# From Macro to Micro
# A case of a successful implementation of a novel sales forecasting methodology of great practical implications

**Maya Dori Arbiv**

Doctorate Thesis Dissertation

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Ph. D. program in Economics, Management and Organization (DEMO)

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# Abstract

Our doctorate thesis offers a novel sales forecasting model in order to predict the sales of products in different market segments, cultures, stages of the product life cycles and in different intra-product portfolio dynamics. The four empirical studies of our thesis are driven by the identified need for a pragmatic, robust and accurate sale forecasting tool for companies and by the lack of literature and tools that can cover the entire width of our problem statements. The forecasting models are based on company´s external inputs (macroeconomic indicators) that allow us to overcome the challenge and the dependency of gathering the company y´s internal information for a sales forecast and on the other hand offers a new external perspective on the sales potential of the products and it also allow us to explore the role of macroeconomic model in the decision-making process at the micro company´s level. The forecasting models presented in this thesis were used in many of Hewlett–Packard´s high profile decision making processes ranging from market sizing, forecasting of the company´s revenue, establishing sales quotas for the sales force as well as R&D investment decisions in new products.

The forecasting models show, through empirical study number 1 ,that to correctly capture the unique characteristics of each of the product lines, the set of macroeconomic indicators that are used as inputs needs to be singular and adapted to the drivers of the demand generation for the products. With these findings, empirical study number 1, sheds empirical light to the new institutional theoretical framework. Empirical study number 2 shows that in order to correctly capture the sales demand in a country or a culture one has to understand the culture´s characteristics and reflect them in the inputs used for the forecasting model. With these empirical study findings we provide support to the marketing adaptation school of thoughts. Empirical study number 3 proves that the models forecast accurately products regardless of their product life cycle stages which is an essential attribute to ensure the wider usability of the models in comparison to other forecasting methodologies described in the literature. Empirical study number 4 takes the individual forecast models of two products and compare them to the actual sales results of these products. The assumption of the analysis is that the deviations between the forecasted units and the real units sold of each of the product are explained by the portfolio dynamics between the two products and thus quantifies the portfolio dynamic. The introduction of a third product and its impact on the other two existing product is also discussed in empirical study number 4 leading to better understanding of the role of management in product portfolio decision making and contributing to the product portfolio management literature.

**Keywords**: *Forecasting, sales forecasting, demand forecasting, institutional theory, Bass model, product life cycle, marketing standardization, marketing adaptation, product portfolio, product portfolio management, national culture, management decision making*

# Acknowledgements

When I was a primary school student in Israel, I often used to stay during the afterschool hours and teach myself science at the small school library. While I was there, every time I lifted my eyes from the books I could see in front of me on one of the walls the phrase “A man is not more than the mold of the landscapes of his homeland” (Shaul Tshernichovsky). More than 30 years have passed and many kilometers away in the new place I call now home, I still hold this sentence to be true.

I am not more than the mold of the landscapes of my homeland, to where my grandparents immigrated and established their new life starting all over again but writing their own book of life and giving hope for a better world after the Second World War.

I am not more than the mold of the landscapes of my homeland, as I’m the daughter of my parents and the older sister to my sister and brother. For all my parents’ love and efforts I would like to thank them deeply. My mother and father have big part in my achievements.

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# 1 Introduction

Our thesis offers a novel sales forecasting model for high tech products. It does so for various market segments, cultures, stages of the product life cycles and for the different intra-product portfolio dynamics that a product might have with other products in the same product line. Our thesis is driven by the identified need for a pragmatic, robust and accurate sale forecasting tool for companies such as Hewlett-Packard and by the lack of literature that covers the entire width of our questions.

We are using macroeconomic indicators as a basis for sales forecasting. Our decision of not using company´s internal data streams from the nature of this data. Internal information can be either incomplete, missing, spread across various department or biased. This makes our model, on the one hand, more accessible to firms and, on the other hand, more objective by not including different departments´ likely biases. Apart from facilitating an accessible and objective forecast, the use of external macroeconomic indicators also allows us to explore their role in the decision-making process at the micro level. This special link between the macro and the micro is at the core of our four empirical studies. Thus, the four empirical studies detailed in our thesis represent a rare opportunity of connecting theoretical frameworks with the empirical demonstration of the theories. Among the theories that are being demonstrated empirically in our thesis there are the New Institutional theory, the Bass model as a forecasting tool improvement, Product portfolio dynamic and the marketing strategy debate for international companies, namely the Standardization vs. Adaptation.

Sales forecasting is an essential building block in many of the companies' strategic decisions such as defining the markets for products, analyzing products and product potential in different markets, planning corporate strategies, defining distribution channels, product pricing and determining profit and sales potential. In addition to being essential in companies´ strategic processes, sales forecasting is also key in many operational decisions such as, developing sales quotas, determining the number and allocation of salespeople, product production planning, constructing advertising and marketing budgets, determining inventory standards and more. Inaccurate forecast, therefore, often leads to business losses evident in both the cost of goods return and opportunity loss. This is especially the case in high value products industries. Thus, the absence of solid forecasting models in companies' strategic and operational processes is the underlying motivation for our thesis.

Likewise, in their paper summarizing the Bass model research in the last 25 years, Meade and Islam (2006) have identified forecasting with multinational models as one of the potentially most interesting future research areas. The reason they gave for this identification was that more and more multinational companies launch cross borders products and therefore, face challenges in forecasting the sales in such a complex environment.

## 1.1 The price of uncertainty

Forecasting is considered by Chambers et al. (1971) as "the third rail of business". In virtually every decision they make, companies today consider some kind of sales/demand forecast. Sound predictions of demands and trends are no longer luxury items, but a necessity, if companies are to cope with sudden changes in demand levels and large swings of the economy. Sales forecasting can help companies deal with these challenges as long as the forecasting tools are accessible, accurate, simple and insightful.

The importance of accurate and accessible forecasting cannot be stressed enough and there is an ample recognition in both the managerial and the academic literature of the importance of sales/demand forecasting as key in many strategic planning and operational processes. Mentzer and Bienstock (1998) and Makridakis and Hibon (2000) pointed that forecast of sales influences numerous decisions at the organizational level. Agrawal and Schorling (1996) also claimed that accurate demand forecasting plays an important role in profitable retail operations. In the managerial literature we find numerous stories of companies and sometimes even entire industries that have made grave strategic errors because of inaccurate industrywide demand forecasts. Among the most known business stories we can find the following:

- In 1974, U.S. electric utilities made plans to double generating capacity by the mid-1980s based on forecasts of a 7% annual growth in demand. Such forecasts are crucial since companies must begin building new generating plants five to ten years before they are to come on line. But during the 1975–1985 period, load actually grew at only a 2% rate. Despite the postponement or cancellation of many projects, the excess generating capacity has hurt the industry financial situation and led to an increase in the electricity bills of the consumers.
- The petroleum industry invested $500 billion worldwide in 1980 and 1981 because it expected oil prices to rise 50% by 1985. The estimate was based on forecasts that the market would grow from 52 million barrels of oil a day in 1979 to 60 million barrels in 1985. Instead, demand had fallen to 46 million barrels by 1985. Prices fell, creating huge losses in drilling, production, refining, and shipping investments.
- In 1983 and 1984, 67 new types of business personal computers were introduced to the U.S. market, and most companies were expecting explosive growth. One industry forecasting service projected an installed base of 27 million units by 1988; another predicted 28 million units by 1987. In fact, only 15 million units had been shipped by 1986. By then, many manufacturers had abandoned the PC market or gone out of business altogether.

The need for an accessible and an accurate forecasting methodology is even stronger for high tech companies. These companies were defined by Clarke and Stough (2001) as any industry having twice the number of technical employees and double the R&D outlays of the average and also as companies that are engaged in the design, development, introduction of new products and innovative manufacturing processes, or both, through the systematic application of scientific and technical knowledge. Also considered to be high tech companies those who participate in a business with high-tech characteristics: the business requires a strong scientific/technical basis; new technology can obsolete old technology rapidly; and as new technologies come on stream, the applications they create revolutionize demand. Anyway you define it, a high-tech industry faces special challenges not encountered by other more stable industries and, therefore, the need for demand forecasting that can help decide on the technology R&D investments, sales channels, etc. is even stronger in high tech companies.

In spite of the critical role of sales/demand forecasting tools in the companies' and especially to high tech companies' survival, only few companies are really good at forecasting, and there can be big penalties for being wrong. In fact, a survey of more than 500 senior executives completed by the world-known consulting firm, KPMG and that was cited by the Harvard Business Review, Bartlow et al. (2016), shows that only 1% of companies hit their financial forecast over three years, and only one forecast out of five are within 5% forecasting accuracy. On average, according to the survey, companies forecasting was off by 13% and that forecasting inaccuracy had a very big impact of the company's shareholder value of not less than 6%.

## 1.2 Why do managers need forecasting tools

We live in a world of uncertainty where an effective forecast could serve as a useful compass helping management to navigate with informed intuition through the market turbulences. Saffo (2007) stresses the importance of forecasting as a way of broadening management's understanding by revealing overlooked possibilities and exposing unexamined assumptions regarding hoped-for outcomes. At the same time, it narrows the decision space within which they must exercise their intuition. The forecaster's job according to Saffo (2007) is to define the range of possibilities in a manner that helps the decision maker exercise strategic judgment. Saffo (2007) also makes a distinction between a "prediction" and a "forecast". According to this distinction, "prediction" is possible only in a world in which events are preordained and no amount of action in the present can influence future outcomes. However, the reality is quite different – little is certain and our current actions and decisions in the present shape how things could turn out in the future. "Forecast" on the other hand, looks at how hidden currents in the present signal possible changes in direction of markets. Thus, the primary goal of forecasting is to identify the full range of possibilities in their various levels of probabilities. Whether a specific forecast actually turns out to be accurate is only a part of the picture. Unlike a prediction, a forecast must have logic to it. The forecaster must be able to articulate and defend that logic. Moreover, Management, the end user of the sales forecast, must understand enough of the forecast process and logic to make an independent assessment of its quality and to properly account for the opportunities and risks it presents. The wise end user of a forecast is not a trusting by stander but a participant and, above all, a critic. We will validate through empirical study number 4 the power of managerial decisions demonstrating that management has a key role in making decisions that can change the business reality. Our forecasts models are not "predictions" but forecasting tools that management can use in order to make decisions that can change the future of the company and the market both in the short and the long term.

To cater to all these challenges management must have access to accurate and robust forecasting technics. With "access" we refer to being able to have a forecast that will provide him or her with the tools to make decisions. These tools should not be necessarily perfect from the academic point of view but tools that adhere to some statistics minimum base lines and that are accessible and simple for them to understand and trust. According to Georgodd and Murdick (1986) improving a firm's forecasting competence even a little can yield a competitive advantage. A company that is right three times out of five on its judgment calls is going to have an ever-increasing edge on a competitor that gets them right only twice out of five.

Managers are facing with numerous challenges from strategic to operational and they are paid for and expected to ensure that the company is profitable. Sales/demand forecasting for the company´s products is useful as it can help management make the numerous decisions at every stage. At each stage of the life cycle of a product, from conception to steady-state sales, the decisions that management must make are characteristically quite different, and they require as accurate as possible forecasting to answer these challenges. For example, at the product development stage the questions would be about the amount of development effort, product design, business strategies, alternative growth opportunities to pursuing product X, should the company enter these markets, how to allocate R&D efforts, how successful will different product concepts be, how will product X fit into the markets five or ten years from now and the like. Later on, at the early introduction of the product, the decisions are about the optimal facility size, marketing strategies, distribution channels and pricing and when the product is at rapid growth the questions are around facility expansion, marketing strategies, production planning and sales coverage. Before a product can enter its (hopefully) rapid penetration stage, the market potential must be tested out and the product must be introduced and then more market testing may be advisable. At this stage, management needs answers to these questions: what shall our marketing plan be? Which markets should we enter and with what production quantities? How much manufacturing capacity will the early production stages require? As demand grows, where should we build this capacity? How shall we allocate our R&D resources over time? When the product is at a steady state the decisions that must be made are around promotions, special pricing, production planning and inventory management.

Each of the product life cycle stages represents a long chain of decisions and challenges for the company's management. So many decisions to be made and the risk in getting them wrong is high and expensive to both the management and the company. To answer all these important questions at every stage of the product life cycle, the company´s management will need access to demand/sales forecasting tools.

## 1.3 A success story - The use of our forecasting models at Hewlett-Packard

We offer a robust sales/demand forecasting tool to help companies make numerous strategic and operational decisions regardless of the product line, product life cycle stage or geographic coverage. Such a flexible and robust forecasting tool has countless implications to companies. One company that already successfully tested and implemented our forecasting/demand forecasting tool in its strategic and operational decisions making processes is Hewlett-Packard.

Hewlett-Packard is an important company of high tech products and like several other market players it is characterized by the rapid development of science and technology, with increasingly frequent products upgrades and with more products having shorter life cycle. The short life cycle of the technology products is a result of science and technology updating faster, commodities becoming more personalized and functional products being combined with innovative products. In such a market where product life cycle is shorter, there is an increasing need for management to have access to a robust sales forecast and so was the case for Hewlett-Packard which faced many of these challenges in its forecasting activity. An article called "Forecasting for short-lived product: Hewlett-Packard's journey", published by two Hewlett-Packard' s employees, Burruss and Kuettner (2003), recognized that "the forecasting methods in use today are often poorly suited to the consumer electronics industry, because they assume that products have a fairly long life cycle, which is often not the case in this industry" and described how Hewlett-Packard's Strategic Planning and Modeling group (SPaM) consequently developed a forecasting methodology, called the Product Life Cycle (PLC). The method is specifically designed to forecast products with high uncertainty, a steep obsolescence curve, and a short life cycle. At the heart of this methodology from 2003 was the use of forecasting by analogy before any demand is realized for new products mainly inkjet Desktop printers. In general, until 2010 the forecasting methodology applied by most of the departments of Hewlett-Packard was mainly based on extrapolation of previous year sales results plus the estimated sales results of the new product launch sales that was estimated by the product managers. This forecasting methodology often created frustration as after a good sales year the bar was usually set higher, creating the sense that the sales people are becoming "victims" of their own success. The worse was after an extremely good year followed by an extremely bad year where the gap between the forecasted sales results and the actual sales was the widest. In addition, the forecasting based on extrapolation also required the collaboration of several departments within the company, the finance department had to provide gross margin calculation for the products and currency level estimations, the strategic marketing department had to provide products sales forecast for the coming year, the current business department had to provide the year´s actual information of the units sold, the product mix from every country, the sales pricing of each country as well as other information. Such a forecasting exercise represents a challenge where most of the effort actually goes to gathering the internal information rather than assessing how well the past year´s information will serve as a good basis to the next year´s sales results.

In the last years, our forecasting models took an important part in several of Hewlett–Packard´s high profile decision making processes ranging from market sizing, company's revenue forecasting, establishing the sales quota for the sales force and deciding which products justify the investment required in R&D. Our sales/demand forecasting tool were tested and used by Hewlett-Packard for several product lines in several countries and in several stages of the product life cycle. Playing a critical role in the decision making processes at Hewlett-Packard, in order to validate their accuracy, our models were compared to the latest actual sales results. In addition to the forecasting accuracy requirement, our forecasting models provided Hewlett-Packard with insights on the reasons for the expected market demand changes. These insights are enabled in our forecasting model by the usage of the macroeconomic indicators that best correlate to the market of the products. The macroeconomic indicators that we chose were closely related to the sales enablers of the products and therefore, the forecasted changes in the demand could always be explained by the changes in the sales enablers as they were captured in the macroeconomic indicators.

Our forecasting models were used in numerous occasions during several years in Hewlett – Packard. Between 2010 and 2012, in the midst of deep world economic crises, our forecasting models were at the heart of tough decision making process for Hewlett-Packard R&D product investments. Similar to any multinational company with several product lines, Hewlett-Packard acts as an investment fund that carefully assesses its different products R&D investments. In multinationals, different product lines are, in reality, competing with each other for the company´s funding and each product division is therefore required to submit its sales forecast to secure its future R&D funding. Our forecasting models provided a market size forecast for future products reflecting the market potential for these products as well as their revenue estimations based on additional parameters such as expected market share and product pricing. The forecasting models were updated and reviewed every three months by the company´s top managers and were used these models to assess the market potential and the Return of Investment (ROI) of the products that often implied many millions of dollars.

From 2012 to 2014 our models were used by Hewlett-Packard´s European directors extensively for other high profile decision making processes. One such process was establishing the sales quotas and sales objectives for the different countries. It was an annual process with a great impact on the entire sales force remuneration, as their salaries depended on achieving the sales quotas that were establish based on our forecasting models. The risk in wrongly setting the sales quota is double fold. If the company sets the sales quotas too high, the sales goals will not be met and the commission-driven sales force will become less engaged and may leave the company. If the company sets the sales quota too low, the sales force will not sell more than the established sales quota leaving revenue in the market to be picked up by competitors while their sales commission is fully paid for a job only partially done. Therefore, our sales forecasting models had to be accurate and cultural adaptive in order to correctly forecast the sales quota in the amalgam of countries that composes the sales region.

In parallel to establishing the sales quotas, from 2012 to 2014 the European managers of Hewlett-Packard used our forecasting models to negotiate the sales targets that were given by the Hewlett Packard ´s headquarters and to establish the sales and pricing strategy in order to achieve these sales targets. Every year, Hewlett-Packard's headquarters provide sales revenue targets and financial guidelines. The regional managerial teams have to prepare their own assumptions with regards to the sales forecast of their region and compare it to the headquarters´ next year's financial guidelines proposal before it becomes a commitment. It is a though negotiation process where both sides have a lot at stake. If the region takes the headquarters´ proposal and commits to it without a double check, the risk of not meeting the financial commitment agreed implies multiple risks to the company's employees and to the company's investors. To mitigate this risk, the regions´ management needs to provide solid reasons, backed up with numbers, as to why the financial targets should be different than the headquarters´ proposal in order to commit to an achievable financial target. In this tough and complex negotiation process, completed every year in which, our forecasting models where instrumental in helping the region commit to achievable sales and financial targets.

In 2014, our forecasting models were at the heart of another set of important decisions that needed to be made about a new product introduction. The new product had to coexist with several generations of products in the portfolio and the forecasting model helped the management to quantify dynamics between the different products at the portfolio and decide on the actions required to balance the new product mix. The fact that the company´s managers were able to quantify in advance the dynamics between the several generations of products enabled the management to provide clear guidelines to the new product introduction as well as to the sales force. This resulted in one of the best product introductions in this product line´s history.

From 2014 onwards, the Silicon Valley pioneer Hewlett-Packard, underwent a tectonic shifting process. On November 2, 2015, the 76 years old company, has split into two companies, HP Inc. (HPQ) and Hewlett Packard Enterprise (HPE). The shares of the two independent entities started trading on the New York Stock Exchange on November 2, 2015. The market also identified that the two new companies are indeed different and on the first day of trading, the companies' shares moved in opposite directions. HP Inc.'s shares rose 13% to close at $13.83 while Hewlett Packard Enterprise's fell 1.6% to close at $14.49.

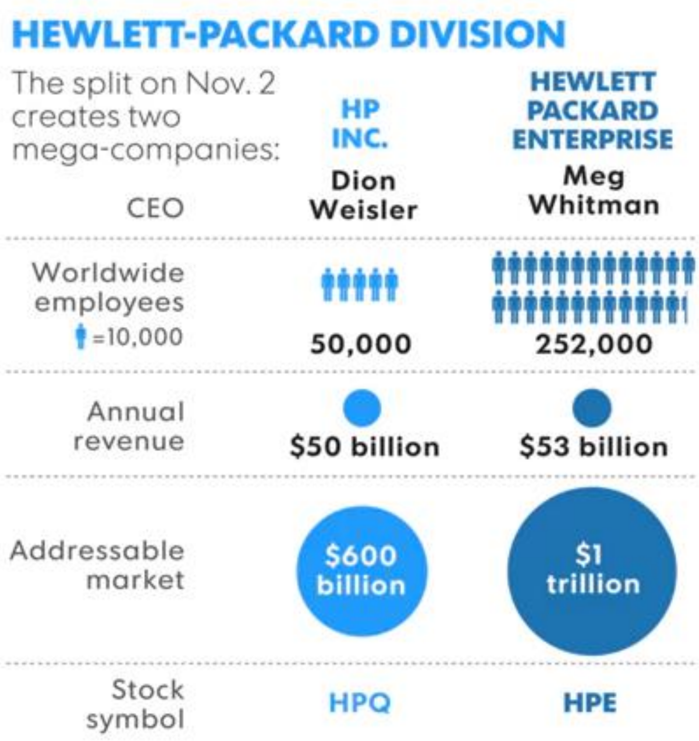



**Figure 1 Hewlett-Packard split in 2015**

**Source: Market Realist Inc.**

According to Market Realist Inc., the split of Hewlett-Packard was first announced on October 6, 2014, as part of the company's five-year plan to turn around its business, which has been hit by the emergence of cloud technology and continued softness in PC (personal computer) shipments. HP Inc. will focus on PCs and printers, while Hewlett Packard Enterprise, or HPE, will focus on servers, storage, the cloud, networking, services, and software. Meg Whitman the former CEO of Hewlett-Packard (2011-2015) and the CEO of the Hewlett-Packard Enterprise from 2015 said that "as two independent, industry-leading companies, Hewlett-Packard Enterprise and HP Inc. can drive more focused business strategies, innovation roadmaps, and go-to-market models. The separation will also present better choices for investors by creating two distinct and attractive investment profiles."

| HP Inc. Printing and personal systems | Hewlett-Packard Enterprise Data center and infrastructure |
|---|---|
| Desktops | Servers |
| Laptops | |
| Tablets | Storage |
| Chromebooks | |
| Workstations | Networking |
| Displays and monitors | |
| Thin clients | Software |
| Printers | |
| Peripherals | Cloud |
| POS equipment | Services |

**Figure 2 Hewlett-Packard markets division after the split**

**Source: Market Realist Inc.**

The company´s split had a huge impact on all the business aspects of the two newly formed companies. According to the market analyst, Market Realist, Hewlett-Packard has already reduced its workforce by 80,000 to 85,000 during the process of the split, and expected to cut around 30,000 more jobs in its enterprise segment in the following years. After the company's split, our forecasting model were not used.

In summary, between 2010 and the company's split announcement in 2014, our forecasting models proved time and time again to be reliable tool in several of the most strategic decisions that Hewlett-Packard´s managers and executives had to make. The models helped the company gain and save money in all these strategic decisions from product R&D investments to correctly distributing the sales quotas to the countries and helping launch new products while avoiding cannibalization of products in the company´s portfolio.

## 1.4 Does sample size matter?

The successful implementation of our sales/demand forecasting models at Hewlett-Packard represent an important proof point for our forecasting model usefulness and need for multinational companies such as Hewlett-Packard.

Hewlett-Packard´s management was looking for forecasting tools that comply with the base rules of statistics and, at the same time, help its managers make tough decisions.
The company´s management was very satisfied with our models and acknowledged them to be insightful and useful while the right balance between accuracy and accessibility.

One of our forecasting model´s constraints from a statistical point of view may be its limited data points. Our models use between 4 to 9 data points representing between 4 and 9 years of product history. This possible limitation, however, must be taken at its industry context of the challenge of managing products with a short life cycle. In high tech markets a 4 year-old technology is considered to be mature and at 9 years on the verge of becoming obsolete. The short life cycle of most of the high tech products is an inherent limitation on our forecasting models as it would be in any other fast moving industry from fashion to technology. Because the life cycles of technology products are too short for standard time-series forecasting methods (not longer than three-four years), one of the most important ways of overcoming the challenges of managing supply chains for such products is to find appropriate forecasting methodologies Fisher and Raman (1999). The standard forecasting methods require some historical data, which are often unavailable at the time when the forecasts are being performed for products with a short life cycle Lin (2005). The life cycle profiles for these products are different from profiles of a standard life cycle. They have a high introduction spike, a gradual leveling-off of sales in the maturity phase, and then a swift decline in sales when a new generation of products is introduced e.g. Wu and Aytac, (2007).

We do not deny the valid economic reason behind having an optimal size of data sample. An under-sized study can be a waste of resources for not having the capability to produce useful results, while an over-sized one uses more resources than necessary. Sample size is beyond a statistical theoretical discussion, especially in experiments involving human or animal subjects where sample size is a pivotal issue for ethical reasons. An under-sized experiment exposes the subjects to potentially harmful treatments without advancing knowledge. In an over-sized experiment, an unnecessary number of subjects are exposed to a potentially harmful treatment, or are denied a potentially beneficial one.

For such an important issue in life science and medical research, there is a surprisingly small amount of published literature. Important general references include Mace (1964), Kraemer and Thiemann (1987), Cohen (1988), Desu and Raghavarao (1990), Lipsey (1990) and Odeh and Fox (1991). There are numerous articles, especially in biostatistics journals, concerning sample-size determination for specific tests. Also of interest are studies of the extent to which sample size is adequate or inadequate in published studies; see Freiman et al. (1986) and Thornley and Adams (1998).

The theoretical statistical framework of the optimal sample size is the central limit theorem that states that the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed. The theorem deliberately does not define what “large” means. If it could be proven that it is 30, or any other number for that matter, the theorem would have said so. But it does not. If the central limit theorem is silent about the meaning of “large,” where does the classical reverence for 30 as the sample size come from? In reality, it comes from artificial computer simulation experiments presented in introductory textbooks. These experiments take repeated idealized computer samples (assuming no error component) from a normal distribution, sometimes from skewed distributions. But we know that many attributes in real life are not normally distributed. For example, consumer purchases follow a negative binomial distribution and not a normal distribution. Admission in maternity wards will likely follow Poisson distribution rather than a normal distribution. In a simulation exercise involving four different underlying distributions (normal, uniform, beta and gamma) carried out by Professor Murtaza Haider of the Ted Rogers School of Management, it took a sample of 4,500 (not 30) for the t-value to converge precisely to the z-values needed for a normal distribution. This is after assuming perfect random sampling, 100 per cent response rate, and no coverage error.

The central limit theorem is a very important theorem in statistics. It provides the basis for much of our sampling procedures. The fact that even small samples can converge to normality is interesting and has profound implications for marketing and social research. But it stretches credulity to take an inductive leap and believe that, therefore, the number 30 has magical properties and would work irrespective of the underlying distribution, irrespective of where and how sample is chosen, irrespective of clustering, irrespective of non-randomness, and irrespective of other non-sampling errors that accompany marketing research studies. The central limit theorem simply does not say it, nor is there any empirical support for it.

The questions of small sample is more critical and more frequent at the pharmaceutical and medical research. Studies with a small number of subjects have several very important advantages as they can be quick to conduct with regard to enrolling patients, reviewing patient records, performing biochemical analyses or asking subjects to complete study questionnaires. Therefore, an obvious strength is that the research question can be addressed in a relatively short space of time. Furthermore, small studies often only need to be conducted over a few centers. Obtaining ethical and institutional approval is easier in small studies compared with large multi-center studies. This is particularly true for international studies. It is often better to test a new research hypothesis in a small number of subjects first. This avoids spending too many resources, e.g. subjects, time and financial costs, on finding an association between a factor and a disorder when there really is no effect.

Small studies can also make use of surrogate markers when examining associations, i.e. a factor that can be used instead of a true outcome measure, but it may not have an obvious impact that subjects are able to identify. For example, in lung cancer, the true end-point in a clinical trial of a new intervention is overall survival: time until death from any cause. ''Death'' is clearly clinically meaningful to patients and clinicians, thus if the intervention increases survival time this should provide sufficient justification to change practice.

Surrogate end-points are often associated with more events, which are observed relatively soon after the intervention is administered; therefore, subjects may not require a long follow-up period. Both of these characteristics allow a smaller study to be conducted in a short space of time. Observing no change in the surrogate marker usually indicates there is unlikely to be an effect on the true end-point, thus avoiding an unnecessary large study.

The small sample studies in the world of medical research are not rare events in spite of their implications on the patients' health a good example of that is that the editorial board of the European Respiratory Journal often review very interesting studies but based on small sample sizes. While the board encourages the best use of such data, editors must take into account that small studies have their limitations.

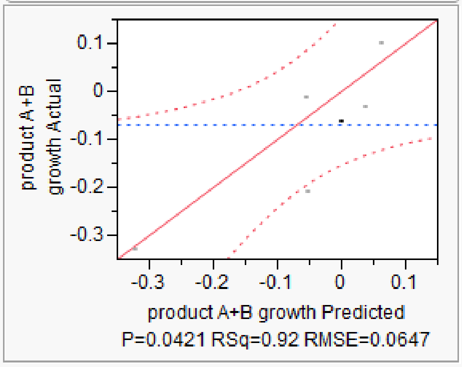
In summary, we recognize that one of the theoretical limitations of our forecasting models from an academic point of view lays at the small data sample that was used as a consequence of the nature of the products. However, there are several facts that tilt the scale toward accepting and embracing our forecasting models as great contribution to the managerial and scholar literature in spite of their limitation. **The first** is the fact that in spite of the possible limitation of small data sample size, our models were used by Hewlett-Packard to make informed decisions. **The second** is the fact that the theoretical reason behind the ideal sample size does not necessarily imply that 4-9 data points is not valid. **The third** is the fact that even in clinical trials with human patients it is admitted to create new treatments and new drugs at a “life or death” situations based on small sized sample research. **The fourth** reason is that the forecasting models are not only useful at the managerial pragmatic level but also at the scholar and academic level as they prove empirically, as it will be discussed at length in our thesis, some of the most known theoretical frameworks in social science and marketing such as New Institutional Theory, Standardization versus Adaptation as the best marketing strategy for the company that looks for expanding its markets beyond its home country.

Last but not least, **the fifth** point is the fact we consulted with the Applied Statistics Department - Servei d'Estadística Aplicada of the Universidad Autónoma of Barcelona about the small sample size of our models that derives from the nature of the products. The Statistics department stated several reasons for their approval of the small sample size of our forecasting models. The first was that any empirical study has to use the sample data that is available to it even if it means using only few data points. The second reason was directly linked to our specific econometric models quality. Our models have high R^2s, the F tests indicate that the R^2s are significantly different from 0, the coefficients of the explanatory variables are significant and their standard errors are not high. The statistics departments stated that the quality of our models, in spite of the small data sample, proves that our models cannot be a result of a “random walk” and therefore concluded there was something profound in our models that overcomes the limited sample size. Consequently, the statistics department academic judgement was that our forecasting models are useful from a practitioner point of view. All these five proof points give us the confidence to claim that the advantages of our forecasting models outweigh the sample size theoretical limitation.

## 1.5 Trying to improve our data sample size

Even though the theory, academy and also the practice support the validity of our small sized forecasting models, we made the effort of increasing the data points. These efforts and their results are detailed in this section. Our models might be based on small sample data but they do not ignore or violet the baseline rules of the statistics validity of our models. All our models have an R^2 of above 80% with the dependent variables statistically significant and we looked for even more ways to make our models more statistically valid. One of the theoretical options to increase the number of data points could have been to use quarterly macro and sales data instead of annual data that were used in the models and by that multiply our sample size by four. Our models are originally created based on annual sales data and annual macroeconomic indicators. We used annual data and not quarterly data that could have multiplied our forecasting sample size by four, from 4 data points to 16, and make them more valid from statistical point of view. We limited our models to annual sales and macro sample data for several reasons. **The first and the main reason** for using annual data is directly related to the decision making horizon. The types of decisions that require our forecasting models were strategic ones such as R&D investments, setting sales quotas, new product launch, etc. These decisions are related to structural and more profound currents of the markets and are best reflected in annual data. As a proof point to that, we can highlight that the annual dependent variables in our sales forecasting models were statistically significant. In the following figure we demonstrate one of our forecasting model using only 4 annual data points and using as an independent variable annual GDP growth rates.

**Actual by Predicted Plot**




**Summary of Fit**

| | |
|---|---|
| RSquare | 0.917533 |
| RSquare Adj | 0.8763 |
| Root Mean Square Error | 0.064718 |
| Mean of Response | -0.06982 |
| Observations (or Sum Wgts) | 4 |

**Analysis of Variance**

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 1 | 0.09320221 | 0.093202 | 22.2522 |
| Error | 2 | 0.00837689 | 0.004188 | Prob > F |
| C. Total | 3 | 0.10157911 | | 0.0421* |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.110502 | 0.033488 | -3.30 | 0.0809 | -0.254591 | 0.0335869 |
| GDP growth | 5.9136574 | 1.25363 | 4.72 | 0.0421* | 0.5197214 | 11.307593 |

**Figure 3 The statistics results of our forecasting model using annual data points**

As shown in the summary above of this model that is based on annual sales and macroeconomic indicator which is annual GDP , the model shows and R square adjusted of 87.63% and the level of confidence of the model (1-α) set to 95.8% and the annual independent variable “GDP growth” is statistically significant at 95.8% as well.

**The second reason** for not using quarterly data is also related to how the macroeconomic data is gathered annually versus quarterly, making the annual data more accurate as usually quarterly GDP for example is done with a smaller sample and has some estimations done (often based on last year's data). Annual GDP on the other hand is usually the most accurate measure with a larger sample and more revision time between collection of data and its publication.

To support our claim that the annual macroeconomic indicators are different and more accurate than the quarterly macroeconomic indicators we bring a quote from the OECD publication “Quarterly National Accounts” that describes the sources and methods used by OECD member countries in composing and reporting their macroeconomic indicators. In its explanation, the OECD confirms that there are great differences between the aggregation of quarterly data and annual data causing differences in the level of accuracy: "Although the increased use of input-output techniques for quarterly accounts may give the impression that exactly the same methodology is used for quarterly and annual accounts, this is seldom if ever the case." (OECD P. 8). The OECD also admits that the quarterly macroeconomic indicators are less accurate than the annual macroeconomic indicators. "While all national accounts contain elements of unreliability, special uncertainties attach to quarterly national accounts because the basic statistics from which they are derived tend to be less complete than those used in preparing annual estimates." (OECD P. 16)

In our forecasting models, it is also evident, as shown in the following figure, that the same macroeconomic indicator that was statistically significate when it was taken at its annual form becomes statistically irrelevant and does not contribute to a statistically meaningful forecasting model. We would like to highlight that the model has not changed and the only change is by introducing a higher frequency data from annual to quarterly and this change created a model that stops being statistically significant or even valid.

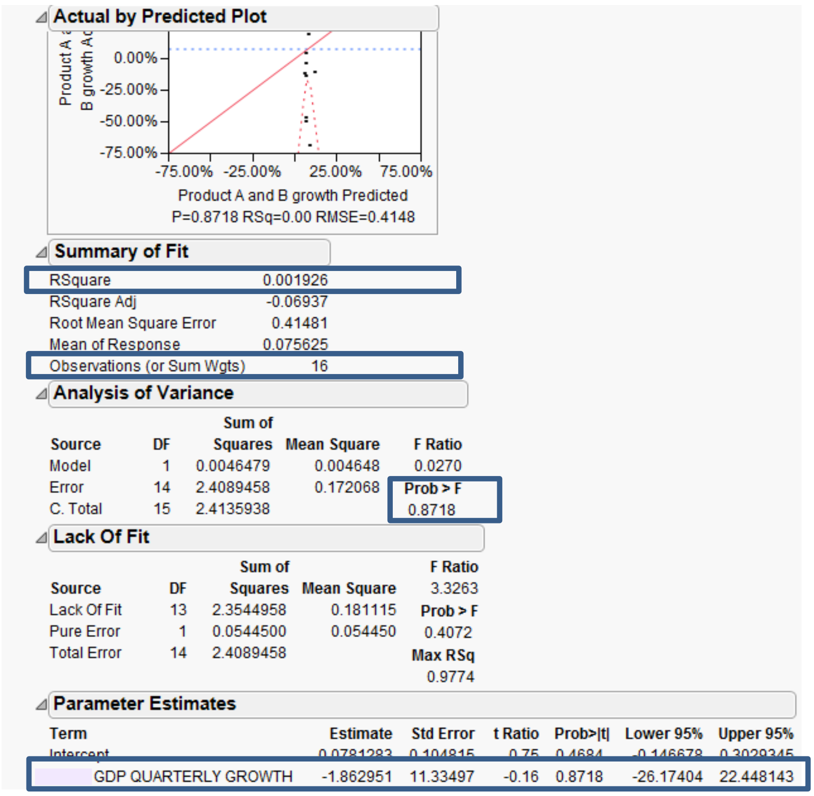



**Figure 4 The statistics results of our forecasting model using quarterly data points**

As shown in the figure above, statistics summary of this model that is based on quarterly sales and macroeconomic indicator which is quarterly GDP, the model shows and R^2 adjusted of -6.93% and the level of confidence of the model (1-α) is set to 12.82% and the quarterly independent variable “GDP growth” is non-statistically significant at 12.82% as well.

**The third reason** for not using the quarterly data in spite of its theoretical statistical advantage was that quarterly data points are heavily subjected to seasonality effect related to short term decisions that the middle management can make. Among these decisions that can change the sales in the short term, we can find price promotions and competition moves. These decisions require very close monitoring and fast decision making. This part of the quarterly decision making is based on information that can usually discovered and covered by the company´s sales calls. There is no advantage in using macroeconomic-indicators-based-forecasting model for something that can be brought to the management attention by talking to the sales force.

We tested the seasonality effect at the quarterly data sample and added to the model dummy independent variables representing each one of the 4 quarters and controlling for seasonality. Adding the dummies to the quarterly forecasting model has improved substantially the model in comparison to the quarterly model without the dummies but still it was far from the annual forecasting model from the statistics point of view. The following figure summarizes the statistics results of the quarterly model with the dummy variable reflecting the seasonality. As shown in the following figure, the seasonality dummy values were statistically significant variables at the quarterly models but none of the independent variables that were statistically significant at the annual models was statistically significant at the quarterly forecasting models.

**Summary of Fit**

| | |
|---|---|
| RSquare | 0.649201 |
| RSquare Adj | 0.521638 |
| Root Mean Square Error | 0.277437 |
| Mean of Response | 0.075625 |
| Observations (or Sum Wgts) | 16 |

**Analysis of Variance**

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 4 | 1.5669078 | 0.391727 | 5.0893 |
| Error | 11 | 0.8466859 | 0.076971 | Prob > F |
| C. Total | 15 | 2.4135938 | | 0.0144* |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 0.0773522 | 0.070147 | 1.10 | 0.2937 | -0.077041 | 0.2317453 |
| EMEA GDP QUARTERLY GROWTH | -1.28538 | 7.80226 | -0.16 | 0.8721 | -18.45804 | 15.88728 |
| Du_Q[1] | -0.478335 | 0.120935 | -3.96 | 0.0023* | -0.744512 | -0.212159 |
| Du_Q[2] | 0.222455 | 0.120698 | 1.84 | 0.0924 | -0.043199 | 0.4881092 |
| Du_Q[3] | -0.07162 | 0.121992 | -0.59 | 0.5690 | -0.340123 | 0.1968835 |

**Effect Tests**

| Source | Nparm | DF | Sum of Squares | F Ratio | Prob > F |
|---|---|---|---|---|---|
| GDP QUARTERLY GROWTH | 1 | 1 | 0.0020891 | 0.0271 | 0.8721 |
| Du_Q | 3 | 3 | 1.5622599 | 6.7655 | 0.0075* |

**Figure 5 The statistics results of our forecasting model using quarterly data points and controlling for seasonality effect**

We show in the above figure the statistics summary of this model that is based on quarterly sales and macroeconomic indicator which is quarterly GDP and controlled for seasonality by the quarterly dummy variables. The model shows an R square adjusted of 52% and the level of confidence of the model (1-α) set to 85.6%. One of the quarterly dummy variables, the one that represents the first quarter of the year was statistically significant while the rest of the independent variables including the "EMEA GDP growth" quarterly variable are non-statistically significant. The reason that only the first quarter is statistically significant could be that among the four quarters the first is the most representative of the entire year´s trend. The reason for us to believe that the first quarter represents best the sales potential is due to its proximity to the forecasting time.

The conclusion from this effort of increasing the sample size by using quarterly data instead of annual data is that increasing the data points in itself does not improve the statistics validity of the model in comparison to the original model which uses only 4 annual data points. It could be that the quarterly data contains too much "noise" that do not allow the macroeconomic indicators capture more structural currents that can be useful for the forecasting models.

There could be many other reasons for the quarterly data to be less valid for our model but one thing from this experiment is very clear. It is evident that at least in our models, the smaller but higher quality data samples contributed more to a statically valid model than the sample size that was 4 times bigger.

# 2 The problem statements

Our doctorate thesis offers a novel forecasting model in order to predict the sales of products in different market segments, cultures, stages of the product life cycles and in different intra-product portfolio dynamics. The four empirical studies of our thesis are driven by the identified need for a pragmatic, robust and accurate sale forecasting tool for companies and by the lack of literature and tools that can cover the entire width of our questions. The forecasting models are based on company´s external inputs (macroeconomic indicators) that allow us to explore their role in the decision-making process at the micro company´s level. The forecasting models presented in this thesis were used in many of Hewlett-Packard´s high profile decision making processes ranging from market sizing, forecasting of the company´s revenue, establishing sales quotas for the sales force as well as R&D investment decisions in new products.

## 2.1 Problem statement number 1: limited usage of the existing forecasting tools

There are many forecasting methodologies suggested by both scholars and managerial consultants such as Bass (1969), Heeler and Hustad (1980), Mahajan et al. (1990), Jain (1992), Bass et al. (1994), Callen et al. (1996), Prybutok et al. (2000), Erdem et al. (2005), Chang et al. (2005), Chang and Liu (2008), Tanaka (2010), Zliobaite et al. (2012) and many more.

However, in spite of the abundant forecasting methodologies in the literature, and the critical role of the forecasting for the companies, none of the existing forecasting method has been established itself as a standard forecasting method and most of the existing forecasting methodologies are not part of the companies forecasting methodologies and the usage level of the forecasting methodology among firms is very low. Armstrong and Pagell (2003) claim that only 3% of the published papers about forecasting are found useful enough to be used in practice.

It is intriguing to try and understand the huge gap between the need for forecasting tools for strategic and operational decision making of the company and the extremely low usage of forecasting tool in reality. The reason suggested for the very low usage of the forecasting tools by firms by Hogarth (2006) is that companies need simpler forecasting models as simpler models are also proven to be more accurate than complex ones in many situations. It seems that the forecasting methodologies are perceived by the companies as too statistically sophisticated and as those that would require resources that only few companies could afford. Most of these forecasting methods require certain econometric and mathematical skills to master and therefore are not within the reach of many companies and their managers. In addition, many of these forecasting methods require ample data from the company that is spread among different departments in different data bases and that each department acts as a “gate keeper” for its information. Due to all of the above limitations it is not surprising that not all academic forecasting methods and techniques are used in practice by the companies.

Using macroeconomic indicators in our forecast model help overcome many of the forecasting challenging for companies. First and foremost, macroeconomic indicators as inputs means that our forecasting model does not require company´s internal data that can be either incomplete, biased, missing or spread across various departments such as in the case of Hewlett-Packard. The use of external data in the form of macroeconomic indicators, makes our forecasting model more accessible to firms and more objective in its results as the different departments´ natural biases are not reflected at the model´s results. It will also help the companies adopt the forecasting model as it is not a result of one specific department´s data.

In addition, we use linear regression in our model which mathematically is very simple, which could help the forecast methodology more accessible for companies. Another advantage of the linear regression is in its simplicity. The literature brings ample evidences that statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones (Makridakis et Al. (1982) and Makridakis and Hibon (2000)). Gigerenzer and Goldstein (2002) also showed recently that simple statistical forecasting rules, which are usually simplifications of classical models, have been shown to make better predictions than more complex rules, especially when the future values of a criterion are highly uncertain.

In our forecasting model the simplification is manifested in the usage of a linear regression and the small amount of macroeconomic indicators and data points used in the regression.

## 2.2 Problem statement number 2: multinationals marketing strategy dilemma

Multinational companies are especially interested in understanding culture differences as it affects their sales in the different countries. Different tastes and cultural nuances are very important to take into account in order to sell the right products to the right people or package and communicate the value of the same product in a different way to different people.

