model including additional firm observations from the period 2009-2013. The results can be found in the third column of table 3. The effect of the crisis is reflected by a decrease in the short-run persistence measure ($\hat{\lambda}$) to 0.260.¹¹ The impact of the remaining explanatory variables remains constant with the exception of long-term debt. The respective coefficient remains positive but becomes significant. This implies that during macroeconomic crises debt can enable firms to make investments that lead to growth and a specific critical firm size and market position that ensures competitiveness. Furthermore, the difference in the coefficients for long-term debt between the US and the EU becomes significant.

6. Conclusions

The food processing industries in the US and in the EU differ strongly with respect to the size of firms. In the US the average food processor is significantly larger than in the EU and PSM has been used to derive samples of comparable firm size. The present article analyzes the drivers of profit persistence in the US food processing sector and compares the results with those of the matched EU sample. To our knowledge, such an analysis -in particular for the US- has not been carried out before.

The main drivers of ‘abnormal’ profitability in the US food processing sector turn out to be firms’ size, growth and financial risk. Larger firms achieve a higher level of ‘abnormal’ profits, a result that has also been previously obtained for the EU (Hirsch and Gschwandtner 2013). Thus, large firms may be able to perform more advertising, have higher consumer reputation and are better able to cope with competition pressures. The influence of firms’ growth is significantly different between the US and the EU. While it is positive in the US it is insignificant in the EU. This may be the case because while growing firms have to take into consideration higher costs that may decrease profitability. By having easier access to debt, US firms are presumably able to better counteract this potentially negative effect of growth. And this points toward the next significant difference between the US and the EU. While long-term risk impacts negatively on ‘abnormal’ profit in the EU it impacts positively on firms in the US when observations that fall into the period of the economic crisis and its aftermaths are included. As discussed before, long-term debt can enable firms to make the necessary investments that

¹¹ However, this decrease is not statistically significant.

help to ensure competitiveness in times of crisis. In the EU firms indebted in the long run find it more difficult to cope with risk. Finally, firms in the US and the EU differ with respect to the impact of industry growth on ‘abnormal’ profit. The fact that firm and industry growth have a different impact is not necessarily a contradiction. While growing firms in the EU may face difficulties that lower their profitability, the fact that the industry as a whole grows may impact positively on the perception of consumers and may increase firms’ profit. Growing firms in the US may find it easier to cope with competition, while the fact that the industry as a whole grows may make this competition process more ferocious which in turn impacts negatively on firms’ ‘abnormal’ profit.

Some shortcomings of this article are the omission of important intangible firm-specific resources such as R&D activity, patents, reputation, and ownership structure due to data unavailability. Second, the fact that we only consider firms that report ROA observations over a ten year period raises the question whether results are affected by an upward survivorship bias. For example, Gschwandtner (2005) shows that surviving firms have in general higher profit persistence than firms that exit the market due to bankruptcy. However, AMADEUS only reports 1.4% of exiting firms as bankrupt while the majority of firms exiting the database during the analyzed time span are either acquired or part of merger activity. Although for the US sample similar information is not available the majority of firms with less than 10 ROA observations shows missing values in the middle of the analyzed time frame implying that data incompleteness in those cases is not a sign for firm exit but rather of flaws in the database. The extent of survivorship bias in both samples should therefore not be significant. Third, compared to NEIO approaches which allow a detailed modeling of specific sub-industries the present analysis can only provide overarching insights on the structural drivers of profitability across industries of the food sector.

The results have not only purely descriptive value but can also be useful when designing policies aimed at supporting food sector firms or the food sector as a whole. This is important as today firms are facing economic circumstances characterized by reduced entry barriers and possibilities to operate in previously hardly accessible foreign markets. Those developments are a consequence of intensified globalization represented by trade agreements such as the NAFTA or the formation of a single market for goods and services within the EU. However, these deregulations of borders and international trade have led to a significant intensification of competition among firms across many sectors. The comparably low short-run persistence values ($\hat{\lambda}$) which have been estimated for the US and EU food industry also reflected this

development. Thus, competition seems to be working and a necessity for anti-trust measures at the processing-industry level cannot be evidenced.

