Dynamic versus Static Inefficiency Assessment of the Polish Meat-Processing Industry in the Aftermath of the European Union Integration and Financial Crisis.

Magdalena Kapelko

Wroclaw University of Economics, Institute of Applied Mathematics, Department of Logistics, ul. Komandorska 118/120, 53-345 Wroclaw, Poland, e-mail: magdalena.kapelko@ue.wroc.pl

Tel.: +48713680479; Fax: +48713680334.

Abstract.

This paper assesses the dynamic inefficiency of the Polish meat processing industry during the period between 2004 and 2012. This study employs also a comparison of dynamic with static inefficiency measures to address the importance of accounting for adjustment costs when measuring a firm's inefficiency. Dynamic and static cost inefficiencies and their decomposition into technical, allocative, and scale inefficiency are derived using Data Envelopment Analysis. Results showed that firms' low levels of dynamic cost inefficiency were mainly due to dynamic allocative inefficiency rather than technical and scale inefficiency. The 2008 financial crisis appears to have hampered firms' dynamic technical performance, but has also had a positive influence on the dynamic allocative and scale inefficiencies. We further show that the average static measures tend to underestimate all inefficiency components compared to dynamic counterparts.

Keywords: dynamic inefficiency, static inefficiency, Data Envelopment Analysis, meat processing industry.

JEL codes: C61, D24, D61, D92, L66.

1. Introduction

Most contemporary measurement frameworks of economic performance rely on static inefficiency measures that ignore the intertemporal linkages of production decisions and assume a short-run steady state of production in which quasi-fixed inputs are unchanged. In recent years, these weaknesses of static frameworks have redirected researchers' interest to the dynamic inefficiency measurement, in which current production decisions (for example, investment in capital) constrain or enhance future production possibilities. Dynamic inefficiency models can be broadly classified into two main groups.[1] The first group includes studies within dynamic network Data Envelopment Analysis, which take the view of multistage production systems in which an output in one stage is used as input in the next stage, such as the works of Färe and Grosskopf (1996), Nemoto and Goto (2003), Sueyoshi and Sekitani (2005), Chen (2009), or Chen and Van Dalen (2010). In the second group, the intertemporal linkage of firms' production decisions is based on adjustment costs associated with changes (expansion or contraction) in quasi-fixed factors induced by investments (Silva & Stefanou, 2003; 2007). Hence, in this approach the adjustment of inputs and outputs to their optimal levels is not instantaneous, but occurs only by imposing some adjustment costs.[2] Such an approach can be particularly important for capital-intensive industries such as food processing, which lack short-run flexibility due to adjustment costs (Morrison Paul, 1997). This study employs the dynamic inefficiency model that builds on adjustment cost theory to assess dynamic inefficiency of European food-processing firms.

Food manufacturing is one of the most important sectors in the European economy, ranking first in turnover and employment in the manufacturing sector of various European countries (Wijnands et al., 2008). Polish food manufacturing is not an exception, and is the country's largest manufacturing sector, accounting for 17 percent of total manufacturing employment and 18 percent of total turnover in the manufacturing industry (European Commission, 2011). Within Polish food manufacturing, the meat-processing industry is the dominant sector, representing 30 percent of employment and 30 percent of turnover in food manufacturing in 2012 (Eurostat, 2014). The Polish meat sector is very fragmented with many small and medium-sized firms and a very few large ones (Rau & Van Tongeren, 2009). Two events in the last decade have marked this sector in Poland. The first one was the Poland's accession to the European Union (EU) in 2004. After meeting the initial EU requirements, the country experienced substantially accelerated growth in the meat-processing

[1] An excellent review of dynamic inefficiency measurement can be found in Fallah-Fini et al. (2014).

[2] Adjustment costs represent resources spent due to investment in new capital, for example, the cost of installing a new machine or the cost of learning to use this new machine.

sector because of flourishing exports of meat products and new opportunities for innovations. The second event was the 2008 financial crisis that slowed production and decreased turnover in this sector.

Although there are a considerable number of studies on agricultural efficiency (see, for example, Aramyan et al., 2006 or Oude Lansink et al., 2002), studies of food processors are scarcer, with a few notable exceptions. For example, Shee and Stefanou (2015) applied traditional and endogeneity-corrected stochastic production frontiers to a sample of Colombian food manufacturers and found the average technical efficiency of all food industry equaled 62.1 percent, with meat processing scoring the highest average efficiency of 66 percent. Using nonparametric Data Envelopment Analysis (DEA) for Greek food manufacturing, Dimara et al. (2008) reported a relatively low level of technical efficiency, with average values of 0.243, as well as a relatively high level of scale efficiency, scoring 0.674 on average. Also using the nonparametric framework, Ali et al. (2009) addressed food manufacturing in India and found relatively high efficiencies for the gross sector, 0.902 in technical efficiencies and 0.870 in scale efficiencies. Among Indian food sectors, meat processing presented 0.911 of technical efficiency and 0.655 of scale efficiency. Focusing on efficiency in a specific food-manufacturing sector include studies on dairy processing in Australia and Spain, cheese production in France (Doucouliagos & Hone, 2000; Kapelko & Oude Lansink, 2013; Chaaban et al., 2005), and oils in Spain and India (Dios-Palomares & Martínez-Paz, 2011; Amarender Reddy & Bantilan, 2012). The literature also includes studies using DEA or stochastic frontier to investigate the efficiency of various manufacturing sectors, including food manufacturing. Among these are research by Sun et al. (1999) that found food processing in China to be among the moderately performing sectors, with an average technical efficiency of 0.63, and the study by Kim and Han (2001) of Korean manufacturing sectors that reported the food industry to have the second highest estimate of technical efficiency, equal to 0.775.

