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Kriging analysis of an integrated demand management process in softwood industry

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Abstract: Objective: This paper aims to develop a basic understanding of a demand management process integrating sales and operations planning (S&OP) and order promising in a Make-To-Stock environment and to compare different demand management policies. **Contribution:** Typical researches about demand management processes analyze few system specifications or vary few potential factors one at time. Yet, we can get additional insights by employing design of experiments (DOE). **Methodology:** For making promises, we compare a First-Come First-Served approach to an approach using nested booking limits and giving advantage to profitable customers and attractive periods. Considering various sequences of order arrival, we generate Kriging metamodels that best describe the nonlinear relationships between the simulation responses and system factors for Canadian softwood lumber firms. We employ a Latin hypercube design to take into account different environmental scenarios. **Results:** Our analysis reveals the potential to improve the performance of the demand management process if we know high-priority customers needs before fulfilling less-priority orders and if we use nested booking limits concept.

Keywords: Integrated demand management process, Revenue management, Sales and operations planning, design of experiments, Kriging, softwood lumber industry.

1. INTRODUCTION

1.1 Motivation and background

This research is motivated by the need of Canadian softwood lumber firms operating in a supply-constrained environment and facing heterogeneous and seasonal market, to improve their demand management process and to anticipate how this process will perform in different situations. The dominant thinking currently in the Canadian lumber industry is to maximize the production volume with the available resource, which is constrained by raw material availability and complexity of divergent production processes. Although sawmills are operating at full capacity most of the time, they are not taking advantage from seasonal fluctuations of prices and from the willingness of some customers to pay more for better services. For this end, an integrated demand management process (IDMP) has been proposed by Ben Ali et al. (2014). They integrate sales and operations planning (S&OP) and order promising models, particularly those based on revenue management (RM) concepts. Our paper aims i) to develop a basic understanding of this process facing various sequences of order arrival and taking various market disturbances into account and ii) to compare different management policies.

To efficiently make sales decisions, the impact of relevant factors affecting the IDMP performance must be well understood. Based on multiple meetings with softwood lumber managers, we identify that sales managers have two principal preoccupations: to maximize margin profits and to sell scarce products to the right customer at the right time. The simulation of the IDMP proposed by Ben Ali et al. (2014) offers the possibility to experiment several demand management approaches and to measure the impact of different factors on the IDMP performance. However, it is inefficient to vary factors one at a time (Kleijnen et al. (2005), Montgomery (2009), Law and Kelton (2000)) since it fails to consider any possible interactions between factors and nonlinear relationships. Therefore, using design of experiments (DOE) becomes substantial in order to lead sales managers in softwood industry to good practices in different situations.

1.2 Related literature

S&OP and Revenue management in manufacturing:

S&OP is a tactical process which supports cross-functional integration (Oliva and Watson, 2011) and links company strategy and operational planning. Although there is diverse researches available concerning S&OP implementation (Pedroso et al., 2016), systematic revues of Thom et al. (2012) and Tuomikangas and Kaipia (2014) show that there is still a need for "more in-depth case studies with multiple perspectives to provide a deeper understanding and guidelines for companies to manage the S&OP implementation challenges". In this context, this paper aims to provide a better understanding of the link between the S&OP and the order promising function, particularly when the organization strategy focuses on customer heterogeneity.

While S&OP makes mid-term decisions, order promising is a real-time problem which has impacts not only on company profitability and customer service level in the short, medium and long term, but also has significant influence on scheduling and execution of manufacturing and logistics activities

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(Pibernik and Yadav, 2009). When all demand cannot be fulfilled, introducing RM in order promising activity can be considered as a powerful tool ensuring higher profitability and forging a stronger relationship with customers less sensitive to price (Stadtler and Kilger, 2005). First studies about the application of RM concepts in manufacturing were in Make-To-Stock (MTS) contexts (Meyr (2009) and Quante et al. (2009)). Later, more advanced works have been proposed for Assemble-To-Order environment (Gao et al. (2012) and Guhlich et al. (2015)) and Make-To-Order environment (Spengler et al. (2007) and Volling et al. (2011)).

