Is the merger worth it? Evaluating the effect of mergers of companies on their financial indicators via latent growth curve model (Pilot study)

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Abstract:

Our paper represents a pilot analysis and contribution to the understanding of the successful implementation of mergers in the geographic context of Central Europe and offers a foundation for future research. The analysis is based on a robust and unique dataset of 783 companies that merged in the Czech Republic over the past decade, representing a substantial proportion of merging companies in the region during the period under review. The study utilises financial statements from the merging companies, covering the period from the decisive merger day – that is, before any effects of the merger could materialise and the five years following it. Unlike traditional studies that predominantly rely on univariate methods, this research employs a comprehensive approach to analysing longitudinal, cross-industry post-merger data via latent growth curve models. This combination of dataset size and analytical depth has not been explored in this context before in the Central European region.

Klíčová slova: Effect; Mergers; Latent growth curve model; ROA.

JEL klasifikace: G34, O16.

1 Introduction

The issue of mergers has been the subject of interest in a number of expert studies. The key question that each study seeks to answer is whether mergers can improve the underlying economic performance of merging companies in the short, medium and long-term period, identify the causes of this improvement, or explain why mergers fail. Most studies, as our literature review shows, focus mainly on a sectoral view of mergers without a deeper analysis of the cross-sectoral effects of mergers. Quantitative analyses are then usually based on samples of a few dozen merged companies in economically developed markets or mainly in the Asian region. In

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terms of the impact of mergers in the Central European region, a deeper analysis is completely lacking or based only on partial case studies that do not allow generalising the conclusions reached. Similarly, the question of whether the merger will affect the economic results and production capacity of companies that show positive economic results before the merger in the same way compared to those companies that, on the contrary, are in economic problems in the period before the merger, has not been investigated yet.

This paper seeks to fill this gap using Latent Growth Curve Model (LGCM) of ROA looking for an answer to the question of whether, thanks to the merger, the companies achieve better economic results than before the merger. If it can be demonstrated that a merger contributes to improving the economic performance of the companies involved, it becomes a relevant factor for managers to consider in order to maintain the competitiveness of the firms they lead. On the contrary, if the results indicate a deterioration in the economic situation of the merged companies, managers should choose other tools to strengthen the development of their companies. In addition, answering the above questions could help business managers determine the optimal timing of the merger process, enabling them to maximise potential benefits while avoiding possible pitfalls associated with mergers.

Based on the information from numerous studies of post-acquisition performance, ROA is found to be the most applied accounting measure of the companies' post-merger performance (King et al., 2004). The ROA indicator represents a primary economic indicator showing the company's ability to appreciate the assets entrusted to it. It is thus an ideal indicator for analysing the production capacity of companies in comparison to the state before and after the merger. It is applicable across industries and firms of different sizes, making it a universal metric. This is especially useful because different industries have varying levels of asset intensity. Comparing ROA across industries helps normalise the analysis. It is also one of the most watched indicators of the financial analysis of commercial entities, as it quickly shows inter-company comparisons within one country and, when excluding the effects of different taxes and interest rates on the profit of companies, it also allows a simple comparison of results across different countries. ROA also has been used extensively in prior research on mergers and acquisitions as a reliable profitability indicator (e.g., Alexandridis et al., 2017; Andrade et al., 2001). Its use in this study aligns with established methodologies, ensuring comparability with other studies in the field. ROA is also straightforward to calculate and interpret, ensuring that results are accessible to both academics and practitioners. While more complex metrics (e.g., EVA, Tobin's Q) could offer additional insights, they also introduce challenges related to data availability, assumptions, and interpretability. ROA is consistently reported in financial statements, ensuring data availability and reliability. Other performance indicators (e.g., sector-specific KPIs) may not be uniformly available or comparable across all firms, especially in cross-industry studies like this one.

In our study, sector-specific data and detailed information about other financial indicators were unavailable. ROA served as a proxy to capture general trends, as it is less influenced by sectoral accounting differences compared to ratios like gross profit margin or net profit margin. While using only ROA may not capture every dimension of merger success, it provides foundational insights into post-merger profitability trends. This study serves as a baseline, and future research can build on these findings by integrating additional metrics or industry-specific measures.

It is also important to investigate whether there is a significant difference in the economic impact of mergers between companies that exhibited economic distress measured by a negative ROA before the merger and companies that had a positive ROA before the merger.

This paper aims to contribute to the discussion on the effectiveness of mergers by examining whether companies achieve improved economic performance in the post-merger period. Thus, our analysis serves as a pilot study, utilising latent growth modelling to gain a better understanding of performance trends following mergers.

Given the practical and theoretical importance of M&A (and a great deal of literature on the topic), it is surprising that there has not been much empirical attention concerning the analysis of longitudinal data of accounting-based measures in time after the merger. Most of the studies focus on evaluating mergers from some specific industry. That is in contrast to the cross-industry aggregated data analysed in our paper which we consider to be innovative in M&A investigation. Nevertheless, some overview of how the topic of M&A performance is studied in other financial papers may be valuable for the reader and we provide original literature review of the research in this field.

As shown by a number of studies (Levy, Sarnat, 1999; Mueller, 2003; Motis, 2007; etc.), the main motive for mergers is usually an increase in the economic efficiency of the merging companies. This can be achieved by fulfilling other motives of mergers, which are mainly motives of operational synergies, financial synergies, economies of scale, increase in market power, diversification of risks, etc.

But some findings in corporate finance literature state that M&A tend to destroy value for acquirers rather than create. One of the most significant pieces of evidence was provided in the study from Andrade et al. (Andrade et al., 2001), where the authors concluded that the net wealth effect of takeover is negative for acquirers. But to demonstrate also some contradictory outcomes here, we use the study from Alexandridis (Alexandridis et al., 2017), which differentiate from other studies by focusing on acquisition investments post-2009s, to shed light on how things change for M&A after the 2008 financial crisis.

