Expert Systems with Applications: X 5 (2020) 100027

Contents lists available at ScienceDirect

Expert Systems with Applications: X

journal homepage: www.elsevier.com/locate/eswax

Role of inventory and assets in shareholder value creation

Olli-Pekka Hilmola[a,b]

[a] LUT University, Kouvola Unit, Prikaatintie 9, FIN-45100 Kouvola, Finland
[b] Tallinn University of Technology (Taltech), Estonian Maritime Academy, Kopli 101, 11712 Tallinn, Estonia

ARTICLE INFO

Article history:
Received 15 October 2019
Revised 3 February 2020
Accepted 4 March 2020
Available online 13 March 2020

Keywords:
Inventory management
Assets
Financials
Shareholder value
Efficiency
Theory of constraints

ABSTRACT

In this study is examined the role of inventories and assets in the financial and shareholder value creation of a company. Research builds several Data Envelopment Analysis (DEA) models (staged), and tests their connections with each other. Research concerns publicly traded manufacturing and trade companies of Finland and three Baltic States (Estonia, Latvia and Lithuania) during the years 2010–2018. Logical and in two stages proceeding DEA efficiency model gets statistical significance, and there is support that inventory and asset related measures will lead to revenue, profits and cash flow, which together will eventually result in higher shareholder value (like stated in operations and supply chain management theories such as theory of constraints). However, this finding has weakness as explanation power is low, and there is a lot of noise. It could also be so that inventories and assets are part of bunch of other inputs, which together directly create shareholder value. Therefore, it remains as an open question whether inventory and assets should be managed through classical and logical stages in companies through organization hierarchy, or if inventory and assets should be just a part of group of factors, which together aim to increase shareholder value.

1. Introduction

In Operations and Supply Chain Management (OSCM) research inventory management is seen as an essential part of success, and inventory amounts should always be decreased, if it is possible without hurting internal efficiency, deliveries and/or sales too much. Contrary to financial and asset perspectives, in OSCM, inventory is seen as a liability rather than an asset class (like Theory of Constraints or Just in Time branch; (de Haan & Yamamoto, 1999; Eroglu & Hofer, 2011; Ikeziri, de Souza, Gupta & Fiorini, 2019). It is also argued in these OSCM theories that efficient inventory management will result on higher sales, profits and profitability. Empirical findings from the retail sector argue that it is not necessarily gross or profit margin, that matter, as margins may be low, but on the other hand inventory turns are high (Gandhi & Shankar, 2016; Gaur, Fisher & Raman, 2005). This will eventually lead to high return on investment and absolute profits. Lower inventory also enables strategic flexibility or agility (Purvis, Gosling & Naim, 2014), helping company to better adapt to market and technological changes. Low inventory also drives production processes, streamlines the supply chain and lowers used lot sizes (or even individualistic lot sizes of one). With the argued inventory linkage to financial success of company, it is evident that inventory must have role in shareholder value creation (in this research defined as changes of adjusted annual share prices). If inventory has such a critical role in short-term financial success and strategic flexibility, then it must have clear connections to shareholder value. However, this all was commonly agreed upon before the global financial crisis of 2008–2009, but thereafter implemented low (or zero) interest rates have since changed the common opinion. Based on recent studies, it is found that increasing inventories are the fact among companies (and in some industries, Moser, Isaksson & Seifert, 2017), and these could enable even shareholder value creation success in this new environment (Bendig, Brettel & Downar, 2018; Steinker & Hoberg, 2013). These recent empirical studies in the field argue that inventory can grow during the short-term to enable responsiveness, however, in the longer-term it should stay in good level, and not to deteriorate to lower inventory turns and constantly higher inventory holdings.

In this research empirical material is gathered from smaller European countries (Finland and three Baltic States: Estonia, Latvia and Lithuania), and selected companies represent manufacturing and retail. Domestic markets in these countries are small and experiencing aging population effects, so most of the companies have significant international operations as well. Research data arising

