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Financial performance and firm efficiency of automotive manufacturers and their suppliers A longitudinal data envelopment analysis

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ABSTRACT

A data envelopment analysis (DEA) is presented to assess evolutions of firm efficiency and financial performance in automotive supply chains.

A sample of 32 decision-making units (DMUs), 17 globally operating original equipment manufacturers (OEMs) and 15 key suppliers from the automotive industry, is in focus of this analysis in which cost levels and capital requirements are put into relation to sales growth and profit. Cost of goods sold, operating capital, and net fixed assets represent the financial input of a company while sales growth and earnings before interest and taxes (EBIT) reflect the financial output. The financial performance of a firm is indicated by its efficiency, calculated by an input-oriented variable returns to scale model. A multiple linear regression analysis reveals which operational performance factors are predictors of financial performance. A longitudinal DEA approach that covers the years from 2003 to 2017 is chosen to reveal performance evolutions over time. In order to analyze the stability of relationships between efficient firms (peers) and inefficient ones (followers) over time, changes in the performance relationship network are assessed in a graph-theoretic approach. In this study, geographical and structural specifics of DMU groups are taken into account. The study reveals similarities and differences between OEMs and their suppliers regarding the importance of value drivers and detects periods of performance losses and recovery from the global economic crisis.

KEYWORDS: Automotive industry · Data Envelopment Analysis · Financial performance · Supply networks

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1. INTRODUCTION

Measuring and managing performance and efficiency is crucial for a firm's financial success. Performance management in manufacturing systems – aka production economics (Rasmussen, 2013) – is subdivided into the two areas of operational performance and financial performance, respectively (Gomm, 2010). Operational performance management focuses on the influences of operational activities and processes on selected performance factors such as service level or cost efficiency. A good example is presented by Dörnhöfer et al. (2016) who elaborate on operational performance management at the example of an automobile original equipment manufacturer's (OEM) logistics. Financial performance management focuses on the interplay of different financial performance factors and the resulting implications for company value or overall financial success of a firm as exemplified by, e.g., Brandenburg, Seuring (2011) who benchmark value impacts of consumer goods manufacturers. The coherence of these two fields is modeled and empirically studied by Zhu (2000).

Company value is affected by profit- and capital-related factors which in turn can be strongly influenced by operations excellence and supply chain performance (Christopher, Ryals, 1999; Pfohl, Gomm, 2009). Numerous cross-sectoral analyses strive for determining predictors of financial success while other studies aim at assessing the operational and financial performance in a particular industry (see Shi, Yu, 2013, for a related review). Performance aspects of automotive supply chains are studied by, e.g., Wagner et al. (2009), Saranga, Moser (2010) or Brandenburg (2016).

Data Envelopment Analysis (DEA) is a method to rank and assess the performance of enterprises and other organizations which is more sophisticated than simple performance ratios and other naïve efficiency measurement models (Büschken, 2009). Thus, DEA is a widely applied powerful tool to measure and compare the relative efficiency of organizations (Charnes et al., 1978; Banker et al., 1984; Hatami-Marbini, Toloo, 2019).

The study at hand analyzes and compares automotive OEMs and their suppliers thereby deliberately focusing on financial performance only. This approach complements SCM studies that assess non-financial indicators of operational performance such as service level or lead time.[1] Broadening the view from the non-financial performance dimension to the financial one that is directly linked to a firm's financial success is required to determine how SCM contributes to company value (Christopher, Ryals, 1999; Brandenburg, 2013). We conduct a longitudinal DEA study to compare automotive companies regarding their efficiency and financial performance, to identify predictors of firm efficiency and to assess financial performance evolutions in the automotive industry. In contrast to most other DEA studies that include non-financial operational metrics or company-internal primary data, this one focuses only on publicly available financial figures from annual reports thereby offering a financial analyst's view on performance applying scientific rigor. A sample of OEMs and their key suppliers is in focus of this analysis in order to disclose similarities and differences between both company groups. The longitudinal approach covers the years 2003 to 2017 and, thus, sheds light on changes in the competitive environment of the considered industry. In addition to conventional analyses based on the Malmquist index and its components, we develop and apply a new graph-theoretic approach to assess the dynamics of firm efficiency and performance relationship networks over time. Thus, the paper at hand provides novel empirical insight into efficiency and company performance and also presents a methodological contribution for DEA-based assessments of panel data.

The remainder of the paper is organized as follows. Literature on performance benchmarking and DEA is reviewed in Sect. 2. Sect. 3 gives a detailed introduction into the research method applied in this study. In this context, aspects of scientific rigor and implementation are considered. The results of the analysis are presented and interpreted in Sect. 4. The paper ends with a discussion of findings and concluding remarks in Sect. 5. The appendix of the paper contains detailed information on the assessed firms and the applied performance metrics as well as tables with numerical results and the source code used for programming of the DEA analysis.

2. BACKGROUND

2.1. Performance benchmarking

This subsection focuses on financial performance and related value impacts. For comprehensive reviews of operational performance, we refer to, e.g., Gunasekaran et al. (2001) or Gunasekaran et al. (2004). The financial performance of a company is indicated by (i) accounting-based metrics that measure a firm's capital utilization, e.g. return on assets (ROA) or return on investment (ROI), profitability, e.g. return on sales (ROS), or cash flow and by (ii) market-based indicators such as Tobin's q or the Sharpe ratio that determine the value of a firm (Shi, Yu, 2013). Such aggregate metrics can be decomposed into profit- and capital-related performance factors as conceptualized by, e.g., Christopher, Ryals (1999). On the operational performance level, financial factors are complemented by non-financial ones that are related to, e.g., delivery reliability, flexibility, speed or quality aspects (White, 1996). In production economics, the performance of a unit is measured by its productivity defined as the ratio of (one or more) generated outputs to (one or more) consumed inputs or by its efficiency defined as the actually achieved performance level compared to the one that can be achieved (see, e.g., Rasmussen, 2013, Chap. 6).

In general, sophisticated systems are required to measure and manage the different dimensions of performance (see, e.g., Maestrini et al., 2017) or to assess, compare, and improve the relative performance of companies and other organizations by benchmarking (Maire et al., 2005). In contrast to performance indicators that compute productivity scores by simple output-input ratios, DEA is a comprehensive and sophisticated analysis method to determine multi-dimensional frontiers that maximize diverse outputs with different input combinations or minimize combinations of required inputs for various outputs (Tsionas, 2003; Büschken, 2009; Bogetoft, Otto, 2011; Lampe, Hilgers, 2015).[2] While linear regression studies are often based on large cross-industry firm samples with several thousands of firm-year-observations (FYOs) (see, e.g. Shi, Yu, 2013), comparably small samples are sufficient to obtain meaningful results

1 See, e.g., Corsten et al. (2011) for an empirical analysis of operational performance in supplier-buyer relationships of the automotive industry or Dörnhöfer et al. (2016) for logistics performance measurement in automotive companies.

2 See, e.g., Hollingsworth, Smith (2003) or Emrouznejad, Amin (2009) for the consideration of ratio data in DEA.

from DEA studies if homogeneity of the sample (e.g. regarding sector or technology) is ensured.

DEA is widely used for ranking and performance benchmarking (see, e.g., Adler et al., 2002; Liu et al., 2013a,b; Ruiz, Sirvent, 2016, for related reviews and methodological guidelines), especially in context to operations and supply chain management (see, e.g., Liu et al., 2000; Liang et al., 2006; Xu et al., 2009; Yang et al., 2011, for related approaches). Recent studies apply DEA to assess supply chain performance under consideration of dynamics and resilience (see, e.g., Goodarzi, Saen, 2016; Sabouhi et al., 2018; Ramezankhani et al., 2018; Kalantary, Saen, 2018).

2.2. DEA studies based on accounting data

Non-financial factors usually complement financial ones as inputs or outputs in DEA studies (see, e.g., Reiner, Hofmann, 2006; Saranga, Moser, 2010; Jain et al., 2011; Fazlollahi, Franke, 2018; Liu et al., 2018). However, in comparison to operational figures, choosing accounting data as inputs or outputs for DEA may be advantageous in several regards. First, comparability of the considered data is ensured by local Generally Accepted Accounting Principles (GAAP) and the increasing adoption of International Financial Reporting Standards (IFRS) as well as independent auditing of annual reports (Rodríguez-Pérez et al., 2011; Harrison, Rouse, 2016). Second, annual report data is increasingly available in electronic form provided by commercial or publicly available databases (Demerjian et al., 2012; Harrison, Rouse, 2016). Third, accounting data enable comprehensive assessments of firm performance with a wide coverage of companies, because the accounting system is the backbone of any enterprise (Harrison, Rouse, 2016).

As a consequence, DEA studies that are based on accounting data have gained popularity for 30 years. A total of ten studies listed in Tab. 1 confirm this trend and inform about inputs, outputs and related scope. These studies provide insights into how to conduct DEA benchmarking based on accounting data.

Sales and profits represent the most prominent DEA outputs while the considered DEA inputs are more diverse. Some assessments are based on inputs chosen only from the income statement (Oral, Yalalan, 1990) or only from the balance sheet (Smith, 1990; Düzakın, Düzakın, 2007) while most DEA studies combine income-related factors with asset- and capital-related ones. Joo et al. (2011) decompose ROA to determine adequate inputs and outputs. In addition to financial inputs, Zhu (2000) and Bowlin (2004) consider the number of employees as a non-financial input which is derived from annual report data.

The considered studies combine different methods and procedures for comprehensive performance assessments. Demerjian et al. (2012) combine DEA with linear regression to determine predictors of firm efficiency. Rodríguez-Pérez et al. (2011) choose two sets of DEA data to investigate on the differences between fair value accounting and historical-cost-based valuations. Zhu (2000) combines factors of profitability and marketability aspects in a two-stage input-output system.

A majority of studies focus on a single industry sector, while three studies conduct a cross-industry analysis to compare firms from different sectors (see Zhu, 2000; Düzakın, Düzakın, 2007; Demerjian et al., 2012). None of these studies has put a particular focus on the automotive industry.

Regarding the considered time horizon, a better balance is observed. Four snapshot assessments compare company performance in a single year and four longitudinal DEA studies allow assessing the dynamics of efficiency over several years. Two studies do not disclose the considered time horizon. The longitudinal approaches apply ratio analyses (Bowlin, 1999; Feroz et al., 2003) or window analyses that evaluate moving averages of several periods (Bowlin, 2004). Demerjian et al. (2012) conduct a large scale multi-period and cross-sector panel data analysis in order to determine and compare the firm efficiency and its influencing factors. In addition to window and ratio analyses, changes over time can be assessed based on the Malmquist index that measures technical change and frontier-shift of a DMU over time (Liu, Wang, 2008). Such studies are conducted by, e.g., Pires, Fernandes (2012) and Gitto, Mancuso (2012) evaluating the financial efficiency and operational performance of airlines and airports.

Tab. 1 also sheds light on a methodological aspect. DEA studies are often based on considerably smaller sets of companies, especially when a particular industry sector is in focus. Some analyses even comprise less than 20 firms or less than 100 FYOs.