But these studies apply a static view of inefficiency that does not account for intertemporal linkages of production decisions. Also, the knowledge of the empirical differences between static and dynamic frameworks is very fragmented. Some attempts to compare dynamic and static inefficiency include the work of Kapelko et al. (2014), who compared the average results for dynamic and static inefficiency indicators in the Spanish construction sector, and Nick and Wetzel (2014), who contrasted these indicators for electricity distribution and transmission companies in the US. Also studying US electric transmission operators, Von Geymueller (2009) undertook comparative analysis of static and dynamic frameworks; however, this study focused on a slightly different dynamic approach and contrasted only the technical efficiency indicators. To the best of our knowledge, such comparisons for input/output mixes of benchmarked firms have never been undertaken.

Therefore, the objectives of this paper are twofold. First, we want to empirically analyze the dynamic inefficiency of the Polish meat-processing firms in the context of Polish accession to the EU and the recent financial crisis. We believe this study is the first to assess the dynamic inefficiency of food manufacturing sector in Europe. Our second objective is to shed light on the importance of using the dynamic framework and investment-related adjustment costs through a comparison of dynamic inefficiency measures with their static counterparts. To make this comparison, we contrast the dynamic and static inefficiency measures for clusters of input/output mixes. This paper adapts a DEA framework for the computation of dynamic cost inefficiency for the sample of Polish meat-processing firms during 2004–2012. We decompose dynamic cost inefficiency into dynamic technical inefficiency, dynamic scale inefficiency, and dynamic allocative inefficiency following the approach developed in Kapelko et al. (2014). We compare the dynamic measures to those arising from the traditional static models, computed using the static directional distance function of Chambers et al. (1996).

In the next section we describe the technical details of the dynamic production framework applied in this paper, followed by a section that presents the data and variables. Next, we provide the empirical results for Polish meat-processing firms, focusing on the comparison between dynamic and static inefficiency. The final section summarizes the study and provides concluding remarks.

2. Methodology

In this section, we begin with an explication of dynamic technical inefficiency, and then formulate the dynamic intertemporal cost minimization problem to assess dynamic cost inefficiency. Next we summarize the decomposition of dynamic cost inefficiency into dynamic technical inefficiency under variable returns to scale (VRS), dynamic scale inefficiency, and dynamic allocative inefficiency, which we use in the empirical application of this paper.

2.1. Dynamic Technical Inefficiency

Based on Silva and Stefanou (2003), the input requirement set in the dynamic production framework is defined as:

$$V(y:K) = \{(x,I) \text{ can produce y, given K}\} \tag{1}$$

where y denotes a vector of M outputs, x denotes a vector of N variable inputs, K denotes a vector of F quasi-fixed factors, and I reflects a vector of F gross investments (change in quasi-fixed factors, that is a dynamic factor) of $j = 1,..,J$ firms. The input requirement set is assumed to have the following properties: $V(y{:}K)$ is a closed and nonempty set, has a lower bound, is positive monotonic in variable inputs x, negative monotonic in gross investments I, is a strictly convex set, and output levels y increase with quasi-fixed inputs K and are freely disposable. The property associated with gross investments implies a positive cost when investment in quasi-fixed inputs occurs; therefore, quasi-fixed factors are available at increasing unit costs. This property explicitly incorporates the adjustment costs in the dynamic production framework.

Silva and Oude Lansink (2013) showed that the input requirement set defined above could be fully characterized by the dynamic directional distance function. The input-oriented dynamic directional distance function is defined as:

$$\vec{D}^i(y,K,x,I;g_x,g_I) = \max\{\beta \in \Re : (x-\beta g_x, I+\beta g_I) \in V(y{:}K)\}, \qquad (2)$$
$$g_x \in \Re^N_{++},\, g_I \in \Re^F_{++}, (g_x, g_I) \neq (0^N, 0^F)$$

if $(x-\beta g_x, I+\beta g_I) \in V(y:K)$ for some β, $\vec{D}^i(y,K,x,I;g_x,g_I) = -\infty$, otherwise. In this formulation, (g_x) and (g_I) represent the directional vectors for inputs and investments, respectively, while the superscript i refers to the index for inputs. The input-oriented dynamic directional distance function measures the maximal translation of (x, I) in the direction defined by the vector (g_x, g_I), which keeps the translated input combination interior to the set $V(y{:}K)$. In particular, this combination is defined by simultaneously contracting variable inputs in the direction of g_x and expanding the dynamic factor of gross investments in the direction of g_I. In the above equation, β represents the proportion in which the input combination (x,I) is scaled; therefore, it is a measure of dynamic technical inefficiency. The properties of dynamic input distance function are described in Silva and Oude Lansink (2013).

The input-oriented dynamic directional input distance function as represented by (2) can be determined using DEA as follows:

$$
\begin{aligned}
\vec{D}^{i}(y,K,x,I;g_x,g_I \mid C) = \max_{\beta,\gamma}\ & \beta \\
\text{s.t.}\ & \\
& y_m \le \sum_{j=1}^{J} \gamma^j y_m^j,\quad m=1,\dots,M; \\
& \sum_{j=1}^{J} \gamma^j x_n^j \le x_n - \beta g_{x_n},\ n=1,\dots,N; \\
& I_f + \beta g_{I_f} - \delta_f K_f \le \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j),\ f=1,\dots,F; \\
& \gamma^j \ge 0,\ j=1,\dots,J.
\end{aligned} \tag{3}
$$

where γ^j is a vector of weights that are assigned to each observation j when constructing the dynamic frontier, while C in the $\vec{D}^i(\cdot \mid C)$ indicates the assumption of constant returns to scale (CRS). The first, second, and third constraint reflect the strong disposability of outputs, inputs, and investments, respectively. The fourth constraint guarantees the non-negativity of γ^j. The input-oriented dynamic directional input distance function, shown by the above program, measures the dynamic technical inefficiency of the firms under CRS (TIE).

