國立臺灣大學管理學院國際企業學研究所

碩士論文

Graduate Institute of International Business

College of Management

National Taiwan University

Master Thesis

以層級貝氏模型預測廠商異質性下之銷售量
—以晶片廠商為例

Forecasting Sales Volume of Industrial Product with Firm Heterogeneity—Case of Mobile Phone Chipset

林平

Ping Lin

指導教授：任立中 博士

Advisor: Lichung Jen, Ph.D.

中華民國 99 年 6 月

June, 2010

Abstract

Sales forecast has been an integral part of business planning, especially to the high-tech industry where product life cycle is short and intensive capital expenditure is required. However, forecasts in industrial product are usually less accurate and companies tend to adopt different forecast practices compared with consumer product industry. Coupled with the fact that the market structure for high-tech industry has been undergone several waves of evolutions, forecast method should be modified to adjust for improvements.

This research paper proposed using a 2 level Hierarchical Bayesian Model that takes customer heterogeneity into account. The first level will address the aggregate factors affecting sales in the industry, whereas the second level utilizes firm specific factors to explain variations among customer purchasing behavior. Empirical analysis was accomplished with the data that recorded sales volume and firm attributes of 8 key accounts from an IC design company.

Key word: forecast, industrial product, Hierarchical Bayesian

Contents

Exhibits

Graphs

Chapter 1 Preface

1.1 Background

Sales forecast has long been considered an integral part of business planning, since it is one of the most important inputs for managerial decision making process and affects several aspects of organization strategy. In the short-run, it influences supply side behavior such as manufacturing and pricing; whereas in the long run, firms must choose suitable R&D and capital expenditure based on their strategic goals under its forecasted growth potential and demand. That is to say, the accuracy of sales forecast has a drastic impact on successful business operation that maximizes profit and minimizes cost or investment loss. Makridakis (1990) discovered that among the 175 companies he surveyed, 92 percent of them deemed forecasting is a major attribute for their company's success.

This is even more so for high-tech sector. This industry has a notably shorter product life cycle due to the well-established Moore's Law—in 1965, which states that the number of transistors that can be placed on an integrated circuit will double every 18 months and thus prompting dramatic increase of computing power and innovation for IC related products. Under this extreme pace of product replacement, near-term excess inventory as a result of imprecise sales forecast translates to loss from product obsolescence. In the long run, false expectation to future growth in demand will lead to untimely investment that drastically raises the degree of operational risk and puts a heavy burden on the company financially. As such, management in high-tech sector eagerly seeks more effective forecast methods and variables to capture the change in demand.

Important as it is, sales forecast is never an easy task judging on the ever changing business environment and fast evolving market structure. To say the least, the boundary between each market has been broken and a lot of international players are now joining the industry and competing with other international suppliers for buyers form different regions of the world, making macro-economic performance and regulation in foreign countries relevant issues to consider when forecasting company sales.

To make things even more complicated, the structure within a certain market has becoming more and more complicated as a lot of the traditional business models gradually lose its profitability and new ways of formulating a value chain emerge, bringing more market players into the industry. As a result, the interplay between supply and demand can seldom be accurately captured with a general model ignoring the different behaviors of each market player.

These factors—jumps in technology and product, cross-national operation, and different forms of purchaser-supplier relationship—have rendered forecasting a challenging but crucial task that this research attempt to probe into. Both related theories and empirical studies will be touched on to present a comprehensive view.

1.2 Research Purpose

The purpose of this study can be viewed as an endeavor in answering these propositions:

A. Reviewing existing forecasting theories to draw useful insights into current forecasting

B. Understanding features of the high-tech industry and how current forecasting model should address these business changes

C. Discovering the external drivers affecting general sales volume in the industry

D. Discovering the respective attributes that influence purchasing behavior across different accounts in a certain company

E. Proposing a forecasting methodology that exploits these relevant information in the most accurate way

1.3 Framework

The research is composed of 5 chapters. Following this chapter that provides basic introduction of the research motive, chapter 2 will outline the academic basis of this research covering fields such industry overview, forecast theories and methods, and would then focus specifically on the forecast of industrial product as the primary concern. Chapter 3 discusses the research methods utilize in this paper, including two statistic parameter estimation methods—Maximum Likelihood Estimation Method(MLE method)and Hierarchical Bayesian Method (HB method)—and one algorithm, Markov Chain Monte-Carlo method. Empirical analysis will be recorded in Chapter 4 along with summary reports of the data, construction of the forecasting model, and forecasting results. Finally, Chapter 6 concludes with managerial implications and some suggestions on modifying existing forecasting practice. Limitation on the research and future directions for further study will also be covered in this chapter.

Chapter 2 Literature Review

This chapter will first look into the specific industry sector of interest—namely the high-tech industry. By examining the operation environment, market structure, and customer characteristics, the key drivers and suppressants can be identified for input screening for model building in the next chapter.

Then, a review on the development of in-corporate forecasting will serve as the start point for constructing a model in the aim of providing companies a better capture of their sales outlook. Finally, a comparison between different forecasting forms will be conducted to augment the discussion and solidify the choice of the model in this paper.

2.1 High-tech Industry Overview

High tech industry includes a wide range of production business and there are no strict criteria to separate high-tech business to those of "non-high-techs." Nevertheless, OECD methodology in classifying product category uses R&D intensity— industry R&D expenditure divided by industry sales— as the standard for identifying high-tech industries. Under this methodology, industries with high R&D intensity such as Medical, precision & optical instruments (ISIC/NACE 33), Pharmaceuticals (ISIC 2423 / NACE 2441 & 2442),Radio, television & communication equipment (ISIC/NACE 32), Office, accounting & computing machinery (ISIC/NACE 30),Aircraft & spacecraft (ISIC/NACE 353),and Management activities of holding companies (ISIC/NACE 7415), belong to the high tech sectors. These industries create value mainly with its immense ability to innovate and invent— a classic case of "knowledge economy."

A known trait for high-tech product demand is its sensibility to macroeconomic environment. From demand side factors, shrinking purchasing power from its end-user in a weak economy will impact high-tech industry especially hard due to its "luxury good" nature. From supply side, reduced ability for manufacturer to fund necessary production activities in a less liquid capital market will curb the manufacturer from producing its optimal quantity.

Samuelson and Nordhaus(2001)defined income elasticity as "the percentage change in the quantity demanded to the percentage change in disposable income." It is a measure to capture the degree of impact on consumption of a certain product when income level changes. For a given demand function Q(I, P) of a good, the income elasticity, ϵ_d , can be calculated as :

$$\epsilon_d = \frac{\partial Q}{\partial I} \times \frac{I}{Q}.$$

The greater the elasticity, the greater the effect income change will have on the consumption of this product. For goods with income elasticity equal to 1, the "normal goods", 1 percent change will bring about exactly 1 percent change in the quantity demanded. For "inferior goods", those with income elasticity smaller than 1, 1 percent change in income will only produce less than 1 percent change in consumption, meaning that as income increase, consumers demand less of that product. On the other hand, some goods, the "luxury goods", have income elasticity greater than 1. This implies that during boom periods, people consume more of this type of goods as a result of increase in personal wealth. However, as economy weakens, the drop of demand of this type of goods will be greater than the drop of income. High-tech products such as consumer electronics or sophisticated machinery are usually treated as luxury goods with income elasticity greater than 1 in economic analysis. Therefore, many high-tech firms experience cyclical sales performance, outperform ordinary manufacturing companies in peak and underperform at valley.

Another reason high-tech industries is especially prone to changes in business environment relates to the company's cost of capital and ability to obtain capital. For example, higher interest rate not only tightens the company's ability to invest and pursue future growth, but also affects company's cost of inventory and in terms changes their purchasing behavior. In other words, in addition to having a negative impact on both direct and derived demand, economic downturn will also harm supplier.

Himmelberg (1994) showed that the rate of technology acquisition has a statistically significant relationship with capital market performance with data from 179 firms in high-tech sectors. He implied that if external funding becomes scarce, smaller companies have to rely on internal finance, which may not be as affluent as other liquidity sources. Without sufficient investment in R&D, the key production input of their products, will not be enough to support fast business growth and expansion. The dismal outlook of capital market will disrupt high-tech companies from normal course of production more than other firms in other industries.

