Contents available at: Sri Lanka Journals Online

Tropical Agricultural Research

Journal Home Page: https://tar.sljol.info

RESEARCH

Technical Efficiency of the Food Manufacturing : A Stochastic Frontier Analysis of European Firms

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ARTICLE INFO

Article history:
Received: 20 September 2023
Revised version received: 03 March 2025
Accepted: 10 March 2025
Available online: 01 April 2025

Keywords:
Technical efficiency
Food manufacturing
Stochastic frontier model
Translog production function
European Union

Citation:
Rajapakasha, R.M.H.V. and Prasada, D.V.P., (2025). Technical Efficiency of the Food Manufacturing: A Stochastic Frontier Analysis of European Firms. Tropical Agricultural Research, 36(2): 106-116.

DOI: https://doi.org/10.4038/tar.v36i2.8930

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ABSTRACT

The European Union accounts for the world's largest food and beverage manufacturing industry. It contributes to more than one-third of global food exports. The disruption of the supply chains of energy and fuel due to political unrest in the continent has worsened the efficiency outlook of the region's food industry which was just starting to recover from COVID-19 shock. In this study, a stochastic frontier estimation using the translog production function was employed to assess the technical efficiency of the European Union food industry. Cross-sectional data from 1,516 food manufacturing firms of 27 European Union countries corresponding to the period 2020-2021 was used for empirical analysis. The inefficiency effect model included the factors identified in the blueprint developed by the European Commission to make the transition pathways of industrial ecosystems possible. The study estimated the input elasticities with respect to capital and labor were 0.24 and 0.47, respectively. The overall technical efficiency of the European Union food industry was estimated at 0.81. The firm size, firm age, custom and trade regulations, tax rates, bonuses related to performance and political instability emerged as statistically significant drivers of inefficiency. Expanding firm size and regulating tax rates and custom regulations are revealed to be the most influential factors to improve efficiency. Country variation is significant and a common policy independent from politics to improve micro-environment of food manufacturing firms is likely to reduce country variation according to the model results.

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INTRODUCTION

The European Union remains the top global food trader due to its quality and unique competitiveness of processed food products. More than 70% of agricultural produce within the European Union are transformed into manufactured food products (European Commission, 2023). The European food industry is the world's leading exporter and it contributes 35.7% of global food exports (Food and Agricultural Organization, 2022). The main categories of the European Union's food exports are cereal preparations, dairy produce, meat products, beverages and spirits that show 9.2%, 8.4%, 7.9% and 17.2% of shares in total food exports, respectively (European Commission, 2022).

Currently, the European Union faces challenges in food manufacturing and processing mainly due to disruptions in energy supply. Among other pressures, Russia-Ukraine conflict has caused blockages to supply chains of fuel, coal and natural gas to the Europe. Natural gas contributes to 32.7% of energy consumption by the industrial sector of the European Union after electricity (European Union, 2023). Energy crisis hikes the energy prices while resulting in high input prices, hence high commodity prices (European Council, 2023). In 2022, agro-food exports from the European Union to the global market showed 31% increase than in 2021. But this increase is basically due to the nearly 100% rise in prices but not the rise in volumes of production (European Commission, 2022). The challenge to increase the volumes of food products against the energy crisis and related issues remains unresolved. With respect to the energy crisis, the European Commission and the Industrial Forum of the European Union together have developed a blueprint for transition pathways to improve the micro-environment for the industries to achieve higher efficiency, focusing on infrastructure, investments and funding, regulations and public governance, research and innovation, skills, social dimensions and sustainable competitiveness (European Commission, 2023).

The assessment of technical efficiency in food manufacturing firms is commonly done through two primary approaches: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). SFA, a parametric technique, is particularly useful for accounting for random errors and unobserved heterogeneity, making it a popular choice in settings with potentially unmeasured factors influencing efficiency (Battese & Coelli, 1995). Several factors affect the technical efficiency of food manufacturing firms, including firm size, capital intensity, labor quality, and the degree of technological innovation. Wessler (2022) highlights that larger firms in the food manufacturing sector tend to exhibit higher technical efficiency due to economies of scale. Similarly, the impact of labor quality has been emphasized in studies focusing on skill levels and training, where higher-skilled labor is positively correlated with better technical efficiency (Färe et al., 2004). Furthermore, the adoption of advanced technologies has been shown to improve efficiency by optimizing production processes (Tsimiklis and Makatsoris, 2019).

