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MONTE CARLO SIMULATION FOR STRESS TESTING ENDOGENOUS PROFITABILITY FACTORS DURING POLYCRISIS: A CASE STUDY FROM THE POULTRY SUBSECTOR

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Abstract: *Can historical company data help estimate future performance during economic uncertainty? This study investigates whether past business cycles can be used to estimate profitability in the context of a polycrisis – a period marked by overlapping disruptions such as avian influenza, COVID-19 trade restrictions, extreme weather events, and rising feed and energy prices. These shocks have severely impacted agro-related industries, such as poultry processing. Focusing on three Central European poultry processing companies, we use Monte Carlo simulations for stress testing their profitability for the 2023 period, aiming to support financial planning by analysing firm-specific, endogenous, management-controllable factors. Return on Sales (ROS) and Return on Equity (ROE) are used to evaluate profitability, incorporating variables such as euro exchange rates in the case of export-driven firms. Our results indicate that Company "A," characterized by stable operations, had the lowest probability of negative ROE, while Companies "B" and "C" demonstrated greater volatility. We found that the model provides a good estimate of the factors affecting the companies' profitability that are directly or indirectly reflected in their accounting data. Indicating that the test could be a valuable tool for supporting managerial decision-making in financial planning, though further refinements are needed to enhance accuracy.*

Keywords: *Monte-Carlo Simulation, Profitability, DuPont analysis, Poultry subsector*
(JEL code: G17, C15)

INTRODUCTION

Our research objective is to examine how historical data from previous business periods can be used to estimate future performance in an extreme economic environment. With the goal to support financial planning for business management in today's increasingly volatile economic environment by focusing on endogenous factors that could be more directly controlled by firms' management.

To this end, we examined three poultry processing companies in a case study, since this sector serves as an ideal candidate, as it was affected by multiple interlinking crisis factors throughout the recent periods, making long-term financial planning challenging. These negative effects include the avian flu and COVID-19 epidemics and the rise in energy and feed prices that were particularly pronounced in Central Europe's agricultural and agro-related companies.

According to Morin and Kern (1999) who first defined polycrisis, the greatest challenge today is the "interconnected and overlapping set of crises" that affect all of humanity. In their view, the challenge for the 21st century is not a single threat - such as climate change - but a complex set of interrelated and intertwined problems, a phenomenon they define as polycrisis (Morin and Kern, 1999).

Some literature takes a different approach to the polycrisis, viewing it as an umbrella term that includes new crises affecting the European Union and the consequences of the previous crisis of 2007-2009 (Zeitlin et al., 2019; Meissner and Schoeller, 2019). In contrast, according to Lawrence et al. (2022, 2024), similar to the work of Morin and Kern (1999), a "global polycrisis occurs when crises in multiple global systems become causally entangled in ways that significantly degrade humanity's prospects" (Lawrence et al., 2022). In their view, the crises of recent decades have been closely interlinked, building on each other's consequences, thus reinforcing and reshaping their effects, even reducing some of them (Lawrence et al., 2024).

In contrast to polycrisis—which refers to the interaction of several independent yet interrelated systemic shocks—systematic risk concerns vulnerabilities embedded within a particular system. It is an embedded risk that is not considered a risk and is therefore not necessarily monitored. However, a system-wide assessment may reveal that it has hidden risk potential that could negatively affect the overall performance of the system if certain factors change (Kaufman, 1996; Kaufman and Scott, 2003). The 2008 economic crisis is an often-cited example of this type of risk. But the impact of systematic risk originates in one system and spills over through the interaction of other areas, affecting their performance or output (Aven, 2016).

Conversely, when a system experiences several adverse events simultaneously or sequentially that interact to cause widespread losses, we speak of compound risk (Lal et. al., 2012). According to Liu and Huag (2014), compound events occur when complex processes are extended but are not always directly related (Liu and Huang, 2014; Zscheischler et. al. 2020). Importantly, however, this risk also originates within a single system and spills over to other areas through interactions with them (Sulfikkar Ahamed et. al., 2023).

Where polycrisis differs from systematic and compound risk is in both the origin and nature of the interactions. Both systemic and compound risk report negative, mutually reinforcing events, whether they occur in finance, agriculture, or other areas. In the case of polycrisis, the interaction of these events does not necessarily lead to an increased adverse impact. In addition, systemic and compound risks originate within a single system and spill over into other fields. Polycrisis, on the other hand, deals with the interaction of events occurring independently in separate systems. The effects of the last 5 years have emerged within several structurally independent systems with predominant interactions. Thus, polycrisis as a concept can better describe the risks of this period –under which we aim to estimate the profitability of three selected firms – than the other two concepts.