2.2. *Dynamic Cost Inefficiency*

At any base period $t \in [0,+\infty)$, firms can be assumed to intertemporally cost minimize following the optimization problem defined as:

$$
\begin{aligned}
& W(y,K,w,c) = \min_{x,I} \int_{t_o}^{\infty} e^{-rs}\left[w_s' x_s + c_s' K_s\right] ds \\
& \text{s.t.} \\
& \dot{K}_s = I_s - \delta K_s,\ K(t_o) = k \\
& \vec{D}^i(y_s,K_s,x_s,I_s;g_x,g_I) \ge 0,\ s \in [t,+\infty)
\end{aligned} \tag{4}
$$

where *W(·)* represents the discounted flow of costs in all future time periods (the value function), *w* denotes the vector of *N* prices of variable inputs, *c* denotes the vector of *F* rental cost prices of quasi-fixed factors, *r* is a discount rate, *δ* is a diagonal matrix with depreciation rates, $\dot{K}$ reflects the vector of net investments (gross investments minus depreciation rate×capital), and *k* represents a vector of initial quasi-fixed factors at a certain point in time. The subscript *s* denotes the (future) time periods; subscripts of variables have been suppressed if they represent the current time period t. The above program reflects the fact that firms minimize the flow of future costs over time, restricted by the input-oriented dynamic directional distance function.

Following Silva and Oude Lansink (2013), we expressed (4) in terms of the current value, which yields the Hamilton-Jacobi-Bellman (H-J-B) equation:

$$
\begin{aligned}
rW(y,K,w,c) = \min_{x,I} & \left[w'x + c'K + W_K{}'(I-\delta K)\right] \\
& \text{s.t.} \\
& \vec{D}_i(y,K,x,I;g_x,g_I) \geq 0,
\end{aligned} \tag{5}
$$

where $W_K = W_K(y,K,w,c)$ is the vector of shadow values of the quasi-fixed factors. The shadow values of the quasi-fixed factors measure the decrease in the long-run costs due to the increase in the initial stocks of quasi-fixed factors by a marginal unit.[3]

Equation (5) can be quantified applying the following DEA model:

$$
\begin{aligned}
rW(y,K,w,c) = \min_{x,I,\gamma} & \left[w'x + c'K + W_K{}'(I-\delta K)\right] \\
& \text{s.t.} \\
& \sum_{j=1}^{J} \gamma^j y_m^j \geq y_m, \; m = 1,\ldots,M; \\
& x_n \geq \sum_{j=1}^{J} \gamma^j x_n^j, \; n = 1,\ldots,N; \\
& \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j) \geq I_f - \delta_f K_f, \; f = 1,\ldots,F; \\
& \gamma^j \geq 0, \; j = 1,\ldots,J; \\
& x_n \geq 0, \; n = 1,\ldots,N; \\
& I_f \geq 0, \; f = 1,\ldots,F;
\end{aligned} \tag{6}
$$

[3] The shadow values of quasi-fixed factors are calculated as a separate exercise to the quantification of all DEA problems. In particular, following Kapelko et al. (2014), these values are generated using a quadratic specification of the optimal value function and rewriting it as: $w'x = rW(y,K,w,c) - c'K + W_K{}'(I-\delta K)$. After fitting this specification, the shadow values of quasi-fixed factors are obtained using the parameter estimates.

The first four constraints can be interpreted analogously to (3). The fifth and sixth constraints guarantee the non-negativity of variable inputs and gross investments.

With the solution of program (6), we can generate dynamic overall cost inefficiency (OIE) measure, following Silva and Oude Lansink (2013), as:

$$OIE = \frac{w'x + c'K + W_K(.)'(I - \delta K) - rW(y,K,w,c)}{w'g_x - W_K(.)'g_I} \quad (7)$$

2.3. Decomposition of Dynamic Cost Inefficiency

Kapelko et al. (2014) developed the decomposition of overall dynamic cost inefficiency into dynamic technical inefficiency under variable returns to scale (VRS), dynamic scale inefficiency, and dynamic allocative inefficiency. Here we summarize this decomposition.

The difference between overall cost inefficiency (OIE) and dynamic technical inefficiency under CRS (TIE) yields the measure of dynamic allocative inefficiency (AIE). The dynamic directional input distance function under VRS ($\vec{D}(y,K,x,I;g_x,g_I \mid V)$ that measures dynamic technical inefficiency under VRS (TIEV) is obtained by adding the constraint $\sum_{j=1}^{J}\gamma^j = 1$ to program (3). The difference between $\vec{D}(y,K,x,I;g_x,g_I \mid V)$ (TIEV) and $\vec{D}(y,K,x,I;g_x,g_I \mid C)$ (TIE) is a measure of dynamic scale inefficiency (SIE). Therefore, the final decomposition can be summarized as:

$$OIE = TIEV + SIE + AIE \quad (8)$$

The values of overall dynamic cost inefficiency and its components are bounded below by 0, where values equal to 0 indicate that the firm is dynamically efficient, while values greater than 0 reflect respective dynamic inefficiency of the firm. More details on this decomposition can be found in Kapelko et al. (2014).

3. Data and Variables

The data used in this study was drawn from the AMADEUS database, which is a Bureau van Dijk dataset containing financial accounts of European companies. Our analysis was based on an unbalanced panel dataset of 197 Polish companies in the meat processing industry (NACE Rev. 2

code 10.1). We had a total of 1,117 observations between 2004 and 2012, representing small, medium-sized, and large meat-processing firms, according to the European Union's definition of firm size (European Commission, 2003). To obtain the dataset used for analysis, we first removed any firms with missing observations as well as any outliers, because DEA frontiers are very sensitive to the presence of outlying and atypical observations. To detect outliers, we followed Simar's (2003) proposal based on the application of the order-m efficiencies of Cazals et al. (2002), and discovered 6.5 percent of the observations in the dataset were outliers.