Hax and Candea(1984) proposed an Economic Order Quantity (EOQ) model that help firms to estimate the optimal purchasing level with minimum annual total cost. This model should be relevant in discussing sales volume in high-tech industry because a huge portion of the demand is derived demand—the customer of a manufacture in the high-techs sector will most likely be selling to another down-stream manufacturer who uses the components he purchased to assemble or produce something closer to the consumer end. In other words, the demand in high-tech industry in fact largely comes from inventory purchase, and will be influenced by the factors that decide the buying firms purchase quantity—making EOQ a relevant discussion here. EOQ model assumes that

A. demand is continuous at a constant rate,

B. the inventory process continues indefinitely,

C. quantities ordered, storage capacity and available capital are without constraints,

D. replenishment is instantaneous,

E. costs are time invariant,

F. no shortages are allowed,

G. quantity discounts are not available.

Under these assumptions, the economic ordering quantity refers to the quantity that minimizes annual total cost including holding cost, ordering cost, and carrying cost— can be obtained at

$$Q^* = \sqrt{2AD/_{rc}}$$

where A represents the fixed ordering cost; D the fixed demand rate; r the inventory carrying cost; and c the unit procurement cost. Following researchers such as Goyal (1985), Chand and Ward (1987),Aggarwal and Jaggi (1995) have probed further into this relationship. Some even made further adjustment to carrying cost, r. For example, Berling (2008), argued the use of interest rate combined with expected price decrease. However, the relationship between current interest rate and purchasing quantity is yet clear-cut. For one thing, higher interest rate could imply smaller purchasing volume if the purchasing firm has to borrow for to pay and thus raising carrying cost. This would results in a negative correlation between purchase quantity and interest rate. However, in business practice nowadays, it is common that the payment to supplier occurred at a later period after the receipt of materials without charging interest. As a result, this transaction can actually be viewed as an interest-free loan from the suppler to the purchaser. Thus, all else being equal, a positive correlation between interest rate and purchase quantity should be observed. The higher the interest rate, the larger quantity a purchasing firm should order to exploit this benefit. The final effect depends on the difference of interest cost and benefit that varies across firms.

In conclusion, because of the high income elasticity of the end-product, high capital expenditure need, and the derived demand considerations of purchasing behaviors in the high-tech macro-economic factors such as GDP growth, inflation rate and interest environment, along with seasonal effects, are drivers one should consider in formulating a forecast model.

2.2 Industrial Product Forecast

As mentioned in the first section, the major proportion of demand in high-tech industry is derived demand composed of material purchase for manufacture of end product. That is to say, compared with consumer products that have direct linkage to demand and preference, the forecasting of industrial product will have a different focus that need to factor the change of industry and firm behavior into account; it will also take more effort to reach accuracy because of the distance between the producers and end demand.

Dalrymple (1987) found that in practice, firms producing industrial product prefer the use of sales force composite, a forecasting method of summing the sales expect of every member of the sales team on their respective responsible regions to estimate total future demand, is more heavily used compared with forecasting conducted by companies that sell consumer products. Usually, industrial products have a more concentrated client base; in other words, the customer pool is composed of a limited amount of key accounts rather than the mass general consumers in consumer product. This concentration has raised industrial product’s reliance on customers because the lost of a single customer can translate into huge sum of loss in revenue compared with the marginal loss of an individual consumer in consumer product business. It has also made relationship management to these key accounts more important. As a result, sales representatives become the person closest to demand and understand the situations of customers' best.

On the other hand, Herbig et al (1994) also found in his survey on 150 companies that compared with their consumer product counterparts, companies in industrial product industry will allocate more focus on industrial analysis and the trend of the market. Herbig, who uses high-tech industry to illustrate this point, stated that in industries where technological innovation plays a heavy role in shaping consumer behaviors, the future demand of existing products highly volatile and uncertain. As a result, companies are more concerned about the competitive situations and relative competitive advantage across different players in the market because this would be the determinant for their sales volume in the long run. They will also conduct analysis on industry trend to capture the potential technology transition, which is less common in consumer products.

Because of the complicated market structure and uncertain product life, the accuracy for industrial product is generally perceived to be lower than consumer product by both researchers and management in practice. Dalrymple (1975) conducted a survey on 175 representative companies to study the forecast practice among different industries. The forecasting methods of these firms were diverse and varied substantially : qualitative measures included executive opinion, leading index, and life cycle analysis; quantitative methods ranged from simulation, diffusion index, exponential smoothing, moving average, regression, input-output model…etc; mixed methods like sales force composite, intention-to-buy survey, trend projection were also adopted. Among these miscellaneous means of forecasting, nevertheless, the error rate for industrial product is significantly higher than consumer-oriented firms, the former being 7.65 percent and the latter 6.7 percent. Also, Dalrymple's research indicated the wider the operation a company has, the greater error rate this company will encounter. Combined with the discussion in the beginning of this chapter, this implies that high-tech manufacturing firms targeting at international industrial companies will experience a higher than average error rate in forecasting.

Concluding from the above literature, future demand for industrial products depends largely on a selected few customers, involves a wider range of locations, and faces high uncertainty due to fast-changing technology. The forecasting results generally come with higher error rates and rely more on sales personnel understanding of the region or segment.

2.3 Heterogeneity Among Purchasers

As mentioned in the previous section, customer pool for industrial product companies are relatively concentrated and individual contribution of a key account could be significant to the total sales. Naturally, one would think that a thorough study on these major customers should reveal crucial information for prediction of future purchasing buying behavior. It would also be quite feasible since most of the buyers are companies with global presence and data can be obtained through direct public information collection or indirect estimation from other second-sources. Therefore, one reasonable and cost-effective method to improve forecasting results would be to incorporate purchaser behavior analysis into regular forecasting.

For consumer behavior analysis, one usually would take out demographic variables such as gender, age, or nationality…etc—corporate equivalents of these demographic attributes would be its different business models. Various aspects of business model involve an enterprise's role in the value chain, its main clients and suppliers, operational regions, and competitive strategies…etc. A study into business model will help the company to understand the different factors driving the purchasing behavior of each customer and in turn achieve results similar to customer behavior analysis that eventually can be utilized to improve customer retention and assist the company in further develop sales promotion strategy.

In recent years, business models have undergone several waves of transition due to the intensifying focus on specialization in each link of the high-tech industry, the economic transformations in developing countries, and awareness for brand value. In the 1980s, major high-tech companies in developed countries conducted a series of vertical disintegration and outsourcing in an attempt to focus on their core competency of R&D and reducing manufacturing cost. This change has brought about the formation of OEMs (Original Equipment Manufacturer) in developing countries in south eastern Asia. These companies are purely manufacturing companies that accept orders from these high-tech companies and do not own the capability to design their own product. In 1990s, further emphasis on operation streamlining from leading high-tech companies and heated competition among OEMs prompted ODMs (Original Design Manufacturer) to come into existence. ODMs tried to differentiate themselves from OEMs by providing one-stop shopping services that cover design, procurement and manufacturing of the end product. Their services cater to the specific needs of each client, and these leading technology firms at the top of the value chain are only responsible for the marketing of the product, which, in fact seize the most value proposition of total profit. Now, as margin begins to dwindle, some of these OEMs or ODMs have strived to move upward the value chain by venturing into private brand, and started to sell their products to Europe and America. For one thing, these various forms of business model can affect factors in common practice of sales forecast for industrial product such as competitive analysis and industrial trend. More importantly, they also signify different company attributes such as their respective end consumer segments or ability to have supernormal earnings as an influence of brand value that would eventually reflect in different purchasing patterns.

While consumer heterogeneity has been a major issue in marketing science and a proliferation of literature on various products, industries can be found; yet, heterogeneity in purchasing firms has remain largely untapped and is to be addressed more in literature. More research effort should be dedicated to make use of the information possible to be yielded with customer features.