LITERATURE REVIEW

There has been a long discussion in the relevant literature on whether firm or sector-specific factors influence firm performance to a more considerable extent (Bamiatzi and Hall, 2009; Goddard et al., 2009; Sala-Ríos, 2024). Sector-specific factors such as market concentration, sector growth rate, etc., are some of the key strategic factors that influence firms' performance. In contrast, firm-specific factors place the management of resources, their efficient use, efficient management of capital structure, etc., as key elements of profitability. In addition to these, many researchers also highlight the location of a firm as an important factor that determines its profitability (Arias et. al., 2020; Castro Aristizabal et. al., 2019).

When comparing the various - firm, industry, and location - factors, several authors, including Nanda and Panda (2018), Blažková and Dvouletý (2018), Alarussi and Alhaderi (2018), Pervan et. al. (2019), Aryantini and Jumono (2021), Sala-Ríos (2024), highlight company-specific factors as significant elements that influence the profitability of firms. Examples of such factors include firm size (as total sales), age, asset utilization (as asset turnover ratio), and capital structure (as financial leverage). Older and larger firms can leverage their accumulated knowledge and built-up knowledge capital to achieve higher profits. In addition, companies that can use their assets more efficiently can achieve higher returns on their assets and improve their performance. A negative relationship between capital structure and profitability can be highlighted, as a company can choose to finance a larger share of its activities from equity or debt, thus affecting its return on equity differently.

Based on the previous works, our profitability estimates primarily consider firm-specific factors. These are variables that companies can actively influence and manage, thereby directly impacting their financial performance, reacting to the changes in the economy. Location-specific factors were not included, as the selected firms operate in nearly identical geographical contexts and are similarly affected by polycrisis-related factors, rendering such variables largely irrelevant in this analysis.

Our method of choice for stress testing and estimating the distribution of profitability variables is Monte-Carlo simulation, which is widely used to evaluate the riskiness and return on investment of projects (Montes, et al., 2011; Senova et al., 2023), to manage the risk of financial forecasts (Liu, et. al., 2022), to optimize and plan production activities and budgeting (Janeková,et. al. 2015; Koroteev et. al. 2022). As well as for profitability estimation, where it allows the estimation of multiple scenarios to support effective decision-making (Montes et al., 2011; Ölçen, 2025). A key advantage of MC simulation lies in its flexibility: it accommodates non-linear distributions of input variables and allows for the simultaneous analysis of multiple parameters. Additionally, it can be effectively applied even when only aggregate data are available, without requiring full access to raw datasets. Compared to other methods, such as bootstrapping, MC simulation is also less computationally intensive, making it well suited for multi-level modelling (Preacher and Selig, 2012; Pavlik and Michalski, 2025).

Our simulation-based stress test was built on the basis of the annual reports of the selected companies, using 6 years of historical data to estimate the profitability of the firms for the period 2023 using the logic of the DuPont analysis (Aulová et al., 2019; Pavković et al., 2022). The analysis of the profitability situation examines the efficiency of the use of assets and resources owned by the firm (Szekeres and Orbán, 2018; Saus–Sala et al., 2021; Tömöri et al., 2021; Zielińska-Chmielewska et al., 2021).

The most commonly used metrics for assessing the profitability of companies are Return on Sales (ROS), Return on Assets (ROA) and Return on Equity (ROE), which can be examined in conjunction with each other using (Husain et al., 2020). Some literature (Ladvenicová et al., 2019; Fenyves et al., 2019; Kishibayeva and Jaxybekova, 2023) defines the DuPont model as a financial analysis and planning tool designed to present the factors affecting a company's return on equity using simple accounting relationships to help understand the effects of these factors. It is argued that the model allows for the evaluation of the components of ROE and helps management to assess the potential impact of strategic initiatives on financial performance (Jape and Malhotra, 2023).

Given the structure of the DuPont model, we had to account for multiple input parameters that are not necessarily linearly related (Fairfield and Yohn, 2001). To manage these complex interdependencies efficiently and to reduce computation time, we selected Monte Carlo simulation as our method of choice for the stress test, owing to its high flexibility and suitability for handling non-linear relationships.

