MASTER

A market based sales & operations planning optimization tool for a commodity segment

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A Market Based Sales & Operations Planning Optimization Tool for a Commodity Segment

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Abstract

The research conducted in this thesis describes how supply chain dynamics influence industry level demand volatility, and subsequently how a firm's supply position and price setting influence their market share in order to improve demand forecasting at SABIC. The results are combined to develop an integrated Sales and Operation Planning tool that can help make financially driven decisions about production, inventory, and price setting which predict firm sales and enables SABIC to improve profits of the polypropylene-based pipe commodity segment.

Management Summary

This Master's thesis applies to the petrochemical industry and SABIC in particular. It extends research on the effects of different market factors influencing industry demand volatility at the polymer echelon and sales at SABIC for the polypropylene-based pipe segment. We analyze the downstream supply chain of a commodity segment (polypropylene based pipe) and improve predictability of upstream demand movement. Subsequently we investigate how SABIC's supply position in the market together with their price setting affect their market share. As such, we take a two-step market based approach to investigate how demand arrives at SABIC and how they can influence this. The outcomes of the analyses are used to build a tool that helps make financially-driven decisions in their monthly Sales & Operations Planning process.

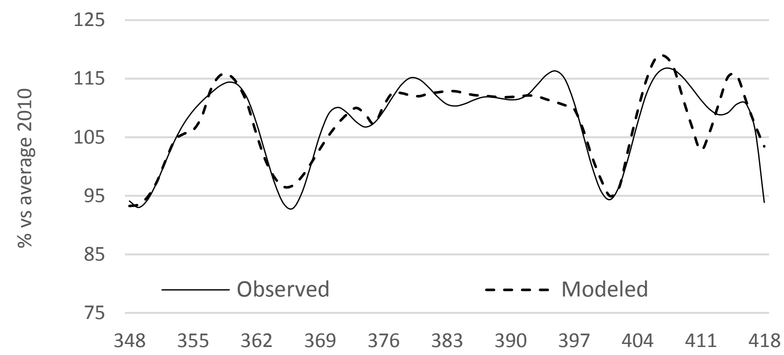
Research

The goal of any mature S&OP process is to align demand and supply on one hand, and to optimize profit on the other (Thomé et al., 2012a). While SABIC focusses the S&OP such that their stock levels are close to an economically determined optimal stock, the financial impact of their S&OP decisions is unknown. Volume push and inventory ramp up decisions are made on industry demand movement. Earlier research, which make use of system dynamics models, confirms industry demand volatility can be explained by supply chain dynamics (Udenio, 2014), and price dynamics induced by traders (Stuijts, 2014). Still demand input at SABIC is still based on traditional time series forecasting. Furthermore commodity literature describes how a market price is a result of an equilibrium of supply and demand, consequently price setting different from the market price and a certain supply position in the market will affect the demand arriving at firm level. To what extent, and the magnitude of these effects influence the demand arriving at SABIC is unknown Aligned with the decomposition between industry and firm demand three research questions have been defined:

A) *Can the current system dynamics model at SABIC be adjusted to predict the industry demand volatility of PP pipe products, and to what extend are price dynamics influencing trader (de)stocking behavior.*
B) *How is SABIC supply position influencing demand arriving at SABIC?*
C) *What is the relation between price-setting and the demand at SABIC?*

Industry demand volatility

We constructed a system dynamics model based on earlier research by Stuijts (2014) using end consumer demand and price as exogenous variables to predict the industry demand level at the upstream polymer echelon. Findings are in line with earlier research, traders play a role in upstream demand volatility by buying from the polymer producers when their expectation of the price is low and selling it to the converters when the expectation of the price is high. This disturbs real demand signals and consequently creates bullwhip behavior. We found that converters start buying from traders when the price starts rising but quickly turn back to polymer producers before the price settles in a peak. Therefore traders reduce their risk exposure by dedicating a smaller portion of their available inventory to pipe grades. As shown in the figure above the model has a good fit of industry demand volatility, explaining 84.1% of the variance.



Modeled versus observed industry demand volatility over a period from August 2013 to December 2014

Factors influencing market share

In order to make the step from industry demand to firm demand, we investigated how SABIC's price setting and supply position (consisting of their inventory position and production position) influence their market share. The market was split up in three configurations: short (demand > supply), balanced (demand ≅ supply), and long (demand < supply).

We found that price setting above the market price positively influences their market share in a short market, and negatively influences their market share in a balanced market. Surprisingly we did not find a negative relation in the long market. This implies that in a short market management can be aggressive with their price setting from the beginning of the month while in a balanced market they should be careful and align their price with the market price.

Only in the short market we found that a strong inventory position enables SABIC to have a higher market share, while in a balanced and even in long market we found that a strong production position contributes to a higher market share. In a market where demand exceeds supply it is thus important to have ample inventory in place to quickly respond to the needs of the customers. In a more saturated market it is more important to be able to adjust to the needs of the customer with production.

Joint model

A non-linear programming model translating industry demand into firm demand was constructed using the supply positioning and price setting influences. The model optimizes three months and uses industry movement to exploit the influences of inventory, production and price to maximize revenue or profit. While optimizing towards revenue, choices are made to constantly push product into the market, this leads to undesired high levels of inventory. Profit optimization yields more promising results. Inventory levels are kept low while a desirable balance between price and market share is sought to increase profit margin.

Recommendations to SABIC

SABIC is not a price leader in the pipe market which makes them unable to influence the market price. Since polymer prices are also more volatile since the economic crisis in 2008 we recommend SABIC management to use the system dynamics model as an extensive scenario-based testing tool to see how industry demand at the polymer echelon reacts to certain realistic changes in price.

Next to industry demand being sensitive to changes in the market price, firm demand is also sensitive to price setting that deviates from the market price. Different markets account for different effects of price setting on estimated sales volume. SABIC should consider these effects already during the S&OP while they agree on a sales volume, instead of trying to sell for the best price afterwards. In line with this we recommend to use the optimization model during the S&OP as extra input besides the current process, and exploit ways to adjust inventory, production and price setting in order to adjust their expected market share and increase profit.