2.3. DEA studies of the automotive sector

The automotive industry is an important macroeconomic factor for markets and economies around the globe that represents about 25 million jobs in Europe, the US and Japan (Mohr et al., 2013). The used manufacturing technologies are similar and financial performance is important to all automotive companies worldwide, although the shareholders' financial expectations traditionally differ between strong requirements arising from the US and UK stock markets and rather moderate shareholder value orientation in continental Europe and Japan (Froud et al., 2002). Due to declining sales shares of established markets, automotive firms must exploit the growth potential of emerging economies (Mohr et al., 2013). Within the next few years, the industry will have to find ways of compensating for falling margins and rising investment, e.g. by strengthening cost and capital efficiency (Kuhnert et al., 2017–2018). Different studies report the need to improve the management of cost, cash and inventory in automotive supply chains (see, e. g., Christopher, Gattorna, 2005; Grosse-Ruyken et al., 2011; Lind et al., 2012; Wuttke et al., 2013). Within

Table 1: DEA studies based on accounting information

Study	Inputs	Outputs	Sector	Year(s)	# DMUs / # FYOs
Oral, Yalalan (1990)	Personnel exp., admin exp., interests paid, deprec.	Income, interests earned	Banking	Undiscl.	20 / Undiscl.
Smith (1990)	Equity, debts	Shareholders earnings, interests paid, taxes paid	Pharma-ceuticals	1984	47 / 47
Bowlin (1999)	Operat. exp. Identifiable assets	Sales, operat. profits, operat. cash flows	Defense business	1983–1992	18 / 180
Zhu (2000)	Assets, equity, employees (revenues, profits)	Mkt. value, Total returns, EPS (revenues, profits)	Fortune 500	1995	500 / 500
Feroz et al. (2003)	Sales, total assets, equity	Net income	Oil & gas	1973–1992	26 / 520
Bowlin (2004)	Total assets, operat. exp., PPE, employees	Cash flows[a], income[a], sales, mkt. value, mkt. returns	Defense business	1988–1997	16 / 160
Düzakın, Düzakın (2007)	Net assets, equity, debts	Profit	Various	2003	500 / 500
Joo et al. (2011)	Assets[a], cash, deprec. & amort. A/R, INV, COGS, SG&A[b]	Revenues[a]	Retail	Undiscl.	14 / Undiscl.
Rodríguez-Pérez et al. (2011)	Total exp., fin. invest.[a], land & building, other assets	Total revenue	Insurance	2003	85 / 85
Demerjian et al. (2012)	PP&E, operat. leases, R&D, purch goodwill, COGS, SG&A other intangible assets	Sales	Various	1980–2009	43 – 5,000[c] / Undiscl.

DMUs = Number of decision-making units, # FYOs = Number of firm-year-observations.
[a] Different types of the factor considered.
[b] Inputs considered in different models.
[c] 5,000 firms in 43 sectors.
A/R = Accounts receivables, COGS = Cost of goods sold, EPS= Earnings per share, INV = Inventory, PPE = Property, plant & equipment
SG&A = Selling, general, and admin. expenses.

the last ten years, the financial performance assessment of car companies and automotive supply chains has become a highly relevant research area (related studies are presented by, e.g., Wagner et al., 2009; Saranga, Moser, 2010; Brandenburg, 2016).

Some DEA studies take a particular focus on the automotive industry. Saranga (2009) combine two-stage DEA with Ordinary Least Square (OLS) regression analysis to evaluate operational efficiency and its determinants at 50 Indian automotive suppliers. The study reveals that supplier efficiency plays an important role in the automotive industry, because supplier parts pass down savings to the OEMs, and that capital- and inventory-related factors significantly influence firm efficiency. New methods to evaluate the performance of car dealers are presented by Toloo, Ertay (2014) and Biondi et al. (2013) and illustrated using vendors from Turkey and Italy, respectively. Azadeh et al. (2017) combine DEA and principal component analysis to improve the influences of Six Sigma deployment on job characteristics at an Iranian car producer. Ramezankhani et al. (2018) apply dynamic network DEA to measure and evaluate a supply chain performance in the Iranian automotive market from different sustainability and resilience viewpoints. Piran et al. (2016) elaborate on performance impacts of product modularization at a bus manufacturer. The analysis exemplifies that product modularization significantly improves the efficiency of product engineering and production processes. Lertworasirikul et al. (2011) illustrate the application of inverse DEA for the case of variable returns to scale at the example of motorcycle-part companies.

3. RESEARCH METHOD

3.1. Overall approach

The literature review presented in Sect. 2 illustrates the adequacy of DEA for firm efficiency analysis and benchmarking as well as the suitability of accounting data as a basis for related studies. However, to the best of our knowledge, a DEA study that assesses the financial performance of automotive companies based on accounting data has not yet been conducted. The study at hand aims at filling this gap by elaborating on four research questions:

1. Which characteristics of performance relationship networks of the automotive sector can be detected?
2. Which financial performance factors do predict (relative) firm efficiency in the automotive industry?
3. Which dynamics does (relative) firm efficiency show in the considered time horizon?
4. What similarities and differences between automotive OEMs and their suppliers can be observed?

The general idea of the study is to combine DEA with linear regression and a dynamic efficiency analysis. This is done in the following four steps.

1. Conduct DEA to determine the efficiency score for each firm and each period.
2. Conduct OLS multiple linear regression to identify significant influencing factors of efficiency.
3. Conduct a dynamic efficiency analysis to investigate the time series data for productivity changes by the Malmquist index and to assess evolutions of the performance relationship networks by a graph-theoretic approach.
4. Compare the two company samples regarding the results obtained for each sample.

In contrast to most empirical-quantitative studies on financial and operational performance in explanatory approaches, this one is an exploratory study that seeks new insights into phenomena of firm performance in the automotive sector. Findings are obtained by observing and interpreting results of the analysis and not by formulating and testing hypotheses.

3.2. DEA model building

Selecting inputs and outputs. In total, five factors of a firm's financial success were chosen as three inputs and two outputs for the DEA model: Cost of goods sold (*COGS*), operating capital (*OC*), i.e. the sum of inventory and trade receivables, and property, plant & equipment (*PPE*) measuring a firm's fixed capital represent the financial inputs that a firm consumes. Sales (*S*) and earnings before interest and taxes (*EBIT*) serve as generated outputs which measure the financial success. These five factors represent the profitability and the capital requirements of a firm as conceptualized by, e.g., Christopher, Ryals (1999) thereby reflecting the return that a company achieves on its capital employed. As illustrated in Fig. 1, profit- and capital-related factors represent inputs while sales, being affected by customer markets, and earnings, being crucial for shareholders and capital markets, are outputs. It is to be noted that some firms made financial losses during the financial crisis and, thus, some of the outputs take negative values. Since the automotive industry is an asset-intensive sector, we focus on operating capital, defined as the sum of the asset positions inventory and trade receivable, to cover current assets of a firm. This ensures non-negativity of all inputs.

Selecting the DEA model. Several DEA modeling approaches exist (see, e.g., Cooper et al., 2007; Cook, Seiford, 2009, for a detailed comparison). The DEA model of choice is selected by considering problem characteristics and model properties (see Tab. 7 in Appendix 6.1 for a comparison of DEA model characteristics). A unit-invariant input-oriented DEA model formulation with variable returns to scale is found appropriate for the purpose of this study (see Appendix 6.2 for the DEA model formulation). Unit

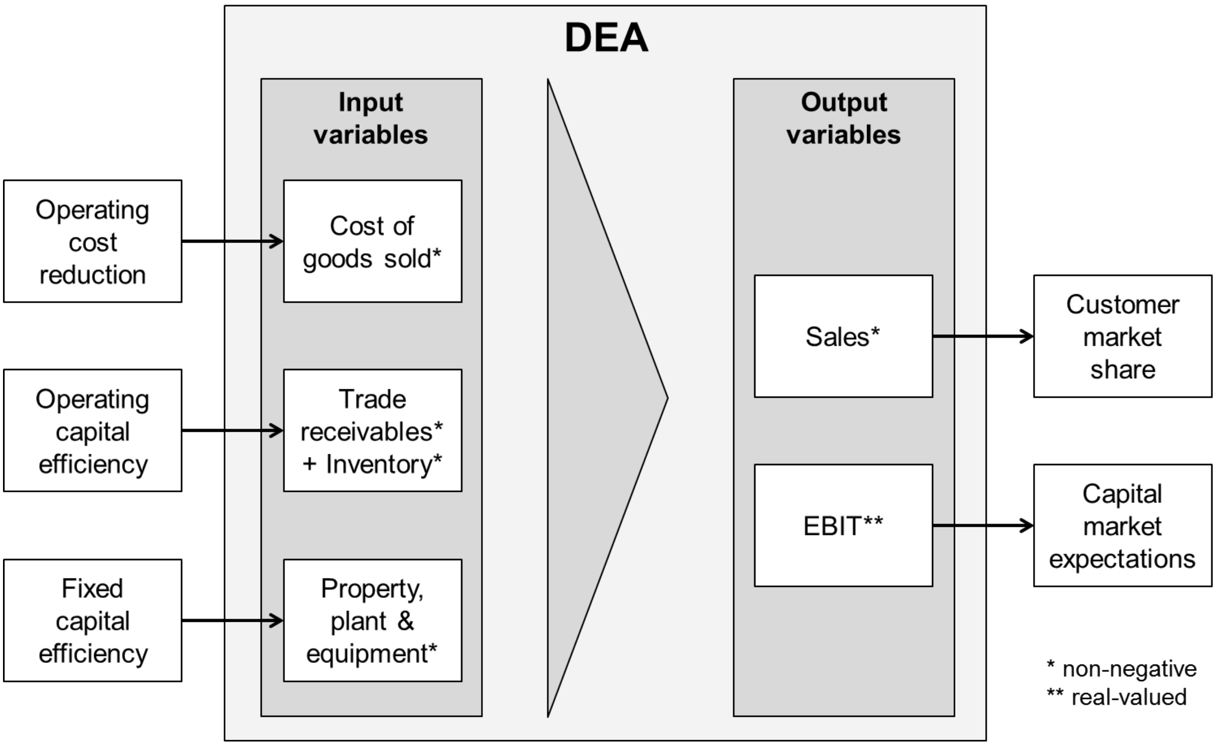

Fig. 1: Inputs and outputs of the DEA model.

invariance is required, because different firms from the company sample may use different currency units to measure the financial positions in their annual reports. The selected DEA model needs to allow outputs to be negative, because some firms made loss instead of profit in particular during the economic crisis. Since we deliberately (and also for technical reasons) focus on selected factors of overall firm performance thereby omitting variables such as marketing expenses or payment terms, we follow recommendations of Galagereda, Silvapulle (2003) and choose a DEA model with variable returns to scale. Taking into account that (dis-)economies of scale are observed in the firm sample (see Sect. 4.2), the model choice is in line with Reiner, Hofmann (2006) who applied a variable returns to scale model when analyzing DMUs that may not operate at optimal scale. To test the robustness of the obtained results, we have also conducted DEA runs with bootstrapping based on an algorithm for bias correction as suggested by Simar, Wilson (2007).

3.3. Regression analysis

Performance metrics. We conduct regression analyses in order to test which profit- or capital-related performance metrics predict firm efficiency. Profit-related performance metrics comprise sales growth ($SG_{o,t}$), EBIT margin ($EBITM_{o,t}$) and the COGS-to-sales ratio ($CR_{o,t}$). Capital-related peformance metrics reflect the fixed capital performance measured by PPE-to-sales ratio ($PPER_{o,t}$) and the working capital performance indicated by the operating capital cycle ($OCC_{o,t}$) or the cash conversion cycle ($C2C_{o,t}$). Formal definitions and calculation schemes of the metrics are listed in Appendix 6.4.

