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Demand planning and sales forecasting for motherboard manufacturers considering dynamic interactions of computer products

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A R T I C L E I N F O

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A B S T R A C T

Demand planning (DP) and sales forecasting (SF) are two critical issues to achieve successful supply chain analytics. Generally, DP refers to determining the aggregate demand for a common component or sub-assembly required by various finished products. In contrast, SF is conducted to estimate sales revenues of the firms. In the past, DP usually focused on optimizing resource allocation while SF is roughly based on historical data. In reality, DP and for the upstream motherboard and SF for the firm closely rely on the estimation of sales volumes of the downstream computer products. Meanwhile, the dynamic interactions between the main competitors significantly influences the performance of SF. To highlight the impacts of demand uncertainties and dynamic interactions, this research presents a novel framework to overcome difficulties: (1) demand uncertainties arising from seasonal variations and cyclic trends in computer products are captured, (2) DP and SF consider the change of product volatility, (3) the dynamic interactions between the MB and computer products are considered to elicit managerial insights. Experimental results show that the presented framework successfully achieves the above-mentioned goals and has potential to be generalized to other industrial components.

1. Introduction

Motherboard (MB) is a key component that mechanically fastens and electrically connects resistors, capacitors, inductors, processors, chipsets, and interface controllers. The name, "mother", means that all components attached to printed circuit board form an interface to communicate and functionalize computer products, such as desktops, laptops, servers, printers, etc. On the one hand, demand volatility and seasonal variations arising from downstream products (vertical relationships) results in difficulties in conducting effective demand planning (DP) and sales forecasting (SF) for upstream component manufacturers (Shapiro, 2006; Cho & Lee, 2013; Saleh, Rabie, & Abo-Al-Ez, 2016). On the other hand, technology competition or complementary dynamics between downstream products (horizontal relationships) also leads to obstacles in achieving successful DP and SF (Hood, Bermon, & Barahon, 2003; Jacobs & Chase, 2015; Tsai, Hsu, & Balachandran, 2013). Demand uncertainties composed of cyclic variations mixed with trends tend to rise and fall within specific time durations. This phenomenon can be partially explained by the so-called "*bullwhip effect*": a small variation in the downstream viewed as a ripple can be amplified as a big variation in the upstream (Miller & Park, 2005; Addo-Tenkorang & Helo, 2016; Stevenson, 2015).

As a consequence, a systematic way to capture both vertical and horizontal relationships that can link DP into SF is necessary to achieve successful supply chain management (Guidolin, Guseo, & Mortarino, 2019). Specifically, demand uncertainty arising from downstream computer products can be roughly attributed to several reasons (Holt, 2004; Huang, Chang, & Chou, 2008; Ziser, Dong, & Wong, 2012; Wang & Chien, 2016; Aryal, Liao, Nattuthurai, & Li, 2018): (1) smartphones and tablets have more or less replaced the conventional desktops and laptops. Meanwhile, smartphones have also killed low-end digital cameras (demand-pull transition), (2) artificial intelligence, big data, and cloud computing have significantly increased the requirements for servers and high-end graphics cards (technology-push transition), (3) smart cars are expected to boost automotive applications of MB (new applications of existing technologies), (4) internet of things (IOT) and cyber-physical systems (CPS) have dramatically brought about a rising wave of smart-home appliances (extensions of existing technologies). Hence, this research accommodates both vertical and horizontal relationships to incorporate them into DP and SF (Wang & Chen, 2019).

To respond to demand uncertainties and product volatility, sensitivity analyses with respect to computer products (desktop, laptop,

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server, printer) and MB can help firms better estimate its production capacity and sales revenues. For instance, a manager needs to know the impact on the firm if a computer product is expected to grow or decline by 10%. To conduct data-driven decision making, DP and SF for the upstream components must be linked together and related to the downstream products. Although numerous quantitative techniques have been proposed (Maia & Carvalho, 2011; Saleh et al., 2016; Zhong, Newman, Huang, & Lan, 2016; Al-Musaylh, Deo, Adamowski, & Li, 2018), they have the following drawbacks:

- Mathematical programming usually handles internal resource constraints to determine the optimal capacity without considering external market demand,
- Regression considers the predictors to estimate the outcome but incapable of tackling seasonal effects as well as identifying the *time-lags* between them,
- Time-series can capture "*time-lags*" between the predictors and the outcome but it cannot accommodate the dynamic interactions to reveal managerial insights.

Consequently, a conceptual framework shown in Fig. 1 is presented to highlight the impacts of computer products and dynamic interactions on MB manufacturers. In DP, global sales of computer products drive the demand for MB. In SF, the vertical relationships between the MB and computer products and the horizontal relationships among MB manufacturers concurrently estimate financial performances. The rest of the study is structured as follows. Section 2 briefly reviews DP and SF in supply-chain analytics. Section 3 details the proposed framework. Experimental results are justified in Section 4. Discussions and research limitations are described in Section 5. Conclusions and future work are shown in Section 6.