Preface

This thesis is the result of my graduation project for the MSc program in Operations Management and Logistics at the Eindhoven University of Technology.

First of all I would like to thank Matthew Reindorp, it was a pleasure to work with him. By challenging me during our meetings, and critically reflecting on my progress he helped me to develop new insights and explore different paths to bring my research to a higher level. Next my thanks go to Maxi Udenio who partly took over Matthew's supervision when he left, and helped me during the few meetings we had.

I would like to thank SABIC and everyone who helped me for giving me the opportunity to execute this research with them, and make time for me during this chaotic period. Especially my thanks go to Tugce Tali for her supervision, feedback, and support.

Last but not least my I would like to express my gratitude to my parents who supported me in all the choices I made, allowing me to make the absolute most of my time as a student.

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Contents

Abstract IV

Management Summary V

Preface VIII

1. Introduction 11

1.1 Petrochemical Industry 11

1.2 SABIC 11

1.3 Problem statement 11

1.2 Project scope 13

1.3 Project approach 14

2. Relevant Literature and Theory 16

2.1 The process industry 16

2.2 Sales and Operations Planning 16

2.3 Supply chain dynamics – the bullwhip effect 17

2.4 Modeling approach 18

2.5 System dynamics 19

2.6 Commodity pricing 19

3. Research questions & methodology 20

3.1 Research questions 20

3.2 Methodology 21

4. Factors influencing industry demand - supply chain dynamics 22

4.1 Single echelon model 22

4.2 Supply chain model 29

4.3 Conclusion 35

5. Factors influencing firm demand 36

5.1 Supply position and price deviation 36

5.2 Data 36

5.3 Short market 38

5.4 Balanced market 43

5.5 Long market 47

5.6 Conclusions 52

6. S&OP Implementation 54

6.1 Model variables 54

6.2 Model derivation 55
6.3 Model validation 58
6.4 Model solving 59
6.5 Conclusion and discussion 62
7. Managerial insights 64
8. Conclusion and Future research 67
8.1 Conclusions 67
8.2 Limitations 69
8.2 Further Research 69
References 71
Appendix I Regression analysis short market 74
Appendix II Regression analysis balanced market 76
Appendix III Regression analysis long market 79
Appendix IV S&OP Implementation 83

1. Introduction

This chapter gives a brief introduction into the petrochemical industry, and the company at which the research is conducted. This is followed by the problem statement and the scope of the project.

1.1 Petrochemical Industry

The petrochemical industry is an industry that is throughput-focused due to its expensive capital and faces a lot of different market dynamics. The produced chemicals, known as petrochemicals, are derived from petroleum or other fossil fuels like natural gas and coal. Olefins (which largely consist of ethylene and propylene) and aromatics (benzene, toluene, and xylene isomers) make up the two most common petrochemical classes. These are the building blocks for a lot of different product classes including solvents and detergents (aromatics), and plastic and fibers (olefins). The retrieval of olefins and aromatics from either natural gas liquids or naphtha is the first production step in the petrochemical industry.

Since the research concerns a plastic segment, and the olefins ethylene and propylene cover the major part of the petrochemical industry, only the polymerization process will be highlighted as a next step in the production process. Polymerization concerns the bonding of the monomers ethylene and propylene into the polymers polyethylene (PE) and polypropylene (PP). A lot of different types of PE and PP can be obtained by adding different additives into the process. The main applications of PE are in flexible packaging, such as film, food packaging, and carrier bags on the one hand, and rigid packaging, like bottles, cans, crates, and boxes, on the other hand. PP is much stronger and tougher than PE. Its main applications are in stronger packaging, fibers, caps and closure, automotive parts, and pipes.

1.2 SABIC

The Saudi Basic Industries Corporation (SABIC) was founded in 1976 in the Kingdom of Saudi Arabia (KSA) in order to transform natural gas, a useless by-product of oil exploration, into valuable petrochemical products which could be sold. The Saudi Arabian Government owns 70 percent of SABIC shares with the remaining 30 percent held by private investors in Saudi Arabia and other Gulf Cooperation Council countries. Nowadays SABIC has become one of the fastest-growing global petrochemical companies employing 40,000 employees worldwide. At this moment SABIC is the second-largest global diversified chemical company, with operations in more than 40 countries and around 60 world-class manufacturing and compounding complexes across the Middle East, Asia, Europe and the Americas. SABIC is composed of six Strategic Business Units (SBUs): Chemicals, Polymers, Innovative Plastics, Performance Chemicals, Fertilizers and Metals. With their 68.5 million metric tons production in 2014, SABIC recorded a net profit of US$ 6.2 billion, and sales revenues totaled US$ 50.2 billion. Total assets stood at US$ 90.7 billion at the end of 2014.

SABIC set foot in Europe in 2002 when production capacity in the Netherlands and Germany was acquired from DSM. Later they extended their business in Europe by purchasing petrochemical branches from the Huntsman Corporation in the UK in 2006. Their European head office for the chemical and polymers SBU is stationed in Sittard-Geleen (The Netherlands).

1.3 Problem statement

Many firms in the process industry rely on a so called sales and operations planning process (S&OP). The main goal of such a process is to balance supply and demand, but in later stages it is also focused on increasing profit (more detail in section 2.2). SABIC is currently focusing on keeping the stock levels as close as possible to the pre-calculated optimal stock. Although the optimal stock calculation is based on the lowest cost for both inventory as production cycles taking into account a customer service level, the monthly profit impact of S&OP decisions is close to unknown. Yet SABIC desires to make tactical decisions with the focus on generating profit or generating the highest contribution margin in the S&OP. To accomplish this we look at the demand side of the S&OP.

The problem is twofold: 1) SABIC does not know what factors influence industry demand movement. 2) SABIC does not know how their position in the market affects their market share. This makes it difficult for SABIC to predict how demand is going to move in upcoming months, and how they can impact it.