Linear regression models. Multiple linear regression is applied in order to test significant relationships between the above mentioned performance metrics and the DEA efficiency score. In the linear regression models, the metrics sales growth ($SG_{o,t}$), EBIT margin ($EBITM_{o,t}$), COGS-to-sales ratio ($CR_{o,t}$), operating capital cycle ($OCC_{o,t}$) and PPE-to-sales ratio ($PPER_{o,t}$) are chosen as predictors of the DEA efficiency scores $\Theta_{o,t}$ for each firm o and each year t as independent variables. We control for firm size, represented by the natural logarithm of sales volume $\ln S_{o,t}$, and geographical aspects, represented by dummy variables $USA_{o,t}$ and $ASIA_{o,t}$ for the regions USA and Asia in which the headquarters of a considered firm are located. Moreover, the year t and dummies $PRECR_{o,t}$ and $POSTCR_{o,t}$ for the pre- and post-crisis periods before 2008 and after 2010 are chosen as time-related control variables.

The regression model formulation is as follows:

$$\Theta_{o,t} = \alpha + \beta_1 SG_{o,t} + \beta_2 EBITM_{o,t} + \beta_3 CR_{o,t} + \beta_4 OCC_{o,t} + \beta_5 PPER_{o,t} + \beta_6 PRECR_{o,t} + \beta_7 POSTCR_{o,t} + \beta_8 t + \beta_9 \ln S_{o,t} + \beta_{10} USA_{o,t} + \beta_{11} ASIA_{o,t} + \epsilon_{o,t}$$

For the sake of completeness, we execute complementary tests with other OLS regression models in which operating capital cycle ($OCC_{o,t}$) is complemented or replaced by cash conversion cycle ($C2C_{o,t}$).

There is an ongoing academic debate on which type of regression to choose for two-step DEA-regression approaches (see Bogetoft, Otto, 2011, pp. 186–187). Luo, Homburg (2007) apply Tobit regression for the second stage analysis. Hoff (2007) explains that the Tobit approach may even be replaced by OLS regression. Simar, Wilson (2007) consider a bootstrap method advantageous which is applied by Gold et al. (2017) while Friesner et al. (2013, p. 415) argue that "this approach only generates small improvements in second stage estimates". Du et al. (2018) combine DEA and regression analyses to assess Chinese bank efficiency based on panel data of several years. In this study, truncated regression and bootstrapping was applied as well as a simpler OLS regression that ignores the truncation issue. Both approaches turned out to be "robust with respect to the different setups and even methodologies" (Du et al., 2018, p. 758). Banker, Natarajan (2008) analyze the performance of two-stage DEA-regression-approaches by Monte Carlo simulations and observe that OLS regression is appropriate to evaluate productivity impacts and may even be more robust and more appropriate for productivity research than the bootstrapping procedure proposed by Simar, Wilson (2007). Moreover, the results of that study indicate that "DEA-based procedures with OLS (...) or even Tobit estimation in the second stage perform as well as the best of (..) parametric methods in the estimation of the impact (...) on productivity" (Banker, Natarajan, 2008, p. 48). These results are reinforced in Banker et al. (2019) based on an extensive simulation study involving the conclusion that "the simple two-stage DEA + OLS model significantly outperforms the more complex Simar-Wilson model" (p. 368).

For this study, we apply OLS regression for the second stage analysis. This is in line with McDonald (2009, p. 797) who advocates "easy to compute methods, such as OLS, which are understood by a broad community of people". To increase scientific rigor, we complement this OLS approach by Tobit regression (TR) thereby following Hoff (2007) and Luo, Homburg (2007). To ensure robustness of regression results, OLS regression was conducted with pooled, fixed and random effect models (PEM, FEM, REM). The results are listed in Tab. 12 and all observed differences are reported in this manuscript.

3.4. Dynamic efficiency analysis

Malmquist index. We apply Malmquist index and its components to analyze dynamic productivity changes over time (see, e.g. Bogetoft, Otto, 2011; Cooper et al., 2007, for a comprehensive introduction of the Malmquist index). It is a composite metric that combines information on relative efficiency progress of a DMU, known as catch-up effect, with information on the progress in frontier technology around the DMU, named frontier-shift effect (Cooper et al., 2007).

The catch-up CI is defined as the ratio of the efficiency of the DMU in period 2 with respect to the period 2 frontier and the efficiency of the DMU in period 1 with respect to the period 1 frontier. A catch-up $CI > 1$ (respectively $CI < 1$) indicates progress (respectively regress) in relative efficiency from period 1 to 2, i.e. the firm has moved closer to (veered away from) the frontier, while a catch-up $CI = 1$ indicates no efficiency change.

The frontier-shift ϕ, defined as the geometric mean of the efficiency ratios of a DMU in two consecutive periods with respect to the two frontiers, indicates the technical efficiency change of a DMU. A frontier-shift $\phi > 1$ (respectively $\phi < 1$) indicates progress (regress) in the frontier around the DMU between the two consecutive periods, while a frontier-shift $\phi = 1$ indicates the status quo.

The Malmquist index MI is computed as the product of catch-up CI and frontier-shift ϕ. A Malmquist index $MI > 1$ (respectively $MI < 1$) indicates progress (regress) in total factor productivity in two consecutive periods.

We apply this dynamic evaluation approach to shed light on performance evolutions over time. For each period, we count (i) the number of firms which increased, decreased or did not change in total factor productivity (indicated by the Malmquist index MI), (ii) the number of firms which show progress, regress or no change in relative efficiency (indicated by the catch-up CI), and also (iii) the number of firms for which the frontier around the DMU has progressed, regressed or remained stable (indicated by the frontier shift ϕ).

Graph-theoretic approach. In addition to the Malmquist index analysis, a graph-theoretic approach is applied to assess evolutions of the performance relationship network over time. As illustrated in Fig. 2, the performance relationships between the DMUs in each period are represented by a bipartite graph that separates efficient DMUs (named peers) and inefficient ones (named followers). The arrows pointing from a follower to a peer indicate the performance relationships obtained from DEA, i.e. an arrow that points from DMU X to DMU A indicates that A serves as a benchmark for X. The arrows are weighted by the λ values that are obtained by solving the corresponding DEA models. In the illustrated example, three efficient DMUs and three non-efficient ones are detected in each period. In period 1, the DMU C is only self-referencing, i.e., it is efficient without serving as a benchmark to other DMUs.

As depicted in Fig. 2, the bipartite graph that represents the performance relationship network of all considered DMUs evolves over time, i.e., it changes from period to period. DMUs may transit from one partition to the other (like DMUs C and Z in the considered example) and the performance relationships,

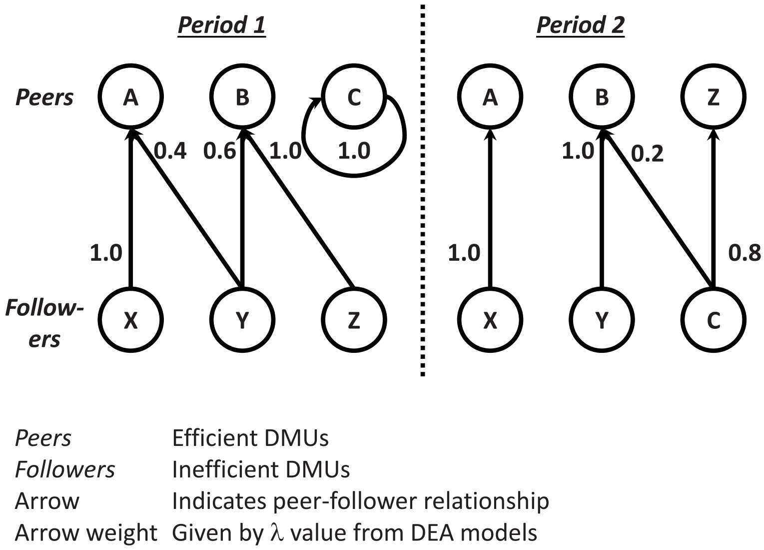

Fig. 2: Performance relationship networks and evolution over time.

named links, indicated by arrows may change (like the relationship between DMUs Y and A in the considered example) as well as the corresponding λ weights (like the weight for arrow pointing from DMU Y to DMU B in the considered example). The number of peers and followers may also change over time (not illustrated in the considered example).

Due to the longitudinal approach of the conducted study, it is possible to assess the evolution of the performance relationship network over time. We analyze firm transits and changes in the number of peers and followers as well as link changes, i.e., the indicated performance relationships between the assessed firms. Higher numbers of changes indicate stronger effects of competition in the industry sector while fewer changes express a more stable competitive situation.

3.5. Data gathering

Sampling. Two samples consisting of in total 32 globally leading firms from the automotive industry including OEMs and their suppliers are compiled for the study at hand. Both samples are based on industry reports issued by International Organization of Motor Vehicle Manufacturers (2012) and by industry experts (Sedgwick, 2013; Chappell, 2018). All evaluated firms are listed in Appendix 6.3.

The OEM sample comprises 17 global automotive manufacturers from Europe (8 firms), Asia (7) and the United States (2). In 2017, these firms accounted for a sales volume of 1,483.5 bn Euro and a production quantity of 67.4 mn cars thereby representing nearly three quarters of the global motor vehicle production (International Organization of Motor Vehicle Manufacturers, 2017).[3]

In addition, a set of 15 parts suppliers (14 European firms and 1 from the US) is selected from the top 100 global and the top 50 European OEM parts suppliers listed by Sedgwick (2013). In 2013, the sample represented more than 60% of the European OEM parts suppliers market and about one quarter of the global OEM parts supplier market.[4] In 2017, these firms achieved a total sales volume of 278.2 bn Euro and hold strong positions in the automotive supplier markets worldwide (Chappell, 2018).

Data collection. Financial data for each firm of the two samples is collected from the financial databases Amadeus and Morningstar and from the annual reports of the respective firm. The time horizon chosen for the longitudinal analysis ranges from 2003 to 2017 and, thus, covers the period of the economic crisis[5]. The circumstance that the fiscal year of some of the assessed firms slightly differs from the calendar year is taken into account. In such cases, the considered reporting periods begin and end one or two quarters later than the considered planning horizon. Using annual report data ensures that financial figures of multi-national enterprises are consolidated under consideration of company-internal currency effects.

3 Even without consideration of Volvo's and Scania's production quantities, the OEM sample represents 71% of the total number of motor vehicles globally produced in 2017.

4 According to Sedgwick (2013), the selected suppliers represent 62% of the European and 24% of the global OEM automotive part sales 2012.

5 The financial crisis started in 2008 and showed the strongest economic impacts until 2010.

3.6. Scientific rigor and implementation issues

Scientific rigor. DEA requires comparability of the evaluated DMUs. Due to this prerequisite, many studies are limited to a focused comparison of firms with similar production technologies from the same industry sector. In the study at hand, firms are considered as units that make decisions on the generation of sales and profit based on the consumption of cost and capital. Hence, we can relax the requirement of comparable production technologies and broaden our perspective to a comparison of automotive suppliers including chemical firms, electronics companies or automotive parts suppliers.