Our selected firms are located in the poultry processing sector which is part of the manufacturing industry and is mainly involved in the processing of raw materials produced in the primary sector. Due to the sector's location, it has operated in a highly turbulent environment since 2015 shaped by overlapping adverse events. Extreme weather anomalies – including recurrent drought, heatwaves, and sudden frosts – have affected feed-grain yields across Europe, increasing livestock purchase and feed costs (Lhotka and Kyselý, 2022; Tripathy and Mishra, 2023). These pressures were reinforced by the post 2022 surge in grain and energy prices (Smeets and Beach, 2023). At the same time, recurrent outbreaks of Highly Pathogenic Avian Influenza (HPAI) have imposed substantial operational and biosecurity costs, including culling and supply disruptions driving up costs even more. Additional trade restrictions during the COVID-19 pandemic further constrained export reliant processors and disrupted input supply chains (Rizou et al., 2020; Choi et. al., 2021; Sarkis, 2020; Tömöri et al., 2022; Raj et. al., 2022). Together, these events formed a polycrisis context that has amplified profit volatility within the poultry subsector (Radin et. al. 2017; Padilla et. al., 2025).

Though this subsector is not unique in experiencing high volatility during the examined period or in other polycrisis adjacent periods. Similar patterns of cost-driven profitability instability have been observed across several agri-food industries. For instance, pork processors have been affected by recurrent outbreaks of African Swine Fever (ASF), while dairy and beef cattle industries have faced disruptions linked to Foot-and-Mouth Disease (FMD) and Bovine Viral Diarrhea Virus (BVDV). These sectors have also been exposed to sharp input-price shocks and export-market disturbances similar to those observed recently in poultry processing. However, the poultry subsector is particularly vulnerable due to the epidemiological characteristics of HPAI: the virus persists longer outside its host and is more readily spread by migratory wildlife, making outbreaks both harder to contain locally and more frequent than in other livestock sectors (Rypuła et. al., 2020; Halasa et. al., 2020; Marschik et al., 2021).

Although the present case study focuses on poultry processors, the Monte Carlo–DuPont framework is broadly applicable across other agri-food industries that exhibit comparable interactions of virological, market-based, and cost-side shocks (Wu and Perrings, 2018; Brown et. al., 2021; Seeger et. al., 2021; Verhagen et al., 2021; Szymańska and Dziwulaki, 2022).

MATERIALS AND METHODS

Monte Carlo simulation was originally a stochastic simulation method used in mathematics to solve differential equations, whereby a large number of output values can be generated simultaneously from a large number of uncertain input variables that take random values with a given probability distribution, and then can be statistically evaluated. In Monte Carlo simulation, the normal distribution function of a variable is obtained as an empirical distribution of simulated values (Hamad, 2019; Becsky-Nagy et al., 2024).

The required data were obtained from the financial statements of the examined companies between 2017 and 2022, which are typically an informative tool for investors (Table 1.). After defining the problem, the second step in the application of the method is, the selection of the input variables of the model under uncertainty and the determination of the parameters that influence their probability distribution (Figure 1). For these indicators, if they are normally distributed, it is necessary to determine their expected values and their standard deviations, assuming that their expected value will be spread around the historical average and thus less likely to take a value further from the average (McLeish, 2005; Cevallos-Torres and Botto-Tobar, 2019; Fabianová et al., 2023).

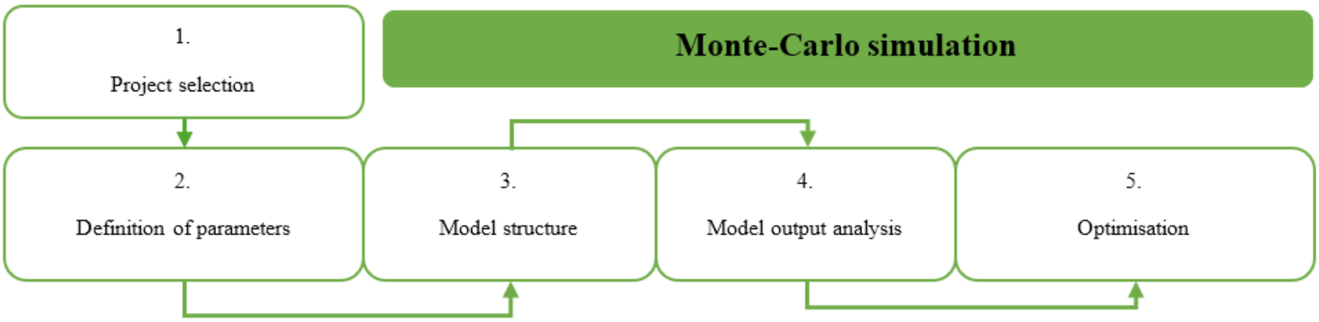
Table 1. Net sales revenue, ROS and ROE values between 2017 and 2022*