2. Literature review on supply chain analytics

Business analytics has been incorporated into supply chain management to form the paradigm of supply chain analytics (SCA). In the perspective of SCA (Trkman, McCormack, Oliveira, & Ladeira, 2010; Zhong et al., 2016; Aryal et al., 2018), this research aims at linking two critical issues: demand planning (DP) and sales forecasting (SF). To conduct aggregate DP, an operation manager needs to plan strategic actions a priori and respond to the optimistic or pessimistic sales volumes of downstream products. In contrast, to conduct precise SF, a financial manager needs to take both vertical relationships (between the upstream component and downstream products) and horizontal relationships (between firms) into account (Shapiro, 2006). Therefore, DP and SF for the upstream component must be linked into the prediction of the downstream products although demand is volatile and uncertain (Huang et al., 2008; Wu & Chuang, 2010; Wang & Chen, 2019).

2.1. Operation and demand planning (DP)

Operation and demand planning is a well-known concept to set up a time phase to align production orders with customer deliveries, taking into account material availability, resource availability and knowledge of future demand (Bertrand & Rutten, 1999). Generally, it consists of the following steps: (1) Determining suitable product mix and capacity load to meet customer requirements. (2) Preparing the required resources to match the preset production level. (3) Delivering production orders and scheduling the activities in the manufacturing facility and plants. Managers often conduct planning in terms of the available resources required to produce finished goods (Stevenson, 2015). Unfortunately, unexpected demand uncertainties or seasonal variations usually form obstacles in achieving successful DP. Capacity strategies, such as expansion, contraction, and wait-and-see, need to be flexibly adjusted (Miller & Park, 2005; Chen, Chen, & Lu, 2013; Chen, Chen, Pratama, & Tu, 2018; Wu & Chuang, 2010, 2012). An operation manager needs to carefully think about: "*What kind of capacity is suggested?*" and "*How much capacity should be prepared*?" Insufficient capacity results in lost sales while excessive capacity leads to sunk cost due to unfulfilled orders.

In practice, decision-making on capacity allocation can be treated as a mathematical-programming problem, including real options (Hood et al., 2003; Huang et al., 2008), dynamic programming (Wu & Chuang, 2012), mixed integer programming (Chen et al., 2013), and meta-heuristics (Chen et al., 2018). Clearly, most of the aforementioned studies focused on internal resource constraints to determine the optimal product mixes with respect to different technology generations and manufacturing sites. In contrast, the impacts of external markets, demand uncertainties, and the relationships between the upstream components and the downstream products are rarely addressed. To conduct data-driven decision making (Sahay & Ranjan, 2008; Cho & Lee, 2013; Lau, Ho, & Zhao, 2013; Wang, Cheng, & Deng, 2018), strategic DP for upstream components closely relies on the prediction of downstream products.

2.2. Sales and sales forecasting (SF)

Forecasting can assist a firm in achieving better inventory control and financial estimation. Typical forecasting methods are either qualitative or quantitative (Lau et al., 2013; Jacobs & Chase, 2015).

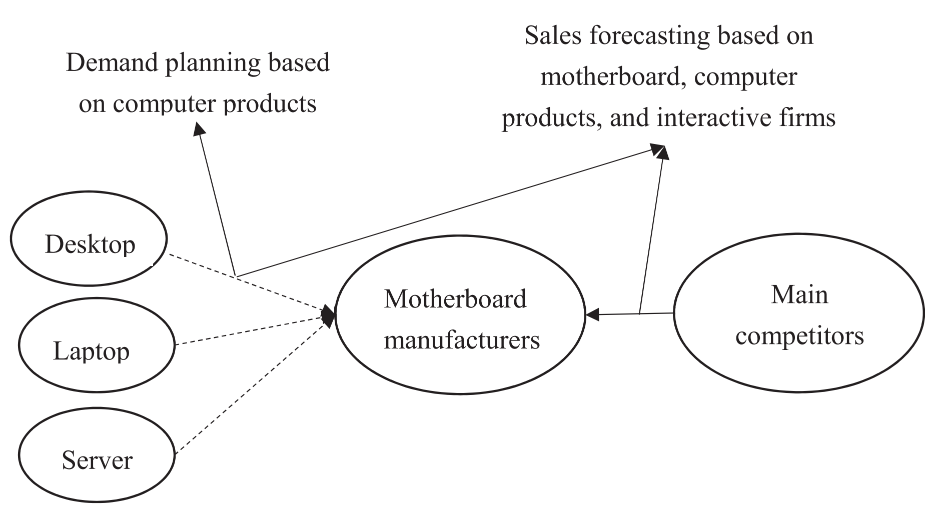

Fig. 1. Conceptual research framework.

Qualitative schemes include panel consensus, Delphi method, historical analogy, and market research. Sales managers, financial managers, and production managers meet together, discuss, and communicate with each other to reach a consensus. Obviously, qualitative schemes are too reliant on expert opinions and lack evidence to support decision making. In contrast, quantitative schemes including regression methods and time-series models are systematic, reliable and persuasive (Weron, 2014; Stevenson, 2015; Guidolin et al., 2019). Mathematically, regression methods can identify the causalities between the predictors and the dependent outcome whereas time-series predicting future values of the outcome based on its historical data can accommodate seasonal variations or linear trends (Wang et al., 2018).