As the level of global trade increases, corporations around the world have a growing need for establishing the right strategy to deal with the sales of products in very distinctive cultures e.g. Elinder (1961), Diehl et al. (2005), Advertising Age, (2005). The marketing academic literature is divided between those who favors replicating the methodology of the company at its base country to other markets that it expands, called “Standardization” e.g. Fatt (1967), Buzzell (1968), Levitt(1983), Kotabe(1990), Yip (1996), Friedman (2005) and those who believe that each new market requires culture specific marketing tools from the company, called “Adaptation” e.g. Jain (1989 ), Kashani (1989), Ruigrok and van Tulder (1995), Papavassiliou and Stathakopoulos (1997), Czinkota and Ronkainen (1998), Paliwoda and Thomas (1999).

The impact of national culture has become one of the most important topics also in management research e.g. Leung et al. (2005), Friedman (2005), Gelfand et al. (2007), Tsui et al. (2007) and Triandis (2008) and Sirkin et al. (2008). Most of the efforts exerted by cross cultural researchers have been directed towards uncovering and explaining e.g. Earley and Singh (1995) and Chen et al. (2003) or finding better ways to uncover and explain cross-cultural differences e.g. Kitayama, (2002), Brockner (2003), Von Glinow et al. (2004) and Tsui et al. (2007). In parallel to the management research, there is literature that classifies the cultural dimensions e.g. Hofstede (1980) and Triandis and Gelfand (1988) have ultimately supported effects of national cultures. These studies did account for individuals' differences in attitudes within a nation and also made cross-cultural comparisons.

In our empirical study, we combine sales forecasting on the same product with selecting three distinctively different cultures. We show that the best forecasting accuracy is reached when the macroeconomic indicators are selected and treated based on the uniqueness of the culture. This validates empirically that the cultures are in fact different and that affects the sales patterns of each of the culture. It also proves that the best marketing strategy for multinational companies lays in the adaptation of its marketing activities to the different cultures.

Our empirical study number two tests the sales forecasting models created at the empirical study number one and explores their behavior under different cultures. We offer in our thesis a two-level test to the Adaptation-versus-Standardization debate. Our first hypothesis tests whether a global sales forecasting model works at the same accuracy level at a geographically aggregated level and at its sub-geography level. In case that the testing this hypothesis results in that the global model does not work well at the sub levels, the standardization approach at its extreme will be discarded.

Our second hypothesis will check the best forecasting model at a sub-regional level. By finding a country specific sales forecasting model we will provide additional support to the adaptation approach.

The novelty of our contribution to the adaptation-versus-standardization debate is of double fold: the first contribution is by the fact that it provides strong empirical support to the adaptation approach in the two hypotheses mentioned above and the second contribution is by the methodology applied that uses external factors to the companies. Most of the literature about standardization and adaptation that is mentioned in our literature review uses internal factors related to the companies themselves such as pricing, resources etc. Our thesis contributes to the debate by using forecasting models which are based on macroeconomic indicators hence uses firms´ external factors to guide both management and scholars in this decision.

## 2.3 Problem statement number 3: product forecasting at different stages of the product life cycle

Bass (1969) sets the academic framework for product life cycle, where product´s life is divided into five different segments. Nevertheless, the Bass model fails to serve as a forecasting tool. Bass and many others have offered several studies that tried to improve Bass original model e.g. Robinson and Lakhani (1975), Mahajan and Peterson (1985), Norton and Bass (1987), Gatignon et al. (1989), Mahajan et al. (1990), Baptista (1999), Mahajan et al. (2000a,b) and Meade and Islam (2001).

Our forecasting model offers an alternative to the Bass model as a method of forecasting. In addition to being a forecasting alternative method, our thesis also proves to overcome some of Bass´ most known forecasting limitations. The classic Bass model does not provide explanation or forecasting capabilities to the product´s initial stage, the takeoff e.g. Golder and Tellis (1997) nor the sales decrease right after the product take off, also known as, the chasm e.g. Moore (1991) and later on was coined a "saddle" by Goldenberg at al. (2002).

Our model overcomes both the takeoff and the saddle challenges present in the Bass model by the fact that it has proven to forecast well products in different stages of their life cycle.

## 2.4 Problem statement number 4: limited tools for product portfolio management

Portfolio management for product innovation is one of the most important senior management functions according to Roussel et al. (1991) and Cooper and Kleinschmidt (1996). Faced with rapidly changing technologies, shorter product life cycles, and heightened global competition, more than ever, how a business spends its technology dollars and resources is paramount to its future prosperity and even its survival.

If we accept the fact that an innovation introduced into a market cannot remain isolated, we have to accept the possibility that another innovation or existing product can both positively or negatively influence its diffusion process. The market success of a given innovation may even be aided by another product (multi-product interactions) or product generation (successive generations).

The classical diffusion models such as Bass (1969), Kalish (1985) do not consider relationships between different product categories; thus they do not take into account the fact that the adoption of an innovation does complement, substitute, eliminate or enhance the adoption of another product(s) (or vice versa). A later Bass paper, Norton and Bass (1987), takes into account multiple generation products but the assumption of having a consistent coefficient across generations that this paper is based upon has received criticism from Islam and Meade (1997). In general, in spite of the fact the several generation of products coexisting is a very common thing, there is relatively little attention to it from the academic literature, Shocker et al. (2004).

Coexisting products could influence each other in several possible ways; they can create acceleration of the product adoption as the technology develops and that could substitute each other as new product generation takes the place of an old one. There is not a clear answer to the question whether the diffusion accelerates across technology generations and Stremersch et al. (2010) has been offering contradicting answers to this question.

Another product portfolio dynamic that raise the interest of the academic researchers is the product substitution. Some of the diffusion models have threated the substitution questions as upgrading e.g. Norton and Bass (1987, 1992) and Bass and Bass (2001, 2004) and cannibalization e.g. Mahajan and Muller (1996). Our model quantifies the product substitution/cannibalization/upgrade phenomenon and demonstrates that indeed as Goldenberg and Oreg (2007) defined the “laggards”, we have also witnessed in our research leapfrogging of the laggards’ users between the old generations of product to the newest products.

Our model is using external data to the company in the form of macroeconomic indicators which allows us to quantify the impacts of the intra-product portfolio synergies and interaction. In particular, our empirical study number four shows indication of acceleration in the adoption rates of the newer generations of products and these results support the analysis of Van Bulte (2000, 2002) that also found conclusive evidence that such acceleration does indeed occur.

# 3 Literature Review

## 3.1 Product forecasting

Our model is a product sales forecasting tool, a subject that can be found in many publications in the marketing science literature. The breakthrough publication of product diffusion model was the publication of *"A new product growth model for consumer durables"* by Frank Bass (1969). The original Bass model is driven by the basic premise of diffusion theory, which suggests that inter-personal communication significantly influences the diffusion process. Therefore, sales, Y, are modeled as a function of the cumulative past sales by typically using the differential equation form $f(Y) = \frac{dY}{dt}$.

The basic Bass model assumes that marketing effects can be implicitly captured by the diffusion parameters. This model is the conceptual basis of other diffusion models that have been suggested in the past and it is currently and in the past used as a benchmark model in the literature. But despite this popularity, its forecasting quality is not universally convincing, especially prior to the sales peak (Boswijk and Franses (2005), Heeler and Hustad (1980) and Mahajan et al. (1990)). To improve the performance of the Bass model, numerous extensions have been proposed such as models that have explicit consideration of marketing variables, in particular pricing. One of the most notable extensions was proposed by Jain (1992) and integrates the Bass approach into the proportional hazard (PH) model. The PH model is composed of a baseline hazard function that captures the longitudinal regularities in duration time dynamics and an exponential function of covariates that proportionately adjusts the baseline hazard up or down to reflect the effect of marketing variables . Jain used the hazard function of the Bass model as the baseline hazard.

Another interesting extension is the Generalized Bass model (GB model) proposed by Bass et al. (1994). The GB model reduces to the basic Bass model if the relative changes in the period-to period values of the marketing variables are constant. Thus, the Bass model achieves approximately the same fit as the GB model in the case of almost constant relative changes. Like the PH model, it is able to explain the deviations of the actual data from the smooth and symmetric curve of the basic Bass model when the causal effects of the marketing variables are statistically significant. This, however, means that neither the PH model nor the GB model captures the actual effect of price in the sense of democratization of innovation.

Bass et al. (2000) empirically compared the basic Bass model, the GB model and the PH model in terms of forecasting accuracy and reported that the latter performs better than the GB model, and the GB model performs better than the Bass model.

Tsai and Yiming (2011) use the Bass growth and the Lotka-Volterra equation to predict the equilibrium between the different sizes of LCD TVs. The Lotka-Volterra model was developed to model interaction between two competing species based on logistic curve offset by Chakraborty et al. (2007) and Delgado and Suarez (2007) and extended to analyze technological diffusion in competitive or collaborative markets suggested by Watanabe et al. (2003), Tang and Zhang, (2005) and Castiaux, (2007). Zliobaite et al. (2012) offer a predictors-based sales forecasting tool for the retail food business.

In parallel to the variances to the Bass diffusion approach, Decker and Gnibba-Yukawa (2010) has developed a Utility-Based approach in successfully analyzing consumer behavior in high tech markets. The utility based approach describes individual buy/no-buy decisions of consumers from the utility-theoretic point of view and transform the utility from getting the product to a purchase probability. In this case, the market development is explained by the changing utility of an innovation over time.

There are two ways to consider the effect of interpersonal communication within the utility-theoretic approach. One possibility is to use the Bayesian framework and explicitly model how product quality perception and uncertainty about the product change after having obtained new word-of-mouth information. Erdem et al. (2005) used this approach to investigate information search and purchase behavior in the personal computer (PC) market. However, since it requires extensive individual-level data, its applicability to the present sales forecasting task is limited. The effect of interpersonal communication can also be modeled by using the time since product introduction or by using the number of adopters as an independent variable in the utility function. Jun and Park (1999) as well as Jun et al. (2002) followed this idea and modeled purchase behavior regarding successive generations of technological innovations.

In addition to the Bass and utility models and their derivatives, in the field of forecasting in general the literature offers a prolific array of mathematical methods. The existing quantitative approaches include heuristic methods such as time series decomposition and exponential smoothing as well as time series regression and autoregressive and integrated moving average (ARIMA) models. However, Chu and Zhang (2003) claimed that linear methods have major limitations since users are unable to consider the complex relationships in the data into those forecast except for seasonal analysis. There are, therefore, researches on nonlinear modeling approach with neural networks. Interest in using artificial neural networks (ANNs) for forecasting has led to a tremendous surge in research activities in the past decade. While ANNs provide a great deal of promise, they also embody much uncertainty. Researchers to date are still not certain about the effect of key factors on forecasting performance of ANNs. Elkateb et al. (1998) proposed that neural network (NN) model in electric load forecasting showed better performance than ARIMA models. Prybutok et al. (2000) also reported the superiority of ANN method in forecasting ozone concentration. However, Callen et al. (1996), Darbellay and Slama (2000), and Kirby et al. (1997) reported the opposite results. Their findings revealed that neural network is not superior to the time series models even if the data is nonlinear. In addition, Faraway and Chatfield (1998) reported that a neural network model requires experimental efforts and traditional modeling skills in order to fix each product forecast settings. These problems, thus, illustrate that ANN method is not the best forecasting method for those industries with short life cycle or wide variety products.

However, some other trials for combining clustering technique and forecasting method have been reported successful results e.g. Chang et al. (2006).

Tanaka (2010) proposes a forecast model for irregular and nonlinear sales items names an NM method. This method predicts the future M day accumulated sales forecast based on the past nth day accumulated sales results. Shah (2012) offers a fuzzy based method for non-stationary, non-linear time series as an improved prediction for many different types of data such as university enrolment, sales of chemical product and India´s GDP. Karniouchina (2011) emphasize the predictive capabilities of the virtual stock markets for gestalt-like products (movies, music records, theatrical plays etc.).

The various forecasting methods found in the literature can be expressed in the following figure:

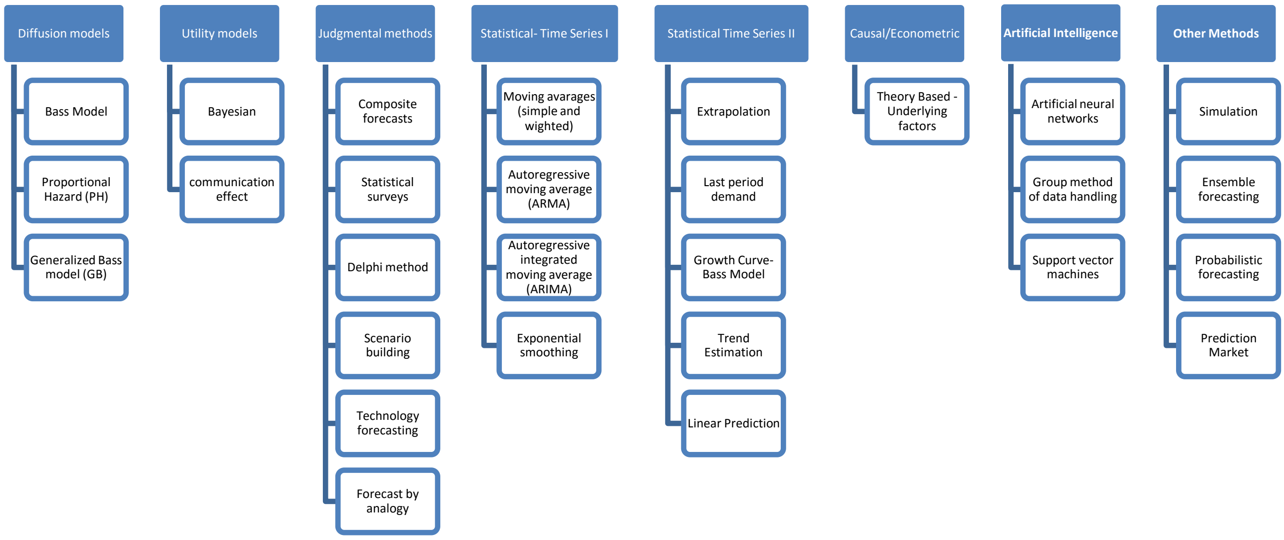



**Figure 6: The classification of forecasting methods**

**Source: aggregated information by Maya Dori**

These forecasting methods are rarely stand-alone methods and they are usually interlinked and combined with each other. Figure 4 summarizes some of the observed connections between the various forecasting methods. Such as between the causal method and Forecast by analogy or between scenario building and simulation

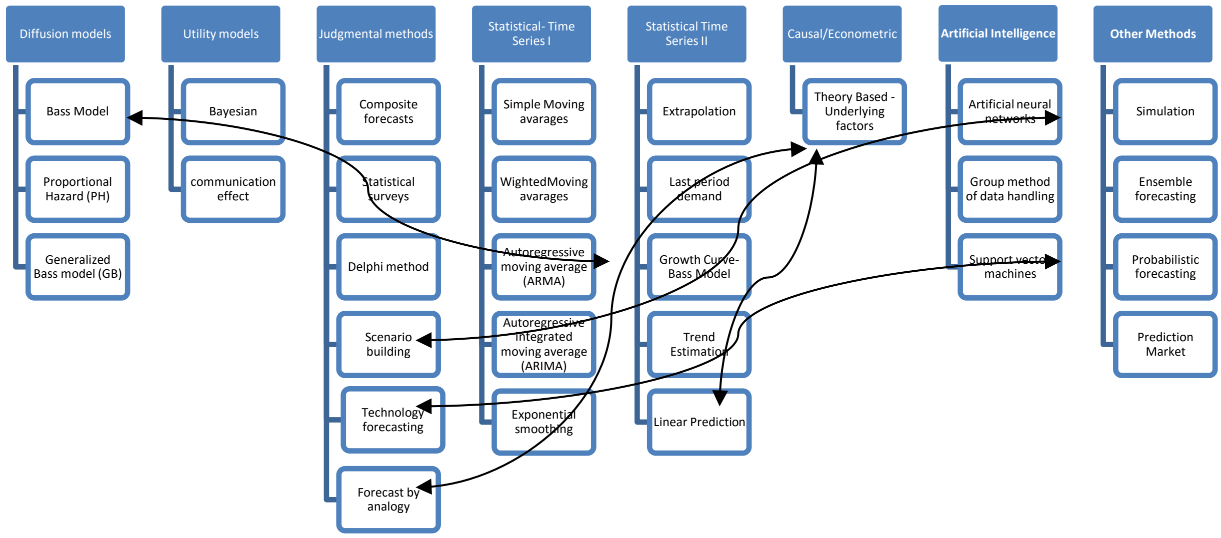



**Figure 7: The relationship between the forecasting methods**

**Source: aggregated information by Maya Dori**

Presently, no method has been established as a standard forecasting method for those nonlinear products and all of these methods require certain econometric and mathematical skills to master and, therefore, they are not within the reach of many company managers.

## 3.1.1 The ingredients of a good forecasting model recipe

### 3.1.1.1 Keep it simple

We aim to propose a sales forecasting model that is simple and easy to implement in the high tech industry. This is in line with the literature evidences in Makridakis et al. (1982) and Makridakis and Hibon (2000) that statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones. Gigerenzer and Goldstein

(2002) also showed recently that simple statistical forecasting rules, which are usually simplifications of classical models, have been shown to make better predictions than more complex rules, especially when the future values of a criterion are highly uncertain. In our model the simplification is manifested in the usage of a linear regression and the small amount of macroeconomic indicators used in the regression.

The most influential paper on empirical comparisons of alternative forecasting methods is that of Makridakis, et al (1982) called the M-competition. The M-competition was followed by other competitions, the most recent being the M3-Competition by Makridakis and Hibon (2000). The three M competitions consisted of an invitation to predict thousands of time-series drawn from various areas of economic activity and different forecast horizons by volunteers' researchers in any of the forecasting methods that the researchers desired. Then these forecasts accuracy were compared and ranked. One of the main conclusions of all the M-competitions was that statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones. The possible reason given by Makridakis and Hibon (2000) that simple methods can outperform, in certain cases, statistically sophisticated ones, is that simple methods usually identify and extrapolate the trends and other patterns in the data that are influenced by strong cycles of varying duration and lengths whose turning points cannot be predicted, making them behave like a random walk.

#### 3.1.1.2 Linear regression has some inherent advantages

Our suggested forecasting models are based on the widely spread regression analysis which entered the social science in the 1870s with the pioneering work of Francis Galton. According to Armstrong (2001), Grove and Meehl (1996) and Armstrong (2012), regression analysis provides an objective and systematic way of analyzing data. As a result, decisions based on regressions are less likely to be subject to bias, they are consistent, the basis for the decisions can be fully explained, and they are generally useful. The gains are especially well documented when compared to judgmental decisions made based on the same data

There are ample evidences in Armstrong (1985) and in Allen and Fildes (2001) indicating that regression analysis often provides useful forecast. We chose regression analysis as an ideal method for our forecasting model since the regression-based forecast is most effective when dealing with small numbers of variables and when there are well established causal relationships. The macroeconomic indicators that we chose for the linear regressions are the actual drivers of the demand for the products sales—for example the demand for retail catalogues for printing demand or the credit availability to purchase expensive printing equipment.

### 3.1.1.3 Prior Meta-analysis

Regression analysis as a "per se" method is not better or worse than any of the known forecasting methods. However, it can be very powerful if a prior Meta-analysis is done, according to Cumming (2012) it can give better results than other more sophisticated forecasting methods. Armstrong (1968 a,b), and Armstrong (2012) also agree with this claim.

It is also recommended to have a theory about the sales drivers of the product lines. Our models are based on such meta-analysis that suggests which variables to include, specifying the expected direction of the relationship and specifying the nature of the functional form, ranges of magnitudes of relationships and the size of expected magnitudes of those relationships. It is also important to determine the relationships that can be measured outside of the model, based on either common knowledge (for example, adjusting for the indicators' growth or transforming the data to a first derivative basis) or analyses of other data.

In 1974, Dawes and Corrigan reported the following interesting experiment: instead of using weights in a linear model that have been determined by the least squares algorithm, they use weights that were chosen at random (between 0 and 1) but subject to having the appropriate sign. The results of this experiment were most surprising to scientists brought up in the tradition of least-squares. The predictions of the quasi-random linear models were quite good and, in fact, on four datasets, they exceeded the predictions made by human judges who had been provided with the same data (i.e., values of the predictor variables). Dawes and Corrigan outlined that one of the reasons for the success of their method was that in prediction, having the appropriate variables in the equation may be more important than the precise form of the function.

Therefore, a key to the model reliability would be the careful decision over the selection of the macroeconomic indicator/s, the way of using them in the regression model and the expected sign of the coefficient. The forecasters' knowledge of the market could help them choose the right indicators and discarding those that give unrealistic coefficients signs and reducing in this way the amount of variables in the linear regression.

### 3.1.1.3.1 "Less" is "More"

Part of the simplicity and accuracy of our models arrives from the fact that we use very few independent variables in the regressions model. This is in line with The Normative Theory of Choice that provides numerous evidences that the less variables in the linear regression the more accurate the model is. In the Normative Theory of Choice, the values of alternatives are typically assessed by calculating a weighted sum of outcomes. Thus, in expected utility theory, the utilities of outcomes are weighted by their probabilities of occurrence. Similarly, in the additive form of multi-attribute utility theory, the utility of an alternative $\mathrm{Y_i} = (X_{i1}, X_{i2} \ldots, X_{ik})$ is determined by the function:

$$\mathrm{U(Y_i)} = \sum_{j=1}^{k} W_j U(X_{ij})$$

**Equation 1: The Normative Theory of Choice**

Where U(.) denotes utility and the wj are weighting parameters subject to the constraint

$$\sum_{j=1}^{k} W_j = 1$$

**Equation 2: The utility equation under the normative theory of choice**

Models such as the one in Keeney and Raiffa (1993) have a "gold standard" status in decision making because they essentially define what is "optimal." Moreover, they seem to make good sense in that they consider all the information and weight it appropriately. But do people need to consider all the information when they make a decision? Could they actually do "better" if they ignore some information? One of the first researchers to examine this issue was Thorngate (1980). Using simulations, Thorngate investigated how often various heuristic strategies would select the highest expected value alternatives from different choices sets. In short, the criterion was a weighted sum (i.e., similar to equation above) and the heuristic models only used part of this information. For example, the most successful strategy in the simulation was one that assumed all probabilities were equal. Thorngate's results were surprising in that the more successful models had success rates of 75% and more when selecting the best from two to four alternatives. Clearly, for models to be effective, it was not necessary to use all the information. However, would it be possible to remove this design constraint and observe situations where “less” was “more”? Moreover, whereas one might justify models that use less information by accepting an accuracy-effort tradeoff, are there situations where one does not have to make this tradeoff? Gigerenzer and Goldstein (1996) indicated two ways in which “less” might be “more.” Significantly, both involve the use of a heuristic decision rule exploiting an environmental “niche” (or task) to which it is well adapted.

In our forecasting model we have selected the macroeconomic indicators for each product line very carefully based on relevance criteria. The macroeconomic indicators chosen are the most relevant to the reason of purchase of the products. Obviously it is a simplification but we preferred to keep it simple and most relevant in order to avoid the usage of numerous factors that will make the interpretation of the results more difficult to understand.

#### 3.1.1.4 Use common sense which is not the most common of all senses

Likewise, there are evidences in Jorgensen (2007) and Berg et al. (2008) that the average accuracy of expert-judgment based effort estimates is higher than the average accuracy of software based models or that judgmental inputs into model increase its accuracy. Human judgment can be demonstrated to provide a significant benefit to forecasting accuracy but it can, according to Lawrence (2006), also be subject to many biases.

We apply judgment in our Meta-analysis by selecting the most adequate macroeconomic indicators and their form of use for each of the market forecast. In addition, the models should be revised to make sure that they still make sense in the fast changing market. Rising competitive technology or major change in the rules of the game could easily make the model irrelevant if it is not updated with these changes.

## 3.2 The Institutional Theory

In addition to the complexity of most forecasting methods, the Bass model and its extensions, the diffusion models and their derivatives as well as the various quantitative approaches to sales forecasting seems to ignore the business environment, the country or the area in which the company is operating. We claim that economic environmental factors have major influence on the firms' results as they shape the company's growth boundaries and often drive the company's strategy and actions. Even though companies in the same economic/cultural regions may have very different business models to compete and thrive in their markets, they are all, first and foremost influenced by the exogenous factors of the business macroeconomic environment.

The theory that supports our claim that the environment shapes the company´s results is the Institutional Theory and our proposed model steams from it. According to the Institutional Theory, Institutions are made up of formal rules, informal norms and the enforcement characteristics that determine economic performance. While the formal rules can be changed overnight, the informal norms are strongly rooted in the culture and can change only gradually over time. Thus, many of the environmental forces on organizations are typical to that environment and are unlikely to change rapidly.

The institutional theory started with Veblen and other researchers such as John R. Commons, Wesley C. Mitchell of the American school of institutional economics, who described economic behavior as socially determined and saw economic organization as a process of ongoing evolution. This evolution was driven by the human instincts of emulation, predation, and workmanship, parental bent and idle curiosity. Veblen wanted economists to grasp the effects of social and cultural change on economic changes. In The Theory of the Leisure Class, Veblen (1899), the instincts of emulation and predation play a major role. Veblen particularly strongly rejected any theory based on individual action or any theory highlighting any factor of an inner personal motivation and considered such theories as "unscientific."

The New Institutional Economics (NIE) as represented by Douglass North along with Ronald Coase and Oliver Williamson is an attempt to incorporate a theory of institutions into economics by arguing that what characterizes economies are not institutions, ideas or ideologies but efficient markets-both economic and political. The new institutional economics fits in with neo-classical theory as it begins with the scarcity hence competition postulate; it views economics as a theory of choice subject to constraints; it employs price theory as an essential part of the analysis of institutions; and it sees changes in relative prices as a major force inducing change in institutions. The new institutional economics does not only fit to the neo classical economy theory but it also modifies and extends it. In addition to modifying the rationality postulate, it adds institutions as a critical constraint and analyzes the role of transaction costs as the connection between institutions and costs of production. It extends economic theory by incorporating ideas and ideologies into the analysis, modeling the political process as a critical factor in the performance of economies, as the source of the diverse performance of economies, and as the explanation for "inefficient" markets.

Our thesis will contribute to the Institutional theory and the New Institutional by showing a strong connection between the High Tech products sales and the markets in which these products are being sold as represented by several macroeconomic indicators. The New Institutional Economics Theory establishes the type of connection between macro level activities, which are exogenous to the firms, and the micro level which are the companies themselves and their products. Institutions are a major factor in shaping economic outcomes. Despite the diversity of the NIE´s views on the various definitions of institutions at least two characteristics are recurring in these NIE discussions. First, theoretical analysis is often embedded in a historical narrative or complemented with empirical case studies. Second, the analysis is committed in providing an explanation which focuses on the micro-foundations of the link between institutions and economic outcomes. Therefore, the NIE typically seeks to provide micro-explanations often using the rational-choice-theory when explaining the role of institutions. The work of Douglass North (1990) falls into that category. However, an explanation based on the micro level only, such as that based on the rational choice theory, is not complete according to Cyril (2012), and as it was already claimed in the early literature by researchers such as Field (1981, 1984) that said that at least some macro structures or institutions must be taken as exogenous in any micro explanation. Cyril (2012) explains it using game theory and claiming that Institutions produce downward effects, shaping each agent's action in the game. Moreover, in a game-theoretic framework, macro-structures are constitutive of individual agency since, without them, agents would often be unable to choose. Our paper also demonstrates that these macro structures are essential for a better forecasting model.

In spite of the fact that institutions are a critical pillar of the NIE in explaining the Macro to Micro connection, there is not yet an accepted definition of “institutions” in economics. In the one hand, North (1990) defined Institutions as “the rules of the game”. On the other hand, Hodgson (2006 P. 18) defined institutions as “systems of established and embedded social rules that structure social interactions” and as “social structure” he considered “all sets of social relations, including the episodic and those without rules, as well as social institutions”, Hodgson (2006 P. 17).The nature of an institution consists of observable and non-observable components. Among the formal components are rules, norms and organizations while non-observable ones are tacit beliefs, sentiments etc. According to Cyril (2012), economic studies of the relationship between institutions and economic performance usually take only the measurable, observable component of the institutions due to the fact that the informal components are hard to measure or even to observe. However, unobservable institutional components could be as powerful as observable ones and, therefore, we need to be taken into consideration.

The NIE offers a connecting framework between the cultures at the macro level and business results at the micro level. A key talisman in discussions about the relation between "macro" and "micro" is a famous framework placed by James Coleman in his book Foundations of Social Theory (1990). There, he describes graphically his theory about the relationship between the macro and the micro structures in what is often referred to as "Coleman's Boat", “Coleman´s Bathtub” or simply “Coleman´s Diagram”. The Coleman Diagram bellow is one of the most useful expository vehicles for thinking about multi-level issues in social science research. The diagram portrays macro-micro-micro-macro relations as a sort of rhombic figure with causal relations going down from macro (e.g. institutions) to the conditions of individual actions which then give rise to individual actions that in turn aggregate up to macro outcomes.

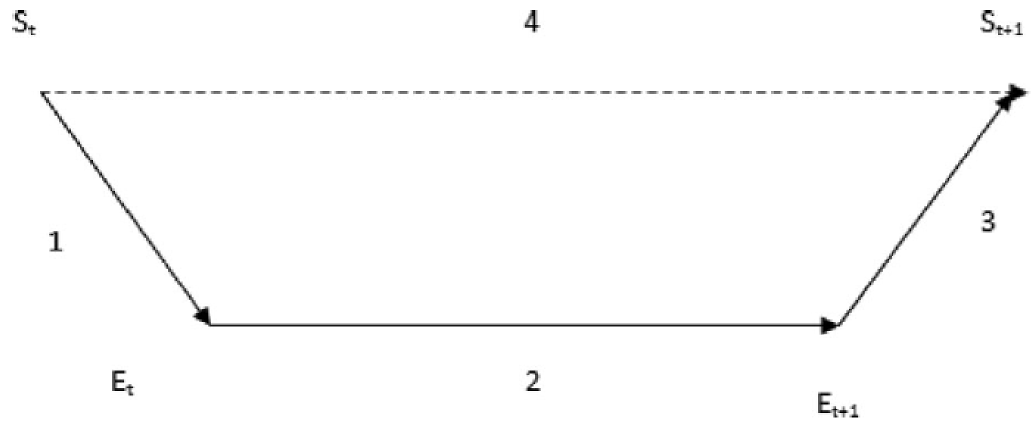



**Figure 8: Coleman´s Diagram**

The core of Coleman´s argument is that while social sciences are essentially committed to providing explanations of the relation between two macro states (S(t) and S(t+1)) marked as relation 4 in the diagram, they cannot do so directly because relation 4 is not causal but only statistical. Therefore, Coleman claims that the explanation must engage with the micro-elements in the original state (E(t)) and the final stage (E(t+1)) in relation 2. These micro elements are responsible for the transition of the macro elements from their original state (S(t)) to their final state (S(t+1)). The micro elements in social science are formed by individual´s actions and their interaction. In our thesis we will refer to the micro elements as the users of technology that can be individuals or small companies.

Relation 1 is the macro to micro relation which indicates how individuals' actions are influenced by the macro state of the system. The relationship described in arrow 1 in Coleman´s table is crucial to define the type of link between macro and micro elements and it is the foundation of our model. Relation 2 is the micro to micro relation through which the micro elements act and interact. Relation 3 is the micro to macro relation which accounts for the interaction between micro elements aggregate into their new patterns at the macro level.

The analytical branch of social science  such as Hedstrom (2005), Hedstrom and Bearman (2009) has developed the fundamental concept of social mechanisms to formalize the processes behind relations 1, 2 and 3 and defined it as "a constellation of entities and activities that are organized such that they regularly bring about a particular type of outcome (. . .) we explain an observed outcome by referring to the mechanism by which such outcomes are regularly brought about" , Hedstrom and Bearman (2009 P. 5). Following this definition, Institutions are in fact a social outcome. Therefore, on Coleman´s diagram the state S(t) can be defined as a set of norms, rules and organizations while the state S(t+1) is defined by the aggregated behavior at the micro level.

At first glance this relationship might be perceived as a "cause and effect" one, however Coleman and other rational-choice-oriented sociologists do not accept this definition in its face value. In fact, they could offer a definition similar to Granovetter (1985) saying that the individuals' actions take place in network of relationships, occupations and opportunities. This network of relationships proposes constraints on individual choice but they cannot be defined as a cause to the individuals' actions. This approach of recognizing that individual actions taken place in a prior network of interactions and positions is the "Methodological individualism". When we add to the methodological individualism the non- random/structured component we arrive to "structural individualism" that, according to Udehn (2001), could explain Coleman´s diagram.

According to Udehn (2001) in the Structural Individualism the individuals occupy positions and "they enter relations that depend upon these positions. The situations they face are interdependent, or functional related, prior to any interaction. The result is a structural effect, as distinguished from a mere interaction effect", (Udehn; 2001 P. 304)

These interactions between agents are the non-random/structural components, which are an essential part of the structural individualism. According to Hedstrom (2005) these interactions do not possess any ontological power and hence relationship number 1 in Coleman´s diagram does not represent a downward causation.

Therefore, the next question that should be asked is what is the nature of the relationship between the macro structure and the micro structure if such relationship is not causal?

Some social scientists such as Abell et al. (2010) define this relationship as "supervenience". Supervenience is a functional relation between two levels of properties and it indicates that a higher level property is defined by the lower level properties that constitute it. Macro structures are constitutive of individual actions, independently of any claim regarding possible causal relationship between institutions and individual actions.

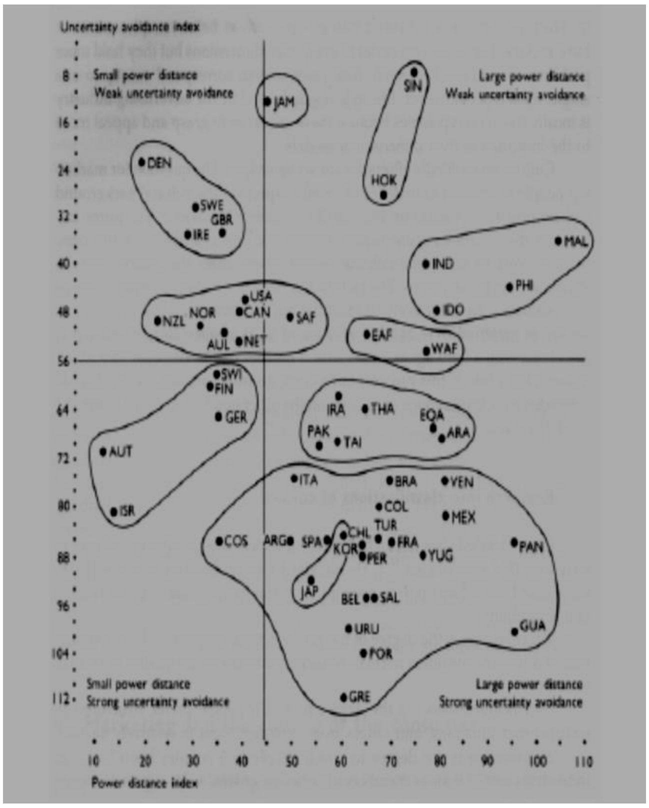
Others, such as Cyril (2012), define this relationship as a correlated equilibrium by using elements from game theory, and conclude that "whatever nature of the correlated device, we can consider that the downward effect captured by the correlated equilibrium operates through the formation of the players beliefs" , Cyril (2012 P. 338) . Hence, he proposes to call this kind of downward effect triggered by institutions a belief-mediated downward effect. This definition of institutions as correlated equilibrium can be used to demonstrate that the relationships between institutions and individuals are constitutive relationships and helps to constitute the common understanding of institutions which is a must to produce the downward effect. Greif (2002, 2006) gives narratives related the formation of commercial associations in the middle age mostly induced by the surrounding macroeconomic circumstances reinforcing in a vivid historical example the importance of macro structures as inputs in micro reactions explanations.

Based on the NIE it can be expected that different geo-political regions will behave differently. They will be different at the micro level and therefore will be different at the macro level as well. Therefore, we would explore next the possibility that cultures are institution based on the definition of the NIE.

## 3.3 Cultures as institutions

Culture as institutions or as a reflection of Institution at the micro level, can be defined as "the collective programming of the mind which distinguishes the member of one group or category from those of another, Hofstede (1991). It comprises shared values, understandings, assumptions and goals of this group resulting in large part in common attitudes, codes of conduct, expectations and in practices that guide and control certain norms of behavior e.g. Hofstede (1980). Cultural studies show that there are considerable differences in values and attitudes around the world e.g. Hofstede (1991) and Schwartz (1994).

The impact of national culture has become one of the most important topics in management research such as Gelfand et al. (2007), Leung et al. (2005), Triandis (2008), Tsui et al. (2007) and also in the managerial practice such as Friedman (2005) and Sirkin et al. (2008). Most of the efforts exerted by cross cultural researchers such as Earley and Singh (1995) and Chen et al. (2003) have been directed towards uncovering and explaining, or finding better ways to uncover and explain cross-cultural differences such as Brockner (2003), Kitayama, (2002), Tsui et al., (2007) and Von Glinow et al. (2004). Since Hofstede (1980) proposed the cultural dimension at the national level in the 1970´s, many scholars such as Triandis and Gelfand (1988) have verified the effects of national cultures using his cultural dimensions. Although some criticism surfaced that Hofstede (1980) ignored propensities of members in a nation, it is worthwhile to note that Triandis et al. (1988) have ultimately supported effects of national cultures by accounting for individuals' differences in attitudes within a nation and by making cross-cultural comparisons.




| | | | | | |
|---|---|---|---|---|---|
| ARA | Arabic-speaking region | HOK | Hong Kong | PHI | Philippines |
| ARG | Argentina | IDO | Indonesia | POR | Portugal |
| AUL | Australia | IND | India | SAF | South Africa |
| AUT | Austria | IRA | Iran | SAL | Salvador |
| BEL | Belgium | IRE | Ireland | SIN | Singapore |
| BRA | Brazil | ISR | Israel | SPA | Spain |
| CAN | Canada | ITA | Italy | SWE | Sweden |
| CHL | Chile | JAM | Jamaica | SWI | Switzerland |
| COL | Colombia | JAP | Japan | TAI | Taiwan |
| COS | Costa Rica | KOR | Korea South | THA | Thailand |
| DEN | Denmark | MAL | Malaysia | TUR | Turkey |
| EAF | East African region | MEX | Mexico | URU | Uruguay |
| FIN | Finland | NET | Netherlands | USA | United States |
| FRA | France | NOR | Norway | VEN | Venezuela |
| GBR | Great Britain | NZL | New Zealand | WAF | West African region |
| GER | Germany West | PAK | Pakistan | YUG | Yugoslavia |
| GRE | Greece | PAN | Panama | | |
| GUA | Guatemala | PER | Peru | | |

**Figure 9: Countries map based on Hofstede´s dimensions: Power Distance and uncertainty avoidance**

**Source: Hofstede (1980)**

As mentioned earlier, there are four cross-cultural classification systems exist which report data from a large number of countries, allowing for cross-cultural comparisons. The first, developed by Hofstede (1980), identifies five value dimensions based on fundamental problems which all societies face. The second, based on Schwartz's (1994) seminal work on human values, outlines seven national-cultural domains. The third, a World Values Survey, advanced by Inglehart (1997), reveals that a wide range of attitudes and values are reflected in just two major dimensions – the polarization between traditional values and secular-rational values; and the polarization between survival values and self-expression values. The final framework – entitled GLOBE – offers a new alternative. Drawn from organizational and management science, GLOBE outlines nine cultural dimensions and differentiates between societal values and societal practices.

The name GLOBE refers to the Global Leadership and Organizational Behavior Effectiveness Research Project. The Globe study, a global investigation program that analyzes the relationship between national culture, organizational culture and leadership identifies 10 cultural clusters that are differing considerably in nine dimensions. GLOBE's major premise and finding is that leader effectiveness is contextual, that is, it is embedded in the societal and organizational norms, values, and beliefs of the people being led. In other words, to be seen as effective, the time-tested adage continues to apply: "When in Rome do as the Romans do." The cultural dimensions at the heart of the Globe study are:

1. **Power Distance**: The degree to which members of a collective expect power to be distributed equally.
2. **Uncertainty Avoidance**: The extent to which a society, organization, or group relies on social norms, rules, and procedures to alleviate unpredictability of future events.
3. **Humane Orientation**: The degree to which a collective encourages and rewards individuals for being fair, altruistic, generous, caring, and kind to others.
4. **Collectivism I (Institutional)**: The degree to which organizational and societal institutional practices encourage and reward collective.
5. **Collectivism II (In-Group)**: The degree to which individuals express pride, loyalty, and cohesiveness in their organizations or families.

6. **Assertiveness:** The degree to which individuals are assertive, confrontational, and aggressive in their relationships with others.
7. **Gender Egalitarianism**: The degree to which a collective minimizes gender inequality.
8. Future Orientation: The extent to which individuals engage in future-oriented behaviors such as delaying gratification, planning, and investing in the future.
9. **Performance Orientation**: The degree to which a collective encourages and rewards group members for performance improvement and excellence.

As a first step to gauge leader effectiveness across cultures, GLOBE empirically established nine cultural dimensions that make it possible to capture the similarities and/or differences in norms, values, beliefs –and practices—among societies. They build on findings by Hofstede (1980), Schwartz (1994), Inglehart (1997), and others. This first step allowed GLOBE, as shown in the figure bellow, to place 60 of the 62 countries into country clusters, similar to those by Ronen and Shenkar (1985), Inglehart (1997), and Schwartz (1999).

The GLOBE culture clusters are:

**Anglo:** Australia, Canada, England, Ireland, New Zealand, South Africa and United States

**Latin Europe:** France, Israel, Italy, Portugal, Spain, Switzerland (French speaking part)

**Nordic Europe:** Denmark, Finland and Sweden.

**Germanic Europe:** Austria, Germany, Netherlands and Switzerland (German speaking part)

**Eastern Europe:** Albania, Georgia, Greece, Hungary, Kazakhstan, Poland, Russia and Slovenia.

**Latin America:** Argentina, Bolivia, Brazil, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Mexico and Venezuela

**Sub-Saharan Africa:** Namibia, Nigeria, Zambia and Zimbabwe.

**Middle East:** Egypt, Kuwait, Morocco, Qatar and Turkey.

**Southern Asia:** India, Indonesia, Iran, Malaysia, Philippines, Thailand.

**Confucian Asia:** China, Hong Kong, Japan, Singapore, South Korea and Taiwan.

Cultural similarity is greatest among societies that constitute a cluster; cultural difference increases the farther clusters are apart. For example, the Nordic cluster is most dissimilar from the Eastern European. The following figure represents the clusters and the distances closeness of the clusters to each other.

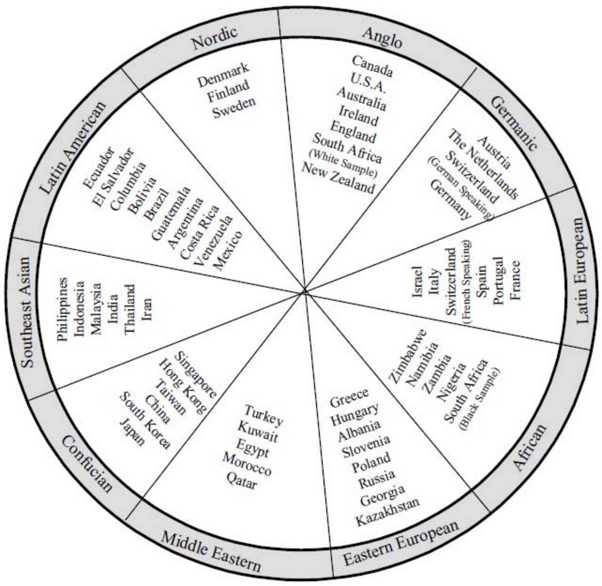



**Figure 10: The Countries clusters according to GLOBE.**

**Source: Adapted from House at Al. (2004)**

In order to characterise three of the cultures used at the empirical part we took the Globe country indexes for each of the 9 dimensions (Annex 1) and compared their values to the median of the worldwide sample. Whenever the median of the culture was higher than that of the total sample we marked it in H (= High) when it was equal or lower to the median of the sample we marked it as L (= Low). The following table summarises these findings:

| | Germanic | Latin Europe | Anglo |
|---|---|---|---|
| Uncertainty Avoidance | H | L | H |
| Power Distance | L | H | L |
| Collectivism I (Institutional) | L | L | H |
| Collectivism II (In-Group) | L | L | L |
| Gender Egalitarianism | L | L | L |
| Assertiveness | H | H | H |
| Future orientation | H | L | H |
| Performance orientation | H | L | H |
| Humane Orientation | L | L | H |

Table 1: The dimensions index levels for the Germanic, Latin Europe and Anglo clusters at the GLOBE research

The Germanic culture cluster, based on the above table, shows high practices scores for Performance Orientation, Uncertainty Avoidance, Future Orientation and Assertiveness, but low practices scores for Human Orientation, Institutional Collectivism, and In-Group collectivism. In other words, societies in the Germanic Europe cluster rely on more assertive and individualistic approaches which are futuristic, well defined, result oriented and often harsh, reflecting the technocratic orientation of the Germanic societies.