According to Cooper et al. (2007, p. 116), the number of DMUs (n) should not be less than the combined number of inputs and outputs ($m + s$) to ensure efficiency discrimination among the DMUs. As a rule of thumb, it is recommended to choose the number of DMUs not less than $\max\{m \cdot s, 3 \cdot (m + s)\}$ (Cooper et al., 2007, p. 116) and also not less than $2 \cdot m \cdot s$ (Dyson et al., 2001; Sarkis, 2007, p. 307). Each company sample comprises at least 15 DMUs which are assessed under consideration of 3 inputs and 2 outputs. Thus, the rule of thumb is fulfilled. Moreover, the sizes of the firm samples (in total 32 DMUs and 480 FYOs) are comparable to the samples size of earlier studies (see Tab. 1). The company samples cover considerable shares of the automotive OEM and supplier markets and, thus, adequately represent these industry segments.

Complementing the DEA model with input-oriented variable returns-to-scale by DEA runs with bootstrapping ensures robustness of obtained results and, thus, increases the scientific rigor of the study.

Regression analyses were conducted by models with pooled (PEM), fixed (FEM) and random effects (REM) and by Tobit regression (TR). Most results and observations were consistent between these approaches. Thus, the obtained regression results are considered robust. However, all ambiguous or conflicting regression results are reported in the manuscript. In order to check the adequacy of our regression approach with regard to endogeneity issues, we have executed Hausman tests for the regression models. The test results did not show an indication for endogeneity (see Tab. 12).

Regarding the dynamic efficiency analysis it is to mention that the Malmquist index may show a systematic bias and, thus, does not necessarily measure productivity changes accurately in presence of non-constant returns to scale (Grifell-Tatjé, Lovell, 1995). Hence, the results of the dynamic efficiency analysis are interpreted carefully and with a particular consideration of the graph-theoretic approach. Since each of the conducted dynamic analyses is based on the pairwise comparison of only two consecutive years of the considered time horizon, long-term inflation rate effects can be neglected in the dynamic performance assessment.

Implementation issues. The DEA is implemented in the object-oriented programming environment R version 2.15.2 and its benchmarking library (R Core Team, 2012; Bogetoft, Otto, 2011; Behr, 2015).[6] IBM SPSS Statistics Version 21.0.0.0 is used for the linear regression analysis (IBM, 2012). The software tools are run on a system with Intel CoreTM i7-2637M CPU with 1.70 GHz and 8 GB RAM operated with Microsoft Windows 7 Professional SP 1.

4. DATA ANALYSIS AND RESULTS

4.1. Firm efficiency analysis

Firm efficiency is determined by in total 15 DEA runs, one for each year of the considered horizon. OEMs as well as suppliers are ranked by the number N^{eff} of years in which a particular firm is efficient, i.e. achieves an efficiency score $\Theta = 1$, and by calculating the arithmetic average Θ^{avg} of all efficiency scores it has obtained in the considered years. Leaders and laggards, i.e. highest and lowest ranked firms, of each company sample are listed in Tab. 2, the complete rankings are listed in Tabs. 8 and 9 in the appendix of the paper. The numbers for N^{peer}, N^{foll} and $\Sigma\lambda$ are determined based on the λ values of each DEA run.[7] For each firm o, N^{peer} determines the number of links to efficient companies to which that particular firm references when not being efficient. Accordingly, N^{foll} gives the number of links from inefficient companies that reference to that particular firm o when it is efficient. For each firm o, $\Sigma\lambda$ is the sum of all λ values assigned to references from inefficient companies to firm o.

The DEA runs show that two OEMs and four suppliers achieved the highest efficiency score in each year thereby showing that leaders in each group continuously maintained their competitive position. Most of the laggards achieved efficiency in hardly any year[8] which shows their general inability to achieve an overall market-leading performance. General Motors Company being ranked fourth of all OEMs shows that high efficiency levels can be achieved and maintained in any region, the US as well as the EU or Asia.

As indicated by N^{foll} and $\Sigma\lambda$, the three OEM leaders also attracted the highest number of links from followers and the strongest references. This

6 See Appendix 6.6 for the source code.

7 Example: Honda Motor Co. Ltd. achieved highest efficiency in $N^{eff} = 14$ years. In these 14 years, in total $N^{foll} = 70$ links from inefficient companies referenced to Honda Motor Co. Ltd., indicated by the λ values of the respective DEA runs which in total summed up to $\Sigma\lambda = 44.643$. In one year, Honda Motor Co. Ltd. performed inefficient and in this year, four other firms acted as peer to Honda Motor Co. Ltd., again indicated by the λ values of the respective DEA runs.

8 OEMs: Volvo Group in 2008 and 2012, Nissan Motor Co. Ltd. in 2018 and Mitsubishi Corp. in 2003 – Suppliers: Mahle GmbH in 2007 and 2014 and VALEO SA never.

Table 2: DEA results for OEMs and suppliers

Company	N^{eff}	Θ^{avg}	Θ^{sd}	Θ^{min}	Θ^{max}	N^{peer}	N^{foll}	$\Sigma\lambda$
Peugeut SA	15	1.000	0.000	1.000	1.000	0	57	32.367
Scania AB	15	1.000	0.000	1.000	1.000	0	61	40.393
Honda Motor Co. Ltd.	14	0.999	0.004	0.984	1.000	4	70	44.643
...	...	...	...	...	...	...	...	...
Volvo Group	2	0.927	0.046	0.849	1.000	42	2	2.335
Nissan Motor Co. Ltd.	1	0.877	0.072	0.696	1.000	42	0	1.000
Mitsubishi Corp.	1	0.832	0.070	0.723	1.000	34	1	1.053
BASF Group	15	1.000	0.000	1.000	1.000	0	36	20.587
Trelleborg AB	15	1.000	0.000	1.000	1.000	0	23	23.739
Bayer AG	15	1.000	0.000	1.000	1.000	0	52	21.491
Svenska Kullagerfabriken AB	15	1.000	0.000	1.000	1.000	0	43	34.260
...	...	...	...	...	...	...	...	...
Plastic Omnium Co.	5	0.890	0.102	0.722	1.000	37	1	5.000
ZF Friedrichshafen AG	5	0.759	0.255	0.309	1.000	33	7	7.018
Mahle GmbH	2	0.778	0.243	0.255	1.000	43	0	2.000
VALEO SA	0	0.823	0.106	0.547	0.948	53	0	0.000

OEMs (suppliers) are listed in the upper (lower) part of this table. N_o^{eff} = total number of years in which the firm was efficient. N^{peer} = total number of peers to which the firm referenced. N^{foll} = total number of followers that referenced to the firm. $\Sigma\lambda$ = cumulated λ values a firm attracted when being efficient.

is in contrast to the group of suppliers' leaders. In this group, Bayer AG (N^{foll} = 52) has attracted more than twice the number of links from followers than Trelleborg AB (N^{foll} = 23, representing only the 7th highest number of links). As indicated by $\Sigma\lambda$ = 34.260, Svenska Kullagerfabriken AB attracted the strongest references from followers. The $\Sigma\lambda$ value is about 50% higher than the ones of the other supplier leaders which, however, all achieved maximum efficiency in every year (N^{eff} = 15). These observations suggest that performance relationships of suppliers' leaders are more heterogeneous than performance relationships of manufacturers' leaders.

As indicated by N^{peer}, OEM laggards with N^{eff} < 3 establish in total 34 to 42 links to efficient firms while supplier laggards with N^{eff} < 3 establish in total 43 to 53 of such links. Although the supplier sample is smaller, supplier laggards establish a larger number of reference links. This indicates that supplier laggards choose from a larger variety of benchmarks.

Summing up N^{eff}, we see that an OEM is deemed to be efficient in 56% of all cases and a supplier in 60% of all cases while the number of self-referencing efficient firms considerably differs between both samples (36 OEMs vs. 45 suppliers, see Tab. 3). As illustrated in Tab. 3, the OEM sample and the supplier sample are comparable regarding the number of followers that a peer attracts (on average 2.3 for OEMs and 2.2 for suppliers) and of peers to which a follower refers as benchmarks (on average 3.0 for OEMs and 3.3 for suppliers). In each sample, followers refer to a maximum of 5 peers (Isuzu Motors Ltd. in 2012,

Table 3: Comparison of performance relationships at OEMs and suppliers

Company sample	# peers of a follower avg	min	max	# followers of a peer avg	min	max	# Self-references
OEMs	3.0	2	5	2.3	0	9	36
Suppliers	3.3	1	5	2.2	0	9	45

Table 4: Insights gained from regression

Variable	OEMs Impact	OEMs Exception*	Suppliers Impact	Suppliers Exception*
		Predictor variables		
$SG_{o,t}$	insig.	TR ^{n}	insig.	TR ^{n}
$EBITM_{o,t}$	neg.	PEM ^{i}	pos.	FEM ^{i}, REM ^{i}
$CR_{o,t}$	neg.		neg.	
$OCC_{o,t}$	neg.		neg.	PEM ^{i}, TR ^{i}
$PPER_{o,t}$	neg.		ambig.**	
		Control variables		
$\ln S_{o,t}$	pos.		neg.	FEM ^{i}, REM ^{i}
t	insig.		insig.	PEM ^{n}
$PRECR_{o,t}$	insig.		insig.	
$POSTCR_{o,t}$	insig.	FEM ^{n}, REM ^{n}	insig.	
$USA_{o,t}$	pos.	REM ^{i}	pos.	REM ^{i}
$ASIA_{o,t}$	insig.		n.a.	

* PEM = Pooled effects model, FEM = Fixed effects model,
REM = Random effects model, TR = Tobit regression
** PEM ^{i}, FEM ^{p}, REM ^{p}, TR ^{n}
^{n} = negative significant impact indicated
^{i} = no significant impact indicated
^{p} = positive significant impact indicated

Plastic Omnium Co. in 2010 and Autoliv Inc. in 2008) and peers attract a maximum of 9 followers (Daimler Group in 2013 and Faurecia Group in 2008). These figures indicate that the structural characteristics of the performance relationship networks of both samples are comparable, although as explained earlier OEMs and their suppliers show different performance relationships of leaders and laggards.

4.2. Predictors of firm efficiency

The linear regression analysis sheds light on the performance factors that predict firm efficiency. As R^2 and adjusted R^2 of the PEM indicate, about 40% of firm efficiency (about 25% for supplier) is attributable to the performance metrics which are considered in the regression models.[9] The complete statistics are listed in Tab. 10 – 13 in the appendix of the paper. The regression results summarized and compared in Tab. 4 illustrate that OEMs and their suppliers show similarities and differences regarding the observed significant relationships between firm efficiency and the dependent variables.[10]

Surprisingly, sales growth ($SG_{o,t}$) does not significantly affect firm performance.[11] This observation suggests that OEMs as well as suppliers operate in saturated markets that offer only limited growth potential. In contrast, the COGS-to-sales ratio ($CR_{o,t}$) shows a strong negative and significant influence on firm performance. As a consequence, firms from both clusters have to carefully manage their cost of goods sold in order to stay competitive. However, earnings do not necessarily predict firm efficiency. The obtained results suggest that EBIT margin ($EBITM_{o,t}$) has a significant negative impact on firm efficiency of OEMs while the efficiency of suppliers is postively influenced by this factor.[12] This observation proposes that car manufacturers in contrast to automotive suppliers are not exposed to high profit pressure.