2.4 Multi-level Forecast Model

Chapter 2 reviews the basic dynamics of high-tech industry and past forecast literature relating to this sector. Specifically, from both demand and supply aspect, high-tech industry is prone to macro-economic environment for several factors, such as high income elasticity of the end product, and sensitivity to interest rate due to funding constraint and inventory cost. Also, the huge portion of high-tech industry output are industrial products with markets facing derived demand. Forecasting for these products differ from that of consumer products in that buyers are more concentrated, product life cycles are shorter and contingent to industrial development, and with higher error rate. However, since the sales volume of a company largely depends on a number of key accounts, it should be useful to utilize purchaser specific attributes to further capture variation in demand.

The conclusion leads to the use of a model combining both macro-economic factors affecting general quantity demanded and the use of respective customer features to explain dissimilarities across key accounts of a certain company. In other words, beside projecting future demand with a top-down approach using economical variables that impact sales of the industry, this forecast model must also take the heterogeneity among its major customers to consideration so as to estimate the respective variation in purchasing quantity each customer might have given its individual business model and the behavior under the business model it adopts. By implementing a two-stage model to fine-tune for specific variations that a general model fails to account for, the aggregate forecast result can expect to be more accurate.

Although current literature lack similar application on industrial product, similar research came be found on consumer products. One research by Lo et al. (2008) on LCD monitor market first used variables related to macro-economic situations to generate forecast for the LCD market as a whole and then fine-tuned the result with different product attributes in this category. The model proposed involved a hierarchical forecasting with 3 levels of model showed below. It first projected the quantity demanded with economic variables such as GDP per capita in major markets and interest rate; then each product group were divided by a certain attribute such as resolution or monitor size and a corresponding model was constructed for each category; lastly, the forecasts results were applied to different geographical regions and combined to produced the final estimation. This hierarchical model that pooled together factors in external environment and specific market attribute can be further extended in the forecast of industrial product.

Chapter 3 Research Method

The research methods employed in empirical analysis include two parameter estimation methods and one simulation algorithm. For model parameter estimation, we compare the traditional Maximum Likelihood Estimation method with Hierarchical Bayesian method to find out the strengths and weaknesses of the two. The purpose is to propose an estimating method with higher reliability and better accuracy. In the case of Hierarchical Bayesian model, Markov Chain Monte-Carlo simulation is used to generate the parameters of posterior probability distributions.

3.1 Hierarchical Bayesian Method

Classical statistics developed estimate based on sampling theory, which generates the parameter estimation purely based on the sample data. In contrast, Bayesian statistic method is developed from Bayes' Theorem. The parameter estimation process involves combining sample observations with prior information to come up with the posterior probability distribution for the parameter. The estimate is then generated while minimizing the expected loss.

Although Bayesian estimates are not unbiased, but they satisfy consistency because they are generated while minimizing estimation error and mean square loss. Combined with intensive use of prior information in the sample, Bayesian estimates also satisfy sufficiency. Therefore, Bayesian estimates still have good properties. Furthermore, one can compute posterior probability density function for parameters with Bayesian method to bring additional insight into analysis.

While Bayesian statistics overcomes the problem of high estimation error with classical statistics under limited sample size, Hierarchical Bayesian method further takes into account the “unobservable heterogeneity” between each subject and uses it to modify the projected values respectively. As such, Hierarchical Bayesian method can offer an even more accurate estimation than Bayesian method. Compared with Bayesian method that makes assumption of one prior probability distribution, Hierarchical Bayesian method makes multiple levels of assumptions on prior probability distribution—the first level is aimed at capturing the variation in a single subject, whereas further levels will probe into the unobservable heterogeneity contributed to these differences. This process is done by the construction of multiple stages models. The “within-subject” model is a linear regression model that leads to a matrix of individual-level regression coefficients. The independent variables in this level are general variables used for explaining the differences in observations for a subject. In the later stages, “between-subject” models come into play in the form of multivariate regression models that portray the relation between the coefficients from the previous level with subject heterogeneity. By doing so, Hierarchical Bayesian method will allow for “multiple sources of uncertainty” (Lenk, 2001) when explaining variation in observed samples. Managers and researchers alike will benefit from the additional information brought by the use of multiple-stage models.

With the feature mentioned above, Hierarchical Bayesian method not only allow forecast in both aggregate level and individual subject level, but actually has a mechanism to modify the estimate itself when additional posterior information. As the sample of a subject increases, the parameter estimate will be influenced by its heterogeneity—i.e. its posterior probability distribution—more than it is by the within-subject estimation—the prior probability distribution that represent the first level estimation. This self-modifying mechanism will be especially useful in forecasting with limited values, because it at most gives estimation close to the prior probability distribution. Therefore, it is even more accurate than simple Bayesian method.

Researchers have derived and proved that the posterior mean for a Hierarchical Bayesian parameter estimate is actually a convex combination of the within-subject MLE (M) estimate and the between-subject estimate. That is to say, the bayes estimator can adjust for the original MLE estimates between the two depending on their relative accuracy. If more subjects are involved in the estimation process, more weight would be put on within-subject estimator and the Bayes estimator will eventually tilt toward a value near MLE estimator. In other words, Bayes estimator will not differ much from MLE estimator in large samples; its value is better distinguished when samples are limited.

3.2 Markov Chain Monte-Carlo Methodology

Markov Chain Monte-Carlo Methodology is an extension of Bayesian estimation. It treats the joint posterior distribution as the target distribution and simulates it with Markov Chain. Then, Gibbs sampling will be employed to obtain estimation for parameters by iteration. Gibbs sampling will use the previous sampling to condition later samplings, and current sampling result is only affected by the previous sampling, which is in line with the characteristics of Markov Chain. The iteration process takes the previous sampling result as the given condition of current sampling that enters into the conditional distribution. This repeating sampling process with updated conditional posterior distribution will help the result to approximate the real posterior distribution.

Chapter 4 Empirical Analysis

4.1 Sample Summary

The following empirical analysis utilizes data drawn from the sales record of a leading IC design house in Taiwan. The time range of the record ranged from January, 2006, to March, 2009, a total of 39 periods of monthly sales quantity. In this product category, the company has acquired 40 customers by the end of the record period. These customers are generally mobile phone manufacturing companies that either produces mobile phone under their own brand or companies providing EMS (electronic manufacturing service) to international mobile phone companies that wish to streamline their process. These mobile phone makers purchase chipsets used in handsets from the IC design company and assemble it to their products along with other components to make a complete cell-phone. In other words, the product of this IC design company does not share directly link to mobile phone end-users; rather, it is offered to derived demand from mobile phones makers.

Since the beginning of this data set, the company has collect another set of information of the top 8 accounts, which accounted for 60% of the sales volume in year 2006. The information included is listed below. Segmentation is used to distinguish the business model of the key accounts itself, including pure IC design

House, ODMs, and mobile phone companies with their own brands. On the other hand, sales mode refers to the customers of different business models of these key accounts, including mobile phone companies (both in China and overseas), mobile phone operators (both in China and overseas), PCBA (Printed Circuit Board Assembly, meaning that the company process the chipset in to PCBA and sell it to medium/small size mobile phone manufacturers), and Open BOM (Browser Object Model, offering design service for major mobile phone companies). Sales region refers to the location of the customers of the key accounts.

The summary statistics of the sales quantities of the 8 accounts are listed below. Considering these 8 accounts altogether, sales quantity has a positive skewness, which is to say that the observation shows a tendency to be smaller than mean. Also, sales volume of these 8 accounts, plotted in Graph 2, showed high variation across month. When constructing a forecast model, one should be careful in the possible seasonality issue and include variables that might mitigate this effect.