1) Industry demand

The 2008 credit crisis triggered by the fall of the Lehman Brothers led to an increase in demand volatility at the polymer echelon (Corbijn, 2013). Figure 1 shows the demand drop in 2009 and the increased volatility in the period that follows. Udenio et al. (2014) found that simultaneous destocking throughout the supply chain could explain a major part of the structural bullwhip experienced in the petrochemical industry. Nowadays relatively stable end market demand still propagates through the supply chain, changing into more volatile demand in more upstream markets. It is very difficult to capture this volatility by traditional time series forecasting, but from previous work we know a great deal can be explained by supply chain (Udenio et al., 2014) and price dynamics (Corbijn, 2013; Stuijts, 2014).

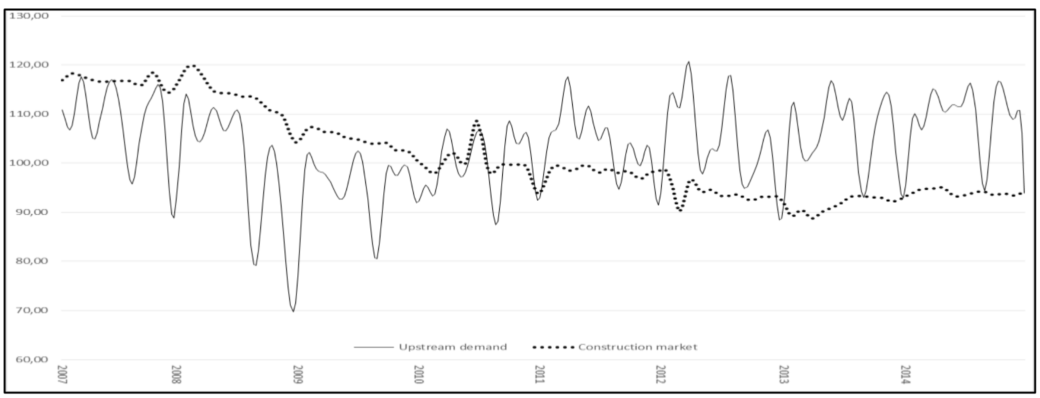


Figure 1 *Upstream demand volatility*

Demand planning at SABIC is based upon the expected demand given by the Demand Chain Coordinator (DCC). The expected demand is calculated on basis of a monthly sales office forecast, historical data, a planner's own experiences and knowledge about the different grades at the moment of planning. It is thus partly based on time series forecasting. The demand planners therefore produce an already 'constrained' demand forecast which is used to make decisions in the S&OP. The demand forecast is constrained because it is mainly based on past data, there is little empirical knowledge to what extend different factors in the supply chain influence real demand at SABIC. This 'unconstrained' demand, which takes supply chain dynamics into account, is of much higher value in the S&OP. This is because the volume push and production ramp up decisions are made on expectation of demand movements. The unconstrained demand represents how end market (consumer) demand is updated through the supply chain and eventually arrives at SABIC, it therefore gives a better representation of the market movements. By incorporating unconstrained demand data in the S&OP, SABIC can make a better evaluation whether pushing volume or ramping up production adds value to the company, tactical decision making would therefore be improved. Thus insights and predictability of industry demand movement is of high value since safety stock can be reduced while keeping customer service level at a desired high level (Grimson, Pyke, 2007).

2) Market share
Commodity literature (described in more detail in section 2.6) describes that the market price, is the realization of an equilibrium of supply and demand in the market. Under the assumption that the firm is not a market leader in the commodity segment, competitors will not follow when they decide to deviate their price from the market price. Deviating will result in a change in the demand arriving at the firm yet the magnitude of this deviation is unknown. Next to this the total industry supply contributes to the equilibrium in the market. SABIC's position in this industry supply will likely affect the share of the market they can get, yet the influence is unknown.

1.2 Project scope
The thesis is based on the industry and firm demand analyses of the polypropylene part of the pipe segment, further mentioned as PP Pipe. For SABIC the pipe segment is defined as those polymers which are converted into industrial plastic pipes which are used in houses and infrastructure projects.

The supply chain
Final customer demand is linked to industry demand for the pipe polymers by a downstream supply chain consisting of a trader, converter, and distributor echelon. The modeled chain is represented in figure 2 by the echelons surrounded by the dotted box. The total supply chain of the pipe polymers includes the chemical producers and is displayed for completeness.

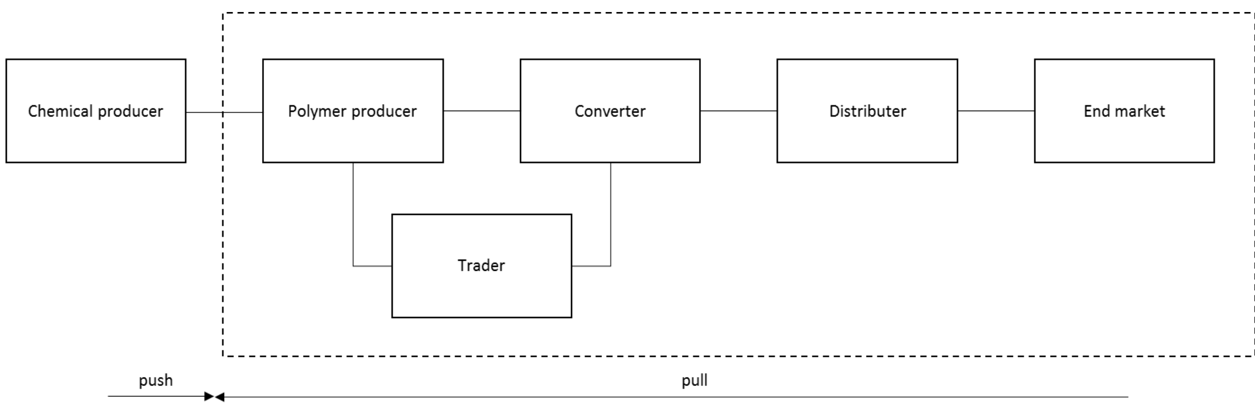


Figure 2 *Pipe polymer supply chain, the area in the dotted box represents the part of the supply chain in scope*

Commodity supply chains are often influenced by so called "traders". These are third parties that do not add value to the product but merely make use of price fluctuations to buy plastic polymer granules from the polymer producers and sell these to the converters at strategic moments in time to make a profit.