E-mail address: olli-pekka.hilmola@lut.fi

https://doi.org/10.1016/j.eswax.2020.100027

from these smaller countries is simultaneously strength and weakness of this study, and its generalization. As said, companies are typically rather international, but on the other hand, their public stock trading at exchanges is having moderate or low volume as compared to other larger countries. This is the main limitation of this study – operative performance changes do not necessarily turn to shareholder value immediately. All four countries are part of the European Union, and in the recent years they all have joined the Euro currency area (Finland being founding members as Estonia joined 2011, Latvia in 2014 and Lithuania in 2015). Before joining the Euro currency, all three Baltic States had very stable currencies – practically Estonia and Lithuania had more than decade same peg rate to Euro (prior joining Euro zone), and Latvia's situation did not differ that much as its currency rate movements were ±1% to Euro (Anghel, Pinzaru, Dinu & Treapat, 2014). All four countries have enjoyed from on-going lowering of interest rates during the examination period (2010–2018), and in recent years interest rates have started to approach zero. This study does not include year 2009 in the analysis as the global financial crisis hit abnormally hard to some of these countries, especially Baltic States (Hilmola, 2013), where Gross Domestic Products declined by 15–19%. Research problem of this study could be stated with following research questions: What is the role of different inventory and asset measures in financial and shareholder success of a company (efficiency in terms of how converting from inputs to stated outputs)? What is the route to shareholder value creation, indirect vs. direct, or both? DEA models in this research work follow Theory Of Constraints (TOC) approach, where traditional staged model from inventory (all inventory classes from balance sheet in total) and assets (all balance sheet assets in total) result to intermediate output success of financial measures, and eventually to shareholder value (Gupta, 2012; Hilmola & Gupta, 2015; Ikeziri et al., 2019). DEA has been used in small extent within TOC frameworks, and mostly research works have concerned manufacturing job-shop scheduling (Arango-Marín, Giraldo-García & Castrillión-Gómez, 2014), constraint identification and elevation in manufacturing (Shurrab, Al-Refaie, Mandahawi & Shurrab, 2018) as well as building supply chains towards leagility (Banerjee & Mukhopadhyay, 2016). Contribution of this work is to enlarge DEA in TOC reasoning of inventory, assets and operational performance, which is argued to lead into financial success and shareholder value.

This research is structured as follows: In Section 2, previous DEA efficiency research works is reviewed, which have used inventory (and assets) in their evaluation models of for-profit companies. Research methodology and environment follows in Section 3, where used DEA models of this study are introduced and correlation analysis is being completed between different variables. Section 4 provides empirical data analysis, where causality and regression models between different DEA models are thoroughly analyzed. Research is concluded in Section 5, where also new avenues for future studies are being proposed.

2. Role of inventory and assets in DEA research

Since the seminal research published from DEA efficiency evaluation method, there has been four decades of time to make research works from different disciplines. As thousands of research works have already been published (Emrouznejad & Yang, 2018) estimated that until 2016 the total amount of DEA journal publications was 10,300), it is evident that inventory efficiency has been dealt with in earlier research. A literature review revealed that most often inventory and assets are considered in retail sector efficiency evaluations (Gandhi & Shankar, 2016; Joo, Nixon & Stoeberl, 2011; Mhatre, Seong-Jong & Lee, 2014; Wu, Kao, Wu & Cheng, 2006), and surprisingly very rarely in that of manufacturing or production (Dev, Shankar & Debnath, 2014). Sometimes inventory or inventory efficiency are not considered at all, but it is being examined from the efficiency of managing inventory through existing resources (Jatuphatwarodom, Jones & Ouelhadj, 2018) or from critical parameters causing inventory, like supply lead time and review period frequency (Dev et al., 2014). These two studies had also different outputs (in Jatuphatwarodom et al., 2018: inventory costs, delivery time & turnover rate; in Dev et al., 2014: fill rate) as compared to rest of the research. In other research works, which are directly dealing inventory and asset efficiency, they were typically including inventory in absolute terms (nominal value; Joo et al., 2011; Mhatre et al., 2014; Wu et al., 2006), but in one study inventory turns were taken as an input (Gandhi et al., 2016). Joo et al. (2011) examined efficiency through three different models (motivated by return on assets methodology), which included different sub-classes of assets in two models (current, fixed and other assets, and in another one cash, accounts receivable and inventory). Similarly, Wu et al. (2006) included in the model current assets separately. For output, DEA models typically used revenue or sales (Joo et al., 2011; Mhatre et al., 2014; Gandhi et al., 2016), however, Wu (2006) included both sales and gross margin.

Findings of retail sector DEA efficiency analyses contained quite much variation in efficiency, even if the retail sector should have small differences between companies due to high competition and small margins. Wu et al. (2006) study find that different sub-sectors of retail have very different efficiency levels, with textile sales being the most difficult to manage efficiently. General merchandise and vehicle part sales had much higher average efficiency values. Wu et al. (2006) also examined the relationship of different input items on sales and gross margin. Their regression model indicated that higher inventory investment would result on lower sales, however, the statistical significance of this was not high enough. Typically, other studies concluded that Walmart was exemplary in its efficiency (Gandhi et al., 2016), whatever the DEA model being used (Joo et al., 2011). Margins of Walmart are not high, however, asset turns are high and capital is employed very efficiently, which ensures high performance. In recent years, we have witnessed a remarkable decline of traditional retailers e.g. in USA, and those being hurt most could be found from these earlier studies as being the lowest performing and having declining efficiency in the observation period (see e.g., Joo et al., 2011; Mhatre et al., 2014). So, high efficiency in the traditional model seems to provide some hedge in the era of technological change.