The food manufacturing industry in Europe is highly heterogeneous, and technical efficiency can vary significantly across sub-sectors. For instance, studies have shown that efficiency levels in the dairy sector differ from those in meat processing or beverage industries, largely due to differences in input requirements and production processes (Kumbhakar & Lovell, 2000). Additionally, regional factors, such as the level of industrialization, infrastructure quality, and access to markets, influence the efficiency of food manufacturers. Kuosmanen & Kortelainen (2005) examine the variation in technical efficiency among food firms in different European countries, highlighting that firms in more industrialized countries such as Germany and the Netherlands tend to exhibit higher efficiency levels compared to firms in Eastern Europe. Moreover, inefficiency may arise due to market imperfections, such as imperfect competition or access to credit. Barros (2005) reports that food manufacturing firms operating in more competitive environments were more likely to exhibit higher levels of efficiency. This suggests that fostering competition and improving access to financing can be effective strategies for enhancing technical efficiency in the sector.

Governments and regulatory bodies have used findings from efficiency studies to shape policy decisions aimed at improving competitiveness and sustainability. For example, subsidies for technological upgrades or training programs can be directed toward less efficient firms to enhance overall industry productivity. Additionally, food safety regulations and environmental policies are crucial factors that can both positively and negatively impact efficiency. For instance, stringent food safety standards may impose additional costs but can also lead to long-term gains in productivity by standardizing production processes (Sandberg et al., 2023).

The energy crisis and related issues facing the European Union are mostly unfavorable for its food manufacturing sector. It lowers the productivity of the European Union's food industry while reducing its competitiveness globally. Therefore, urgent actions are needed to admit the food industry of the European Union into the twin green and digital sustainable transition, both to overcome above-mentioned challenges and to retain its competitiveness to survive when these actions are implemented. In this context, it is important to identify the most significant key elements mentioned in the transition blueprint that affect the efficiency of the food industry the most.

This study was conducted to assess the technical efficiency of the European Union food industry by employing a stochastic frontier estimation using the translog production function. The analysis performed would contribute to benchmarking the input-output efficiencies with relation to a large sample of food manufacturing firms in the context of the factors listed in the transition blueprint of European commission. It will be helpful to improve the resilience and long-term sustainability of industry to combat against external shocks of the economy and the resource scarcities.

METHODOLOGY

Stochastic frontier model

In 1977, Aigner, Lovell and Schmidt and Meeusen and van den Broeck independently proposed the stochastic frontier model (Eqn. 1) in the form of,

$$ln\, q_i = x_i\beta + v_i - u_i \qquad \text{(Eqn. 1)}$$

where; $q_i$is the output of i[th] firm; $x_i$is the vector containing logarithms of the inputs; β is the vector of unknown parameters; v_i is the symmetric error variable which is independently and identically distributed normal random error term; u_i is the non-negative random error term associated with technical inefficiency. Both error variables are uncorrelated with the explanatory variables in x_i.

In many studies, both Cobb-Douglas and translog production functional forms have been used in the stochastic frontier model to assess the technical efficiency (Bravo-Ureta and Evenson, 1994; Coelli and Battese, 1992; Coelli and Battese, 1995; Coelli and Battese, 1996; Mulwa and Kabubo-Mariara, 2017; Osmani et al., 2016; Oyakhilomen et al., 2015; Piesse and Thirtle, 2000; Pinheiro and Bravo-Ureta, 1997; Rada et al., 2010; Squires and Tabor, 1991; Sultana et al., 2022; Taraka et al., 2010; Ume et al., 2021; Yilmaz et al., 2020). Cobb-Douglas function only shows a first-order relations (Coelli et al., 1998). Translog functional form which shows second-order relations was chosen against the Cobb-Douglas functional form because of its flexibility over the Cobb-Douglas functional form.