Nevertheless, pressure on the margins and competitiveness of food processors is further intensified by increasing uncertainty in raw material markets and strong concentration in retail sectors. (Schiefer 2011). While five-firm concentration ratios already exceed 70% in many EU member countries concentration is slightly weaker in the US retail sector, but shows an increasing trend (Wijnands *et al.* 2007; Wood 2013). A high and constantly growing share of private labels further increases power imbalances between processors and retailers (European Commission 2011). In the EU the food sector has already drawn attention of competition authorities with a focus of retailer's buyer power vis-à-vis the producers (European Competition Network, 2012). The present results confirm the need for policy interventions at the downstream level. Moreover, the positive impact of firm size and growth on profitability indicates that small firms and firms with low growth are in a disadvantageous position. Thus, policy measures which address the industry could focus on a decrease of administrative burdens particularly for the large number of small enterprises. Furthermore, policy actions that decrease unfavorable financial risk factors -particularly short term risk in the US and long term risk in the EU- might strengthen processors and help to counter power imbalances. Finally, the US results indicate that in times of economic crisis measures that facilitate access to long term debt can counter the negative impact of the crisis.

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Tables

Table 1. Key indicators US and EU food processing industry (2011)

	US	EU-28	EU (Be, Fr, It, Sp, UK)
Sales (bn. \$)^a	808.233	1,344.441	715.656
No. of firms	30,384	289,199	160,504
Employees (m.)	1.559	4.284	1.770

<i>Size class distribution (%)</i>						
<i>0-9 employees</i>		50.62		78.68		85.74
<i>10-19</i>		13.11		10.86		7.07
<i>>20</i>		36.27		10.46		7.19
 <i>Available size classes for >20 employees^b</i>						
	<i>20-99</i>	15.45	<i>20-50</i>	5.79	<i>20-50</i>	4.34
	<i>100-500</i>	7.14	<i>50-250</i>	3.80	<i>50-250</i>	2.28
	<i>>500</i>	13.70	<i>>250</i>	0.86	<i>>250</i>	0.57

Data sources: Eurostat (2014) and USDoC (2014)

Notes: food processing industry in the EU-28 defined as NACE Rev. 1.1 division 15 i.e. 'Manufacture of food products and beverages'. US food processing industry defined by NAICS codes 311 'Food manufacturing' and 3121 'Beverage manufacturing'

^a Value of shipments for the US

^b Data based on identical size classes for the EU and US food processing industries is not available for firms with > 20 employees.

Table 2. Descriptive statistics of firm and industry characteristics

Variable	US		EU-5			
	Mean	Stdv.	Initial sample (no. of firms=5,494; n=71,422)	Stdv.	Matched sample (no of firms=1,911; n=24,843)	Stdv.
<i>Firm characteristics</i>						
ROA	0.032	0.138	0.059	0.065	0.053	0.053

Firm size (m. \$)	2,483.136	5,453.379	19.167	162.633	52.590	272.584
Firm growth	1.122	0.414	1.188	15.430	1.284	17.384
Market share (%)	2.332	5.990	7.530	14.869	16.138	21.466
Short-term risk	0.667	0.448	1.269	2.729	0.879	0.805
Gearing	1.260	8.580	1.787	4.766	1.674	4.521
<i>Industry characteristics</i>						
CR4/HHI	0.4890	0.187	0.039	0.079	0.047	0.080
Industry size (bn. \$)	22.428	20.341	3.878	5.732	4.155	5.368
Industry growth	1.020	0.187	1.402	6.121	1.411	5.931
<i>Size class distribution (no. of firms and %)^a</i>						
<i>Large</i>	91 (72.8)		246 (4.5)		242 (12.7)	
<i>Medium</i>	21 (16.8)		537 (9.8)		513 (26.8)	
<i>Small</i>	13 (10.4)		1355 (24.7)		978 (51.2)	
<i>Micro</i>	0 (0.0)		3356 (61.1)		178 (9.3)	