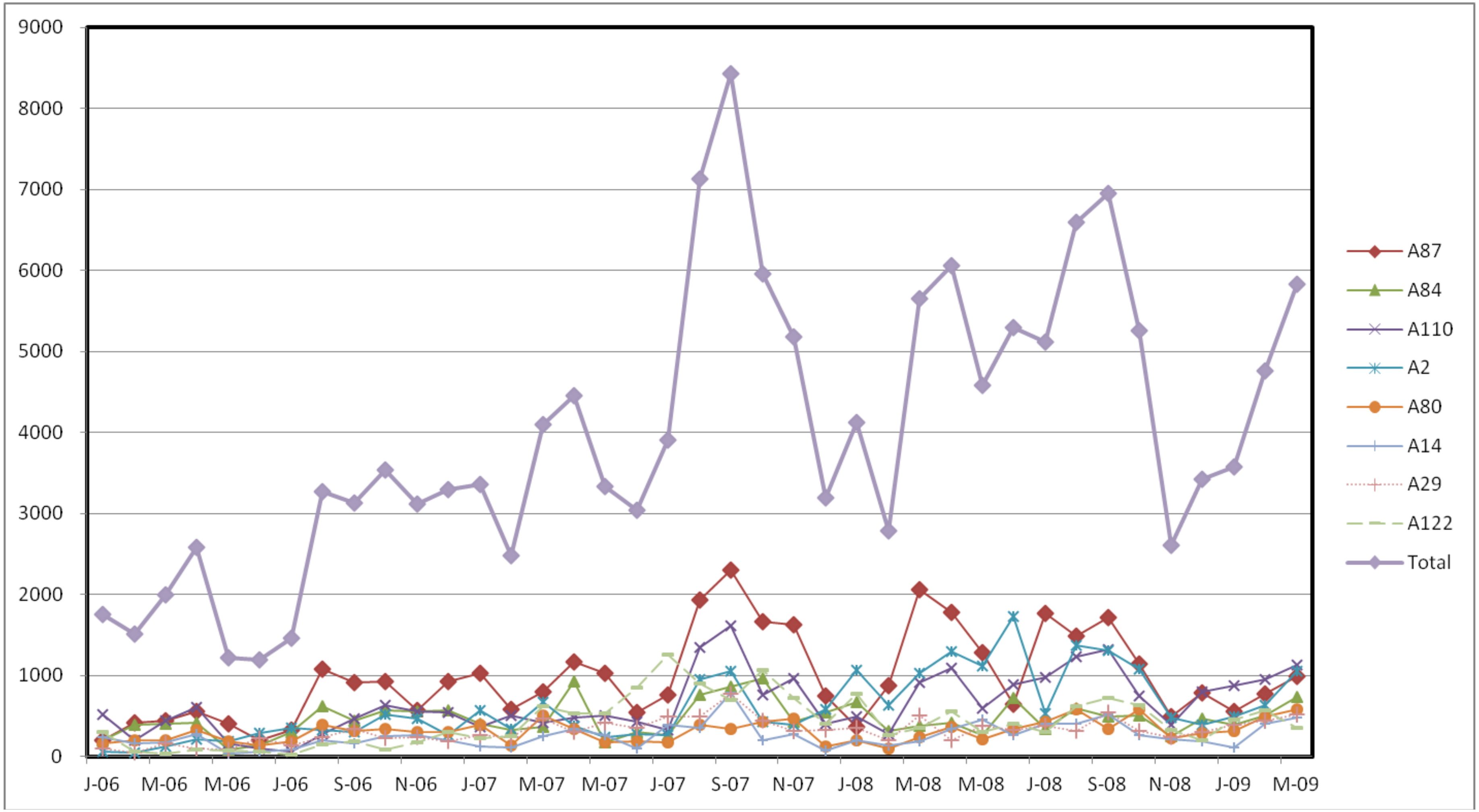
Exhibit 1 Account Information

Customer Attributes	Categories
Segmentation	IC design house, ODM, Brand
Is ERP/MRP employed?	Yes; No
When is ERP/MRP employed	Date
Inventory Policy	Days of Inventory
Publication Time of Financial Report	Date
	Sales mode (%)
	China Brand
	China Operator
	PCBA
	Open BOM
	Overseas
Shipment Information	Sales Region (%)
	China
	Russia
	Taiwan
	India
	South Eastern America
	Latin America
	ROW

Source: company data

Exhibit 2 Descriptive Statistics of 8 Accounts (sales quantity in thousands)

Account	N	Minimum	Maximum	Sum	Mean (Std. Deviation)	Std. Deviation	Variance	Skewness	Kurtosis
A87	39	204	2299	37843	970.333 (87.471)	546.254	298393.070	0.740	-0.304
A84	39	81	967	18009	461.769 (33.446)	208.869	43626.340	0.593	0.119
A110	39	64	1615	25324	649.333 (58.951)	368.147	135532.439	0.693	0.007
A2	39	45	1734	23457	601.462 (66.307)	414.087	171468.255	0.915	0.050
A80	39	102	587	11965	306.795 (21.383)	133.537	17832.167	0.492	-0.540
A14	39	39	784	9846	252.462 (23.890)	149.194	22258.992	1.303	2.875
A29	39	50	774	12354	316.769 (24.012)	149.956	22486.866	0.593	0.901
A122	39	18	1255	16425	421.154 (48.080)	300.258	90155.081	0.800	0.283
Total	39	1192	8431	155223	3980.077 (280.839)	1753.839	3075950.757	0.474	-0.215
Valid N	39								



Graph 1 Monthly Sales Quantity (in thousands)

4.2 Model Construction

As discussed previously, the HB model will involve 2 stage of analysis—the first stage will be a structural form model using macro-economic variables as explanatory variables to represent the general factors influencing sales of each customer. Then, the second stage will draw insight from a model that incorporates firm specific features to allow adjustment for each account's heterogeneity. For the purpose of out-sample forecasting comparison, 3 periods of observation will be reserved and 36 periods will be used for parameter estimation. Data for aggregate level were extracted from TEJ database (Taiwan Economic Journal); for individual level, firm attributes in Exhibit 1 are used as explanatory variables of the model.

In both the aggregate and individual stage, step-wise regression procedure is adopted to choose variables with the maximum collective explanatory power from the pool of relevant factors initially proposed in Exhibit3. By doing so, the number of variables will be reduced since variables with less contribution will be screened out. Only those with highest relevancy will be retained. As noted in later sections, most of the sales of end product are directed toward China region. Consequently, macro-economic situations in China would be the most relevant issue in the aggregate level. Therefore, it makes more sense that many macro-economic indices entertained in the model are China-based statistics instead of the world. Also, industry specifics such as demand/supply conditions and compliments demand are considered to relate to the characteristics of technological product forecasts, which emphasize on industrial competitive and trend analysis. For example, BB ratio is an indicator of demand/ supply strengths in semi-conductor industry. Dividing total industry order quantity with number of orders filled, it measures the degree of demand exceeds current supply capacity. A BB ratio over one signifies greater demand than current supply, whereas a BB ratio less than one imply oversupply in the industry.

Exhibit 3 Initial Macro-economic Variable Pool

Category	Variable
Capital Market	◆ NumStock :the numer of stock that company has issued ◆ StockA :A Stock index in China ◆ StockB :B Stock index in China ◆ LoanRate :current one-year borrow rate in China ◆ AvgRate:current one-year average rate in China ◆ DIProj :numbers of direct investment projects in China
International Trade	◆ Exchage Rate :RMB to TWD
Price Index	◆ CPI:consumer price index in China ◆ CCI:consumer confidence index in China ◆ PMI:purchase manager index in China
Infrustructure	◆ TeleServ :Telecom Service Availability in China ◆ TeleIm :Telecom Equipment & Services Import In China ◆ TeleEx:Telecom Equipment & Services Export In China
Supply/ Demand/ Complements	◆ BBRatio:Book-to-Bill ratio ◆ NumPhone :industry sales volume of mobile phone in China ◆ LCD:Small Size LCD shipment
Economic indices	◆ Leading :Leading Macro-Economic Climate Index in China ◆ Concur:Coincident Macro-Economic Climate Index in China ◆ Warning :China Monitoring Signals of Macro-Economic Climate Index in China

Exhibit 4 Aggregate Variables

Category	Code	Definition
Seasonality	Yt-12	sales quantity lag 12 periods
Macro-economic	LoanRate	China Official Interest Rates of Loans (1 year)
	Concur	China Macro-Economic Climate Index
	Warning	China Monitoring Signals of Macro-Economic Climate Index
	PMI	Purchase Manager Index
Demand/Supply	BBRatio	Book-to-Bill ratio
Complements	lnLCD	Small Size LCD shipment; taking natural logarithms