The Anglo culture cluster, based on the above table, shows high practices scores for Performance Orientation, Uncertainty Avoidance, Future Orientation, Institutional collectivism, Humane Orientation and Assertiveness, but low practices scores for In-Group collectivism and power distance. Put differently, societies in the Anglo cluster rely on more assertive and individualistic futuristic approaches.

The Latin Europe cluster, based on the above table, is distinguished by weak practices scores for uncertainty avoidance, Institutional Collectivism, In-group collectivism, performance orientation and Humane Orientation, indicating the effective autonomy orientation and the risk taking of the Latin European societies. The Latin European cluster on the other hand is distinguished by high score for Assertiveness and power distance, indicating the desire of this society to distribute evenly the power and the control of the country´s resources.

In the empirical study we have selected three countries representing three culture clusters according to the Globe research: Germany, Spain and United Kingdom. The following table summarises the characteristics of these countries according to the Globe research in comparison to the world wide median score:

| | Germany | Spain | UK |
|---|---|---|---|
| Uncertainty Avoidance | 5,19 | 3,97 | 4,65 |
| Power Distance | 5,395 | 5,52 | 5,15 |
| Collectivism I (Institutional) | 3,675 | 3,85 | 4,27 |
| Collectivism II (In-Group) | 4,27 | 5,45 | 4,08 |

| | | | |
|---|---|---|---|
| Gender Egalitarianism | 3,08 | 3,01 | 3,67 |
| Assertiveness | 4,64 | 4,42 | 4,15 |
| future orientation | 4,11 | 3,51 | 4,28 |
| performance orientation | 4,17 | 4,01 | 4,08 |
| Humane Orientation | 3,29 | 3,32 | 3,72 |

Table 2: The dimensions of the index levels for Germany, Spain and United Kingdome at the GLOBE research

Even though both United Kingdom and Germany belong to culture clusters that are risk averse, as shown in the table above, looking at the GLOBE data at the country level we observe noticeable difference in their averseness degrees. Among the three countries the country with the highest uncertainty avoidance score is Germany.

The way the individuals and firms interact with each other is driven by the norms (formal and non-formal) and since these norms are culture specific we would expect these interaction to be regional specific and that they cannot be found at the same way in other regions with different culture characteristics and therefore, we would expect that the adoption of products would be different in different cultures. The different behavior patterns reflecting the different cultures should be noticeable in the sales forecasting in each market.

## 3.4 International Adaptation versus global Standardization

Cultural differences have also influence on the marketing strategy of multinational companies and the field of international marketing literature often deals with the multinational companies´ fundamental decision. Multinational companies have to decide on whether to use a standardized marketing mix (product, price, place, promotion, people, process management, etc.) with a single marketing strategy in all countries, a strategy known as “Standardize” or to adjust the marketing mix to fit the unique dimensions of each potentially unique local market, a strategy known as “Adaptation”.

As the level of global trade increases, corporations around the world have a growing need for knowledge of foreign cultures and for the right strategy to deal with the sales of products in very distinctive cultures. Diehl et al (2005) provides some eye opening data regarding the importance of foreign business to multinational companies. According to their study, large retail chains such as Netherland's Ahold, Belgium's Delhaize Le Lion or Germany's Metro sell their products to consumers in 25 to 35 countries. For some of these chains, 80% of their sales come from outside the home market. This trend is not unique to European companies; McDonald's sells nearly two-thirds of their burgers outside of the United States, while Toyota sells more of its vehicles in the U.S. than it does in Japan. Because consumers are increasingly found abroad, advertisers must devote an ever-rising percentage of their advertising budgets to foreign markets. For example, the American company Procter and Gamble (P & G). P & G spent 3.57 billion dollars (U.S) selling its products within the U.S., but 4.35 billion dollars communicating with consumers around the rest of the globe (Advertising Age, 2005).

For such companies, a profound knowledge of foreign cultures is vital, in order to effectively communicate and operate worldwide. When it comes to the right way to extract value of foreign operations there is a debate over the extent of standardization or adaptation which are the two extremes of the multinational operations pendulum within the field of international marketing. This debate commenced as early as 1961, when Elinder (1961) considered it with respect to worldwide advertising. Nearly half a century later, the debate on standardizing marketing internationally, is ongoing (e.g. Vrontis and Kitchen (2005)). Even a cursory review of the literature identifies two main approaches with remarkable longevity, namely, adaptation and standardization of international marketing tactics.

Supporters of standardization such as Fatt (1967), Buzzell (1968), Levitt (1983) and Yip (1996), viewed markets as increasingly homogeneous and global in scope and scale and believed that the key for survival and growth is a multinational's ability to standardize goods and services. Supporters of standardization stipulate that consumers´ needs, wishes and requirements do not vary significantly across markets or nations and that the world is becoming increasingly similar in terms of environmental factors and customer requirements. Irrespectively of their geographical locations, consumers have the same demands, in other words, that the world is flat (Friedman, 2005). This view was echoed in Levitt´s paper (1983) arguing that standardization of the marketing mix and the creation of a single strategy for the entire global market offers economies of scale in production and marketing and moreover is consistent with what he described as the “mobile consumer”.

Levitt (1983) asserted that well-managed companies moved from an emphasis on customizing items, to offering globally standardized products that were advanced, functional, reliable and low in price. In Levitt’s view, global companies will achieve long-term success by concentrating on what everyone wants rather than worrying about the details of what everyone thinks they might like. Papavassiliou and Stathakopoulos (1997) suggested four main reasons that make Levitt’s thesis appealing. First, it allows multinational companies to maintain a consistent image and brand identity on a global basis. Second, it minimizes confusion among buyers that travel. Third, it allows the multinational company to develop a single tactical approach. And, fourth, it enables the company to take advantage of economies of scale in production and experience and learning curve effects. Therefore, standardization has been argued to have several benefits and advantages across the various aspects of the marketing mix as also concluded by others as Kotabe (1990) and Vrontis and Thrassou (2007). Some of these benefits are economies of scale across the elements of the marketing mix, cost reduction and transfer of expertise etc. Vrontis and Thrassou (2007) present in a study of companies in the United Kingdom, a framework that highlights the advantages of standardization across the elements of the marketing mix which the author believes is relevant for other companies in different countries.

The following figure summarizes the main benefits of standardization as they described in the literature:

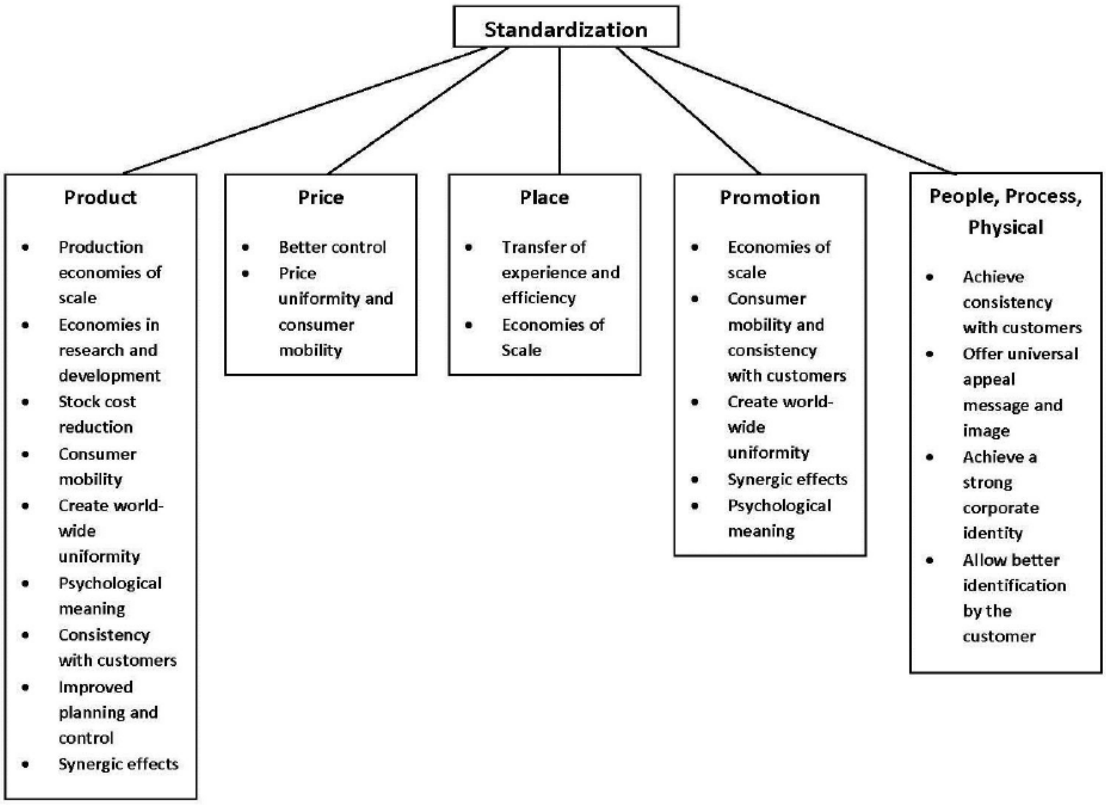



**Figure 11: The main benefits of Standardization**

Source: "why companies standardize" Verontis et Al. (2007) as presented at Amuah H. (2012)

However, the standardize view at its extreme level remains in sharp contrast to what our sales forecasting models suggest. Our models show that the evident culture differences lead to the conclusion that a better strategy for multinational companies is to adapt their marketing mix and go-to-market to the local culture or at least to take the culture differences into consideration when forecasting the market potential of their new commercial frontier. Therefore, we suggest to adopt an "adapt" strategy over "standardize" in their marketing approach.

The adaptation advocates such as Kashani (1989) indicate difficulties in using a standardized approach and therefore support market tailoring and adaptation to fit the "unique dimensions" of different international markets as Thrassou and Vrontis (2006). More specifically, supporters of the international adaptation school of thought such as Papavassiliou and Stathakopoulos (1997) argue that there are insurmountable differences between countries and even between regions in the same country. It is argued in Czinkota and Ronkainen (1998) that marketers are subject to a number of macro-environmental factors, such as climate, race, topography, occupations, taste, law, culture, technology and society. Paliwoda and Thomas (1999) expand this list to include consumer tastes, disposable income, taxation, nationalism, local labor costs, literacy and levels of education. Followers of this school stipulate that multinational companies should find out how to adjust their marketing strategy and tactics (marketing mix elements) in order to fit market requirements. Not only that, supporters of adaptation declare that the assumptions underlining global standardization philosophy are contradicted by the facts. “Standardization is at best difficult and, at worst, impractical”, Jain (1989, P. 71). Globalization, according to Ruigrok and van Tulder (1995) seems to be as much overstatement as it is an ideology. Ruigrok and van Tulder (1995) went so far as to state that it is impossible to market effectively by using the same marketing mix methods and marketing strategies everywhere. In addition, Helming (1982) and Youovich (1982) challenge the basic assumption of the standardization approach and argue that similar buying motives for consumers on an international basis may, at best, be simplistic and at worst, dangerous. Thus, supporters of international adaptation argue that tailoring marketing mix elements is essential and vital in meeting the needs and wants of target markets. To them, marketing mix elements cannot be standardized, as international markets are subject to differential macro and micro-environmental factors, constraints and conflicts. In the same line of pro-adaptation thought, Lipman (1988) supports that for many the global-marketing theory itself is bankrupt and bunk. In fact, the concept that once sent scores of executives scrambling to reconfigure marketing strategies now has many feeling duped. Not only are cultural and other differences very much still in the ascendancy, but marketing products in the same way everywhere can scare off customers, alienate employees and blindside businesses to their customers’ real needs.

The following figure summarizes the main benefits of adaptation as they described in the literature:

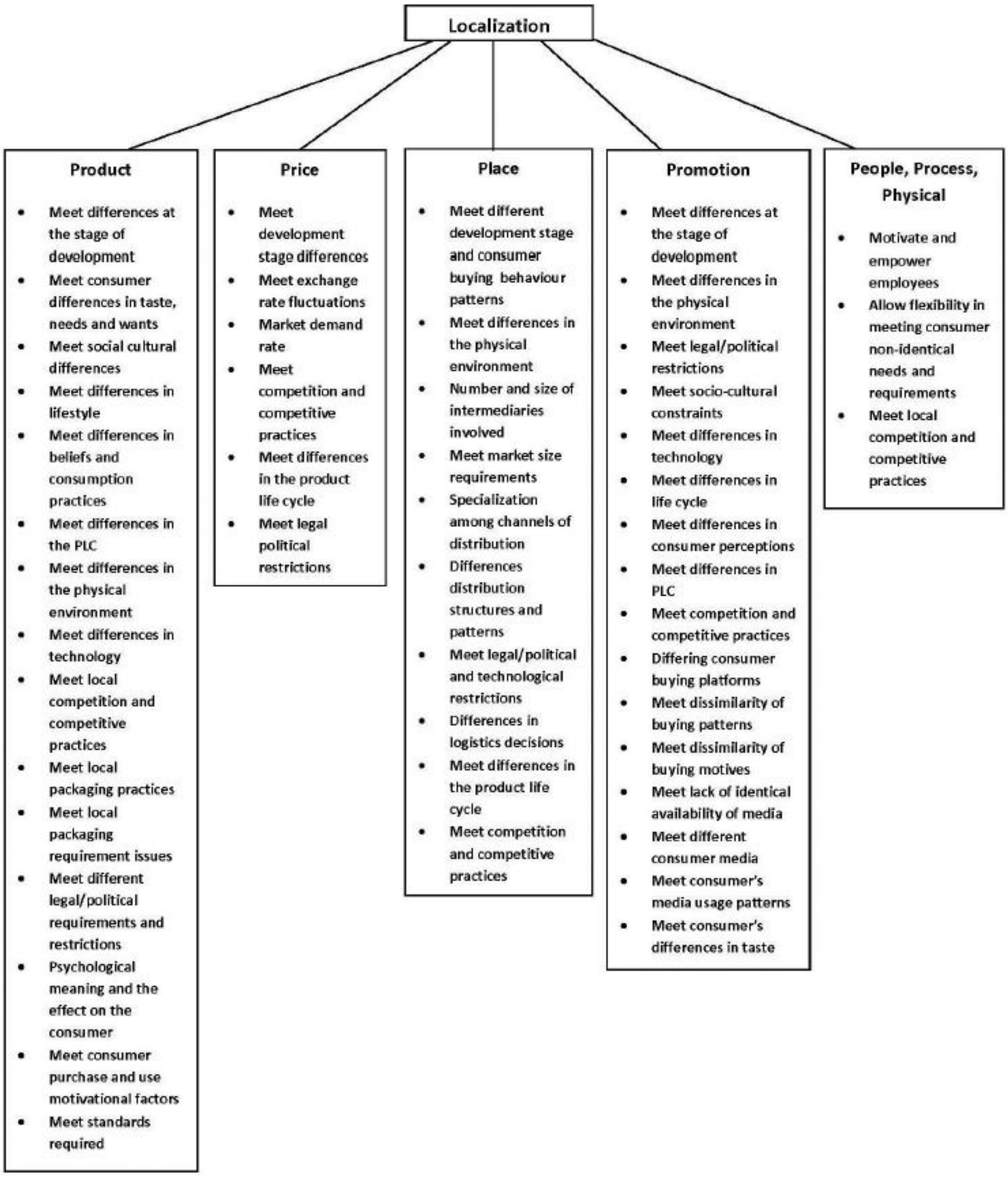



**Figure 12: The main benefits of Adaptation**

Source: "why companies standartize" Verontis et Al. as presented at Amuah H. (2012)

Both schools of thought in themselves appear to be sensible, logical and coherent, highlighting the advantages and benefits that a multinational company could gain by using any approach. It is only when one focuses on the extreme position of either, such as in Kitchen (2003), Vrontis (2003) and Soufani et al. (2006) that they often become impractical and incoherent. Marketing reality for multinationals does not lie in either of these two polarized positions, as both processes are likely to coexist, even within the same company, product line, or brand.

Literature quoting practical evidence suggests that companies make contingency choices, which relate to key determinants in each circumstance (Vrontis et al., 2006).

The decision whether to standardize or adapt should not be a dichotomous one. Some academics suggest that standardizing tactics combined with and adaptation tactics to different market conditions is necessary e.g. Peebles et al. (1977), Quelch and Hoff (1986), Light (1990) and Vrontis and Vronti (2004). For these authors, standardisation and adaptation is not an all-or-nothing proposition, but a matter of degree. Heterogeneity among different countries does not allow full standardisation. On the other hand, the huge costs involved in adaptation and the benefits of standardisation, may not allow adaptation to be used extensively e.g. Vrontis (2005). Nanda and Dickson (2007) concentrate on three factors to examine standardisation/adaptation behavior: homogeneity of customer response to the marketing mix, transferability of competitive advantage and similarities in the degree of economic freedom. He notes that even in countries with similar cultures (e.g. across the European Union) there are differences in customer needs and wants. Furthermore, they argue that standardisation will be successful when the homogeneity of customer response and the degree of similarity in economic freedom is high and competitive advantages are easily transferable.

A good balance point between standardization and adaptation could be found in Hassan et al. (2003) who suggest different ways of global market segmentation that are useful for decisions on brand standardization versus adaptation. They specify three main segmentations: group of countries demanding similar products, different countries with the same product and universal segments that present in many or most countries. Moreover, macro (economic, technological, geographic, political, etc.) and micro (lifestyles, attitudes, consumer tastes and preferences) forces should be highly considered by multinational companies operating in the global marketing arena.

## 3.5 The forecasting model framework

Our work shows that there is a strong link between macroeconomic conditions and companies' business environment that directly influence the company's financial results. This demonstrated relationship is strong evidence to the fact that companies in spite of their different business models are above all submitted to the global market´s caprice supporting.

The suggested model is based on macroeconomic data; in fact, we will apply regression analysis for estimating causal macroeconomic coefficients from historical data. Theory, prior research and expert domain knowledge are used to specify relationships between a variable to be forecasted and explanatory variables at the Meta-analysis stage.

The model offers a forecast for the future unit growth by selecting macroeconomic indicators sets that are related to the product line and that show high correlation to the market product sale and through extracting the coefficients between these indicators and hardware sales growth. The selection of the macroeconomic indicators is not random. They are carefully selected as indicators related to the reasons of purchase of the products. The way the indicators are being used is part of the intelligence that the forecaster needs to put into it in order to make it part of a decision tool.

The advantage of using macroeconomic indicators as a basis for the econometric forecasting model is of threefold:

- Macroeconomic indicators are widely available and most of them are frequently updated.
- They are exogenous and independent to management decision making.
- Macroeconomic indicators' limitation in forecasting unexpected events is well known and this opens up the discussion on how decisions that are taken today could influence a theoretical straight line future forecast.

### 3.5.1 The Macro to Micro path

The Macro to Micro path consists of macroeconomic indicators that are used to forecast the market size units' growth. The market forecasted units represent are the market opportunity of the company. The Company´s market share is them multiplied by the units' market amount to establish the forecasted company´s units.

To establish the position that the company will have in the future market size the forecaster takes the current market share of the company and adds or subtracts to that the future products or the lack of product launches for the forecasted year. Once the forecaster has the market size and the company´s estimated market share she obtains the forecasted amount of units to be potentially sold by the company for that year. Then, in order to forecast the revenue from this estimated amount of units, the forecaster needs to establish the selling price of these units. She does so by taking into account the current units selling price, estimate the future price erosion due to market share gain objectives and due to competitive pressure (Nash Equilibrium), and so (ignoring product mix impact for simplification) have a forecast for the company´s future year revenue. Our thesis details the models to forecast the market size units' growth. The following drawings summarize the path from the macro level to the micro level. Where the macro level is the market opportunity calculated by the econometric models based on macroeconomic indicators. To obtain the units that potentially will be sold in the market in a certain year. Each of the market players obtain a certain share in the market that leads to the number of units that a specific firm sell within this market. Then multiplied by the estimated future selling price we obtain the company´s revenue.

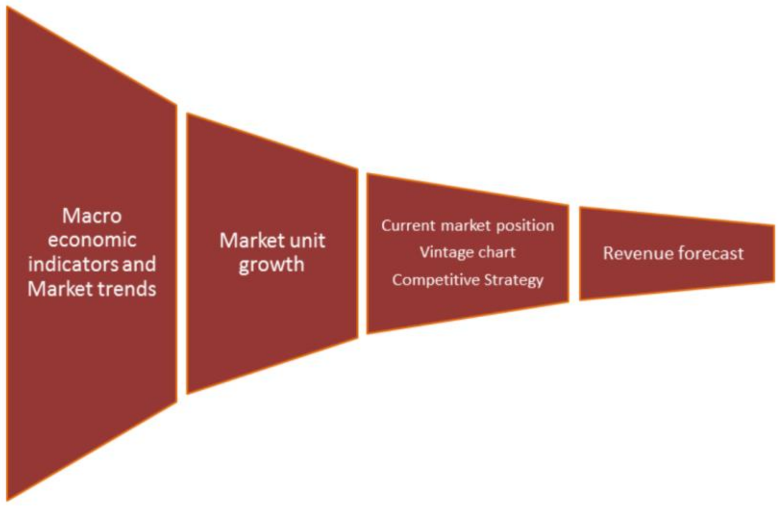



**Figure 13: Our Macro to Micro Path**


**Figure 14: The relationship between the Macro and Micro components**

## 3.6 Product life cycle

Ever since Bass published his iconic, elegant and mathematically innovative diffusion of the innovation model in Bass (1969), scholars have related to the Bass model and many have connected his model with the product life cycle stages as a popular research topic such as in Robinson and Lakhani (1975) and Gatignonet al. (1989).

However, in spite of the fact that the Bass model has been refined a number of times through the years by Bass himself and others, his original forecasting caveats remain the same and in many papers it was concluded that preparing a forecast by using the classic Bass model can be still a very much inaccurate exercise. In our thesis we will discuss three of the caveats of the classical Bass model and its derivatives, namely the Bass´ forecasting accuracy, its inability to forecast based on few data points and its inability to fit to non-smooth sales results into the product sales curve. In contrast to these Bass model caveats, our thesis is perfectly able to reflect take offs, saddles, turning points and any other changes in the product sales that cannot not be reflected in the Bass smooth product curve. In comparison to the proliferation of the Bass model´s derivative papers, the diffusion modelling of multiple generation products has received less attention, though the number of publications in this area is steadily growing (Islam and Meade (2006)). The growing interest in this area can be attributed to reducing lifecycles of products and dominance of high technology products in the market.

Our thesis will address the limitations of the Bass model in forecasting sales at a multi generation´s environment and will answer two of the long-lasting academic literature questions regarding multi-generations products: whether product adoption accelerates between the products technology and whether the new product technology substitute the previous one.

The spread of an innovation in a market is termed “diffusion”. Diffusion research seeks to understand the spread of innovations by modeling their entire life cycle from the perspective of communications and consumer interactions. Traditionally, the main thread of diffusion models has been based on the framework developed by Bass (1969). The Bass model considers the aggregate first-purchase growth of a category of a durable good introduced into a market with potential m. The social network into which it diffuses is assumed to be fully connected and homogenous. At each point in time, new adopters join the market as a result of two types of influences: external influences (p), such as advertising and other communications initiated by the firm, and internal market influences (q) that result from interactions among adopters and potential adopters in the social system. The Bass model states that the probability that an individual will adopt the innovation — given that the individual has not yet adopted it—is linear with respect to the number of previous adopters. The model parameters (p, q, and m) can be estimated from the actual adoption data. Parameter estimation issues are discussed in Sultan et al. (1990), Van den Bulte and Lilien (1997), Lilien et al. (2000), Bulte and Stremersch (2004), Van den Venkatesan et al. (2004), Boswijk and Franses (2005) and Jiang et al. (2006). The proliferation of newly introduced information, entertainment, and communication products and services and the development of market trends such as globalization and increased competition have resulted in diffusion processes that go beyond the classical scenario of a single market monopoly of durable goods in a homogenous, fully connected social system. The diffusion modeling literature since 1990 has attempted to extend the Bass framework to reflect the increasing complexity of new product growth in the context of the multi-channel ways of product communication.

### 3.6.1 The Bass model for product life cycle forecasting

During the post-World War II period (1945-1960), sales of new consumer durables followed an S-Shaped pattern over time (Bass, 1969). However, as new consumer electronic products remained analog devices rather than digital ones, the pace of technological change was relatively slow by today's standards. Frank Bass, was the first to build a product life cycle model for the consumer appliance industry. His model is known as the Bass Diffusion Model. With that, he predicts initial household sales of consumer durable goods category by year.

The Bass´ product life cycle model separates consumers into five different segments; Innovators, Early Adopters, Early Majority, Late Majority and Laggards. **Innovators** are the consumers who seek new experience with technology. Through their experience and "word of mouth," **early adopters** drive the initial sales growth. Once the technology is accepted as mainstream with the **early majority** group, growth begins to accelerate. When the **late majority** adopts, the product enters into its mature phase with slower growth. Finally, the **laggard group**, the only people on the block without the new technology, adopts, and then the product life cycle is completed.

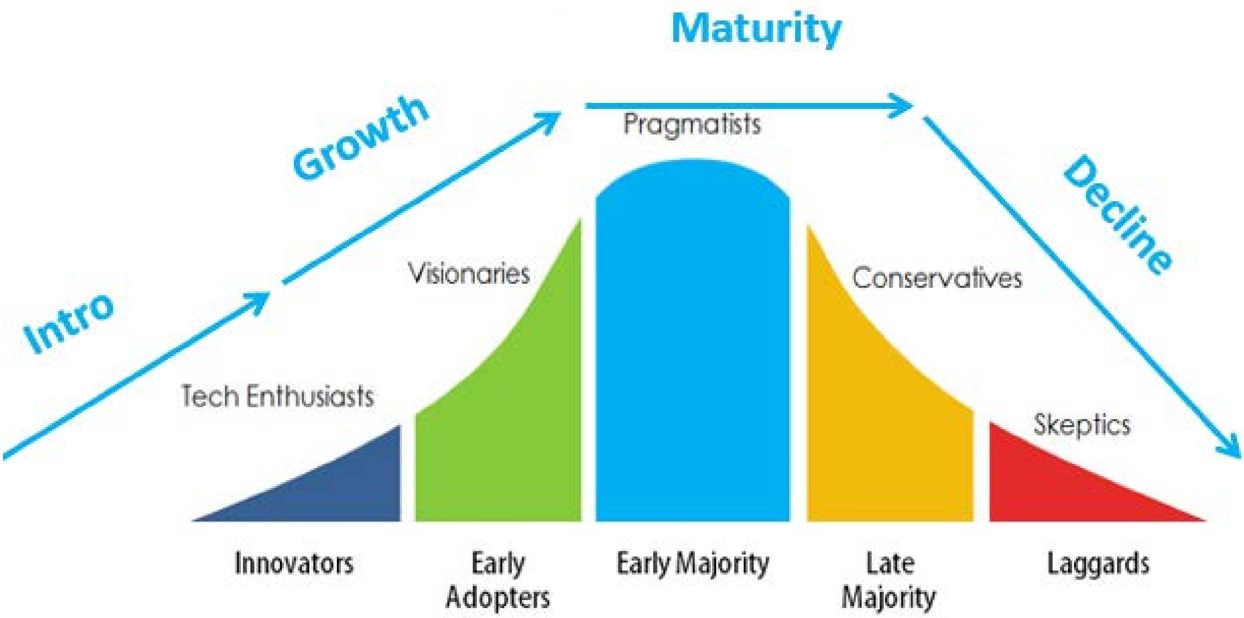



**Figure 15: Bass classical model**

**Source:** [http://www.free-power-point-templates.com/articles/new-product-diffusion-curve-slide-for-powerpoint/](http://www.free-power-point-templates.com/articles/new-product-diffusion-curve-slide-for-powerpoint/)

These Bass five consumer segments are translated into four stages of the product life cycle: Introduction, growth, maturity, and decline.

**The introduction phase** has a slower growth since at the initial state not enough advertising budget is allocated, distribution channels are not well established and people who sell the product are not yet fully trained

**The growth phase** reflects the highest rate of customers' acceptance where the product is being purchased at its most rapid phase.

**The maturity phase** the market saturation level for the product has been reached as most potential buyers have already purchased.

**The decline phase** the product sales rate decelerates and eventually decreases.

These phases of the product life cycle can generate S shaped market diffusion over time

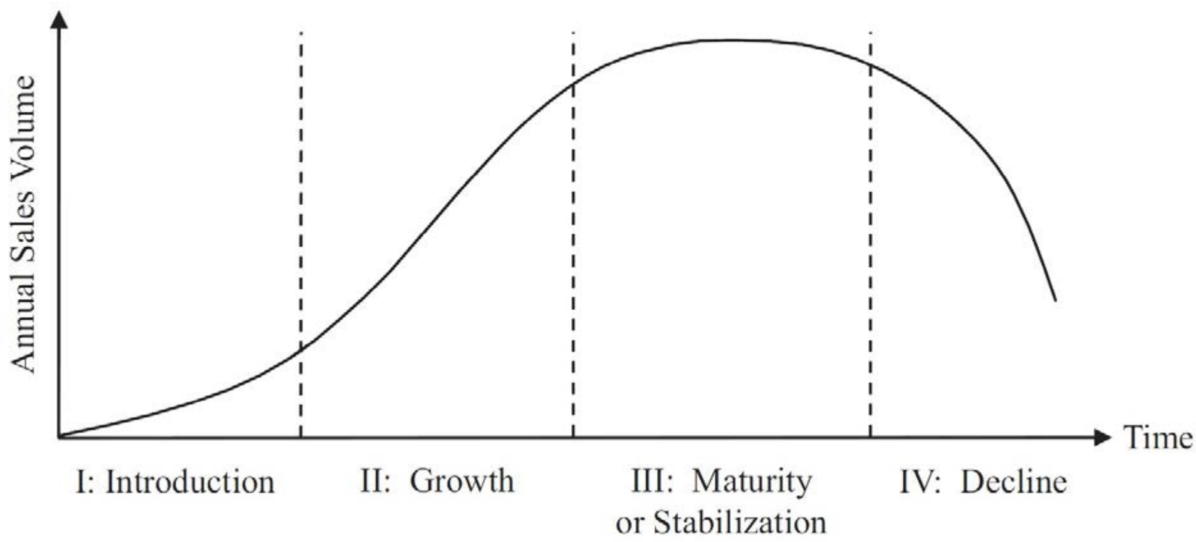



**Figure 16: Bass classical product life cycle model**

**Source: Malakooti (2013)**

## 3.6.2 The Bass model as a forecasting method: limitations and improvements

### 3.6.2.1 Limitation # 1: product forecasting accuracy

Although the Bass 1969 model was elegant and innovative from a mathematical perspective, it was not quite so good for forecasting and therefore the original Bass model has been refined a number of times through the years by Bass himself and others. The main modelling developments in the period 1970 onwards have been in modifying the existing models by adding greater flexibility to the underlying model in various ways. The main categories of these modifications are listed in table 3, and in each case, the citations of a pioneering paper are quoted as a proxy for research activity in this area.

However, in spite of the fact that, as it can be observed from the summary table 1 below, there was an extensive work done to further develop and improve the Bass model, it is still relatively easy to find applications where the Bass model validity is dubious.

| | The development on the original Bass model | Authors and year |
|---|---|---|
| 1. | the introduction of marketing variables in the parameterization of the models | Robinson and Lakhani (1975) |
| 2. | generalizing the models to consider innovations at different stages of diffusions in different countries | Gatignon et al. (1989) |
| 3. | generalizing the models to consider the diffusion of successive generations of technology | Norton and Bass (1987) |
| 4. | Reviews of diffusion models | Mahajan and Peterson (1985, 1993), Mahajan et al. (2000a,b) |
| 5. | Bass diffusion model review from an economic viewpoint; focuses on the diffusion of process between firms and the roles that geography and inter-firm networks play in knowledge transfer. | Baptista (1999) |
| 6. | Offer a research agenda for the development of a sounder theory for diffusion in a marketing context and more effective practice:<br>• increasing the understanding of the diffusion process at the level of the individual exploiting developments in hazard models as a means of incorporating marketing mix variables<br>• investigating the nature and effect of supply and distribution constraints modelling and predicting product take-off<br>• Empirical comparisons with other sales forecasting models | Mahajan, Muller and Bass (1990) |
| 7. | • Improvements to the Bass model validity: The product should be adoptable rather than consumable (i.e. there should be an obvious upper bound to the saturation level).<br>• Statistical validity: the estimation of model parameters should be subject to significance tests demonstrable. | Meade and Islam (2001) |

| | | |
|---|---|---|
| | • Forecasting ability and validity: The forecast should be contextually plausible and the forecast should be accompanied by some measure of uncertainty, ideally a prediction interval | |

Table 3: The main categories of the modifications on the Bass model

To give a simple example of by how far the original Bass model was an inaccurate forecasting method we give this example from the original Bass paper from 1969. In late 1966, the Bass model predicted that U.S. color television sales would peak at 6.7 million units in 1968. But color television sales first peaked in 1973 when more than 50% of U.S. households had a color TV, and then again in 1994 when 24.7 million units were sold. The reason for its low forecast accuracy might be because the model was based on annual data, and it took several years after the launch to accumulate enough observations to estimate the model parameters with any degree of confidence. Bass himself commented in his 1969 paper: *"Some kind of estimate is possible with only three (annual) observations… Any such estimate should be viewed with some skepticism… The parameter estimates are very sensitive to small variations in three observations. Before applying estimates obtained from a limited number of observations, the plausibility of these estimates should be closely scrutinized."(Bass (1969) page 222-223).*

### 3.6.2.2 Limitation # 2 phenomena that do not fit the typical Bass model

In the past decade, a stream of literature has emerged to examine the turning points in the product life cycle that are not included in the classic Bass model smooth-adoption curve (figure 13) such as takeoff, which occurs at the beginning and saddle, which occurs during early growth. The classic Bass model starts with spontaneous adoption by an initial group of adopters but does not provide explanations for the mechanisms that lead to this initial adoption, or takeoff. Studies on takeoff focus on this initial stage and explore the market's behavior and the interface between adoption and the start of communication interactions.

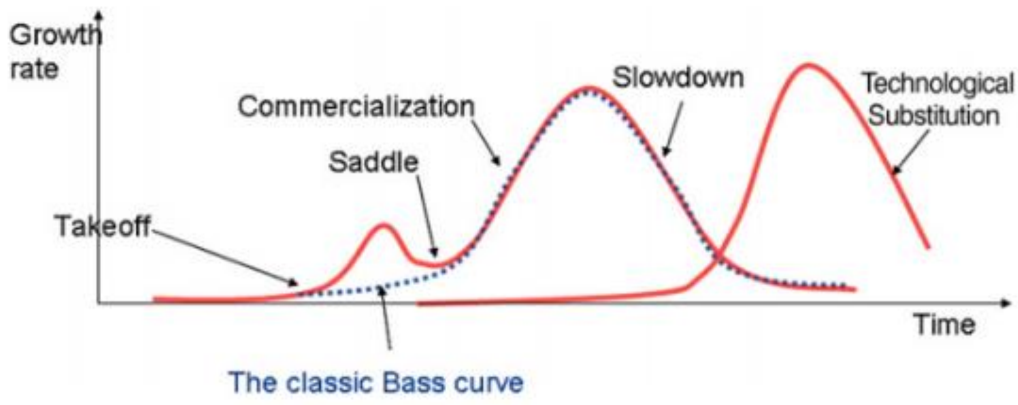



**Figure 17: Potential turning points in the product life cycle**

**Source: Peres et al. (2010)**

Golder and Tellis (1997) defined takeoff time as the time at which a dramatic increase in sales occurs that distinguishes the cutoff point between the introduction and growth stage of the product lifecycle. The importance of takeoff time to the firm is quite clear: a rapid increase in sales requires substantial investments in production, distribution, and marketing, which most often involve considerable lead time to put into place successfully. Golder and Tellis (1997) found that the average time to takeoff for categories introduced after World War II was six years and that average penetration at takeoff was 1.7% of market potential. Price at takeoff was found to be 63% of the original price. Other studies have investigated factors that influence time to takeoff. Accelerating factors are price reduction, product category (brown goods such as CDs and television sets take off faster than white goods), and cultural factors such as masculinity and a low level of uncertainty avoidance as studied in Foster et al. (2004) and Tellis et al. (2003).

Following takeoff, diffusion models predict a monotonic increase in sales up to the peak of growth. However, in some markets a sudden decrease in sales may follow an initial rise. This decrease in sales was observed by Moore (1991), who denoted it as the chasm between the early and main markets, and this concept was later formalized and explored by Mahajan and Muller (1996); Goldenberg et al. (2002); Golder and Tellis (2004); Muller and Yogev (2006); Van den Bulte and Joshi (2007); Vakratsas and Kolsarici (2008); and Libai et al. (2008). Goldenberg et al. (2002) referred to the phenomenon as a “saddle” and defined it as a pattern in which an initial peak arrives before a substantial depth and duration that is followed by increased sales that eventually exceed the initial peak.

Saddles are turning points that can represent periods of exceptional opportunity or caution to the company management and therefore it is very important for the manager to know whether or not the forecasting technique anticipates these fundamental shifts.
While a saddle can be attributed to causes such as changes in technology and macroeconomic events, it can also be explained by consumer interactions. Golder and Tellis (2004), as well as Chandrasekaran et al. (2006), have claimed that the saddle phenomenon can be explained using the informational cascade theory. Small shocks to the economic system such as a minor recession can temporarily decrease the adoption rate, and the decrease is magnified through the informational cascade. These findings regarding the takeoff and saddle demonstrate that there are phenomena that do not fit the typical Bass model bell-shaped sales curve.

### 3.6.3 Technology generations and substitution

In theory, the basic diffusion process is terminated by a decay of the number of new adopters and saturation of the market potential. In practice, however, products are often substituted with newer generations of products with more advanced attributes. Since the pioneering work of Fourt and Woodlock (1960) and Bass (1969) many marketing scientists have proposed sales growth models to measure the effectiveness/success of a new idea or new product among target populations. This high level of interest in measuring the diffusion of innovation has resulted in a large body of publications (table 1). In comparison, the diffusion modelling of multiple generation products have received less attention, though the number of publications in this area is steadily growing (Islam and Meade (2010)). The growing interest in this area can be attributed to reducing lifecycles of products and dominance of high technology products in the market.

#### 3.6.3.1 The limitations of the Bass model in multi-generation technology

The classical diffusion models as Bass (1969) and Kalish (1985) do not consider relationships between different product categories; thus they do not take into account the fact that the adoption of an innovation does complement, substitute, eliminate or enhance the adoption of another product(s) (or vice versa). If we accept the fact that an innovation introduced into a market cannot remain isolated, we have to accept the possibility that another innovation or existing product can both positively or negatively influence its diffusion process. The market success of a given innovation may even be aided by another product (multi-product interactions) or product generation (successive generations).

Norton and Bass (1987) model is a classic example of multiple generation model, which is again built upon the Bass model. In the model it is assumed that the coefficients of innovation and imitation remain unchanged from generation to generation of technology. But many authors have argued against this assumption. Islam and Meade (1997) have tested the hypothesis of coefficient constancy across generation of Norton–Bass model. Their empirical work relaxed the assumption of constant coefficient. They proposed that the coefficients of later generation technology are constant increment/decrement over the coefficients of the first generation. Mahajan and Muller (1996) proposed a model, which is again an extension of Bass model to capture simultaneously both the substitution and diffusion patterns for each successive generation of technological products. Speece and MacLachlan (1995), Danaher, Hardie and Putsis (2001), developed a model in a different way by incorporating price as an explanatory variable.

Shocker at al. (2004) point out the relatively little attention that multi-product growth models have received compared to other topics dealing with the diffusion of new products. Therefore the models of technology generations should be distinct and should identify the potential market for each generation, the growth rate of consumer preference towards a generation and repeat buying behaviors.

### 3.6.4 Does product adoption accelerate between different technologies?

New product growth across technology generations has generated a growing interest among marketing scholars such as Bass and Bass (2001, 2004), Mahajan and Muller (1996), and Norton and Bass (1987, 1992). A major issue examined by these researchers is whether diffusion accelerates between technology generations. This question has practical importance for forecasting as projections regarding the growth of advanced generations of a product must often be made during the early stages of product penetration or before launch and are thus based on using diffusion parameters from previous generations.

As Stremersch et al. (2010) pointed out; the literature offers contradicting answers to the question of whether diffusion accelerates across technology generations. The key finding (or assumption) of several studies across multiple product categories is that growth parameters are constant across technology generations e.g.), Norton and Bass, (1987, 1992), Kim et al. (2000), Mahajan and Muller (1996) and Bass and Bass (2004). Bayus (1994), for example, used a proportional hazard model to analyze the diffusion of four generations of personal computers and concluded that the average product lifespan did not decline over time. This was true even when moderating variables (such as year of entry and technology used) were included. Exceptions to this premise were provided by Islam and Meade (1997) and Pae and Lehmann (2003), who demonstrated that the results can be an artifact of the difference in the length of time covered by the data series used in the analysis; their findings were subject to criticism by Van den Bulte (2004).

In a contradiction to the stability of growth parameters across generations, there is a great body of evidence in Van den Bulte and Stremersch (2004, 2006) suggesting that the overall temporal pattern of diffusion of innovation accelerates over time. A recent analysis by Van den Bulte (2000, 2002) found conclusive evidence that such acceleration does indeed occur. Van den Bulte investigated the issue of acceleration by adopting the Bass model with the internal influence parameter (q) set to zero and running the model on 31 product categories in consumer electronics and household products. The average annual acceleration between 1946 and 1980 was found to be around 2%. Exceptions to this generalized finding are rare Bayus (1994) and contested on the grounds of estimation bias and invalid inference as in Van den Bulte (2000).

These two research streams form an intriguing paradox: It seems that, in the same economy, an acceleration of the diffusion of innovations over time should be reflected in an acceleration of diffusion of technology generations that succeed one other; however, the diffusion rates of sequential technology generations remain constant.

A resolution to the paradox was suggested recently by Stremersch et al. (2010), who noted constant growth parameters across generations but a shorter time to takeoff for each successive generation. They investigated whether the faster takeoff of successive generations is due to the passage of time or to the generational effect. They defined technology generation as a set of products similar in customer-perceived characteristics and technology vintage as the year in which the first model of a specific technology generation was launched commercially. Using a discrete proportional hazard model in 12 product categories, Stremersch, Muller, and Peres (2010) found that acceleration in time to takeoff is due to the passage of time and not to generational shifts. Thus, time indeed accelerates early growth, whereas generational shifts do not.

### 3.6.5 Does new product technology substitute the previous one?

The issue of technological substitution has raised questions related to the heterogeneity in the adopting population. Goldenberg and Oreg (2007) proposed a redefinition of the “laggards” concept; they suggested that laggards from previous product generations may often become innovators of the latest generation because of leapfrogging. Thus, for example, in the early days of the MP3 revolution, an early adopter of MP3 could be a user of a Walkman cassette player who did not adopt CD technology and decided to upgrade by leapfrogging to an MP3 player. Hence, early adopters of MP3 players were not necessarily innovative; some may have been leapfrogging laggards from previous generations. Thus, firms should approach them with the appropriate marketing mix tools and not treat them as innovators.

The entry of a new technology generation complicates the growth dynamics and generates consumer-related processes that are not observed in single-generation diffusion. First, the entry of a new generation is usually considered to increase the market potential. In addition, customers can upgrade and replace an old technology with a new one. On the other hand, individuals who belong to the increased market potential might decide eventually to adopt the older generation of the product and, hence, cannibalize the new technology's potential. If there are more than two generations, adopters can skip a generation and leapfrog to advanced versions. This means that the entry of a new technology reveals heterogeneity in the adopting population that was not realized in a single generation scenario.