The DEA model was specified for one output, two variable inputs, and one quasi-fixed input. The inputs and output were measured in millions of Polish zloty (PLN). Output was proxied by the firms' revenues from their profit and loss accounts, taken directly from the AMADEUS database. This variable was deflated to 2003 constant prices using the producer price index for the food manufacturing industry. Variable inputs consisted of labor costs and material costs from the firms' profit and loss account, both extracted directly from the AMADEUS database, and further deflated using the labor cost index in the industry and the producer price index for nondurable consumer goods, respectively. The quasi-fixed input was measured as the beginning value of fixed assets (that is, the end value of fixed assets in the previous year) from the firms' balance sheets, which were deflated using the producer price index for investment goods. We also considered the gross investments in quasi-fixed inputs, measured as the deflated beginning value of fixed assets in year *t+1* minus the deflated beginning value of fixed assets in year *t*, plus the deflated beginning value of depreciation in year *t+1*. Depreciation, which is firm-specific, was directly obtained from the AMADEUS database and deflated using the producer price index for investment goods.

All of the price indices used to deflate inputs and output were supported by the Eurostat (2014) database and were used to compute dynamic cost and allocative inefficiencies as an approximation of the prices of variable inputs. Following Serra et al. (2011), we computed the rental cost price of quasi-fixed factor as: $c_i = (r + \delta_i)z_i$, where r is the interest rate, δ_i is depreciation rate, and z_i is the price index of quasi-fixed input. The interest rate r was defined as annual money market interest rate in Poland obtained from the Eurostat (2014) database.

Table 1 provides a summary of the main statistics for the input and output variables for the analyzed sample of Polish meat-processing companies for 2004–2012. The data shows considerable differences between the firms' inputs and outputs, as reflected by the coefficient of variation. In particular, firms' investments were characterized by the highest variation.

--- Insert Table 1 about here ---

4. Results

4.1. Static and Dynamic Inefficiency in the European Union and Crisis Periods

First, we summarized the decomposition of dynamic cost inefficiency into dynamic technical inefficiency, dynamic scale inefficiency, and dynamic allocative inefficiency, as shown by equation (8). We compared these components with traditional static inefficiency measures derived from the static directional distance function of Chambers et al. (1996).[4] The values of directional vectors applied for inputs (g_x) and investments (g_I) were the quantity of variable inputs and 20 percent of the size of the capital stock, respectively. We further computed the difference between static and dynamic measures, which could be relevant to evaluate the importance of adjustment costs on different inefficiency components in the Polish meat-processing industry. These analyses are undertaken for the whole period 2004–2012, and also for two time periods constituting the EU phase (from Poland's entry into the EU in 2004 until the economic crisis began in 2008) and the economic crisis period (from 2008 until 2012).

Table 2 summarizes the arithmetic means of dynamic and static inefficiencies for the whole period and for the European Union and crisis periods separately. The table 2 also includes the results for the Simar–Zelenyuk (S-Z) adapted Li test (Simar & Zelenyuk, 2006) used to assess the statistical significance of the differences between dynamic and static measures as well as between the European Union and crisis periods for dynamic and static measures separately.[5]

--- Insert Table 2 about here ---

The first notable finding shown in table 2 is the larger inefficiency values for dynamic measures compared with static measures, regardless of the time period analyzed. The difference between overall dynamic cost inefficiency and overall static cost inefficiency for the entire 2004–2012 period is more than 0.18, which is mainly driven by the differences between dynamic and static allocative inefficiencies exceeding 0.07. A higher level of dynamic allocative inefficiency than static can be explained by the quasi-fixed nature of capital. In particular, it suggests that firms in the sample face more problems when choosing the mixture of variable and quasi-fixed inputs than the mixture of variable inputs only, given the respective input prices. Technical and scale

[4] The calculations of dynamic and static inefficiencies were undertaken using GAMS programme.

[5] The null hypotheses tested were (1) the distribution of dynamic inefficiency measure in the whole period/EU period/crisis period is the same as distribution of static inefficiency measure in the whole period/EU period/crisis period, and (2) the distribution of inefficiency measure (dynamic/static) is the same for the EU and crisis period.

inefficiencies are also higher in dynamic than in traditional static frameworks. The differences between static and dynamic measures found are statistically significant, according to the S-Z test results. These findings indicate that the consideration of adjustments costs induced by investments rendered very pronounced effects on the inefficiency measurement. Higher dynamic inefficiencies than static counterparts suggest that firms were especially inefficient with quasi-fixed factors and investments. Therefore, the results demonstrate the importance of dynamic input on inefficiency of Polish meat-processing firms.

Comparing the European Union and the crisis periods, the overall dynamic cost inefficiency decreased quite considerably. This drop was statistically significant, according to the S-Z test results. The main source of the dynamic inefficiency decrease during the crisis was the considerable and statistically significant decrease in dynamic scale inefficiency. Hence, during the crisis, the combination of inputs and outputs of Polish meat-processing firms became less scale inefficient. Also, dynamic allocative inefficiency decreased significantly during the crisis, which implies that, on average, firms in the sample become more efficient at choosing their cost minimization input combinations. On the other hand, dynamic technical inefficiency emerged as sensitive to the recession; that is, the average dynamic technical inefficiency significantly increased during the crisis as compared with the European Union period. This finding implies that on average, Polish meat-processing firms used their inputs less efficiently, which suggests that the appearance of crisis had at least a short-term detrimental impact on technical efficiency.