		2017	2018	2019	2020	2021	2022
Company "A"	Net sales revenue	104 024	126 448	120 771	106 620	131 067	183 101
	ROS	11,3%	13,5%	9,2%	4,6%	9,4%	11,6%
	ROE	30,9%	51,3%	27,7%	12,2%	24,4%	32,5%
Company "B"	Net sales revenue	29 651	29 877	29 526	29 031	30 148	35 530
	ROS	0,7%	-0,2%	0,1%	4,4%	5,4%	7,5%
	ROE	2,6%	-1,0%	0,4%	16,4%	17,5%	23,9%
Company "C"	Net sales revenue	18 127	18 938	23 940	26 885	25 168	29 015
	ROS	0,5%	-0,7%	1,1%	1,0%	-0,4%	4,6%
	ROE	1,6%	-2,4%	4,8%	5,3%	-1,8%	22,2%

**Net sales revenue in thousand EUR*

Source: Authors' compilation based on companies' annual reports

Figure 1. Monte-Carlo simulation steps



Source: Authors' compilation based on Fabianová et al., 2023

The third step is to set up a model to derive the output values to be estimated from the input data. The model must be set up in such a way that it ensures the iteration of several random outcomes as a function of the mean (m) and standard deviation (σ) of the specified input data. The future outputs thus generated can be used for probabilistic analysis, which is the next step in the simulation (Thomopoulos, 2013).

In our simulation-based stress test, we treated the following firm-specific input variables as probability distributions:

• the expected percentage change in domestic (DOT) turnover (marked with: gDOM)

• the expected percentage change in export earnings (EXP) (if the export activity was significant for the company, with an indication: gEXP)

• the expected value of own capitalised performance (marked as CVOP)

• the expected value of the material ratio (ratio of material costs to turnover) (denoted MAr)

• the expected value of the wage ratio (ratio of personnel costs to turnover) (marked Wr)

• the expected value of the depreciation ratio (the ratio of depreciation to turnover) (denoted as DEPr)

• the expected percentage change in total assets (TA) (marked with: gTA)

These companies are predominantly involved in intracommunity trade so the appropriate EUR exchange rate was taken as a benchmark at the estimation of the export revenue, if it was significant. Based on the experience of the years under review, our assumptions are: that the change in equity (EQ) is influenced only by the profit after tax derived from the above data, the expected value of other income and expenses offset each other, and the profit on financial operations (PFO) in the last year (due to the predictable nature of the majority of interest rate repayments) is assumed to remain unchanged (and excluding the effect of exchange rate differences).

Lastly to validate our assumption that the profitability indicators follow normal distribution, we tested the historical values of both ROS and ROE utilizing the Shapiro-Wilk test. The test was conducted on the six-year period under review. In all three cases the test yielded p-values above the 0.05 significance level, indicating that the null hypothesis – that the samples originate from normally distributed population – could not be rejected for our input variables. This result supports the use of the normal distribution as a modelling approximation.

However, due to the limited sample size – six historical years –, the statistical power of the Shapiro–Wilk test is inherently low, meaning that moderate deviations from normality may remain undetected. Consequently, while the empirical distributions do not contradict the normality assumption, the resulting probability distributions should be interpreted with caution from a robustness perspective. Even so, it is assumed that the profitability of firms follows past growth trends. The possible outcomes of profitability may deviate both positively and negatively from the average, but their magnitude can be considered proportional to the fluctuations observed in previous years. In light of these considerations, we think that the normal distribution provides a good approximation for modelling the probability distribution of profitability in 2023, and it also offers ease of implementation in the simulation process. Thus, the random numbers can be generated (1):

$$X \sim N(m_X, \sigma_X^2) \tag{1}$$

We calculate the total sales revenue (S) according to equation (2):

$$S = DOT_{2022} * (1 + X_{gDOM}) + EXP_{2022} * (1 + X_{gEXP}) \tag{2}$$

and then, according to equation (3), the profit after taxation (r^{TAX}):

$$Profit = [S + X_{CVOP} - S * (X_{MAr} + X_{Wr} + X_{DEPr}) + PFO] * (1 - r^{TAX}) \tag{3}$$

and hence the Return on Equity (4), taking into account the expected change in total assets (TA), in accordance with Du Pont:

$$ROE = \frac{Profit}{S} * \frac{S}{TA_{2022} * (1 + X_{gTA})} * \frac{TA_{2022} * (1 + X_{gTA})}{EQ_{2022} + Profit} \tag{4}$$

Given the output dataset (in which the number of iterations is n), the probability that the ROE will take a negative value can be estimated according to (5):

$$P(ROE < 0) = \frac{n|_{ROE<0}}{n} \tag{5}$$

Finally, as a last step, if necessary, the model can be further optimised if the probability variables change too much or to an extreme. One way of doing this is to refine the model parameters in order to reduce the extreme outcomes between the randomly generated values and thus make them more similar to the normal distribution we have assumed (Papadopoulos and Yeung, 2001). In the next section, we present the results of the model and the conclusions drawn from them, which are then compared with the companies' actual 2023 figures.