Pipe products mainly go into three different end markets: construction market, energy sector, and the agricultural sector. Nearly 70% of all pipes go into the construction market which is why this study is focused on polymers going into the construction market. Due to data availability the geographical scope of the project is EU27. Imports into and exports out EU27 are left out.

Commodity market
Polymer producers function as the upstream echelon in the chain under study. They add value by polymerizing small molecules known as monomers into a bonded chain or network (Painter & Coleman, 1997). The main input monomer is propylene (C_3H_6) which respectively result in polypropylene (PP). These polymers have, due to the addition of different additives, a wide variety of properties.. Commodities are products of uniform quality that are produced in large quantities by many different producers and to which the law of one price applies (O'Sullivan, 2003). Due to the similarities in the market space of commodities, the results of this study can be generalized to other commodity markets.

S&OP
The research is conducted with a focus on improving decision making of SABIC's tactical planning process: the sales and operations planning process (S&OP). At SABIC tactical planning is a monthly process. This planning process, as shown in figure 3, requires inputs from responsible managers from several departments within the Chemical and Polymer business unit (SBU), who sit together in the Value Teams (VTs) and Business Teams (BTs) and discuss market forecasts and price developments (business forecast), planned sales, production capacities, and other tactical constraints. It is the task of the Demand and Supply Chain Planning departments to put together an aligned, consistent plan which includes an agreed sales, supply and inventory plan, and is agreed upon by all parties involved.

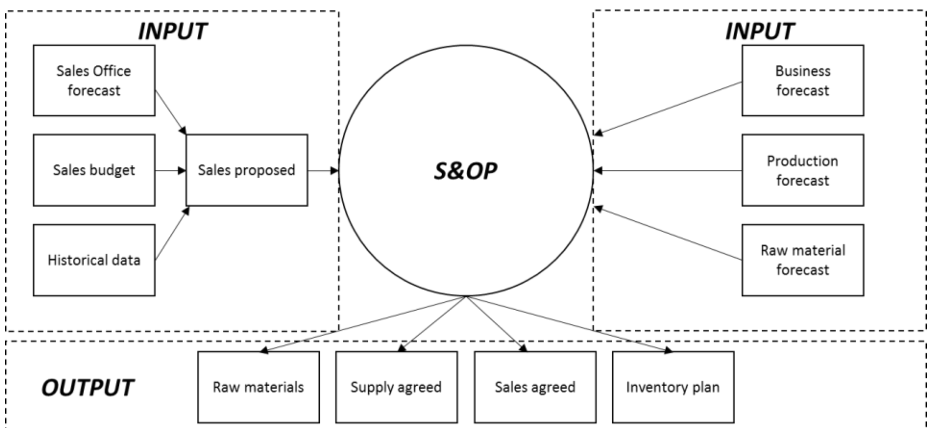


Figure 3 *SABIC's sales & operations planning process*

The overarching goal of these resulting plans is not only to be in balance volume wise; among all balanced plans, the one generating maximum Cash Flow Return of Investment (CFROI) must be selected. This means maximize utilization of the production plants given the available feedstock as well as keeping inventory levels in line with the optimal stock levels.

1.3 Project approach

The remainder of the thesis is organized as follows: Chapter 2 gives a structured outline of the reviewed literature focused on the main concepts. The research questions and methodology are discussed in chapter 3. Chapter 4 addresses the first research question by adjusting the existing system dynamics model for the commodity segment, and analyzing trader behavior. Subsequently chapter 5 addresses the second and third research question by investigating how different market factors influence demand at SABIC. Chapter 6 goes into the development of a model that can be implemented in the S&OP process.

The findings from chapters 4-6 are translated into managerial insights in chapter 7, and finally the main conclusions and limitations of the project are discussed in chapter 8.

2. Relevant Literature and Theory

This section gives a brief outline of the reviewed literature, focusing on the key concepts used in this research. First the process industry is briefly described, followed by tactical decision making in a sales and operations planning process. Second supply chain dynamics and the choice for system dynamics are described, and it concludes with a review of commodity pricing.

2.1 The process industry

The petrochemical industry is part of the process industry. The definition of process industries is given by the APICS' (American Production and Inventory Control Society):

"Process Industries are businesses that add value to materials by mixing, separating, forming or chemical reactions. Processes may be either continuous or batch and generally require rigid process control and high capacity investment".

This industry mainly uses commodity products and has a narrow product assortment, but a high demand per product (Fransoo & Rutten, 1994). A Commodity product is a product of uniform quality that is produced in large quantities by many different producers (O'Sullivan, 2003). The main feature to win an order in the process industry is a low price and delivery guarantee instead of product features and speed of delivery in the discrete industry. Next to commodity products there are also specialty products. These are products with specific properties which cannot be produced equally by all players in the market and can therefore differentiate on product quality. These are usually produced in smaller batches but are still considered part of the process industry.

The production process is characterized as a flow-process which implicates high changeover times, low work in process and high volumes. The production equipment is specialized and highly capital expensive, routings are fixed and flexibility is low (Silver, Pyke, Peterson, 1998). The production is mostly focused on a make-to-stock policy, due to high orders and high changeover times and is desirable since the product characteristics are nearly equal and the customer has no specific product requirements. Therefore in process industries the long term planning is focused on capacity expansion in order to fulfil the market demand with similar products and on short term it is focused on maximum utilization of capacity.

2.2 Sales and Operations Planning

A widely used process in the process industry to keep operational cost low is a sales and operations planning process. A Sales and Operations (S&OP) process is a cross-functional process to develop tactical plans that provide management the ability to strategically direct its businesses to achieve competitive advantage on a continuous basis (Thomé, Scavarda, Fernandez, Scavarda, 2012a, 2012b). The process links a company's corporate strategic plan to daily operations plans to balance demand and supply (Gregory, 1999; Dwyer, 2000; Wight, 1999), with the intention to meet customer demand at the highest levels, while at the same time, maintaining reduced inventories and minimized supply chain operating costs (Lapide, 2004). Thomé et al. (2012a) mention the main features of an S&OP process, namely:

- it is a cross-functional and integrated tactical planning process within a firm;
- it integrates all of the plans of a business in a unified plan;

- it has a planning horizon that ranges from less than three months to more than 18 months;
- it bridges strategy and operations (Feng and Sophie D'Amours, 2008); and
- it creates value and is linked with firm performance (Grimson and Pyke, 2007; Nakano, 2009).