The first stage aggregate model was derived in the form of multiple regression and can be written as

$$Y_i = X_i\beta_i + \epsilon_i \quad for \quad i = 1, \dots, 8,$$

Because a lagged 12 period variable is included, the original data size of 36 has been reduced to a size of 24 effective samples. Therefore, the dependent variable, Y_i, is a 24×1 vector, representing the 24 period monthly sales quantity of account i. X_i is a 24×8 matrix, composed of the values of 7 selected economic variables (listed in Exhibit 4, including intercept) in the 24 periods. β_i is a 8×1 vector of regression coefficients obtained by regressing the sales quantities of account i on these 8 explanatory variables. Finally, ϵ_i is the normally distributed error term vector. The prior probability density function for the variance σ^2 is an Inverted Gamma Distribution written as

$$[\sigma^2|r_0, s_0] = IG\left(\sigma^2\middle|\frac{r_0}{2}, \frac{s_0}{2}\right).$$

In the individual level, β_i will be treated as the dependent variable that would be influenced by firm specific attributes. In order to compare forecast results, the MLE method is also employed to generate parameter estimation. The MLE estimation of β_i would be

$$\hat{\beta}_i = (\mathbf{X}_i'\mathbf{X}_i)^{-1}\mathbf{X}_i'\mathbf{Y}_i \ .$$

Exhibit 5 Correlation Matrix of Aggregate Variable and Sales

	Sales	LoanRate	PMI	BBRatio	LCD	Concur	Warning
Sales	1.000	0.705	-0.265	-0.819	0.908	0.098	0.062
		0.000[a]	0.118	0.000	0.000	0.570	0.718
LoanRate	0.705	1.000	0.205	-0.765	0.669	0.680	0.680
	0.000		0.231	0.000	0.000	0.000	0.000
PMI	-0.265	0.205	1.000	0.133	-0.345	0.705	0.705
	0.118	0.231		0.438	0.039	0.000	0.000
BBRatio	-0.819	-0.765	0.133	1.000	-0.780	-0.280	-0.314
	0.000	0.000	0.438		0.000	0.098	0.063
LCD	0.908	0.669	-0.345	-0.780	1.000	0.044	0.042
	0.000	0.000	0.039	0.000		0.800	0.808
Concur	0.098	0.680	0.705	-0.280	0.044	1.000	0.942
	0.570	0.000	0.000	0.098	0.800		0.000
Warning	0.062	0.680	0.705	-0.314	0.042	0.942	1.000
	0.718	0.000	0.000	0.063	0.808	0.000	

a. P-Value

At the aggregate level, loan rate has a positive correlation with sales quantity, suggesting that firms would rather view storing inventory as an alternative way of funding similar to an interest rate free loan from the seller. Thus, the higher the current interest rate is, the more then would order since it become relative cheap to stock materials. On the other hand, BB ratio shows a negative correlation with sales. This could be interpreted as an adjustment process of supply and demand. If current BB ratio is high, meaning order has exceeded available capacity, sales would decline. This is either done with a price hike from the suppliers or purchasers would have satisfied the necessary level of stock and reduced ordering. On the other hand, shipmentof complement goods of mobile phone chipset, small size LCD that functions as the screen for handsets, has a strong positive correlation with sales. This is in line with economic intuition that the more chipsets are sold to make mobile phones, the more LCDs are needed to go with it.

The variables selected here can be categorized into 4 types of indices. A lagged variable is included to address seasonality problem, which can be observed clearly from the pattern of monthly sales data. Then, 4 economic factors are deemed to be effective in influencing aggregate sales volume, namely interest rate, 2 economic indices, and 1 price index. Because these customers are manufacturing purchasing product as inventory, PMI is in place of CPI (Consumer Price Index).

Book-to-Bill ratio is the measure in semi-conductor industry, which is the amount booked divided by the amount billed. It reflects the relative strength in demand as compared with supply. A Book-to-Bill ratio larger than 1 signifies the industry has a demand stronger than capacity, a sing welcomed by the producers. Reversely, when Book-to-Bill ratio falls below 1, the producers are essentially over-supplying and either their price will suffer or the average cost will rise due to slack capacity.

Exhibit 6 Individual Variables

Category	Code	Definition
Business Model	Segment	Dummy variable; Brand=1, otherwise=o
Inventory Policy	Inventory	Days of Inventory
Sales Region	China	percentage of end-product sales allocated the area
	Russia	
	India	
	Latin AM	

The second stage model regresses the aggregate coefficients on account attributes to adjust for individual heterogeneity for each customer. It can be expressed as

$$\beta_i = \Theta_i' z_i + \delta_i \quad for \ \ i = 1, \ldots, 8 \, ,$$

$$\beta_i = \Theta_i{}' z_i + \delta_i \ for \ i = 1, \ldots, 8,$$

$$[\delta_i | \Lambda] = N_7(\delta_i | 0, \Lambda).$$

z_i is the vector of covariates for account i and Θ is a 7×8 matrix of regression coefficients because 6 variables representing individual account heterogeneity are selected in this level (including intercept). δ_i here is a 1×8 vector of error terms. Note that the smaller covariance matrix of δ_i , Λ, is, the more variation in individual account from the predicted value of aggregate level is explained by firm attributes. Its prior probability density function is an Inverted Gamma Distribution

$$[\Lambda | f_0, G_0^{-1}] = IW_{24}(\Lambda | f_0, G_0^{-1}).$$

3 categories of account attributes have entered into the second stage model, namely type of business model, inventory policy, and sales region. In order to verify on the value-adding effect of branding generally claimed, a dummy variable "Segment" is created. Accounts operating under its own brand were given a value of 1 to distinguish it from other business models such as ODM or IDH, in which cases a value of 0 were assigned. Inventory policy refers to the days of inventory stocked before this customer sells it to its clients. In addition, different composition of sales region mix is also a relevant issue in the individual level. The

percentage of final product sold in each region of the world, most notably the "BRICS", are shown to influence the quantity demanded by the key accounts. It is the geometric average percentage across the data period.

4.3 Results & Forecast

This section will present the empirical results with the model mentioned previously, including preliminary data examination, parameter estimation and also forecast comparison between the two methods.

Summary statistics for the explanatory variables in both aggregate and individual level are given below. In accordance with sales pattern, macro economic variables have a high degree of variation with large standard deviation and range. For example, among these 36 periods, China Monitoring Signals of Macro-Economic Climate Index (Warning) can be as low as 78.7 to as high as 121.3, reflecting the economic cycles experienced during the observed time. Naturally, business cycles will lower forecast accuracy; however, it might as well be improved with additional insight into the second level, which would address different sensitivities of each account to the general environment.

Exhibit 7 Summary Statistics for X

Variable	Mean	Std. Deviation	Minimum	Maximum
Yt-12	5.757	0.830	2.890	7.740
LoanRate	6.911	0.640	5.310	7.470
Concur	101.917	1.882	95.510	103.420
Warning	109.717	12.256	78.700	121.300
PMI	52.596	5.007	38.800	59.200
BB Ratio	0.873	0.082	0.700	0.998
lnLCD	14.790	0.404	13.982	15.507

The second stage would regress β_i on individual firm attributes, of which summary statistics are listed in the following Exhibit 8.

One thing worth pointing out in firm attributes is the importance of sales to China. Each of the 8 accounts have their own specialized regions; yet at least 20% of their sales has to do with China, with the most focused one devoted 80% of the sales in serving customers at that region. Latin America would be another major region that has strong demand for the end product. One would reasonably expect the tremendous impact the demand from China could have on their sales volume, and in turn, the influence on these companies’ purchase from the company.

Exhibit 8 Summary Statistics for Z

Variable	Mean	Std. Deviation	Minimum	Maximum
Inventory	28.750	8.763	15.000	45.000
China	0.563	0.205	20.0%	79.5%
Russia	0.032	0.036	0.0%	10.0%
India	0.106	0.109	0.0%	30.0%
Latin America	0.058	0.085	0.0%	25.0%

The breakdown of account attributes are given below. Once again, it can be observed that none of the regions possess the same degree of influence compared with China. Also, notice that these 8 largest accounts all have their sales mainly directed to the emergent markets. Sales to the “BRIC” region have contributed at least 50% of their total sales. One may refer that this is a reflection of the high potential of these developing economies where demands are not fully satisfied and populations are huge. Nevertheless, one should bear in mind that as mentioned in literature review, common practice for business intelligence collection in industrial product business—including the company discuss in this research— is to rely on sales force composite. In other words, these figures are estimation of sales personnel of their respective accounts/regions and may suffer distortion from lack of factual base.