The relevance of integrating order promising with tactical planning tasks was exhibited in a built-to-order context by Volling and Spengler (2011), which explicitly model order promising and master production scheduling as distinct and interdependent planning functions. In order to consider mid-term market seasonality and customer differentiation, Ben Ali et al. (2014) integrated order promising based on RM concepts and S&OP. Existing studies dealt separately with S&OP and RM in complex manufacturing situations. Among all these researches, none have employed DOE.

DOE for simulation systems in supply chain settings and Kriging metamodeling:

Kleijnen et al. (2005) summarize the main goals of DOE as: 1) developing a basic understanding of a particular simulation model or system by analyzing factor effects, 2) finding robust decisions and 3) comparing the merits of various decisions or policies. Factorial designs (full or fractional) are the most popular DOEs used in supply chain settings, but the disadvantage of these designs that the number of scenarios grows exponentially when the number of factors or the number of factor levels increase. Taguchi (1987)'s designs are also widely common to identify robust decision factor settings. These designs are limited to main-effects, which is too restrictive for simulation environments (Kleijnen et al., 2005). Employing finer grids (more than two or three levels) for some factors is important to view nonlinear relationships. Using Latin Hypercube Designs (LHD) makes the samples more uniformly spread in the design space (Cavazzuti, 2013). These designs are applied in both deterministic and random simulation experiments and assume that an adequate metamodel is more complicated than a low-order polynomial one(Kleijnen, 2017). Among such metamodels, Kriging generates smooth metamodels, possibly with local hilltops (Kleijnen et al., 2005). LHD is the most popular design used with Kriging in simulation analysis. Our study is among the firsts in literature to combine LHD and Kriging in a supply chain setting to analyze factor effects and to compare different demand management policies.

1.3 Contribution and paper structure

Overall, the contributions of our paper are: (1) we propose a procedure to experiment different demand management approaches and to analyze the behavior of an IDMP facing various sequences of order arrival and taking various market disturbances into account, (2) we employ a design of experiments and we use LHD and Kriging metamodeling to scan relevant market factors on the IDMP performance. The proposed approach is relatively new in theory and in particular for demand management purpose in a supply chain setting. Finally, (3) we provide guidance for firms operating in supply-constrained environment, such as Canadian softwood firms, to choose the best approach/practice in different market situations.

The remainder of this paper is organized as follows. In Section 2, we describe the industrial context. Section 3 exposes the chosen factors and the response measures. We present the procedure adapted to analyze the behavior of an IDMP facing various sequences of order arrival and taking various market disturbances into account, and to experiment different demand management approaches. Section 4 rationalizes how experiments have been performed and analyzes results, while Section 5 concludes this research and provides industrial recommendations.

2. INDUSTRIAL CONTEXT

Market characteristics: Confronting various trade and economic pressures, Canadian softwood lumber companies try hardly to remain profitability and to maintain positive profit margins(Dufour, 2007). In this context, the studied firm is an illustrative case inspired by softwood lumber manufacturers located in Eastern Canada. In this region, lumber manufacturers offer their products to Canadian market, Northeastern American market and others. A large portfolio of products is offered to heterogeneous customers, having different attitudes and priorities. Home improvement warehouse companies and housing component manufacturers, for example, are willing to pay more for better services. Other customers, such as dealers and distributors, are more sensitive to price.

Demand characteristics: Demand for softwood lumber products greatly exceeds supply. In addition, prices are expected to move higher going into some periods of the year as demand increases. Most of these seasonal fluctuations in softwood lumber prices can be explained by demand seasonality related to construction activities.

Sawmills/production characteristics: The studied network is composed from 3 sawmills with the same capacity and dispersed over Quebec province. Sawmills can be considered as an MTS environment as its activities are driven by forecasts. Unlike traditional manufacturing (i.e. assembly) which have a convergent product structure, sawmills have complex transformation processes with heterogeneous raw materials (great diversity in terms of wood quality, diameters, length, etc.), divergent product flows (generating many products at the same time) and radically different planning problems to be solved by each mill.

Although most of the time sawmills operate at full capacity, products are not always available in stock at the right time to take advantage of price fluctuation for many reasons. First, there is almost no flexibility in raw material availability, depending on regulations of forestry activities and on the seasonal nature of harvesting operations, which limits the variation in the lumber sawing process. Second, production operations are complex since divergent processes force different products to be made dependently.