Comparison of results in static inefficiency measures between the European Union and crisis periods revealed a quite different story. The overall cost static inefficiency increased slightly, but statistically significantly, in the crisis period because of the increase in allocative and technical inefficiency, despite a decrease in scale inefficiency. Therefore, although the trends for the crisis impact for overall and allocative static inefficiencies were opposite to the overall and allocative dynamic inefficiencies, the technical and scale inefficiencies reacted to the crisis in the same way in both static and dynamic frameworks.

The analysis of the dynamic inefficiency measures for the whole period 2004–2012 showed that dynamic allocative rather than technical and scale inefficiencies was the main source of dynamic cost inefficiency for the Polish meat-processing firms. This finding may indicate that firms in the sample had more problems combining the variable and dynamic factors of production in optimal proportions than using the existing dynamic production technology potential. Considerable cost savings could be obtained, as shown by the average dynamic cost inefficiency of 0.652 during 2004–2012. The average dynamic allocative inefficiency of 0.277 found for the period implies that Polish meat-processing firms could have reduce costs by 27.7 percent through improvement on the mix of variable and quasi-fixed factors of production, in light of prevailing prices. The average value of dynamic technical inefficiency for 2004–2012 was 0.229, which indicates that firms could have improved usage of their dynamic production technology potential by 22.9 percent, reducing variable inputs and increasing investments given outputs. Finally, these results confirm that dynamic scale inefficiencies of firms in the sample had an average value of 0.146, which means that during 2004–2012 firms could have reduced the differences of long-run CRS and VRS costs by 14.6 percent through reductions in variable inputs and increases in investments. When switching to the static inefficiency measures for the whole 2004–2012 period, conclusions regarding inefficiency measures were similar to dynamic; however, the differences between contributions of allocative and technical inefficiency to the overall inefficiency were slightly smaller than in the case of dynamic measures. Overall, the relatively high level of inefficiency found in this study can be caused by factors related to the management of firms and controlled by management; in other words, by the poor management of firms' resources. However, it is also possible that factors outside the control of firms' managers – such as the impact of governmental or EU regulatory actions – are partly reflected as inefficiency

Because there are no dynamic inefficiency studies of the food-manufacturing sector, we cannot make a direct comparison to previous literature; however, in comparison with Shee and Stefanou (2015), Dimara et al. (2008), and Sun et al. (1999) our study had lower technical inefficiency estimates, while Ali et al. (2009) and Kim and Han (2001) reported similar technical inefficiency levels to our findings. Interestingly, our results of the comparison between dynamic and static measures contrasted somehow with studies of Kapelko et al. (2014) and Nick and Wetzel (2014), which showed that dynamic cost inefficiency was mainly caused by dynamic technical inefficiency in construction and electricity distribution companies, respectively. This contrast might suggest that adjustment costs associated with investments play different roles in different economic sectors.

4.2. Groups of Input/Output Ratios and Dynamic and Static Inefficiency Measures

At the next stage of analysis, we used cluster analysis to identify any statistical groups for the firms' input/output ratios, and then we associated static and dynamic inefficiency measures with developed groups of these ratios. Such an analysis allowed us to assess the differences between static and dynamic frameworks with regard to the relations between input/output mixes and inefficiency measures. This analysis was important because it could reveal some additional evidence on the presence of adjustment costs and the significance of dynamic input in the Polish meat-processing industry.

Cluster analysis defines a distance measure between different objects, which then allows the most similar objects to be determined. Once distances are defined, the clustering method can function in a stepwise manner to form an agglomeration of divisive clusters (so called hierarchical clustering), or, if the number of clusters is known, the groups that form the most homogenous clusters are identified in the iterative process (so called nonhierarchical clustering). In this study, we combined both methods of clustering for ratios of fixed assets/revenues, material costs/revenues, and labor costs/revenues. First, we applied hierarchical clustering, and identified two clusters.[6] Then, starting from the predefined number of clusters as two, we performed nonhierarchical cluster analysis to refine the results. Finally, we used discriminant analysis to verify whether the formation of cluster groups was correct, and found the accuracy of the classifications was 100 percent, which confirmed that the formed clusters were valid. Table 3 shows the clustering results for ratios of fixed assets/revenues, material costs/revenues, and labor costs/revenues, that is, the average values and standard deviations of ratios for cluster groups. The table 3 also shows the results of the Wilcoxon test for the differences in input/output ratios between cluster groups.[7]

--- Insert Table 3 about here ---

The cluster analysis shown in table 3 reveals that group 1 was characterized by significantly lower average values of the ratio of fixed assets to revenues, as compared with group 2 (approximately five times lower). Group 1 also had approximately two times lower average values of the ratio of labor cost to revenues than group 2, differences that were statistically significant. On the other hand, group 1 had a higher ratio of material cost to revenues than group 2, a difference that also was statistically significant. Overall, the results indicated that group 1 was formed by firms with the lowest ratios of fixed assets and labor cost to revenues, and highest ratios of material cost to revenues. Hence, firms in group 1 can be characterized as being less capital and labor intensive, but more material intensive.

Next, we associated the groups of input/output ratios with dynamic and static inefficiency measures. Table 4 presents the average values with their standard deviations of dynamic and static

[6] It is worth pointing out that there are no completely satisfactory methods for determining the number of clusters. In this study, we applied criteria from Calinski and Harabasz (1974) and Duda and Hart (1973), which both indicated the division into two clusters was the most appropriate.