Surprisingly, none of the diffusion models have yet offered a comprehensive treatment of these dynamics. Studies so far have focused on one or two of these aspects, such as upgrading as in Bass et al. (2001, 2004) and in Norton and Bass (1992) and on cannibalization as in Mahajan et al. (1996).

Normative decisions are also influenced by intergenerational dynamics. Several papers, Padmanabhan and Bass (1993), Danaher et al. (2001) and Lehmann and Esteban-Bravo (2006), have investigated optimal pricing decisions under technological substitution. However, with the exception of Lehmann and Esteban-Bravo (2006), these studies did not address the dynamics of specific groups of adopters.

While models for the diffusion of technology generations have existed for a while, major questions remain unanswered. According to traditional approaches, the new generation eventually replaces the older generation; however, this is no longer the case. For many products, old and new generations coexist for a long time. In the mobile phone industry, the number of subscribers to analog phones continued to increase long after digital technologies became available. Use of older handset types in emerging economies challenges manufacturers to cope simultaneously with multiple technology generations. The two most frequently cited models of technological substitution, developed by Norton and Bass (1987) and Mahajan and Muller (1996), are restrictive in their treatment of the coexistence of multiple generations. They also provide little insight into other substitution issues, such as leapfrog behavior, and the differences between adopter groups (e.g. new customers joining the category vs. upgraders).

## 3.7 Product portfolio managerial literature review

Portfolio management for product innovation is one of the most important senior management functions e.g. Roussel at al. (1991) and Cooper and Kleinschmidt (1996). Faced with rapidly changing technologies, shorter product life cycles, and heightened global competition, more than ever, how a business spends its technology dollars and resources is paramount to its future prosperity and even its survival. Indeed portfolio management is the manifestation of a business's strategy – it dictates where and how the company invests for the future. It can be said that portfolio management treats R&D investments much like a fund manager in the stock market treats financial investments.

According to the Product Development Institute (The PDI, co-founded by Dr. Scott J. Edgett and Dr. Robert G. Cooper) , companies adopt portfolio management to establish a dynamic design process that allows them to constantly consider and revise their new product development projects from the following perspectives: evaluate, select and prioritize new projects, accelerate, kill or de-prioritize existing projects, allocate and reallocate resources to active projects. The portfolio decision process is characterized by uncertain information, dynamic opportunities, multiple goals, project interdependence and multiple decision makers. The portfolio decision process encompasses and sometime overlaps numerous decision-making processes within a company's business, including periodic reviews of all projects in the total portfolio (i.e., examining all projects holistically, as well as evaluating them against each other), making go/kill decisions about individual projects on an ongoing basis and developing new product strategies for the business (complete with strategic resource allocation decisions). In brief, where to focus, how to focus and what to measure are crucial factors in influencing innovation success.

It deals with issues such as maximizing the value of the portfolio, hence the return on R&D spending, an appropriately balanced portfolio and a portfolio investment strategy that is aligned with the company's overall business strategy.

Product portfolio management considers many unique aspects of the problem which makes it one of the most challenging decision-making faced by business today: First, new product portfolio management deals with future events and opportunities thus much of the information required is either uncertain or unreliable. Second, the decision environment is a very dynamic one: the status and prospects for projects in the portfolio are ever changing, as new information becomes available. Third, the projects in the portfolio are at different stages of completion, yet all projects compete against each other for resources, so that cost benefit analysis to compare the projects must be done even though the level of information about each project is different. Forth, the resources to be allocated across projects are limited and therefore often there need to be made some painful tradeoffs between the projects.

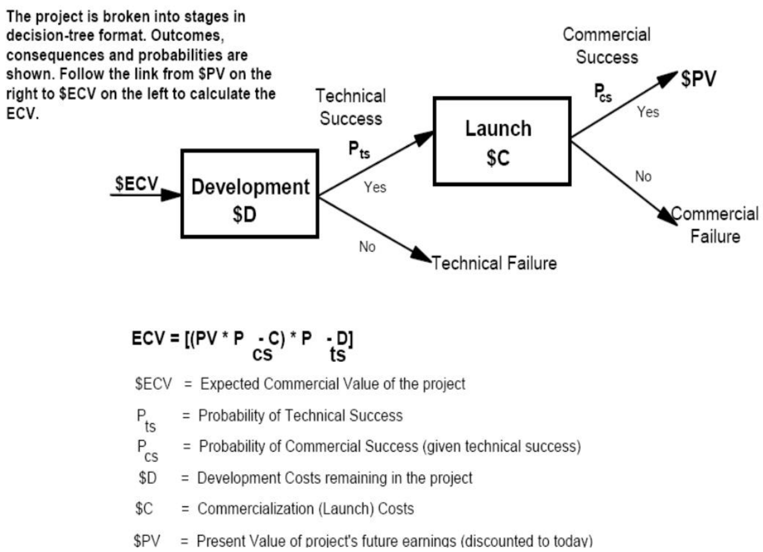



**Figure 18: Determination of Expected Commercial Value of a project**

**Source: Stage gate international ©**

Ben Almojuela, the Associate Technical Fellow in Product Development at Boeing Commercial Airplanes, offered a comprehensive definition for portfolio management as "a dynamic decision process in which a set of active new product and R&D projects is regularly evaluated, prioritized, and selected based on the goal of obtaining the greatest possible value from the organization's limited resources." Goldense (2005 P. 2). According to this definition, portfolio management is composed of the following six elements: project evaluation, resource allocation across projects, corporate resource allocation, strategizing, project prioritization and project selection. Almojuela also outlined the benefits of portfolio management in ten key areas:

1. Timing - Ensures that products and technology are delivered to market at the target time.
2. Projects - Defines projects or sets of projects to address scenarios on the roadmaps in accordance with strategic concepts. Focused on projects and project attributes that affect portfolio management outcomes.
3. Resources - Aligns resources, work statement and resultant risk levels. Resource allocation is a major goal.
4. Planning - Critical to long-range planning and execution of plans. Creates a framework and helps collect data for further planning activities.

5. Decisions - Makes tactical (execution of the strategy) decisions. Strongly influences strategic decisions. Decision-making systems embedded in the process.
6. Communication and Collaboration - Imposes a common nomenclature for stakeholders to support critical decision-making. Facilitates structured discussions and dialogs.
7. Synergy - Critical macro-process for bringing ideas all the way to market. Strong synergy with project management and technology planning.
8. Strategy - Uses strategy-related criteria to facilitate decision-making and aligning product & technology development with corporate & product strategy.
9. Risk - Addresses risk in terms of multiple scenarios for product developments. Risk is explicitly evaluated at each stage of gated process within portfolio development.
10. Alignment - Aligns work statement, resources for each project or set of projects within the portfolio. Aligns development with decision-making process.

The importance of benchmarking and identifying the drivers of a new product introduction success is huge for both companies and scholars.

According to a survey done by Cooper and Kleinschmidt (1996) there are several key factors for successful products developments. One of the most notable conclusions in this best practices survey is the importance of a strategic vision. According to the survey top performer companies possess a product innovation strategy, driven by the leadership team and its strategic vision for the business.

This innovation strategy consists of a number of elements, including the business's goals for product innovation for example, 3M's goal of "percentage of sales from new products" has been adopted by many firms, and how the business's new product effort ties into its overall business goals.

Part of the innovation strategy is the companies´ top management decision on where to focus its R&D efforts along with how the business plans to win in each area. Successful companies also may create an environment to foster the development of innovative new products for example, P&G's strategy of "connect and develop" or working with partners to develop new products outside the corporation. The academic literature review has discussed extensively the Bass model and its extension with a special focus on their limitations for product forecasting, forecasting accuracy and the exclusion of turning points (takeoffs, and saddles) which are typical phenomenon in products life cycle. Following, we have reviewed the academic literature of sales forecasting in a multigenerational product environment which is of a growing interest but nevertheless was not considered by the classical Bass model. Next we have discussed the literature of products dynamics such as products acceleration, substitution and cannibalization.

The managerial literature review has focused on product portfolio management which is one of the most important senior management functions along with product development which is key for any company's success and survival. The literature review of the managerial literature has covered the industry practice as well as providing examples from companies such as Boeing, P&G, 3M and more about their product portfolio management and product development.

## 3.8 The forecasting accuracy literature

In this section we will describe the forecasting accuracy measurements that are found in the literature. We used these forecasting accuracy measurements in our empirical studies section in order to calculate the in-series accuracy of the models.

In spite of the fact that most social scientist learn to identify the "Goodness" of the linear regression model through using the least squares algorithm and conclude that when the overall relationship is statistically significant (when R^2 is above a reasonable threshold) the model is good, there are other factors that can influence even more the model´s "Goodness". In practice and also in the literature for example in Hanke and Reitsch (1995 P. 120) and Bowerman et al. (2004 P. 18) forecast accuracy is typically measured using the Mean Absolute Percent Error or MAPE and it was also the primary measure in the M-competition described in Makridakis et al. (1982). However, Makridakis, Wheelwright and Hyndman (1998 P. 45) warn against the use of the MAPE in some circumstances.

Additional accuracy measurements were also offered in the literature, Armstrong and Collopy (1992) recommended the use of Geometric Mean Relative Absolute Error - GMRAE, Median Relative Absolute Error - MdRAE and Symmetric Median Absolute Percentage Error - MdAPE. Fildes (1992) recommended the use of MdAPE and GMRAE (although he described the latter as the relative geometric root mean square error or GRMSE). Hyndman and Koehler (2005) recommend using Mean Absolute Scaled Error – MASE and the Mean Absolute Erorr - MAE or in its variant as Mean Absolute Deviation - MAD are both recommended as the primary forecasting accuracy measure by Sanders. Statistically, MAPE is defined as the average of percentage errors. Most practitioners, however, define and use the MAPE as the Mean Absolute Deviation divided by Average units. This is in effect a volume weighted MAPE. This is also referred to as the MAD/Mean ratio.

To quantify the in-series accuracy of the proposed models we will use the following accuracy measurements:

Mean Absolute Deviation (MAD)
Mean Percent Error (MPE)/ Mean Forecasting Error (MFE)
Weighted Absolute Percent Error (WMAPE)
MAD-Mean Ratio
Forecasting Efficiency Quotient
R-Square
Mean Squared Error (MSE)
Root Mean Square Error (RMSE)
Median Absolute Percent Error (MdAPE)

Let $\mathrm{D}_t$ denote the observation at time t and $F_t$ denote the forecast of $\mathrm{D}_t$. Then define $\mathrm{E}_t$ the forecast error $\mathrm{E}_t = \mathrm{D}_t - F_t$.

**Mean Absolute Deviation (MAD):** The MAD is a measure of the average error size for the forecasts and indicates the average deviation from historical demand. Because the MAD is calculated with absolute values, it does not take into account the direction of those deviations (i.e. whether they are above or below historical demand).

$$MAD = \frac{\sum_{t=1}^{N} |E_t|}{N}$$

**Equation 3: The MAD formula**

**Mean Percent Error (MPE)/Mean Forecasting Error (MFE):** Measures average deviation of forecast from historical data.

$$MFE = \frac{1}{n}\sum_{t=1}^{n}(D_t - F_t)$$

**Equation 4: The MPE/MFE formula**

**Weighted Absolute Percent Error (WMAPE):** Measures the weighted absolute deviation of forecast from historical as a percentage of historical data.

$$WMAPE = \frac{\sum \left|\frac{D_i - F_i}{D_i}\right| * D_i}{\sum D_i}$$

Equation 5: The WMAPE formula

**Forecasting Efficiency Quotient (FEQ):** The FEQ measures the forecasting improvement over the average as the baseline forecast

FEQ = (CV* – WMAPE)/CV*

CV* = Coefficient of Variation

**Equation 6: The FEQ formula**

**Mean Squared Error (MSE)**: MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated.

$$MSE = \frac{\sum_{t=1}^{N} E_t^2}{N}$$

**Equation 7: The MSE formula**

**Root Mean Square Error (RMSE):** measure of the difference between values predicted by a model and the values historically observed from the environment that is being modeled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} E_t^2}{N}}$$

**Equation 8: The RMSE formula**

**Median Absolute Percent Error (MdAPE):** The middle value of all the percentage errors for a data set when the absolute values of the errors (negative signs are ignored) are ordered by size.

# 4 The research approach

To answer the four problem statements described in section 2, we embarked on four empirical studies. The empirical study that lays the foundations to the other three is empirical study number one where we have designed and tested an innovative forecasting tool that uses macroeconomic indicators as an input for the products sales output. Then in the following two empirical studies we test the capabilities of the macroeconomic based forecasting model that was created at empirical study number one. The forecasting model capabilities that were tested in empirical study number two is the cultural adaptability, in other words, how the macroeconomic-indicator-based forecasting model adapts to different business cultures and forecasts accurately the sales in these local markets. The other forecasting model capabilities that were tested in empirical study number three is the product life cycle adaptability, hence, how the macroeconomic based forecasting model adapts to different product life cycle and forecasts accurately the sales in the different product life cycle stages. After noticing that the macroeconomic based forecasting model is adaptable to the product life cycle, we used this important capability to quantify product portfolio dynamics which is at the heart of empirical study number four.

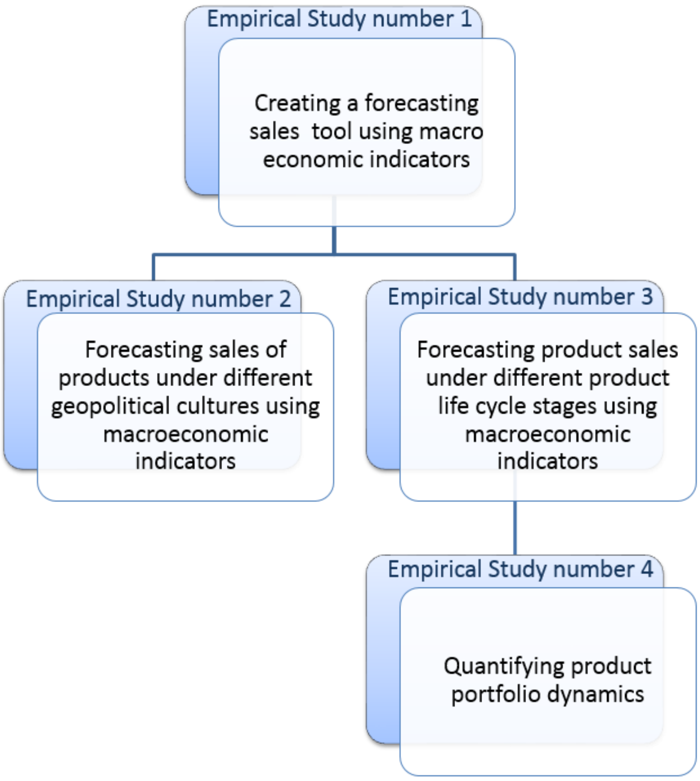



**Figure 19: The empirical studies flow**

### 4.1.1 Introduction to empirical study number 1

Empirical study number 1 intent to provide a simple and robust tool for sales forecasting for high tech products and to provide greater insight into how the institutional theory framework represented by the macroeconomic indicators helps us obtain such a forecasting tool. Empirical study number one discusses the connection between macroeconomic indicators with the microeconomic sales forecast of three different high tech product families and suggests accurate and robust sales forecasting econometric model for each of the three product families based on the singular relationship between the macroeconomic indicators and the products families. We focus on three different markets and, in particularly, we examine the special relationship between specific sets of macroeconomic indicators and these markets. We propose forecasting models based on these relationships between the product lines and the macroeconomic indicators and we also quantify the model´s accuracy and fit by using the widely used forecast accuracy measurements. We later find support for our hypotheses that the relation between each product line and the suggested macroeconomic indicators sets is unique and we show how replacing these sets with other macroeconomic indicators results in worse off models. Furthermore, we also show that the suggested models are robust enough to provide insights into the future growth forecast. Our results highlight the importance of considering the different macroeconomic indicators due to differences in markets of the product lines and its consequences on differences in product purchase drivers. Finally, the empirical study shows a strong explanatory connection be provide an empiric proof to the institutional theory.

### 4.1.2 Introduction to empirical study number 2

Empirical study number two tests the sales forecasting models created at the empirical study number one and explores their behavior under different cultures. It discusses the adaptation of the macroeconomic-indicators-based sales forecasting models to three very different geo-political cultures and shows that our model adapts well to the cultural diversity and forecast at a high level of accuracy the sales of high tech products in various geo-political markets. We wanted to check whether the forecasting model tested in empirical study number one is adaptable to different cultures and gives good forecasting results also under different cultures. We wanted to provide an empiric proof for the best strategy for multinational companies going abroad whether it is standardization of the processes or adaptation to the local markets. Our forecasting model revealed the cultural differences when we applied them in different geopolitical markets. Empirical study number two is exploring the link between business culture differences and forecast accuracy. In particular, it shows how the culturally-adapted model has higher forecast accuracy.

The theoretical framework of empirical study number two is the New Institutional Economics theory that sees individuals, and in our case, firms, as part of a bigger framework that influences them. In support to the New Institutional Economics theory, in our thesis we show strong evidences that the underlying factors of the same market in different countries are unique to each country. The New Institutional Economics Theory supports our approach that effective forecasting must consider cultural features at the meta-analysis stage. Our model proves the institutional theory´s premise that the individual level, and in our case, the product industry, is subject to cultural and market idiosyncrasies.Therefore, the precise question to be answered in empirical study number two is whether the same set of macroeconomic indicators works in a similar way in several geopolitical markets and If that is not the case, we explore the better set of macroeconomic indicators for a more accurate forecast.

In empirical study number 2 we show that when we take the same product line in three countries representing different cultures, the macroeconomic indicator that better predicts the sales of the product line is different. Thus we will demonstrate that the macroeconomic indicators sets are unique to their geographical regions even for the same product line. This finding supports the need to adapt the company's marketing mix to each geo political region. This approach is called "adapt" and it is one of the two possibilities established in the marketing literature to companies' marketing activity approach in different markets. The other option is to standardize. Empirical study number two shows that since the set of macro indicators is unique to the three geo political regions (even for the same product line), standardizing the company's marketing activities in global markets might result in not realizing the full potential of these markets.

### 4.1.3 Introduction to empirical study number 3

Empirical study number three takes the model that was tested in empirical study number one and check its behavior in different stages of the product life cycle. Identifying the exact stage in of the product within the product life cycle is critical for designing the marketing efforts needed to promote the product's sales. It is also important to ensure that our model forecasts accurately independently of the product life cycle stage of the products. Therefore, empirical study number three is driven by the desire to extend the model in empirical study number one to different stages of the product life cycle stages.

It is generally accepted that high-technology products follow a basic lifecycle (PLC) that characterizes both the product's development and the market's reaction to this product. This product lifecycle or technology adoption lifecycle indicates what stage of technology adoption the product is in. Its creation is based on the fact that consumers tend to self-segregate themselves along an axis of increasing risk (or risk tolerance), with the risk immune forming the innovators. These factors influence the required strategy for the product, dictating marketing, technology and pricing strategies. Moreover, the proper strategy "does not just change as we move from stage to stage, it actually reverses the prior strategy," as Geoffery Moore states in his book "Inside the Tornado" (1995).Obviously, this reversal in the required strategy presents great problems for the high-tech industry. Moore (1999) states that, "significant marketing expenditure and risk ultimately hinge on a choice about where the product is in the Technology Adoption Life Cycle" ("Inside the Tornado" chapter 6). Unfortunately, however, it is not an easy task to determine what phase of the life cycle a product is in. "In particular, it will be easy for some people to think we are in one stage of the market, while others think we are in another. If this is allowed to persist, people will be working at cross purposes - violently."

Indeed, understanding the life cycle of a product is important to a business for a number of reasons. One important reason is that understanding the stages of the PLC will help a business to manage its cash flow. When the product is launched into the market the business incurs significant costs in marketing and sales. Sales revenue in the introductory stage is unlikely to cover costs. As the product moves into its growth phase, the cost of promoting the product should decrease as cash flow from product sales increase and the business can see a profit. Profits should continue through maturity until sales fall as the product begins to decline. Knowing in which phase of the PLC that product is allows to determine the pricing strategies, for example 'buy one get one free' offers or any other forms of discounts would be more appropriate at the mature or decline PLC stage to encourage more sales. Other pricing strategies can be used at appropriate stages of the PLC, for example a business can use price skimming when the product is first launched by charging high prices. The aim of skimming is to gain high profits in the early stages of the PLC. Skimming is successful when the product is new and different so that consumers will pay a high price for being the first to have it. The opposite strategy to skimming is termed penetration pricing, this means setting a low price when the product first enters the market. The aim is to get the maximum possible market share quickly and to shorten the launch stage of the PLC. Penetration pricing is appropriate for a follower company that launches its first product that aims to compete with an existing products of a market leader for example. Due to the importance of determining in which stage of the PLC the product is encountered, our empirical study number three tests the macroeconomic-indicators-based sales forecasting model in products in different life cycles.

### 4.1.4 Introduction to empirical study number 4

Empirical study number four considers three generations of products and uses the macroeconomic-indicators-based forecasting model to assess the impact of the introduction of the newer generation of products on the overall company´s performance.

Unlike more stable industries, high-tech firms must constantly be in a strategy development phase and their flexibility and agility to react to the ever-changing market and technological landscapes are crucial to their survival. These companies are in desperate need of assistance in developing new products with the newer technology developments. This often means that high technology products come in generations and that companies launch a continuous innovation without withdrawing the earlier one(s) from the market. Hardware and software components of computers are examples of such products. Thus a consumer can evaluate the technologically enhanced product on the merit of earlier generations. This evaluation can be based upon relative utility, price difference etc. A consumer goes through a more complex decision making process as compared to products with only one generation. Thus the modelling process for technology generations is somewhat different from the traditional model of single generation product. When a new technology is introduced in the market, it not only attracts first time purchasers but also previous buyers who would upgrade their products. This factor adds more complexity to the modeling and has lately captured the attention of researchers (Islam and Meade, 2006).

Having several product generations available at the same time means that the consumer can evaluate the technologically-enhanced product, not only for their own merit, but also on the merit of earlier generations. Those customers who decided not to buy the first product may decide to do so now or those who already have the former product generation may decide to trade up or trade in their products for the newer generation of products. Thus, a consumer goes through a more complex decision making process as compared to products with only one generation. Thus, multigenerational products could bring intra products portfolio dynamic such as: cannibalization of one products sales by the newer product generation, faster price erosions of both products and of course the competition may also react to the changes in the product portfolio by launching its own products in market niches that the product portfolio of the other company were left unattended. Therefore, the impact of the product portfolio dynamics on sales makes it an important point to consider when one is offering a forecasting model for high tech products. Empirical study number four considers three generations of products and uses the macroeconomic-based forecasting model to assess the impact of the introduction of the second generation of products on the overall company´s performance in addition to quantifying the dynamics between the products and the influence they had on each other. By using macroeconomic indicators which are external factors to the company´s decisions and control to forecast the company´s sales we neutralize the impact of the products dynamics and therefore we are able to quantify the dynamics between the products and how they influence each other´s sales results.

# 5 Empirical study number 1

## 5.1 The product lines tested

The application of the New Institutional Theory is shown through the forecasting models of hardware units' sales of the following three different product lines:

1. PLI – A high value product line.
2. PLT – A large format product line.
3. PLG – A large format product line.

PLI is a product line of high value units. PLI´s average selling price range is between USD$ 300k and USD $3M. PLI products are used for high quality catalogues of all kinds, marketing collateral, Photographs, digital book publishing and trans-promotional printing. The worldwide units' market size is couple of thousands of units sold by various presses manufacturers every year. This market exists for several years already but the technology behind it was not widely accepted by the market until 2008. The market is a high-growth competitive market.

PLT is a product line for technical drawings and for topographic maps. The PLT´s unit average selling price range is USD$ 2k and USD$ 30K. The clients who purchase these plotters are usually Architects, Engineering companies, Construction firms and reprography firms. The market was redefined in 2007 by a technology breakthrough that allows the productivity required in the market. The PLT market is of a flat growth.

PLG is a product line for professional photographs and Print Service providers. PLG´s units average selling price range is between USD$5k and USD$30k. The clients of these units are professional photographers, and professional service providers to retailors. The PLG market is of a mild growth.

The three product lines are different as they represent different technologies, offering different value proposition to their clients and this the clients' typology is different for each of the three product lines.

| | PLT | PLG | PLI |
|---|---|---|---|
| Product description | A large format product line | A large format product line | A high value product line |
| HW Value range | USD$ 2k and USD$ 30K | USD$5k and USD$50k | USD$ 300k and USD $3M |
| Market growth | Flat growth | Moderate growth | High-growth |
| Competition landscape | A duopoly but mainly dominated by one manufacturer | largely dominated by one manufacturer | A competitive market with various players |

**Table 4: The characteristics of the product lines tested**

## 5.2 The model set up

Empirical study number one takes the constitutive relationship between macro market conditions and the sales of hardware units and uses macroeconomic indicators to forecast the sales growth rate of the several product lines.

The PLI units' growth forecasting model is based on two macroeconomic indicators: the GDP growth rate and the credit availability and correlates it to the actual PLI units Year-over-Year growth. This set of macroeconomic indicators was found to be better correlated as well as they were good proxies to the demand drivers of the PLI units' sales.

Using the Coleman´s diagram we could describe the PLI forecasting model in the following graphical way:

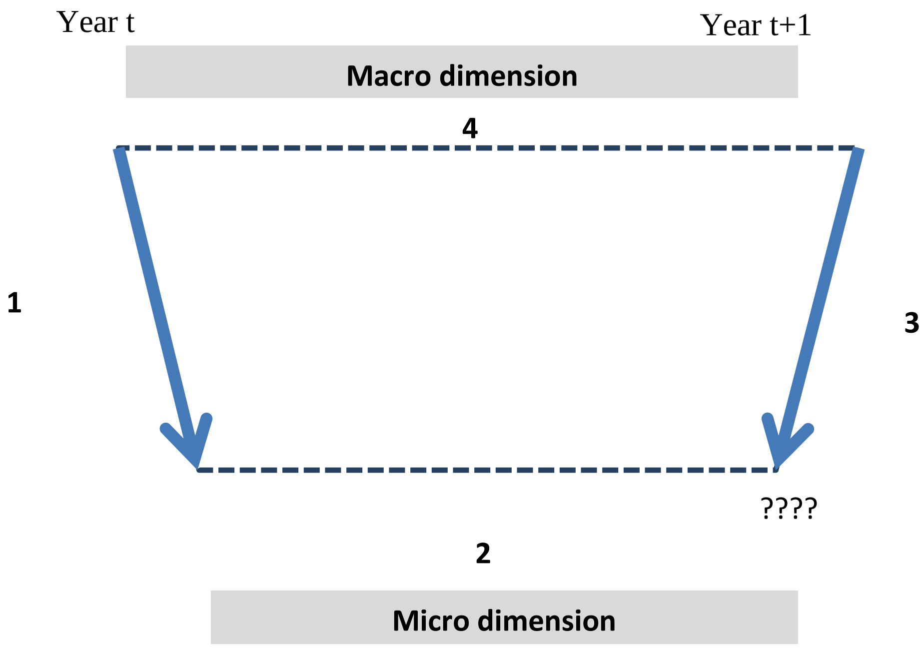



**Figure 20: The Coleman theorem**

Relationship 1: the Macro to Micro relationship in time t and it was defined by Coleman as a supervenience relationship. We quantify this relationship by using a multi-variant time series analysis in order to obtain the correlations between the Macroeconomic indicators and the PLI sales growth that constitute the micro level.

Relationship 2: the Micro to Micro dimension between time t to time t+1 reflects the firms actions, decisions and performance that combined lead to the sales growth. However, the activity of the firms is irrelevant to our models as our model does not take relationship 2 as an input. The sales growth level at time t+1, micro t+1, is the output of our models that is not calculated through relationship 2 but through relationship 1, 4 and 3. We first establish the relationship between Macro t to Micro t (relationship 1). Then we use external forecasts to establish the state at Macro t+1 (relationship 4). Then by using the correlation from relationship 1 and the macro t+1 forecast, we calculate through relationship number 3 the micro state at t+1.

Relationship 3: The Micro to Macro relationship in time t+1. Our model revert the arrow direction of the relationship of the Micro to macro. The reason for this is that we use the Macro state at time t+1 in order to forecast the sales growth in time t+1 which is the micro dimension. This is done by using a linear regression with the pre-established correlations from relationship 1.

Relationship 4: The Macro to Macro relationship. In the original Coleman theorem this relationship is unknown and the macro state at time t+1 is forecasted by aggregating all the outputs of the activity at the micro level at time t+1. Our model´s objective is to forecast the micro results in t+1. This is done by using the macro t to macro t+1 forecasts for the macro economic indicator. The known relationship between the micro and the macro at time t (relationship 1) and the third party economic outlook for the macro level at t+1, allows us to forecast directly from the macro level at t+1 the micro level at t+1.

## 5.3 The macroeconomic Indicators selection criteria

The following Macroeconomic indicators were considered at the Meta-analysis stage for the forecasting models of the three product lines:

1. Gross Domestic Product (GDP)
2. Retail Trade sales
3. Credit conditions and availability (Credit tightening)
4. Capital expenditure in the Construction Market
5. Equipment Depreciation in the Construction Market
6. Outdoor advertising

These macroeconomic indicators are provided by several data providers who publish historical data and also forecasted future data for the markets in the different countries.

In our research we have used the data from March 2012 and July 2012 provided by the Global Insight Company for the Retail Sales, Construction market and GDP. Outdoor advertising is based on December 2011 data from Zenith Optimedia and Credit conditions was the data published in June 2012 by the European Central Bank based on a survey of 192 European banks. With the exception of the Credit tightening, all the data was on a country level, which was aggregated when needed to a region level. It is important to mention, and later it will be demonstrated, that the set of indicators used for each of the product lines´ forecasting models is unique to the product line that it was chosen for. In the following section, we explain in great details the rationale behind the specific selection of each of the macroeconomic indicators for each of the product lines and empirical studies.

## 5.4 The rationale of the selection of the macroeconomic indicators

As shown, PLI, PLT and PLG are three different product lines and would potentially require, according to the institutional theory, different sets of macroeconomic indicators as a basis for their forecasting models. The first step for the selection of the macroeconomic indicator/s was to have a theory in the meta-analysis stage on the markets of the products and the ways by which these products are used.

The macroeconomic indicators (relationship 4) were used to forecast the micro level results (line 2) of the company´s sales as described in the following Coleman diagram:

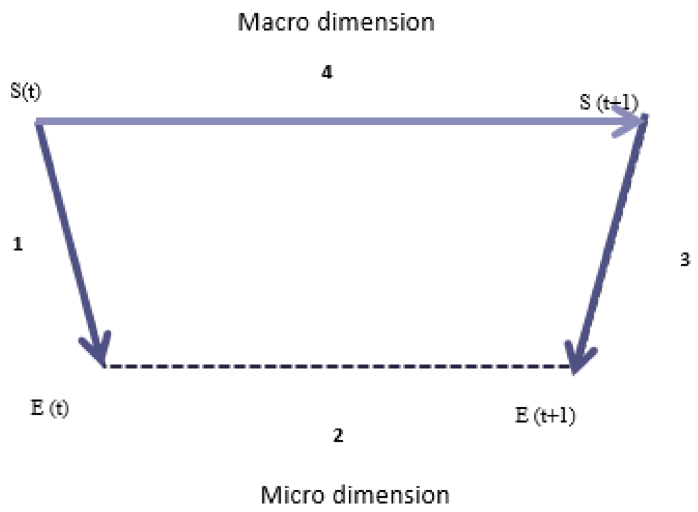



**Figure 21 : The usage of the macroeconomic indicators**

### 5.4.1 The macroeconomic indicators for the forecasting model of Product Line PLT

The PLT products are sold mainly to Architects, Engineering companies, Construction firms and Reprography firms (who sell them to the other three clients 'groups). This led us to look for a macroeconomic indicator that represents the market in which all these clients are operating in and to which the prints outputs serve. We found this market to be the construction market and the indicators that are related to the equipment purchase decisions in the Construction market which are the Capital Expenditures and the Depreciation of equipment. The construction Capital expenditures and the market depreciation indicators are the quantification of investments and depreciation in the construction market in each country in billions of Dollars. Since construction market is big part of the GDP of a country we also found a positive correlation between the PLT product market sales and the GDP. Nevertheless, the construction market is a much better proxy to the PLT market than GDP and therefore, in spite of the positive correlation also found with GDP, we chose to use the construction market indicators for the PLT model.

The decision to purchase a printer for the technical applications is related to Investment in the Construction Market. The concept of investment is captured through the Capital Expenditure (CapEx). Capital expenditure is a long-term investment process in which a firm purchases fixed assets for manufacturing or operating activities. The firm generally uses capital assets for several years. Capital expenditure levels are important because they provide insight into senior management's confidence in future economic trends. The investment decisions in the market are also captured through the Depreciation growth of the market. Depreciation is an accounting method that helps a company allocates the cost of a fixed asset over several years. A fixed asset, also known as capital asset, is a resource that a firm intends to use in operating activities for more than 12 months. Examples include property, plants and equipment such large format plotters to print the drawings and construction plans and maps.

We found that the PLT units growth correlates best with the growth of the Construction market Depreciation and the changes in speed if the Capital Expenditure of the Construction

Market. The higher growth of Depreciation and growth speed of capital expenditure, the higher PLT units' growth.

It is important to mention that the form of construction CapEx that best fits the PLT market is the first derivative of the construction CapEx. Meaning, that the PLT market is sensitive to changes in the speed of investment in the Construction market and not only to the growth of the Construction Capital Expenditure. That means that even if the construction market continues to grow but the speed of the growth is decreasing, there will be a decrease in the growth of the sales of the PLT units.

This phenomenon was observed after 2009 where the construction market dropped to never-seen-before-levels. Until 2009 the construction market grew steadily and this sensitivity to its growth speed was not observed. As of 2009 changes in speed of growth of the construction CapEX (when the market declines less or grows more) can explain the peaks of recovery or sudden drops in the PLT units' growth between 2009 and 2011.

The following graph shows this change in paradigm. As of 2009 where the first derivative of the construction CapEx growth is very similar to the PLT units growth and the construction CapEx growth is no longer able to explain the PLT units growth.

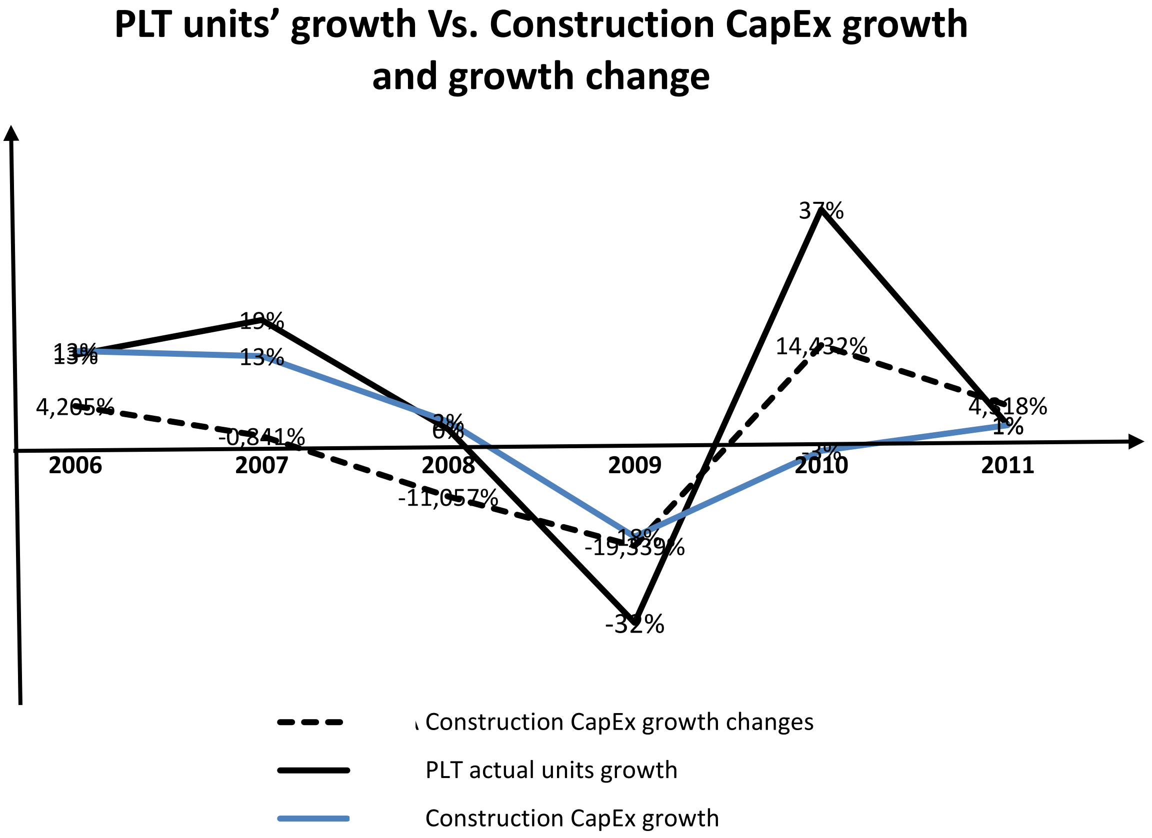



**Figure 22: PLT units' growth Vs. Construction CapEx growth and growth change**

## 5.4.2 The macroeconomic indicators for the forecasting model of Product Line PLG

The second market in our research is PLG which its main applications are decoration, signage and display. These applications are closely related to retail companies who often publish their promotions and products information in their point of sales such as many signs you find in your visit to the super market for example. The two macroeconomic indicators that were found to better explain the PLG market growth were Retail sales and also outdoor advertising.

Outdoor advertising is an indicator that encompasses the advertising expenses of most of the world´s countries for non-electronic advertising and non-magazines advertising. However, this indicator does not work well in all the regions checked, perhaps due to difficulties in data collection of this market in some countries, and therefore this indicator in most cases was replaced by the retail sales indicator in our models.

The PLG units´ growth shows a positive correlation to the Retail market sales growth and to the changes in speed of the Retail market sales and thus the form of the Retail sales indicator that follows the PLG market growth is the Retail sales growth and the Retail sales growth first derivative.

The following graph shows a comparison between the PLG Year-over-Year growth of the units sold and the retails sales growth speed. In the flowing graph, it can be appreciated that as of 2009, the first derivative of the retail sales follows best the PLG market units' growth.
This actually makes sense if we take into account the retail market characteristics where Inventory and promotions are planned ahead, anticipating any change in the consumption.

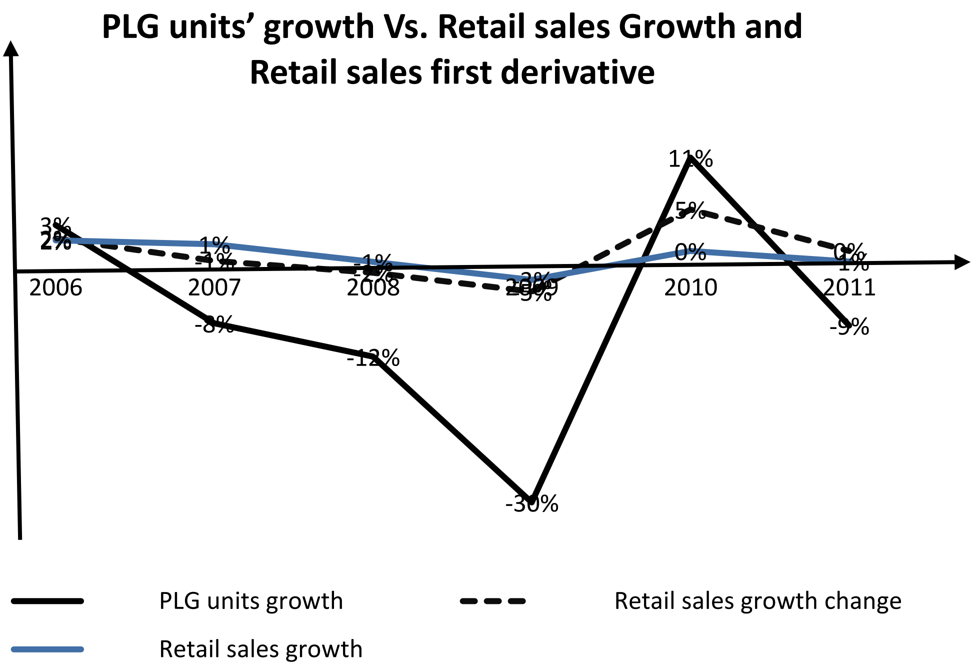



**Figure 23: PLG units' growth Vs. Retail sales Growth and Retail sales speed**

### 5.4.3 The macroeconomic indicators for the forecasting model of Product Line PLI

Our third product line, PLI, is very much related to the general economic activity of the market and therefore its forecast is encompassed by the GDP. Also, in countries where the retail industry drive these applications the PLI market is highly correlated also to the retails sales indicator. The retail sales indicator is published by various data provider and captures the size in Millions of dollars of the retails market of each country.

The PLI units are expensive equipment and their selling price is between 300k USD$ to 3M USD$. We suspected and later on confirmed that the demand could be also influenced by the availability of credit to purchase the PLI units. We added to the model the credit impact on the PLI sales by using an indicator that represents the credit environment, Credit availability. Credit availability captures the negative impact of the banks´ tightening credit conditions. This data is an indicator published by the European Central bank that it is based on a survey of 192 banks in the European Union regarding the quarterly credit conditions and availability to small and medium sized enterprises. We took item 1.2 in the CEB questionnaire that checked the loan supply to small and medium size enterprises that is backwards looking three months data. We converted it to annual data by looking for the yearly average. Then, the 2008 number was set as a base to the following year´s credit availability data with each year´s average banks response added to the previous year. As showed in the following graph, PLI´s year-over-year growth pattern is very similar to that of GDP growth. However, GDP growth explains only part of the growth of the PLI market growth. Due to the high value of the units their sales are also sensitive to credit availability and not only to the rate of the economy growth. When credit conditions are tightening like in the last couple of years, PLI´s growth is moderating in spite of some positive changes of the GDP growth.

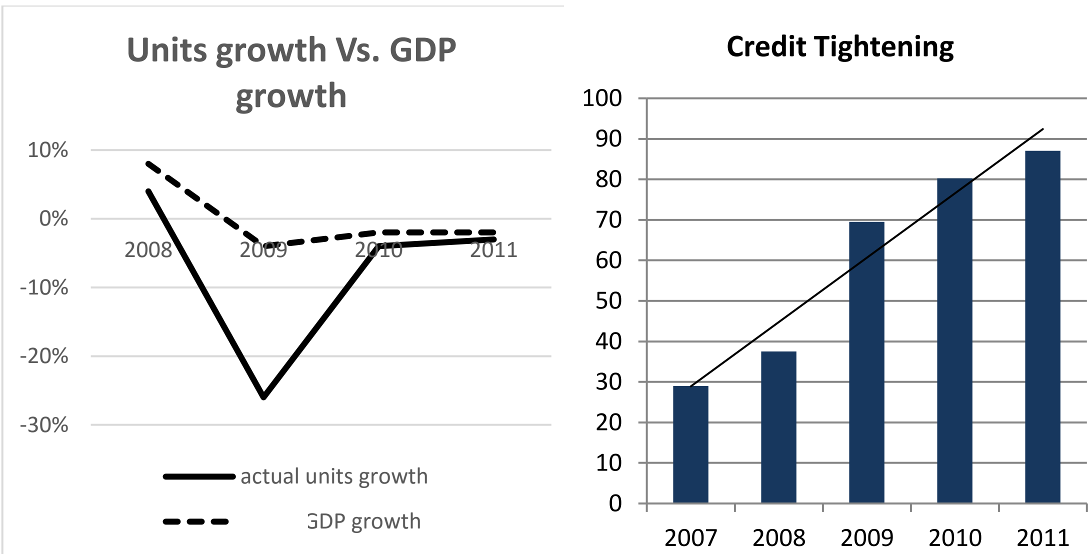



**Figure 24: PLI units' growth Vs. GDP growth and credit tightening**

**Source: IDC market report and European central bank**

Applying the methodology previously described here, we determine the units' growth based on our forecasting model.