The paper from Trujillo et al. (Trujillo, 2019) explores the causal effect of M&A on the financial performance of companies from the U.S. generic drug industry between 1996 to 2017, using firm's financial and accounting data. The focus on causal effect here is already of additional value compared to other empirical studies on this topic, but the authors go even further and incorporate comparison with the performance of similar companies that did not merge on top of that. Results show that firms engaged in M&A experienced a decrease in operating profits of about 3.6 % in the year following the M&A and about 2.9 % decline up to 4 years after the takeover, despite the fact that these companies experienced higher profits in years prior to the deal closure.

Ibrahimi and Meghouar (Ibrahimi; Meghouar, 2019) were investigating a sample of 90 French companies involved in a merger or major acquisition between 2005 and 2014. The studied mergers and acquisitions were horizontal in nature and the goal of the case study was to identify a group of mergers that creates value and a group that destroys value and determine which accounting indicators are the primary sources of this Binary classification. The authors were using stepwise multiple linear regression to model the relationship between the variables.

Typical findings from early studies were suggesting that M&A did not increase acquiring firm value, assessed by either short-term (Jarrell et al., 1989) or long-term performance measures (Loderer et al., 1992). More precisely, acquisitions were often found to destroy acquiring firm value (Seth et al., 2002; Moeller et al., 2003) and produce highly volatile market returns (Pablo et al., 1996).

A large body of literature indicates that merger activities per se do not improve post-acquisition performance (Benitez et al., 2018; Badreldin et al., 2009). Other studies then show that a merger can only have a limited effect and even then only on a certain type of companies (Valouch; Králová, 2012).

The results of numerous empirical studies go even further, showing that well over half of mergers and acquisitions in the past century failed to create the expected value. In numerous cases, value was destroyed, and the company's performance after the deal closure dropped significantly below its pre-takeover level. (Eccles et al., 1999). Some more recent studies are even more specific, stating that "the failure rate of M&A is around 50 %" (Schoenberg, 2006) or even that "more than 61 % of the mergers and acquisitions are not successful" (Jindal, 2016). These results are consistent with a lot of other different works that have shown a decrease in profits following an M&A (for example Moeller et al., 2005; Bouwman et al., 2007; Betton et al., 2008).

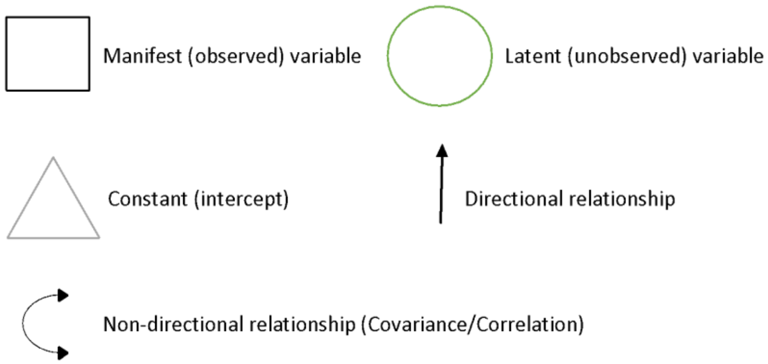
Our paper is based on (Búci, 2018; Búci, 2021), which it draws from and further develops some conclusions in more depth.

2 Methodology

This paper brings another perspective on the topic. In contrast to the mostly small, industry-specific data used in other papers, we analyse extensive longitudinal cross-industry aggregated data of post-merger accounting-based measures. To account for the complexity of longitudinal post-merger financial indicators development, affected by time-varying and time-invariant exploratory variables, we perform latent curve modelling rather than univariate analysis predominantly used in this area.

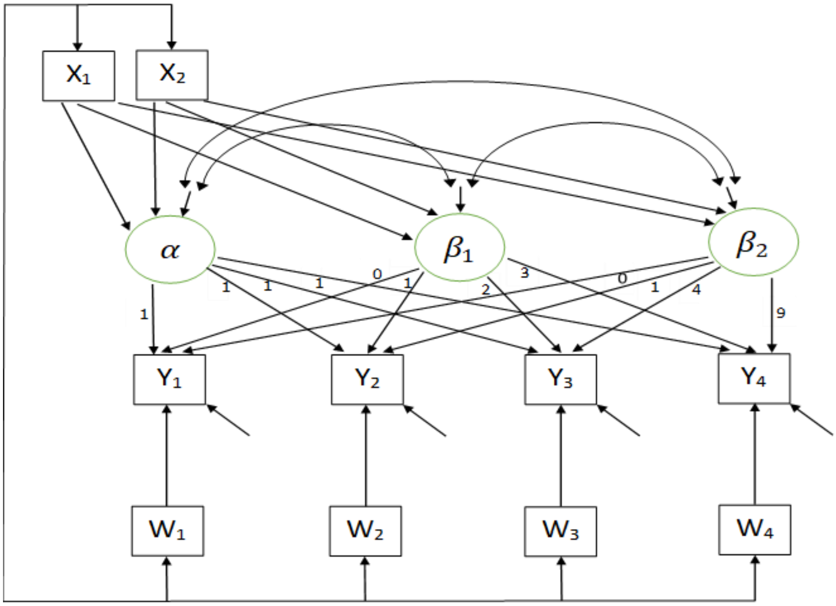
Latent growth models enable a more detailed analysis of indicator trajectories over time, representing a significant advantage over conventional univariate methods focused on year-on-year changes. Latent Growth Curve Models (LGCM) are based on Structural Equation Models (SEM) building blocks with latent variables. The LGCM approach allows each case in a sample to follow a unique trajectory of the variable of interest over time, as the intercept and slopes (treated as latent variables) are modelled as random effects. Figure 1 introduces the symbols used to visualise SEM diagrams, along with additional techniques derived from the SEM framework.

Fig. 1 Symbols used to create SEM diagrams.



