Finanțat de Uniunea Europeană
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Digitalization and firm performance – the chicken or egg dilemma

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Twenty-fourth International Working Seminar on Production Economics
Industry 4.0 and digital supply chains
Innsbruck, Austria, 23-27.02.2026

Agenda

1. Introduction, context and literature

2. Sample and methodology

3. Results

4. Discussion and conclusion

From our previous study to a new research question

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Studies that examine the impact of digitalization on the business and financial performance of companies.

Author(s)	Country	Industry/Firms	N (final sample)	I4.0/digital manufacturing		Financial performance measures						Lagged effect	Method
				Technologies	Data source	ROE	ROA	Sales/ Profit	Asset turnover	Other indicators	Data source		
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Conventional Explanations

- Different **financial indicators** used (ROA, ROE, revenue growth, turnover)
- Heterogeneous **measurement of digitalization**
- Ignoring **time-lag effects**

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Our Proposition

- The relationship between **digitalization** and different **performance indicators** may be more complex.

The implicit assumption in the literature

Some example of works examining the relationship between digitization and financial performance: Alkaraan el al. (2022), Cheng et al. (2023), Guo et al. (2023), Lin et al. (2023), Yonghong et al. (2023), Zhao et al. (2024)

Our observations:

1. Most empirical work treats digitalization as exogenous to performance
2. Direction is typically assumed as digitalization → performance
3. In contrast to other fields, such as finance, causality in this context has surprisingly not yet been formally tested

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This represents the research gap we aim to address: specifically, to test the potentially bidirectional relationship between digitalization and firm performance, **while explicitly accounting for lagged effects**

Data and methodology

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2.	We **created a measure for digitalization** based on the **frequency of digitalization-related terms**, recognizing the lack of commonly accepted metrics in the literature.

2.1.	First constructed the so-called **Overall Digitalization Index**, which includes 142 digitalization-related terms.
2.2.	We developed sub-indices by grouping these 142 terms in a way that allows us to distinguish between, **traditional digital technologies**, **advanced digital technologies**, and **AI-related technologies**.

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4.	Finally, the data is analyzed using **Dumitrescu and Hurlin (2012) heterogeneous panel Granger causality test**.

Data and methodology

The sample was constructed through a systematic multi-stage selection process to ensure relevance, data availability, and consistency across firms.

Sample	The sample of companies comprised the **200 largest OEMs** and **suppliers** in the **automotive industry**, including battery manufacturers.	The analyzed **timeframe spanned from 2012 to 2024**. This period was chosen as it starts from the emergence of the term "Industry 4.0" in 2012.