In this study, World Bank Enterprise Survey (2020-2021) data of 1,516 food manufacturing firms in the European Union were analyzed in translog functional form (Eqn. 2).

$$lnq_i = \beta_0 + \beta_1 lnx_1 + \beta_2 lnx_2 + \beta_3(lnx_1)(lnx_2) + 0.5\beta_4(lnx_1)(lnx_1) + 0.5\beta_5(lnx_2)(lnx_2) + v_i - u_i \qquad \text{(Eqn. 2)}$$

The output variable (q_i) was the value of sales output in the fiscal year preceding the time of the survey. The input variables were the values of capital (x_1) and labor (x_2) in the same fiscal year. β and random error terms, v_i and u_i are the same as mentioned earlier.

Inefficiency effect model

The inefficiency random error term (u_i) in the stochastic frontier model is related to technical inefficiency as follows: (Eqn. 3)

$$te = \exp(-u_i) \qquad \text{(Eqn. 3)}$$

Further, the inefficiency random error term can be regressed with exogenous variables related to technical inefficiency (Bravo-Ureta and Evenson, 1994; Coelli and Battese, 1995; Kumbhakar and Lovell, 2000; Piesse and Thirtle, 2000; Pinheiro and Bravo-Ureta, 1997) to assess the nature of relationship between exogenous variables and the technical inefficiency. The inefficiency effect model with exogenous variables (Eqn. 4) takes the following form:

$$u_i = z_i\delta + w_i \qquad \text{(Eqn. 4)}$$

where; u_i is the random error variable associated with technical inefficiency; z_i is the vector of explanatory variables related to inefficiency; δ is the vector of unknown parameters in the inefficiency model; w_i is the random variable in the inefficiency effect model which is not identically distributed nor non-negative (Coelli and Battese, 1995).

In this study, the explanatory variables in z_i vector were related to the elements in blueprint developed by the European Commission. The inefficiency model variables were firm size, firm age, firm ownership, legal status of the firm, having a quality certificate, having a technology permit, having a web site, running loans, research and development activities, private security, purchasing fixed assets in last fiscal year, having performance indicators, performance bonus for the workers, conducting formal trainings, labor obstacle, land obstacle, electricity obstacle, transport obstacle, having a permit obstacle, finance obstacle, influence of tax rate, custom and trade regulations, safety regulations, hygiene regulations, environmental regulations, competition from informal firms, political instability, corruption and crime.

Maximum likelihood estimation

In stochastic frontier models, there can be seen two types of random error terms, both normally distributed constant error term and truncated version of half-normal error term which is non-negative nor constant. Therefore, the maximum likelihood method is more suitable than the ordinary least squares method as it estimates linear regression models with non-constant error terms. Maximum likelihood estimates for the vector of β coefficients can be obtained by maximizing probability density function or log-likelihood function (Coelli et al., 1998). Maximizing log-likelihood function with respect to β is equivalent for minimizing the sum of squares (Coelli et al., 1998).

If the coefficients of vector δ are equal to zero, then the technical inefficiency effects are not related with the z_i variables (Coelli and Battese, 1995). Therefore, null hypothesis for the inefficiency effect model mentioned in Eqn. 4 can be written as (Eqn. 5),

$$H_0: \delta_i = 0 \qquad \text{(Eqn. 5)}$$

$$H_1: \delta_i \neq 0 \qquad \text{(Eqn. 6)}$$

If δ_i is not equal to zero, then reject the null hypothesis and accept the alternative hypothesis (Eqn. 6). Alternative hypothesis implies that the inefficiency effects are related to the z_i variables. The significance of the variables was assessed by the z-value (Eqn. 7). If |z| exceeds the critical value, $z_{0.95} = 1.645$ at 5% level of significance, then the z_i variable has a significant effect on inefficiency. (Coelli *et al*., 1998).

$$\text{Z-value} = (\delta_i - H_0) / SE(\delta_i) \qquad \text{(Eqn. 7)}$$

The estimations were done using the STATA statistical software package.