[7] The null hypothesis in this case was: the distribution of the first group of input/output ratio is the same as the distribution of the second group of input/output ratio. Please note that the Simar and Zelenyuk (2006) test was not an appropriate test in this context, because we were testing the differences between input/output ratios and not between inefficiency measures.

inefficiency measures for cluster groups identified by input/output ratios. This table also presents the results of S-Z test statistics.[8]

--- Insert Table 4 about here ---

Interpreting the results in table 4 for overall inefficiency, we observed that group 1 was the worst with regard to overall dynamic inefficiency—it had the highest values of inefficiency—and the differences between the groups were statistically significant, according to results of the S-Z test. At the same time, compared to the second group, this cluster had considerably lower values of ratios of fixed assets to revenues as well as slightly lower values of labor costs to revenues, but higher values of the ratio of material costs to revenues. Hence, in the Polish meat-processing industry, firms with high overall dynamic inefficiency, on average, tend to employ fewer fixed assets and labor inputs relatively to output, but use more material costs relatively to output. The comparison between dynamic and static overall inefficiencies for clusters groups in table 4 revealed only a small variation between clusters groups for average static measures. Also, the small differences encountered were significant at the 10 percent level, according to the S-Z test. Moreover, the ratio of input of fixed assets relatively to revenues showed the largest difference between clusters compared with other ratios and the behavior of overall inefficiency for cluster groups differed between static and dynamic frameworks; therefore, we can conclude that the impact of adjustment costs and the changes in the capital stock through investments was mainly manifested in the ratio of fixed assets to revenues.

The overall inefficiency decomposition for cluster groups provided additional insights into the differences between dynamic and static frameworks. The upshot of table 4 shows that for the two clusters identified similar patterns arise for static and dynamic technical inefficiencies; in other words, the group of Polish meat-processing firms characterized by the lowest values of fixed assets and labor costs relatively to output and the highest values of material costs to output was the group with the highest dynamic and static technical inefficiencies. Hence, interestingly, the firms that were more material-intensive were less technically efficient, both in dynamic and static terms. In addition, we can conclude that the similar behavior of input/output ratios made firms more or less

[8] The main null hypothesis was: the distribution of dynamic (static) inefficiency measure for group 1 of input/output ratio is the same as the distribution of dynamic (static) inefficiency measure for group 2 of input/output ratio. In addition, we also compared dynamic and static measures within cluster groups; in this case, the null hypothesis was: the distribution of dynamic inefficiency measure for group 1 (group 2) of input/output ratio is the same as the distribution of static inefficiency measure for group 1 (group 2) of input/output ratio.

technically efficient in dynamic and static inefficiency approaches. Similar to overall inefficiency, the variation in technical inefficiency between clusters was especially large for dynamic technical inefficiency. However, the results in table 4 indicate that there were some differences between dynamic and static scale and allocative inefficiencies for the cluster groups. Choosing the dynamic technology, firms that employed lower values of fixed assets and labor costs and higher values of material costs relatively to output were more scale and allocatively inefficient. This finding suggests that Polish meat-processing firms in the sample achieved better dynamic inefficiency outcomes in their scale and allocative dimensions using more capital assets—such as machinery and equipment—more labor inputs, and fewer materials. However, the differences between clusters of dynamic allocative inefficiency were not statistically significant. The opposite trend was observed for static scale and allocative inefficiencies; however in this case, the differences between clusters were not statistically significant, according to the S-Z test results.

5. Conclusions

This paper assessed the dynamic inefficiency of Polish meat-processing industry during 2004–2012, a period encompassing two important events that impacted this sector: Polish integration with the European Union in 2004 and the 2008 financial crisis. This study contributes to the literature as the first study to analyze the dynamic inefficiency of European food processing firms. The dynamic inefficiency measurement accounts for adjustment costs induced by firms' investments. This paper also adds to the literature a comparison of dynamic inefficiency measures with their static counterparts, analyzing the clusters of input/output mixes that firms use. In this way, we aimed to find empirical evidence for the importance of considering adjustment costs and investments when deriving inefficiency measures. Data Envelopment Analysis is used to compute dynamic and static cost inefficiencies and their decomposition into technical, scale, and allocative inefficiency.

This study showed that allocative rather than technical and scale inefficiency dominated dynamic cost inefficiency of Polish meat processing industry during 2004–2012. Therefore, firms in the sample performed better in exploring their dynamic production technology potential than in combining variable and quasi-fixed factors in optimal proportions. The average dynamic cost inefficiency of 0.652 is due to dynamic allocative inefficiency, accounting for 0.277, rather than dynamic technical inefficiency reaching 0.229 and dynamic scale inefficiency 0.146.

The results of this study offer some interesting insights on the effects of the recent financial crisis on the dynamic inefficiency of Polish meat-processing firms. Comparing dynamic inefficiencies for the European Union and crisis periods, we found evidence to support the notion that the crisis has increased dynamic technical inefficiency. Therefore, we confirmed that the crisis has hampered the productive performance. On the contrary, the recent crisis appeared to have enhanced dynamic overall, scale and allocative efficiencies of Polish meat-processing firms, which suggests that the worsening of economic environment is not detrimental to dynamic overall, scale and allocative efficiencies.

Our results also showed that the average dynamic measures differed considerably from static counterparts, providing insights into the importance of adjustment costs arising from investments in the Polish meat-processing industry. In particular, average static measures tended to underestimate all inefficiency components of cost, technical, scale, and allocative inefficiency, suggesting that firms in the sample were largely very inefficient in their use of quasi-factors and investments. The analysis of inefficiency measures by clusters of input/output ratios allowed us to deepen our conclusions regarding the comparison between dynamic and static inefficiencies. In particular, we found that Polish meat-processing firms that used less capital and labor assets and more material inputs relatively to output achieved much worse dynamic inefficiency results – overall, scale, and allocative – although such differences were not presented for static counterparts. However, similar patterns for input/output clusters were found for dynamic and static technical inefficiencies. We concluded also that the impact of adjustment costs is manifested mainly in the ratio of fixed assets to output.