RESULT AND DISCUSSION

The expected distribution of the ROS and ROE data series generated from 15.000 iterations using the random number generator after setting up the model is illustrated in a box-plot diagram in Figure 2., while Table 2. presents the distribution parameters (mean and standard deviation) of the model input data. Also to quantify the difference between the simulated and actual 2023 values, deviation percentages were calculated (6):

$$\text{Diviation (\%)} = \frac{Profitability_{2023} - Simulated\ Profitability_{2023}}{Simulated\ Profitability_{2023}} \tag{6}$$

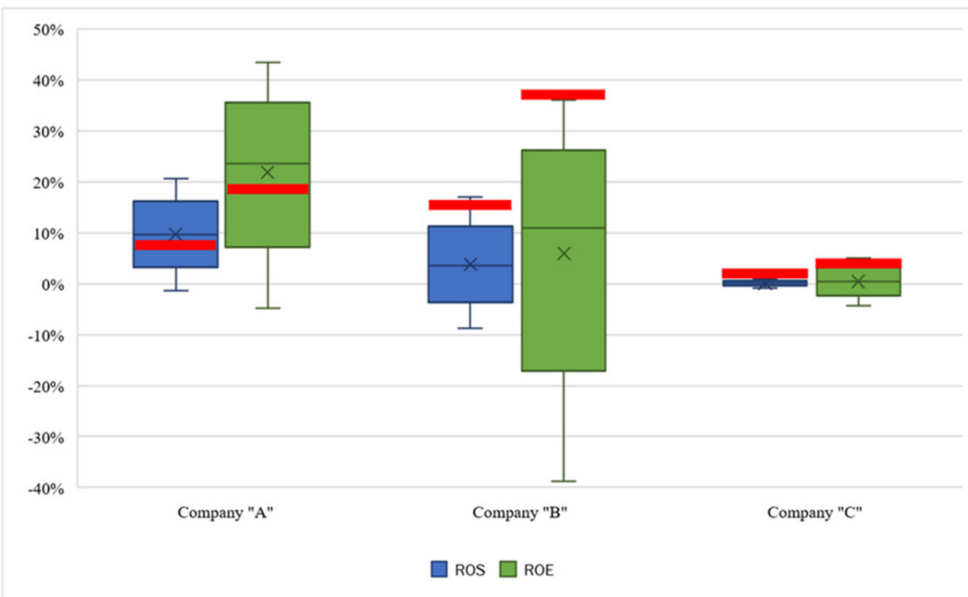
“A” Company’s performance, both in terms of revenue and capital, based on 15.000 possible output data sets, is likely to be positive in 2023, when the company's ROS is expected to pick up between -1% and 20%. On average, the cases studied show a ROS of 9,68% and a standard deviation of around 3%, which can be considered low overall. This is basically due to the high number of iterations and lower variances of the input parameters affecting the results. In contrast, if we broaden the range of variables considered to include changes in all assets and thus calculate the ROE, we obtain a much larger and broader distribution of results. The ROE values for Company “A” average 23,40% with a standard deviation of around 6,27%. The 2023 figures confirm the conclusions drawn from the model. Company “A”'s ROE value was 18,58%, within one standard deviation of the average, and a similar trend can be observed for ROS with 7,86%.

Table 2. Average and Scatter of Monte-Carlo Simulation data

Title	Company “A”		Company “C”		Company “B”	
	Average	*Standard deviation*	*Average*	*Standard deviation*	*Average*	*Standard deviation*
Domestic turnover growth rate (%)	24,73%	25,54%	11,68%	11,87%	9,32%	11,03%
Export turnover (EUR) growth rate (%)	9,65%	23,15%	13,35%	17,01%	-	
EUR/HUF exchange rate	382,04	8,37	382,04	8,37		
CVOP (EUR)	853 725	3 190 923	210 521	325 080	385 238	297 463
Material ratio (%)	77.48%	2,41%	79,76%	1,46%	77,94%	2,81%
Wage ratio (%)	9,66%	1,58%	15,25%	1,25%	14,51%	1,77%
DEP ratio (%)	2,37%	0,43%	3,39%	0,24%	3,92%	0,27%
Change in total assets (%)	18,82%	16,73%	17,35%	40,70%	16,55%	23,69%

Source: Authors' own calculation based on companies' annual reports

Figure 2. Company “A”, “B” and “C” Possible Distributions of ROS and ROE (%)