RESULTS AND DISCUSSION

Sample description

The sample included 1,516 food manufacturing firms belonging to 27 European Union countries, namely, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. Firm characteristics of the sample have been described under firm size, firm age, ownership and legal status (Table 1). Each of the three categories of firm size, namely, small, medium and large-scale, consisted of nearly one third of the total sample. The scaling system was based on 100-point system of 5-19 points for small-scale, 20-99 points for medium-scale and more than 100 points for large-scale. About 90.5% of the sample had domestic ownership. Nearly 9.5% of firms had foreign ownership as the primary owner is a foreign national resident in the country. More than half of the sample (55.5% of the sample) were shareholding companies with non-traded shares or shares traded privately. From the total firms, 24.6% had legal status of limited partnership. Other firms have small percentages of sole proprietors and shareholding companies with shares traded in stock market that publicly trade their shares. About 80.5% of the sample had been established for less than 50 years.

Exogenous variables in the inefficiency model include both categorical variables and dummy variables (Kang *et al.*, 2018). Most of the dummy variables were related to innovation and infrastructure development (Table 2). About 55.9% of firms had internationally recognized certifications such as International Organization for Standardization (ISO) for manufacturing and services and/or Hazard Analysis and Critical Control Point (HACCP) for food. Most of the companies did not have a technology license from a foreign owned company. Therefore, only a very low percentage (13.6%) of firms had access to foreign technology. Most of the firms did not invest in formal research and development activities. It was a very low percentage (25.3%) of firms that gave the employees the chance to develop new products. Also, 45.4% of firms use performance indicators to assess performance. About 80.7% of firms had their own website.

Table 1. Sample description on firm characteristics

Variable	Category	Number of firms	Sample share
Firm size	Small	569	37.5%
	Medium	569	37.5%
	Large	378	24.9%
Firm age	<50 years	1220	80.5%
	>50 years	296	19.5%
Ownership	Domestic	1372	90.5%
	Foreign	144	9.5%
Legal status	Private shareholder	841	55.5%
	Stock market shareholder	123	8.1%
	Sole proprietor	139	9.2%
	Limited partnership	374	24.6%
	Other	39	2.6%

Table 2. Sample description on innovation and infrastructure development

Variable	Number of firms	Sample share
Quality certificate	848	55.9%
Technology license	207	13.6%
Web site	1223	80.7%
Loans	868	57.2%
Research and development	384	25.3%
Private security	962	63.4%
Fixed assets	848	55.9%
Performance indicators	689	45.4%
Performance bonus	402	26.5%
Trainings	652	43.0%

Table 3. Sample description on obstacles

Variable	No obstacle (%)	Minor obstacle (%)	Major obstacle (%)	Moderate obstacle (%)	Severe obstacle (%)
Land obstacle	33.11	25.99	11.68	24.27	4.95
Labor obstacle	66.42	12.93	6.33	11.74	2.57
Electricity obstacle	44.33	12.07	13.92	10.62	19.06
Transport obstacle	44.85	19.59	11.74	17.35	6.46
Permit obstacle	48.15	19.39	8.84	20.05	3.56
Finance obstacle	53.50	17.88	9.50	16.09	3.03
Tax rate	24.54	17.88	19.13	25.86	12.60
Custom and trade regulations	60.22	16.82	6.00	14.71	2.24
Safety regulations	37.73	25.13	11.02	23.09	3.03
Hygiene regulations	38.13	25.00	10.42	22.36	4.09
Environmental regulations	37.86	24.60	10.06	24.08	3.36
Informal sector competition	54.49	16.29	8.11	17.55	3.56
Political instability	46.77	17.94	11.02	17.15	7.12
Corruption	60.09	13.39	7.85	13.79	4.88
Crime	63.39	17.74	4.82	12.07	1.98

The rapid diffusion of new digital technologies requires science and technology qualifications among the list of shortage employment (European Labor Authority, 2022). Following "three Cs", COVID-19 pandemic, climate change and conflicts, the firms were facing an imbalance in the labor market. A significant number of employees had not returned to their pre-pandemic jobs when restrictions were removed (European Labor Authority, 2022). According to the results, the percentage of firms that have given formal training for the employees was 43.0%. There were a considerable number of food manufacturing firms that did not hold formal trainings for their employees for the technological diffusion. Also, a very low number of firms (26.5%) offered bonuses for the workers based on performance. A considerable number of firms (57.2%) depended on running loans, and 55.9% had purchased fixed assets of land, buildings, machinery and equipment while expanding the business during last fiscal year.