To highlight research contribution, Table 1 briefly compares this research to the past studies. Apparently, most past studies treated DP and SF independently and most of them have the following drawbacks: (1) in demand planning, mathematical programming has been adopted to optimize resource allocation without considering external environments, such as associated products and main competitors. Meanwhile, demand volatility and seasonal variations are not effectively captured, (2) in sales forecasting, time-series is constructed but only based on historical data. Time-lags between the predictors and the outcome are failed to be included. Similar to demand planning, the impacts of downstream computer products and dynamic interactions between main competitors are rarely considered in sales forecasting, and (3) although very few studies address the impacts of dynamic interactions, only LV model is considered without benchmarking. In practice, it's difficult for managers to successfully conduct sensitivity analyses without capturing the relationships between the products and the component (MB) and between the firm and its competitors.

To facilitate research gaps, this research adopts hybrid models because of the following reasons (Box, Jenkins, & Reinsel, 2005; Al-Musaylh et al., 2018): (1) regression methods can neither capture seasonal variations in computer products nor consider time-lags between the downstream products and the upstream components and (2) time-series models can incorporate demand uncertainties arising from computer products but fail to capture dynamic interactions between the products and the component. In practice, eliciting the dynamic interactions can help managers conduct sensitivity analyses to quantitatively estimate the impacts of growing or declining sales volumes of a product on the upstream component and competing firms.

Table 1
Overall comparison between this research and the past studies.

	Sales/financial forecasting	Demand/operations planning	Dynamic interaction
This research	Dynamic ARIMA	ensemble learning (RF, GB)	VAR, LV
Hood et al. (2003)		stochastic programming	
Miller and Park (2005)		real option	
Wu and Chuang (2010)		dynamic programming	
Ziser et al. (2012)	BPN, SVR		
Chen et al. (2013)		MILP	
Lau et al. (2013)	BPN, MDL		
Chen et al. (2018)		ant colony optimization	
Tsai (2013)			LV
Tsai et al. (2013)			LV
Tsai (2017)			LV
Huang et al. (2008)	simulation	real option	
Wu and Chuang (2012)		stochastic programming	
Al-Musaylh et al. (2018)	MARS, SVR, ARIMA		
Wang and Chen (2019)	ARIMA, MARS, SVR		VAR

% ARIMA: autoregressive integrated moving average, BPN: backpropagation neural network, GB: gradient boosting, LV: Lotka–Volterra, MARS: multivariate adaptive regression splines, MDL: minimum description length, MILP: mixed integer linear programming, RF: random forest, SVR: support vector regression, VAR: vector autoregression.

3. Proposed techniques

Time-series models and ensemble learning are the two common approaches to conduct quantitative forecasting. For clarity, Table 2 compares various schemes in terms of relative strengths or weaknesses. Autoregressive integrated moving averaging (ARIMA) has lots of superiorities, such as capturing seasonal variations and accommodating *time-lags* between the predictors and the outcome. By contrast, ensemble learning, such as random forest (RF) and gradient boosting (GB), is good at prioritizing the degree of importance of the predictors and measuring the impacts of shifting a specific predictor on the outcome. To measure dynamic interactions for conducting collaborative forecasting, vector autoregression (VAR) and Lotka-Volterra models (LV) demonstrate their superiority. In this study, ANN (artificial neural network) and SVM (support vector machine) are not considered because ANN has so-called black box characteristics and SVM is too tedious to solve mathematical programming (Ziser et al., 2012; Lau et al., 2013; Wang et al., 2018; Wang & Chen, 2019).

Thus, Fig. 2 details the presented framework as follows: (1) Global shipments for upstream MB and downstream computer products (desktop, laptop, and server) are collected. (2) Time-series using ARIMA and ensemble learning based on RF and GB are applied to conduct demand planning (DP) and sales forecasting (SF) for MB manufacturers. (3) VAR and LV model are used to elicit the dynamic interactions between MB and computer products and generate managerial insights between MB manufacturers. For clarity, Fig. 3 shows a data-flow plot indicating the input variables and the outcome for various techniques. For ensemble learning and time-series, the causal relationships between the predictors (shipments of computer products) and the outcome (shipments of MB or sales revenues of MB manufacturers) are identified to conduct DP and SF. Similarly, LV models and VAR are responsible for accommodating dynamic interactions to generate managerial insights.

Specifically, the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to measure forecasting errors (Weron, 2014; Wang & Chuang, 2016; Tsai, 2017; Al-Musaylh et al., 2018):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{e_i}{y_i}\right| \tag{3}$$

where n is the number of samples and $e_i = F_i - y_i$ is an error defined as the predicted value (F_i) minus the real data (y_i).

Table 2
Overall comparison between different forecasting techniques.