3. Research methodology

This research concerns manufacturing and trade companies in Northern Europe, and the data consists 33 different companies (Baltic Main List and Baltic Secondary List) from three Baltic States (Estonia, Latvia and Lithuania), and 39 companies from Finland ("industrials", "information technology", "consumer services" and "materials"). Companies are listed in Appendix A, and basically all available companies were included in this study, without any size restrictions. It is notable that not all companies had complete data from the observation period of this study from years 2010–2018. Mostly this was due to public listing of a number of companies during the examination period, so accounting records and stock market share price data were simply unavailable from some years. Annual reports, accounting data, and adjusted share price data (for currency changes, stock splits or reverse splits) were mostly gathered from Nasdaq Baltic (2019) and Nasdaq Nordic (2019) company based information sources or alternatively from company investor webpages. Each company had its own spreadsheet from gathered data, and these were merged together into a database, which was used to get data for efficiency analysis using Data Envelopment Analysis.

Negativity in items such as profit and loss, cash flow and share price change (adjusted, annual) was avoided by adding a fixed amount in all of these in order to have them be on scale from zero onwards (like in other DEA studies, see Pastor & Ruiz, 2007). In profit and loss, it was added 3789,001 EUR (thousands) to each real number, in cash flow the amount was 1454,001 EUR (thousands), while in share price changes it was added one (1). Also inventory turns needed to be modified for the purposes of DEA research as in general it is so that higher input amounts should lead to higher outputs (having the same and consistent direction between inputs and outputs). Therefore, inventory turns was calculated as an inverse number (lower the inventory turns, the higher the input number).

To increase the validity of the following efficiency analyses (e.g. Lin, 2007), correlation analysis was made from the used efficiency model variables (see Table 1 in below). Only adjusted stock price change (%) in annual basis had no correlation at all with other input and output variables. This is somewhat surprising, too, as annual results in terms of profits and losses as well as operative cash flow is analyzed not to have any relation with share price change. Adjusted stock price change (%) was also further analyzed with the effect of time delay of one year or two years (time lag from other variables of this study could be having time lag to grand output – changes of today e.g. in inventory efficiency could be present in adjusted stock price in two years), however, this did not change the situation, and same non-correlation persisted. Similarly, profit and loss was having only two correlations (positive) – these with absolute inventory investment amount and operative cash flow. The third mostly output variable, revenue, had a number of correlations. In statistically significant terms, revenues increase as absolute inventory investment, total assets, and cash flow increase. However, if inventory is getting too large role in total assets (%), then it will decrease revenue as does inverse inventory turns. Among only input variables (which do not represent any model as output), there exist correlations, however, these are in both directions (negative and positive). Interestingly, absolute inventory investment and inverse inventory turns do not have any causality at all. Correlations between input factors could be seen as weakness of this study, but as causalities are in both directions, this should not be major validity issue. Also, many asset-based measures are tied to each other due to industrial branch features, investments made and type of customers served.

As research used number of DEA models, and especially the stage 4 model (Fig. 2) was having so many input-output variables (eight), that it was logical to pool together all observations from different years as a single analyzed group (like Mhatre et al., 2014 did for retail sector analysis, as Kozmetsky & Yue, 1998 did in semiconductor industry). This increased the reliability of results significantly. Efficiency analysis was completed with EMS software (ver. 1.3.0). This software is rather old, but is an often applied program in efficiency analysis. Models in the following assume that efficiency frontier is based on "constant return on scale" (CCR), and models are input driven (Charnes, Cooper & Rhodes, 1978). It could be argued that "variable return on scale" as efficiency frontier should have been used as company sizes differed so greatly in this research work (e.g. revenues from several millions to billions of EUR). However, when running efficiency analyses, it became evident that smaller companies were able to perform well with larger ones, and need for frontier adjustments felt unnecessary.

Regression analysis in the following was firstly completed with Excel's data analysis tool (Excel 2016). Later on regression analyses were also completed and expanded in RStudio (ver. 1.1.456 for Ubuntu/Linux). In the following linear regression models are reported using ordinary least squares models. However, these are supported with Tobit regression models (like Tasnim & Afzal, 2018), which limit regression model to the area from 0 (lower) to 1 (up-

Table 1
Correlation matrix of DEA variables used in research (inputs and outputs; $n = 619$ for variables apart of adj. stock price change, where $n = 586$).