Operating capital ($OCC_{o,t}$) has a significant impact on firm efficiency of car manufacturers while this influence is not fully confirmed for their suppliers[13]. The relevance for OEMs must not be underestimated, because this metric shows the strongest efficiency influence (absolute value of standardized β) of all

9 FEM and REM result in lower R^2 values which suggest that about one third of the observed performance is explained by the models.
10 The bootstrapping approach confirmed the results obtained from the input-oriented DEA model with variable returns-to-scale. Differences between the obtained results are reported in Tab. 11.
11 Only TR shows a significant negative relationship.
12 Significance not confirmed by FEM and REM.
13 PEM and TR did not show any significance.

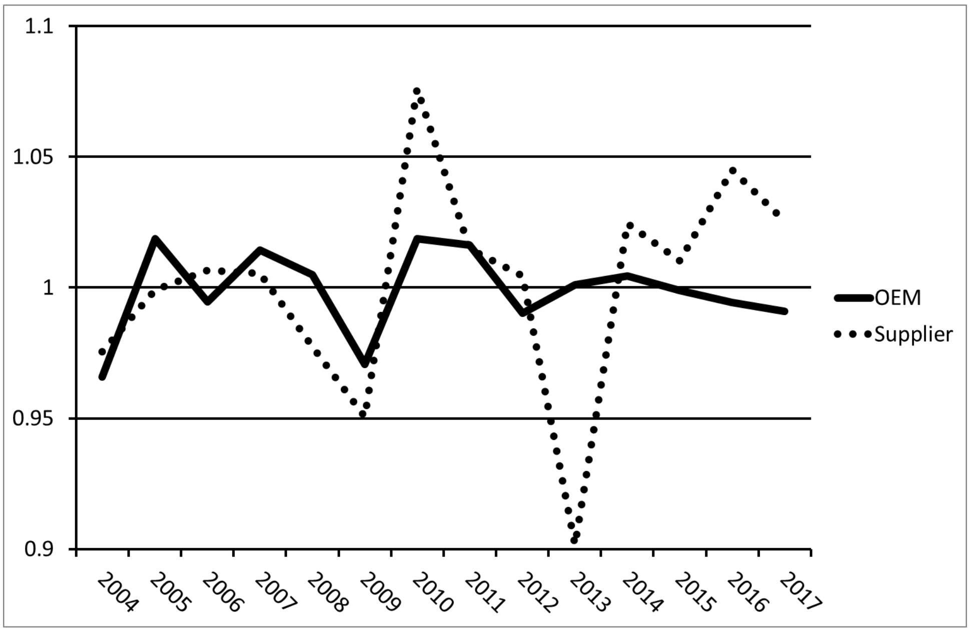

Fig. 3: Annual average Malmquist index over time.

considered factors. Thus, managing inventory and receivables are important tasks for car makers. The significant negative influence of $PPER_{o,t}$ on firm efficiency of OEMs indicates the relevance of capacity utilization for car producers wile ambiguous results are obtained for their suppliers. This observation suggests that PPE is a highly important efficiency factor for OEMs.

Since (nearly)[14] no significant relationship is observed between time-related variables (t, $PRECR_{o,t}$, $POSTCR_{o,t}$) and firm efficiency, we conclude that time aspects are not relevant for firm efficiency. Taking into account that the considered time horizon covers the financial crisis, this result is surprising. In contrast, firm size ($\ln S_{o,t}$) does matter, but for OEMs with a positive significant influence on firm efficiency and for their suppliers with a negative one.[15] Therefore, we argue that larger OEMs exert power while smaller suppliers are more flexible to rapidly react to changes in the demand markets. For car producers as well as for suppliers, the US dummy variable ($USA_{o,t}$) shows a significant positive influence on firm efficiency.[16] This result suggests that the US market stimulates firms more strongly to strive for efficiency, e.g. due to higher relevance of shareholder value and aspects of financialization in the US automotive markets (see Froud et al., 2002, for a related in-depth analysis).

4.3. Dynamic firm efficiency analysis

Malmquist index and its components frontier-shift and catch-up are assessed to capture the dynamic development of firm efficiency in the considered time horizon (see Fig.3 below and Tab. 14 in the appendix of this paper). Moreover, changes in the performance relationship networks over time are analyzed in a graph-theoretic approach.

The performance evolution over time shows major dynamics within and shortly after the financial crisis. For OEMs as well as for suppliers, the annual average Malmquist index strongly declines to a local minimum in 2009 followed by a steep increase to a global maximum in 2010. Taking into account that the global financial crisis began affecting the real economy in 2008 (see, e.g., Hofmann et al., 2011), this regress in total factor productivity can be attributed to the economic crisis. A fast improvement with a maximum in the year after the financial crisis suggests that – at least for the automotive sector – the recession shows a V-shaped economic shock with a rapid recovery, but not a U- or L-shaped one in which the performance decline is followed by a long-lasting period of economic recession.[17]

Decomposing the Malmquist index helps gaining further insights into this phenomenon. Average frontier-shifts lower than 1 reaching local minima are observed in 2009 followed by values larger than 1 reaching global maxima in 2010. In contrast, the average catch-up was greater than 1 in both years. On average, OEMs as well suppliers achieved progress in relative efficiency (indicated by catch-up) while facing a regress in the frontier around them (indicated by frontier-shift). The number of firms showing improvements or deteriorations of frontier-shift

14 See Tab. 4 for exceptions

15 FEM and REM did not show any significance of supplier size.

16 No significance is observed in REM.

17 See, e.g. Carlsson-Szlezak et al. (2020) for a discussion of these three scenarios in context to the Covid-19 pandemic.

confirms this observation (see Tab. 15). The year 2009 shows 22 companies (i.e. nearly 60% of all firms) with frontier-shift regress and only 1 firm with progress, while the opposite is true for 2010 (19 firms with progress vs. 2 with regress). Thus, we conclude that the observed disturbances in total factor productivity are due to macroeconomic effects that affected the productivity of the whole sector and which seem to be compensated within one year.

In 2013/14, the average Malmquist index of the suppliers shows a similar behavior as in 2009/10. A heavy decline in 2013 is followed by a strong increase in 2014. However, the decomposed indices behave differently. In these years, the catch-up is very volatile reaching its global minimum in 2013 followed by a strong increase to a value greater than 1 while the frontier-shift indicates progress in both periods. Therefore, we attribute the disruption and recovery of total factor productivity in these years to performance gains and losses of individual companies rather than to macroeconomic effects that shift the efficient frontiers of the whole group of suppliers.

The graph-theoretic approach helps understanding changes in the performance relationship networks over time (see Tab. 5 for aggregate and Tab. 16 for detailed results). It reveals that major changes in the field of competition, i.e. firms becoming new peers or new followers, occur in times of rather stable overall performance development. In contrast, the group of peers and followers remained rather unchanged during the years of V-shaped overall performance losses and gains during and after the financial crisis.

In contrast to the OEMs, we observe a period without any change between peers and followers in the group of suppliers (2017). Moreover, the suppliers also show a lower maximum number of firm transits (5 transits in 2008 and 2013) than the OEMs (8 transits in 2013). However, as indicated by the coefficients of variation, the supplier sample shows stronger fluctuations between peers and followers than the group of OEMs.

Table 5: Aggregate graph-theoretic results

	min	max	avg	sd	cv
# Link Changes	19	48	27.57	7.28	0.26
# Efficient firms	7	12	9.50	1.50	0.16
# New peers	0	3	2.07	0.96	0.46
# New followers	0	5	2.14	1.46	0.68
# Firm transits	2	8	4.21	1.70	0.40
# Link Changes	16	44	25.57	8.36	0.33
# Efficient firms	6	11	9.07	1.44	0.16
# New peers	0	3	1.43	1.05	0.73
# New followers	0	5	1.43	1.35	0.94
# Firm transits	0	5	2.86	1.30	0.45

OEMs (suppliers) are listed in upper (lower) part of this table.
min = minimum, max = maximum, avg = average, sd = standard deviation, cv = coefficient of variation.

For the suppliers, the year 2008 shows the lowest number of efficient firms (6 suppliers) with the highest number firms becoming followers (5 suppliers) and the highest number of firm transits (5 transits). Due to these observations we argue that already the beginning of the economic crisis caused strong turbulence in the suppliers' performance relationship network. In contrast to the Malmquist index analysis, which indicated a rapid recovery of efficiency and productivity within one year, the graph-theoretic assessment suggests a longer period of performance recovery. The number of firm transits stayed below average for two consecutive years (2009 and 2010), and the number of efficient suppliers remains below average even until 2012. For the performance relationship network of the OEMs, such phenomena are not observed during the economic crisis.

In 2013, the strongest changes in performance relationships in the group of suppliers are observed (44 link changes) followed by 33 link changes in 2014 which in turn is well above average (25.57 link changes). This observation is in line with individual productivity disruptions and recovery detected by Malmquist index analysis as described above.

In the OEM sample, the most firm transits (8) and the hightest number of firms becoming followers (5) as well as the maximum number of link changes (48) occur in 2013. These disturbances are not observed by Malmquist index analysis which raises the question if, in general, the two approaches for dynamic efficiency analysis are complementary or contrasting. To answer this question, a correlation analysis is conducted that compares changes in the Malmquist index and its components to the number of observed changes in the performance relationship network. The results listed in Tab. 6 indicate statistically significant relationships between changes in Malmquist index and catch-up on the one hand and changes in the performance relationship network on the other.

The number of firm transits and the number of companies that become followers are both positively associated with regress in total factor productivity and a loss in relative efficiency. Moreover, regress in total factor is positively correlated to the number of link changes and relative efficiency losses are negatively correlated to the number of efficient firms. These observations exemplify that Malmquist index analysis and the graph-theoretic approach may lead to complementary results for a dynamic efficiency analysis.

Table 6: Relationships between index changes and changes in the performance relationship network

(N = 28)	LC	EF	FO	TR
MI ⇓	0.391**	-0.155	0.392**	0.421**
CU ⇓	0.312	-0.413**	0.573***	0.426**

**** significant on 1%-level (2-tailed),*
*** significant on 5%-level (2-tailed)*
MI ⇓ = number of firms with regress in total factor productivity, CU ⇓ = number of firms with regress in relative efficiency.
LC = number of link changes, EF = number of efficient firms, FO = number of new followers, TR = number of firm transits.

5. CONCLUSION

5.1. Summarized findings

The DEA analysis has shown that over the years leaders and laggards have widely remained in their positions. The groups of OEMs and suppliers, respectively, show similarities with regard to the structural characteristics of their performance relationship networks, in particular regarding the stability of leaders and laggards groups and the number of peers and followers per firm. However, the two groups of firms differ with regard to the performance relationships of their leaders and laggards.

A linear regression analysis has indicated that car producers have to manage both cost and capital in order to maintain or improve their firm efficiency while their suppliers need to focus on optimizing their profits. In contrast, sales growth and increasing market share are less relevant to improve firm efficiency in the automotive sector. Size as well as the geographical position do matter while time aspects seem to be less important for firm efficiency.