Two underlying latent factors, random latent intercept, and random latent slope that form basic linear trajectory model of repeated measures of variable of interest Y, are represented by α and β. Both are exogenous variables which is expressed by being at the beginning of the single-headed arrow, while endogenous variables are being at the end of the single-headed arrow. (Analogously, an extended quadratic model with parameters α, β_1, β_2 is represented in Figure 2.)

Fig. 2 Quadratic latent curve model. Four repeated measures $Y_1, \ldots, Y_4$ represent variable of interest; X_1 and X_2 represent time-invariant covariates; $W_1, \ldots, W_4$ represent time-varying covariates, and α, β_1, β_2 represent random latent intercept, linear slope, and quadratic slope respectively.



The value for the covariance of latent intercept and slope, $\psi_{\alpha\beta}$, is visualised with double-headed arrows. The multiple indicators are the repeated measures of Y over all time points. The constant term represents the mean for the latent intercept, μ_α, and the mean for the latent slope, μ_β. The mean values of the trajectory parameter estimates are sometimes referred to as the fixed effects. The variances of both intercept and slope are random effects.

Endogenous variables always have an attached error term associated with them called a residual or disturbance. Error terms represent something unexplained by the model, meaning they have no direct cause within the model and, thus, are exogenous. While endogenous variables are not allowed to covary, their residuals are allowed to do so. Disturbances, ϵ, of the repeated measures Y at all time points are modelled as latent variables.

The estimated latent trajectory is the focus of LGCM analysis. It is not observed directly, but we infer its existence from the observed repeated measures across the time that are used to estimate this trajectory. They are related to the underlying latent factors through the factor loading matrix. These loadings are typically all fixed. For the latent intercept, the loadings are fixed at 1, indicating that the intercept factor equally influences all repeated measures across the waves of data collection. For the latent slope, various time codings can be applied depending on the intervals between data collections and the nature of the hypothesised growth. Typically, the first value is fixed at 0, allowing the latent intercept to represent the mean value of the outcome variable at the first time point. The subsequent loadings then increase by one (i.e., 0, 1, 2, 3, etc.), reflecting equal intervals between data collection periods.

What LGCM does is that it explicitly models mean and covariance structures among the observed measures. Model-implied means of the repeated measures are entirely determined by means of latent factors, which are estimated. The other parameters that are estimated are the variance of the intercept and slope factors, the covariance between the initial point and rate of change, and the residual variance of the repeated measures, or in other words, variance not explained by the underlying growth process.

The quadratic unconditional model (without explanatory variables) for the i-th subject at time $t = 1,2,\dots,T$ can be expressed as:

$$\begin{bmatrix} y_{i1} \\ y_{i2} \\ y_{i3} \\ \vdots \\ y_{iT} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 2 & 4 \\ \vdots & \vdots & \vdots \\ 1 & T-1 & (T-1)^2 \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_{1i} \\ \beta_{2i} \end{bmatrix} + \begin{bmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \epsilon_{i3} \\ \vdots \\ \epsilon_{iT} \end{bmatrix},$$

where α, β_1, β_2 represent latent trajectory factors. The μ vector represents their factor means and the ζ vector represents their residuals:

$$\begin{bmatrix} \alpha_i \\ \beta_{1i} \\ \beta_{2i} \end{bmatrix} = \begin{bmatrix} \mu_\alpha \\ \mu_{\beta_1} \\ \mu_{\beta_2} \end{bmatrix} + \begin{bmatrix} \zeta_{\alpha i} \\ \zeta_{\beta_{1i}} \\ \zeta_{\beta_{2i}} \end{bmatrix}.$$

The covariance matrix of the equation errors, ζ, among the random intercept (α), linear (β_1) and quadratic (β_2) slope is denoted as follows:

$$\mathrm{VAR}(\zeta) = \begin{bmatrix} \psi_{\alpha\alpha} & \psi_{\alpha\beta_1} & \psi_{\alpha\beta_2} \\ \psi_{\beta_1\alpha} & \psi_{\beta_1\beta_1} & \psi_{\beta_1\beta_2} \\ \psi_{\beta_2\alpha} & \psi_{\beta_2\beta_1} & \psi_{\beta_2\beta_2} \end{bmatrix}.$$

Models can be then extended by implementing time-invariant and time-varying covariates (conditional models). Much more on the methodology of SEM and LGCM can be found in (Schumacker et al., 2016) and in (Bollen, 2005).

3 Application of LGCM to Pre-Post-Merger ROA Data

In our study, LGCM is applied to model the development of companies' return on assets (ROA) across six time points: the year of the merger (time point 0) and five subsequent post-merger years (time points 1 to 5). ROA is treated as the observed outcome variable, measured repeatedly over this six-year period. Importantly, the first measurement reflects the financial performance of the companies at the moment of the merger — that is, before any effects of the merger could materialise. This enables a direct comparison of pre- and post-merger performance within the same model framework.

The latent growth trajectory is defined by three latent growth factors: the intercept, representing the expected ROA at the time of the merger (time 0); the linear slope, capturing the average annual rate of change; and the quadratic slope, reflecting possible curvature in the development over time. These factors are modelled as random variables to account for heterogeneity in individual trajectories. To define the shape of the latent trajectory, the model uses fixed factor loadings from each latent factor to the six repeated ROA measures: (1, 1, 1, 1, 1, 1) for the intercept; (0, 1, 2, 3, 4, 5) for the linear slope, and, (0, 1, 4, 9, 16, 25) for the quadratic slope. These loadings reflect equal time intervals and standard polynomial coding.

The model further includes residual error terms for each observed ROA measure and estimates the variances, means, and covariances of all latent factors. The resulting trajectory represents a model-implied development in ROA following the merger, grounded in pre-merger baseline values.