Actual situation: Whatever the market conditions, the dominant thinking of the Canadian lumber manufacturers is to produce the maximum volume with the available resource. Production is oriented towards large batches resulting in large inventories, low flexibility and low agility. Ben Ali et al. (2014) have shown the potential profit that can be obtained by taking into account demand/price seasonality and by rejecting orders, not only if not enough resources are available, but in anticipation of more valuable ones from profitable customers and for more attractive periods. In fact, they proposed an IDMP that supports sales decisions in a way to maximize profits and to enhance the service level offered to high-priority customers.

3. DOE METHODOLOGY FOR THE IDMP

We follow the pre-experimental steps recommended by Montgomery (2009) for designing and analyzing experiments.

Recognition of the problem:

The main objective of our experiments is to develop a basic understanding of the IDMP proposed by Ben Ali et al. (2014) in various environmental conditions and to compare different demand management policies. In fact, the integration between RM and S&OP is not well understood in both theory and practice. Our paper aims to perform a detailed analysis of this IDMP and to test it facing various sequences of order arrival and various market disturbances.

Selection of performance measures:

The objectives of Canadian softwood sales managers are, first, to maximize profit and sales, and second, to satisfy high-priority customers. Therefore, our results will be analyzed regarding three performance measures (see Figure 1): *The yearly profit margin*, YPM, is calculated as the difference between the total selling price and production and inventory costs. This output is measured over a year to take into account the benefits of tactical planning considering cyclical rise of demand/price. *The yearly sales*, YS, represent the total volume sold and delivered over a year. *The high-priority fill rate*, HPFR, measures the proportion of demand received from high-priority customers that has been fulfilled. While the two first indicators are oriented to evaluate global performance, the last one concerns the service level offered to high-priority customers.

Selection of factors:

In this study, we have categorical decision factors and continuous environmental factors. Combinations of values for environmental factors are called environmental scenarios. Table 1 and Figure 1 expose the different factors and their associated values.

Decision factors:

Two categorical decision factors affecting the system performances are identified based on Ben Ali et al. (2014)'s study and literature review:

1)Order promising approach A reflects how orders have to be fulfilled. Quantities to sell for each customer segment at each period of the year are already set by the S&OP at the tactical level. The first approach (NBL) makes promises using Nested Booking Limits. This RM perception can be applied in a manufacturing setting in order to take advantage of customer heterogeneity and profitability variation over time. According to Talluri and Van Ryzin (2004), setting booking limits is a way to control the availability of capacity. So, this approach can support managers in a supply-constrained environment, such softwood lumber case, to decide which orders should be rejected in anticipation of more valuable orders, not only if not enough resources are available. Further with nesting, capacities overlap in a hierarchical manner depending on the expected profit margin, so that capacities initially designated

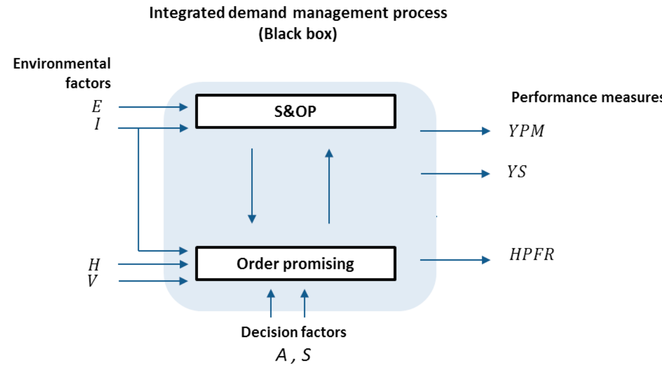

Fig. 1. Performance measures and factors

Table 1. Factors and their associated values

Factor type	Factors		Values/Ranges
Categorical decision factors	Order promising approach	A	{NBL,FCFS}
	Order arrival sequence	S	{ASC,RAND,DESC}
Numerical environmental factors	Demand intensity	I	[1.25%,1.75%]
	Demand forecast error	E	[-20%,+20%]
	Customer heterogeneity	H	[+5%,+25%]
	Coefficient of variation	V	[0,1]

to a specific couple (customer segment, period) can be sold to other couples generating better profits. NBL approach will be compared to a First-Come First-Served approach (FCFS), which simply decides if we accept or refuse each order, based only on resources availability.