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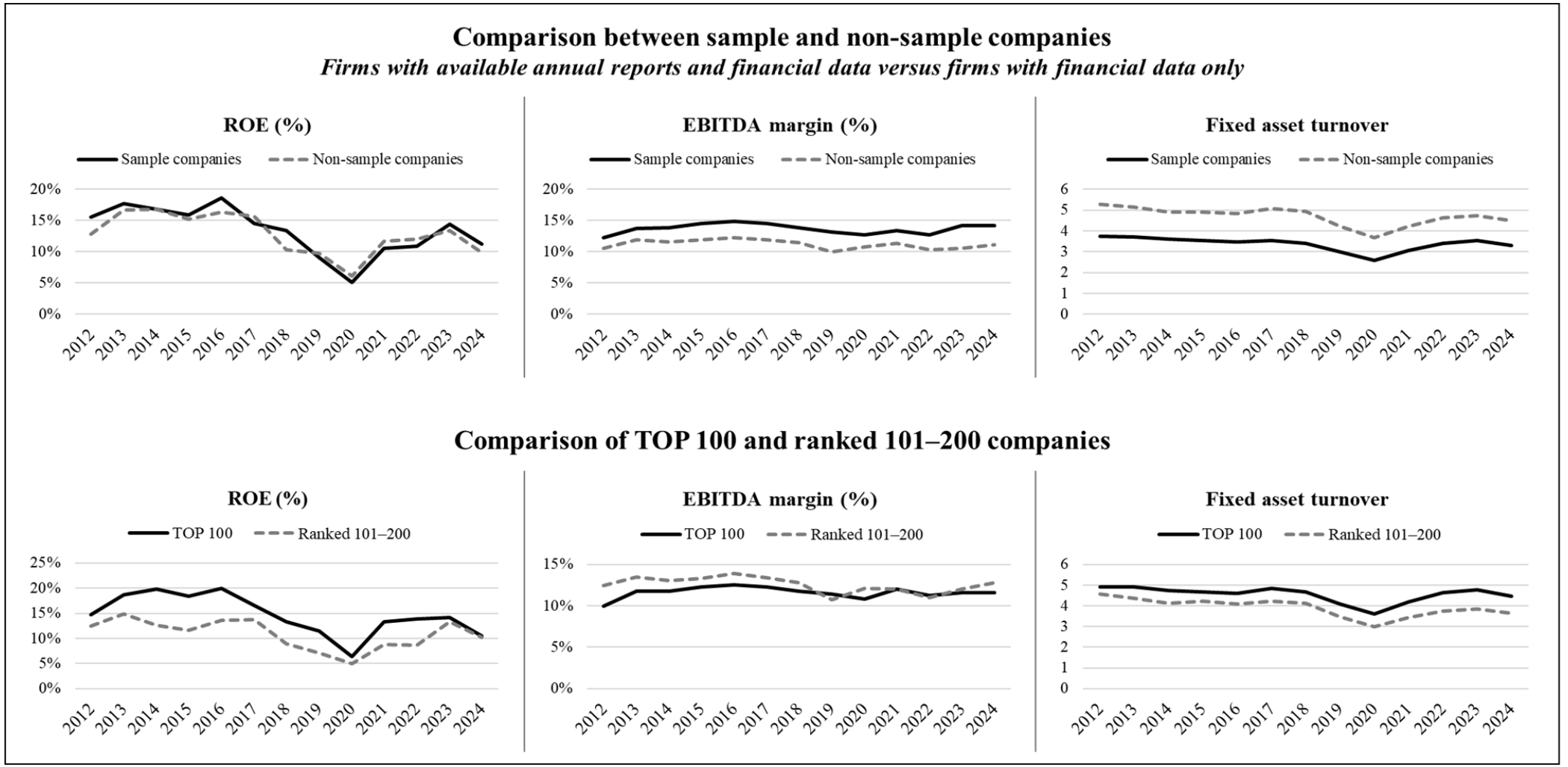
Final sample	After the exclusions, we examined **849 annual reports** from **24 OEMs** and **49 suppliers**. All companies are **publicly listed companies**.	

Data and methodology

Comparison of financial metrics between reporting (final sample) and non- or incompletely reporting (benchmark) companies, and between top 100 and ranked 101–200 companies



Data and methodology

We apply the Dumitrescu–Hurlin (2012) heterogeneous panel Granger causality test to examine the potentially bidirectional relationship between firm-level digitalization and performance.

Test equation for heterogeneous panel Granger causality

$$Y_{it} = \alpha_i + \Sigma\beta_k Y_{i,t-k} + \Sigma\gamma_k X_{i,t-k} + \varepsilon_{it}$$

H_0: homogeneous non-causality (no firm shows causality)

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Why this method?

- Suitable for panels with cross-sectional heterogeneity
- Does not impose homogeneous causal effects across firms
- Tests homogeneous non-causality vs. causality for at least a subset of firms

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A large OEM investing millions in digital transformation will likely see different performance effects than a smaller supplier which just introducing a few digital tools. It would be unrealistic to assume the same effect for both. The Dumitrescu–Hurlin test allows the relationship to differ across firms instead of forcing a uniform impact.

Results in a nutshell

Financial variables *(outcome)*	**Digitalization** *(cause)*	**1 year lag**	**2 years lag**
Fixed asset turnover	Overall digitalization index	**3.367*** **	**3.514*** **
Fixed asset turnover	Traditional digital technologies index	**4.046*** **	**5.349*** **
Fixed asset turnover	Advanced digital technologies index	**1.982** **	**1.763***
Fixed asset turnover	AI index	**4.685*** **	**3.289*** **
EBITDA	Overall digitalization index	1.471	0.841
EBITDA	Traditional digital technologies index	**3.101*** **	**2.918*** **
EBITDA	Advanced digital technologies index	**2.442** **	0.471
EBITDA	AI index	-0.005	-0.633
ROE	Overall digitalization index	**2.124** **	**2.918*** **
ROE	Traditional digital technologies index	**5.606*** **	**3.603*** **
ROE	Advanced digital technologies index	**3.616*** **	**4.395*** **
ROE	AI index	0.325	**1.764***