	Inventory {I}	Inventory turns (rev.) {I}	Inventory (assets-%) {I}	Assets {I}	Revenue {O/I}	Profit/loss {O/I}	Cash Flow (operative) {O/I}	Adj. stock price change {O}
Inventory {I}	1.000							
Inventory turns (revenue) {I}	−0.078	1.000						
Inventory (assets-%) {I}	−0.189***	0.384***	1.000					
Assets {I}	0.863***	−0.105**	−0.243***	1.000				
Revenue {O/I}	0.868***	−0.126**	−0.227***	0.938***	1.000			
Profit/loss {O/I}	0.181***	−0.034	−0.053	0.042	0.056	1.000		
Cash Flow (operative) {O/I}	0.659***	−0.094*	−0.182***	0.612***	0.701***	0.481***	1.000	
Adj. stock price change {O}	−0.041	0.049	0.024	−0.037	−0.046	0.038	0.000	1.000

*** statistically significant with <0.001 level.
** statistically significant with <0.01 level.
* statistically significant with <0.05 level.

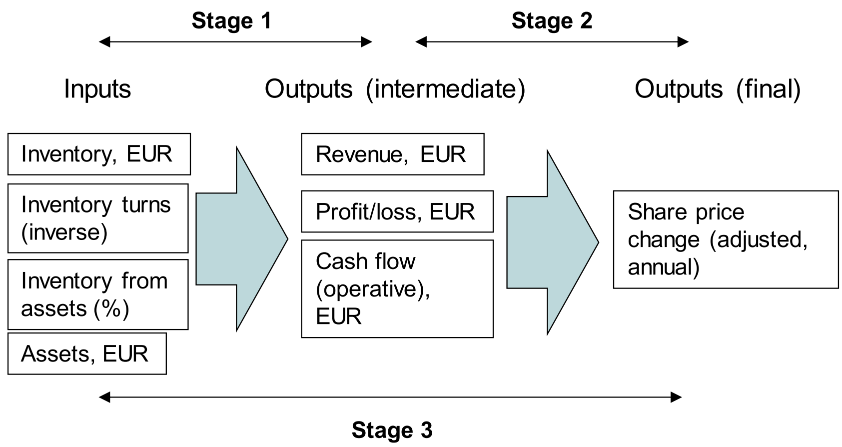

Fig. 1. Staged DEA model used for the role of inventory and assets (stages 1–3).

per limit). In the analysis significant differences between two regression model approaches were not found, and research supports further findings of McDonald (2009) .

4. Empirical data analysis

Logic from inventory and asset inputs to revenue, profits and cash flow, and eventually to shareholder value creation sounds reasonable and logical, but in this efficiency study this is only supported in moderate fashion. Fig. 3 illustrates DEA efficiency correlation between models of transforming inventory and asset inputs to revenue, profits and cash flow (stage 1) and then turning these intermediate outputs to inputs and seeing as true output adjusted share price change (stage 2). Regression model between these two DEA models is very poor in explanation power (R^2 being 1.87%), but it is statistically significant (both fixed term and co-efficient are having *p*-value of <0.001). However, as examining in details Fig. 3, it seems that most of the companies are having positive regression relationship in two models, but then there are some companies, which are clearly over-performing in stage 2 of DEA model. This basically means that adjusted stock price change has been achieved with rather mediocre input performance (revenues, profits and cash flow). In regression line of Fig. 3, when efficiency of DEA model at stage 1 improves with one percentage point, it will lead to improvement of stage 2 model with 0.1005 percentage points. As Fig. 1 regression is ordinary least squares model, correlation data was also used to estimate Tobit regression model (with lower limit of 0 and upper limit of 1; see Appendix B for details). This model also supports argument existence of route from stage 1 to stage 2, however, the co-efficient in Tobit regression is pretty much the same as in Fig. 3.

Interestingly, there exists causality between DEA models of stage 2 and stage 3. Performance is statistically significant, and linear regression curve proceed in rather equal fashion – if stage 2 model improves one percentage point, then stage 3 model improves by 0.9746 percentage points (explanation power of regression model is rather high, R^2 being 51.8%). Causality is having some weaknesses as heteroscedasticity seems to be present, and in some observations both DEA models could give highest possible frontier performance (1 or 100%), while the other is much lower. Overall, it seems that inventory and asset inputs do have role, but it could be a merely direct role to shareholder value creation. Tobit regression model (Appendix B) similarly shows statistical significance and co-efficient with Fig. 4 model.

Direct model from inputs to shareholder value (stage 3) is also having causality with initial model (stage 1), where inventory and assets were connected to revenue, profits and cash flow (Fig. 5).