	ARIMA	VAR	RF	GB	LV
Capturing seasonal variations	*	*			
Extracting key predictors			*	*	
Estimation of confidence intervals	*	*			
Accommodation of time-lags	*	*			*
Collaborative forecasting		*			*
Sensitivity analysis	*		*	*	

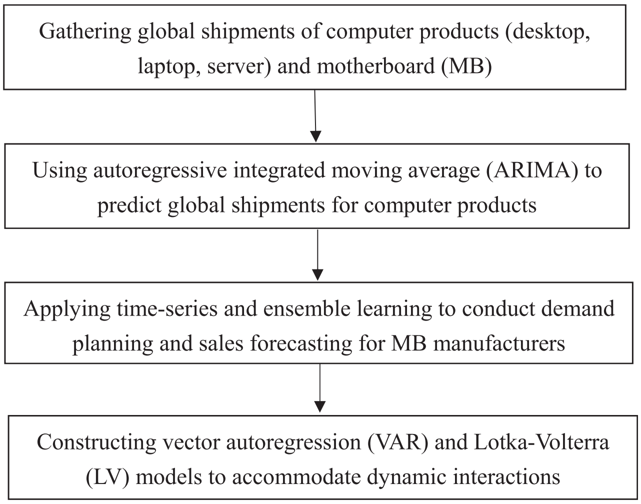

Fig. 2. Proposed methodological techniques.

3.1. *Time-series*

Autoregressive integrated moving average (ARIMA) is selected to construct time-series models for conducting DF. Demand for downstream products or upstream components tend to rise and fall within a specified time duration owing to seasonal variations and uncertainties. Thus, ARIMA is appropriate to take these cyclic components in to account. ARIMA has generally two types: self ARIMA and dynamic ARIMA. Self ARIMA only considers the historical values of the outcome to predict its future values. In contrast, dynamic ARIMA concurrently considers the historical values of the predictors and the outcome to predict future values of the outcome. For convenience, a general ARIMA is mathematically formularized as (Box et al., 2005):

$$\varphi(\mathrm{B})(1 - \mathrm{B})^d z_t = \theta(B)a_t, \tag{4}$$

$$\varphi(\mathrm{B}) = \varphi_0 - \varphi_1 B - \varphi_2 B^2 - \cdots\varphi_p B^p, \tag{5}$$

$$\theta(\mathrm{B}) = \theta_0 - \theta_1 B - \theta_2 B^2 - \cdots\theta_q B^q, \tag{6}$$

where $\varphi(\mathrm{B})$ is called an autoregressive operator with an order p, $\theta(\mathrm{B})$ is called a moving average operator with an order q, and B is a backward-shift operator. However, the stationary series may contain seasonal (cyclic) components. In addition to the three common parameters, (p, d, q), seasonal parameters, (P, D, Q), are added to generate a more general form called seasonal ARIMA (Cho & Lee, 2013; Wang et al., 2018):

$$\Phi(\mathrm{B}^s)\varphi(\mathrm{B})(1 - \mathrm{B})^d(1 - \mathrm{B}^s)^D z_t = \Theta(B)\theta(B^s)a_t, \tag{7}$$

$$\Phi(\mathrm{B}^s) = \Phi_0 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots\Phi_p B^{ps}, \tag{8}$$

$$\Theta(\mathrm{B}^s) = \Theta_0 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots\Theta_q B^{qs}, \tag{9}$$

where $\Phi(\mathrm{B}^s)$ is a seasonal autoregressive operator (order p), $\Theta(\mathrm{B}^s)$ is a seasonal moving-average operator (order q), and $\mathrm{B}^s$is a backward-shift operator.

Vector autoregression (VAR) does not strictly separate all of the variables into the predictors or the outcome. It treats all variables as the factors within a dynamic system so they can be mixed to predict each other. In reality, many possible combinations of the predictors can be considered. To reduce computational complexity, Granger causality test is required to determine whether the predictor is significant or not (Granger, 1969). For simplicity, a bivariate system with VAR (2) is formulated as follows:

$$\begin{bmatrix} \mathrm{Y}_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \mathrm{c}_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}\begin{bmatrix} \mathrm{Y}_{1,t-1} \\ Y_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}\begin{bmatrix} \mathrm{Y}_{1,t-2} \\ Y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \tag{10}$$

where Y1 and Y2 are mutually estimated, an order two (maximal time-lag) is assumed without loss of generality, c_i is the intercept, a_{ij} is the slope of the previous period, b_{ij} is the slope of the last two period, and ε_{it} represents a residual. If a multivariate VAR with order p is considered, a matrix form should be used to generalize Eq. (10).