To explain variability in these trajectories, **time-invariant** covariates *(Size and ROA_Zero)* are used to predict the latent growth factors. Size is a binary variable indicating whether the company's assets exceeded €10 million at the time of the merger *(Size = 1)* or not *(Size = 0)*, distinguishing small (0) versus big (1) companies. ROA_Zero is a binary indicator distinguishing companies with positive (*ROA_Zero = 1*, initial profit) versus negative (*ROA_Zero = 0*, initial loss) pre-merger return on assets in the year of the merger. It captures companies' initial profitability and allows the model to evaluate whether post-merger trajectories differ depending on pre-merger financial condition.

We included *Size* and *ROA_Zero* as covariates because both capture key aspects of pre-merger firm characteristics that may influence post-merger success. Company size plays an important role in merger implementation, as the process tends to be significantly more complex for large companies. While the merger of smaller companies is often straightforward, larger mergers involve intricate procedures and organisational challenges that may affect the outcome. Similarly, the company's pre-merger profitability — whether it starts from a positive or negative ROA — may shape its post-merger trajectory.

Additionally, the interest rate (R) of the Czech National Bank is included as a **time-varying** covariate, affecting ROA across all post-merger years. Its effect is constrained to be constant over time to allow for interpretation as an average influence.

This variable was incorporated not only due to its role in determining the cost of debt (particularly relevant in the Czech context, where companies are predominantly financed through bank or other types of loans), but also because it serves as a reliable macroeconomic indicator of the broader economic environment. This conditional LGCM structure enables us to explore both the average development in ROA and the extent to which company-level characteristics and macroeconomic context influence post-merger performance.

4 Data and Measures

The analysis is based on a large dataset of 792 merged companies, representing all 2,396 companies that successfully completed a merger transaction in the Czech Republic between 2001 and 2011. This data was collected from the financial statements of all the publicly available companies disclosed on the website of the Czech Trade register. Unfortunately, not all of the 2396 merged companies disclose this kind of data that we could use for our analysis. And even if the companies do that, there are a lot of statements (especially from older years) that are scanned in a very bad quality or scanned incorrectly which makes them unreadable and thus unprocessable. In addition, a lot of data is incomplete or the statements over the post-merger years are incoherent. Lastly, some merged companies were forced to cease their economic activity in the observed period after the merger. Thus, we could not further include data from such companies in the analysis. All of this resulted in a final dataset comprising 792 companies. Therefore, the results are derived from a subset of companies following the obligation to make their financial statements public and can be generalised to similar companies. Data is available on request. The distribution into the cohorts[1] is depicted in Table 1, where the x denotes the available accounting information in respective years for each cohort (where the first x for the cohort represents the year of the merger) and N is the number of companies in each cohort, divided in the number of small (the value of total assets less than €10 million) and large companies (more than €10 million).

[1] The cohort represents the number of companies that have undertaken the merger in the same year, conveying the fact that the observed performance after the merger was taking place in the same years.

Tab. 1 Distribution of the cohorts of the merging companies over the observed period. Total N=792 companies comprise of 358 small companies and 434 large companies.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	N	Small	Big
1.cohort	x	x	x	x	x	x	.	.	.	.	.	.	.	.	.	.	28	15	13
2.cohort	.	x	x	x	x	x	x	.	.	.	.	.	.	.	.	.	35	23	12
3.cohort	.	.	x	x	x	x	x	x	.	.	.	.	.	.	.	.	38	22	16
4.cohort	.	.	.	x	x	x	x	x	x	.	.	.	.	.	.	.	38	17	21
5.cohort	.	.	.	.	x	x	x	x	x	x	.	.	.	.	.	.	12	8	4
6.cohort	.	.	.	.	.	x	x	x	x	x	x	.	.	.	.	.	68	22	46
7.cohort	.	.	.	.	.	.	x	x	x	x	x	x	.	.	.	.	63	26	37
8.cohort	.	.	.	.	.	.	.	x	x	x	x	x	x	.	.	.	12	7	5
9.cohort	.	.	.	.	.	.	.	.	x	x	x	x	x	x	.	.	183	80	103
10.cohort	.	.	.	.	.	.	.	.	.	x	x	x	x	x	x	.	191	79	112
11.cohort	.	.	.	.	.	.	.	.	.	.	x	x	x	x	x	x	124	59	65

To evaluate the effect of mergers, we analyse company performance over a five-year period following the merger. As the key performance indicator, we use return on assets (ROA), measured annually in the year of the merger and in each of the five subsequent post-merger years. The ROA in the year of the merger (time point 0) reflects the sum of the ROA values of the two merging companies while they were still operating as separate entities. From the first post-merger year onward, ROA values are derived from the financial statements of the newly merged company.

ROA is a standard profitability ratio and has been widely used in post-acquisition research as a primary accounting-based measure of performance (King et al., 2004). The formula for ROA used in this study is as follows:

$$ROA = \frac{EBIT}{Total\ Assets}$$

reflecting the ability of the company to generate profitable sales from its primary business operations. Generally, ROA values over 5% are considered good, and values over 20% exceptional. However, we consider the observations with ROA values that exceeded the 0.1% quantile on each tail of the distribution in any observed year to be outliers that might skew the estimated general trajectory. There were only nine such companies. After removing them from a dataset, the final dataset comprised 783 companies. Table 2 shows the basic statistics of these companies. The number after the ROA column name indicates the year after the merger occurred.

Tab. 2 Means, Standard Deviations, and Correlations of repeated measures of ROA for 783 companies

	ROA	ROA1	ROA2	ROA3	ROA4	ROA5
ROA	1.0000					
ROA1	0.4830	1.0000				
ROA2	0.3614	0.4896	1.0000			
ROA3	0.3316	0.3465	0.5414	1.0000		
ROA4	0.3670	0.3735	0.5009	0.5554	1.0000	
ROA5	0.2862	0.2947	0.3566	0.3327	0.6462	1.0000
Mean	0.0525	0.0512	0.0494	0.0455	0.0513	0.0605
SD	0.1171	0.1380	0.1148	0.1307	0.1099	0.1309

Although the mean values of ROA over the whole sample indicate a convex quadratic trend, the trajectory can be very different if we split companies into two groups based on initial ROA values. The first group includes companies generating profits before the merger (582 companies), and the second group comprises those reporting losses (201 companies). Table 3 shows the means and standard deviations of ROA for these two groups.