Source: Authors' own calculation based on companies' annual reports

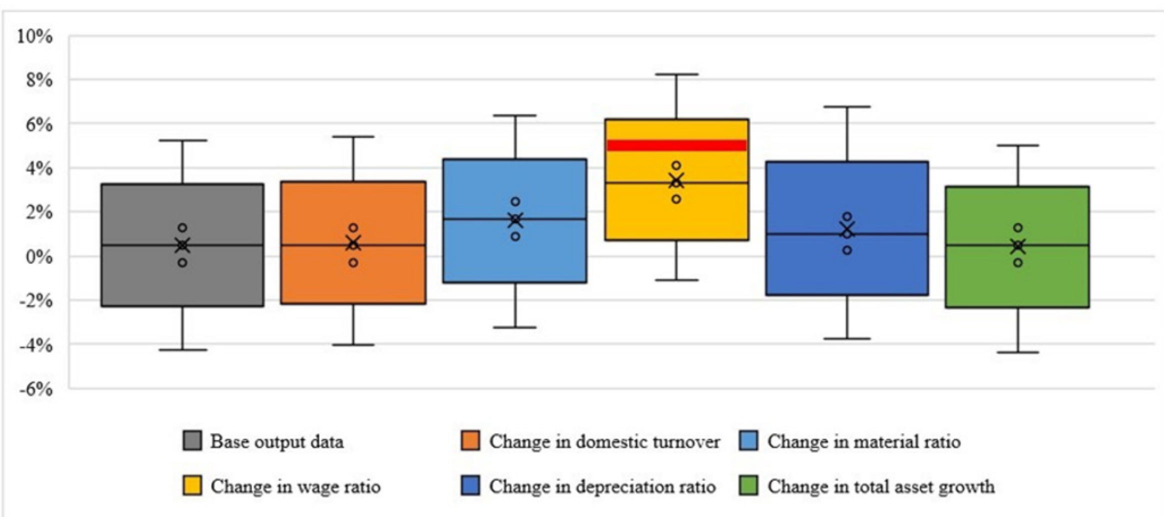
But the fall in export performance in Company “A”'s sales activity increased the outcome of extreme cases to a greater extent, although the favourable trend of rising exchange rates – with the company's larger foreign currency holdings – was able to minimise these negative swings, so that the company's estimated ROS was less likely (p<0,1%) to take a negative value, which is also supported by the actual ROS value in 2023. The probability that the company's ROE is expected to exceed its ROS is estimated to be more than 98%, due to the company's outstanding business policy, which has included several positive investments in the recent period, such as the acquisition of a slaughterhouse, which subsequently increased its sales performance and the revenue per total assets. The improved sales have also led to a gradual increase in the company's equity, and the simulated values estimated this change. In terms of percentage differences, the actual ROS (7,86%) was 18,8% below the simulated mean (9,68%), while the actual ROE (18,56%) was 20,6% lower than the simulated average (23,40%), indicating that the model captured the firm's typical performance accurately.

In the case of Company “B”, the fluctuations in the company's turnover, profit after tax, total assets and equity were much higher during the period of the study. The impact of these is also noticeable in the estimated ROS and ROE. In the case of ROS, this broader effect means in particular that it has a higher probability of taking a negative value of around 12%. Based on the ROS estimate, a maximum over 17% and a minimum -9% return on sales can be expected by the company's management, due to the lower performance of the company in its early years, which determined the initial distribution parameter, followed by a more drastic positive turnaround over the next 4 years. This growth potential, however, was not fully captured by the model, with a ROS value of 15,16% in 2023. This ROS value exceeded the simulated mean (3,57%) by 324,69%, but remained 10,59% below the maximum simulated ROS value (16,96%). Figure 2 shows that the ROE of the company could change much more in the period to 2023. One of the reasons for this was the company's major investment project launched in 2021, which continued in 2022 with the establishment of a subsidiary. This resulted in a more significant increase in the company's equity multiplier (EQM) value and a more significant decrease in rotation speed of total asset due to an increase in the value of total assets. The inclusion of a drastic change in the company's performance resulted in a slightly more extreme estimate. The model also failed to adequately capture the growth potential, as the company's 2023 ROE value was 36,53%, which was above the simulated average (10,20%) by 258,05%, while also exceeding the maximum estimated ROE (36,03%) by 1,39%. These results are surprising given the model, but based on more detailed profitability analysis, this increase in the company's performance was expected. In the more recent periods, the company has not only increased its horizontal scope of activities, but has also engaged in major development initiatives and launched a significant marketing campaign to strengthen its brand with the help of its parent company. Overall, the outstanding growth potential could not be addressed by the model and the actual 2023 figures were caught either in the upper quartile or fell outside of the estimation range. In contrast, the result for Company “A” was much more consistent despite the decline in export activity during the polycrisis, the company's growth rate was steadier, resulting in a more balanced estimate that was a good approximation of the actual data.