The obstacles faced by the firms were included in the inefficiency model as categorical variables (Table 3). There were five categories reported depending on the degree of the obstacle, namely, no obstacle, minor obstacle, major obstacle, moderate obstacle and severe obstacle. The highest obstacle was found in tax rate as it shows 57.59% for major, moderate and severe categories together. Electricity seems to be a major or higher obstacle for 43.3% of the firms. Land was a major or higher obstacle for 40.9% of the firms. Other obstacles have percentages below 40% for major or higher categories.

Translog production function

According to the maximum likelihood estimates in the stochastic frontier model, the input elasticities of capital and labor were 0.24 and 0.47 respectively. It means that 1% increase in capital and labor will result in 0.24% and 0.47% increase in output value. The first order coefficients of translog production function in the stochastic frontier model, can be interpreted as elasticities of output with respect to inputs (Coelli et al., 1998). Both capital and labor were significant in the production function as $|z|>1.645$ (Table 4). The country variation was found to be significant within the European Union for the food manufacturing industry.

Technical efficiency

Technical efficiency measures the ability of the firms to obtain the maximum output from given inputs (Coelli et al., 1998). Overall technical efficiency of the European Union food manufacturing was 0.81. It means that the European Union firms produce 81%of the maximum output achievable from available inputs. It shows that the European Union's food industry is mostly technically efficient. The highest average technical efficiency (more than 0.90) was shown by the countries Italy, Luxembourg and Romania. The lowest average technical efficiency less than 0.75 was shown by the countries Austria, Netherlands, Finland, Belgium and Germany (Table 5).

Six exogenous variables significantly influence the technical inefficiency as they show |z| value higher than 1.645 (Table 6). They are firm size, firm age, performance bonus, tax rate, custom and trade regulations and political instability. Firm age, performance bonus and political instability showed positive coefficients in the inefficiency model while firm size, tax rate and custom and trade regulations showed negative coefficients. If a variable has a positive sign in the coefficient, it means that the inefficiency increases with a unit increase of factor variable. If a variable has a negative sign in the coefficient, it means that the inefficiency decreases with the increase of variable. Thus, the firm level inefficiency decreases with the increase in firm size, tax rate and custom and trade regulations for import license. The inefficiency increases with the increase in firm age, performance bonus and political instability.

Table 4. Estimates of maximum likelihood method for translog production function

Variable	Coefficient	Standard error	z-value	P>|z|
Constant, β_0	3.8503	0.5897	6.53	0.000
Capital, β_1	0.2426	0.1184	2.50	0.040
Labour, β_2	0.4670	0.1584	2.95	0.003
Cap*Lab, β_3	-0.2121	0.0187	-11.33	0.000
Capital^2, β_4	0.2189	0.0144	15.21	0.000
Labour^2, β_5	0.2220	0.0274	8.11	0.000

Table 5. Country -wise mean technical efficiency in food manufacturing (estimated)

Country	Efficiency	Country	Efficiency	Country	Efficiency
Austria	0.7057	France	0.8085	Malta	0.8855
Belgium	0.7378	Germany	0.7437	Netherlands	0.7218
Bulgaria	0.8386	Greece	0.8388	Poland	0.7798
Croatia	0.8572	Hungary	0.7976	Portugal	0.8233
Cyprus	0.8068	Ireland	0.8061	Romania	0.9003
Czech	0.8137	Italy	0.9231	Slovakia	0.7727
Denmark	0.8143	Latvia	0.8628	Slovenia	0.8193
Estonia	0.8020	Lithuania	0.8347	Spain	0.8310
Finland	0.7376	Luxembourg	0.9091	Sweden	0.8771