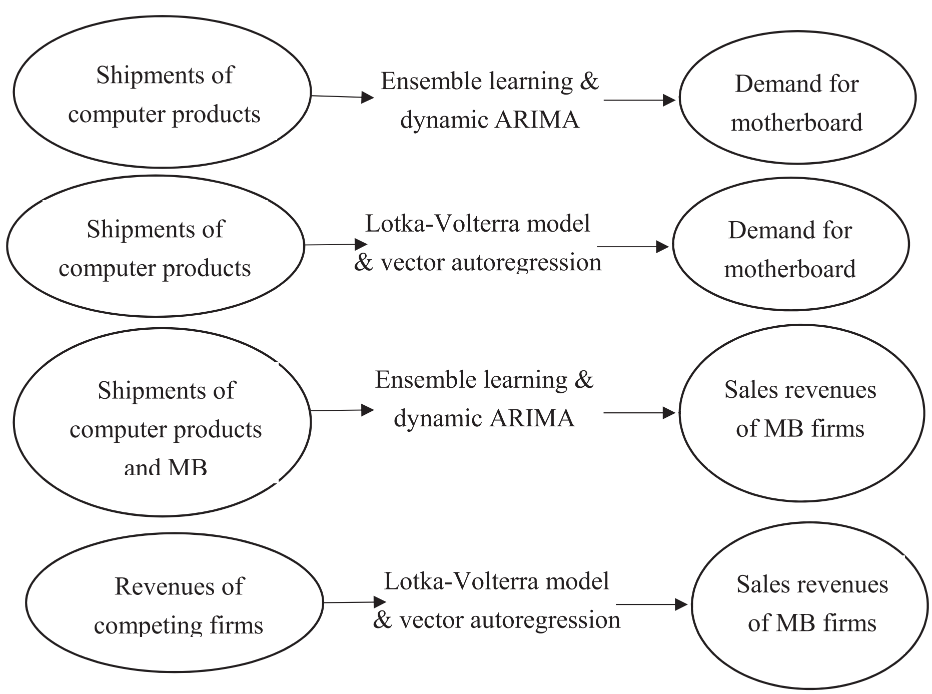

Fig. 3. Visualization of data-flow in demand planning and sales forecasting.

3.2. Ensemble learning

Ensemble learning algorithms, such as random forest (RF) and gradient boosting (GB), are usually composed of decision trees. Each tree is built based on an independent set of random vectors that are generated from a fixed probability distribution (Breiman, 1997). Ensemble method constructs a set of base models from different training data to conduct aggregate decision making. For a classification problem, the result refers to majority voting among various classification trees. For a regression problem, the result refers to an average of predictive results of various regression trees (Tan, Steinbach, & Kumar, 2010). RF, as indicated by its name, randomly selects the combinations of predictors and training samples. For clarity, assume an ensemble system consisting of 30 weak classifiers, each of which has a high error rate, $\varepsilon = 0.35$. Using the binominal principle, the minimal error rate of ensemble learning can be theoretically reduced to $e = \sum_{i=16}^{30}\binom{30}{i}\varepsilon^{i}(1-\varepsilon)^{30-i} = 0.03$. In simple words, more than half base machines are wrong, the ensemble system can make incorrect prediction. In general, its performance is much better than a single decision tree.

GB originated from Breiman (1997) and Friedman (1999) allows optimization of an arbitrary differentiable loss function (gradient descent and boosting). Gradient boosting implies using “gradient descent” with plugging a loss function, $(y-f(x))^2/2$. An easy way to explain GB is least-square regression, where the goal is to train a model to generate predictive values, $f(x) = \hat{y}$, by minimizing the mean squared error, $(\hat{y}-y)^2$, where y and $\hat{y}$ mean actual values and fitted values. Suppose at iteration m, the procedure of GB is described as: $f_{m+1}(x) = f_m(x) + h(x) = y$, in which h function is in a residual form ($h(x) = y - f_m(x)$). Mathematically, GB seeks an optimal approximation, $\hat{f}(x)$, in the form of the weighted sum of residual functions:

$$\hat{f}(x) = \sum_{i=1}^{n} w_i h_i(x) + w_0 \tag{11}$$

where n is the number of samples, w_i and w_0 are the fitted slopes and the intercept to minimize the loss function $h(x)$ and $h_i(x)$comes from individual weak base models.

3.3. Lotka-Volterra (LV) model

Lotka-Volterra (LV) model can be used to describe the dynamic interactions between the products. Based on the logistic equation, the LV model can characterize the relationships between two interactive firms, products, and brands. Two differential equations are illustrated as follows (Tsai, 2013, 2017; Tsai et al., 2013):

$$\frac{dx_1}{dt} = a_1x_1 - b_1{x_1}^2 - c_1x_1x_2, \tag{12}$$

$$\frac{dx_2}{dt} = a_2x_2 - b_2{x_2}^2 - c_2x_1x_2, \tag{13}$$

where x_i can be modeled by adopting users, shipments, revenues, etc., a_i denotes the ability of itself, b_i refers to the limitation of the object during market expansion, c_i describes the interaction between the object and its rival. In equilibriums, the differential values in Eqs. (12) and (13) are zeros. Thus, the two objects can be mutually estimated and predicted as: $x_1 = (a_1 - c_1x_2)/b_1$ and $x_2 = (a_2 - c_2x_1)/b_2$. To use discrete data, differential equations need to be transformed into difference equations:

$$x_1(t+1) = \frac{\alpha_1 x_1(t)}{1+\beta_1x_1(t)+\gamma_1x_2(t)}, \tag{14}$$

$$x_2(t+1) = \frac{\alpha_2 x_2(t)}{1+\beta_2x_2(t)+\gamma_2x_1(t)}, \tag{15}$$

where $a_i = \ln\alpha_i$, $b_i = \beta_i\ln\alpha_i/(\alpha_i-1)$, and $c_i = \gamma_i\ln\alpha_i/(\alpha_i-1)$ are used to estimate three important parameters required in constructing LV models. The original LV model can be generalized to include more entities at a time. For clarity, managerial insights regarding the parameters in LV models are described in Table 3. The relationships between two interactive objects (products, brands, technologies) can be one of the six types: pure competition (mutually harmful), predator–prey (one benefits but the other is harmed), mutualism (mutually beneficial), amensalism (one suffers but the other is unaffected), commensalism (one benefits but the other is unaffected), and neutralism (mutually independent). Apparently, LV model can well capture dynamic relationships between the related objects and incorporate them into regression models to generate managerial implications.