In the case of Company “C”, unlike its two predecessors, we see a slightly more pessimistic estimate: while the average of the possible outcomes examined is approximately 0,1%, and the standard deviation is 0,22%. The ROS indicator results are more concentrated for the company, which may have been driven mainly by fluctuations in its sales activity of the same magnitude between 2017 and 2021, which were only offset by a larger positive spike in 2022. This implies that the company's profitability can take on a larger spread and thus equity investment in the company can be considered riskier than in the case of Company “A” or “B”. This is also evident in the estimated performance for 2023: the probability that the company's ROE will be negative is estimated at around 34%, the highest of the three companies. Taking into account changes in total assets and equity does not change this value, but merely magnifies the dispersion of expected results. However, this multiplier effect is lower than in the case of “B” and “A”. Although the company had the highest probability of a negative return, it was not unprofitable in 2023, with a ROS value of 1% and an ROE of 4,79%. So, similar to Company "B", the top quartile estimates were proved by the model. The actual ROS (1%) exceeded the simulated mean (0,09%) by 1055,86% and surpassed the maximum expected ROS (0,89%) by 12,02%, which indicating that the model underestimated the magnitude of the firm's positive outlier performance. Likewise, the 2023 ROE (4,79%) surpassed the simulated mean (0,46%) by 949,35%, while remaining 5,49% below the maximum expected ROE (5,07%).

Figure 3 illustrates how the distribution of Company “C”'s ROE data series in the simulation-based stress test would change, if the average parameter of one of the input variables were to be replaced by the average parameter of the same input value of Company “A”.

Figure 3. Distributions of the ROE value of Company “C” if one of the input data is replaced by the values of Company “A”



Source: Authors' own calculation based on companies' annual reports

It is observed that the most effective change in its business policy would be to reduce its wage ratio, rather than to adjust its material ratio, depreciation ratio or sales growth rate to that of Company “A”, which would increase the maximum ROE by 1-1,5% and reduce the probability that it would not be negative by 15-25%. By contrast, a significant reduction in the wage ratio would, ceteris paribus, reduce the probability of the return on equity becoming negative by 33,5%, while increasing the maximum ROE by 3%. One way of reducing this cost ratio could be to phase out the company's "Care for the Family" incentive scheme. Indeed, as the company supplementary annex comprises, its long-term application has increased the number of overtime hours and weekend production times, for which extra benefits are paid to employees, but as the results show, their reduction could significantly improve the company's ROE, while it could expand its foreign partners base. This support scheme was rolled out in 2023, which allowed the company to increase its ROE to 4,79%. Our findings on the reduction of the wage ratio are therefore validated, and if we observed Figure 3, the 2023 factual figure falls within one standard deviation of our revised estimate. Calculating the percentage difference between the actual ROE value and the new simulated average ROE confirms this improvement. The 2023 ROE value being only 43,62% above the new simulated mean (3,34%), which is a 905,72% improvement from our original simulation. So, although our original model was only able to capture the upper quartile of the actual values, the model rerun on the basis of the propositions was able to estimate these values more accurately.

The diverging performance of the three companies is illustrated by the simulation, which takes into account extreme changes over 6 years. The changes in this polycrisis period were undoubtedly observed in the estimated ROE of the companies.

The expected return on equity ratio for Company “C” is in the narrowest range, approximately -4% to 5%, with a median value of around 0,46%, significantly lower than the other two competitors. This was also due to past fluctuations in the company's sales activity. Indeed, the company continuously invested during the period under examination, increasing its total assets. In many cases, the positive effects of these increases were diminished by fluctuations in the company's sales activity, either directly through the ROS indicator or indirectly through the EQM. As a result, the effects of the company's exceptional performance in 2022 were estimated to be negatively affected by the weak performance in earlier periods.

Company “A” is still very likely to increase its profitability, and a significant decrease is unlikely. In the case of Company “B”, the distributions are more balanced between periods of higher and lower performance so that it considers the more extreme cases, but if the calculation were only based on the last 4 years, a much more optimistic picture would emerge. However, there is still no doubt that the company's performance is likely to continue to improve.

Company “C”'s situation, on the other hand, is much more confusing. The company has few commercial partners and basically failed to take advantage of the market opportunity created by the coronavirus in certain regions to strengthen its position in European markets, and diversify its partnerships, but has instead increased its exposure to the country of the parent company, which seemed to be more favourable to it during this period. It experienced the consequences of this in 2021 with the introduction of trade restrictions in the region due to the epidemic. Still, it is questionable whether it could build this experience into its business strategy after its outstanding performance in 2022. In terms of investment policy, it has phased out the "Care for the Family" subsidy scheme, which has improved the company's bottom line as estimated by the model. In addition, a major investment project was completed during this period, resulting in the modernisation of its machinery and real estate. As a result of these, the company was able to remain profitable in 2023 although by a small margin.