*Bold: significant values at *** p<=0.001; ** p<=0.05; * p<=0.10*

Results in a nutshell

Digitalization *(outcome)*	**Financial variables** *(cause)*	**1 year lag**	**2 years lag**
Overall digitalization index	EBITDA	**1.817***	1.003
Traditional digital technologies index	EBITDA	**3.497*****	**3.508*****
Advanced digital technologies index	EBITDA	1.543	**2.645*****
AI index	EBITDA	**3.075*****	**1.655***
Overall digitalization index	Fixed asset turnover	**1.681***	**1.867***
Traditional digital technologies index	Fixed asset turnover	0.845	1.288
Advanced digital technologies index	Fixed asset turnover	**2.402****	1.604
AI index	Fixed asset turnover	1551	**4.242*****
Overall digitalization index	ROE	0.322	**3.442*****
Traditional digital technologies index	ROE	1.249	**2.52****
Advanced digital technologies index	ROE	0.464	**1.765***
AI index	ROE	**4.684*****	**4.214*****

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Conclusions: Digitalization → Performance

Main findings

- Digitalization significantly improves firm performance within **1–2 years**
- **Fixed Asset Turnover** shows the strongest and most consistent effects → improved **operational efficiency**
- EBITDA results are weaker and less consistent – aligned with prior literature (ex. Benedek et al., 2025; Yonghong et al., 2023)

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Sub-index insights

- **Traditional digital technologies** affect all financial measures across time horizons → likely due to the long presence of these technologies in companies
- **AI technologies** show limited short-term financial impact → many firms are still in early implementation phases

Reverse Direction: Performance → Digitalization

Key insight

- Financial performance also predicts subsequent digitalization
- This direction is underexplored in the literature

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Patterns

- EBITDA affects digitalization in both short and longer horizons
- ROE influences digitalization mainly in the longer term
- Fixed Asset Turnover has the weakest reverse effect

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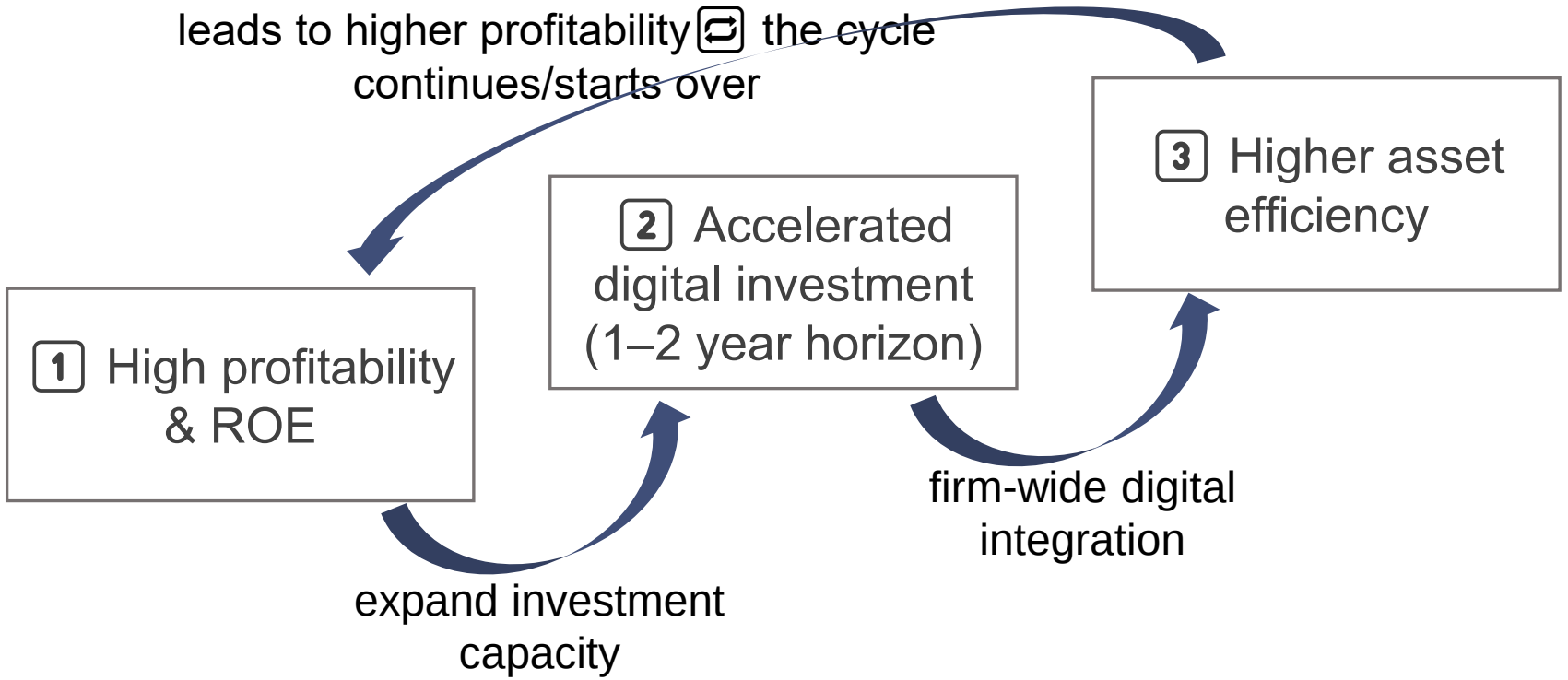
AI-specific conclusion