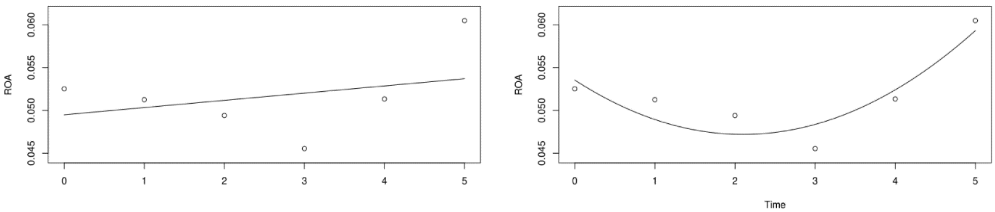
Tab. 3 Means and Standard Deviations of repeated measures of ROA for companies with initial values below and above zero.

	ROA	ROA1	ROA2	ROA3	ROA4	ROA5
Mean init loss	-0.0583	-0.0278	0.0001	-0.0040	0.0007	0.0137
SD init loss	0.0834	0.1677	0.1202	0.1396	0.1116	0.1161
Mean init profit	0.0908	0.0786	0.0664	0.0627	0.0688	0.0766
SD init profit	0.1016	0.1143	0.1078	0.1231	0.1039	0.1320

5 Results

Descriptive statistics in the previous section suggest that the mean values of ROA over time follow a quadratic rather than linear post-merger trajectory. However, testing that assumption and fitting the individual trajectories is necessary before any further modelling. Thus, we perform first the fit indices for unconditional (without any explanatory variables) latent growth curve models, where ROA over time is modelled via both linear and quadratic trend. The models' fit indices for linear [p(χ^2) = 0.0000, TLI = 0.9241, 90 % CI for RMSEA = (0.0852, 0.1154)] and quadratic [p(χ^2) = 0.0000, TLI = 0.9634, 90 % CI for RMSEA = (0.0520, 0.0880)] trajectories suggest a bad fit for both unconditional models as χ^2 p-value is significant for both. However, the TLI and RMSEA of the quadratic trajectory indicate moderate to great fit. The visualization of both fitted curves of observed ROA means over time, in addition to Table 2, is presented in Figure 3.

Fig. 3 Comparison of fitted linear and quadratic curve to observed means of ROA over time.



As the quadratic trajectory fits the data better, the quadratic unconditional model will be improved further.

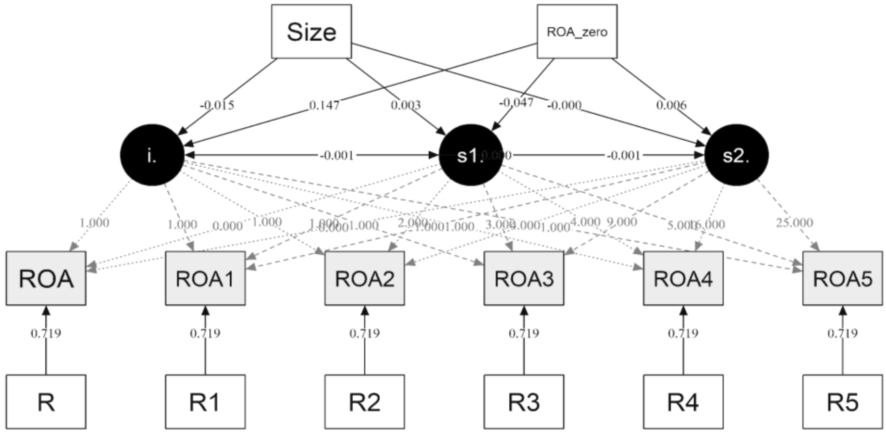
To develop the conditional model, we incorporate both time-invariant and time-varying covariates into the model. The final quadratic model includes the binary time-invariant covariates *Size* and *ROA_Zero*, as well as the time-varying covariate *Interest Rate*. These variables, along with their coding and rationale for inclusion, are described in detail in Chapter 3.

A graphical representation of the model, including the covariates *Size*, *ROA_Zero*, and *Interest Rate (R)*, is shown in Figure 4 as a path diagram. The corresponding table (Table 4) presents model fit indices, parameter estimates, and regression coefficients. By including both time-invariant and time-varying covariates in the quadratic model, the fit indices improved: the TLI increased to 0.9743, approaching the ideal value of 1, and the RMSEA decreased to 0.0310, remaining safely below the 0.05 threshold.

In the conditional model, estimates of the latent intercept and slopes must be interpreted in conjunction with the effects of the covariates. Meaning, e.g., the model implied mean value of intercept −4.02% represents the model implied mean value of ROA on the day of the merger for small companies that belong to the group of mergers with the reported loss (negative ROA) at the time of the merger.

The mean latent intercept $\mu_\alpha = -0.0402$ is statistically significant (p = 0.0014), which is not surprising given that the model includes the ROA_Zero covariate that explicitly separates companies based on their initial ROA values. Since the intercept represents the expected ROA at the time of the merger for the reference group (companies with negative initial ROA and small size), a negative and statistically significant estimate is consistent with the definition of this group.

Fig. 4 Path diagram of conditional LGCM for ROA i. represents intercept μ_{α}, s1. represents linear slope μ_{β_1}, s2. quadratic slope μ_{β_2}; R, R1, …, R5 represent time-varying covariate Interest Rate regressed onto the repeated measures of ROA; binary Size and binary ROA zero represent time-invariant covariates. Solid arrows represent regression paths from time-invariant covariates to latent growth factors; the corresponding estimated coefficients are also reported in Table 4. Dashed arrows indicate fixed factor loadings used to define the latent growth trajectory (intercept: 1, 1, 1, 1, 1, 1; linear slope: 0, 1, 2, 3, 4, 5; quadratic slope: 0, 1, 4, 9, 16, 25).