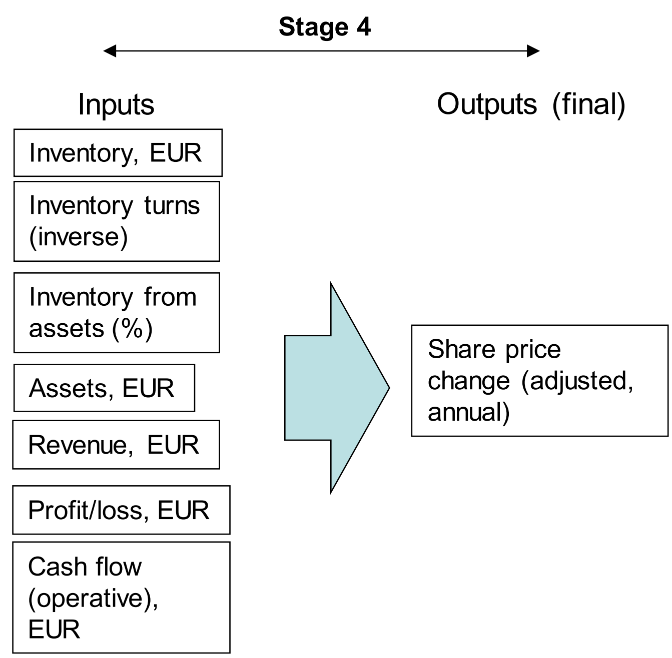

Fig. 2. Staged DEA model used for the role of inventory and assets (stages 4).

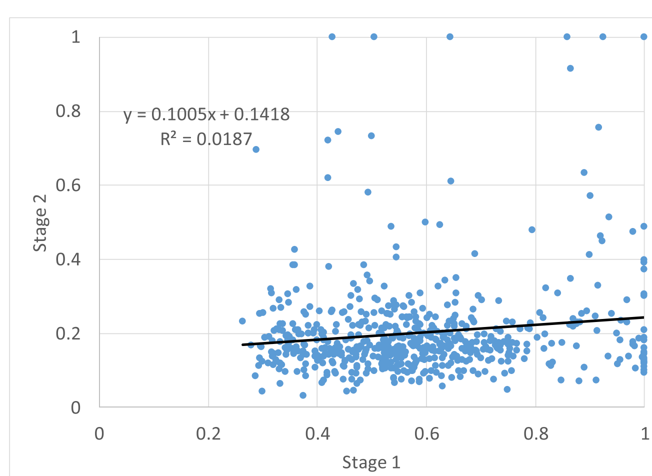

Fig. 3. DEA efficiency correlation with regression model between stage 1 model (x-axis) and stage 2 model (y-axis).

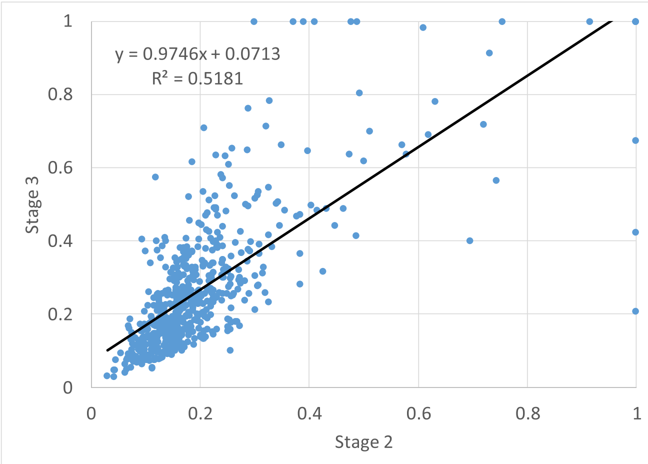

Fig. 4. DEA efficiency correlation with regression model between stage 2 model (x-axis) and stage 3 model (y-axis).

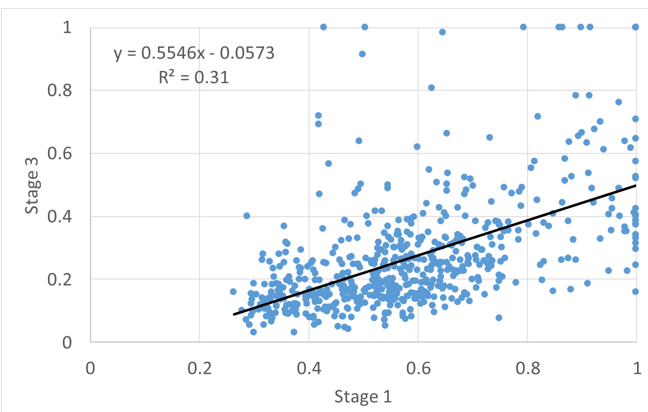

Fig. 5. DEA efficiency correlation with regression model between stage 1 model (x-axis) and stage 3 model (y-axis).