- AI already improves **asset turnover**
- No clear impact yet on ROE or EBITDA
- Implementing AI appears to require a **strong financial base**

Toward a “Digitalization–Performance Value Spiral”

The reinforcing dynamic



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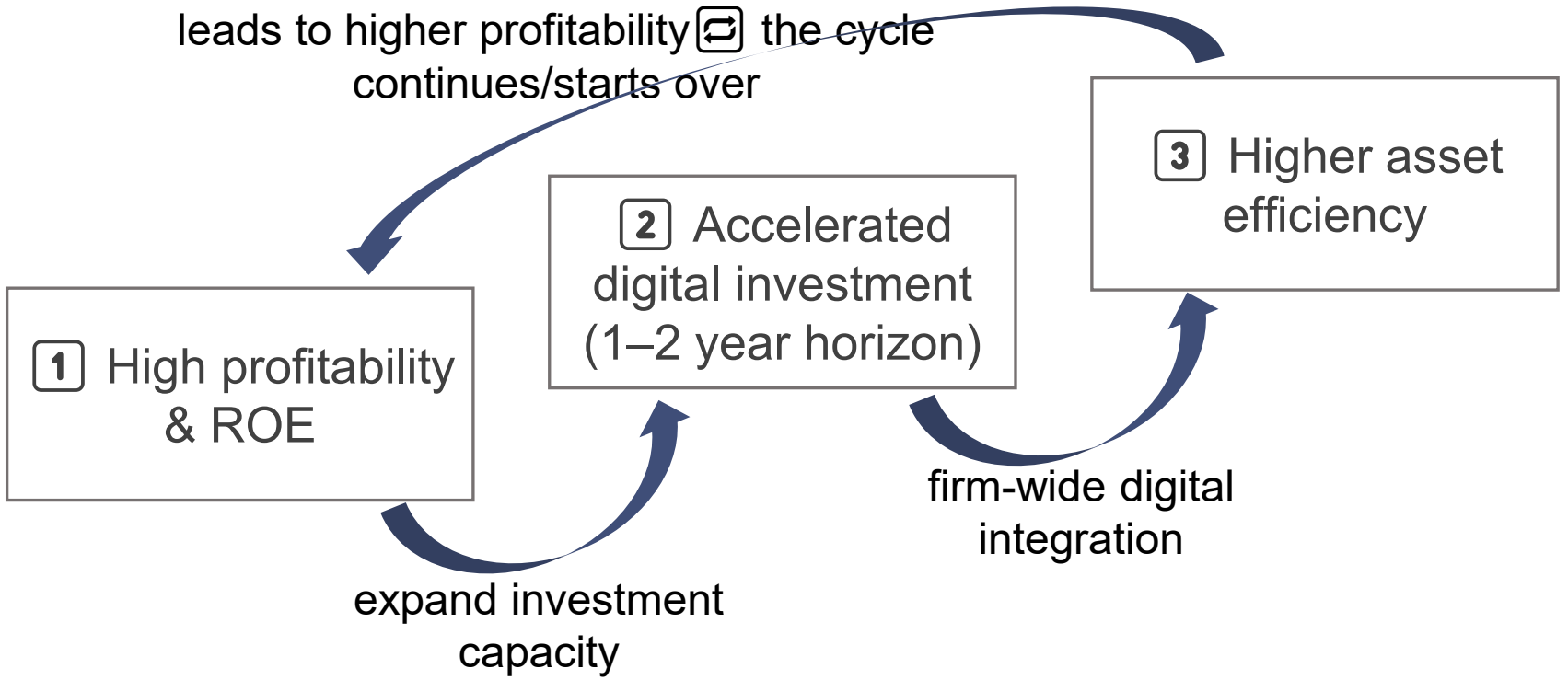

The strategic objective for the top management of a large automotive company is to move the firm upward along the “Digitalization–Performance Value Spiral”

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Thank you for your attention!