2)Order arrival sequence S reflects how orders are coming at real-time level. In this study, we consider three sequences: an ascendant sequence (ASC) where orders are received in an ascending order of priority, a random sequence (RAND) where orders from different segments are randomly received, and finally a descendant sequence (DESC) where orders are received in a descending order of priority. S can be considered as a decision factor, since in our industrial context, sales managers can simulate high-priority customers to know their needs before receiving less-priority orders.

Environmental factors:

Environmental factors are uncontrollable in the real-world, but they are estimated and approximately controlled for experimental purpose. Based on the different market challenges faced by softwood sales managers, we select four relevant environmental factors. Each factor can take a numeric value in a defined range.

1)Demand intensity I is introduced at S&OP level and at real-time level. It represents the percentage of production capacity required to fulfill the demand such as Forget et al. (2009). The demand intensity of 100% has been estimated by pushing infinity of supply into the supply chain and observing the maximum production output that can be produced. Since demand greatly exceeds supply in softwood lumber context, we vary I between 1.25% and 1.75%, similarly to Dumetz et al. (2015).

2)Demand forecast error E is introduced at S&OP level. Similarly to Azevedo et al. (2016), forecast of all products in all weeks presents an error E between -20% and +20 % in terms of demand volumes (already affected by I).

3)Customer heterogeneity H is introduced at real-time level and reflects the selling prices offered by different customer segments: High-priority segments are ready to pay H% more than the market price, while low-priority segments pay H% less than the market price. Medium-priority segments represent the majority of customers and the price that they will pay is equal to market price.

4)Coefficient of variation V reflects the demand variability (such as in Quante et al. (2009)) and is introduced only at the real-time level. Order size is affected by a standard deviation = V $\times$ average order size, while the average order size is calculated as total demand (already affected by I) divided by a fixed number of received orders.

Choice of experimental design:

We choose to cross a high-resolution design for categorical decision factors (all combinations are considered) with an LHD for numerical environmental factors, as shown in Figure 2. Each combination of decision factors is simulated for each environmental scenario (i.e. combination of the environmental factors). For each environmental scenario, we estimate the mean and variance of simulation responses over n replicates per combination of decision factor values. So, six Kriging metamodels will be obtained by the end, one for each decision factor combination. LHD is selected so that the environmental factors will be uniformly spread in the experimental region. We consider $m = 24$ rows for the LHD, so the total number of runs per replicate is $6 \times 24 = 144$. [1]

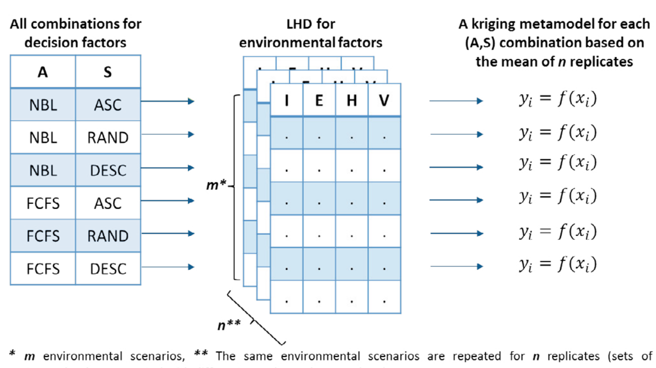

Fig. 2. Framework for the methodology proposed

4. DOE AND PERFORMANCE ANALYSIS

4.1 Performing the experiments

The LHD is designed in JMPs experimental design software. Since we are considering stochastic demand, the simulation of the 24 different environmental scenarios (LHD scenarios) was replicated 3 times. So, a total of $6 \times 24 \times 3 = 432$ runs were performed and each run takes approximately 24 hours.

Randomness in our experiments concerns generating orders and includes inter-arrival times, delivery delays and quantity required by an order: (1) The inter-arrival times between successive orders depends on product required and on customer segment and follows Poisson distributions. (2) The delivery delays depend on customer segments, i.e. on customer sensitivity to pay more for a shorter delay. Delivery delays follow a triangular distribution whose parameters are respectively set to (1, 2, 3) periods for high-priority segments and (1, 3, 4) periods for other segments. (3) Quantity required by each order depends on product required and follows a normal distribution. For each product, the mean of the distribution is calculated as the weekly demand forecasts divided by a fixed weekly number of orders. The mean is multiplied by the coefficient of variation V to have the standard deviation.