Exhibit 9 Attribute Information

Account	Segment	Inventory	China	Russia	India	LatinAM	Sum
A87	0	30	78.0%	0.0%	9.0%	1.5%	88.5%
A84	1	30	60.0%	3.0%	5.0%	0.0%	68.0%
A110	0	30	65.0%	3.0%	12.0%	10.0%	90.0%
A2	1	30	50.0%	0.0%	0.0%	0.0%	50.0%
A80	1	45	20.0%	10.0%	0.0%	25.0%	55.0%
A14	0	15	35.0%	7.0%	30.0%	0.0%	72.0%
A29	1	20	62.5%	1.0%	23.5%	5.0%	92.0%
A122	1	30	79.5%	1.5%	5.0%	5.0%	91.0%

The estimated coefficients are presented in the following pages. Because the inclusion of lagged 12-period value, the actual observations used for estimation were only 24 data points extracted from the original pool. As a result, fewer estimates can reach a statistically significant t-value. For the second stage, only 8 observations were used to estimate Θ_t, making it even harder to demonstrate statistical significance. Nonetheless, the covariance matrix of δ_t , Λ, showed extremely small values, showing effectiveness of the estimation.

The coefficient matrix showed results somewhat different from that of initial correlation matrix analysis, and this has once again justified the need to construct a second level model to fine-tune for individual heterogeneity. For example, while LoanRate shared a positive correlation with sales using the summative data, the coefficient of it for some accounts are negative. For similarly statistically significant level in lagged value Yt-12, A2 has a positive value while

A80 a negative one. Even variables with the same signs across account, such as BB ratio, have a difference in the degree of influence. Clearly there is a need to further probe into individual factors contributing to these differences.

A look into the second level would show some enhancing or mitigating effects the firm specific attributes have on the aggregate level coefficient. These firm attributes either increase or decrease the importance of the macro-variables in explaining sales quantity. For example, the dummy variable, “Segment”, has a coefficient of 0.616 on BB ratio. Given the fact that BB ratio showed negative contribution to sales quantity, firms having a Segment value equals to 1— namely, those operate under their own brand – will react less negatively to high BB ratio. One may as well say that firms with their own brands are more resistant to the dynamic adjustment of demand/supply of the industry and will have a smoother sales pattern compared with those adopting non-branding business models.

On the other hand, one can also see that a negative reaction to BB ratio will be intensified if the account puts its emphasis on some geographical regions. With a Θ coefficient of -5.500, 1 more percentage of end-product sales allocated in the China region will affect the coefficient for BB ratio in the aggregate model to reduce by 5.5%. The same is true for Latin American region—1 more percentage of end product sold to Latin America will reflected in 3.54% lower coefficient for BB ratio in aggregate level. One may consider these two regions to be more aggressive in terms of adjustment to imbalanced supply/demand. Alternatively, one could reason that the two regions are more sensitive to shock and having clients making transaction in these areas will make the sales of the company more volatile.

Comparison between A87 and A122 would be a vivid example of the interplay of firm attributes in determining coefficients in aggregate level. The 2 companies have the highest percentage sold to China and Latin America, with A122 slightly higher in both regions. As a consequence, they are both more vulnerable to BB ratio. However, coefficient of BB ratio for A122 is slightly lower despite higher sales in volatile regions. The reason being is that A122 is a branded company, which can enjoy some mitigating effect to ameliorate the negative impact from supply/demand side. Interestingly enough, this finding is in line with contemporary perception that branding will bring more value-added to the company and make its customers less price sensitive during a time when the market is saturated with oversupply.

Exhibit 12 presents the covariance matrix of error term, Λ. As mentioned in previous discussion on estimating methods, one benefit of Bayesian statistics is effectiveness, which means smaller estimation error. By observing, one can easily tell that these values are so small as to be negligible. Even though coefficients in individual level failed to reach statistic significance, an extremely small estimation matrix still implies that models at aggregate level and individual level combined have been able to explain for most of the variations in sales quantity.

Exhibit 10 Estimates of β_t

Account	Intercept	Yt-12	LoanRate	PMI	Concur	Warning	BBRatio	lnLCD
A87	-5.623	0.031	0.084	0.090*	0.131	-0.054	-3.140*	0.143
	(7.953)[a]	(0.230)	(0.383)	(0.036)	(0.097)	(0.033)	(1.243)	(0.347)
A84	-3.962	0.050	0.702*	0.033	0.138	-0.044	-1.571	-0.241
	(6.795)	(0.200)	(0.324)	(0.036)	(0.088)	(0.029)	(0.938)	(0.343)
A110	-5.516	0.062*	-0.020	0.043	0.100	-0.029	-2.900*	0.344
	(7.768)	(0.146)	(0.313)	(0.036)	(0.094)	(0.029)	(1.112)	(0.337)
A2	-3.656	0.464	-0.027	0.005	0.116	-0.019	-0.927	-0.170
	(6.661)	(0.195)	(0.315)	(0.037)	(0.091)	(0.031)	(1.120)	(0.377)
A80	-3.973	-0.403*	0.690	0.022	0.087	-0.054	-0.629	0.253
	(10.974)	(0.140)	(0.410)	(0.036)	(0.130)	(0.032)	(1.582)	(0.404)
A14	-4.571	0.365	-0.425	0.025	0.092	-0.008	-0.614	0.104
	(6.245)	(0.287)	(0.383)	(0.036)	(0.092)	(0.032)	(1.586)	(0.383)
A29	-4.083	0.258	-0.242	0.028	0.063	-0.009	-1.683	0.339
	(7.596)	(0.253)	(0.348)	(0.038)	(0.098)	(0.033)	(1.328)	(0.374)
A122	-4.428	0.079	0.337	0.047	0.189*	-0.071*	-2.920*	-0.307
	(7.424)	(0.152)	(0.302)	(0.036)	(0.094)	(0.029)	(1.123)	(0.343)

a. Std. Deviation of estimation

* Statistic significance at 0.1 confidence level

Exhibit 11 Estimates of

	Intercept	Yt-12	LoanRate	PMI	Concur	Warning	BBRatio	lnLCD
Intercept	-2.473	2.149	-2.570	-0.151	0.100	0.154	1.694	-0.481
	(8.842)[a]	(3.218)	(3.447)	(2.998)	(3.005)	(2.977)	(4.955)	(3.472)
Segment	1.169	-0.043	0.309	-0.017	0.007	-0.003	0.616	-0.171
	(6.967)	(0.497)	(0.582)	(0.450)	(0.454)	(0.454)	(1.413)	(0.580)
Inventory	-0.045	-0.050	0.069	0.005	-0.002	-0.004	-0.018	0.020
	(0.419)	(0.093)	(0.100)	(0.088)	(0.089)	(0.088)	(0.134)	(0.100)
China	-2.034	-0.485	0.661	0.086	0.156	-0.103	-5.500	-0.338
	(9.402)	(1.473)	(1.656)	(1.362)	(1.358)	(1.354)	(3.586)	(1.688)
Russia	-0.157	-2.219	4.892	-0.009	0.615	-0.365	-1.335	-3.938
	(10.051)	(7.752)	(8.066)	(7.130)	(7.210)	(7.128)	(9.629)	(8.182)
India	-2.288	-2.314	1.689	0.225	-0.322	-0.126	-0.062	2.558
	(9.752)	(5.863)	(6.193)	(5.538)	(5.549)	(5.488)	(8.050)	(6.289)
LatinAM	-0.914	0.340	-3.128	-0.151	-0.092	0.153	-3.540	1.814
	(10.031)	(5.334)	(5.791)	(4.982)	(5.002)	(5.019)	(8.296)	(5.770)