The dynamic efficiency assessments reveal strong firm efficiency losses in 2009 caused by the economic crisis which are followed by considerable improvements of total factor productivity in 2010. While these effects are observed for both firm samples, another dip in productivity is observed in 2013 for suppliers only. In general, suppliers show stronger fluctuations between peers and followers than OEMs. Strong turbulence in the performance relationship network are observed during the economic crisis as well as in the years 2013/14.

For OEMs as well as for their suppliers, performance evolutions show V-shaped dynamics with strong declines in one year followed by quick recovery in the year after. This suggests a certain robustness of automotive supply chains against economic shocks.

5.2. Scientific contribution

In the broad domain of performance measurement and management, the study at hand contributes to a better understanding of financial performance and success. The study complements earlier works on operational performance of automotive OEMs as presented by, e.g. Dörnhöfer et al. (2016) and studies on financial performance and resulting value impacts as analyzed by, e.g. Brandenburg, Seuring (2011) or Brandenburg (2016).

From the empirical point of view, this study identified relevant factors of firm efficiency in the automotive industry and revealed similarities and differences between OEMs and their suppliers. Moreover, the analysis exemplified macroeconomic influences as well as sector-specific impacts on firm efficiency and competitiveness. These findings deepen the understanding of efficiency and performance in automotive supply networks.

From the methodological perspective, a graph-theoretic interpretation of performance relationships and a related approach to assess dynamics of firm efficiency represent scientific contributions of the study. These approaches can easily be transferred to other longitudinal DEA studies.

5.3. Managerial implications

The study at hand has confirmed the importance of cooperation and collaboration in automotive supply chains. Decision-makers may find suggestions for cooperative cash management in daily operations and for cooperation initiatives in macroeconomic crisis periods.

OEMs and their suppliers differ with regard to relevant predictors of firm efficiency. In contrast to suppliers who should focus on profit optimization, OEMs also need to optimize their capital efficiency. This may suggest decision-makers at OEMs to grant cash discounts to suppliers in order to simultaneously improve their own capital efficiency and increase their suppliers' profit. Rather than improving their cost position at their suppliers' expense, OEM and suppliers should strive for joint cost efficiency improvements and fair distribution of financial benefits and created value. In periods with macroeconomic challenges or crises, strong OEMs may help their suppliers survive in order to safeguard continuous supply.

5.4. Limitations and future prospects

Future research perspectives arise from limitations of the conducted study. The aggregate assessment of high-level performance indicators and efficiency metrics does not inform about details on operational level. Case study research would allow for an in-depth analysis of the assessed firms and could complement the analyses presented in this paper. Applying the approach to other sectors would enable a cross-industry comparison of different business environments and other fields of economic competition. Longitudinal analyses of a longer time horizon or explanatory studies on company performance in the automotive sector could complement the one presented here. Such empirical studies could elaborate on performance impacts of, e.g., the Diesel scandal or the Covid 19 pandemic. In general, we see that the area of performance benchmarking and efficiency assessment still merits future research efforts.

6 APPENDIX

6.1. DEA model characteristics

Table 7: Summary of DEA model characteristics (Cooper et al., 2007, p. 115)

Model		CCR-I	CCR-O	BCC-I	BCC-O	ADD	SBM
Data	X	Semi-p	Semi-p	Semi-p	Free	Free	Semi-p
	Y	Free	Free	Free	Semi-p	Free	Free
Trans.	X	No	No	No	Yes	Yes[a]	No
Invariance	Y	No	No	Yes	No	Yes[a]	No
Units invariance		Yes	Yes	Yes	Yes	No	Yes
Firm efficiency Θ^*		[0, 1]	[0, 1]	(0, 1]	(0, 1]	No	[0, 1]
Tech. or mix		Tech.	Tech.	Tech.	Tech.	Mix	Mix
Returns to scale		CRS	CRS	VRS	VRS	C(V)RS[b]	C(V)RS

[a] *The additive model ADD is translation invariant only when the convexity constraint is added.*
[b] *C(V)RS means constant or variable returns to scale according to whether or not the convexity constraint is included.*

6.2. DEA model formulation

$$
\begin{aligned}
&\min \Theta_{o,t} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_{j,t} \cdot COGS_{j,t} \leq \Theta_{o,t} \cdot COGS_{o,t} \\
& \sum_{j=1}^{n} \lambda_{j,t} \cdot OC_{j,t} \leq \Theta_{o,t} \cdot OC_{o,t} \\
& \sum_{j=1}^{n} \lambda_{j,t} \cdot PPE_{j,t} \leq \Theta_{o,t} \cdot PPE_{o,t} \\
& \sum_{j=1}^{n} \lambda_{j,t} \cdot S_{j,t} \geq S_{o,t} \\
& \sum_{j=1}^{n} \lambda_{j,t} \cdot EBIT_{j,t} \geq EBIT_{o,t} \\
& \sum_{j=1}^{n} \lambda_{j,t} = 1 \\
& \lambda_{j,t} \geq 0 \qquad \forall \qquad j = 1, \ldots, n
\end{aligned}
$$

6.3. DMU samples

The DMU sample of 17 OEM consists of the following enterprises: BMW Group, Daimler Group, Fiat Group, Ford Motor Company, General Motors Company, Groupe Renault, Honda Motor Co. Ltd., Isuzu Motors Ltd., Mazda Motor Corporation, Mitsubishi Corporation, Nissan Motor Co. Ltd., Peugeot SA, Scania AB, Suzuki Motor Corporation, Toyota Motor Corporation, Volkswagen Group, Volvo Group.

The DMU sample of 15 global OEM suppliers comprises the following enterprises: Autoliv Inc., BASF Group, Bayer AG, Continental AG, Faurecia Group, Georg Fischer Automotive AG, Infineon Technologies AG, Leoni AG, Mahle GmbH, Plastic Omnium Co., Robert Bosch GmbH, Svenska Kullagerfabriken AB, Trelleborg AB, Valeo SA, ZF Friedrichshafen AG.

6.4. Performance metrics

The performance metrics are calculated for each firm o and each year t:

Sales growth:
$$SG_{o,t} = \frac{S_{o,t} - S_{o,t-1}}{S_{o,t}}$$

EBIT margin:
$$EBITM_{o,t} = \frac{EBIT_{o,t}}{S_{o,t}}$$

COGS-to-sales ratio:
$$CR_{o,t} = \frac{COGS_{o,t}}{S_{o,t}}$$

PPE-to-sales ratio:
$$PPER_{o,t} = \frac{PPE_{o,t}}{S_{o,t}}$$

Operating capital conversion cycle:
$$OCC_{o,t} = DSO_{o,t} + DIH_{o,t}$$

Cash conversion cycle:
$$C2C_{o,t} = DSO_{o,t} + DIH_{o,t} - DPO_{o,t}$$

Days sales outstanding:
$$DSO_{o,t} = \frac{TR_{o,t}}{S_{o,t}} \cdot 365$$

Days inventory held:
$$DIH_{o,t} = \frac{INV_{o,t}}{COGS_{o,t}} \cdot 365$$

Days payables outstanding:
$$DPO_{o,t} = \frac{TP_{o,t}}{COGS_{o,t}} \cdot 365$$

6.5. Numerical results

Tabs. 8 and 9 contain the DEA results for OEMs and suppliers, respectively. The OLS regression model summary is presented in Tab. 10 while results of OLS regression and Tobit regression are presented in Tabs. 11 and 13, respectively. The results of the dynamic efficiency assessment are listed in Tab. 14 (Malmquist index, catch-up and frontier-shift), Tab. 15 (progress and regress of productivity, relative efficiency and frontiers) and Tab. 16 (detailed results of the graph-theoretic assessment). For the R source code, the reader is referred to Appendix 6.6.

Table 8: DEA results for OEMs

Company	N^{eff}	Θ^{avg}	Θ^{sd}	Θ^{min}	Θ^{max}	N^{peer}	N^{foll}	$\Sigma\lambda$
Peugeut SA	15	1.000	0.000	1.000	1.000	0	57	32.367
Scania AB	15	1.000	0.000	1.000	1.000	0	61	40.393
Honda Motor Co. Ltd.	14	0.999	0.004	0.984	1.000	4	70	44.643
General Motors Comp.	13	0.994	0.020	0.918	1.000	6	12	15.250
Mazda Motor Corp.	12	0.993	0.020	0.923	1.000	12	25	18.403
Suzuki Motor Corp.	11	0.988	0.022	0.930	1.000	13	29	21.760
Toyota Motor Corp.	11	0.981	0.039	0.882	1.000	12	13	13.756
Volkswagen Group	10	0.964	0.063	0.806	1.000	15	9	12.785
Daimler Group	10	0.956	0.080	0.713	1.000	13	25	16.164
Ford Motor Comp.	9	0.970	0.052	0.814	1.000	16	8	11.757
Isuzu Motors Ltd.	7	0.939	0.069	0.757	1.000	23	5	7.282
Fiat Group	5	0.906	0.099	0.743	1.000	31	6	6.588
Groupe Renault	4	0.967	0.036	0.874	1.000	35	10	6.451
BMW Group	3	0.917	0.094	0.723	1.000	37	2	3.012
Volvo Group	2	0.927	0.046	0.849	1.000	42	2	2.335
Nissan Motor Co. Ltd.	1	0.877	0.072	0.696	1.000	42	0	1.000
Mitsubishi Corp.	1	0.832	0.070	0.723	1.000	34	1	1.053

N_o^{eff} = total number of years in which the firm was efficient. N^{peer} = total number of peers to which the firm referenced. N^{foll} = total number of followers that referenced to the firm. $\Sigma\lambda$ = cumulated λ values a firm attracted when being efficient.

Table 9: DEA results for suppliers

Company	N^{eff}	Θ^{avg}	Θ^{sd}	Θ^{min}	Θ^{max}	N^{peer}	N^{foll}	$\Sigma\lambda$
BASF Group	15	1.000	0.000	1.000	1.000	0	36	20.587
Trelleborg AB	15	1.000	0.000	1.000	1.000	0	23	23.739
Bayer AG	15	1.000	0.000	1.000	1.000	0	52	21.491
Svenska Kullagerfabriken AB	15	1.000	0.000	1.000	1.000	0	43	34.260
Georg Fischer Automotive AG	14	0.968	0.120	0.518	1.000	4	34	29.902
Autoliv Inc.	12	0.982	0.049	0.808	1.000	13	34	26.096
Leoni AG	9	0.960	0.075	0.742	1.000	14	2	10.481
Faurecia Group	9	0.869	0.175	0.469	1.000	16	48	22.534
Infineon Technologies AG	8	0.906	0.189	0.259	1.000	23	4	8.501
Continental AG	6	0.941	0.065	0.791	1.000	29	8	6.855
Robert Bosch GmbH	6	0.917	0.165	0.499	1.000	29	7	6.536
Plastic Omnium Co.	5	0.890	0.102	0.722	1.000	37	1	5.000
ZF Friedrichshafen AG	5	0.759	0.255	0.309	1.000	33	7	7.018
Mahle GmbH	2	0.778	0.243	0.255	1.000	43	0	2.000
VALEO SA	0	0.823	0.106	0.547	0.948	53	0	0.000

N_o^{eff} = total number of years in which the firm was efficient. N^{peer} = total number of peers to which the firm referenced. N^{foll} = total number of followers that referenced to the firm. $\Sigma\lambda$ = cumulated λ values a firm attracted when being efficient.