In order to evaluate the model´s forecasting capabilities we compared the model in-series forecasted units with that of the actual units sold. This comparison shows that the model forecasts the HW units' growth very similar to the actual units' growth thus, the model predicts relatively well PLI units' growth trend.

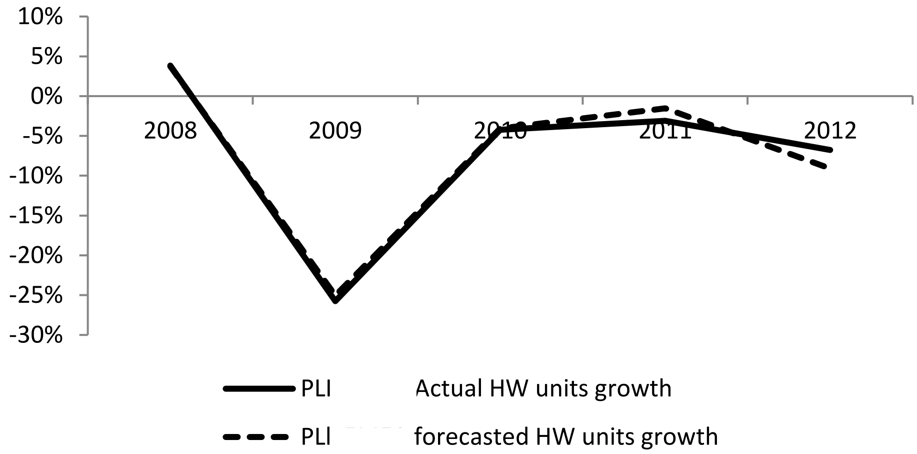



**Figure 25: PLI model forecast units' growth Vs. Actual units' growth**

The next step was to convert the forecasted unit´s annual growth rate to units' annual amount and compare this model forecasted units amount to the actual PLI annual units sold. The result of this comparison is displayed in the following figure. Also in absolute units numbers, when looking at the actual units sold and the units predicted to be sold through the model it is also appreciated that the model explains well the historical trajectory of the PLI sales.

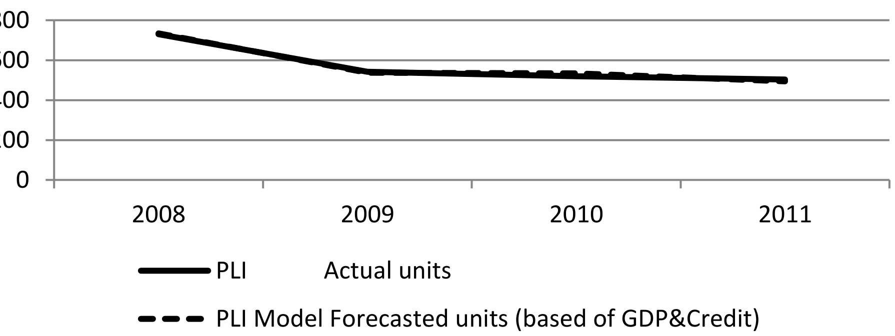



**Figure 26: Model Forecast units Vs. Actual PLI units**

Applying known accuracy tests on the model, we receive the following results as shown in the following table:

| Forecast Metrics | PLI model based on GDP and Credit availability |
|---|---|
| Mean Absolute Deviation (MAD) | 0.97 |
| Mean Percentage Error (MPE) | 5% |
| Weighted Absolute Percentage Error (WMAPE) | -13% |
| MAD-Mean Ratio | -0.13 |
| **Forecasting Efficiency Quotient** | **0.91** |
| **R-Square** | **99%** |
| Mean Squared Error (MSE) | 0.58 |
| Root Mean Square Error (RMSE) | 0.76 |
| Median Absolute Percentage Error (MdAPE) | -0.04 |

**Table 5: The PLI model forecasting accuracy metrics results**

## 5.5 Empirical study number 1 first attribute - explanatory capability

By explanatory capability we refer to the ability of the models to project based on the historical sales and using the sales enablers as dependent variables at a very good accuracy. This is also the accuracy can be backward checked in reference to the historical sales known as in-series forecasting capability. The explanatory capability of the models is a very important attribute of these models to make them an insightful tool. We will demonstrate that the usage of macroeconomic indicators representing the sales enablers as dependent variables in the forecasting models can explain well the historical units' sales growth. We will look at this attribute from the three different product lines/markets perspectives.

### 5.5.1 The explanatory capability of the forecasting model for PLT

We structured a PLT units´ growth regression model based on the construction Depreciation growth and the CapEx growth speed. The PLT forecasting model had an **$R^2$ of 91% at a confidence level of 93% (1-α)**. The model is based on the correlation between the yearly PLT units' sales growth and the construction Depreciation CapEx growth speed. One of the two independent variables was statistically significant and the other one helped increase the explanatory level of the models in comparison to other models and therefore we decided to keep it as one of the two independent variables even though it was not statistically significant. The equation that represents the relationship between the PLT units' market growth and the macroeconomic indicators is:

$$Y_t = A + \beta_1 CapExGrowthChange_t + \beta_2 Depr.Growth_t$$

$Y_t$ =PLT units' growth rate at year t

$A$ = Intercept

$CapExGrowthChange_t$ = Construction market capital expenditure growth rate change at year t

$CapExGrowth_t - CapExGrowth_{t-1}$

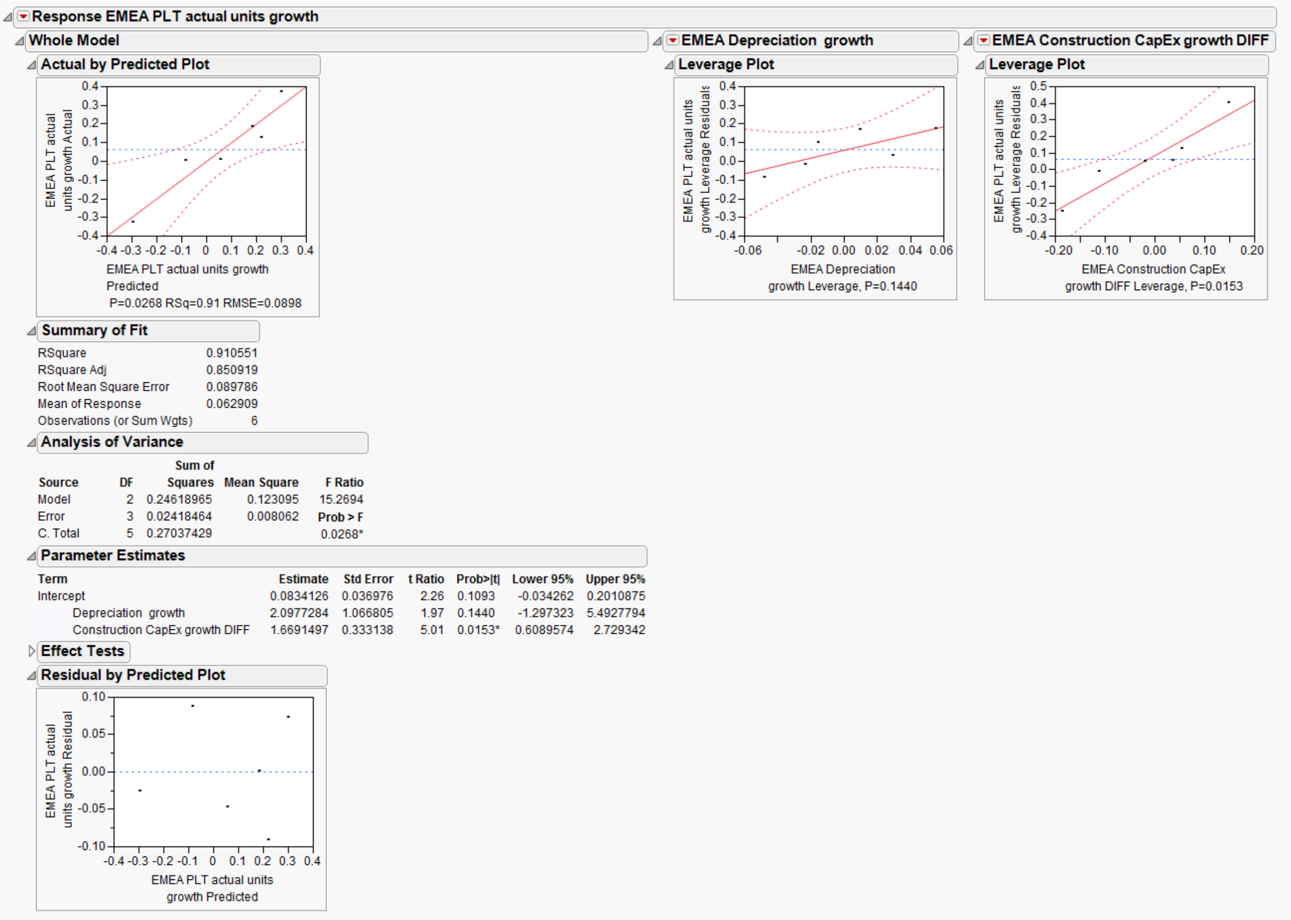
$Depr.Growth_t$ = construction market depreciation growth rate

$\beta_1$ = PLT Units growth rate Coefficient with CapEx growth speed change

$\beta_2$ = PLT Units growth Coefficient with Depreciation growth rate

**Equation 9: PLT units 'market forecasted growth equation**

This actually makes sense if we take into account the construction market itself. The equipment purchase for construction planning and design are planned ahead, anticipating changes in growth speed of construction.




Summary of Fit

| | |
|---|---|
| RSquare | 0.910551 |
| RSquare Adj | 0.850919 |
| Root Mean Square Error | 0.089786 |
| Mean of Response | 0.062909 |
| Observations (or Sum Wgts) | 6 |

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 2 | 0.24618965 | 0.123095 | 15.2694 |
| Error | 3 | 0.02418464 | 0.008062 | Prob > F |
| C. Total | 5 | 0.27037429 | | 0.0268* |

Parameter Estimates

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 0.0834126 | 0.036976 | 2.26 | 0.1093 | -0.034262 | 0.2010875 |
| Depreciation growth | 2.0977284 | 1.066805 | 1.97 | 0.1440 | -1.297323 | 5.4927794 |
| Construction CapEx growth DIFF | 1.6691497 | 0.333138 | 5.01 | 0.0153* | 0.6089574 | 2.729342 |

**Figure 27: PLT Model forecast**

A comparison between the model forecasted units growth, using the construction CapEx growth speed and the Construction market Depreciation Growth, and the actual units sold shows that the units' growth model forecast is very close to the actual units' growth and therefore, shows that the model predicts relatively well the growth trend. The fact that the model is able to explain the past units growth gives assurance that the correlation between the macroeconomic indicators and the product line is not a coincidence.

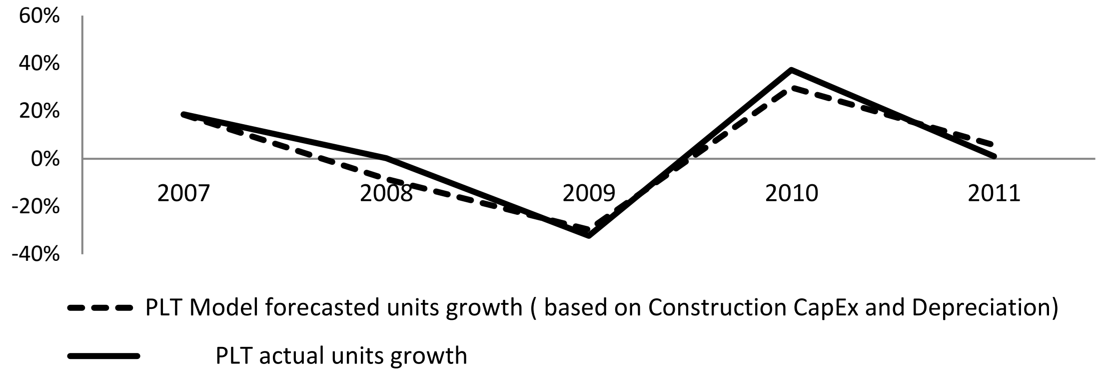



**Figure 28: PLT Model forecast Vs. actual PLT units growth**

The next step was to convert the forecasted unit´s annual growth rate to units' annual amount and compare this model forecasted units amount to the actual PLT annual units sold. The relationship between the forecasted units' growth and the annual forecasted units can be described in the following equation:

$$U_t = U_{t-1}(1+Y_t)$$

or alternatively

$$U_t = U_{t-1} \times (1 + A + \beta_1 CapExGrowthChange_t + \beta_2 Depr.Growth_t)$$

$U_t$ = PLT units at year t

$U_{t-1}$ = PLT units at year t-1

$Y_t$ = PLT unit´s forecasted growth rate for year t

**Equation 10: PLT forecasted units 'market quantity equation**

When looking at the actual units sold and the units predicted to be sold through the model as displayed in the following graph it is appreciated that the model explains well the historical trajectory of the PLT sales.

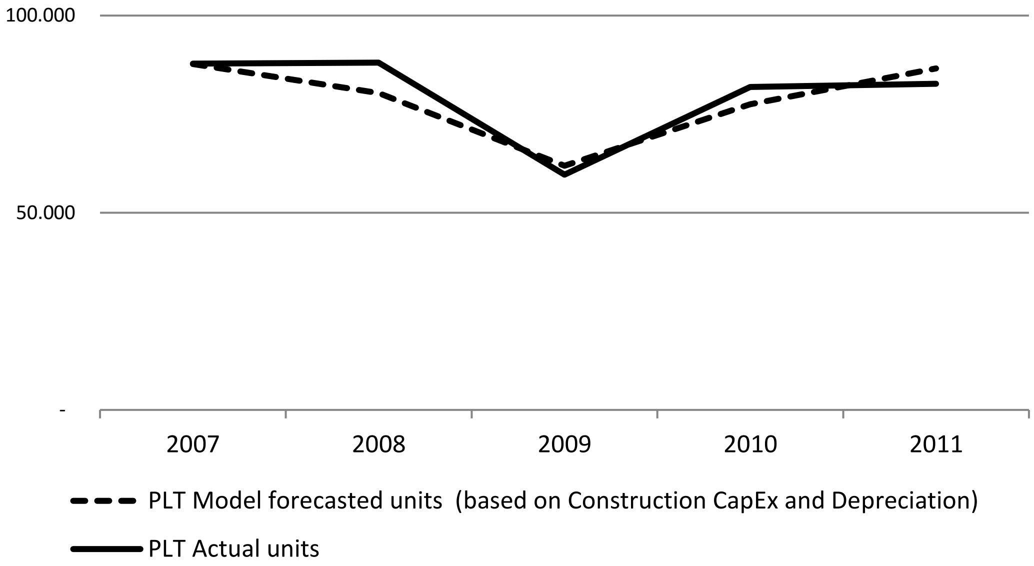



**Figure 29: PLT units: Model Vs. Actual**

To quanitify the PLT model in-series forecasting accuracy, we show in the table bellow the model´s results through some of the convetional forecasting accuracy measurment explained in the previous subsections.

| Forecast Metrics | PLT model based on the Construction Market |
|---|---|
| Mean Absolute Deviation (MAD) | 5.4 |
| Mean Percent Error (MPE) | 450% |
| Weighted Absolute Percent Error (WMAPE) | 86% |
| MAD-Mean Ratio | 0.9 |
| Forecasting Efficiency Quotient | 0.77 |
| R-Square | 91% |
| Mean Squared Error (MSE) | 40.3 |
| Root Mean Square Error (RMSE) | 6.3 |
| Median Absolute Percent Error (MdAPE) | 0.45 |

**Table 6 : The PLT model forecasting accuracy metrics results**

### 5.5.2 The explanatory capability of the forecasting model for PLG

The model´s aim is to forecast the following year PLG units' growth. The model is based on the correlation between the yearly PLG units' sales growth, as reported by IDC, and the Retail growth and the first derivative of the retails indicator. One of the independent variables is statistically significant and the other one helped increase the explanatory level of the models in comparison to other models and therefore we decided to keep it as one of the two independent variables even though it was not statistically significant.

The equation that represents the relationship between the PLG units' market growth and the macroeconomic indicators is:

$$\mathrm{Y}_{\mathrm{t}} = A + \beta_1 \mathrm{Re}\,tailSGrowth_{\mathrm{t}} + \beta_2 \mathrm{Re}\,tailSGrowthChange_{\mathrm{t}}$$

$\mathrm{Y}_{\mathrm{t}}$ = Model forecasted PLG units' growth rate at year t

$\mathrm{Re}\,tailSGrowth_{\mathrm{t}}$ = Retail sales growth rate at year t

$\mathrm{Re}\,tailSGrowthChange_{\mathrm{t}}$ = Retail sales growth rate speed change ( $\mathrm{Re}\,tailSGrowth_{\mathrm{t}} - \mathrm{Re}\,tailSGrowth_{\mathrm{t-1}}$ )

$\beta_1$ = PLG Units growth rate Coefficient with Retail sales growth

$\beta_2$ = PLG Units growth Coefficient with Retail sales growth rate speed change

**Equation 11: PLG units' market forecasted growth equation**

The comparison between the Retail sales growth and growth speed changes, and the actual units sold shows that the model units forecast is very close to the actual PLG units' growth thus, the model predicts relatively well the growth trend which is very important for planning purposes. The following graph shows the comparison between the forecasted PLG Year-over-Year units' growth and the actual PLG units' growth rate.

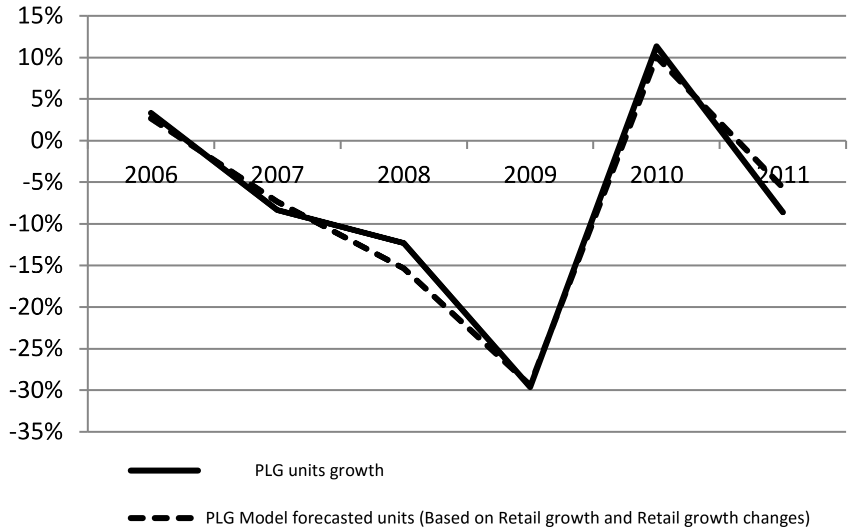



**Figure 30: PLG Model forecast Vs. Actual PLG units' growth**

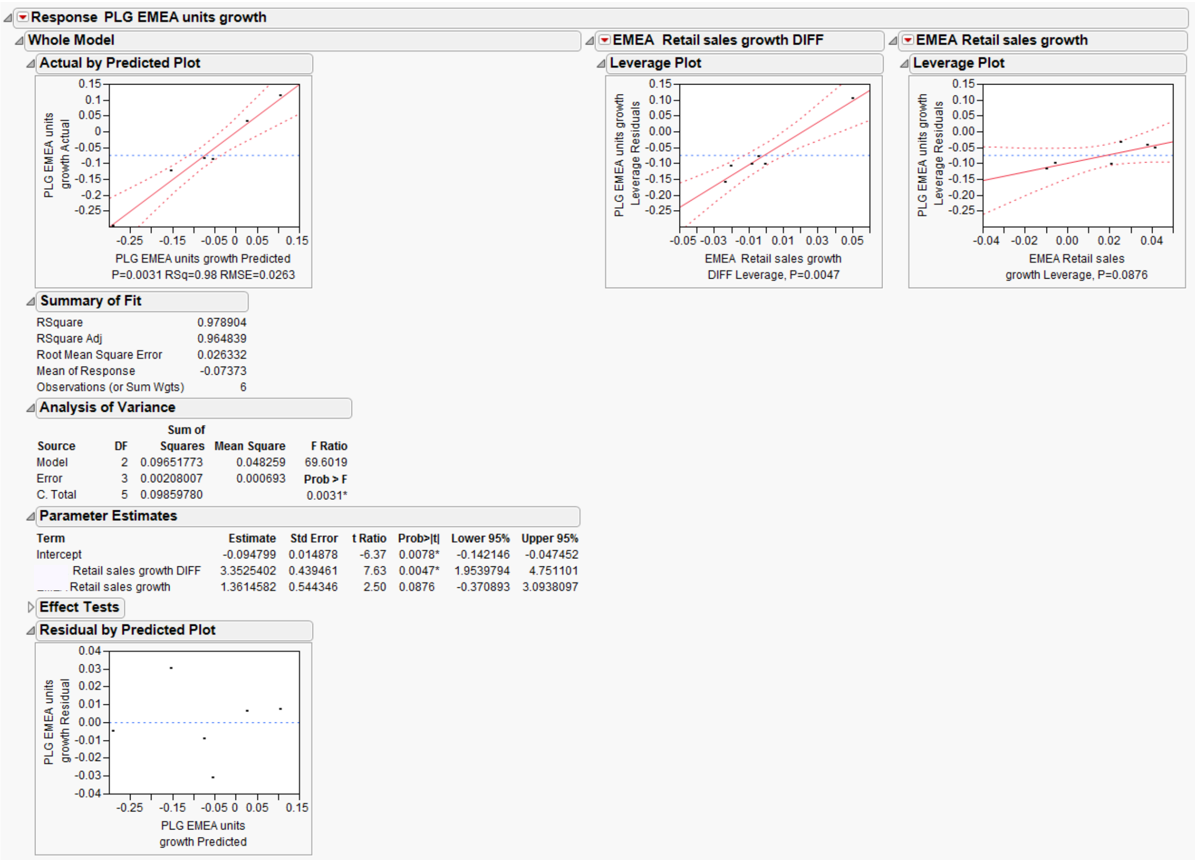



**Figure 31: PLG Model forecast statistics results**

The next step was to convert the forecasted unit´s annual growth rate to units' annual amount and compare this model forecasted units amount to the actual PLG annual units sold.

The relationship between the forecasted units' growth and the annual forecasted units can be described in the following equation:

$$U_t = U_{t-1}(1 + Y_t)$$
$$U_t = U_{t-1}(1 + A + \beta_1 RetailSGrowth_t + \beta_2 RetailSGrowthChange_t)$$

$U_t$ = PLG units at year t

$U_{t-1}$ = PLG units at year t-1

$Y_t$ = PLG unit´s growth rate forecasted for year t

**Equation 12: PLG forecasted units 'market quantity equation**

When looking at the actual units sold and the units predicted to sold through the model it is also appreciated that the model explains well the historical trajectory of the PLG sales as shows in the following graph.

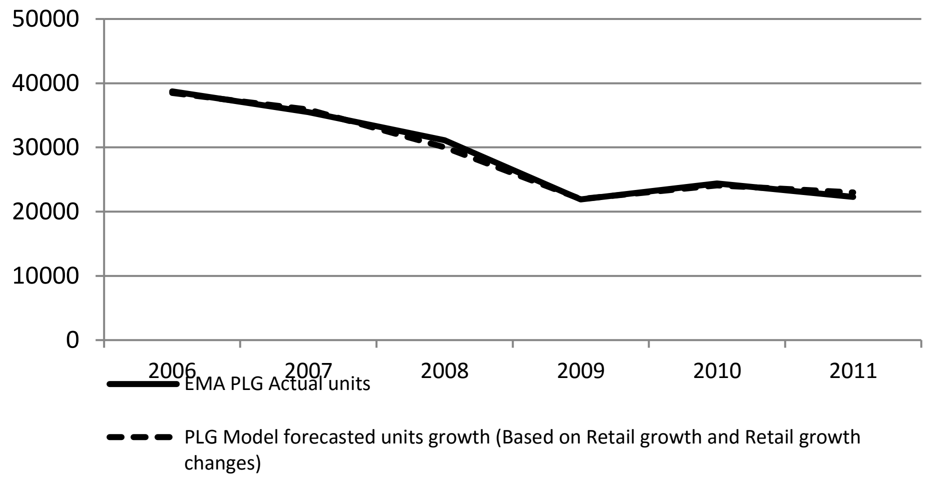



**Figure 32: PLG units: Model Vs. Actual PLG units**

To quanitify the PLG model in-series forecasting accuracy, we show in the table bellow the model´s results through some of the convetional forecasting accuracy measurment explained in the previous subsections.

| Forecast Metrics | PLG model based on the Retail Market |
|---|---|
| Mean Absolute Deviation (MAD) | 1.5 |
| Mean Percent Error (MPE) | 9% |
| Weighted Absolute Percent Error (WMAPE) | -21% |
| MAD-Mean Ratio | -0.2 |
| Forecasting Efficiency Quotient | 0.89 |
| R-Square | 98% |
| Mean Squared Error (MSE) | 3.5 |
| Root Mean Square Error (RMSE) | 1.9 |
| Median Absolute Percent Error (MdAPE) | -0.06 |

**Table 7 : The PLG model forecasting accuracy metrics results**

### 5.5.3 The explanatory capability of the forecasting model for PLI

A model was constructed to forecast the PLI units' growth based on the correlation between the GDP growth and the credit availability of the region and the actual PLI units Year-over-Year growth. The PLI forecasting model had an **R^2 of 98% at a confidence level of 98% (1-α)**. The model is based on the correlation between the yearly PLI units' sales The GDP growth and the credit tightening. Both independent variables are statistically significant.

The equation that represents the relationship between the PLI units' market growth and the macroeconomic indicators is:

$$Y_t = A + \beta_1 GDPGrowth_t + \beta_2 CreditTight_t$$

$Y_t$ = Model forecasted PLI units' growth rate at year t

$GDPGrowth$ = GDP growth rate at year t

$CreditTight_t$ = Credit conditions tightening at year t ( $CreditTight_{t-1} + CreditTight_t$ )

$\beta_1$ = PLI Units growth rate Coefficient with GDP growth

$\beta_2$ = PLI Units growth Coefficient with Credit Condition tightening

**Equation 13: PLI units 'market forecasted growth equation**

A comparison between the model forecasted units (using GDP growth and credit tightening) and the actual units sold shows that the model units growth forecast shows that it is very close to the actual units' growth. The model predicts relatively well PLI units' growth trend.

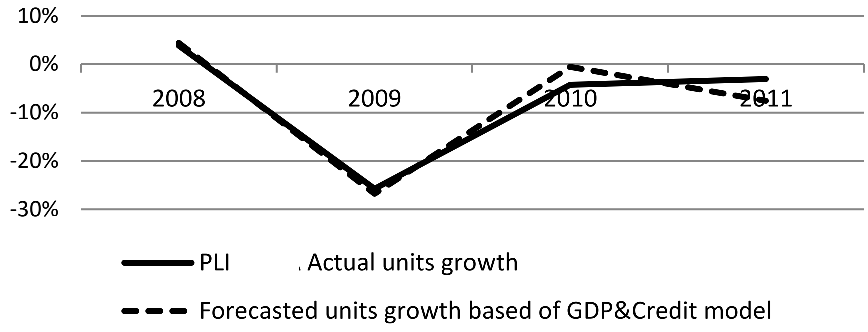
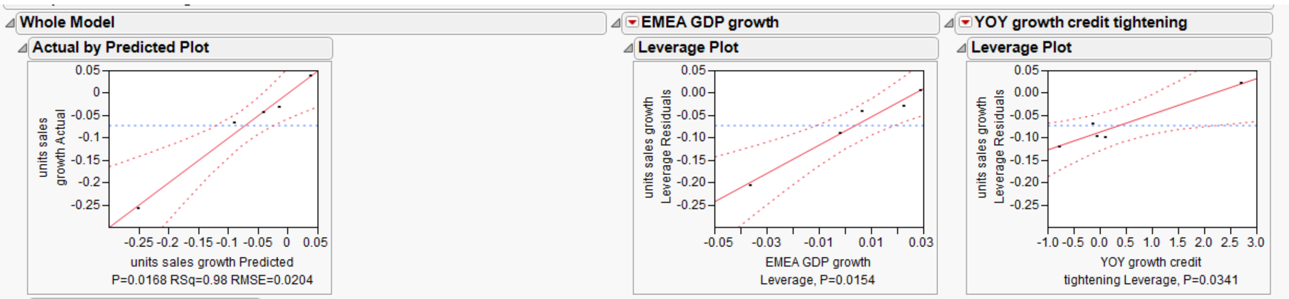



**Figure 33: PLI model forecast units' growth Vs. Actual units' growth**




Summary of Fit

| | |
|---|---|
| RSquare | 0.983153 |
| RSquare Adj | 0.966306 |
| Root Mean Square Error | 0.020358 |
| Mean of Response | -0.072 |
| Observations (or Sum Wgts) | 5 |

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 2 | 0.04837229 | 0.024186 | 58.3573 |
| Error | 2 | 0.00082890 | 0.000414 | Prob > F |
| C. Total | 4 | 0.04920119 | | 0.0168* |

Parameter Estimates

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.098562 | 0.009528 | -10.34 | 0.0092* | -0.139559 | -0.057565 |
| GDP growth | 3.1580585 | 0.396494 | 7.96 | 0.0154* | 1.4520829 | 4.8640341 |
| YOY growth credit tightening | 0.0398096 | 0.007546 | 5.28 | 0.0341* | 0.0073419 | 0.0722774 |

Effect Tests

Residual by Predicted Plot

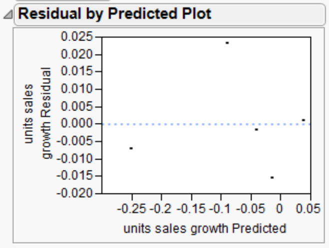



**Figure 34: PLI model forecast**

The next step was to convert the forecasted unit´s annual growth rate to units' annual amount and compare this model forecasted units amount to the actual PLI annual units sold.
The relationship between the forecasted units' growth and the annual forecasted units can be described in the following equation:

$$U_t = U_{t-1}(1 + Y_t)$$
$$U_t = U_{t-1}(1 + A + \beta_1 GDPGrowth_t + \beta_2 CreditTight_t)$$

$U_t$ = PLI units at year t

$U_{t-1}$ = PLI units at year t-1

$Y_t$ = PLI unit´s growth rate forecasted for year t

**Equation 14: PLI forecasted units 'market quantity equation**

Also in absolute units numbers, when looking at the actual units sold and the units predicted to be sold through the model it is also appreciated that the model explains well the historical trajectory of the PLI sales.

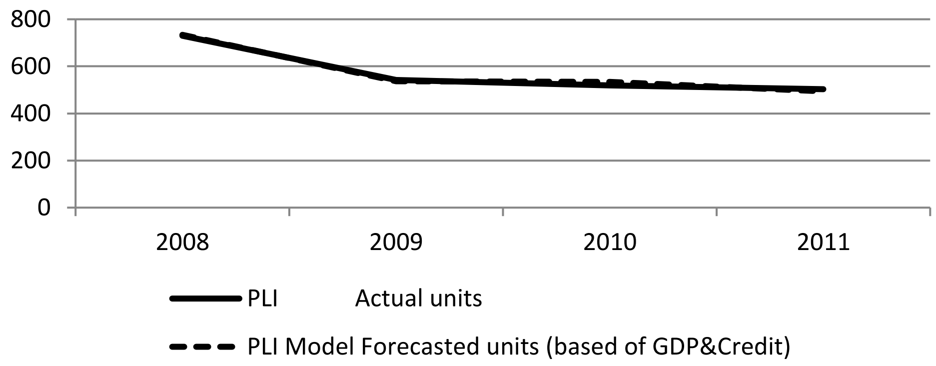



**Figure 35: Model Forecast units Vs. Actual PLI units**

To quanitify the PLI model in-series forecasting accuracy, we show in the table bellow the model´s results through some of the convetional forecasting accuracy measurment explained in the previous subsections.

| Forecast Metrics | PLI model based on GDP and Credit tightening |
|---|---|
| Mean Absolute Deviation (MAD) | 2.4 |
| Mean Percent Error (MPE) | -19% |
| Weighted Absolute Percent Error (WMAPE) | -33% |
| MAD-Mean Ratio | -0.3 |
| Forecasting Efficiency Quotient | 0.81 |
| R-Square | 93% |
| Mean Squared Error (MSE) | 8.7 |
| Root Mean Square Error (RMSE) | 3.0 |
| Median Absolute Percent Error (MdAPE) | -0.45 |

Table 8 : The PLI model forecasting accuracy metrics results

## 5.6 Empirical study number 1 first attribute - Forecasting predictability

The ability of the models to forecast the market demand is crucial for companies. A company prepares its strategic and operational plans totally different depending if the market is expected to grow, decline or stay flat. A growing market calls for recruiting of more employees, increasing marketing and operating budgets, increase of manufacturing plans etc. While a declining market calls for layoffs and shrinking marketing and operating budgets and reduced manufacturing plans etc. Therefore it is critical that the market forecasts will give a reliable indication as to where the market is going. The models in-series accuracy to the past sales was demonstrated in the previous sub section of this thesis. In this subsection we wanted to demonstrate the future forecasting predictability capability if the proposed models. In other words, how well these models in the different markets predict the market growth trends.

In order to answer this question we have compared the models' annual forecasted growth for the following year with the growth results of the first quarter of the year. We have taken the size of the market of the first quarter of Calendar Year 2012 (Q1CY12) and compared it to the market size of the first quarter of the previous year 2011 (Q1CY11). This growth rates comparison is therefore seasonality adjusted growth and gives an indication of by how much the market grew or declined between the two years.

These quarter-over-quarter growth rates were compared to the models' yearly forecasted growth rate. This is of course not a "like-for-like" comparison since the model is forecasting the yearly units' growth rate while here we compare it to the first quarter growth between the two years. However we truly believe that the comparison between the first quarters of each of the two years could be compared to the model´s yearly forecast since the growth rate of the first quarters could serve as a proxy to the year over year growth. And therefore this comparison could be used to show the model´s robustness in predicating the market growth trend.

The models' forecasts give the following year's growth rate. This forecasted annual growth rate is in fact the compounded growth rate of the four quarters of the year and not the first quarter growth rate in comparison to previous year last quarter of the first one and therefore we do not expect the quarter over quarter growth to be identical to the models forecasted annual growth rate. However, if the forecasted growth rate trend (positive, negative and order of magnitudes) is similar to the quarter- over-quarter growth results it is a good indication for the forecasting trend capabilities of the suggested models.

This comparison was repeated to all the regional models presented in this research:
The PLT market model's annual growth rate forecast based on the forecasts of the Construction market was a slight positive growth of 2%. The first quarter of the year in comparison of the first quarter of the previous year shows a positive growth of 14%. Thus, we can conclude that the model predicted the market positive growth trend. The PLG market model's annual growth rate forecast based on the forecasts of the Retail market was a negative growth of -6%. The first quarter of the year in comparison of the first quarter of the previous year shows a negative growth as well of -12%. Thus, the model predicted well the market negative growth trend. The PLI market model's annual growth rate forecast based on the forecasts of the GDP and credit availability assumption of continuity of the 2011 conditions was a negative growth of -12%. The first quarter of the year in comparison of the first quarter of the previous year shows a negative growth as well of -33%. Thus, the model predicted well

the market negative growth trend. Thus, the three Macroeconomic indicators-based models predicted the market trend well. These results are summarized in the following table.

| Product line and region | Q1CY2011 over Q1CY2012 growth | Model yearly forecasted Units' growth |
|---|---|---|
| PLT Market units growth | 2% | 14% |
| PLG Market units growth | -12% | -6% |
| PLI Market units growth | -33% | -12% |

Table 9 : The 2012 forecast compared with Q1CY2011- Q1CY2012 growth

Even in this back-of-the-envelope comparison between the models and the actuals it is shown that the models accurately forecast the direction of the expected growth, being negative or positive. It seems like a trivial thing but for management forecasting the direction of the growth is absolutely critical for decision making. In a growing market the company needs to plan to have more resources such as sales people and technician to install and fix the machines. The sooner the managers gets the forecast the better he/she can react to that as all these people will need onboard trainings and will not be able to yield results within the first 6 months at least. A negative growth means that the market is decreasing and it is time to stop hiring and optimize resources.

## 5.7 The singular relationship between the forecasting models and the macroeconomic indicators selected

After being introduced to the markets and the macroeconomic indicators that are related to them, the questions arise are whether it is a coincidence that all three market models using macroeconomic indicators work relatively well and what will happen if we choose different macroeconomic indicators. Would they work the same? As stated earlier, the macroeconomic indicators that were chosen for each of the models were not random and we chose them since they are related to the growth drivers of the applications that are the outputs of these machines and therefore we do not expect the indicators to work well for other models but theirs. The Institutional theory drives the intuition that since the forces shaping each of the markets are unique to the environment in which the firm is operating in, the macroeconomic indicators that relate to that market should be unique as well.

In order to resolve this doubt we have decided to check what happens to the models in-series accuracy when other macroeconomic indicators are applied in the models. For simplicity purposes and to ensure that the selection of the macroeconomic indicators is unbiased we checked the three models using the other two models macroeconomic indicators. Therefore, we structured for example a new PLT model based on the macroeconomic indicators of PLI and PLG and the repeating a similar procedure for the other two markets.

The following step was to compare these two new models´ accuracy with the original model results to see whether the usage of another set of indicators improves or not the performance of the model with the original set of macroeconomic indicators. For convenience, at the end of each model’s comparison there is a comparative table displaying the accuracy factors of the three models: with the original set of indicators and with the indicators of the other two product lines. Where the first column of the table shows the comparison between the product line units’ growth and the indicators, the second column shows the model forecasted units’ growth and the actual units’ growth and the third column shows the model forecasted units and the actual units in absolute numbers.

### 5.7.1 The singular relationship between the forecasting model for PLT and its macroeconomic indicators selected

We showed that using construction CapEx growth speed change and the Depreciation growth of the construction market the model explains well the historical PLT sales pattern. Will that attribute also obtain using Retail sales growth and growth speed, which is at the base of the PLG model, or GDP growth and credit tightening, which are at the core of the PLI model?

When the PLT model is constructed with the PLG's indicators, by using the correlation obtained between the PLT units' growth and retail sales growth and speed changes, as can be seen in the first column of the following comparative table, the retail sales growth speed fails to describe the 2008 units' growth drop. Consequently, as shows in the second column, when the retails indicator is put in the model it fails in both forecasting the big units drop in 2008. This flaw makes the Retail sales indicator unsuitable for the forecasting model of the PLT.

When the PLT model is constructed with the PLI's macroeconomic indicators (Using the correlation between the PLT units growth and the GDP growth and Credit tightening), as can be seen in the first column of the following comparative table, GDP grow is similar to the PLT units. This is not a surprise at all as the construction sector is highly correlated to GDP and the construction sector itself is a big influencer to the GDP growth (and decline) in many regions.

Even if the construction sales are correlated to the GDP, the GDP growth is not the form of the indicator which tracks well the PLT market. That form would be the GDP growth speed which is the equivalent to the Construction CapEX growth speed that was at the core of the PLT original model. In addition to that point of the GDP indicator's form, the PLI model is not only based on GDP growth but also on credit availability which is not relevant to the PLT market since the units don't cost as much. The PLT model using the GDP and credit tightening fails to predict the 2010 PLT units' growth rate and 2011's drop in growth. Thus, we can conclude that the Retail sales as one set of indicators and GDP and Credit tightening as another set of indicators do not explain the PLT market as well as the Construction market indicators do. It makes sense that the PLT model gives better results if is based on Construction market and not on Retail sales as these products are hardly used in this space. In addition as explained, credit availability is irrelevant for the PLT units

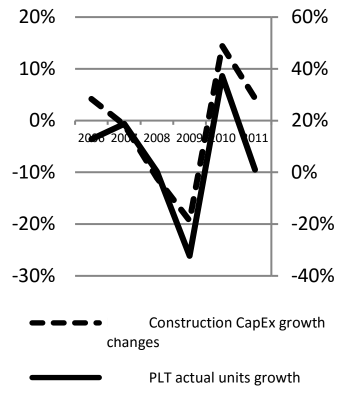
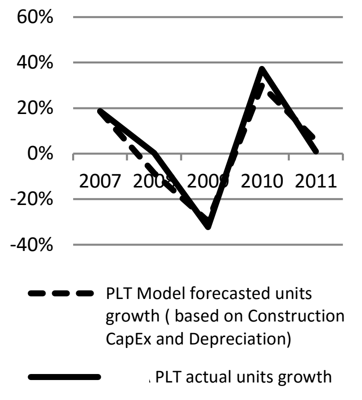
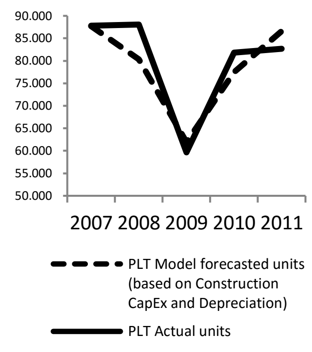
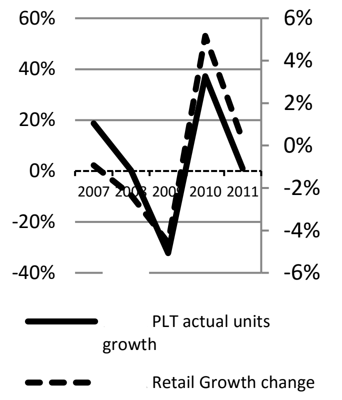
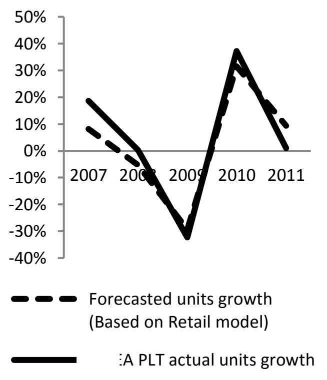
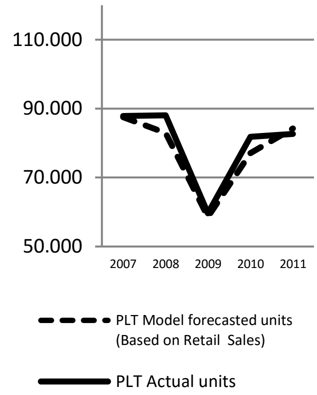
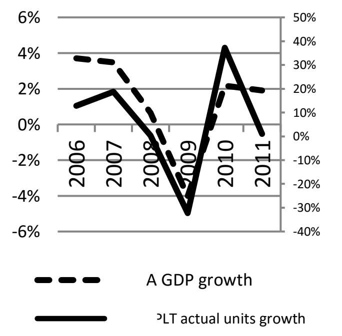
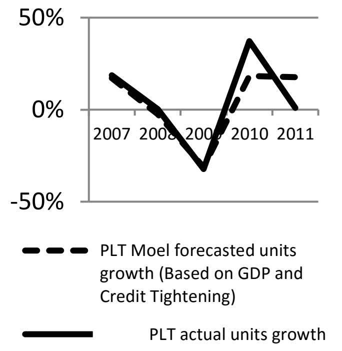
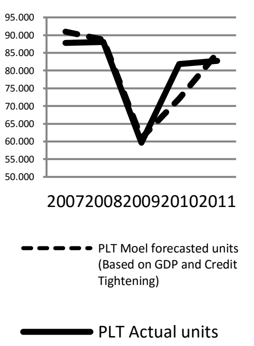
| | PLT units growth Vs. macro indicator´s growth | Model forecast Vs. Actual PLT units growth | Model Vs. Actual PLT units |
|---|---|---|---|
| PLT Based on the Construction Market (PLT's original model) |  |  |  |
| PLT Based on Retail sales (PLG's model) |  |  |  |
| PLT Based on GDP and Credit tightening (PLI's model) |  |  |  |

Table 10 : PLT forecast based on three different Macroeconomic Indicators sets

When the three PLT models are compared by their forecasting accuracy, it shows that the majority of the forecasting accuracy factors support the Construction market-based model for the PLT forecasting.

| Forecast Metrics | PLT model based on the Construction Market | PLT model based on the Retail Market | PLT model based on GDP and Credit |
|---|---|---|---|
| Mean Absolute Deviation (MAD) | 5.4 | 7.3 | 7.7 |
| Mean Percent Error (MPE) | 450% | 203% | -96% |
| Weighted Absolute Percent Error (WMAPE) | 86% | 115% | 123% |
| MAD-Mean Ratio | 0.9 | 1.2 | 1.2 |
| Forecasting Efficiency Quotient | 0.77 | 0.69 | 0.67 |
| R-Square | 91% | 87% | 75% |
| Mean Squared Error (MSE) | 40.3 | 60.2 | 113.0 |
| Root Mean Square Error (RMSE) | 6.3 | 7.8 | 10.6 |
| Median Absolute Percent Error (MdAPE) | 0.45 | 0.69 | 0.47 |

Table 11 : The three PLT forecasting model accuracy metrics results

### 5.7.2 The singular relationship between the forecasting model for PLG and its macroeconomic indicators selected

We showed in the previous section that the Retail sales growth and growth speed explains well the PLG past sales pattern. Is that attribute could also be obtained using Construction CapEx growth speed and the depreciation growth which at the base of the PLT model? or only by GDP growth and credit tightening, which are at the core of the PLI model? When the PLG model is reconstructed with the PLT's model indicators (by using Construction CapEx growth speed and the depreciation growth), as can be seen in the first column of the following comparative table, the Construction market indicators fail to describe the 2008 units growth and the 2007 units drop. Consequently, as shows in the second column, when the construction indicator is put in the model it fails in both forecasting the units growth in 2007 and in 2008. The Construction indicators predict positive units' growth in 2011 which is absolutely not the case for the PLG market in 2011. This makes the construction market based indicators unsuitable for the forecasting model of the PLG. This result makes sense if we take into account that the PLG units are not used for construction related drawings. When the PLG model is reconstructed with the PLI's (by using GDP growth and Credit tightening), as can be seen in the first column of the following comparative table, GDP grow is similar to the PLG units. When adding the credit tightening to the model, the model fails to explain the 2010 units' growth and the 2011 units' decline which makes it unsuitable for model forecasting of PLG. This result makes sense if we take into account that the PLG units are at a very specific market (professional photography) or for signage and display that are not directly linked to the general economy as it is represented in the GDP. Hence, both intents to look for correlation between the PLG units and the Construction sales and GDP growth and credit tightening give worse off results. Therefore, the best suited indicator for the PLG market is the Retail sales indicator.