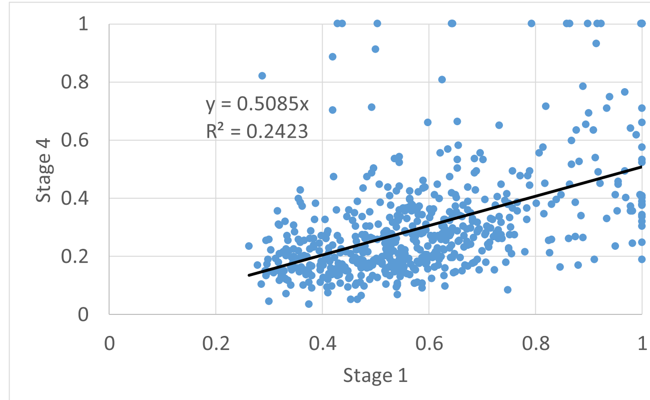

Fig. 6. DEA efficiency correlation with regression model between stage 1 model (x-axis) and stage 4 model (y-axis).

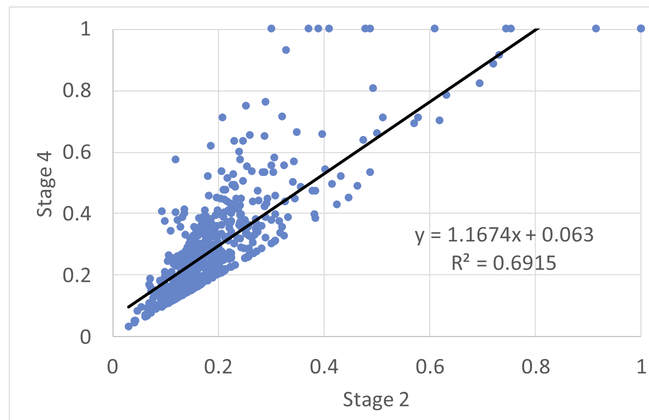

Fig. 7. DEA efficiency correlation with regression model between stage 2 model (x-axis) and stage 4 model (y-axis).

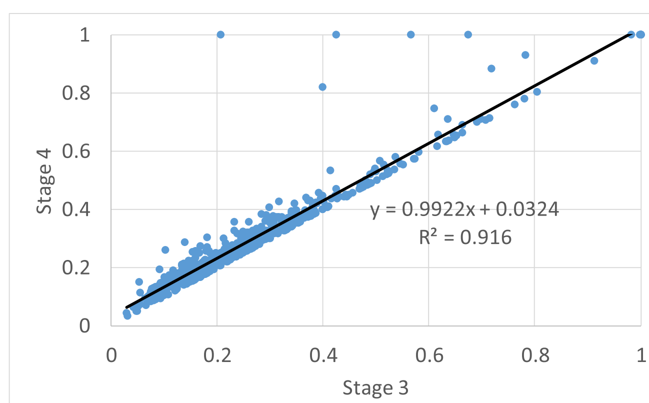

Fig. 8. DEA efficiency correlation with regression model between stage 3 model (x-axis) and stage 4 model (y-axis).

Every time stage 1 model improves by one percentage unit, it leads to improvement of 0.5546 in stage 3 model. Therefore, causality is not as strong as in previous model, however, it surely exists. Explanation power of model is also rather high, 31% (R^2 value). Model is also statistically significant. Again, Tobit regression model is showing similar results (Appendix B), and it is statistically significant and the co-efficient is rather similar with Fig. 5.

Causality between DEA model stage 4 and other three models (stages 1 to 3) was rather interesting as in all three situations correlation is positive, and regression models are all statistically significant (Figs. 6 to 8). Explanation power is lowest in between stage 4 and stage 1, where scatter plot observations are having more variation around linear curve. However, explanation power is 24.23%, and regression model contains only coefficient as fixed term is not statistically significant. As efficiency in stage 1 model improves by one percentage point, then this corresponds to change of 0.5085 percentage points in stage 4 model. The same applies to Tobit regression model (Appendix B), where model is statistically significant (one fixed term, Intercept 1 is not, like ordinary least squares model in Fig. 6), and the co-efficient is similar to Fig. 6.

As DEA models in stages 2, 3 and 4 share plenty of similarities in inputs and have the same output, efficiency results are in the same neighbourhood, and explanation power is high in both of the models (in Fig. 7, it is 69.15%, and in Fig. 8, it is 91.6%). It is interesting to note that stage 2 model (using as inputs revenue, profits and cash flow), improvement will result in much higher improvement in stage 4 model. This again illustrates further connection between inventory and asset management on shareholder value creation. Between DEA models stage 3 and 4 improvement in efficiency, the former will result in similar kind of magnitude change in the latter one. However, the models are rather similar, so this was expected. Tobit regression models for stages 2 & 4 (Fig. 7) and stages 3 & 4 (Fig. 8) show similar results, and they are both statistically significant. In both Tobit models, co-efficient is having somewhat higher values, especially in stage 2 & 4 model. However, in this latter model, interpretation of results is rather difficult as heteroscedasticity is clearly present (in Tobit model there was warning about Hauck-Donner effect).