Table 10: Regression model summary

Model	R^2	R^2_{adj}	Std. error	F	Durbin-Watson Stat.
OEM_01	0.467	0.441	0.05282	18.009	2.142
OEM_02	0.283	0.249	0.06125	8.128	2.165
OEM_03	0.529	0.504	0.04978	21.037	2.128
Supplier_01	0.277	0.240	0.12941	7.612	1.806
Supplier_02	0.272	0.235	0.12983	7.434	1.798
Supplier_03	0.290	0.250	0.12855	7.346	1.818

*The prefix OEM_* (Supplier_*) indicates the considered firm sample. The suffix indicates if only $OCC_{o,t}$ is considered (*_01) or only $C2C_{o,t}$ (*_02) or both factors (*_03).*

Table 11: Complete OLS regression results

Variable	OEM _01	OEM _02	OEM _03	Supplier _01	Supplier _02	Supplier _03
$SG_{o,t}$	-0.037	-0.096	0.036	-0.02	-0.011	-0.007
	(-0.674)	(-1.495)	(0.674)	(-0.037)	(-0.177)	(-0.121)
$EBITM_{o,t}$	-0.091	-0.061	-0.151***	0.232***	0.215***	0.211***
	(-1.549)	(-0.887)	(-2.669)	(3.176)	(2.904)	(2.880)
$CR_{o,t}$	-0.451***	-0.392***	-0.463***	-0.436***	-0.326***	-0.522***
	(-7.982)	(-6.025)	(-8.676)	(-3.924)	(-4.005)	(-4.381)
$OCC_{o,t}$	-0.578***	n.a.	-1.019***	-0.128	n.a.	-0.416**
	(-11.476)	(n.a.)	(-10.822)	(-.1.153)	(n.a.)	(-2.231)
$C2C_{o,t}$	n.a.	-0.378***	0.523***	n.a.	0.015	0.261*
	(n.a.)	(-6.327)	(5.425)	n.a.	(0.188)	(1.915)
$PPER_{o,t}$	-0.109**	-0.128**	-0.112**	-0.063	-0.055	-0.118
	(-2.079)	(-2.104)	(-2.276)	(-0.935)	(-0.810)	(-1.624)
$PRECR_{o,t}$	-0.024	-0.074	-0.004	-0.128	-0.135	-0.103
	(-0.287)	(-0.763)	(-0.049)	(-1.256)	(-1.321)	(-1.007)
$POSTCR_{o,t}$	-0.156	-0.118	-0.175*	-0.048	-0.030	-0.067
	(-1.521)	(-0.992)	(-1.803)	(-0.368)	(-0.232)	(-0.511)
t	0.164	0.079	0.207*	-0.280*	-0.307*	-0.215
	(1.273)	(0.533)	(1.696)	(-1.773)	(-1.965)	(-1.344)
$\ln S_{o,t}$	0.145***	0.167**	0.060	-0.144**	-0.140**	-0.154**
	(2.608)	(2.521)	(1.088)	(-2.214)	(-2.157)	(-2.387)
$USA_{o,t}$	0.180***	0.167**	0.193***	0.135**	0.134**	0.126**
	(3.091)	(2.473)	(3.516)	(2.147)	(2.123)	(2.014)
$ASIA_{o,t}$	-0.028	-0.071	0.010	n.a.	n.a.	n.a.
	(-0.534)	(-1.166)	(0.205)	(n.a.)	(n.a.)	(n.a.)

*The prefix OEM_* (Supplier_*) indicates the considered firm sample.The suffix indicates if only $OCC_{o,t}$ is considered (*_01) or only $C2C_{o,t}$ (*_02) or both factors (*_03). The table lists standardized regression coefficients β and t-statistics (in parentheses). Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

For model OEM_01, the results obtained by the bootstrapping approach differ as follows from the ones reported in Tab. 11 above:

– *The influence of $PPER_{o,t}$ is not significant.*
– *A weak positive significant influence of time t is detected.*

For model Supplier_01, the results obtained by the bootstrapping approach differ as follows from the ones reported in Tab. 11 above:

– *A weak negative significant influence of operating capital OCC_o,t is detected.*
– *A weak negative significant influence of $PRECR_{o,t}$ is detected.*
– *The impact of size ln $S_{o,t}$ is not significant.*

Table 12: Comparison of PEM, FEM and REM results

Variable	OEM PEM	OEM FEM	OEM REM	Supplier PEM	Supplier FEM	Supplier REM
$SG_{o,t}$	-1.8e-02	1.2e-02	6.5e-03	-3.6e-04	2.0e-03	3.6e-03
	(-0.674)	(0.523)	(0.273)	(-0.037)	(0.236)	(-0.430)
$EBITM_{o,t}$	-1.4e-01	-2.1e-01**	-2.2e-01**	6.9e-01***	2.7e-01	4.1e-01*
	(-1.549)	(-2.251)	(-2.349)	(3.176)	(1.135)	(1.826)
$CR_{o,t}$	-3.9e-01***	-2.3e-01***	-3.1e-01***	-5.7e-01***	-1.4e-00***	-1.0e-00***
	(-7.982)	(-3.925)	(-5.798)	(-3.924)	(-6.187)	(-5.534)
$OCC_{o,t}$	-5.2e-04***	-4.1e-04***	-4.6e-04***	-4.3e-04	-1.6e-03***	-1.3e-03***
	(-11.476)	(-7.173)	(-8.555)	(-.1.153)	(-3.360)	(-2.937)
$PPER_{o,t}$	-2.2e-02**	-2.1e-02**	-2.3e-02**	-2.2e-02	8.1e-02***	4.6e-02*
	(-2.079)	(-2.098)	(-2.306)	(-0.935)	(2.833)	(1.857)
$PRECR_{o,t}$	-3.7e-03	-7.3e-03	-3.4e-03	-4.2e-02	-1.0e-02	-1.5e-02
	(-0.287)	(-0.641)	(-0.298)	(-1.256)	(-0.354)	(-0.505)
$POSTCR_{o,t}$	-2.2e-02	-2.8e-02**	-2.4e-02*	-1.4e-02	2.1e-02	1.1e-02
	(-1.521)	(-2.207)	(-1.870)	(-0.368)	(0.655)	(0.340)
t	2.9e-03	4.7e-04	2.8e-03	-1.0e-02*	-7.8e-03	-6.9e-03
	(1.273)	(0.231)	(1.368)	(-1.773)	(-1.473)	(-1.354)
$\ln S_{o,t}$	1.2e-02***	9.0e-02***	2.2e-02**	-1.5e-02**	6.9e-03	-1.3e-02
	(2.608)	(4.849)	(2.545)	(-2.214)	(0.333)	(-1.069)
$USA_{o,t}$	3.9e-02***	n.a.	2.1e-02	8.0e-02**	n.a.	1.2e-01
	(3.091)	(n.a.)	(0.824)	(2.147)	(n.a.)	(1.522)
$ASIA_{o,t}$	-4.0e-03	n.a.	-2.5e-03	n.a.	n.a.	n.a.
	(-0.534)	(n.a.)	(-0.159)	(n.a.)	(n.a.)	(n.a.)
R^2	0.467	0.328	0.323	0.277	0.337	0.296
adj. R^2	0.441	0.249	0.290	0.240	0.255	0.261
F-statistic	11.492***			28.055***		
χ^2		7.379			8.356***	

*PEM = Pooled effect model, FEM = Fixed effect model, REM = Random effect model. The table lists non-standardized regression coefficients β and t-statistics or z-values respectively (in parentheses). F-statistic resulted from F test (PEM vs. FEM), χ^2 resulted from Hausman test (FEM vs. REM) conducted. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 13: Tobit regression results

Factor	OEM Coefficient	OEM St. err.	OEM z val.	Suppliers Coefficient	Suppliers St. err.	Suppliers z val.
*** Intercept	-9.055	8.900	-1.017	0.097	25.014	0.004
$SG_{o,t}$	-0.017	0.048	-0.348	-0.006	0.02	-0.287
$EBITM_{o,t}$	-0.313*	0.183	-1.715	0.985*	0.52	1.892
$CR_{o,t}$	-0.805***	0.120	-6.693	-2.157***	0.446	-4.837
$OCC_{o,t}$	-0.001***	0.000	-9.395	-0.001	0.001	-0.846
$PPER_{o,t}$	-0.042**	0.018	-2.247	-0.093**	0.046	-2.041
$PRECR_{o,t}$	-0.015	0.026	-0.588	0.006	0.072	0.077
$POSTCR_{o,t}$	-0.043	0.029	-1.502	-0.056	0.082	-0.677
t	0.005	0.004	1.190	0.002	0.013	0.128
$\ln S_{o,t}$	0.024***	0.009	2.668	-0.064***	0.018	-3.528
$USA_{o,t}$	0.095***	0.027	3.481	0.194**	0.087	2.22
$ASIA_{o,t}$	0.011	0.015	0.731	n.a.	n.a.	n.a.
Log(scale)	-2.444***	.075	-32.562	-1.524	0.084	-18.195

*Significance: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.*
Lower bound: 0, upper bound: 1.
Scale: 0.0868, Resid. d.f.: 225, Log likelih.: 42.059 D.f.: 13, Wald stat.: 134.969 D.f.: 11.

Table 14: Malmquist index, catch-up and frontier-shift

Year	OEM			Supplier		
	MI	CI	ϕ	MI	CI	ϕ
2004	0.966	1.003	0.964	0.976	1.293	0.842
2005	1.019	1.026	0.993	0.999	0.997	1.002
2006	0.995	0.999	0.996	1.007	1.004	1.003
2007	1.014	1.015	0.999	1.006	1.003	1.004
2008	1.005	0.998	1.008	0.977	0.956	1.026
2009	0.971	1.009	0.963	0.951	1.027	0.932
2010	1.019	1.005	1.014	1.076	1.026	1.049
2011	1.016	0.999	1.017	1.015	0.994	1.022
2012	0.990	0.994	0.998	1.004	1.039	0.969
2013	1.001	0.963	1.044	0.902	0.883	1.057
2014	1.005	1.044	0.965	1.025	1.024	1.002
2015	0.999	1.026	0.976	1.010	1.022	0.998
2016	0.994	0.991	1.004	1.045	1.070	0.981
2017	0.991	0.969	1.025	1.025	0.950	1.085

MI = Malmquist index, CI = catch-up, ϕ = frontier-shift.

Table 15: Progress and regress of productivity, relative efficiency and frontiers

Year	OEMs						Suppliers					
Year	MI		CI		ϕ		MI		CI		ϕ	
	$\Uparrow$	$\Downarrow$	$\Uparrow$	$\Downarrow$	$\Uparrow$	$\Downarrow$	$\Uparrow$	$\Downarrow$	$\Uparrow$	$\Downarrow$	$\Uparrow$	$\Downarrow$
2004	3	10	7	3	1	12	3	7	6	2	1	9
2005	8	3	8	2	2	9	5	2	4	2	3	4
2006	7	5	6	5	4	8	5	2	3	3	4	3
2007	9	3	6	3	6	6	5	4	3	4	6	3
2008	4	7	3	6	6	5	2	7	1	8	5	4
2009	4	9	5	3	1	12	1	9	5	4	0	10
2010	9	3	4	4	10	2	9	0	7	1	9	0
2011	9	4	4	4	11	2	6	5	2	7	9	2
2012	2	11	5	5	4	9	5	4	7	1	2	7
2013	10	5	5	7	12	3	2	8	2	6	4	6
2014	8	4	9	0	1	11	6	4	4	3	5	5
2015	6	6	5	4	4	8	5	4	4	2	3	6
2016	10	4	7	4	10	4	5	3	4	2	4	4
2017	5	8	3	7	7	6	5	5	0	6	7	3

$\Uparrow$ = progress, $\Downarrow$ = regress.
MI = Malmquist index, CI = catch-up, ϕ = frontier-shift.