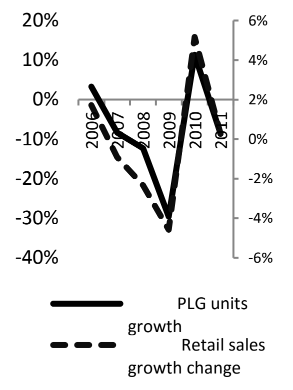
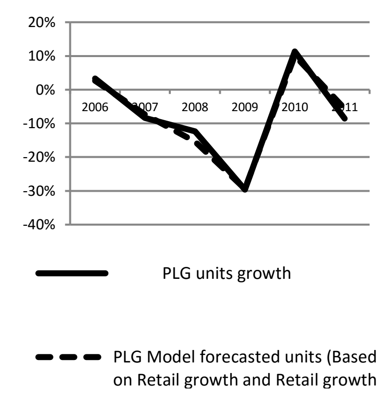
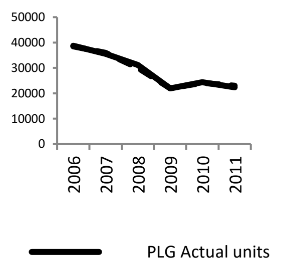
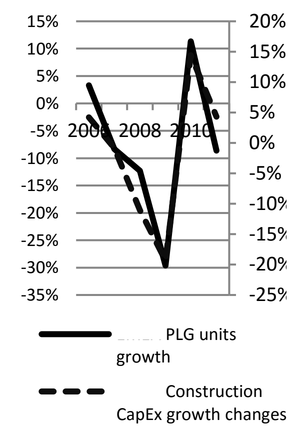
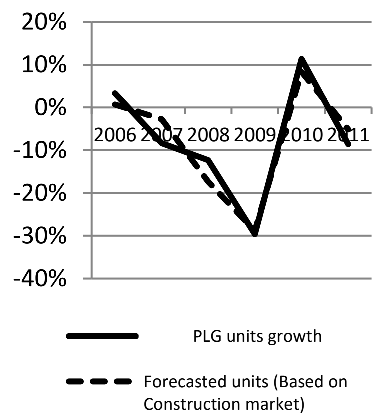
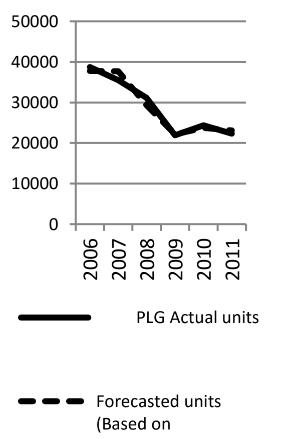
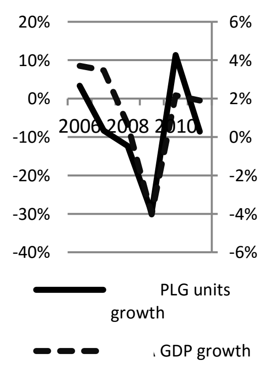
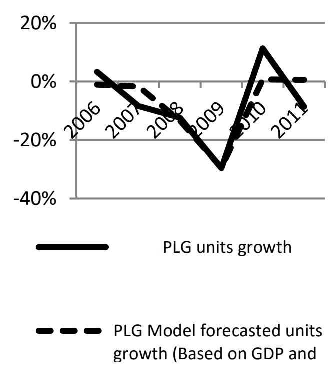
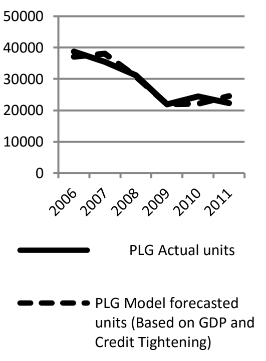
<table>
<tr><th></th><th>PLG units growth Vs. macro indicator´s growth</th><th>Model forecast Vs. Actual PLG units growth</th><th>Model Vs. Actual PLG units</th></tr>
<tr><td>PLG Based on the Retail Market (PLG’s original model)</td><td></td><td></td><td></td></tr>
<tr><td>PLG Based on The construction Market (PLT’s model)</td><td></td><td></td><td></td></tr>
<tr><td>PLG Based on GDP and Credit tightening (PLI’s model)</td><td></td><td></td><td></td></tr>
</table>

Table 12 : PLG forecast based on three different Macroeconomic Indicators sets

When the three PLG models are compared by their forecasting accuracy, it shows that the majority of the forecasting accuracy factors support the Retail market based model for the PLG forecasting.

| Forecast Metrics | PLG model based on the Retail Market | PLG model based on the Construction market | PLG model based on GDP and credit |
|---|---|---|---|
| Mean Absolute Deviation (MAD) | 1.5 | 3.4 | 5.3 |
| Mean Percent Error (MPE) | 9% | 29% | 68% |
| Weighted Absolute Percent Error (WMAPE) | -21% | -46% | -72% |
| MAD-Mean Ratio | -0.2 | -0.5 | -0.7 |
| Forecasting Efficiency Quotient | 0.89 | 0.76 | 0.62 |
| R-Square | 98% | 91% | 73% |
| Mean Squared Error (MSE) | 3.5 | 14.1 | 43.6 |
| Root Mean Square Error (RMSE) | 1.9 | 3.8 | 6.6 |
| Median Absolute Percent Error (MdAPE) | -0.06 | -0.22 | -0.04 |

Table 13 : The accuracy metrics results for the three PLG forecasting models

### 5.7.3 The singular relationship between the forecasting model for PLI and its macroeconomic indicators selected

We showed in the previous section that GDP growth and Credit tightening creates a model that explains well the PLI past sales pattern. Will that attribute also be obtained using Construction sales growth speed which is at the base of the PLT model? Or Retail sales growth speed, which are at the core of the PLG model?

When the PLI model is restructured with the PLT's indicators (by using the construction CapEx and depreciation), as can be seen in the first column of the following comparative table, the model fails to describe the 2008 units growth, the 2010 units drop and the 2011 units growth. Consequently, as shows in the second column, when the construction indicator is put in the model it fails to predict the units' growth in 2008-2011. The construction growth indicator predicts higher units' growth in 2009 which is absolutely not the case for the PLI market in 2009. This makes the construction sales indicator unsuitable for the forecasting model of the PLI. The reason for that is that the PLI market is being hardly used for construction related prints since the PLI units are too expansive with printing quality that is not needed for construction drawings. When the PLI model is restructured with the PLG's indicators (by using the retail sales growth and speed changes), as can be seen in the first column of the following comparative table, the retail market indicators fails to describe the 2008 and the 2011 units growth, consequently as shows in the second column, when the retails indicators is put in the model it fails in both forecasting the big units growth in 2008 and the units' growth in 2011. This makes the retail market indicators unsuitable for the forecasting model of the PLI.

Hence, both intents to look for correlation between the PLI units and the Construction market and Retail market give worse off results. Therefore, the best suited indicators for the PLI market is the GDP growth and Credit tightening conditions.

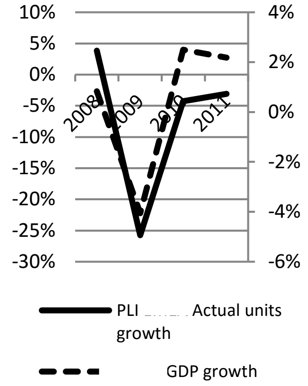
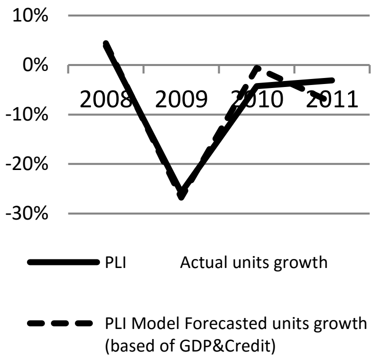
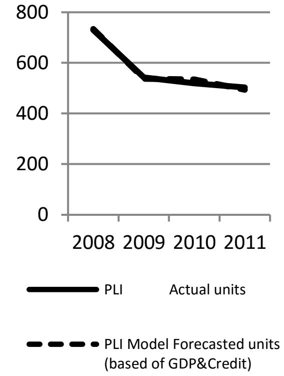
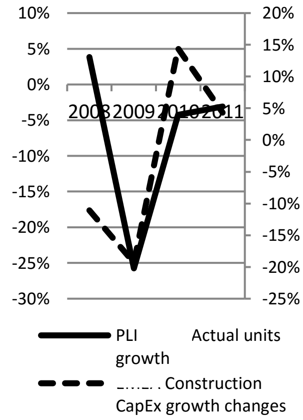
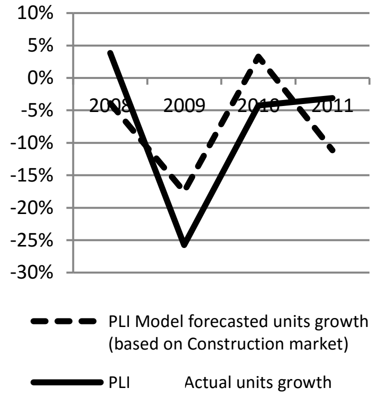
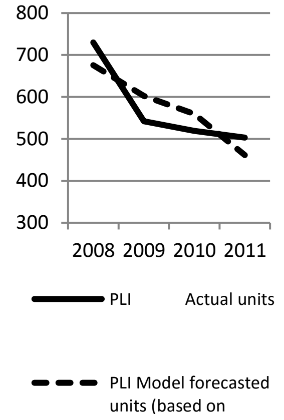
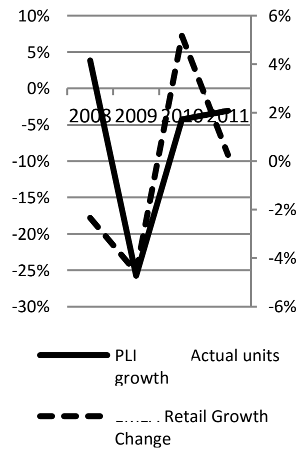
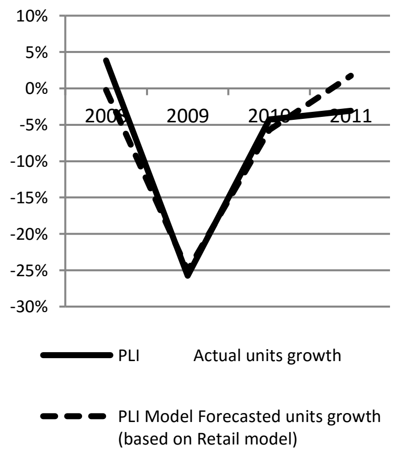
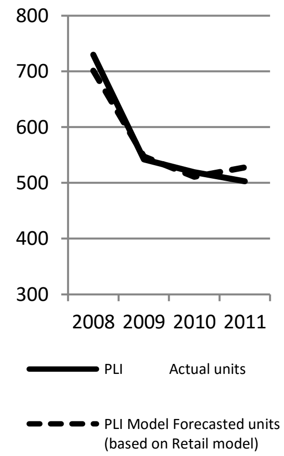
| | PLI units growth Vs. macro indicator´s growth | Model forecast Vs. Actual PLI units growth | Model Vs. Actual PLI units |
|---|---|---|---|
| PLI Based on GDP and Credit (PLI's original model) |  |  |  |
| PLI Based on The Construction Market (PLT's model) |  |  |  |
| PLI Based the Retail Market (PLG's model) |  |  |  |

Table 14 : The PLI forecasts results based on three different Macroeconomic Indicators sets

When the three PLI models are compared by their forecasting accuracy, it shows that the majority of the forecasting accuracy factors support GDP and Credit based model for the PLI forecasting.

| Forecast Metrics | PLI model based on GDP & Credit | PLI based on the Construction market | PLI model based on Retail Market |
|---|---|---|---|
| Mean Absolute Deviation (MAD) | 2.4 | 7.9 | 2.8 |
| Mean Percent Error (MPE) | -19% | 37% | 58% |
| Weighted Absolute Percent Error (WMAPE) | -33% | -108% | -38% |
| MAD-Mean Ratio | -0.3 | -1.1 | -0.4 |
| Forecasting Efficiency Quotient | 0.81 | 0.38 | 0.78 |
| R-Square | 93% | 49% | 91% |
| Mean Squared Error (MSE) | 8.7 | 62.3 | 10.6 |
| Root Mean Square Error (RMSE) | 3.0 | 7.9 | 3.3 |
| Median Absolute Percent Error (MdAPE) | -0.45 | -1.05 | -0.19 |

Table 15 : The accuracy metrics results for the three PLI forecasting models

# 6 Empirical study number 2

The empirical study tests the following two hypotheses:

1. The NIE suggests that the macro level activity is unique to each geo political area in addition; the adaptation approach claims that regional differences are too big to be ignored by the company´s activity. To test this claim of cultural difference of the NIE and the international marketing adaptation approaches, we take a regional sales forecasting model and test its forecasting capabilities in three of the countries that constitute it. If the localized version of the regional model is capable of forecasting well, it would mean that culture differences are big enough to be noticed by it. If the localized regional model fails to forecast well it at the countries level it means that these countries have some characteristics that should be taken into account by a better forecasting model. This potential outcome would support the NIE and the adaptation approach.
2. The international marketing literature debates for many decades on the best marketing approach in firms expanding their activities beyond their home market. To test if countries are in fact different in their sales drivers we search for country- specific forecasting models. By providing country specific sales forecasting models we provide additional support to the adaptation approach.

## 6.1 The model in 3 different geo-political countries

Once we have the model completed from empirical study number one, we are now ready to check whether this model works the same in three different countries. As shown in the previous sections, the sales were best explained by the GDP growth and the credit tightening conditions. The question is: would that be the case for the three selected countries? We will show that these are, without a doubt, three different markets where different drivers influence the units' sales. For the selection of the regions we have used the three regions types described in the GLOBE research: United Kingdom as a representative of the Anglo culture type, Germany as representative of the Germanic culture and Spain as a representative of the

Latin European culture. Each of the three cultures is also different in their countries' economies characteristics.

One of the distinctive characteristics of the UK culture and therefore one of the pillars of the UK economy is its retail sector. Retail is one of the biggest engines of its economy and Retails consumer expenditures account for almost 37% of UK´s GDP as well as in worldwide relative terms the UK retail sector is large as it is the 10$^{th}$ biggest in the world (Euromonitor, 2011). UK also hosts one of the biggest retail companies in the world; The UK-based Tesco is the third-largest retailer in the world measured by revenues after Wal-Mart Stores and Carrefour. In addition, UK´s capital, London is a major retail center and in 2010 had the highest non-food retail sales of any city in the world, with a total spend of around £64.2 billion (Euromonitor 2011). According to the British Retail consortium (BRC), In 2012 UK retail sales were over £311 billion which represented the sales revenue from 9% of all VAT-registered businesses in the UK.

% of GDP

| | | 2011 |
|---|---|---|
| 1 | Venezuela | 33.53 |
| 2 | Ukraine | 31.08 |
| 3 | Colombia | 26.11 |
| 4 | Vietnam | 25.28 |
| 5 | Egypt | 24.71 |
| 6 | Philippines | 24.47 |
| 7 | Morocco | 24.41 |
| 8 | Portugal | 23.60 |
| 9 | Russia | 23.20 |
| 10 | United Kingdom | 22.49 |
| 11 | Argentina | 22.42 |
| 12 | Hungary | 21.96 |
| 13 | Japan | 21.64 |

**Table 16: The worldwide tanking of the Retail sector size by GDP in %**
**(Source: Euromonitor International from national statistics)**

The consumers spending in the UK on retail products is also ranked among as the top 13$^{th}$ place in the world:

% of consumer expenditure

| | | 2011 |
|---|---|---|
| 1 | Saudi Arabia | 47.5 |
| 2 | Ukraine | 47.3 |
| 3 | Russia | 47.1 |
| 4 | Venezuela | 44.1 |
| 5 | China | 43.5 |
| 6 | Colombia | 42.4 |
| 7 | Hungary | 41.7 |
| 8 | Ireland | 40.6 |
| 9 | Argentina | 39.8 |
| 10 | Morocco | 39.4 |
| 11 | Belgium | 39.2 |
| 12 | Japan | 36.8 |
| 13 | United Kingdom | 36.8 |

**Table 17: The worldwide ranking of the Consumer expenditure in Retail out of total expenditure in % (Source: Euromonitor International from national statistics)**

The German economy is characterized by its hardworking highly skilled labor force that contributes to positioning Germany as the fifth largest economy in the world (in PPP terms). Germany is also Europe's largest economy and it is a leading exporter of machinery, vehicles, chemicals, and household equipment. When retail and manufacturing sectors are encompassed together they represent the largest employer and the fourth-largest contributor to value creation in Germany according to a Mckinsey´s report (2008). Germany is very open to external markets as it is the second largest exporter and third largest importer of goods in the world. Yet despite its close links and relationships with other nations around the globe, it retains its own very distinct culture.

% of GDP

| | | 2011 |
|---|---|---|
| 1 | Venezuela | 33.53 |
| 2 | Ukraine | 31.08 |
| 3 | Colombia | 26.11 |
| 4 | Vietnam | 25.28 |
| 5 | Egypt | 24.71 |
| 6 | Philippines | 24.47 |
| 7 | Morocco | 24.41 |
| 8 | Portugal | 23.60 |
| 9 | Russia | 23.20 |
| 10 | United Kingdom | 22.49 |
| 11 | Argentina | 22.42 |
| 12 | Hungary | 21.96 |
| 13 | Japan | 21.64 |
| 14 | Bulgaria | 21.58 |
| 15 | Thailand | 20.71 |
| 16 | New Zealand | 20.39 |
| 17 | South Africa | 20.38 |
| 18 | Turkey | 19.92 |
| 19 | Belgium | 19.90 |
| 20 | Taiwan | 19.79 |
| 21 | France | 19.60 |
| 22 | Poland | 19.28 |
| 23 | Mexico | 19.05 |
| 24 | Austria | 18.77 |
| 25 | Greece | 18.63 |
| 26 | Italy | 18.59 |
| 27 | Chile | 18.55 |
| 28 | Ireland | 18.53 |
| 29 | Finland | 18.50 |
| 30 | Czech Republic | 18.48 |
| 31 | Spain | 18.46 |
| 32 | Hong Kong, China | 18.40 |
| 33 | Canada | 18.39 |
| 34 | USA | 17.62 |

**Table 18: Ranking of the Retail sector size by GDP in %**

**(Source: Euromonitor International from national statistics)**

Long a largely agricultural country, Spain produces large crops and is the world's largest producer of olive oil and Europe's largest producer of lemons, oranges, and strawberries. The major Spanish industries produce textiles and apparel, foods and beverages, metals and metal products, chemicals, ships, automobiles, machine tools, clay and refractory products, footwear, pharmaceuticals, and medical equipment. Fishing is an important source of livelihood, especially on the Atlantic coast, and fish canning is a major industry. Tourism is Spain's greatest source of income.

Spain's greatest trade is with France, Germany, Italy, and Great Britain. Among the leading exports are machinery; motor vehicles; fruit, wine, and other food products; and pharmaceuticals. Major imports include machinery and equipment, fuels, chemicals, manufactured goods, foodstuffs, and medical instruments.

Spain, Germany and the United Kingdome each represent large part of the European economy.

In 2012 Spain accounted for around 7% of EMEA´s GDP and roughly 10% of the European Union economy UK´s GDP accounted for 14% of the EMEA economy and was second to Germany. The German GDP in 2012 accounted for 16% of the EMEA economy making it the largest economy in the whole EMEA economy. Being such an important part of EMEA region we would a priori expect UK and Germany to respond well to the forecasting model produced for the entire EMEA region and therefore, that the EMEA model (adapted to the local UK and Germany's data) would forecast well also the units sales in that region. We used a localized version of a model that is based on EMEA´s data. Hence we used the GDP and credit tightening variables of the central bank of Europe and England and generated new correlation figures to represent the relationship between the PLI units sold in the local regions and the local macroeconomic indicators, namely the local GDP growth and credit availability.

Due to the fact that the UK is not part of the Euro monetary union the credit availability data was taken from the central bank of England. However, it did not improve the model to the levels demonstrated at in the EMEA model. In another attempt to improve the UK localized model we also introduced the European central bank credit availability data and this model gave us worse of results than that of the model using the Central Bank of England credit availability data. For the Spanish localized model we decided to use the European Central Bank data on the credit availability. The reasons for the fact that we opted to use the central European bank credit availability data instead of that provided by the central bank of Spain were that the data provided by the central bank of Spain did not show to have any statistically significant correlation with the sales of the PLI units sold in Spain while the credit availability data provided by the central bank of Europe were statistically significant. The second reason is the size of the Spanish banks within the European Union which is very significant and therefore we felt confident, in that case, to take the European central bank credit availability data as a proxy to the credit availability in Spain.

When the EMEA level GDP and Credit availability were used in the model for UK and Germany the model only partially explained the historical units sales and gave poor in-series accuracy of the UK and German sales as showed in the following graph and table below.

| Forecast Metrics | European model | European localized models | | |
|---|---|---|---|---|
| | | UK | Germany | Spain |
| Mean Absolute Deviation (MAD) | 0.97 | 13.46 | 12.4 | 6.0 |
| Mean Percentage Error (MPE) | 5% | -103% | 0,37 | 0,39 |
| Weighted Absolute Percentage Error (WMAPE) | -13% | -334% | -5,93 | -43% |
| MAD-Mean Ratio | -0.13 | -3.34 | -5.9 | -0.4 |
| Forecasting Efficiency Quotient | 0.91 | 0.09 | 0.31 | 0.33 |
| R-Square | **99%** | **60%** | **70%** | **87%** |
| Mean Squared Error (MSE) | 0.58 | 226.57 | 239.3 | 61.4 |
| Root Mean Square Error (RMSE) | 0.76 | 15.05 | 15.5 | 7.8 |
| Median Absolute Percentage Error (MdAPE) | -0.04 | -1.23 | -0.2 | 0.5 |

**Table 19: The accuracy metrics results of the PLI European localized model forecasting**

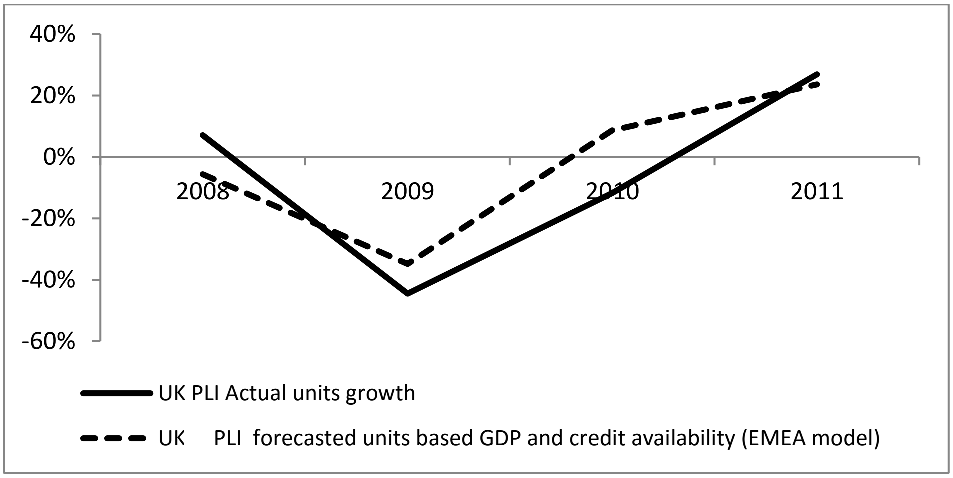



**Figure 36: UK PLI units' growth Vs. the European-based PLI model forecasted units' growth**

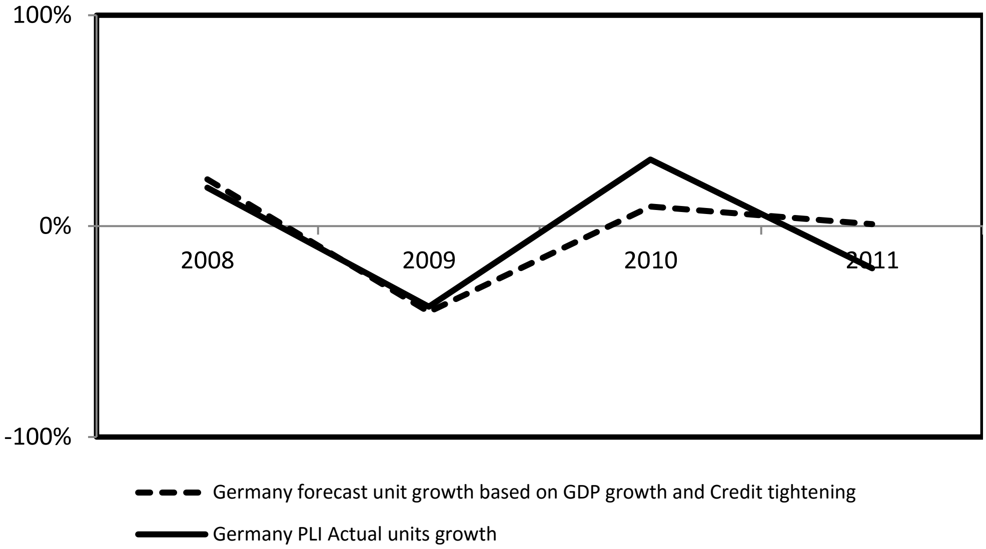
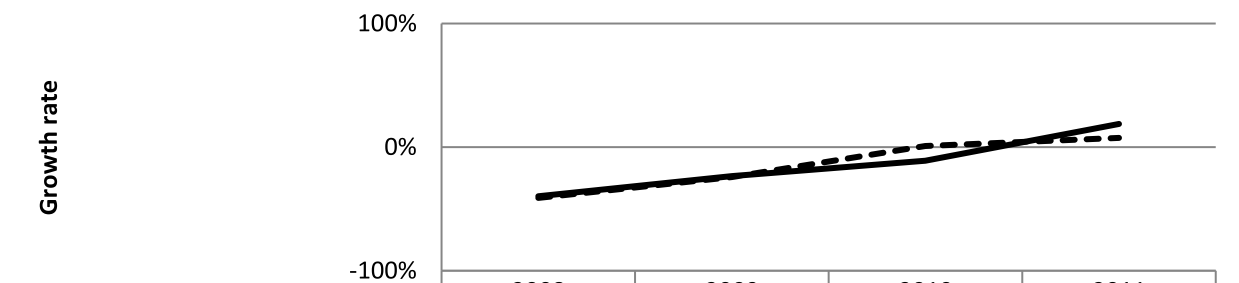



**Figure 37: Germany actual units' growth Vs. Germany forecasted units growth based on the European model**

These results show that two of the EMEA´s largest mature economies are not responding well at all to the European forecasting model while the Spanish forecast model using the European localized model works relatively well. Contrary to what we observed in UK and Germany's case there was a good correlation between the localized EMEA based model and the units sold in Spain. Looking the correlation between the Spanish historical sales and GDP growth in Spain and Credit availability in EMEA (which are both the EMEA level forecasting model indicators) we find a model that explains much better the historical PLI units.




| | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|
| Spain units growth forecast based on GDP and Credit | -41% | -24% | 1% | 7% |
| Spain Actual units growh | -40% | -23% | -11% | 19% |

**Figure 38: Spain units growth Vs. Spain forecasted units growth based on the European model**

This is a surprising result, raises questions and defiantly asking a further deep dive. Are there other stronger factors in Germany and UK that better explain the sales in the local markets? How come that the sales in Spain of all the three economies are actually explained well by the European localized model? What would be the possible reasons for that? Can we find a specific model for these regions that would forecast with accuracy the sales? In what this regional specific model will be different than the European cross-regional model?
We will address these questions in our following section of this thesis.

## 6.2 Conclusions from the localized model

We demonstrated that in spite of the fact that the model works at the European regional level it does not fit as well when it is localised and tested in its sub regions. The evidence is conclusive "localisation" of a global model, in spite of the fact that the European global model was proven to be very robust, surprisingly does not work as well even when we test it in the number one and two economies comprising the EMEA economy, Germany and UK.
Our first conclusion from these results is that the intent of "one size fits all" in forecasting might not be necessarily a good methodology for forecasting in local markets. So perhaps local economies behaviours, reflecting the choices and the decision making processes of its agents are not represented well in a model that is too insensitive to these nuances.
The second conclusion is that there might be specific characteristics to the local economies that would require us to create a new model to better forecast the sales in these markets.
The intriguing results of the localised forecasting models have motivated us to look for models that would work for these two economies better. Thus, leaving behind the failed intend to localise a model and "force" it to work in the local economies level, in the next section we embark on the search of a unique forecasting model for each of the regions.
We were curious to see what would be these local models and what would be the differences between the local models and the "localised model" and what would be the differences between the local model of one economy and the other local economy´s model. In other words, could we put the cultural differences between the British, the Germans and the Spaniards into mathematical formulas?

## 6.3 In a new search of best fitting local models

In this section we search for the forecasting model that gives the best in line accuracy with the sales of the country.

### 6.3.1 The UK economy´s characteristics

As showed earlier, Retail sector occupies a big part and represents an important pillar of the UK´s economy. In addition, the technology units forecasted are also used for retail-related applications. These two important indications made us suspect that retail could be an important potential contributor to the sales forecast of units in the UK. For that end, we have used the UK retail index growth rates as a proxy for the retail sector as a macro structure influencing the micro structure of the units' sales.

We have considered the retail index as a macro level data since it is the aggregation of all the retail micro level activities in the country. In fact, The Retail sales index is considered as key economic indicator and one of the earliest measures of economic activity and it is used to estimate consumer spending on retail goods and the output of the retail sector, both of which are used in the compilation of the national accounts of the United Kingdome. The main output measures include growth of the retail sector for in this year in comparison to that of the previous year, mathematically represented by the first derivative of the retail index.

As mentioned earlier, the sales of the units in the UK were poorly forecasted by the localized European model with GDP and credit availability. Due to the importance of the retail sector to the British society and economy we have decided to check the correlation between the PLI units sold in the UK and the retail sales index. Matching the early indications of the importance of the retail sector, UK´s units sales is highly correlated to retail sales growth and the retail market explains much better the historical sales than GDP and credit availability based European model.

Looking at the correlation between the UK´s historical sales and Retail sales in the UK we find a model that explains much better the historical PLI units in this region as can be observed in the following graphs. Statistically this model gives R^2 adjusted of 86.46%, confidence level (1- α) = 95.4% with Retail index as statistically significant.

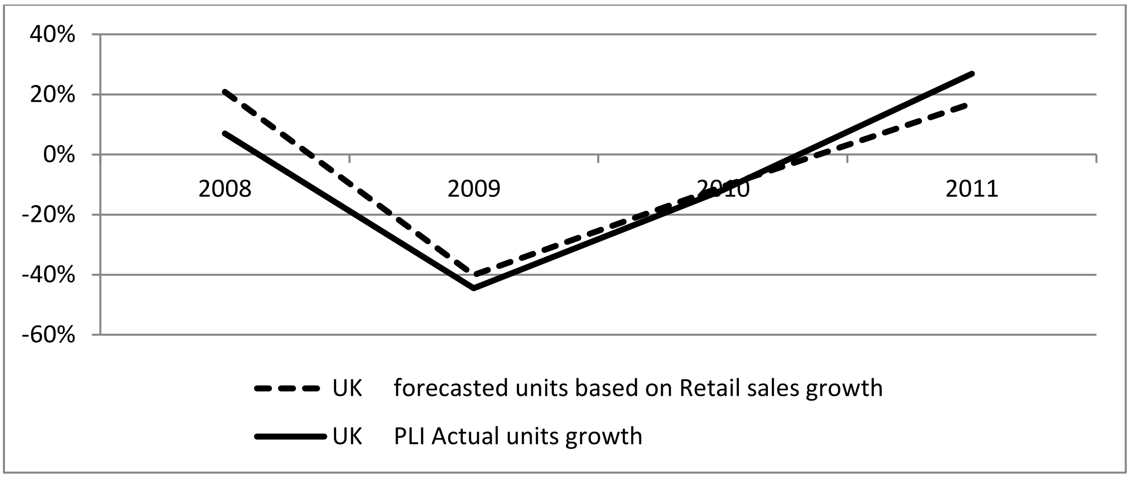



**Figure 39: UK model forecasted units' growth Vs. UK actual units' growth**

| Forecast Metrics | European localized – UK model | The local UK Model (based on Retail sales) |
|---|---|---|
| Mean Absolute Deviation (MAD) | 13.46 | 7.77 |
| Mean Percentage Error (MPE) | -103% | 124% |
| Weighted Absolute Percentage Error (WMAPE) | -334% | -193% |
| MAD-Mean Ratio | -3.34 | -1.93 |
| Forecasting Efficiency Quotient | 0.09 | 0.22 |
| **R-Square** | **60%** | **86%** |
| Mean Squared Error (MSE) | 226.57 | 80.07 |
| Root Mean Square Error (RMSE) | 15.05 | 8.95 |
| Median Absolute Percentage Error (MdAPE) | -1.23 | -1.00 |

**Table 20: The accuracy matric results of the forecasting models for the UK**

### 6.3.2 The German economy characteristics

Encouraged by the importance of the retail sector to the German economy and the forecasting capabilities of the UK model based on the retail index, we tried to apply a retail sector based model to forecast the units sold in the Germany. Since this model works well for the UK we expected to work for the German market as well, however, as can be showed in the following graph this model fails to explain the historical units growth in Germany. In addition, statistically this model is far from being acceptable with R^2 adjusted: 0.36, confidence level (1- α) =76%, the Retail growth indicator as not statistically significant.

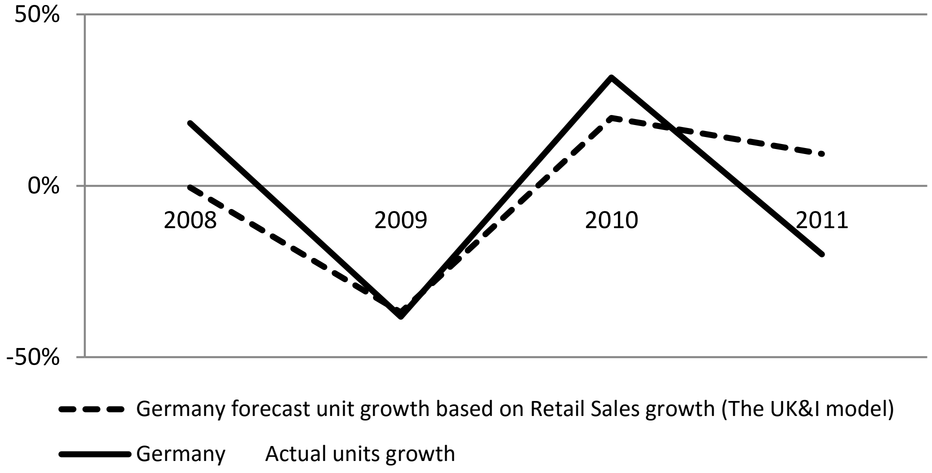


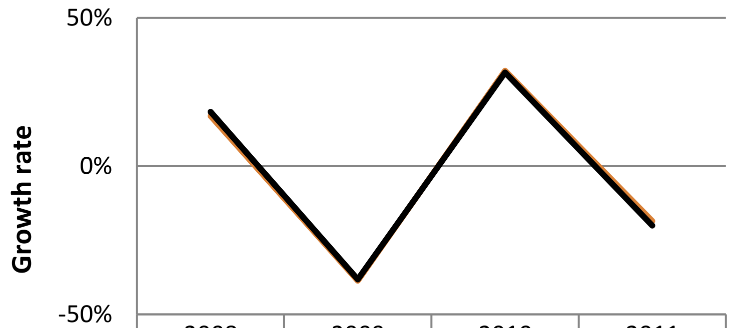

**Figure 40: Germany units' growth Vs. the UK-based model forecasted units' growth**

The question that this result raises is why in spite of the fact that the retail sector is important in Germany using the retail index gives non-conclusive forecasting results.

Therefore we started looking for other cultural and economic characteristics that could explain this puzzling result. The first possible explanation to difference between the German and the UK model is that the Germans are known to be risk averse and very prudent in their investments spending as firms and as individuals and that the uncertainty caused by unemployment means that export growth does not translate into domestic spending and therefore both businesses and people tend to save for the rainy day rather than boost the economy by spending. This claim is supported by Hofstede´s (1980) work and the GLOBE research positioning Germany among the group of the most risk adverse cultures.

Still convinced in the relevance of the retail market on the sales of the PLI units in Germany, we embarked on a search for a better way to reflect the German retail sales as a macro structure that influences the micro structure of the units sales and that would reflect the uniqueness of the German culture risk averseness, the savings “for a Rainey day” and the Germany sensitivity to any early inflation signs. To reflect these culture characteristics we decided to test the correlation between the units sold in Germany and the second derivative of the retails sales growth in Germany. We assumed that using the second derivative of the macroeconomic indicator would reflect the changes in growth rate that the Germans could be so sensitive to. The second derivative is the mathematical representation of the changes in speed of the growth of the economic activity captured by the macro economic indicator. A negative reaction such as a decrease in sales induced by the decrease of the growth of the economic activity will be considered as “prudency”/risk aversion. For example, assuming that in time t the growth rate of the macro economic indicator is 4% and in time t+1 it is 2%. In time t+1 there was a growth in the economic activity represented by the indicator however for a prudent/risk adverse person it will be a bad sign since the speed of the growth was reduced by half. A prudent person or culture who are educated to look for the “clouds before the storm embarks at their door” like in Germany would perceive this decrease in speed as bad news and will call for a halt in its investments and expenses rate.

The forecasting model based on the correlation of the PLI units sold in Germany and the Retail sales growth difference calculated as the second derivative of the retail sales in Germany results in a model that explains much better the historical PLI units’ growth, as shown in the following graphs. In addition, contrary to the European model based on GDP growth and credit availability this new model gives a good model fit with $R^2$ adjusted of 86.46%, confidence level $(1-\alpha)=95.4\%$ and with Retail sales statistically significant.




| | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|
| Germany Forecasted units based on retail sales growth diff | 17% | -39% | 32% | -18% |
| Germany Actual units growth | 18% | -38% | 32% | -20% |

**Figure 41: Germany actual units' growth Vs. Germany forecasted units growth based on the German model**

To summarize, Germany, similarly to the UK, is a market in which the units also correlate to the retail sales but in a surprisingly different way. In Germany the units correlate best to the second derivative of the Retail sales growth. This indicates a mature market that is hyper sensitive to any change in the Retail market speed, in comparison to the UK market. It means that the German market is over-reacting to any little change in the retail growth speed being positive or a negative change.

| Forecast Metrics | Germany | | |
|---|---|---|---|
| | European-localized Model | Retail based model | Second derivative Retail Based model |
| Mean Absolute Deviation (MAD) | 12.4 | 15.3 | 1.0 |
| Mean Percentage Error (MPE) | 37% | 72% | 3% |
| Weighted Absolute Percentage Error (WMAPE) | -593% | -730% | -46% |
| MAD-Mean Ratio | -5.9 | -7.3 | -0.5 |
| Forecasting Efficiency Quotient | 0.31 | 0.28 | 0.22 |
| **R-Square** | **70%** | **58%** | **99.9%** |
| Mean Squared Error (MSE) | 239.3 | 337.0 | 1.1 |
| Root Mean Square Error (RMSE) | 15.5 | 18.4 | 1.1 |
| Median Absolute Percentage Error (MdAPE) | -0.2 | 1.4 | 1.2 |

**Table 21: The accuracy matric results of the three forecasting model for Germany**

The Spanish units correlated with a localized version of the European model that takes into account the GDP growth and credit availability. Contrary to the other two geo-political regions, UK and Germany, in the case of Spain, the localized model gave fairly good forecasting accuracy results. In order to confirm that these results are not random we also applied the UK model based on the retail macroeconomic indicators and then applied the German model based on a variation of the retail based model. After testing these two models, we conclude that both models do not work well for the Spain market, while that the Spanish model based on the localized European model that takes the GDP growth and credit tightening indicators matches well the Spain PLI market. Using the UK model based on retail sales growth results only partially explains the historical sales, as showed in the following graph. In addition the model's fit "wellness" shows difficulties to the fit between Retail Sales growth and the Spain PLI market with R^2 adjusted: -41.46%, confidence level (1- α)=23% and with Retail sales growth indicator not significant statistically.

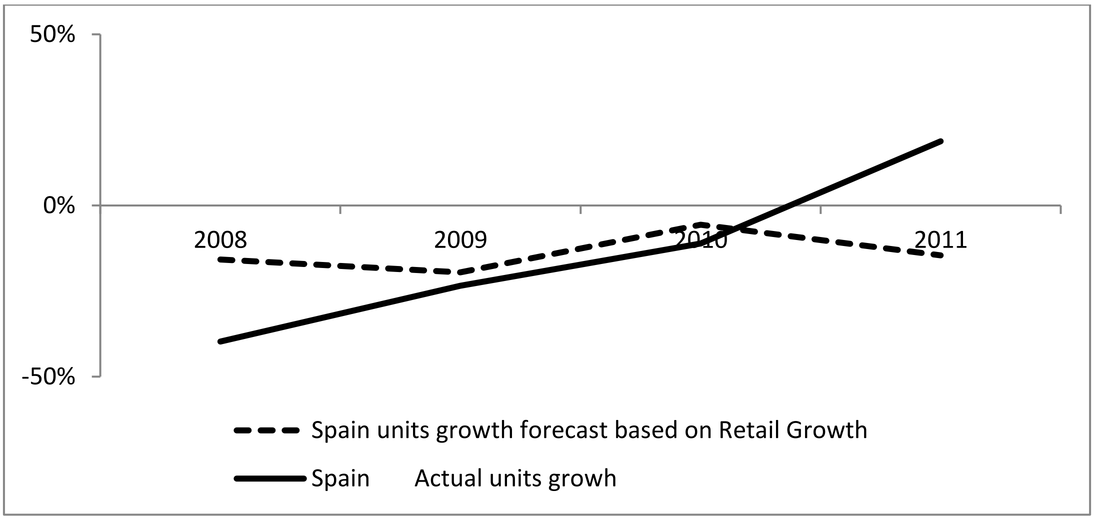



**Figure 42: Spain units' growth Vs. Spain forecasted units growth based on the UK model**

Using the German model, based on retail sales growth speed (first derivative), only partially explains the historical PLI sales, as shown in the following graph. In addition the model's fit "wellness" shows difficulties to the fit between Retail Sales first derivative and the Spain units market with R^2 adjusted: -40%, confidence level (1- α)=24% , Retail sales growth speed indicator not significant statistically.