For each environmental scenario (i.e. combination of values of the environmental factors), a list of orders is generated following the procedure explained above. This list is then sorted differently to have an ascendant sequence (ASC), a random sequence (RAND) and a descendant sequence (DESC). So, for each environmental scenario, three final lists are obtained, sorted respectively by order of priority and by reception date.

To produce different replicates, this procedure of data generation is repeated for the same scenarios, but with different pseudo-random numbers (see Figure 2). Finally, we used the average of all replicates to observe the evolution of performance measures (y_i). For each decision factor combination, Kriging metamodels are constructed to express (y_i) in terms of environmental factors (x_i).

4.2 Performance analysis

Prediction profiles 3 and 4 are drawn based on Kriging metamodels of different performance measures. These graphs show how the predicted response as one factor is changed while the others are held constant at the current values of factors. Current values of factors and current predicted values of responses are presented in red respectively in the x-axis and the y-axis. The yearly profit margin (YPM) and the yearly sales (YS) are respectively expressed in Canadian dollars ($) and on thousand board-feet measure (MFBM).

The comparison between Figures 3 and 4 exhibits that NBL approach offer the best performances in all cases due to its sensitivity to customer profitability. The gap between NBL and FCFS approaches is more pronounced if the high-priority orders arrived after low-priority orders (ASC sequence). Regarding the order arrival sequence, it is obvious that the earlier high-priority orders arrive, the more margin profit we will make.

Figures 3 and 4 lead us to believe that the most pertinent environmental factors affecting the yearly margin profit (YPM) are the demand intensity I and the demand forecast error E. Therefore, we analyze the experimental results through ANOVA (see Figures 5 and 6) to examine the contribution of all factors and interactions for each combination (A,S).

For both demand management approaches, ANOVA tables for the yearly profit margin (YPM) confirm that I and E represent a significant part of the contribution, especially when using NBL approach. However, YPM obtained with FCFS approach is further affected by customer heterogeneity H. This factor penalized more the YPM when high-priority orders arrived after low-priority orders (ASC sequence): since FCFS approach focuses on feasibility rather than profitability, this approach does not anticipate to receive more valuable orders, so capacity can be exhausted by less profitable orders and can not fulfill more profitable orders received later.

[1] 144 will be equal to the number of runs ($2^4 \times 3^2 = 144$) of a full factorial design with 4 two-level factors (A, I, H, V) and 2 three-level factors (S, E). However, much more information can be obtained through our design.