Tab. 4 Parameter estimates, standard errors, and related p-values of the final conditional LGCM of ROA. Model fit indices: p-value (χ^2) = 0.0006, TLI = 0.9743, RMSEA =0.0310; RMSEA 90 % CI= (0.0202, 0.0413)

Parameter	Estimate	s.e.	p-value
Means:			
μ_{α}	-0.0402	0.0125	0.0014
μ_{β_1}	0.0263	0.0106	0.0127
μ_{β_2}	-0.0032	0.0021	0.1269
Variances:			
$\psi_{\alpha\alpha}$	0.0054	0.0007	0.0000
$\psi_{\beta_1\beta_1}$	0.0030	0.0004	0.0000
$\psi_{\beta_2\beta_2}$	0.0001	0.0000	0.0000
Covariances:			
$\psi_{\alpha\beta_1}$	-0.0013	0.0005	0.0104
$\psi_{\alpha\beta_2}$	0.0002	0.0001	0.0666
$\psi_{\beta_1\beta_2}$	-0.0005	0.0001	0.0000

	α		β_1		β_2	
Covariates	Estimate (s.e)	p-value	Estimate (s.e)	p-value	Estimate (s.e)	p-value
Size	-0.0146 (0.0069)	0.0337	0.0027 (0.0059)	0.6517	-0.0001 (0.0012)	0.9177
ROA_Zero	0.1474 (0.0078)	0.0000	-0.0470 (0.0067)	0.0000	0.0063 (0.0013)	0.0000
IR	0.7188 (0.2475) p-value=0.0037					

Therefore, to explain the differences in the post-merger development better, it is valuable to make use of covariate ROA_Zero, even though it makes the parameter estimate of the latent intercept in the model less interpretative.

And although only one of the slope factor parameters suggests a significant difference from zero (latent linear slope), intercept μ_{α} and linear slope μ_{β_1} estimates (−0,0402; −0,0032), and their respective p-values (0,0014; 0,0127) reflect the hypothesised post-merger development in ROA only for small companies reporting losses before the merger (reference group).

The estimated effects of company *Size* on both the linear μ_{β_1} and quadratic μ_{β_2} slopes are not statistically significant ($p = 0.6517$ and $p = 0.9177$, respectively). This indicates that the rate and shape of post-merger ROA development do not differ meaningfully between small and big companies. In other words, the company's size does not appear to influence how ROA evolves over time following the merger.

On the other hand, the group membership based on *ROA-zero* considerably affects both slope factors. The model implies that small companies *(Size=0)* starting at the time of the merger with negative ROA (*ROA_Zero=0)* report on average −4.02% returns on assets, but the ability to generate more profitable sales in these companies is affected positively by the merger. At least in the first years, when the ROA exhibit a rising trend, accounting for the fact that the $\hat{\mu}_{\beta_1} = 0{,}0263$ for linear slope is much greater than $\hat{\mu}_{\beta_2} = -0{,}0032$ for quadratic slope, which is then decelerated in the later years, eventually resulting in the reversed, decreasing trend as an effect of the negative quadratic factor. (However, the negative quadratic slope of – 0.0032 is not statistically significant ($p = 0.1269$), which implies that although some deceleration in the growth trend may occur over time, this effect is weak. This issue will be addressed more specifically in the multiple-group model presented later.)

For companies with initially positive ROA at the time of the merger (ROA_Zero = 1), the model suggests a contrasting development pattern. The estimated average initial ROA for small companies (Size = 0) in this group is 10.72%, calculated as the sum of the latent intercept and the ROA_Zero effect (− 0.0402 + 0.1474 = 0.1072). For large companies (Size = 1), this value is further reduced by 1.46 percentage points due to the negative size effect, resulting in an initial ROA of 9.26 %.

These companies – starting from a profitable position (ROA_Zero = 1) – exhibit an initially declining ROA trajectory following the merger. (The estimated linear slope for small companies with initial positive ROA is − 0.0207, computed as 0.0263 − 0.0470; for big companies it is − 0.0180, computed as − 0.0207 + 0.0027.) However, the downward trend appears to decelerate over time and may eventually reverse (the quadratic slope is for small companies estimated at 0.0031 computed as − 0.0032 + 0.0063; for big companies it is 0.0030, computed as 0.0031 − 0.0001).

The term "may" is crucial here: while the linear slope estimate is negative, the positive quadratic slope is not statistically significant. Thus, although the model permits the possibility of long-term recovery, the statistical evidence supporting such a trajectory remains limited[2].

Interest Rate effect on ROA was proved to be significant and its positive value (estimate = 0.7188, p = 0.0037) suggests that the companies are generating higher returns on assets in years with a higher interest rate in the economy. This is a surprising finding for us, so that we need to make it clear that this is only a correlation finding, and probably not a causal relationship. We raise a hypothesis that might shed more light on why this correlation comes out surprisingly, namely that periods of rising interest rates usually mean that economies are in a growth phase of the cycle, which usually also means that corporate sales are rising. Monetary policy usually responds to the business cycle with a lag, so the rate of growth in sales could be outpacing the rate of growth in interest rates, which could explain the correlation found. However, after a period of time, rising interest rates should, among other things, contribute to a slowdown in revenue growth, which would mean that rising interest rates would start to contribute to a decline in ROA, in line with expectations. Obviously, this hypothesis should be further tested to confirm or refuse it.

In the pair of exogenous variables – *Size* and *ROA_Zero* – only *ROA_Zero* proved to have a significant effect on trajectories. Thus, instead of treating ROA_Zero as a time-invariant covariate in a single-group conditional model, we implemented a multiple-group LGCM based on ROA_Zero group membership. This enables the estimation of separate growth trajectories for companies with positive versus negative profitability at the time of the merger. Moreover, the multiple-group specification provides a more transparent framework for evaluating group-specific model parameters, as it enables formal testing of group-specific intercepts and slopes, including the reporting of their associated p-values, which were not available in the single-group model.