Discussant: DJERDJ HORVAT

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Twenty-fourth International Working Seminar on Production Economics
Industry 4.0 and digital supply chains
Innsbruck, Austria, 23-27.02.2026

Funding

This work was supported by the project entitled

"Strengthening the digitalization of businesses in Eastern Europe – a micro and macro-level approach"

funded by the **European Union – NextGenerationEU** project and the **Romanian Government**,

under the National Recovery and Resilience Plan for Romania,

contract no. 760036/23.05.2023, cod PNRR-C9-I8-CF 198/28.11.2022,

through the Romanian Ministry of Research, Innovation and Digitalization, within Component 9, Investment I8.

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Appendix

Variable categories	Variable names	No. of obs.	Mean	Median	Minimum	Maximum	Standard deviation	Relative standard deviation
Financial performance	EBITDA	935	0,137	0,130	-0,111	0,381	0,061	44%
Earning power	ROE	832	0,134	0,123	-0,694	2,577	0,158	117%
Operational performance	Fixed asset turnover	919	3,422	3,074	0,883	14,675	1,730	51%
Digitalization indices	Overall digitalization index	849	0,229	0,193	0,000	1,000	0,129	56%
Digitalization indices	Traditional digital technologies index	849	0,146	0,118	0,000	1,000	0,111	76%
Digitalization indices	Advanced digital technologies index	849	0,067	0,037	0,000	1,000	0,099	148%
Digitalization indices	AI index	849	0,132	0,110	0,000	1,000	0,102	77%

Table 2: Descriptive statistics of the variables used in our panel data regression analysis

	EBITDA	ROE	Fixed asset turnover	Overall digitalization index	Traditional digital technologies index	Advanced digital technologies index	AI index
EBITDA	1,000						
ROE	0,299	1,000					
Fixed asset turnover	-0,192	0,327	1,000				
Overall digitalization index	0,021	0,035	0,131	1,000			
Traditional digital technologies index	0,066	0,072	0,093	0,727	1,000		
Advanced digital technologies index	0,014	-0,015	0,061	0,692	0,560	1,000	
AI index	0,017	0,097	0,106	0,715	0,472	0,517	1,000

Table 3: The correlation matrix of the variables used

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Overall digitalization index	**0,177**	**0,177**	**0,193**	**0,179**	**0,200**	**0,219**	**0,230**	**0,234**	**0,230**	**0,254**	**0,275**	**0,291**	**0,287**
OEM	0,183	0,189	0,195	0,192	0,226	0,231	0,246	0,240	0,225	0,256	0,286	0,288	0,282
Supplier	0,174	0,171	0,191	0,172	0,186	0,212	0,222	0,231	0,232	0,253	0,270	0,292	0,290
Traditional digital technologies index	**0,105**	**0,103**	**0,115**	**0,114**	**0,134**	**0,146**	**0,160**	**0,161**	**0,155**	**0,166**	**0,166**	**0,170**	**0,171**
OEM	0,093	0,098	0,109	0,114	0,137	0,159	0,172	0,166	0,128	0,147	0,140	0,154	0,145
Supplier	0,112	0,106	0,118	0,115	0,133	0,138	0,153	0,159	0,167	0,175	0,179	0,177	0,185
Advanced digital technologies index	**0,037**	**0,039**	**0,057**	**0,045**	**0,053**	**0,064**	**0,081**	**0,066**	**0,082**	**0,074**	**0,082**	**0,089**	**0,080**
OEM	0,024	0,036	0,049	0,043	0,057	0,053	0,076	0,054	0,061	0,054	0,059	0,066	0,054
Supplier	0,045	0,042	0,062	0,046	0,051	0,070	0,084	0,072	0,092	0,083	0,094	0,101	0,093
AI index	**0,105**	**0,103**	**0,120**	**0,122**	**0,133**	**0,144**	**0,145**	**0,138**	**0,120**	**0,129**	**0,142**	**0,143**	**0,156**
OEM	0,162	0,164	0,158	0,169	0,201	0,203	0,206	0,190	0,148	0,159	0,175	0,185	0,177
Supplier	0,071	0,069	0,097	0,096	0,098	0,112	0,114	0,112	0,107	0,115	0,126	0,123	0,144

Table 4: The evolution of average digitalization indices values in the case of OEMs and suppliers