4. Experimental results

Initially, global shipments for the upstream MB and the downstream computer products are sampled quarterly from 2009/1Q to 2019/4Q. Data samples are collected from mic websites (https://mic.iii.org.tw/aisp/ReportS.aspx?id=CDOC20200429003) and digitimes (https://www.digitimes.com.tw/tech/rpt/datacharts.asp?CnlID= 3). In Fig. 4, it is interesting to observe desktops, laptops, and MB are declining but servers are growing (owing to strong requirements for data centers and high-speed computation). However, the growth of servers still fails to stimulate the sales of MB. Meanwhile, these computer products have obvious seasonal variations (Holt, 2004; Miller & Park, 2005). For visualization, all the data samples are normalized to be between zero and unity (*X-Min/(Max-Min)*). Additionally, the “*time-lag*” phenomenon is clearly observed: sales volumes of desktops, and laptops decline earlier than the shipments of MB. This finding supports global shipments (sales estimation) of computer products can be treated as good leading indicators to predict demand for MB.

4.1. Demand planning (DP) for the motherboard (MB)

Referring to Fig. 1 again, this research highlights a critical concept: computer products substantially drive the demand for MB. Thus, to conduct DP, computer products are treated as the leading predictors while MB is treated as the lagging outcome. Without loss of generality, time-series and ensemble-learning are concurrently adopted for benchmarking. In Table 4, time-series models include self ARIMA (using historical values of MB) and dynamic ARIMA (considering computer products). Not surprisingly, dynamic ARIMA slightly performs better than self ARIMA. Based on Akaike information criterion (Akaike, 1974), significant time-lags between computer products and MB are identified as 0, 3, and 4 (measured in quarters), respectively for desktop, laptop, and server. Ensemble-learning schemes, such as RF and GB, are used for benchmarking. Finally, VAR and LV model are adopted to accommodate dynamic interactions between computer products and the MB.

To conduct DP for MB, GB (1%) surprisingly outperforms the other

Table 3
Relationship description according to the signs of interaction parameters.

c1 c2	Relationship	Explanation
+, +	Pure competition	Both suffer from each other's existence
+, −	Predator–Prey	Entity 2 serves as direct food to entity 1
−, −	Mutualism	The case of symbiosis (win–win)
+, 0	Amensalism	Entity 1 suffers from the existence of entity 2, who is impervious to what is happening
−, 0	Commensalism	Entity 1 benefits from the existence of entity 2, who nevertheless remains unaffected
0, 0	Neutralism	No interaction between each other

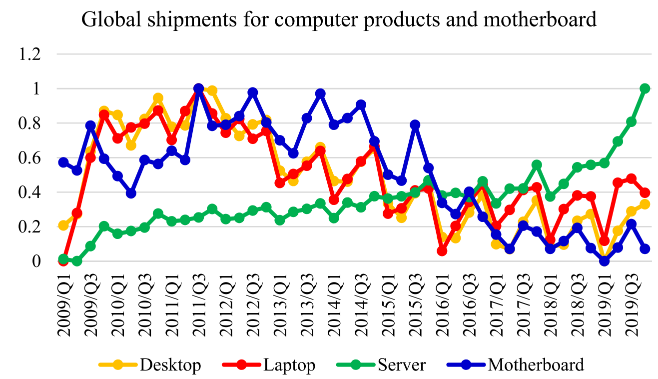

Fig. 4. Global shipments of MB and computer products (normalized scale).

methods in Table 4. All the MAPEs are between 1% and 5%. That means, our research concept is strongly support: DP for the upstream MB can be based on the estimation of the downstream computer products. As we know, VAR treats all of the variables as a system rather than dividing them into either the predictors or the outcome. Thus, VAR can concurrently predict global shipments of computer products and MB. Despite VAR performs better than LV model, it cannot elicit the relationships between computer products and MB. Therefore, LV model is constructed to assist managers in generating managerial insights. In practice, industrial practitioners can collaboratively adopt various ways to conduct DP for MB and achieve multiple goals.

4.2. Sales forecasting (SF) for MB manufacturers

Similar to demand planning, sales forecasting also considers three approaches: time series, ensemble learning, and dynamic interaction. In DP, only computer products are the predictors. In contrast, sales volumes of computer products and MB are used as the predictors in SF. Meanwhile, to accommodate the impacts of dynamic interactions, the three firms, Asus, Msi, and Gigabyte, are selected to judge the validity of this research. Notice that these firms are not only the top three MB manufacturers (Statista) but also worldwide brands in computer products. In terms of sales revenues, Fig. 5 shows that Msi and Gigabyte seem to be more similar to each other than Asus. In Table 5, it is found that RF, dynamic ARIMA, and GB respectively performs the best in Asus (4.7%), Msi (4.2%), and Gigabyte (4.2%). In SF, dynamic ARIMA and ensemble learning (RF and GB) perform slightly better than VAR and LV model because they consider different predictors. Dynamic ARIMA and ensemble learning consider computer products (desktop, laptop, server) and MB as the predictors while VAR and LV model use sales revenues of main competitors as the predictors. Thus, computer products and MB are selected as a basis to conduct sensitivity analyses.