Firm variables: ROA = operating profit/total assets; Firm size = total assets; Firm growth = yearly growth rate of total assets; MS = firm sales/subsector sales; Short-term risk = current liabilities/current assets; Gearing = non-current liabilities/shareholder funds

Industry variables: CR4 = four firm concentration ratio of NAICS industry in %; HHI: Herfindahl-Hirschman index for each NACE sector in the EU sample; Industry size = value of sales of NAICS/NACE industry; Industry growth = Growth rate of value of sales.

Source: Own calculations based on AMADEUS, Eurostat (2014), Compustat and USDoC (2014).

^a To assure comparability for both the EU and the US firms are assigned to size classes based on the SME definition of the European Commission (2005): Micro: total assets <\$ 2.63 million; Small: total assets <\$ 13.14 million; Medium: total assets <\$ 56.51 million. Firms are assigned to these size classes based on their total assets in the first available year

In order to convert €-values into US\$ we use the exchange rate of Aug. 29th 2014 = 0.76 (€/€).

Table 3. Dynamic panel model estimation results

Variables	GMM			OLS	
	US	EU-5 (matched)	US (with crisis)	US	EU-5 (matched)
$\pi_{i,t-1}$	0.292 (2.47)**	0.236 (3.08)***	0.260 (2.77)***	0.530 (21.48)***	0.654 (113.49)***

Firm size	0.012 (2.68)***	0.025 (5.88)***	0.012 (3.02)***	0.009 (4.68)***	-0.000 (-0.10)
Firm growth	0.738 (2.51)**	-0.000 (-1.57)	0.759 (2.79)***	0.653 (4.10)***	0.000 (1.35)
Market share	-0.000 (-0.00)	0.000 (1.02)	-0.000 (-0.06)	0.000 (0.49)	-0.000 (-0.49)
Short-term risk	-0.042 (-2.68)***	-0.035 (-0.99)	-0.043 (-3.27)***	-0.037 (-5.39)***	-0.003 (-5.85)***
Gearing	0.001 (1.51)	-0.000 (-3.34)***	0.001 (2.81)***	0.001 (2.18)**	-0.000 (-2.64)***
CR4 / HHI	0.000 (0.29)	0.003 (0.18)	-0.000 (-0.12)	0.000 (0.32)	0.018 (4.89)***
Industry size	-0.000 (-0.26)	-0.000 (-1.09)	-0.000 (0.29)	-0.000 (-0.22)	0.000 (1.25)
Industry growth	-0.017 (-1.77)*	0.000 (2.14)**	-0.015 (-1.63)*	-0.023 (-1.87)*	0.000 (2.82)***
Constant	-0.875 (-2.69)***	-	-0.891 (-2.97)***	-0.743 (-4.56)***	0.002 (1.05)
Wald χ^2	47.47***	113.29***	56.50***		
Hansen χ^2	20.70 p=0.240	4.41 p=0.354	22.44 p=0.434		
AR(2)	z = -1.04 p=0.298	z = 0.77 p=0.439	z = -1.79 p=0.074		
F				81.26***	1503.57***
R ²				0.404	0.445
N	1,565	24,843	1,840	1,565	24,843

Dependent variable: $\pi_{i,t}$ (abnormal profit)

Firm variables: Firm size = natural logarithm of total assets; Firm growth = yearly growth rate of total assets; MS = firm sales/industry value of sales; Short term risk = current liabilities/current assets; Gearing = non-current liabilities/shareholder funds.

Industry variables: CR4 = four firm concentration ratio of NAICS industry; HHI=Herfindahl Index of NACE industry; Industry size = sales of NAICS/NACE industry; Industry growth = growth rate of value of sales.

Numbers in parentheses are z-/t-values based on robust standard errors.

***, **, * significant at the 1%, 5%, 10% level, respectively.

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