According to Grimson and Pyke (2007) the S&OP process is typically a 5-step process. First there are pre meetings between sales personnel to build a baseline demand forecast. Second are pre meetings with the operations team, operations gathers information about operational restrictions and designs a rough cut supply plan that meets the forecast requirements. Third the whole S&OP team formally meets to agree upon the final operating plan for the next period. The fourth step consist of distributing the agreed upon operating plan to the relevant parties and implement it. Finally the process parameters need to be measured to ensure continuity and improvement possibilities.

In earlier years the goal of a sales and operation planning process was mainly tactical, it was to achieve supply chain balance and operational excellence (Bauman, 2009). Nowadays this is shifting towards linking operations to firm performance: optimize profit (Bauman, 2009; Grimson and Pyke, 2007). This can be accomplished by improving one's S&OP process on five dimensions: Meetings & Collaboration, Organization, Measurements, Information Technology, and S&OP Plan Integration. For extensive elaboration on the different dimensions we refer to Grimson & Pyke (2007).

2.3 Supply chain dynamics – the bullwhip effect

One major influence on various supply chains is the bullwhip effect. This refers to phenomenon where the supplier experiences higher order variance than the buyer. This effect amplifies further upstream in the supply chain (Lee et al., 1997). The bullwhip effect is a serious issue in the supply chain as it can result excess cost due to unplanned or excess operational activities (Lee et al., 1997). Figure 4 gives a graphical representation of the increased volatility in a typical supply chain. The main causes described by Lee et al. (1997) are demand signal processing, the rationing game, order batching, and price variations.

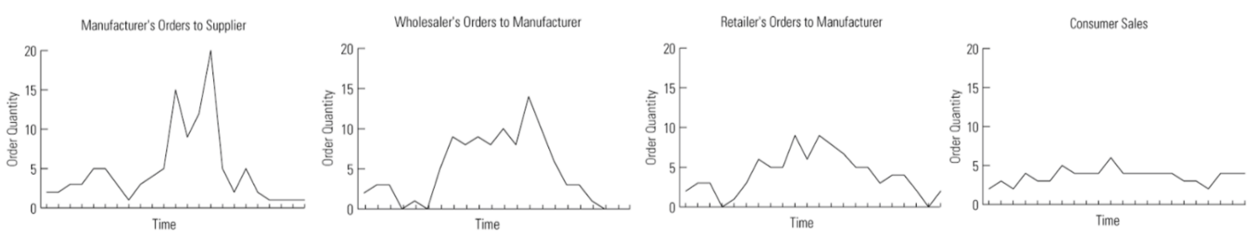


Figure 4 *Increased volatility throughout a supply chain*

Demand signal processing can be described as the situation where demand is non stationary and one uses past demand information to update forecasts. Upstream suppliers trust on the demand information (orders) from the downstream supplier and tend to lose track of the true demand pattern at the retailers end (Lee et al., 1997). In such a supply chain where information sharing is restricted it gives rise to the Burbridge 'Law of industrial dynamics' which can be stated as:

"If demand for products is transmitted along a series of inventories using stock control ordering, then the demand variation will increase with each transfer"

Price fluctuations result in specific buying behavior by customers. When the price is low and the difference between the 'low' and 'normal' price exceeds the inventory holding cost, customers tend to 'forward buy' products, they build up inventory until the price is normal again and then wait for it to deplete. In this scenario customers buy in quantities that do not reflect their immediate needs, as a result the customer's buying pattern does not reflect its consumption pattern, and the variation of the buying quantities is much bigger than the variation of the consumption rate, hence the bullwhip.

Specifically for a commodity plastic Stuijts (2014) investigated whether different players in the market speculate and/or anticipate on oil price fluctuations by buying large quantities when the price is expected to be low and sell when the price is high by setting their price slightly below the market price. The research confirms for the commodity stretch film that these players contribute to demand volatility perceived by the more upstream producer.

Lee et al. (1997) conclude that the bullwhip effect results from rational decision making by members in the supply chain. Companies can effectively counteract the effect by thoroughly understanding its underlying causes. Upstream demand amplification due to supply chain dynamics can be addressed by stabilizing demand, sharing sales forecasts, and shortening the production lead time (Lee et al., 1997).

Ration gaming and order batching are the two other factors responsible for the bullwhip effect. Ration gaming refers to a situation where there is a supply shortage, in this situation customers have to bid on limited supply each one ordering more than they actually need hoping that they will receive more. Order batching is a result of non-zero ordering cost, a result is that ordering equal to incoming demand would be uneconomical. In both situation the suppliers lose track of the end demand, which is inherent to the demand signaling problem, and trigger a bullwhip.

2.4 Modeling approach

Traditional statistical demand forecasting techniques are based on the statistical relations within or between time-series. A time-series is a collection of observations made sequentially through time (Chatfield, 2000). In time-series analysis the main focus is on finding the main properties of the historical output data. Based on the autocorrelation within historical demand data a stochastic process is selected that adequately captures the underlying structure of the times-series. Subsequently, the parameters of this model are estimated and the model is used to extrapolate the historical values into forecasts.

In situations such as the 2008 credit crisis the dynamics are such that the statistical relation within the time-series of historical demand is not representative for future values (Peels et al., 2009). A commodity demand forecast based on traditional statistical forecasting methods (time-series analysis) would therefore not be reliable and incorporating supply chain data in demand forecasting would be a considerable improvement. In line with Peels et al. (2011), Udenio et al. (2014) showed that the perceived demand volatility at the upstream producers is affected by every action and strategic decision taken by companies further downstream in the supply chain.