Table 16: Detailed results of graph-theoretic assessment

Year	OEMs					Suppliers				
	LC	EF	PE	FO	TR	LC	EF	PE	FO	TR
2004	23	7	0	3	3	37	9	2	2	4
2005	23	9	2	0	2	31	11	2	0	2
2006	25	8	2	3	5	16	9	0	2	2
2007	19	10	2	0	2	21	11	3	1	4
2008	31	11	3	2	5	32	6	0	5	5
2009	28	12	3	2	5	20	8	2	0	2
2010	26	11	2	3	5	20	8	1	1	2
2011	25	11	2	2	4	23	7	1	2	3
2012	37	10	3	4	7	28	10	3	0	3
2013	48	8	3	5	8	44	9	2	3	5
2014	30	11	3	0	3	33	10	2	1	3
2015	24	8	0	3	3	20	11	2	1	3
2016	19	8	2	2	4	16	9	0	2	2
2017	28	9	2	1	3	17	9	0	0	0

LC = number of link changes, EF = number of efficient firms, PE = number of new peers, FO = number of new followers, TR = number of firm transits.

6.6. R source code

The following source code is given for 17 firms and 15 time periods. Note that the time periods are sorted in decreasing order, i.e. period p is one year later than period $p + 1$.

```
# open the required library
library(Benchmarking)
# Preprocessing
# 1. Read inputs and outputs from files
sales <- read.csv(”Sales.txt”, header = TRUE, sep=”\t”)
ebit <- read.csv(”EBIT.txt”, header = TRUE, sep=”\t”)
cogs <- read.csv(”COGS.txt”, header = TRUE, sep=”\t”)
oc <- read.csv(”OC.txt”, header = TRUE, sep=”\t”)
ppe <- read.csv(”PPE.txt”, header = TRUE, sep=”\t”)
# // Single period analysis
# 2. Vector declaration
single_eff = NULL
single_supereff = NULL
single_peers = NULL
single_lambdas = NULL
single_eff <- array(1:255, dim=c(17, 15))
single_supereff <- array(1:255, dim=c(17, 15))
single_peers <- array(1:4335, dim=c(17, 17, 15))
single_lambdas <- array(1:4335, dim=c(17, 17, 15))
single_ispeer <- array(1:4335, dim=c(17, 17, 15))
mq_catchup = NULL
mq_catchup <- array(1:238, dim=c(17, 14))
mq_index = NULL
mq_index <- array(1:238, dim=c(17, 14))
for (aa in 1:17) {
        for (bb in 1:17) {
                for (cc in 1:15) {
                        single_peers[aa, bb, cc] = NA
                        single_ispeer[aa, bb, cc] = 0
                        single_lambdas[aa, bb, cc] = 0
                } #endfor (cc in 1:15)
        } #endfor (bb in 1:17)
} #endfor (aa in 1:17)
frt_phinum = NULL
frt_phinum <- array(1:238, dim=c(17, 14))
frt_phiden = NULL
frt_phiden <- array(1:238, dim=c(17, 14))
frt_phione = NULL
frt_phione <- array(1:238, dim=c(17, 14))
frt_phitwo = NULL
frt_phitwo <- array(1:238, dim=c(17, 14))
frt_phi = NULL
frt_phi <- array(1:238, dim=c(17, 14))
# 3. DEA for each of the fifteen periods
for (p in 1:15) {
        # Declare input and output matrices
        inmat = NULL
        outmat = NULL
        inmat = cbind(cogs[, p+1], oc[, p+1], ppe[, p+1])
        outmat = cbind(sales[, p+1], ebit[, p+1])
        # Solve input-oriented VRS model
        e_vrs <- dea(inmat, outmat, RTS=”vrs”, ORIENTATION=”in”)
```

```
        e_svrs <- sdea(inmat, outmat, RTS=”vrs”, ORIENTATION=”in”)
        # Store results
        for (z in 1:length(eff(e_vrs))) {
                single_eff[z, p] = eff(e_vrs)[z]
                single_supereff[z, p] = eff(e_svrs)[z]
        } # endfor (z in 1:length(eff(e_vrs)))
        for (rz in 1:17) {
                for (cz in 1:length(peers(e_vrs)[1,])) {
                single_peers[rz, cz, p] = peers(e_vrs)[rz, cz]
                } # endfor (cz in 1:length(peers(e_vrs)[1,]))
        } # endfor (rz in 1:17)
        for (rz in 1:17) {
                cz = 1
                for (zz in 1:17) {
                        if (single_eff[zz, p] >= 1) {
                                single_lambdas[rz, zz, p] = lambda(e_vrs)[rz, cz]
                                if (lambda(e_vrs)[rz, cz] >0) {
                                        single_ispeer[rz, zz, p] =1
                                } # endif (lambda(e_vrs)[rz, cz] >0)
                                cz = cz+1
                        } # endif (single_eff[zz, p] >= 1)
                } # endfor (zz in 1:17)
        } # endfor (rz in 1:17)
        # Calculate performance of firm f in period p+1
                regarding frontier in period p
        if (p < 15) {
                for (ff in 1:17) {
                        ihmat = NULL
                        ihmat = rbind(inmat, c(cogs[ff, p+2], oc[ff, p+2],
                                ppe[ff, p+2]))
                        ohmat = NULL
                        ohmat = rbind(outmat, c(sales[ff, p+2], ebit[ff, p+2]))
                        frt12_vrs <- dea(ihmat, ohmat,
                                RTS=”vrs”, ORIENTATION=”in”)
                        frt_phiden[ff, p] <- eff(frt12_vrs)[length(eff(frt12_vrs))]
                } # endfor (ff in 1:17)
        } # endif (p < 15)
        # Calculate performance of firm f in period p-1
                regarding frontier in period p
        if (p > 1) {
                for (ff in 1:17) {
                        ihmat = NULL
                        ihmat = rbind(inmat, c(cogs[ff, p], oc[ff, p], ppe[ff, p]))
                        ohmat = NULL
                        ohmat = rbind(outmat, c(sales[ff, p], ebit[ff, p]))
                        frt21_vrs <- dea(ihmat, ohmat, RTS=”vrs”,
                                ORIENTATION=”in”)
                        frt_phinum[ff, p-1] <- eff(frt21_vrs)[length(eff(frt21_vrs))]
                } # endfor (ff in 1:17)
        } # endif (p > 1)
} # endfor (p in 1:15)
# 4. Malmquist analysis
for (p in 1:14) {
        for (zz in 1:17) {
                # Calculate the catchup index for each firm and each period
                mq_catchup[zz, p] = single_eff[zz, p] / single_eff[zz, p+1]
                # Calculate the frontier-shift for each firm and each period
                frt_phione[zz, p] = single_eff[zz, p+1] / frt_phiden[zz, p]
                frt_phitwo[zz, p] = frt_phinum[zz, p] / single_eff[zz, p]
```

```
			frt_phi[zz, p] = sqrt(frt_phione[zz, p] * frt_phitwo[zz, p])
			# Calculate the malmquist index for each firm and each period
			mq_index[zz, p] = mq_catchup[zz, p] * frt_phi[zz, p]
		} # endfor (zz in 1:17)
} # endfor (p in 1:14)
# 5. Save data to file
# Declare transposed matrices
tr_single_eff = NULL
tr_single_supereff = NULL
tr_single_peers = NULL
tr_single_ispeer = NULL
tr_single_lambdas = NULL
tr_single_eff <- array(1:255, dim=c(15, 17))
tr_single_supereff <- array(1:255, dim=c(15, 17))
tr_single_peers <- array(1:4335, dim=c(17, 17, 15))
tr_single_ispeer <- array(1:4335, dim=c(17, 17, 15))
tr_single_lambdas <- array(1:4335, dim=c(17, 17, 15))
tr_mq_catchup = NULL
tr_mq_catchup <- array(1:238, dim=c(14, 17))
tr_mq_index = NULL
tr_mq_index <- array(1:238, dim=c(14, 17))
tr_frt_phione = NULL
tr_frt_phione <- array(1:238, dim=c(14, 17))
tr_frt_phitwo = NULL
tr_frt_phitwo <- array(1:238, dim=c(14, 17))
tr_frt_phi = NULL
tr_frt_phi <- array(1:238, dim=c(14, 17))
# Transpose matrices for writing to files
for (a in 1:15) {
	for (b in 1:17) {
		tr_single_eff[a, b] = single_eff[b, a]
		tr_single_supereff[a, b] = single_supereff[b, a]
	} # endfor (b in 1:17)
} # endfor (a in 1:15)
for (a in 1:17) {
	for (b in 1:17) {
		for (c in 1:15) {
			tr_single_peers[a, b, c] = single_peers[b, a, c]
			tr_single_ispeer[a, b, c] = single_ispeer[b, a, c]
			tr_single_lambdas[a, b, c] = single_lambdas[ b, a, c]
		} # endfor (c in 1:15)
	} # endfor (b in 1:17)
} # endfor (a in 1:17)
for (a in 1:14) {
	for (b in 1:17) {
		tr_mq_catchup[a, b] = mq_catchup[b, a]
		tr_mq_index[a, b] = mq_index[b, a]
		tr_frt_phione[a, b] = frt_phione[b, a]
		tr_frt_phitwo[a, b] = frt_phitwo[b, a]
		tr_frt_phi[a, b] = frt_phi[b, a]
		tr_mq_index[a, b] = mq_index[b, a]
	} # endfor (b in 1:17)
} # endfor (a in 1:15)
# Write transposed matrices to files
write(tr_single_eff, ”SingleEfficiency.txt”, ncolumns = 15,
	append = FALSE, sep = ”\t”)
write(tr_single_supereff, ”SuperEfficiency.txt”, ncolumns = 15,
	append = FALSE, sep = ”\t”)
write(tr_single_peers, ”SinglePeers.txt”, ncolumns = 15,
```

```
        append = FALSE, sep = "\t")
write(tr_single_ispeer, "SingleIsPeer.txt", ncolumns = 15,
        append = FALSE, sep = "\t")
write(tr_single_lambdas, "SingleLabdas.txt", ncolumns = 15,
        append = FALSE, sep = "\t")
write(tr_mq_catchup, "MalmquistCatchup.txt", ncolumns = 14,
        append = FALSE, sep = "\t")
write(tr_frt_phione, "PhiOne.txt", ncolumns = 14,
        append = FALSE, sep = "\t")
write(tr_frt_phitwo, "PhiTwo.txt", ncolumns = 14,
        append = FALSE, sep = "\t")
write(tr_frt_phi, "Phi.txt", ncolumns = 14,
        append = FALSE, sep = "\t")
write(tr_mq_index, " MalmquistIndex.txt", ncolumns = 14,
        append = FALSE, sep = "\t")
```

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