Table 6. Inefficiency effect model results

Variable	Coefficient	Standard error	z-value	P>|z|
Firm size	-1.0988	0.3288	**-3.34**	0.001
Firm age	0.7377	0.4074	**1.81**	0.070
Ownership	-1.0478	0.8977	-1.17	0.243
Legal status of the firm	0.0960	0.1230	0.78	0.435
Quality certificate	-0.4954	0.3308	-1.50	0.134
Technology license	0.5862	0.5029	1.17	0.244
Web site	-0.3282	0.3355	-0.98	0.328
Loans	-0.2779	0.3259	-0.85	0.394
Research and development	-0.7251	0.4991	-1.45	0.146
Private security	0.3529	0.3181	1.11	0.267
Fixed assets	-0.3759	0.3251	-1.16	0.248
Performance indicators	-0.1282	0.4263	-0.30	0.764
Performance bonus	0.9387	0.4344	**2.16**	0.031
Trainings	-0.2066	0.3589	-0.58	0.565
Labor obstacle	0.0584	0.1384	0.42	0.673
Land obstacle	-0.0201	0.1832	-0.11	0.912
Electricity obstacle	-0.1296	0.1155	-1.12	0.262
Transport obstacle	-0.0876	0.1672	-0.52	0.601
Permit obstacle	-0.0710	0.1704	-0.42	0.677
Finance obstacle	0.1514	0.1375	1.10	0.271
Tax rate	-0.2597	0.1315	**-1.97**	0.048
Custom and trade regulations	-1.8812	0.8924	**-2.11**	0.035
Safety regulations	-0.0798	0.1794	-0.44	0.656
Hygiene regulations	-0.0449	0.1633	0.27	0.783
Environmental regulations	-0.1534	0.1872	-0.82	0.412
Informal sector -competition	0.1492	0.1279	1.17	0.244
Political instability	0.2528	0.1367	**1.85**	0.064
Corruption	-0.0869	0.1555	-0.56	0.576
Crime	-0.2035	0.2181	-0.93	0.351

Prob>chi^2 = 0.0001 Log likelihood = -1532 Wald chi^2(5) = 17055

Based on the study findings, there are several ways to reduce the inefficiency of the European Union food manufacturing industry. The first one is expanding the firm size because land and labor obstacles were not significant in the results. Secondly, managing performance via performance benchmarks determined by industry standards is likely to reduce the inefficiency. Also, employee incentives need to be managed effectively without losing efficiency. Further, regulating tax rates and customs relations show promise in reducing inefficiency. Also, significant reduction of old firms as a proportion towards more modernized organizational structures with new technologies is necessary for Europe's food manufacturing sector. The study also highlights that the integration of the European Union as not being a crucial contribution to the performance of the food manufacturing firms. Therefore, a common policy independent from politics to improve the efficiency of food manufacturing firms is a timely option.

Our findings share parallels with other published work on the topic. Larger food manufacturing firms tend to exhibit higher production efficiency due to the ability to invest in advanced technologies and streamline production processes (Wessler, 2022). Additionally, large firms can often negotiate better terms with suppliers and achieve more consistent product quality. While land constraints can be met with intensive and moder technologies, the challenge of labor constraints, such as labor shortages in agriculture or manufacturing, leads firms to invest in automation (Krause & Göbel, 2019). The food manufacturing firms in Europe that adopted continuous benchmarking practices were able to significantly improve efficiency by optimizing their supply chains and reducing waste (Romanello and Veglio, 2022). Focusing on tax and tariff related bottlenecks, Sandberg et al. (2023) reported that lower corporate tax rates and favorable customs relations within the European Union allowed firms to reinvest savings into production improvements, leading to greater efficiency. Modernized organizational structures, such as the adoption of lean manufacturing principles and agile organizational frameworks, have reportedly helped firms to respond more quickly to changes in demand and improve overall efficiency (Tsimiklis and Makatsoris, 2019).

CONCLUSION

We found that the sample of food manufacturing firms displayed relatively high technical efficiency on average with respect to capital and labour productivity. However, the significant country level variation is evidence of both lack of harmonization of technologies and standards. The inefficiency analysis, on the other hand, highlighted important bottlenecks relevant to European firms for maintaining the efficiency levels required for maintaining their position as the market leader in food manufacturing. Among the lagging factors, the study findings shed light on firm size, firm age, performance benchmarks, employee incentives, tax rates and customs relations, and institutional instabilities as points of concern. Each of these elements contributes to a more efficient production process by encouraging better resource allocation, technology adoption, performance tracking, and effective organizational management. Firms that understand and leverage these factors can create a competitive advantage in the highly dynamic and competitive European food manufacturing industry.

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