For a forecasting model to be able to incorporate supply chain dynamics it has to be able to link the different echelons in a supply chain as a series of processes in which specific decisions are made. Both system dynamics models (SD) and discrete event simulation (DES) models are tools able to do this.

However DES models rely on the historical and statistical relations between processes, these do not capture the dynamic relation between price and upstream demand. This dynamic relation is influenced by (delayed) inventory policy updates of the traders and the producers' ability to supply. Moreover Disney et al. (2006) argue that differential equations, the mathematical fundament of System Dynamics, in combination with continuous time are more suitable to analyze such general oscillation behavior of a supply chain, described by the bullwhip.

2.5 System dynamics

The concept of System Dynamics, initially called 'Industrial Dynamics', was developed in the mid-1950s by Forrester (1958), the original definition is "the study of information feedback characterization of industrial enterprise to show how structure, amplification, and time delays interact to influence the success of the enterprise". It takes rational decision making into account as it is a framework for thinking about how the operating policies of a company and its customers, competitors, and suppliers interact to shape the company's performance over time (Lai et al, 2003, p. 266) and is the preferred methodology to replicate and understand the dynamic behavior of complex systems. In a review paper Riddalls et al. (2000) attribute that dynamic simulation gives better insight into strategic and global behavior of supply chains than traditional operations research techniques focusing on tactical control and optimization.

2.6 Commodity pricing

Micro economic theory describes commodity products in a competitive market. Figure 5 shows how the market price (p^*), and sold market quantity (q^*), are a result of the industry demand (D) and the industry supply (S). Industry demand for a commodity is based on the amount of money a customer can spend, the budget. If the price (p) of a product is higher than the customers can buy less quantities due to the budget restriction. This results in the decreasing nature of the demand function. Moreover the industry demand can be seen as the sum of the individual consumer demand (Pindick, Rubinfield, 2014), which is depicted in figure 5.

Another important concept concerning demand is the utility of a commodity to the consumer. A fundamental property results from the intuitive expectation that a consumer gets more satisfaction by consuming greater quantities of a commodity. This forms the concept of marginal utility which represents the change of satisfaction due to a change in consumed quantity. Another property of marginal utility is diminishing marginal utility: consuming larger and larger quantities yields in less and less marginal utility. The measurable consequence of utility is the price that a consumer is willing to pay for a certain commodity. So given the finite budget of a consumer, the preferences of said consumer are reflected in the allocation of resources by the consumer (Baaquie, 2013).

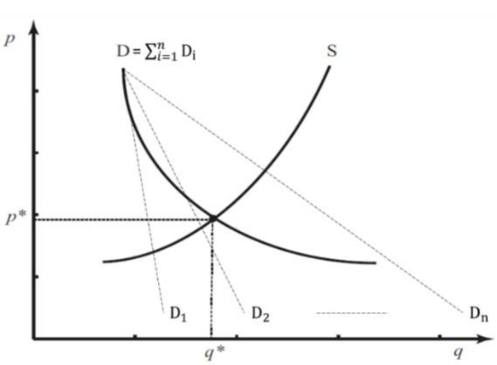


Figure 5 *Market equilibrium and separation of market demand in customer demand*

The supply function depends on the prices of commodities, and determines the quantity of a commodity that producers are willing and able to sell for a given price (Baaquie, 2013). This results in the supply function being increasing of nature since the higher the prices, the more is the producer of a commodity willing to supply the said commodity. The same as with the industry demand, industry supply can be seen as the sum of all individual firm supply in the market.

3. Research questions & methodology

Section 3.1 defines the research questions which relate to the problem statement and literature described in the previous chapters. Section 3.2 concludes the chapter with a description of the research methodology used to answer the research questions.

3.1 Research questions

The aim of this project is to improve SABIC's S&OP process by making it more financially driven. The research is split up into two parts: the analysis and modeling of industry demand using system dynamics, and the analysis and modeling of firm demand using regression analyses. The findings of these models are then combined and a non-linear optimization problem is constructed to provide financially optimized S&OP input.

The literature review mentioned the upstream demand volatility is caused by several factors, demand signal processing and price dynamics are the factors previously researched and will be applied in this thesis as well. Stuijts (2014) developed a system dynamics model at SABIC based on the work of Udenio (2014) to forecast the industry demand of LLDPE stretch film. According to this research, traders seem to play a big role in upstream demand volatility for plastic film products (Stuijts, 2014) and expert interviews also confirm the role of traders in the PP pipe industry. This leads to the first research question of the thesis:

> *A) Can the current system dynamics model at SABIC be adjusted to predict the industry demand volatility of PP pipe products, and to what extend are price dynamics influencing trader (de)stocking behavior?*

In order for SABIC to be make financially driven decision in their S&OP it is necessary to know how different factors influence the demand arriving at the firm. Commodity literature outlined that the market price is a result of the industry demand and industry supply, but the effect of price setting different from the market price is unknown. Next to the price, customers react to the industry supply and will consequently also react to SABIC's position in the industry since they are part of it. It is therefore interesting to know how the subset of customers ordering at SABIC reacts to SABIC supply position and their price setting. This leads to the second and third research question:

> *B) How is SABIC supply position influencing demand arriving at SABIC?*
>
> *C) What is the relation between price-setting and the demand at SABIC?*

The findings from research question A, B and C can be used to construct a model which describes the demand arriving at SABIC given their position in the market and how they set their price. The outcomes of the analysis are used to build a joint model of the industry demand and firm demand drivers in order to improve financial decision making. Specifically the model can be used in a monthly Sales & Operations Planning process to make 1 to 3 month predictions on demand, supply and stock levels. This demand forecast is 'unconstrained' and made up by market influences and expected choices.

3.2 Methodology

The above described research questions can be described as descriptive empirical research as it is primarily interested in creating a model that adequately describes the causal relationships that may exist in reality, which leads to understanding of the processes going on (Bertrand & Fransoo 2002).