a. Std. Deviation of estimation

* Statistic significance at 0.1 confidence level

Exhibit 12 Posterior Estimate of Λ

	Intercept	Yt-12	LoanRate	PMI	Concur	Warning	BBRatio	lnLCD
Intercept	0.372	0.003	0.002	-0.002	0.003	0.000	0.000	-0.003
	(0.441)[a]	(0.204)	(0.180)	(0.244)	(0.199)	(0.202)	(0.187)	(0.246)
Yt-12	0.003	0.280	-0.014	-0.001	0.001	0.000	0.003	-0.002
	(0.204)	(0.240)	(0.144)	(0.177)	(0.156)	(0.148)	(0.152)	(0.189)
Loan Rate	0.002	-0.014	0.313	0.002	0.004	-0.005	0.003	-0.014
	(0.244)	(0.177)	(0.160)	(0.289)	(0.170)	(0.173)	(0.166)	(0.207)
PMI	-0.002	-0.001	0.002	0.263	0.005	-0.001	0.003	-0.003
	(0.199)	(0.156)	(0.149)	(0.170)	(0.226)	(0.143)	(0.150)	(0.178)
Concur	0.003	0.001	0.004	0.005	0.262	-0.001	-0.003	-0.006
	(0.202)	(0.148)	(0.144)	(0.173)	(0.143)	(0.230)	(0.150)	(0.184)
Warning	0.000	0.000	-0.005	-0.001	-0.001	0.265	-0.001	0.004
	(0.187)	(0.152)	(0.144)	(0.166)	(0.150)	(0.150)	(0.232)	(0.187)
BBRatio	0.000	0.003	0.003	0.003	-0.003	-0.001	0.360	0.008
	(0.246)	(0.189)	(0.174)	(0.207)	(0.178)	(0.184)	(0.187)	(0.369)
lnLCD	-0.003	-0.002	-0.014	-0.003	-0.006	0.004	0.008	0.302
	(0.203)	(0.156)	(0.154)	(0.180)	(0.156)	(0.163)	(0.158)	(0.194)

a. Std. Deviation of estimation

* Statistic significance at 0.1 confidence level

Forecasting results are compared against that of MLE method. With MLE method, there was only 1 level of multiple- regression composed of Macro-economic variables. It ignores the difference in firm attributes and attempt to forecast sales quantity solely with variation in aggregate level. The estimates of β_t using MLE are listed below and used for both in-sample and out-sample tests. For in-sample test, the fitted values were compared against the 24 periods of observations used to construct the models. MAPE (Mean Absolute Percentage Error) is calculated for both methods to evaluate the level of deviation of fitted values to actual values. The formula for MAPE is

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\frac{|\hat{y}_t - y_t|}{y_t},$$

where $\hat{y}_t$ is the fitted value for period t and y_t the actual value. The same procedure is taken for out-sample test, which is conducted using the 3 left out periods from January 2009 to March 2009.

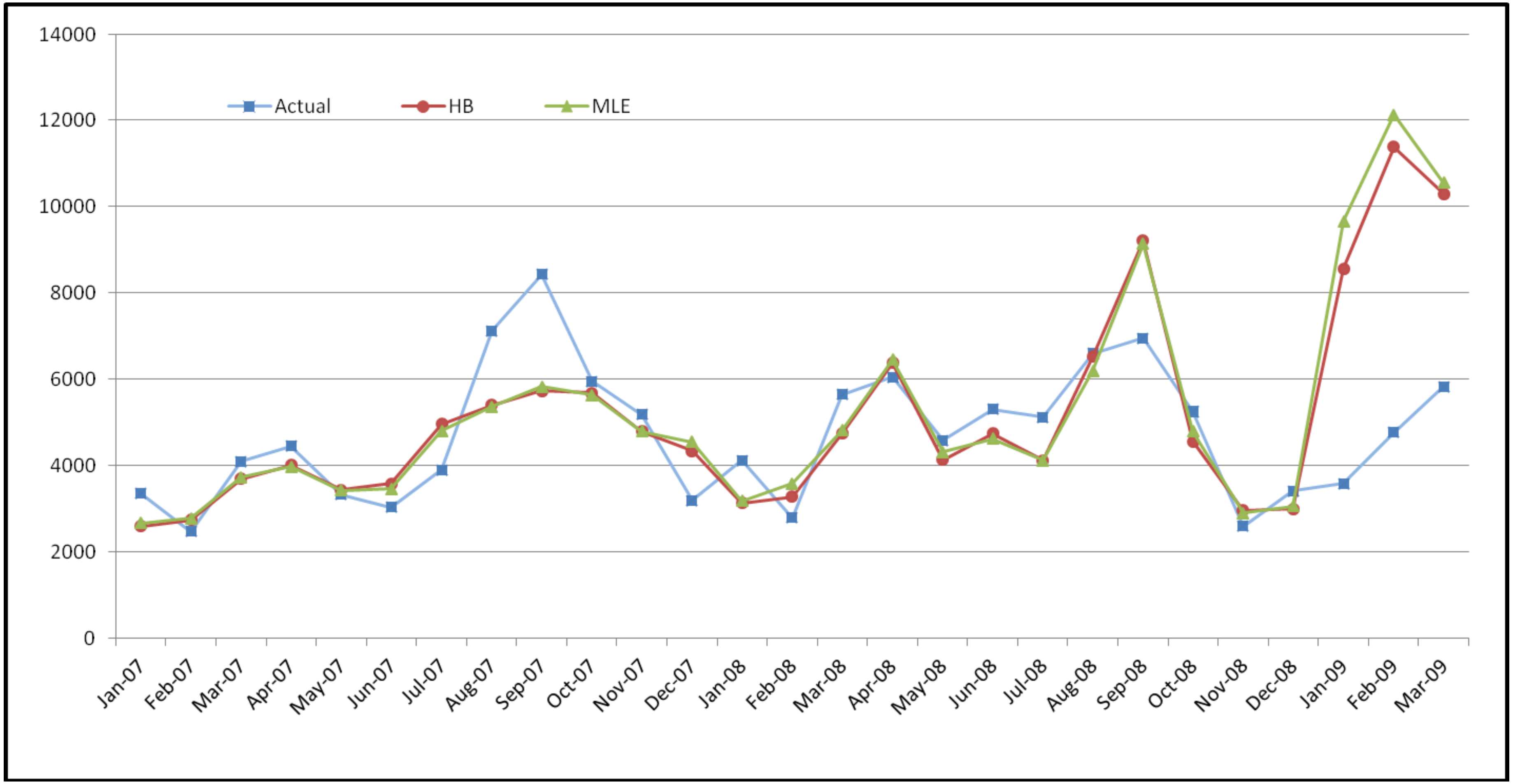
As shown in Graph 3 and the fitted statistics, one can observe that the forecasting power of the two methods is quite similar. MLE method has slightly higher R statistics in in-sample test, whereas HB has lower MAPEs of total sales quantity in both in-sample and out-sample tests.

Exhibit 13 MLE Estimates of β_i

Variable	Mean	Std Deviation
CS	-6.378	18.498
YT_12	0.073	0.301
LoanRate	0.133	0.686
PMI	0.037	0.028
Concur	0.130	0.164
Warning	-0.039	0.028
BBRatio	-1.796	1.580
lnLCD	0.114	0.500

Exhibit 14 Fitted Statistics

Account	In-sample MAPE		Out-sample MAPE	
	HB	MLE	HB	MLE
A87	29.278%	28.929%	481.649%	293.322%
A84	34.616%	27.370%	37.191%	195.834%
A110	26.330%	26.702%	154.665%	261.340%
A2	27.150%	27.552%	42.814%	41.040%
A80	18.295%	17.100%	21.098%	25.727%
A14	20.330%	19.554%	15.343%	9.649%
A29	35.118%	33.543%	65.287%	26.000%
A122	35.750%	35.416%	237.896%	484.872%
Total	15.876%	15.937%	118.300%	135.193%
Multiple R	0.864	0.878		
R-Squared	0.747	0.771		
Error Std. DEV	0.337	0.321		



Graph 2 Forecast Result (8 accounts)

Chapter 5 Conclusion

5.1 Managerial Implications & Suggestions

This study proposed a two stage model to account for both economic influence and firm specific attributes that contributes to the differences in purchase quantity among different key accounts. The purpose of this method is to extend the idea of customer heterogeneity commonly applied in sales forecast for consumer goods to the forecast of industrial products, where a number of key accounts dominate the majority of the sales volume. In estimating the parameters of each level, Hierarchical Bayesian method is applied and MLE method is used as a comparison alternative. When testing the forecast power of the two methods, results are similar with HB slightly better in out-sample forecasting.