5. Conclusions

As was found in the literature review, there are not many research works concerning the role of inventory (and assets) within manufacturing and retail. Most often these models were rather simple, and output was revenue or sales. Attempt in this research work was to expand inventory perspective and models as more complex, and also multi-staged. Output included revenues, profit/loss, cash flow (operative) and adjusted share price change (annual). Inputs were inventory and asset related. While analyzing causality of models, this research gave further proof that inventory and asset measures will lead to intermediate financial success and eventually to shareholder value creation. It is notable that this process has its uncertainty, and error in regression model was high. However, research also indicated other options to inventory relevance exist. It could be so that inventory performance is just bunch of measures, which leads to higher financial performance or shareholder value creation. Some of these models were having high causality with other models, and very low error effect. As a conclusion, it could be stated that inventories (and assets) are still having significant role in financial success and shareholder value creation. It is rather open issue, how this relevance is built in companies – through stages or directly.

For further research in this field, it would be natural to enlarge this study to larger economies, and possibly to main European exchange listed companies or North American ones. The retail sector in these markets has globally leading companies present, which would make examination of this sector fruitful. As manufacturing is increasingly Asian based, this would be another interesting direction to follow. In both of these possible further studies inventory and asset role should be examined further to shed more light on issues found in this research. Another possibility for further research would be to take earlier years in data from times before the global financial crisis. Using older data would enable to examine the era, when there were higher interest rates. This ought to stress the importance of inventory and assets.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Olli-Pekka Hilmola: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Visualization, Investigation, Validation, Writing - review & editing.

Acknowledgements

Author shall give sincere thanks for two anonymous reviewers for their suggestions, corrections and remarks during the review phase. Research also benefitted from valuable comments of Prof. Mahesh Gupta from University of Louisville (USA) during the research process.

Appendix A. . List of companies of this research work

Baltic States

Apranga, Auga, Baltika, Brivais Vilnis, Ditton, Grigeo, Grindex, Grobina, HansaMatrix, Harju Elekter, Kurzemes Atslega 1, Latvijas balzams, Linas, Linas Agro Group, Linda Nektar, Madara, Olainfarm, Pieno žvaigždės, Prfoods, RER, Riga Shipyard, RJR, Rokiškio sūris, SAF, Silvano Fashion, Skano Group, Snaige, Tallinna Kaubamaja, Utenos trikotazas, Valmiera glass, Vilkyškių pieninė, Vilniaus Baldai, and Zemaitijos Pienas.

Finland

Afarak, Ahlstrom-Munksjö, Aspocomp, Cargotec, Componenta, Efore, Elecster, Exel, Glaston, Huhtamäki, Incap, Kamux, Kemira, Kesko, Kesla, Kone, Konecranes, Metso, Metsä, Neo Industrial, Nokia, Outokumpu, Outotec, Ponsse, Raute, Robit, Scanfil, Stockmann, StoraEnso, Teleste, Tikkurila, Tokmanni, Tulikivi, UPM, Uponor, Uutechnic, Vaisala, Valmet, and Wärtsilä.

Appendix B. Tobit regressions for staged DEA efficiency models

Variable	Stage 1 & 2*p* value		Stage 2 & 3*p* value		Stage 1 & 3*p* value	
(Intercept):1	0.1414	***	0.065451	***	−0.06016	**
(Intercept):2	−2.02472	***	−2.073645	***	−1.89134	***
Co-efficient	0.10146	***	1.008733	***	0.56057	***

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Variable	Stage 1 & 4*p* value		Stage 2 & 4*p* value		Stage 3 & 4*p* value	
(Intercept):1	−0.003951		0.020527	*	0.025498	***
(Intercept):2	−1.798547	***	−2.306453	***	−2.912798	***
Co-efficient	0.517239	***	1.407402	***	1.023515	***

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

References

Anghel, L. C., Pinzaru, F, Dinu, M, & Treapat, L. M. (2014). Fixing the central parity and the evolution of the currency within the exchange rate mechanism ii in the countries that joined the Euro zone. *Management Dynamics in the Knowledge Economy, 2*(1), 21–40.

Arango-Marín, J. A., Giraldo-García, J. A., & Castrillión-Gómez, O. D. (2014). Applying TOC heuristics to job scheduling in a hybrid flexible flow shop. *DYNA, 81*(186), 113–119.

Banerjee, A., & Mukhopadhyay, S. (2016). A contemporary TOC innovative thinking process in the backdrop of leagile supply chain. *Journal of Enterprise Information Management, 29*(3), 400–431.

Bendig, A., Brettel, M., & Downar, B. (2018). Inventory component volatility and its relation to returns. *International Journal of Production Economics, 200*, 37–49.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

de Haan, J., & Yamamoto, M. (1999). Zero inventory management: Facts or fiction? lessons from Japan. *International Journal of Production Economics, 59*(1–3), 65–75.