The results of this study imply that there were large dynamic cost inefficiencies in the sample of Polish meat-processing firms, indicating that the analyzed firms had a considerable scope for improvement. Especially, the correction of inappropriate mix of variable and quasi-fixed factors as revealed by the considerable dynamic allocative inefficiencies is a way to improve cost inefficiencies. Our study also suggests that policy makers should be aware of negative effects of the recent economic crisis on the dynamic technical performance of Polish meat-processing firms. This creates challenges for policy makers in defining policy instruments that enhance the efficient use of the existing dynamic technology to catch up to the technology frontier in Polish meat manufacturing firms in times of crisis. Examples of possible goals of such policies include providing access to innovations and stimulating innovative investments and technological improvements.

This study points to a number of directions for future research. First, an interesting line of future research could be to extend dynamic inefficiency study to other economic sectors in which investments and adjustment costs could be important, particularly, service sector firms. Another obvious extension of this study is the future development of the method used herein, which would emphasize the distinction between inefficiency due to factors that are controlled by management and factors that are beyond management's control. Other future research could include in-depth analysis of the factors associated with dynamic inefficiencies of firms.

Our results should be interpreted with certain caution. Because our study focused on a sample of small, medium-sized, and large firms in the Polish meat-processing sector, these results cannot be directly extrapolated to micro firms.

Acknowledgements

Financial support for this article from the National Science Centre in Poland (decision number DEC-2013/11/D/HS4/00252) is gratefully acknowledged. The part of calculations for this article was made at the Wroclaw Centre for Networking and Supercomputing (http://www.wcss.wroc.pl).

References

Aramyan, L.H., Ondersteijn, Ch.J.M., Oude Lansink, A., Van Kooten, O., Wijnands, J.H.M., 2006. Analyzing greenhouse firm performance across different marketing channels. Agribusiness 22, 267-280.

Amarender Reddy, A., Bantilan, M.C.S., 2012. Competitiveness and technical efficiency: Determinants in the groundnut oil sector of India. Food Policy 37, 255-263.

Ali, J., Singh, S.P., Ekanem, E., 2009. Efficiency and productivity changes in the Indian food processing industry: determinants and policy implications. International Food and Agribusiness Management Review 12, 43-66.

Calinski, T., Harabasz, J., 1974. A dendrite method for cluster analysis. Communications in Statistics 3, 1–27.

Cazals, C., Florens, J., Simar, L., 2002. Nonparametric frontier estimation: a robust approach. Journal of Econometrics 106 (1), 1-25.

Chaaban, J., Réquillart, V., Trévisiol, A., 2005. The role of technical efficiency in takeovers: Evidence from the French Cheese Industry, 1985-2000. Agribusiness 21, 545-564.

Chambers, R.G., Chung, Y., Färe, R., 1996. Benefit and distance functions. Journal of Economic Theory 70, 407-419.

Chen, C.-M., 2009. A network-DEA model with new efficiency measures to incorporate the dynamic effect in production networks. European Journal of Operational Research 194, 687–699.

Chen, C.-M., Van Dalen, J., 2010. Measuring dynamic efficiency: theories and an integrated methodology. European Journal of Operational Research 203, 749–760.

Dimara, E., Skuras, D., Tsekouras, K., Tzelepis, D., 2008. Productive efficiency and firm exit in the food sector. Food Policy 33, 185-196.

Dios-Palomares, R., Martínez-Paz, J.M., 2011. Technical, quality and environmental efficiency in the olive oil industry. Food Policy 36, 526-534.

Doucouliagos, H., Hone, P., 2000. The efficiency of the Australian dairy processing industry. Australian Journal of Agricultural and Resource Economics 44, 423-438.

Duda, R.O., Hart, P.E. (1973). Pattern classification and scene analysis. John Wiley & Sons, New York.

European Commission, 2011. Study on the competitiveness of the European meat processing industry. Luxembourg: Publication Office of the European Union. Available: http://ec.europa.eu/enterprise/sectors/food/files/report_compmeat_en.pdf. Accessed 10 October 2014.

European Commission, 2003. Recommendation concerning the definition of micro, small and medium-sized enterprises. Official Journal of the European Union, http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:124:0036:0041:EN:PDF. Accessed 10 October 2014.

Eurostat, 2014. Short-term business statistics.

Fallah-Fini, S., Triantis, K., Johnson, A.L., 2014. Reviewing the literature on non-parametric dynamic efficiency measurement: state-of-the-art. Journal of Productivity Analysis 41, 51–67.

Färe, R., Grosskopf, S. (1996). Intertemporal production frontiers: With dynamic DEA. Kluwer Academic Publishers, Boston.

Kapelko, M., Oude Lansink, A., 2013. Technical efficiency of the Spanish dairy processing industry: Do size and exporting matter? In A.B. Mendes, E.L.D.G. Soares da Silva and J. Santos, eds., Efficiency Measures in the Agricultural Sector, With Applications. Springer, Germany.

Kapelko, M., Oude Lansink, A., Stefanou, S.E., 2014. Assessing dynamic inefficiency of the Spanish construction sector pre- and post-financial crisis. European Journal of Operational Research 237, 349-357.

Kim, S., Han, G., 2001. A decomposition of total factor productivity growth in Korean manufacturing industries: A stochastic frontier approach. Journal of Productivity Analysis 16, 269-281.

Morrison Paul, C.J., 1997. Structural change, capital investment and productivity in the food processing industry. American Journal of Agricultural Economics 79(1), 110-125.

Nemoto, J., Goto, M., 2003. Measurement of dynamic efficiency in production: an application of data envelopment analysis to Japanese electric utilities. Journal of Productivity Analysis 19, 191–210.

Nick, S., Wetzel, H., 2014. The hidden cost of investment: The impact of adjustment costs on firm performance measurement and regulation. EWI Working paper, No 14/03, http://www.ewi.uni-koeln.de/fileadmin/user_upload/Publikationen/Working_Paper/EWI_WP_14_03_Hidden_Cost_of_Investment_Update.pdf. Accessed 15 October 2014.