In simple words, a manager needs to estimate the impact of product volatility (a specific product is expected to grow or decline about 10%) on sales revenues of the firms. In Table 6, sensitivity analyses with respect to three computer products and MB are measured in the percentage ratios: the absolute difference divided by the mean average. In brief, sales revenues of a MB manufacturer can grow or decline arising from any increasing or decreasing sales of computer products or MB. Quantitatively, the degree of change of sales revenues for a specific firm (Asus, Msi, Gigabyte) is due to increasing (decreasing) sales volume of a predictor (desktop, laptop, server, MB) by 10%. Very interestingly, servers, MB, and laptops respectively contribute the most to sales revenues of Asus, Msi, and Gigabyte. In addition, desktops and MB influence Msi and gigabyte more than Asus because Asus is very diverse in its product lines (including smartphones and tablets). In recent years, these three firms continually developed high-performance gaming laptops and graphics cards. In future work, these niche products need to be further included. Another famous company, Acer, is not included because it focuses on computer products without manufacturing MB. For operations managers, sensitivity analysis can provide decision supports in product-family based portfolio analyses (Otten, Spruit, & Helms, 2015; Wang, 2019). For instance, it gives a guideline to set production capacities, prepare inventories (finished goods and industrial components), and optimize resource allocation between different product lines. For financial or sales managers, sensitivity analyses can provide a quantitative basis to estimate the impacts of product volatility on sales revenues. They can think the way to optimize product portfolios depending on profitability (selling price minus manufacturing cost) and the estimation of sale volumes.

5. Discussions

To reveal managerial implications, LV models are applied to analyze the dynamic interactions between computer products and MB component (Table 7) and MB manufacturers (Table 8). Referring to Table 4 (demand planning) and Table 5 (sales forecasting), pairwise regression and collaborative forecasting are mutually constructed. Here, the predictor means the independent variable while the target means the outcome. The relationships between computer products and MB are very interesting and diverse. For instance, the "*commensalism*" relationship between two computer products (desktop and laptop) and MB means sales of desktops or laptops positively benefits demand for MB. However, the relationship between the server and MB, "*neutralism*", implies servers may not be a significant indicator to predict global shipments of MB. Although the performances of LV models are slightly worse than time-series or ensemble learning (see Table 4 again), they can concurrently capture the dynamic interactions between the MB and computer products and reveal managerial implications.

In SF, Table 8 demonstrates the relationships between the three representative firms. It is interesting to find small-scaled firms, such as

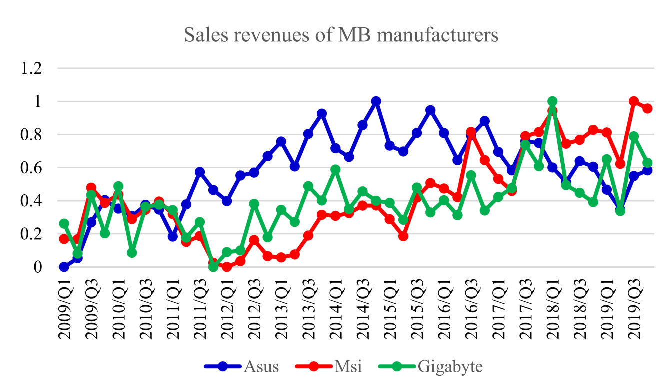

Fig. 5. Sales revenues for MB manufacturers (normalized scale).

Table 4
Demand planning for MB (global shipments in thousand units).

	Time series		Ensemble learning		Dynamic interaction	
	ARIMA	Dynamic	RF	GB	VAR	LV
RMSE	1482.9	1441.74	1182.81	496.57	1167.36	1868.9
MAE	1136.21	1055.04	955.87	344.27	881.77	1457.24
MAPE	0.034	0.032	0.03	0.01	0.027	0.045

Table 5
Sales forecasting for MB manufacturers (sales revenues in million $TWD).

	Asus			Msi			Gigabyte		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
ARIMA	7.984	6.371	0.067	2.155	1.712	0.075	1.467	1.174	0.091
Dynamic	6.268	5.072	0.053	1.135	0.929	0.042	0.918	0.702	0.054
RF	6.134	4.563	0.047	1.452	1.04	0.047	0.967	0.708	0.054
GB	6.47	4.389	0.048	1.518	1.08	0.051	0.705	0.536	0.042
VAR	6.76	5.689	0.06	1.796	1.418	0.062	1.512	1.175	0.09
LV	9.141	7.174	0.078	2.702	2.135	0.099	1.839	1.370	0.107

Table 6
Sensitivity analyses for MB manufacturers (%).