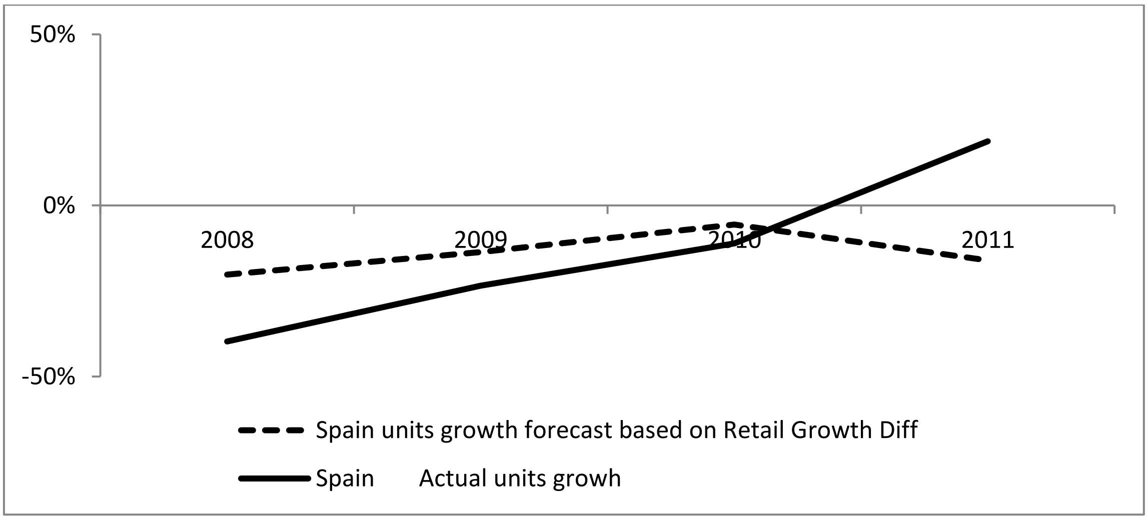



**Figure 43: Spain units' growth Vs. Spain forecasted units growth based on the German model**

The comparison of the accuracy factors of the three models for the Spain units shows the clear advantage of the Spain model over the other two models.

| Forecast Metrics | Spain based on the German Model | Spain based on the UK Model | The Spain Model based on the European model |
|---|---|---|---|
| Mean Absolute Deviation (MAD) | 17.4 | 16.7 | 6.0 |
| Mean Percentage Error (MPE) | 82% | 76% | 39% |
| Weighted Absolute Percentage Error (WMAPE) | -125% | -120% | -43% |
| MAD-Mean Ratio | -1.3 | -1.2 | -0.4 |
| Forecasting Efficiency Quotient | 0.27 | 0.31 | 0.33 |
| **R-Square** | **6%** | **6%** | **87%** |
| Mean Squared Error (MSE) | 429.6 | 431.9 | 61.4 |
| Root Mean Square Error (RMSE) | 20.7 | 20.8 | 7.8 |
| Median Absolute Percentage Error (MdAPE) | -1.5 | -1.5 | 0.5 |

Table 22: The three Spain´s forecasting model accuracy matric results

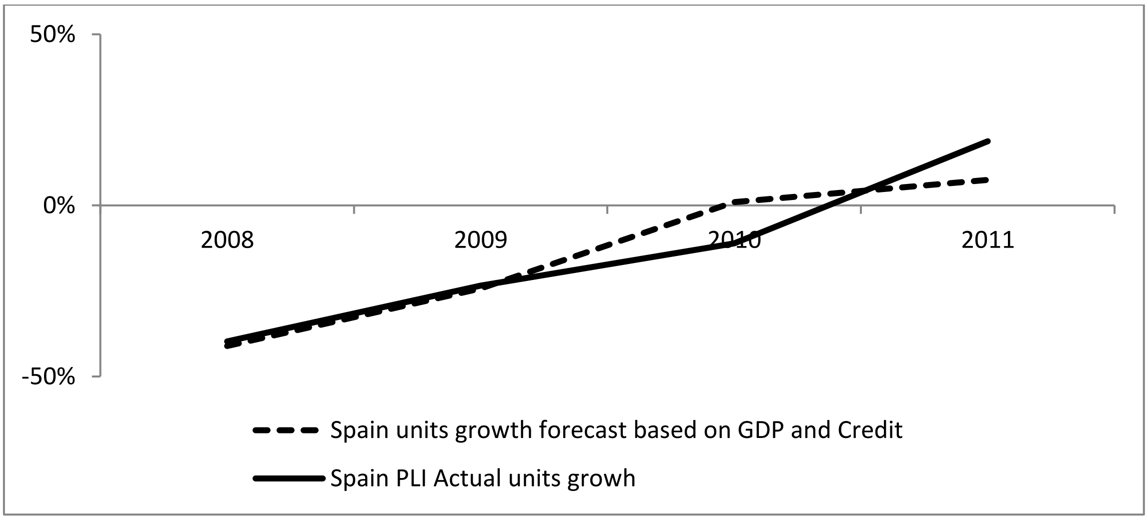



**Figure 44: Spain units' growth Vs. Spain forecasted units growth based on the European model**

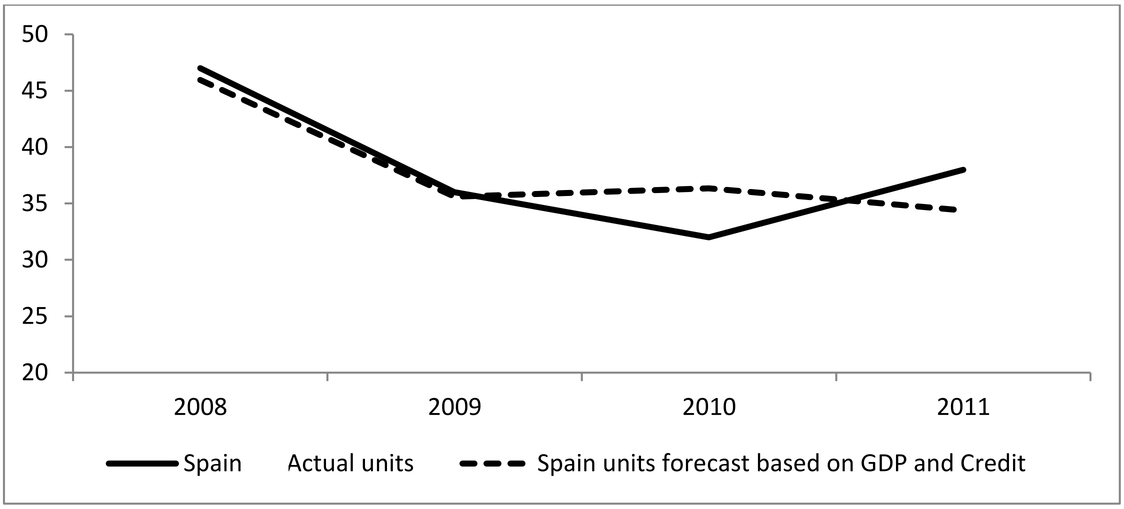



**Figure 45: Spain units' growth Vs. Spain forecasted units based on the European model**

One possible explanation to it is that Retail market is less dominant in the Spanish economy in comparison to the relevance of factors such as availability of credit in the Spanish market and its dependency on credit availability in order to finance investments such as that of the PLI products. The possible explanation for the credit dependency is that private equity and self-funding are less common financing mechanisms than bank credit lines. In addition, these credit lines were severely tightened in the years that are covered in this research which resulted in limited financing tools. One of the potential reasons for the strong correlation between the units' growth and the credit availability in Spain is the dependency of Small and Medium business which are the majority of the businesses in Spain and the majority of the clients of the products on their banks credit lines as their business life-line. The high dependency on banks financing could indicate that self-funding projects or private equity financing are not common in the Spain business culture Spain- These last two points are worth further future investigation.

# 7 Empirical study number 3

In this empirical study we explore the life cycle of three products generations and show that the model is able to forecast well the sales of the products at the different stages of their product life cycles. Then, using the products sales forecasting models and comparing them to the actual products sales, we analyze the different aspects of the introduction of a second product and answer the question whether the introduction of that product, product B, was successful and beneficial to the company while discussing some of the product portfolio dynamics that were created from the two products coexistence. We then discuss the reasons that made the company introduce a third product and the product portfolio dynamic between the three generations of products.

As in the previous empirical study described in our thesis, Empirical study number 3 uses a model that takes the constitutive relationship between macro market conditions and the sales of units and uses macroeconomic indicators to forecast the sales growth rate of the one product line. The forecasting model is based on one or two macroeconomic indicators: the GDP growth rate and the credit availability. When the product capital investment is relatively low, the credit availability indicator is less significant than the GDP growth and therefore for the entry level product, product A, we have used only the GDP growth as a macroeconomic indicator for the forecasting model. However, for product B a much substantial capital investment is required and therefore, in addition to the GDP growth indicator we have used the credit availability indicator in order to forecast the products sales growth correctly. The GDP information is widely available and publically published by many entities. The data we used in this thesis is taken from IHS data base. IHS is a global information company providing market information and forecasts of many macroeconomic indicators. The credit availability information is taken from the Central European bank survey of banks around Europe regarding the credit policy applied to their customers. The part of the survey that is used in this thesis is the loans conditions to small and medium size enterprises.

The empirical study will analyze three products of one product line manufactured and designed by Hewlett Packard, named here as products A, B and C. We will compare their product life cycles and highlight their product portfolio dynamic at the decisions made based on these portfolio dynamics.

## 7.1 Is the empirical test merely anecdotal?

To refute the potential claim that using two products of one company is too firm-specific or even an anecdotal case, we would like to clarify that products A and B represent the two main products in the market. The market of which products A and B are big part of, contains other technology firms such as Hewlett-Packard, Fuji-Xerox, Xerox and Kodak. This market and the number of units sold from each of the players is closely monitored by the International Data Corporation (IDC), an American market research, analysis and advisory firm, specializes in information technology, telecommunications, and consumer technology. According to IDC, these four main players represented 86% to 90% of the total market units in 2008 to 2013. According to the same source, the total worldwide market size of all the products value was estimated in 2010 to be 0.9 billion of USD dollars. Hewlett-Packard is the leader of this 1 Billion USD$ market. According to industry analyst IDC, Hewlett-Packard is the world-wide market leader with more than 50% percent of the market units sold between 2008 and 2013. Consequently, as shown in the following graph, product A and B products sales trend is very much similar to that of the entire market.

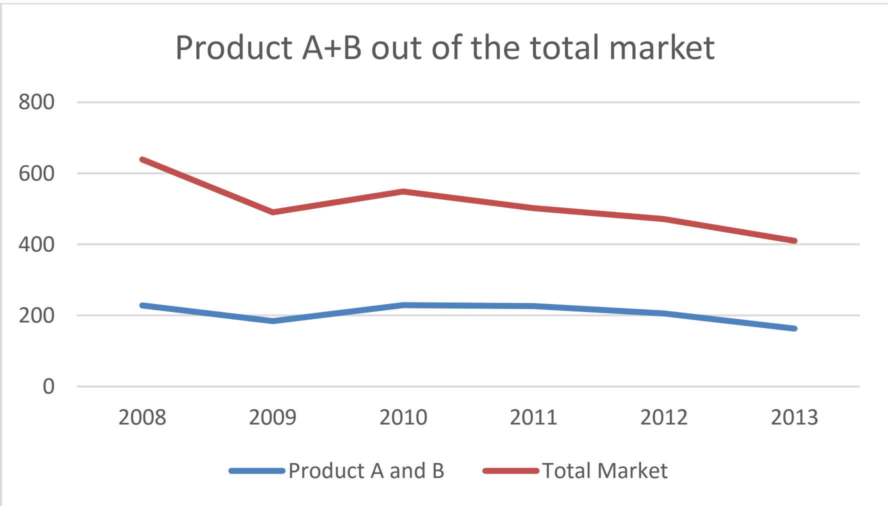
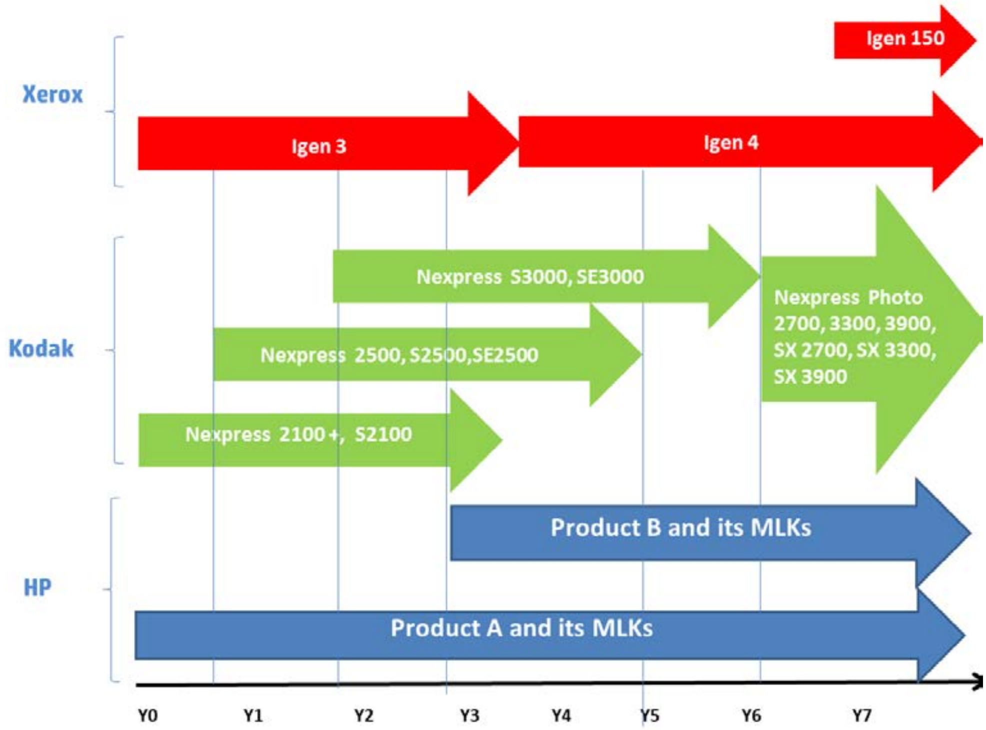



**Figure 46: Total market units Vs. A and B units**

Source: IDC market share report

In Addition, as the market leader, Hewlett-Packard´s decisions and products launches tend to be followed by other technology companies in the market. For example, after Hewlett-Packard launched product B at the end of 2008, Kodak launched another product and upgrades for its existing products in 2009. The following figure summarizes the product launches by the technology players in the market, namely, Kodak, Xerox and Hewlett-Packard.



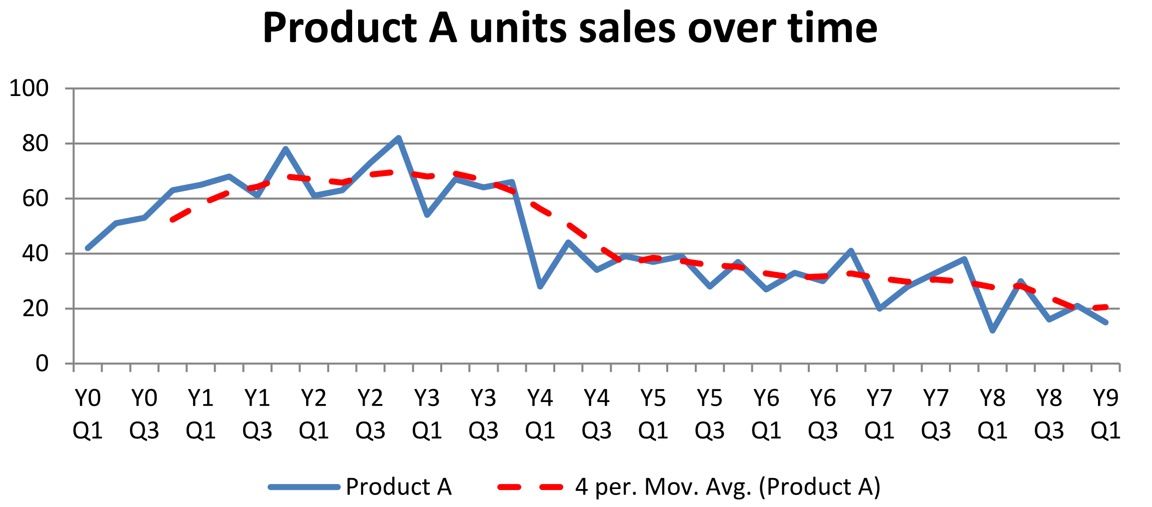

**Y0=2005, Y1=2006, Y2=2007, Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012**

**Figure 47: Product launches of the main technology players**

Source: KODAK and Xerox web sites and IDC Q1CY2014 report

## 7.2 Product A sales forecast and its PLC stages

Product A was introduced by Hewlett-Packard in 2003 and represented the most advanced technology of its time. Product A was at its “maturity” stage by the time we analyzed it for the thesis. The following is a quarterly view of product´s A sales showing the sales results of product A over time:




**Y0=2005, Y1=2006, Y2=2007, Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013, Y9=2014**

**Figure 48: A quarterly view of the sales of product A**

**Source: IDC market reports**

We have created a forecasting model that uses macroeconomic indicators to forecast the sales of Product A based on the IDC market reports. After testing the model with several different macroeconomic indicators, we have found that product A correlates better with GDP growth and that its purchase was most probably self-financed as credit availability, measured by the credit tightening factor, was not statically significant. The forecasting model resulted outcome was **$R^2$ adjusted of 70% at a confidence level of 99% (1-α).** The **depended variable**, GDP was **statistically significant**.

**Summary of Fit**

| | |
|---|---|
| RSquare | 0.739771 |
| RSquare Adj | 0.702596 |
| Root Mean Square Error | 0.113624 |
| Mean of Response | -0.08161 |
| Observations (or Sum Wgts) | 9 |

**Analysis of Variance**

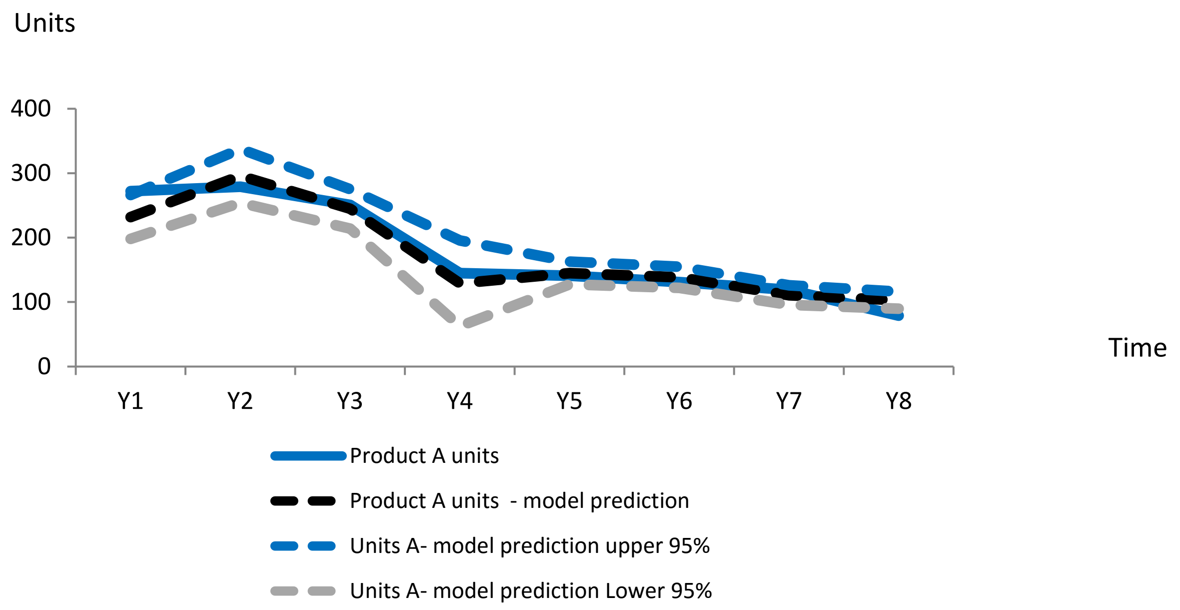
| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 1 | 0.25690792 | 0.256908 | 19.8994 |
| Error | 7 | 0.09037225 | 0.012910 | Prob > F |
| C. Total | 8 | 0.34728017 | | 0.0029* |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.213485 | 0.048046 | -4.44 | 0.0030* | -0.327096 | -0.099874 |
| GDP Growth | 7.5979993 | 1.703253 | 4.46 | 0.0029* | 3.5704471 | 11.625552 |

**Figure 49: Product A forecasting model**

The following graph describes the model forecast and the Product A units sold in an in-series accuracy exercise. The model scores fairly close to the real product A units sales as well as the upper and lower 95% product A sales model forecast. One of the main limitations of the Bass model as a forecasting tool (1969) was its need for many data point to general a forecasting model. Nevertheless, the model we designed for Product A used only nine data points (2005-2013) for a model with high level of statistical accuracy forecasting results.



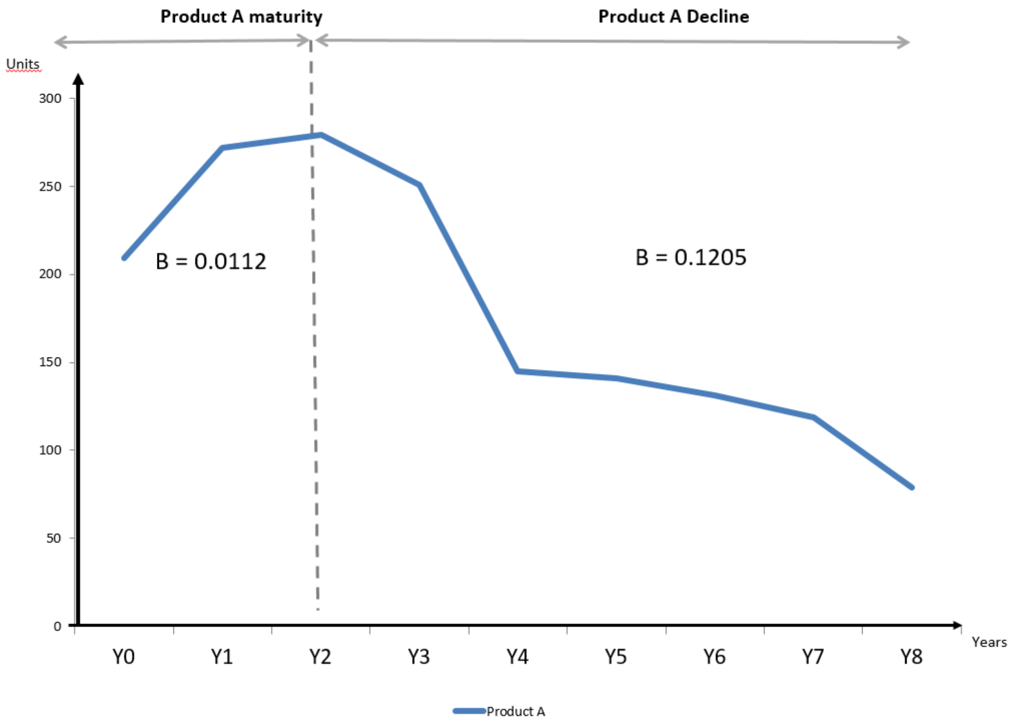

**Y1=2006, Y2=2007, Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013**

**Figure 50: Product A forecasted units vs. units A sold**

During the 9 years of product history, Product A passed through several stages of its product life cycle as can be seen in the graph above. In spite of the very different product life cycle stages, our forecasting model was able to forecast the sales of product A through its various product life cycle stages with a great level of accuracy. It represents not only a contribution to the Bass model and its extensions but also to the product life cycle literature as it does not require to use any of the company´s internal information as selling prices.

It can be observed in the figure bellow that product A was passing through several of its product life cycle stages. It also shown in the graph bellow that 2013 was a transition point between two different life cycle stages of product A, the “maturity” and the “decline” phases.

Following product A life cycle stages, we have separated product A phases to “maturity” and “decline” stages based on their sales growth and tested the coefficient (β) between product A and the macroeconomic indicator GDP. The correlation between the macro indicator and the product A sales growth was 10.75 higher at the “decline” stage of the product than at the “maturity” stage which might indicate that product A is being sold to the late majority and to the laggards customers. This insight tells us that the sales of product A at the decline stage are more correlated to the macroeconomic climate than at the previous stages while the sales at the early stages are less correlated to the macroeconomic indicator. It could be explained by the characteristics of the “early adopters” and the “early majority” who buy the products at the early stages of the product life cycle. These customers tend to have more risk taking attitude than the customers who buy products at later stages of their product life cycle, who are characterized by being more risk averse.  In that case, the difference in the beta between the macro indicator and the sales of a product are rightfully reflecting the type of customers and the life cycle stage of the product.




**Y1=2006, Y2=2007, Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013**

**Figure 51: The coefficients of the sales of product A and the macroeconomic indicator**

## 7.3 Product B sales forecast and its PLC stages

At the second half of 2008, when Product A has reached its rock bottom growth rate levels, Hewlett-Packard launched a new product, product B, with better product attributes than product A. Due to its better product attributes it was also offered at a list price which was double the price of Product A. This is a very common pricing strategy of new product launches called “skimming pricing” where higher prices are charged for the new product as it allows to recover the products research and development sunk costs as soon as possible before the competition steps and lowers the market price. Product B had also unique attributes in comparison to the competition and when it was launched there was no product in the market that could match the productivity and quality of product B. In addition, products A and B had different list prices and product attributed that helped the market distinct and choose between them based on their needs and capital investment capacity. The following graph describes product B attributes and list prices in comparison to the competition and product A.

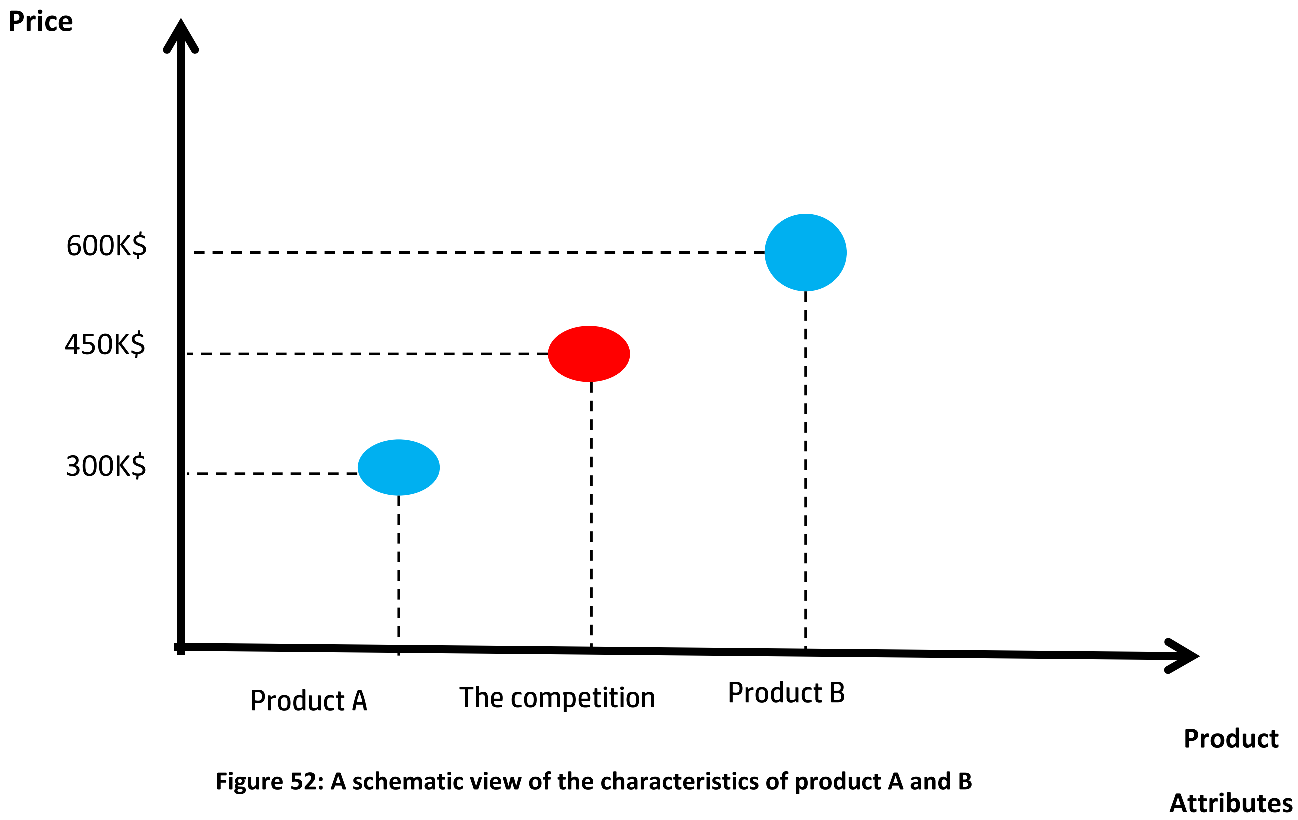
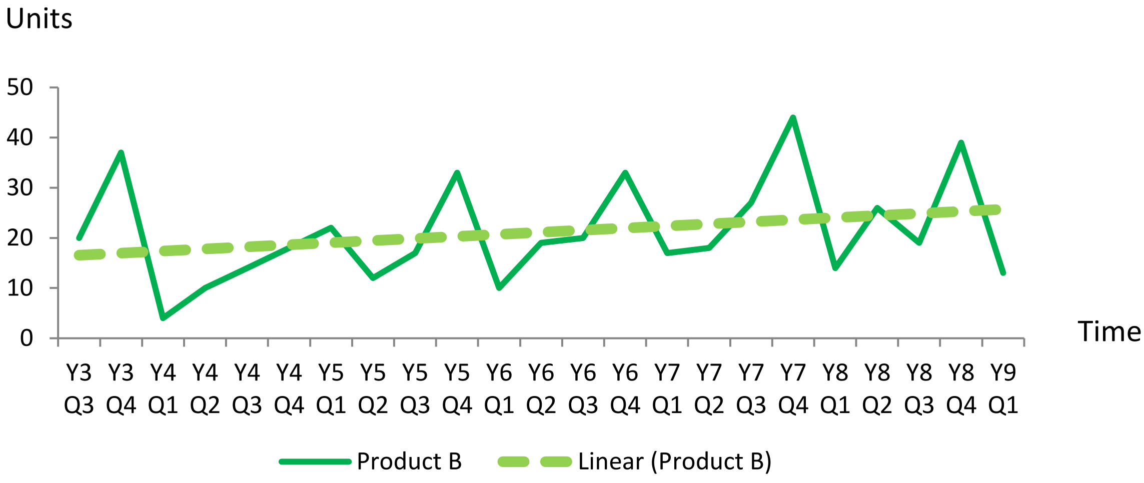



**Figure 52: A schematic view of the characteristics of product A and B**

The sales level of product B was slowly but surely increasing right after the product was launched and during the growth stage of the product.



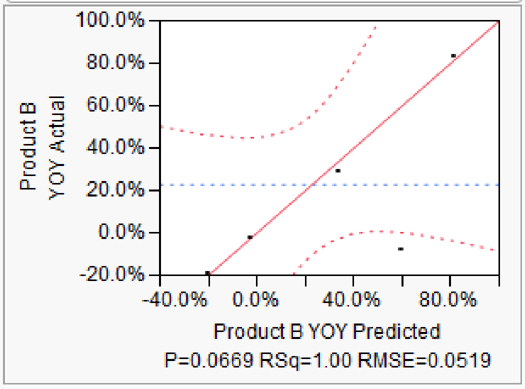

**Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013, Y9=2014**

**Figure 53: Product B sales results by quarter**

(Source: IDC market report)

We have created a forecasting model that uses macroeconomic indicators to forecast the sales of product B. After testing several macroeconomic indicators, we have found that product B correlates better with the GDP growth and the credit availability. It looks that the sales of product B required external financing due to product B list price. Since product B was a new product in the market at the time of the analysis, we had only 4 data points representing the years of the product since its launch and the time of our analysis. As shown in the following figure capturing Nevertheless, with the 4 data point representing the 4 years of product annual sales information, the forecasting model had an **R^2 of 98% at a confidence level of 93% (1-α). Both dependent variables were statistically significant.**

**Actual by Predicted Plot**




**Summary of Fit**

| | |
|---|---|
| RSquare | 0.995528 |
| RSquare Adj | 0.986583 |
| Root Mean Square Error | 0.051908 |
| Mean of Response | 0.2275 |
| Observations (or Sum Wgts) | 4 |

**Analysis of Variance**

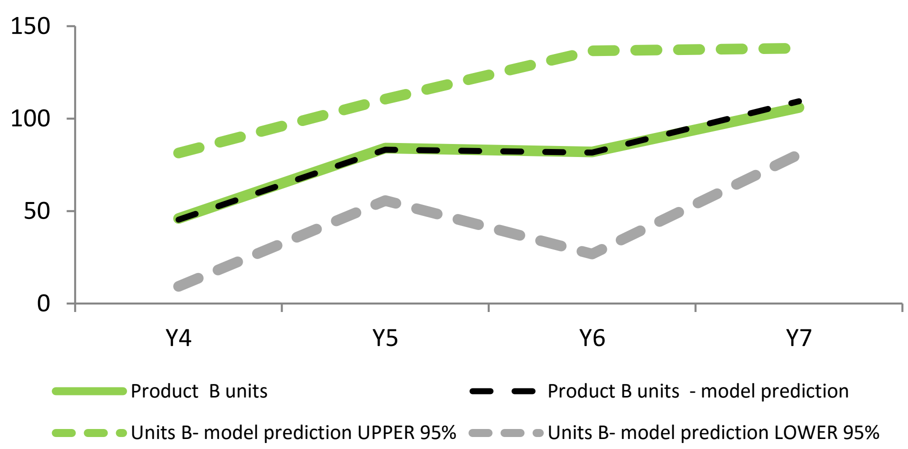
| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 2 | 0.59978057 | 0.299890 | 111.3000 |
| Error | 1 | 0.00269443 | 0.002694 | Prob > F |
| C. Total | 3 | 0.60247500 | | 0.0669 |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 0.1124702 | 0.027778 | 4.05 | 0.1541 | -0.240483 | 0.4654232 |
| GDP GROWTH | 16.023185 | 1.182746 | 13.55 | 0.0469* | 0.9949787 | 31.051392 |
| CREDIT TIGHTENING | -0.568048 | 0.048889 | -11.62 | 0.0547 | -1.189239 | 0.0531423 |

**Figure 54: Product B sales forecast statistics results**

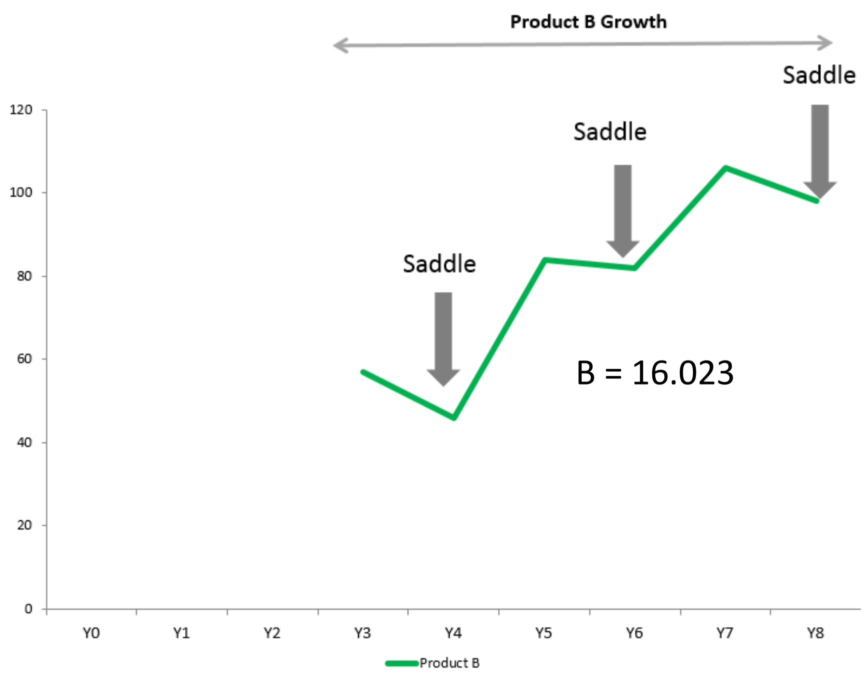
The following graph shows the results of the in-series accuracy exercise of the forecasting model. It shown that the model forecast is fairly close to the real product B units' sales and the upper and lower 95% forecast are close to the real product B sales.




**Y4=2009, Y5=2010, Y6=2011, Y7=2012**

**Figure 55: Product B sales forecast vs the product B units' sales**

Unlike the Bass model (1969) diffusion of innovation smooth curve, in reality, many products sales do not fit to a smooth curve. Product B sales were no exception to this non-smooth product sales reality and during its growth stage, product B had very clear three saddles:




**Y0=2005, Y1=2006, Y2=2009 Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013**

**Figure 56: Product B sales in 2008-2013**

**Source: IDC market report**

Product B was at its "growth" stage in 2008-2012. We analyzed the coefficient (β) between product B and GDP as representing one of the two macroeconomic indicators of the product B forecasting model. The beta at the growth stage of product B is 16.02. The comparison of the GDP coefficient of product B with that of Product A indicates that at its "growth" stage, product B correlates stronger with the macroeconomic indicator than the correlation of product A. In addition, product B had a higher dependency on another macroeconomic, credit availability, than product A and therefore, taking into account the correlation between product B and GDP, as well as product B dependency on the credit availability, we can conclude that product B´s overall dependency on the macroeconomic conditions is higher than that of product A.

# 8 Empirical study number 4

When one is looking at the empirical study in series accuracy levels, she can get the wrong impression that “everything is already written in the stars” and that since the macroeconomic indicators have such a significant level of explanatory capability they are also the sole and the only driver of the sales of the products. This would be a confusion between “forecast” and “prediction” that was mentioned in previous sections of the thesis. In empirical study number 4, we would like to refute the impression that management cannot influence the results of a forecast by empirically showing that the strategic decisions of the management about the product portfolio are critical components in shaping the outcome of the product portfolio sales results.

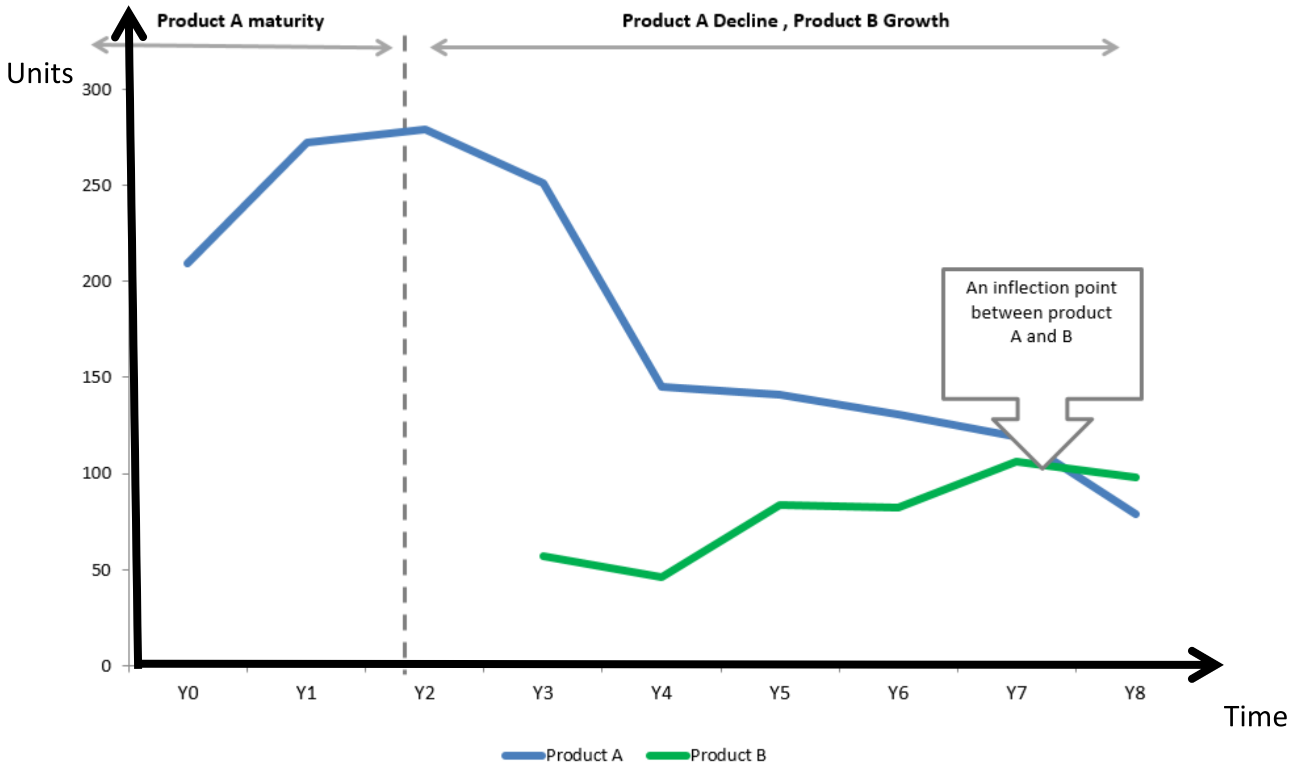
Portfolio-related managerial decisions are divided into short term decisions and long term decisions. The main difference between the short term managerial decisions and the long term ones can be summarized by the understanding that the short term is reflected in “doing things right”. In the short term the product is a “given” and the company´s management needs to decide on the marketing activities to pull the demand for the products which often involves the decision on the pricing strategy that depends on the products price elasticity could increase the demand for a product. The long term decisions on the other hand, are reflected in “doing the right things” meaning that the decisions are about which products to develop for the identified market challenges or for new markets opportunity. The goals of the long term product portfolio decision makings can be summarized in two main tasks:

- The decision on the right mix of products in the product portfolio by determining which product to launch and when and which product to remove from the company´s portfolio.
- The decisions on which market to approach with new products, solutions and often with disruptive technologies.

Empirical study number 4 takes the individual forecast models of product A and B, created in empirical study number 3 and compare them to the actual sales results of these products. This comparison will give us the ability to separate between the expected sales growth from each of the products based on their stand-alone ability in the market and the possible product portfolio decisions and effects that may influence these results. In order to isolate the potential effect of product B introduction on product A, product A forecasting model was based on only three data points, years 2006, 2007, 2008, which are years where product B did not exist or its sales were not yet reflected at the IDC market tracker report. Our model was based on only external information of macroeconomic indicators and that allowed us to isolate the impact of the product portfolio dynamics. The assumption of the analysis is that the deviations between the forecasted units and the real units sold of each of the product are explained by the portfolio dynamics between the two products. The separation of the two source of impacts on sales, that of the product and that of product portfolio, could lead us to answer the question whether the portfolio dynamics of the products was that of “substitution” or “sales acceleration” and consequently we can answer another important question which is whether the launch of product B increased the revenue of the company.

## 8.1 Product B introduction in light of product A existence

Product B was introduced at the end of 2008 and started its “introduction” and “growth” product life cycle stages in parallel to product A´s “maturity” and the beginning of the “decline” life cycle stages. The fact that the two products coexisted during the entire time line covered in this thesis, gave us a unique opportunity to study and observe the dynamics between the two products. As shown in the flowing figure representing the two products´ sales over the years, Product B units’ sales were slowly growing until it eventually matched the sales levels of product A in 2012. In the following year, 2013, the sales levels of product B surpassed the sales of product A for the first time.