Dev, N. K., Shankar, R., & Debnath, R. M. (2014). Supply chain efficiency: A simulation cum DEA approach. *International Journal of Advanced Manufacturing Technology, 72*, 1537–1549.

Emrouznejad, A., & Yang, G. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978-2016. *Socio–Economic Planning Sciences, 61*, 4–8.

Eroglu, C., & Hofer, C. (2011). Lean, leaner, too lean? The inventory-performance link revisited. *Journal of Operations Management, 29*, 356–369.

Gandhi, A., & Shankar, R. (2016). Strategic recourse management and data envelopment analysis for benchmarking of Indian retailers. *Benchmarking: An International Journal, 23*(2), 286–312.

Gaur, V., Fisher, M. L., & Raman, A. (2005). An econometric analysis of inventory turnover performance in retail services. *Management Science, 51*(2), 181–194.

Gupta, M. (2012). Balanced scorecard and theory of constraints: A synergistic framework. *Cost Management, 26*(4), 32–47.

Hilmola, O.-. P. (2013). From bubble to sustainable economy in Baltic states. *Journal of Transport and Telecommunication, 14*(3), 237–249.

Hilmola, O.-. P., & Gupta, M. (2015). Throughput accounting and performance of a manufacturing company under stochastic demand and scrap rates. *Expert Systems with Applications, 42*(22), 8423–8431.

Ikeziri, L. M., de Souza, F. B., Gupta, M. H., & Fiorini, P. C. (2019). Theory of constraints: Review and bibliometric analysis. *International Journal of Production Research, 57*(15–16), 5068–5102.

Jatuphatwarodom, N., Jones, D. F., & Ouelhadj, D. (2018). A mixed-model multi-objective analysis of strategic supply chain decision support in the Thai silk industry. *Annals of Operations Research, 267*, 221–247.

Joo, S.-. J., Nixon, D., & Stoeberl, P. A. (2011). Benchmarking with data envelopment analysis: A return on asset perspective. *Benchmarking: An International Journal, 18*(4), 526–542.

Kozmetsky, G., & Yue, P. (1998). Comparative performance of global semiconductor companies. *Omega, 26*(2), 153–175.

Lin, E. T. J. (2007). Route-based performance evaluation of Taiwanese domestic airlines using data envelopment analysis: A comment. *Transportation Research Part E: Logistics and Transportation Review, 44*(5), 894–899.
McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research, 197*, 792–798.
Mhatre, N., Seong-Jong, J., & Lee, C. C. (2014). Benchmarking the performance of department stores within an income elasticity of demand perspective. *Benchmarking: An International Journal, 21*(2), 205–217.
Moser, P., Isaksson, O. H. D., & Seifert, R. W. (2017). Inventory dynamics in process industries: An empirical investigation. *International Journal of Production Economics, 191*, 253–266.
Pastor, J. T., Ruiz, J. L., Zhu, J., & Cook, W. D. (2007). Variables with negative values in DEA. *Modeling data irregularities and structural complexities in data envelopment analysis*. Boston, MA: Springer.
Purvis, L., Gosling, J., & Naim, M. M. (2014). The development of a lean, agile and leagile supply network taxonomy based on differing types of flexibility. *International Journal of Production Economics, 151*, 100–111.
Shurrab, M., Al-Refaie, A., Mandahawi, N., & Shurrab, S. (2018). A decision-making using data envelopment aggressive formulation and theory of constraints to enhance the PVC production line performance. *International Journal of Industrial and Systems Engineering, 30*(1), 21–39.
Steinker, S., & Hoberg, K. (2013). The impact of inventory dynamics on long-term stock returns – An empirical investigation of U.S. manufacturing companies. *Journal of Operations Management, 31*, 250–261.
Tasnim, N., & Afzal, M. N. I. (2018). An empirical investigation of country level efficiency and national systems of entrepreneurship using Data Envelopment Analysis (DEA) and the Tobit model. *Journal of Global Entrepreneurship Research, 8*, 37. doi:10.1186/s40497-018-0138-y.
Wu, C.-. C., Kao, S.-. C., Wu, C.-. H., & Cheng, H.-. H. (2006). Examining retailing performance via financial index. *Asia Pacific Management Review, 11*(2), 83–92.

PhD Olli-Pekka Hilmola is working as a Professor in LUT University, in Kouvola, Finland. He is affiliated with numerous int. journals through editorial boards, including Industrial Management and Data Systems, Decision Support Systems, and Expert Systems with Applications. dr.. Hilmola has published more than 160 refereed journal manuscripts. He is currently serving as Adjunct Professor in Taltech/EMERA, Estonia.