First of all, the method presented in this research poses an opportunity for management to develop a more customized forecasting procedure that helps them better capture the heterogeneity among customer, which in turn can improve their estimation of the aggregated total demand in this ever-changing business environment. For management, low accuracy in the forecast of high-tech industry has been a problem that is hindering the effectiveness of decisions such as a more efficient production planning or appropriate pricing, and both research and survey have shown that companies manufacturing industrial products tend to conduct sales forecast with different approaches compared with those in consumer product industry. While consumer product industry strives to fully utilize information regarding customers' behaviors to optimize marketing results, same measure is rarely adopted in industrial products, where macro-economic environment and future industry trend have been more of the attention. However, this top-down approach requires more subjective judgment from the management or analysts, whose knowledge and information might be confined. Therefore, if it is combined with another bottom-up approach that address sales forecast from the other side, namely the customers, results produced should be more comprehensive and accurate. Therefore, management might consider modifying their current practice and developing a measure to record the characteristics of their customers. By borrowing the best practice from other industries, they might come up with a model that incorporate different levels of factors affecting their sales and have a better knowledge of future demand.

5.2 Limitation & Future Directions

The most significant limitation of this research is the representativeness of the coefficients. Although they show economic sense when explained, few of them actually show statistic significance due to the constraint of limited observations. Therefore, one should be careful when interpreting the size, relative scale of β_t and Θ_t. Instead using the model in this research for future forecast, it would be safer to say that these models are examples of how client features could be included and help the forecasting quality of the company.

On the other hand, the data of this research is collected from an existing company which has yet to adjust their forecasting system to account for the different customer attribute. Nor do they have very solid idea what are the crucial variables with highest explanatory power. Therefore, when many of the variables contained in the original data do not show high correlation with sales, there might be a great deal of other variables with the same relevancy being left out. This is also a common mis-practice in firms adopting customer database where database failed to collect the most relevant information and responsible personnel could not produce optimal results without these crucial information and sometimes might even have to compromise with currently available variables with small explanatory power. In the future, if information about customer attributes can be further expanded to cover other aspects that might also be relevant in explaining sales variation in individual account, forecast results should be improved. For companies wish to implement this forecasting mechanism, this model misspecification problem resulted from the gap between the forecast practitioners and information collector should be eliminated. It would be more effective to have thorough communication between the sales force composite responsible for collecting client information and the intelligence department who actually do the final modeling. Understanding from each party could assure the company with higher chance of collecting the "right" information that would eventually contribute to better forecasting results.

References

1. 陳靜怡（民 96）。購買量與購買時程雙變量之預測－層級貝氏潛藏行爲模型之建構。台北：國立台灣大學國際企業學研究所博士論文。
2. 林柏全（民 97）。解讀聯發科的成長密碼。新竹：國立交通大學管理學院碩士在職專班經營管理組碩士論文。
3. 呂玉敏（民 94）。應用雙變量層級貝氏模型於顧客價值分析——以購物網站爲例。台北：國立台灣大學商學研究所碩士論文。
4. 魏以恩（民 93）。以 Bass 擴散模式爲基礎建立跨國新產品之銷售預測模型－以在台上映之美國電影爲例。台北：國立台灣大學國際企業學系碩士論文。
5. 吳語軒（民 94）。層級貝氏購買期間模型之比較。台北：國立台灣大學國際企業學系碩士論文。
6. Allenby, G. M., L. C. Jen, et al. (1996). “Economic trends and being trendy: The influence of consumer confidence on retail fashion sales.” Journal of Business & Economic Statistics 14(1): 103-111.
7. Berling, P. (2008). “The capital cost of holding inventory with stochastically mean-reverting purchase price.” European Journal of Operational Research 186(2): 620-636.
8. Chang, C. T., (2002). “Extended Economic Order uantity Model under Cash Discount and Payment Delay.” Information and Management Sciences 13(3): 57-69.

9. Clarke, H. R., (1987). "Economic order quantities with discounting." Engineering Costs and Production Economics 11 (2): 15-22.

10. Dalrymple, D.J. (1975). "Sales Forecasting Methods and Accuracy." Business Horizons. December: 69-73.

11. Dalrymple, D.J. (1987). "Sales Forecasting Practices." International Journal of Forecasting 3: 380-91.

12. de Alba, E. and M. Mendoza (2001). "Forecasting an accumulated series based on partial accumulation: A Bayesian method for short series with seasonal patterns." Journal of Business & Economic Statistics 19(1): 95-102.

13. Fisher, M. and K. Rajaram (2000). "Accurate retail testing of fashion merchandise: Methodology and application." Marketing Science 19(3): 266-278.

14. Ghysels, E. and M. Nerlove (1988). "SEASONALITY IN SURVEYS - A COMPARISON OF BELGIAN, FRENCH AND GERMAN BUSINESS TESTS." European Economic Review 32(1): 81-99.

15. Herbig, P., J. Milewicz, et al. (1994). "Differences in Forecasting Behavior Between Industrial Product Firms and Consumer Product Firms." Journal of Business and Industrial Marketing 9(1): 60–69.

16. Himmelberg, C. P. and B. C. Petersen (1994). "RESEARCH-AND-DEVELOPMENT AND INTERNAL FINANCE - A PANEL STUDY OF SMALL FIRMS IN HIGH-TECH

INDUSTRIES." Review of Economics and Statistics 76(1): 38-51.

17. Hua, Z. S., B. Zhang, et al. (2007). "A new approach of forecasting intermittent demand for spare parts inventories in the process industries." Journal of the Operational Research Society 58(1): 52-61.

18. Jen, L. C., C. H. Chou, et al. (2003). "A Bayesian approach to modeling purchase frequency." Marketing Letters 14(1): 5-20.

19. Lackman, C. L. (2007). "Forecasting sales for a B2B product category: case of auto component product." Journal of Business & Industrial Marketing 22(4-5): 228-235.

20. Lenk, P. (2001). Bayesian Inference and Markov Chain Monte Carlo: 199-240.

21. Lo, S. L., F. K. Wang, et al. (2008). "Forecasting for the LCD monitor market." Journal of Forecasting 27(4): 341-356.

22. Lynn, G. S., S. P. Schnaars, et al. (1999). "Survey of new product forecasting practices in industrial high technology and low technology businesses." Industrial Marketing Management 28(6): 565-571.

23. McDade, S., T. A. Oliva, et al. (2010). "Forecasting organizational adoption of high-technology product innovations separated by impact: Are traditional macro-level diffusion models appropriate?" Industrial Marketing Management 39(2): 298-307.

24. Miltenburg, J. and H. C. Pong (2007). "Order quantities for style goods with two order opportunities and Bayesian updating of demand. Part I: no capacity constraints."

International Journal of Production Research 45(7): 1643-1663.

25. Neelamegham, R. and P. Chintagunta (1999). “A Bayesian model to forecast new product performance in domestic and international markets.” Marketing Science 18(2): 115-136.

26. Nicolau, J. L. and F. J. Mas (2005). “Stochastic modeling - A three-stage tourist choice process.” Annals of Tourism Research 32(1): 49-69.

27. OECD, (2009). Guide To Measuring The Information Society : 19-20

28. Sawhney, M. S. and J. Eliashberg (1996). “A parsimonious model for forecasting gross box-office revenues of motion pictures.” Marketing Science 15(2): 113-131.

29. Stangl, D. K. (1995). “PREDICTION AND DECISION-MAKING USING BAYESIAN HIERARCHICAL-MODELS.” Statistics in Medicine 14(20): 2173-2190.

30. Thomas, D. J., D. P. Warsing, et al. (2009). “Forecast Updating and Supplier Coordination for Complementary Component Purchases.” Production and Operations Management 18(2): 167-184.

31. van de Klundert, T. (2008). “Looking back, looking ahead: Biased technological change, substitution and the wage gap.” Journal of Macroeconomics 30(2): 707-713.

32. Yelland, P. M. (2010). “Bayesian forecasting of parts demand.” International Journal of Forecasting 26(2): 374-396.

33. Yelland, P. M., S. Kim, et al. (2010). “A Bayesian Model for Sales Forecasting at Sun Microsystems.” Interfaces 40(2): 118-129.