Oude Lansink, A., Pietola, K., Bäckman, S., 2002. Efficiency and productivity of conventional and organic farms in Finland 1994-1997. European Review of Agricultural Economics 29, 51-65.

Rau, M.-L., Van Tongeren, F., 2009. Heterogeneous firms and homogenising standards in agri-food trade: the Polish meat case. European Review of Agricultural Economics 36(4), 479-505.

Serra, T., Oude Lansink, A., Stefanou, S.E., 2011. Measurement of dynamic efficiency: a directional distance function parametric approach. American Journal of Agricultural Economics 93(3), 756-767.

Shee, A., Stefanou, S.E., 2015. Endogeneity corrected stochastic production frontier and technical efficiency. American Journal of Agricultural Economics 97, 939-952.

Silva, E., Stefanou, S.E., 2003. Nonparametric dynamic production analysis and the theory of cost. Journal of Productivity Analysis 19, 5-32.

Silva, E., Stefanou, S.E., 2007. Dynamic efficiency measurement: theory and application. American Journal of Agricultural Economics 89(2), 398-419.

Silva, E., Oude Lansink, A., 2013. Dynamic efficiency measurement: A directional distance function approach. Centro de Economia e Finanças da UPorto Working Paper 2013-07, http://cefup.fep.up.pt/uploads/WorkingPapers/wp1307.pdf. Accessed 15 March 2014.

Simar, L., 2003. Detecting outliers in frontier models: a simple approach. Journal of Productivity Analysis 20(3), 391-424.

Simar, L., Zelenyuk, V., 2006. On testing equality of distributions of technical efficiency scores. Econometric Reviews 25, 497-522.

Sueyoshi, T., Sekitani, K., 2005. Returns to scale in dynamic DEA. European Journal of Operational Research 161, 536-544.

Sun, H., Hone, P., Doucouliagos, H., 1999. Economic openness and technical efficiency. A case study of Chinese manufacturing industries. Economics of Transition 7, 615-636.

Wijnands, J.H.M, Bremmers, H.J., Van der Meulen, Poppe, K.J., 2008. An economic and legal assessment of the EU food industry competitiveness. Agribusiness 24, 417-439.

Von Geymueller, P., 2009. Static versus dynamic DEA in electricity regulation: The case of US transmission system operators. Central European Journal of Operational Research 17, 397-413.

Table 1. Descriptive statistics of input-output data of Polish meat processing firms, 2004-2012, MLN PLN, constant 2003 prices

Variable	Mean	St. dev.	Coefficient of variation
Revenues	99.185	122.053	1.231
Fixed assets	22.383	29.499	1.318
Labor costs	4.759	6.648	1.397
Material costs	83.590	103.595	1.239
Investments	3.632	8.271	2.277

Table 2. Decomposition of dynamic and static cost inefficiencies for different time periods

Year	Overall inefficiency	Technical inefficiency VRS	Scale inefficiency	Allocative inefficiency
The whole period				
Dynamic	0.652	0.229	0.146	0.277
Static	0.463	0.168	0.088	0.207
Difference	0.189	0.061	0.058	0.070
S-Z test statistics (differences between dynamic and static)	308.209***	32.501***	96.858***	25.788***
European Union period				
Dynamic	0.767	0.214	0.264	0.289
Static	0.455	0.161	0.133	0.162
Difference	0.311	0.053	0.131	0.127
S-Z test statistics (differences between dynamic and static)	135.545***	7.464***	78.737***	31.206***
Crisis period				
Dynamic	0.596	0.236	0.088	0.272
Static	0.466	0.171	0.066	0.229
Difference	0.130	0.065	0.022	0.042
S-Z test statistics (differences between dynamic and static)	154.198***	27.387***	21.491***	11.615***
S-Z test statistics (differences between periods, dynamic)	145.935***	12.117***	139.440***	10.295***
S-Z test statistics (differences between periods, static)	58.88***	5.200**	25.518***	14.263***

*** significant differences at the critical 1 percent level, ** significant differences at the critical 5 percent level.

Table 3. Clusters of input-output ratios, 2004–2012

Cluster	Fixed assets/Revenues	Material costs/Revenues	Labor costs/Revenues
Group 1			
Mean	0.219	0.851	0.049
Standard deviation	0.143	0.127	0.046
Group 2			
Mean	1.405	0.457	0.088
Standard deviation	0.475	0.238	0.071
Wilcoxon test statistics (differences between group 1 and group 2)	-10.219***	8.632***	-4.307***

*** significant differences at the critical 1 percent level.

Table 4. Dynamic and static inefficiencies for clusters of input-output ratios, 2004–2012

Clusters	Overall inefficiency	Technical inefficiency VRS	Scale inefficiency	Allocative inefficiency
DYNAMIC				
Group 1				
Mean	0.663	0.233	0.147	0.282
Standard deviation	0.121	0.144	0.155	0.164
Group 2				
Mean	0.327	0.093	0.103	0.132
Standard deviation	0.234	0.134	0.132	0.154
S-Z test statistics (differences between group 1 and group 2, dynamic)	26.667***	10.144***	3.023**	-1.643
STATIC				
Group 1				
Mean	0.463	0.169	0.087	0.207
Standard deviation	0.163	0.124	0.123	0.135
Group 2				
Mean	0.459	0.127	0.115	0.216
Standard deviation	0.219	0.172	0.177	0.149
S-Z test statistics (differences between group 1 and group 2, static)	-1.140*	7.389***	-4.460	-0.498
S-Z test statistics (differences between dynamic and static, group 1)	306.706***	33.567***	97.244***	28.362***
S-Z test statistics (differences between dynamic and static, group 2)	1.822*	0.194	-0.848	1.349**

*** significant differences at the critical 1 percent level, ** significant differences at the critical 5 percent level, * significant differences at the critical 10 percent level.