**Y0=2005, Y1=2006, Y2=2009 Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013**

**Figure 57: The sales of product A and Product B 2005-2013**

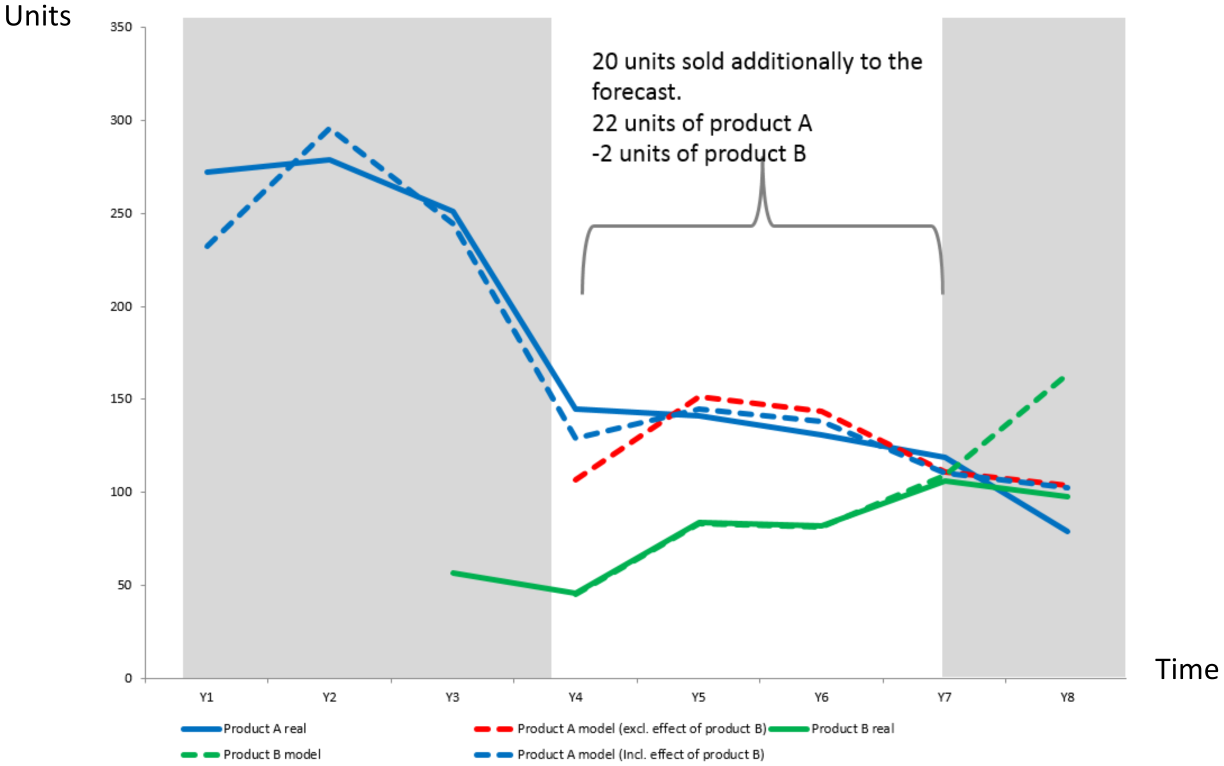
Although product A´s sales were constantly decreasing during the "decline" stage of the product, Product B was not able to outperform Product A units sales during first few years of its existence, from 2008 to 2012. It shows that product B was clearly not substituting completely product A. The longtime that was required for product B to reach the levels of product A also raises the question whether the major R&D and the marketing efforts and investments that were made in launching product B actually paid off for the company. In order to answer these questions, in the empirical study number four we analyze the different aspects of product B results.

## 8.2 Portfolio decision making test #1: Product B from sales perspective

When the actual sales of products A and B are compared with the forecasts of these products from 2009 to 2012, the total balance is positive as more units from product A and B were sold than the forecasted ones. In total, both products contributed to a difference of 22 units between the forecast and the real units sold as reported by IDC.

In 2009, just a few months after the introduction of product B, the sales of product A outperformed the forecast by 38 units, according to IDC market report, meaning that the existing product was outperforming the new product. The possible reasons for what could be related to challenges in new product introduction are widely described in the academic literature. The common wisdom among practitioners such as Morris at al. (1996), Stalk (1988) and Wilson and Norton, (1989), is that the firm should introduce the product as soon as it is available or at maturity of the old generation e.g. Mahajan and Muller (1996). In fact, the decision on what is the right timing to introduce a new generation of a product represents a clear tradeoff for the companies the time to market of introducing products as fast as possible and the performance of their products e.g. Morris at al. (1996). Stalk (1988) coined the term time-based competition to highlight the importance of quick time-to-market in today's intensive competitive environment. Clark (1989) estimates that for a $10,000 car, each day of delay in introducing a new model rep-resents a $1 million loss in profit. A recent McKinsey study reports that, on average, companies lose 33% of after-tax profit when they ship products six months late, as compared with losses of 3.5% when they overspend 50% on product development. In their book “Developing Products in Half the Time”, Smith and Reinertsen (1991) argue that it is necessary to adopt an incremental approach to product innovation in order to reduce time to market. This is because incremental product innovation reduces the amount of effort and learning that must be done and, consequently, the amount of time needed to invest in the new product prior to its launch. Such a perspective has led many companies to adopt time-to-market as their principal product development metric.

The difference between the sales forecast of product B and the actual sales of product B in 2010-2011 as reported by IDC, demonstrates that product B canalized 23 units of product A. In other words, 23 units of product A were not sold due to the existence of product B. However, in 2012, it looks that product B was not impacting the sales of product A as the two forecasting models of product, that includes the product B impact on product A and the one that excludes it, forecasted the same amount of units of product A to be sold that year. In 2012 product A sales outperformed the two (identical forecasts) by 8 units. When we isolate the product B introduction results that are reflected in 2009, we can conclude that, in general, the internal dynamics between the two products generations was that of cannibalization of product A or substitution of product A with product B.




**Y1=2006, Y2=2009 Y3=2008, Y4=2009, Y5=2010, Y6=2011, Y7=2012, Y8=2013**

**Figure 58: products A and B units gain versus forecast**

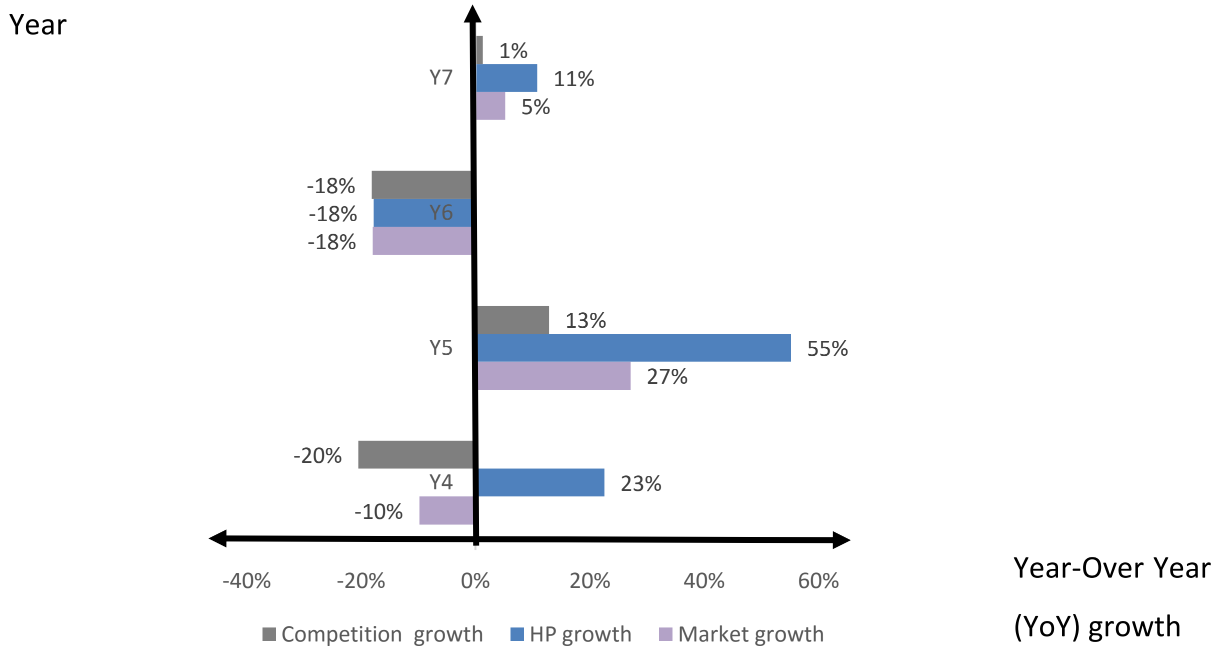
Overall between 2009 and 2012 Product A units outperformed the forecast by 22 units and product B underperformed the model by 2 units. In total products A and B outperformed the forecasted units by 20 units. All these additional units came from product A which could indicate that the introduction of product B did not substitute product A and might create acceleration in the sales of product A.

## 8.3 Portfolio decision making test #2: Product B from revenue perspective

As explained in the previous section, the mix of the products sold in 2009-2012 was skewed toward product A as more of product A were sold than product B. Taking into account that product A selling price was around half of that of product B, as reported by IDC, the company gained several million dollars during years 2009 and 2012 from product B introduction. A single digit million dollar figure in 4 years of sales of product B could be perceived as not such a bad revenue result but If we take into account that the main contributor to this revenue upside was Product A as well as the fact that this additional revenue is probably not covering the R&D costs of developing product B, we find this result as a disappointing one. R&D investments are not shared publically but in general those product investments tend to be more than a single digit million dollar figure in the market of products A and B. Therefore a single digit revenue figure would probably barely cover the investment involved in the development of the new product. In summary, from revenue perspective, it looks that the introduction of product B was a limited success.

## 8.4 Portfolio decision making test #3: Product B from market perspective

According to the IDC market share reports, in 2009, shortly after product B was introduced, the market in which product A and B were part of grew negatively and stood at -10% in comparison to the previous year´s market growth. Hewlett-Packard´s units' growth of products A and B contributed to a positive growth of 23%, as reported by IDC. The competition was lagging behind Hewlett-Packard´s product introduction success and their market growth stood at -20%. The positive product introduction impact continued also in the following year, in 2010 Hewlett-Packards´ units' sales grew double the speed of the market growth speed with 55% and 27% respectively. The positive market growth was mainly attributed to Hewlett-Packards´ product sales performance as the competition grew only 13% that year. 2011 was equally bad to Hewlett-Packard as to it its competitors. In 2012, Hewlett-Packards surpassed, once again, both the market and the competition growth with 11% units' sales growth versus the market's growth of 5% and the competition growth of 1% that year. In summary, based solely on IDC market report, from market perspective, product B helped defend Hewlett-Packards´ position as the market leader, granting the company the privilege of growing faster than its competitors and surpassing the total market growth in most of the years after the introduction of product B. Hence, from market positioning perspective, the introduction of product B was successful.




**Y4=2009, Y5=2010, Y6=2011, Y7=2012**

**Figure 59: Market size growth**

**Source: IDC market report**

## 8.5 A Game changer product portfolio decision

In 2013 that market of product A and B suffered from an adverse economic climate and consequently their sales have declined. During this year product A was at its "decline" stage for several years already and product B was in its "growth" stage that was temporarily hampered by the macro economic conditions, representing a saddle in its growth attributed mainly to the fact that the potential customers for product B could not access credit lines due to the "financial drought". The European banks have reported in the European central bank survey that the credit availability in 2013 has declined by almost 60% between 2012 and 2013. Consequently to the macro conditions headwinds, the market itself was undergoing a significant market restructuring as many of the customers went out of business while others were bought by other companies and struggled to grow their business and to invest in new equipment. The adverse macroeconomic conditions as well as the market restructuring directly influenced and reflected in the units sold in 2013. Using our methodology of analyzing the forecast models with the real units sold as reported in the IDC market report, we clearly see that in 2013 the gap between the sales forecast and the actual sales was 90 units. 65 out of the 90 units were Product B units that was forecasted to be sold but never did in 2013.

The forecasting models demonstrate that products A and B, suffered more than just macroeconomic headwinds and that there might more needed to be done in order to ensure the products sales in the long term. This decision required a change to the future product portfolio and led the company to embark on intensive R&D efforts in order to introduce to these new markets a true disruptive technology.

For several years the company had invested many resources in the creation of a new platform of products for the new markets. These intensive R&D investments were fruitful and in 2013 Hewlett-Packard launched product C. The product was a first of its kind was designed to several new markets that nor product neither A nor B could cater to in the past. The addition of a new generation of products to the company´s portfolio aimed to reshape the market and the company´s portfolio´s dynamic. In the following thesis´ subchapters we will quantify and comment on these impacts.

## 8.6 The results of the new product launch

### 8.6.1 Portfolio decision making test #1: Product C from sales perspective

Product C sales acceptance was good. Soon after its launch in 2013, product C was already 4% of the total units sold in the market according to IDC. The number of product C units sold was growing each year and in 2014 it was already 6% of the total units sold which represents a growth rate of 67%.

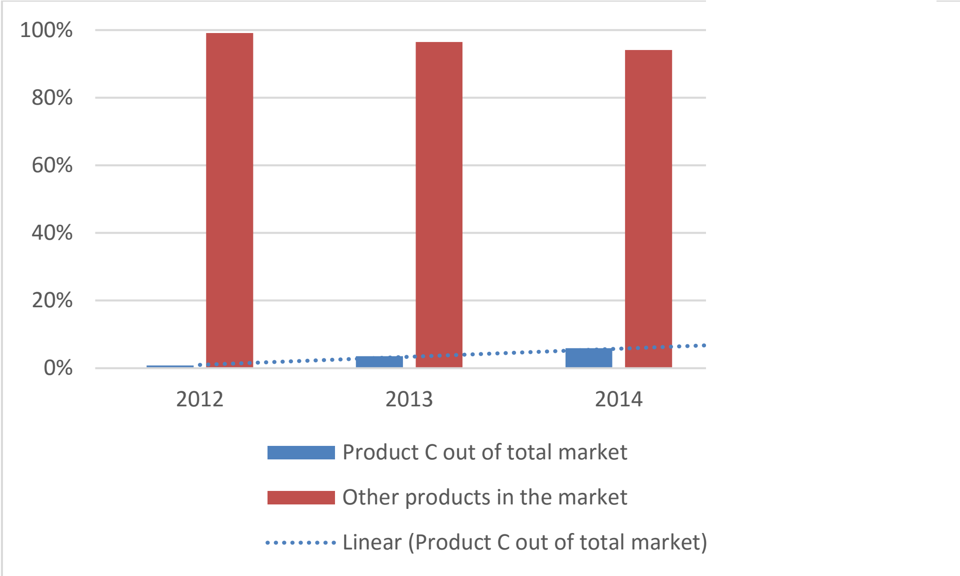
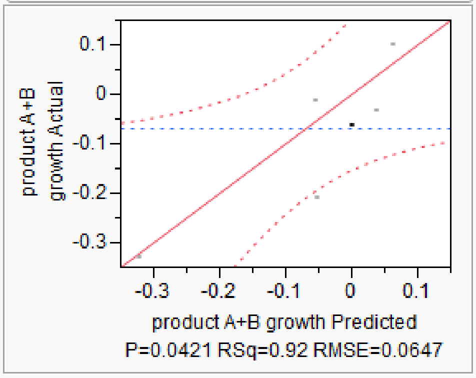



**Figure 60: Product C units out of total units in the market**

However, these positive sales results are not reveling the impact that product C launch had on the other two products in the portfolio. An interesting question to be answered is whether the introduction of product C helped Hewlett-Packard to outperform the sales forecast based on the macroeconomic indicators.  In other words, whether Hewlett-Packard was able to change its "destiny" that was "written in the stars" with the huge investment made in the development of product C.  To answer this important question, we have prepared a forecasting model based on empirical study number one and applied macroeconomic indicators to predict the sales of products A and B together as reported by IDC. The forecasting model is robust and accurate with **R^2 of 87.6%** and probability of **96%** and the **independent variable**, GDP growth, as **statistically significant**.

**Actual by Predicted Plot**




**Summary of Fit**

| | |
|---|---|
| RSquare | 0.917533 |
| RSquare Adj | 0.8763 |
| Root Mean Square Error | 0.064718 |
| Mean of Response | -0.06982 |
| Observations (or Sum Wgts) | 4 |

**Analysis of Variance**

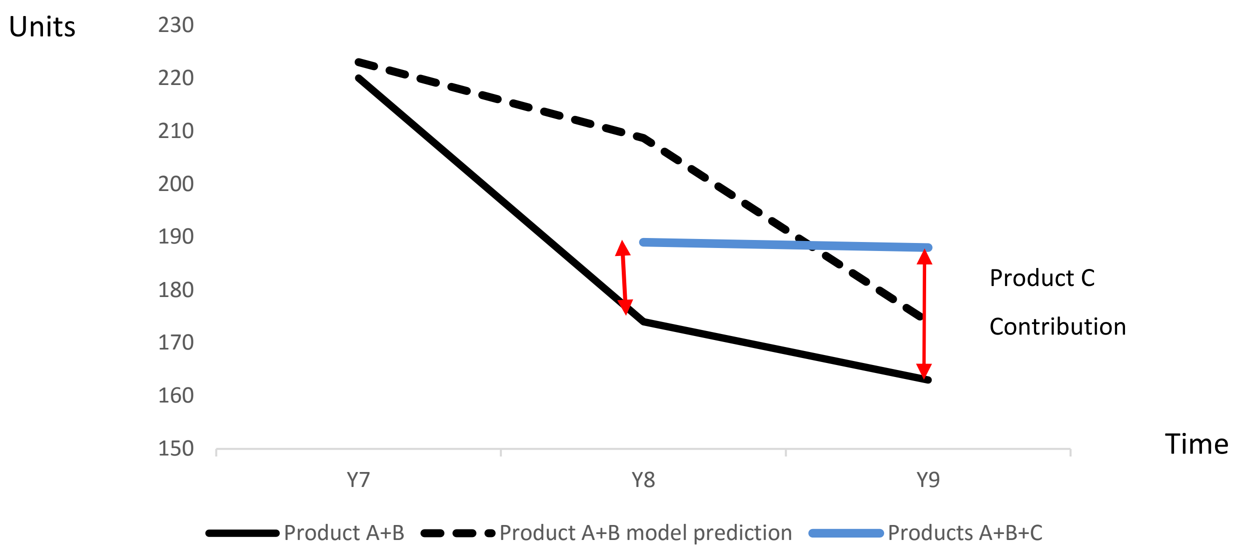
| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 1 | 0.09320221 | 0.093202 | 22.2522 |
| Error | 2 | 0.00837689 | 0.004188 | Prob > F |
| C. Total | 3 | 0.10157911 | | 0.0421* |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.110502 | 0.033488 | -3.30 | 0.0809 | -0.254591 | 0.0335869 |
| GDP growth | 5.9136574 | 1.25363 | 4.72 | 0.0421* | 0.5197214 | 11.307593 |

**Figure 61: The statistical results of forecasting the sales of product A and B as a function of a macroeconomic indicator**

This model predicted that in 2013 and 2014 the sales of products A and B would be higher than there actually were. The introduction of product C in 2013 resulted in reducing the gap between the sales predictions and the actual sales due to the sales of the newly released product C and in 2014 the three product together outperformed the sales forecast of product A and B. Therefore, we can conclude that product C has contributed positively to the sales of Hewlett-Packard and the evidence to it is by the reduction of the gap between the sales forecast and the actual sales in 2013, as reported by IDC, and by the fact that the sales of product A, B and C products outperformed the model sales forecast of product A and B.




**Y7=2012, Y8=2013, Y9=2014**

**Figure 62: Product C contribution to products A and B sales**

### 8.6.2 Portfolio decision making test #2: Product C from revenue perspective

According to the IDC reports, product C selling price was 4 times the price of product A and 2 the selling price of product B this fact combined with the increasing share of the product C in the product mix resulted in a fast growing share of product C in the total revenue results. According to IDC market share report, during the first year of its launch in 2013, the sales of product C contributed to 18% of the total revenue that year and reached 25% in 2014.

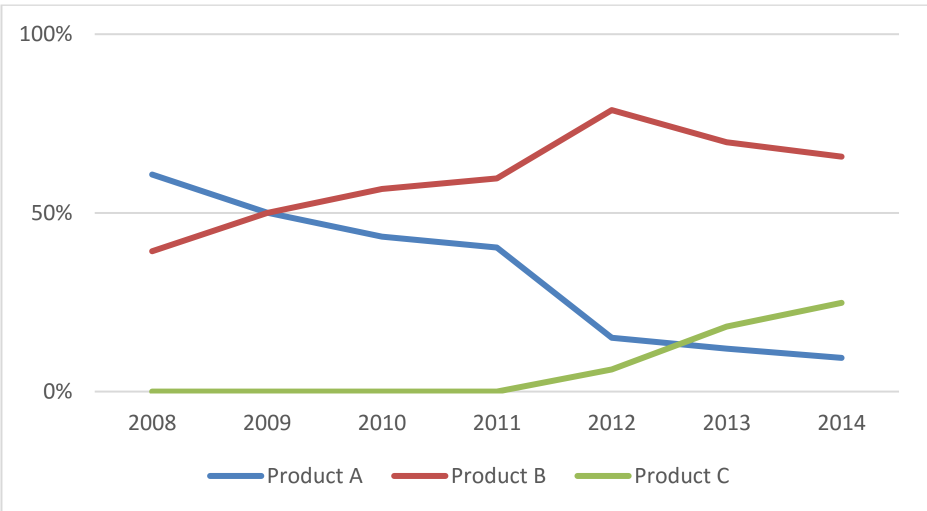
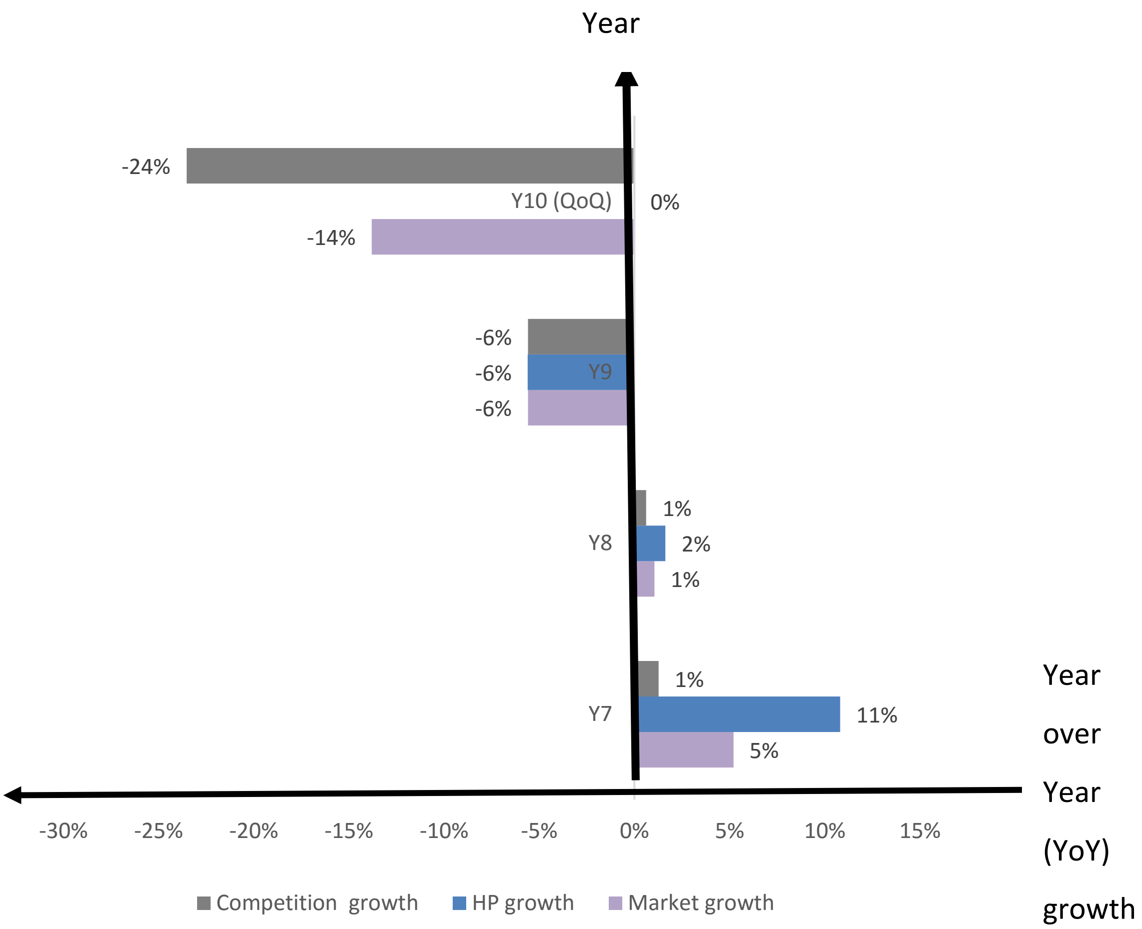



**Figure 63: Product C sales revenue out of the total revenue**

**Source: IDC market report**

### 8.6.3 Portfolio decision making test #3: Product C from market perspective

From market positioning perspective, the introduction of product C paid off for the company. In 2013, shortly after product C was introduced, the market size growth stood at 1% in comparison to the previous year´s size growth. Hewlett-Packard ´s products in that market, products A, B and C, contributed to a positive growth of 2%., double the speed of the growth of the market. The competition was lagging behind Hewlett-Packard´s product introduction success and their market growth stood at 1%. The following year, 2014 was an equally bad year for Hewlett-Packard and for Hewlett-Packard ´s competitors in this product segments. Product C together with product A and B couldn't outperform the market negative growth of -6%. However, in the first quarter of the following year, 2015 Hewlett-Packard ´s products outperformed the very negative market growth trend of -14% as Hewlett-Packard ´s sales were flat while the sales of the competition were -24% less than the equivalent sales of the first quarter of the previous year. In summary, from market perspective, product C continued helping to defend Hewlett-Packard ´s position as a market leader, granting the company the privilege of growing faster than its competitors and surpassing the total market growth in most of the years after the introduction of product C.




**Y7=2012, Y8=2013, Y9=2014, Y10=2015**

**Figure 64: Market size growth**

**Source: IDC market report**

## 8.7 Three generations under one roof: products dynamics

In order to quantify the intra-products relationships we have created a forecasting model for product B based on the sales of product A and C. By doing so we wanted to analyze the impact of the other products on the sales of product B. The model is based on the quarterly sales of product A, B and C of five quarters from 2013 and 2014 as they reported by IDC. In spite of the small amount of data points the model is robust with **R^2 of 89.3%** and probability of **89%.** While designing the forecasting model for product B, we have observed an interesting phenomenon. The sales of product C of the next quarter had an impact on the sales of product B of the running quarter. This indicates a lagging of the sales of press C and a cannibalization of product B by product C. We found this phenomenon a very interesting one as not only it showed a product substitution of product B with product C but also showed the impact of the sales force behavior. A closer look at 2013 sales shows that each sale of product C in 2013 was at the expense of the sale of product B. To be more precise every sale of product C in the following quarter was at the expense of 2.8 units of product B sales in the current quarter. This phenomenon represents a cannibalization or a semi substitution of product B by product C. Inter product portfolio cannibalization has many explanations and it is a result of the multi generations of products where customers/"laggards" are now exposed to an improved product and may decide to delay the purchase of the previous product generation or to upgrade to the newer one e.g. Goldenberg and Oreg (2007). Product C was clearly not replacing completely neither product A or B but was now being sold to customers who would like to continue to innovate and would like to have the state of the art machines to be able to do that and among new customers that could not be targeted with the previous products of the product portfolio. This phenomenon is known as "leapfrogging" e.g. Goldenberg and Oreg (2007).

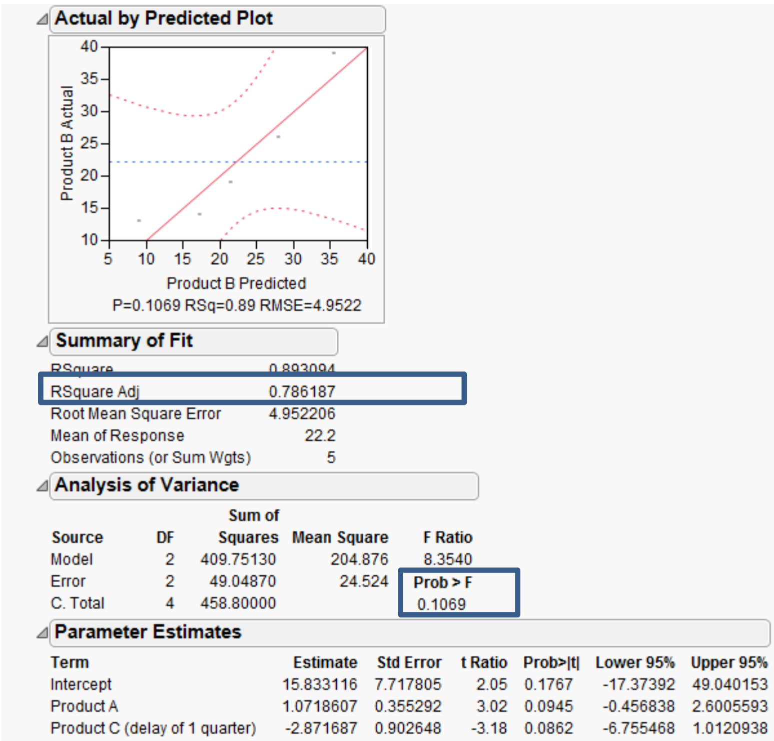



**Figure 65: Product B sales as a function of products C and A**

# 9 The Thesis contributions and limitations

Our doctorate thesis offers a novel sales forecasting model in order to predict the sales of products in different market segments, cultures, stages of the product life cycles and in different intra-product portfolio dynamics. The four empirical studies of our thesis are driven by the identified need for a pragmatic, robust and accurate sale forecasting tool for companies and by the lack of literature and tools that can cover the entire width of our problem statements. The forecasting models are based on company´s external inputs, macroeconomic indicators, that allow us to overcome the challenge and the dependency of gathering the company´s internal information for a sales forecast and, on the other hand, offers a new external perspective on the sales potential of the products. In addition, it allows us to explore the role of macroeconomic model in the decision-making process at the micro company´s level. The forecasting models presented in this thesis were used in many of Hewlett–Packard´s high profile decision making processes ranging from market sizing, forecasting of the company´s revenue, establishing sales quotas for the sales force as well as R&D investment decisions for new products.

The forecasting models show, through empirical study number 1, that to correctly capture the unique characteristics of each of the product lines, the set of macroeconomic indicators that are used as inputs needs to be singular and adapted to the drivers of the demand generation for the products. With these findings, empirical study number 1, sheds empirical light to the new institutional theoretical framework. Empirical study number 2 shows that in order to correctly capture the sales demand in a country or a culture one has to understand the culture´s characteristics and reflect them in the inputs used for the forecasting model. With this empirical study findings, we provide support to the marketing adaptation school of thoughts. Empirical study number 3 proves that the models forecast accurately products regardless of their product life cycle stages which is an essential attribute to ensure the wider usability of the models in comparison to other forecasting methodologies described in the literature. Empirical study number 4 takes the individual forecast models of two products and compare them to the actual sales results of these products. The assumption of the analysis is that the deviations between the forecasted units and the real units sold of each of the product are explained by the portfolio dynamics between the two products and thus, quantifies the portfolio dynamic. The introduction of a third product and its impact on the other two existing product is also discussed in empirical study number 4 leading to better understanding of the role of management in product portfolio decision making and contributing to the product portfolio management literature by providing a real life example.

Our thesis unlocks the combined power of the theoretical and the practical in international commerce and has multilayer contributions. The **first** contribution of this thesis is by offering a reliable, simple and robust sales forecasting which is critical for both strategic and operational decision of firms. **Secondly,** the thesis discusses real-life example of the use of our forecasting model in Hewlett-Packard. **Thirdly**, our forecasting model uses external data which makes our forecasting model more accessible and objective to firms. **Fourthly,** the four empirical studies detailed in our thesis represent a rare opportunity of connecting several theoretical frameworks with their empirical demonstration. Among these theories are the New Institutional theory, the marketing strategy debate for international companies, namely the Standardization vs. Adaptation, product portfolio dynamics, product generations and Bass model (1969) as a forecasting methodology. **Fifthly,** the models proved to be valid to predict sales of products in different market segments, cultures, stages of the product life cycles and in different intra-product portfolio dynamics. **Sixthly**, this thesis also represents an improvement to some of the known pitfalls of the classical Bass model (1969) that is not able to forecast accurately in fast moving high tech markets and also fails to forecast when only limited amount of data points are available for the product forecasting and is unsuccessful to adapt to a non-smooth product sales behaviors. **Seventhly**, our thesis provides a tool for product portfolio dynamics quantification and discusses real-life examples of the impact, consequences and managerial decisions made to tackle these important and common product portfolio issues.

However, there are several limitations to our sales forecasting models. One an important challenge is the number of observations used to estimate the models. This number is small indeed. However, there are two sections in the introduction chapter of this dissertation (sections 1.4 and 1.5) where we try to justify the utility of the models generated although the number of observation used is really small. We want to thank the committee of the DEMO program for providing the assessment of the dissertation and for their comments on this point. Their comments motivated the introduction of these two sections in the introduction. In addition to the small data sample limitation, the sales forecasting models are limited as any other attempt to forecast the future. Forecasting always assumes the risk of unforeseen events affecting the time-series involved which can and do occur from time to time. The model by nature is a simplification of many factors that only part of them are known to the forecaster. As a simplification, if any of these known or unknown factors are changing their weight or trend over time, the model might not be robust enough to take it into account. Apart from the inherent uncertainty attached to any forecast, our models, in addition, try to forecast new and rapidly changing technology which are even harder to predict. Furthermore, the markets subject to our research are in a dynamic competition landscape and therefore the randomness in such series is high as competitive action and reaction cannot always be accurately predicted. In addition, the model is highly depended on the macroeconomic indicators´ own forecast which are limited to the quality and the rigor by which they were done by the data provider. In addition, the macroeconomic indicators such as GDP and credit availability could be very sensitive to the political environment especially in times of economic turmoil. Therefore, the macroeconomic data itself could miss the influences unexpected political dynamics. As a suggestion to future line of investigation, it could be challenging but interesting to gather a robust model, not affected by changes in the weight of the factors or trends over time, and valid for different industries. Another limitation of the forecasting model lays in its dependency of a skilled forecaster to apply it properly. At the heart of the cross-over-point between the micro level, the sales of the product, and the macro, the macroeconomic indicators, lays the forecaster. The forecaster has to have enough familiarity with the products and the customer's behavior in order to choose the right macroeconomic indicator to represent the purchasing dynamics of the products. This understanding level that can be unique to the forecaster and it gives "craftsmanship" flavor to the forecasting model methodology. Therefore, due to the potential singularity of the data and the uniqueness of the forecaster's knowledge, we believe that the main future line of investigation should be the extrapolation of the forecasting model to other products in other markets and perhaps those of a lower technology. This will give the thesis the external validity for its methodology and forecasting capability.

# 10 Annex 1- The GLOBE country scores

| | | Uncertainty Avoidance | Power Distance | Collectivism I (Institutional) | Collectivism II (In-Group) | Gender Egalitarianism | assertiveness | future orientation | performance orientation | Human Orientation |
|---|---|---|---|---|---|---|---|---|---|---|
| German | Austria | 5,16 | 4,95 | 4,3 | 4,85 | 3,09 | 4,62 | 4,46 | 4,44 | 3,72 |
| | Netherlands | 4,7 | 4,11 | 4,46 | 3,7 | 3,5 | 4,32 | 4,61 | 4,32 | 3,86 |
| | Switzerland (German speaking) | 5,37 | 4,9 | 4,06 | 3,97 | 2,97 | 4,6 | 4,73 | 4,94 | 3,6 |
| | Germany* | 5,19 | 5,395 | 3,675 | 4,27 | 3,08 | 4,64 | 4,11 | 4,17 | 3,29 |
| Latin Europe | Israel | 4,01 | 4,73 | 4,46 | 4,7 | 3,19 | 4,23 | 3,85 | 4,08 | 4,1 |
| | Italy | 3,79 | 5,43 | 3,68 | 4,94 | 3,24 | 4,07 | 3,25 | 3,58 | 3,63 |
| | Switzerland (French speaking) | 4,98 | 4,86 | 4,22 | 3,85 | 3,42 | 3,47 | 4,27 | 4,25 | 3,93 |
| | Spain | 3,97 | 5,52 | 3,85 | 5,45 | 3,01 | 4,42 | 3,51 | 4,01 | 3,32 |
| | Portugal | 3,91 | 5,44 | 3,92 | 5,51 | 3,66 | 3,65 | 3,71 | 3,6 | 3,91 |
| | France | 4,43 | 5,28 | 3,93 | 4,37 | 3,64 | 4,13 | 3,48 | 4,11 | 3,4 |
| Anglo | Canada | 4,58 | 4,82 | 4,38 | 4,26 | 3,7 | 4,05 | 4,44 | 4,49 | 4,49 |
| | USA | 4,15 | 4,88 | 4,2 | 4,25 | 3,34 | 4,55 | 4,15 | 4,49 | 4,17 |
| | Australia | 4,39 | 4,74 | 4,29 | 4,17 | 3,4 | 4,28 | 4,09 | 4,36 | 4,28 |
| | Ireland | 4,3 | 5,15 | 4,63 | 5,14 | 3,21 | 3,92 | 3,98 | 4,36 | 4,96 |
| | England | 4,65 | 5,15 | 4,27 | 4,08 | 3,67 | 4,15 | 4,28 | 4,08 | 3,72 |
| | South Africa (white) | 4,09 | 5,16 | 4,62 | 4,5 | 3,27 | 4,6 | 4,13 | 4,11 | 3,49 |
| | New Zealand | 4,75 | 4,89 | 4,81 | 3,67 | 3,22 | 3,42 | 3,47 | 4,72 | 4,32 |
| Nordic | Denmark | 5,22 | 3,89 | 4,8 | 3,53 | 3,93 | 3,8 | 4,44 | 4,22 | 4,44 |
| | Finland | 5,02 | 4,89 | 4,63 | 4,07 | 3,35 | 3,81 | 4,24 | 3,81 | 3,96 |
| | Sweden | 5,32 | 4,85 | 5,22 | 3,66 | 3,84 | 3,38 | 4,39 | 3,72 | 4,1 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Latin America | Ecuador | 3,68 | 5,6 | 3,9 | 5,81 | 3,07 | 4,09 | 3,74 | 4,2 | 4,65 |
| | El Salvador | 3,62 | 5,68 | 3,71 | 5,35 | 3,16 | 4,62 | 3,8 | 3,72 | 3,71 |
| | Colombia | 3,57 | 5,56 | 3,81 | 5,73 | 3,67 | 4,2 | 3,27 | 3,94 | 3,72 |
| | Bolivia | 3,35 | 4,51 | 4,04 | 5,47 | 3,55 | 3,79 | 3,61 | 3,61 | 4,05 |
| | Brazil | 3,6 | 5,33 | 3,83 | 5,18 | 3,31 | 4,2 | 3,81 | 4,04 | 3,65 |
| | Guatemala | 3,3 | 5,6 | 3,7 | 5,63 | 3,02 | 3,89 | 3,24 | 3,81 | 3,89 |
| | Argentina | 3,65 | 5,64 | 3,66 | 5,51 | 3,49 | 4,22 | 3,08 | 3,65 | 3,99 |
| | Venezuela | 3,44 | 5,40 | 3,96 | 5,53 | 3,62 | 4,33 | 3,35 | 3,32 | 4,25 |
| | Mexico | 4,18 | 5,22 | 4,06 | 5,71 | 3,64 | 4,45 | 3,97 | 4,1 | 3,98 |
| | Costa Rica | 3,82 | 4,74 | 3,93 | 5,32 | 3,56 | 3,75 | 3,6 | 4,12 | 4,39 |
| South east Asian | Philippines | 3,89 | 5,44 | 4,65 | 6,36 | 3,64 | 4,01 | 4,15 | 4,47 | 5,12 |
| | Indonesia | 4,17 | 5,18 | 4,54 | 4,68 | 3,26 | 3,86 | 3,86 | 4,41 | 4,69 |
| | Malaysia | 4,78 | 5,17 | 4,61 | 5,51 | 3,51 | 3,87 | 4,58 | 4,34 | 4,87 |
| | India | 4,15 | 5,47 | 4,38 | 5,92 | 2,9 | 3,73 | 4,19 | 4,25 | 4,57 |
| | Thailand | 3,93 | 5,63 | 4,03 | 5,79 | 3,35 | 3,64 | 3,43 | 3,93 | 4,81 |
| | Iran | 3,67 | 5,43 | 3,88 | 6,03 | 2,99 | 4,04 | 3,7 | 4,58 | 4,23 |
| Confucian Asia | Singapore | 5,31 | 4,99 | 4,9 | 5,64 | 3,7 | 4,17 | 5,07 | 4,9 | 3,49 |
| | Hong Kong | 4,32 | 4,96 | 4,13 | 5,32 | 3,47 | 4,67 | 4,03 | 4,8 | 3,9 |
| | Taiwan | 4,34 | 5,18 | 4,59 | 5,59 | 3,18 | 3,92 | 3,96 | 4,56 | 4,11 |
| | China | 4,94 | 5,04 | 4,77 | 5,8 | 3,05 | 3,76 | 3,75 | 4,45 | 4,36 |
| | South Korea | 3,55 | 5,61 | 5,2 | 5,54 | 2,5 | 4,4 | 3,97 | 4,55 | 3,81 |
| | Japan | 4,07 | 5,11 | 5,19 | 4,63 | 3,19 | 3,59 | 4,29 | 4,22 | 4,3 |
| Middle East | Turkey | 3,63 | 5,57 | 4,03 | 5,88 | 2,89 | 4,53 | 3,74 | 3,83 | 3,94 |
| | Kuwait | 4,21 | 5,12 | 4,49 | 5,8 | 2,58 | 3,63 | 3,26 | 3,95 | 4,52 |
| | Egypt | 4,06 | 4,92 | 4,5 | 5,64 | 2,81 | 3,91 | 3,86 | 4,27 | 4,73 |
| | Morocco | 3,65 | 5,8 | 3,87 | 5,87 | 2,84 | 4,52 | 3,26 | 3,99 | 4,19 |
| | Qatar | 3,99 | 4,73 | 4,5 | 4,71 | 3,63 | 4,11 | 3,78 | 3,45 | 4,42 |
| Eastern Europe | Greece | 3,39 | 5,4 | 3,25 | 5,27 | 3,48 | 4,58 | 3,4 | 3,2 | 3,34 |
| | Hungary | 3,12 | 5,56 | 3,53 | 5,25 | 4,08 | 4,79 | 3,21 | 3,43 | 3,35 |
| | Albania | 4,57 | 4,62 | 4,54 | 5,74 | 3,71 | 4,89 | 3,86 | 4,81 | 4,64 |
| | Slovenia | 3,78 | 5,33 | 4,13 | 5,43 | 3,96 | 4 | 3,59 | 3,66 | 3,79 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Poland | 3,62 | 5,1 | 4,53 | 5,52 | 4,02 | 4,06 | 3,11 | 3,89 | 3,61 |
| | Russia | 2,88 | 5,52 | 4,5 | 5,63 | 4,07 | 3,68 | 2,88 | 3,39 | 3,94 |
| | Georgia | 3,5 | 5,22 | 4,03 | 6,19 | 3,55 | 4,18 | 3,41 | 3,88 | 4,18 |
| | Kazakhstan | 3,66 | 5,31 | 4,29 | 5,26 | 3,94 | 4,46 | 3,57 | 3,57 | 3,99 |
| Sub-Saharan Africa | Namibia | 4,2 | 5,29 | 4,13 | 4,52 | 3,88 | 3,91 | 3,42 | 3,67 | 3,96 |
| | Nigeria | 4,29 | 5,8 | 4,14 | 5,55 | 3,01 | 3,79 | 4,09 | 3,92 | 4,1 |
| | Zambia | 4,1 | 5,31 | 4,61 | 5,84 | 2,86 | 4,07 | 3,62 | 4,16 | 5,23 |
| | Zimbabwe | 4,15 | 5,67 | 4,12 | 5,57 | 3,04 | 4,06 | 3,77 | 4,24 | 4,45 |

- An average of east and west Germany´s scores

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