	Desktop	Laptop	Server	MB
Asus	2.7	2.52	15.96	4.72
Msi	8.47	4.13	4.09	8.59
Gigabyte	6.19	11.04	0.42	6.72

Table 7
Dynamic interactions between MB and computer products using pairwise analyses.

Target	Predictor	Parameters (α,β,γ)	Relationship
Desktop	MB	(1.242***, 7.6e−7, 6.121e−6)	Commensalism
MB	Desktop	(8.914e−1***, 1.427e−5***, −7.076e−6***)	
Laptop	MB	(1.571***, 1.059e−5, 3.525e−6)	Commensalism
MB	Laptop	(8.667e−1***, 1.075e−5***, −1.061e−5***)	
Server	MB	(1.769**, 4.467e−5, 1.669e−5)	Neutralism
MB	Server	(1.612**, 8.974e−6, 1.427e−4)	

%Significance level used: ***<0.001, **<0.01, *<0.05, and <0.1.

Table 8
Dynamic interactions among MB manufacturers using pairwise analyses.

Target	Predictor	Parameters (α,β,γ)	Relationship
Asus	Msi	(3.609**, 1.171e−2*, 6.058e−2*)	Predator–Prey
Msi	Asus	(9.499e−1***, 7.840e−3, −2.657e−3***)	
Asus	Gigabyte	(3.045**, 8.876e−3, 8.317e−2.)	Predator–Prey
Gigabyte	Asus	(1.750***, 8.335e−2*, −3.806e−3*)	
Msi	Gigabyte	(1.204***, 4.502e−3, 3.972e−3)	Neutralism
Gigabyte	Msi	(1.952***, 1.117e−1*, −2.469e−2)	

%Significance level used: ***<0.001, **<0.001, *<0.05, and <0.1.

Msi and Gigabyte, seem to be independent with each other although Fig. 5 displays similar patterns in sales revenues. Very interestingly, the relationship between Msi or Gigabyte and Asus is "*predator–prey*". It means both Msi and Gigabyte gradually penetrate Asus's market share. In other words, the growth of sales revenues in Msi and Gigabyte is achieved at the expense of the decline of Asus's sales revenue. Regardless of the entire market is either a growing pie or a fixed pie, apparently, Msi and Gigabyte are harmful to Asus's market shares. Although LV models can help managers elicit the relationships between the firm and its main competitors, it is based on aggregate sales revenues. To further understand the details, the degree of interaction between the firms should be measured in terms of specific product categories.

In this research, two important issues are particularly highlighted: demand planning for motherboard and sales forecasting for MB manufacturers. More importantly, the impacts of downstream computer products and dynamic interactions between main competitors are captured and incorporated into the presented framework (see Fig. 1 again). This research cannot be without limitations. First, only desktops, laptops, and servers are considered to forecast MB. Other products, such as smartphones or tablets, can be included because they can partially replace computer products and thus indirectly influence global shipments of MB. Second, this research focuses on demand planning and sales forecasting. Internal resource constraints (equipment, materials, labor hours, etc.) should be integrated with external markets to conduct collaborative decision-making. Finally, despite time-series can better capture seasonal variations, it cannot accommodate different time-lags between a specific predictor and the outcome (a leading predictor is ahead of the outcome). A well-known deep-learning module, recurrent neural network (RNN), is flexible to accommodate different time-lags, however, it requires sufficient data samples to optimize network-topology parameters.

6. Conclusions

Demand planning (DP) and sales forecasting (SF) are classical, yet, critical to achieve successful supply chain management. In the past, qualitative schemes (Delphi method, market research, panel consensus, historical analogy) and quantitative techniques (mathematical programming, machine learning, time-series) have been proposed to address these issues. Qualitative schemes are mostly reliant on experts' subjective assessments. Although quantitative methods are more convincing, each method has its limitations. Mathematical programming focuses on internal resource constraints but rarely takes external demand and product volatility into account. Machine-learning methods can prioritize the degree of importance of the predictors but they are deficient in capturing the *time-lags* between the predictors and the outcome (Al-Musaylh et al., 2018; Wang et al., 2018). Time-series can capture seasonal effects and accommodate time lags but fail to elicit dynamic interactions between the predictors and the outcome.

To sum up, the presented framework demonstrates the following strengths:

- DP and SF for upstream MB is based on the prediction of downstream computer products. The effects of seasonal variations and time lags are successfully captured,
- Sensitivity analyses are conducted to help managers quantitatively estimate the impact of a growing or declining product on sales revenues of a firm to form a basis of product-mix portfolio management,
- Dynamic interactions including vertical relationships between the MB and computer products and horizontal relationships between the firms, are elicited to reveal managerial insights.

To achieve better product portfolio management and resource allocation, an operation manager needs to take demand uncertainty and product volatility into account: *What happens on the firm if sales volume of a downstream product or an upstream component has increased or decreased by 10%*? *What product should be firstly expanded or contracted*? *How can we enhance profitability in face of dynamically changing sales volumes*? The presented framework systematically guides the firm to coordinate demand planning with sales forecasting. More importantly, the presented framework is promising to be generalized to other industrial components, such as panel display, memory chips, graphics cards, and microprocessors.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2020.106788.

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