Table 5 presents the estimated trajectories for both groups defined by ROA_Zero, along with the corresponding model fit indices

2 While the latent means and regression effects are each associated with their own significance tests, the derived estimates for non-reference groups (e.g., ROA_Zero = 1 or Size = 1) result from linear combinations of parameters and are not accompanied by model-estimated standard errors or p-values. A more differentiated view of the trajectories — including separate parameter estimates and associated significance levels — is provided in the subsequent multiple-group model.

Tab. 5 Parameter estimates, standard errors, and related p-values of multiple-group *LGCM of ROA (ROA_zero* as a group). Model fit indices: *Robust P-value (χ2) = 0.1118, Robust TLI =0.9822, Robust RMSEA =0.0240; Robust RMSEA 90 % CI= (0.0000, 0.0401).*

Negative profitability before the merger

Parameter	Estimate	Std.Err	p-value
Means:			
μ_α	-0.0693	0.0062	0.0000
μ_{β_1}	0.0320	0.0064	0.0000
μ_{β_2}	-0.0034	0.0013	0.0066
Covariances:			
$\psi_{\alpha\beta_1}$	-0.0029	0.0027	0.2752
$\psi_{\alpha\beta_2}$	0.0004	0.0004	0.3517
$\psi_{\beta_1\beta_2}$	-0.0009	0.0004	0.0204
TVC:			
IR	1.3209	0.0000	0.0000

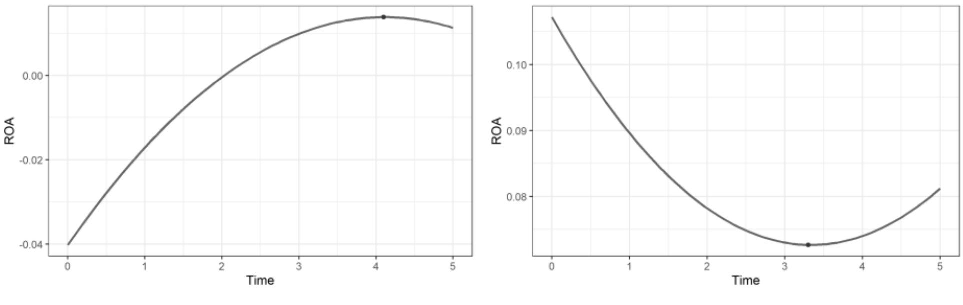
Positive profitability before the merger

Parameter	Estimate	Std.Err	p-value
Means:			
μ_α	0.0861	0.0045	0.0000
μ_{β_1}	-0.0168	0.0032	0.0000
μ_{β_2}	0.0029	0.0007	0.0000
Covariances:			
$\psi_{\alpha\beta_1}$	-0.0008	0.0008	0.2791
$\psi_{\alpha\beta_2}$	0.0001	0.0002	0.4701
$\psi_{\beta_1\beta_2}$	-0.0005	0.0002	0.0033
TVC:			
IR	0.5529	0.2534	0.0291

Based on the multiple-group model output in Table 5, the trajectories of post-merger ROA development differ clearly between companies that reported negative profitability at the time of the merger and those that started from a profitable position. All latent growth factors — the intercept, linear slope, and quadratic slope — are statistically significant in both groups.

For companies with **negative pre-merger ROA**, the model estimates an average return on assets of − 6.93 % at the time of the merger. In the first year following the merger, ROA increases by 2.86 %, to − 4.07% $(-0.0693 + 1 \cdot 0.0320 + 1 (-0.0034) = -0.0407)$. In the second year, it increases by a further 2.18% to –1.89 % (computed as $-0.0693 + 2 \cdot 0.0320 + 4 \cdot (-0.0034) = -0.0189$). For subsequent post-merger years, the trajectory evolves analogously based on the specified linear and quadratic effects — all of which are statistically significant. As illustrated in Figure 5 (left panel), this trajectory initially rises but later flattens and reverses due to the negative quadratic component.

Fig. 5 Model implied trajectory of ROA for companies with negative profitability before the merger on the left and positive profitability before the merger on the right.



For companies with **positive pre-merger** ROA, the model estimates an average return on assets of 8.61 % at the time of the merger. In the first year, ROA declines by 1.39% to 7.22% ($0.0861 + 1 \cdot (-0.0168) + 1 \cdot 0.0029 = 0.0722$). In the second year, it decreases by a further 0.81% to 6.41% ($0.0861 + 2 \cdot (-0.0168) + 4 \cdot 0.0029 = 0.0641$). The lowest value is reached in the third year (6.18%), after which ROA starts to rise again — reaching 7.46% in year five. As shown in Figure 5 (right panel), the trajectory initially declines but gradually recovers, driven by the positive (statistically significant) quadratic trend.

The multiple-group model highlights that the initial profitability condition – as captured by ROA_Zero – plays a fundamental role in shaping the post-merger ROA trajectory. The two groups exhibit markedly distinct patterns of development: while companies with pre-merger losses display an initial recovery followed by deceleration, those with pre-merger profits undergo an initial decline that later reverses. This underscores the importance of financial starting position in merger outcomes. Although the year of the merger (time point 0) serves as a valid baseline for assessing post-merger effects, the interpretation is constrained by the absence of sector-level data and by the lack of historical financial information for the merging entities prior to the merger, as these companies did not yet exist in their final, post-merger form. Future research should address this limitation by incorporating industry classifications and, where feasible, the financial histories of the pre-merger components.

6 Discussion

Our research has produced some unexpected findings, particularly the observation that companies with weaker pre-merger financial performance (as measured by ROA) tend to show short-term improvements following a merger, whereas companies with stronger pre-merger performance often experience a decline. While these patterns are noteworthy, they should be interpreted with caution due to several limitations of our study.