Among Company “B”'s inputs, two of the six examined years were significantly low or even negative, followed by four years of outstanding performance. Therefore, by removing the two low performance periods and looking only at the last four periods, the model should hypothetically be able to provide a more accurate estimate of the company's growth potential. Using this new estimated growth potential in the original calculation, the 2023 actual figures would be better caught by the model.

This growth potential estimate can be observed for Company “A”. The company's performance has not turned negative in the periods under review, although a more moderate decline can be observed, but still an outlier at the sector level. This decline is the reason for the wide range of the estimated ROE in the model, but nevertheless, the simulation was able to estimate the 2023 values with great accuracy due to the company’s stable growth rate and small leverage.

Overall, for Company "B", the model could not account for the high growth potential and, therefore could not capture the 2023 values adequately. In the case of Company "A" due to the steady growth rate over the period of the study it was able to capture actual rates of ROE and ROS. In contrast, Company “C”'s performance in the periods under review has been very extreme. A period of high profits was followed by a period of sharp losses. One of the reasons for these fluctuations is the company's significant exposure to the parent company’s market, where its products are assumed to play a substitutive role. Thus, the company's lack of diversification in its partnerships resulted in highly variable sales trends in the examined period. These high variances in the historical data have been cancelled out in the calculation, resulting in a more concentrated estimate that no longer only includes the adverse effects of polycrisis factors but also the riskiness of the company's activities instead of its growth potential.

Lastly it is important to highlight that all model estimations rely on only six years of historical firm-level data, which inherently limits the robustness of the simulated distributions. With such a short time horizon, the estimated means and variances of the input parameters are more sensitive to year-specific shocks – especially those induced by the polycrisis period – and may not fully represent the underlying long-term dynamics of the firms’ profitability. Therefore, while the simulation-based stress test provides meaningful insights into firm-level profitability under polycrisis conditions, the results should be interpreted with caution. Longer time series or higher-frequency data would be necessary to increase the robustness of the distributional estimates and to better capture the firm performance over time.

CONCLUSION

The objective of this research is to examine, through a case study, the extent to which historical data from previous business periods can be used to estimate future performance in an extreme economic environment. In doing so, it aims to support companies' financial planning for the upcoming financial years.

In building the model, company-specific factors were primarily selected as inputs, as these are within management's control and can be adjusted in response to extreme changes. Using the logic of the DuPont analysis and after reviewing the trends of previous years, we assumed that the company would follow a similar operating trend. Thus, the potential profitability outcomes may deviate positively and negatively from the average, with their magnitude being proportional. Based on this, we assumed the variables would follow normal distribution.

Based on our calculations, the simulation can deal well with factors that affect the profitability of companies, such as changes in raw material and energy prices, or management decisions such as investment, inventory optimisation activities, and all the factors that appear in the companies' accounts, directly or indirectly. On this basis, the Monte Carlo methodology could be a valuable tool for management in supporting financial planning activities. Aiding the controlling functions of companies could help identify areas that may influence future performance.

However, there is still room to optimise the model by incorporating more specific and detailed company-level parameters. As our analysis is based on publicly reported data, it should be considered an external assessment, which limits our ability to examine internal performance drivers—such as the allocation of material and labour costs across operational areas. Another area for improvement is determining the probability factors of firms' financial activities and forecasting high growth potentials. In our model, the results of these financial operations were assumed to be constant due to the high share of interest payable, but in addition to interest payable, exchange rate changes also affected the profitability of the companies, especially for Company "A" and "C", although to a lesser extent. Though the growth potential was estimated from historical data, it did not adequately reflect the real growth rate assumed by Company "B". The estimation might improve for such above average companies if these rates are calculated on the basis of the years during which the performance of these companies has shown a significant upward trend. It should also be noted that only six years of firm-level data were used, which is not ideal for generating robust probability distributions, as estimated means and variances of the input parameters are more sensitive to year-specific shocks. Future research should therefore consider a longer time horizon or higher-frequency data necessary to increase the robustness of the distributional estimates.

DECLARATIONS

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Máté Varga and Patrícia Becsky-Nagy. The first draft of the manuscript was written by Máté Varga, and all authors commented on previous versions of the manuscript. The final draft of the manuscript was critically revised by Patrícia Becsky-Nagy. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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