According to Bertrand & Fransoo (2002) this kind of operations management research can be positioned within the research model by Mitroff, Betz, Pondy and Sagasti (1974) which is displayed in figure 6. It will therefore be used as a framework for answering the research questions defined in the previous chapter. As the work is based on two conceptually independent models, the framework by Mitroff et al. will be applied twice:

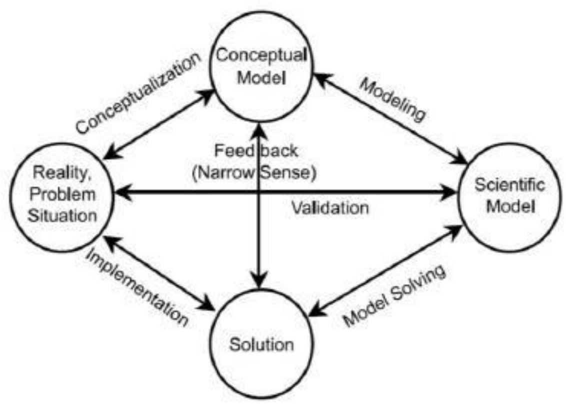


Figure 6 *Research framework by Mittrof et al (1974)*

1. Conceptualization
   - Understand the function, purpose and behavior of the investigated supply chain.
   - Identify variables that are relevant for the modeling phase, based on historical data and semi-structured interviews with experts.

2. Modeling
   - Determine the modeling approach based on the causal relationship between the variables.
   - Determine the appropriate level of detail based on data availability.
   - Build the model in a system dynamics program.
   - Build the model in a regression program.

3. Model solving
   - Application of the model on real-life data from 2008-2014.
   - Thorough analyses of outcomes

4. Implementation
   - Combine results of both models into one model fit for implementation in the S&OP.
   - Evaluate the results of the model compared to the current used planning method.
   - Investigate the implementation potential of the final model for product groups.

4. Factors influencing industry demand - supply chain dynamics

The goal of this chapter is to develop a system dynamics model of the downstream supply chain of PP pipe products in order to answer research question A. The model captures most of the bullwhip effect explained in section 2.3, and clearly present in this market as can be seen in figure 1 in section 1. Section 4.1 describes the structure of a single echelon model. Next in section 4.2 several single echelons are linked to each other representing the full supply chain. In this section also the parameterization of the model, trader and customer buying behavior, and model results are discussed. Finally the chapter end with conclusions.

4.1 Single echelon model

The current supply chain model is an extension of the single echelon supply chain model by Udenio et al. (2013). This model is based on Sterman's managerial decision making supply chain model and has been successful in describing volume flows in the process industry. The model consists of three areas (figure 7): the forecasting and orders area which keeps track of incoming customer orders, maintains the sales forecast and generates material orders. The production area which regulates production and Work-In-Process (WIP) and finished goods inventories, and a delivery area which keeps track of customer deliveries and backlogs. The model assumes no lost sales and is based on continuous time system dynamics simulations.

Because the model consist of several echelons which are connected with each other through deliveries in the production sector from an echelon to the echelon that comes immediately downstream in its supply chain, and incoming orders in the forecasting and order sector parameters and variables are subscripted with an index n with $n \in [1:N]$, 1 being the most downstream echelon (end market), and N being the most upstream echelon, in this case the polymer producers. A list of all parameters, and source of parameter values can be found in table 2.

4.1.1 Forecasting and orders

The forecasting sector maintains a sales forecast by accumulating the differences between the incoming customer demand (O_{n-1}) and the previous forecast (F_n). When demand exceeds the forecast it is updated upwards and the other way around when demand is less than the forecast it is updated downwards. To allow for a smoothing of the forecast, the differences are divided by the forecast adjustment time ($\tau_n(F)$), indicating whether the whole difference or only a fraction is taken into account.

$$\frac{d}{dt}F_n = \frac{O_{n-1} - F_n}{\tau_n(F)} \tag{4.1}$$

At some echelons the supply chain diverges and there are multiple echelons that send their demands. In this case the incoming demand from echelons downstream needs to be normalised by a splitting factor ($\theta_{n,m}$) because the model is calibrated against normalised data as well. The m^{th} order volume of the downstream echelons is multiplied by the m^{th} split factor to calculate the total demand for the echelon. All product split values of one echelon should sum up to 1.

$$O_{n-1} = \sum_m \theta_{n,m} * O_{n-1,m} \qquad \forall \text{n} \quad \sum_m \theta_{n,m} = 1 \tag{4.2}$$

Adjustment orders are generated to close the gap between the actual values of on-hand and supply line inventories and the desired levels. The inventory adjustment time ($\tau_n(S)$), work in process (WIP) adjustment time ($\tau_n(W)$), and supply line adjustment time ($\tau_n(SL)$) represent the time allowed for the inventories to reach the desired levels. They model the behavioral aspect of the order generation; short adjusting times imply nervous buying behavior while long times are equivalent to a smooth ordering strategy.

The outputs of these adjustments can be seen as individual orders. Note that these individual orders can become negative while the minimum order size is zero. The total generated orders (O_n) of an echelon is the sum of the forecast and the adjustments in supply line, inventory, and work in process (WIP).

$$O_n = max\ \{0, F_n + O_n(S) + O_n(W) + O_n(SL)\} \tag{4.3}$$

Material orders are based on an anchor and adjustment heuristic (Tversky & Kahneman, 1974): the sales forecast acts as the anchor, with the adjustment stemming from the difference between actual and target stock, production and supply line levels. The desired inventory level $\hat{S}_n$ is a product of the forecast F_n and the desired inventory coverage $\hat{C}_n$. The current stock level S_n is compared to the desired inventory coverage and the difference is expressed in the inventory adjustment $O_n(S)$.

$$\hat{S}_n = F_n * \hat{C}_n \tag{4.4}$$

$$O_n(S) = \frac{\hat{S}_n - S_n}{\tau_n(S)} \tag{4.5}$$

The desired supply line $\widehat{SL}_n$ consist of the multiplication of the current forecast F_n and the total lead time L_n, the time that it takes to produce and ship one unit of product from the upstream echelon *n* – 1. The desired supply line value is compared to the actual supply line value and the difference is expressed in the supply line adjustment $O_n(SL)$.