Profit-generating companies may pursue mergers primarily for expansion or strategic positioning, rather than as a necessity. However, these types of mergers can bring integration costs, cultural mismatches, or management friction that temporarily reduce efficiency. The eventual recovery in ROA suggests that these companies gradually adapt and stabilise. Alternatively, firms entering the merger from a strong financial position may simply regress toward more typical levels of profitability over time. Their initial high ROA could reflect temporary factors or peak performance, and the post-merger period may simply capture a return to average levels, explaining the early decline in ROA.

However, it is important to note that these interpretations are speculative, as our analysis does not control for other variables that may influence post-merger performance.

Similarly, the observed short-term improvement in companies with negative pre-merger ROA may reflect the merger's role as a temporary catalyst, as loss-making firms often pursue mergers as a corrective measure - streamlining or eliminating inefficient processes and creating a sense of renewal. However, this effect appears to diminish over time, with performance often reverting to pre-merger levels or deteriorating further. Alternatively, managers of underperforming companies may be more motivated to justify the merger by demonstrating rapid post-merger gains. There may also be a stronger external expectation to initiate a turnaround in performance, driving early efficiency improvements. Still, the deeper structural issues may resurface in the longer term, leading to the observed deceleration in ROA growth. Again, without control variables or a broader set of performance indicators, it is not possible to determine whether these changes are directly attributable to the merger itself.

Moreover, our reliance on ROA as the sole measure of performance presents an additional limitation. While ROA is a commonly used indicator, it may not fully capture the complexity of post-merger integration outcomes, especially in the presence of intangible factors such as cultural fit, strategic alignment, or managerial effectiveness.

In light of these limitations, we refrain from making strong practical recommendations. Instead, we suggest that the relationship between merger outcomes and pre-merger financial performance warrants further investigation using more comprehensive datasets and methodologies that incorporate control variables and multiple performance metrics. Such research could help clarify whether the trends observed in our study are robust and generalisable, or whether they reflect context-specific dynamics or unobserved confounding factors.

7 Conclusion

Any merger or acquisition is a complicated transaction that requires quality ad-hoc financial analysis and due diligence. In addition, cultural and other important aspects such as geographical, sectoral, personal and similar considerations need to be taken into account. However, we believe that the research in this paper provides an interesting contribution to the topic of the merger effect.

Mergers and acquisitions are corporate decisions that affect individual business units differently. In addition, there are many related events outside the merger that can affect the post-merger economic impact. And based on our results, it should be acknowledged that the observed change in the observed variables is only to some extent due to the merger.

This study distinguishes itself by leveraging a unique dataset that captures up to six consecutive annual ROA measurements for each company in our dataset following a merger. Such longitudinal financial data at the company level are rarely available in the context of post-merger research, particularly in Central and Eastern Europe. This temporal richness enabled the application of latent growth curve modelling (LGCM), a novel and still rarely applied approach in merger performance research. The use of LGCM allowed for a more refined analysis of post-merger ROA development, capturing both linear and non-linear trends and enabling comparisons between groups of companies with different pre-merger financial conditions.

Our findings suggest that mergers may lead to short-term improvements in financial performance for companies that were underperforming prior to the merger, as indicated by negative ROA values. However, this effect appears to be temporary, with performance often returning to pre-merger levels or deteriorating in the longer term.

In contrast, companies with positive ROA prior to the merger tend to experience a decline in profitability in the years immediately following the merger. Although there may be signs of gradual recovery in later years, the average ROA five years after the merger remains below its pre-merger level. These findings suggest that mergers may not be an effective strategy for improving long-term profitability in already successful firms, at least not without additional strategic or operational adjustments.

Although company size is often assumed to play a critical role in post-merger outcomes, our results suggest otherwise. In the conditional latent growth curve model, the effects of company size on both the linear and quadratic slopes of ROA were not statistically significant. This finding indicates that, at least in our sample, the post-merger development of profitability is not systematically different between small and large companies. This challenges common assumptions in merger analysis.

It is important to emphasise that these conclusions should be interpreted with caution. Our analysis is subject to several limitations, including the absence of some other control variables, the use of ROA as the sole performance metric, and the lack of information on sectoral affiliation or pre-merger performance trajectories. These factors may influence the observed outcomes and limit the generalisability of our results.

Moreover, the motivations behind mergers can vary significantly. While many transactions may be driven by the goal of improving profitability, others may pursue strategic, managerial, or ownership-related objectives. As such, a decline in ROA does not necessarily imply that a merger was unsuccessful from the perspective of the firms involved.

The inclusion of other meaningful variables, such as industry information or knowledge of individual merger motives, could further improve the modelling of latent ROA growth trajectories. While we can safely assume that many of the mergers analysed were realized to improve profitability, we cannot fully expect this to be true for all mergers that occur in the Central European region. Some of the managers of the merged companies had other reasons for the transaction and may thus consider the merger successful despite the negative development of ROA after the merger. The presence of such companies in our dataset would then have a negative effect on the average of the trajectories implied by the model and thus a negative effect on the generalised results and implications.

Despite these limitations, our approach preserves the ability to observe changes in profitability by comparing the financial performance of merging companies at the time of the merger (unaffected by the merger) with the post-merger development of the merged entity. This allows for a meaningful, albeit cautious, interpretation of merger effects.

From a practical perspective, our findings may be of interest to business owners and managers considering mergers as a growth strategy. While we do not recommend relying on mergers as a guaranteed path to improved long-term profitability, particularly for already profitable firms, the short-term improvements observed in underperforming firms may offer opportunities (especially if followed by well-informed strategic decisions). For example, in cases where the sale of a company is planned, correctly timing the transaction within the post-merger period may allow firms to capitalise on temporary performance gains.

Ultimately, mergers and acquisitions are complex undertakings influenced by a wide range of financial, strategic, and organisational factors. We hope that this study contributes to a more nuanced understanding of their potential effects and encourages further research using more comprehensive data and robust methodological frameworks.

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