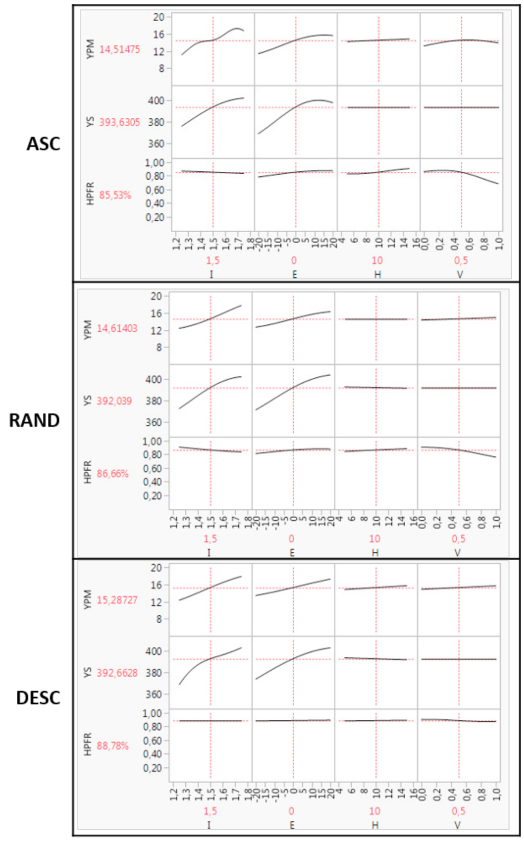

Fig. 3. Performance measures for NBL approach

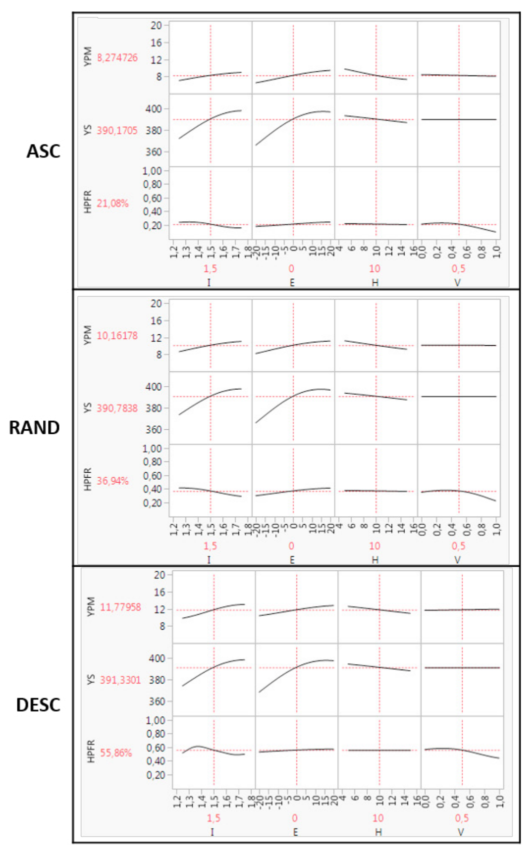

Fig. 4. Performance measures for FCFS approach

		Main Effect	I Interaction	E Interaction	H Interaction	V Interaction
ASC	I	0,6079579	.	0,0505497	0,0019139	0,0008338
	E	0,2881797	0,0505497	.	0,000432	0,0126814
	H	0,0023311	0,0019139	0,000432	.	0,0003564
	V	0,0175068	0,0008338	0,0126814	0,0003564	.
RAND	I	0,6319658	.	0,0108042	0	0,0001169
	E	0,3442535	0,0108042	.	0	0,0016179
	H	0	0	0	.	0
	V	0,011241	0,0001169	0,0016179	0	.
DESC	I	0,6608047	.	0,0004612	1,2517e-5	4,0783e-5
	E	0,3100156	0,0004612	.	3,0153e-5	4,1515e-5
	H	0,0156213	1,2517e-5	3,0153e-5	.	2,8191e-7
	V	0,0129717	4,0783e-5	4,1515e-5	2,8191e-7	.

Fig. 5. ANOVA for YPM obtained with NBL approach

		Main Effect	I Interaction	E Interaction	H Interaction	V Interaction
ASC	I	0,1883345	.	0,00218	0,0076418	0,0000107
	E	0,5002522	0,00218	.	0,0012458	8,532e-6
	H	0,2921827	0,0076418	0,0012458	.	0,00004
	V	0,0080871	0,0000107	8,532e-6	0,00004	.
RAND	I	0,2936191	.	0,0016845	0,0010151	0
	E	0,5155215	0,0016845	.	0,0005513	0
	H	0,1876068	0,0010151	0,0005513	.	0
	V	0	0	0	0	.
DESC	I	0,4267316	.	0,0017955	5,0376e-5	0
	E	0,4908463	0,0017955	.	0,0007674	0
	H	0,0798084	5,0376e-5	0,0007674	.	0
	V	0	0	0	0	.

Fig. 6. ANOVA for YPM obtained with FCFS approach

5. CONCLUSION AND INDUSTRIAL RECOMMENDATIONS

In this paper, we extend the research in demand management for MTS manufacturing systems and analyze via DOE techniques a process integrating S&OP and order promising, considering differentiated demand segments, divergent product structure and facing various market disturbances. Our study is among the few studies that use a Kriging metamodeling based on LHD in supply chain context.

Our simulation results confirm that NBL approach can be a powerful tool to maximize revenues facing different environmental conditions. We show also how order arrival sequence can play a relevant role, especially with high customer heterogeneity. Therefore, sales managers in softwood lumber industry should, first of all, intensify their efforts to know earlier the needs of high-priority customers and to improve the performance of Customer Relationship Management, which is simpler than implanting a new demand management platform. Then, more focus should be given to customer heterogeneity by using an integrated demand management process able to anticipate orders from profitable customers and for more remunerative periods.

Future extensions can be eventually to consider other factors. Finally, it is important to note that both results and methodology can be generalized for other industry sectors.

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