$$\widehat{SL}_n = F_n * L_n \tag{4.6}$$

$$O_n(SL) = \frac{\widehat{SL}_n - SL_n}{\tau_n(SL)} \tag{4.7}$$

In a similar manner as supply line and inventory adjustment, the work in process (WIP) adjustment $O_n(W)$ is modeled. The desired work in process stock $\widehat{W}_n$ is the product of the forecast F_n and production time $\tau_n(P)$. The lead time of the supplying echelon is not taken into account for WIP considerations due to continuous production. To calculate the work in process adjustment $O_n(W)$ the difference between the desired and actual work in process W_n is divided by the adjustment time $\tau_n(W)$.

$$\widehat{W}_n = F_n * \tau_n(P) \tag{4.8}$$

$$O_n(W) = \frac{\widehat{W}_n - W_n}{\tau_n(W)} \tag{4.9}$$

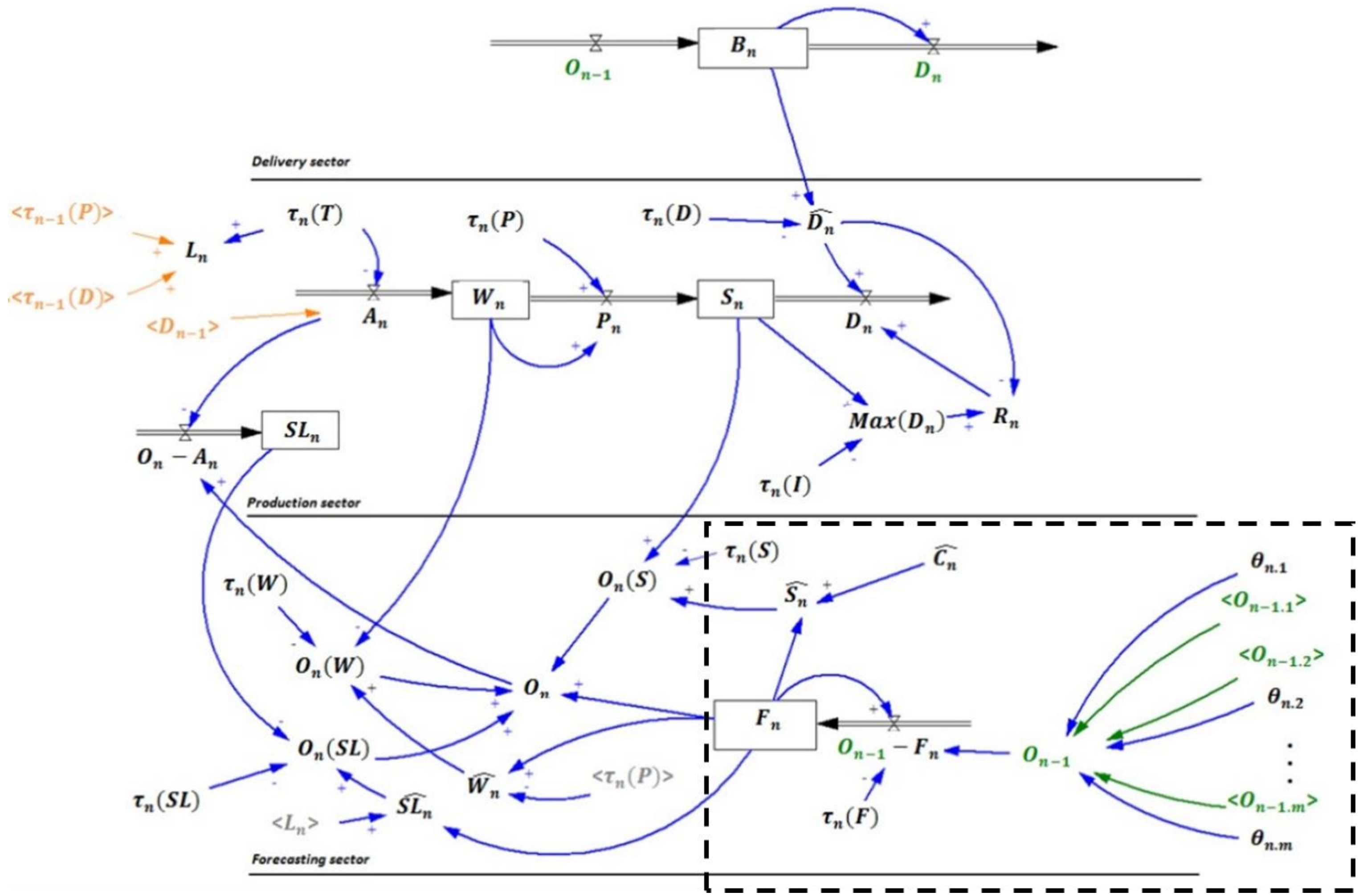


Figure 7 *Single Echelon Model structure: the model consist of a delivery sector where incoming and fulfilled orders are handled, a production sector models the material flow through the echelon, and the forecasting sector which maintains the sales forecast. The area in the dotted box differs in the trader echelon.*

4.1.2 Production

To implement the lead time of incoming products from the upstream echelon n+1 we follow Brandstädter (2013) who states that including production and delivery delay in the total lead time better reflects upstream reality. L_n represents the total lead time of incoming product from the upstream echelon and is the sum of the production time $\tau_{n+1}(P)$, the delivery delay of the product $\tau_{n+1}(D)$, and the transport time $\tau_n(T)$ to ship it from the producing echelon n+1 to the receiving echelon n.

$$L_n = \tau_{n+1}(P) + \tau_{n+1}(D) + \tau_n(T) \tag{4.10}$$

The production sector models the flow of material through the echelon. The incoming material rate A_n is equal to the delivery rate of the immediately upstream echelon D_{n+1} plus a fixed delivery delay of transportation time $\tau_n(T)$.

$$A_n = D_{n+1} + \tau_n(T) \tag{4.11}$$

The supply line rate is the cumulative difference between orders placed and orders received.

$$\frac{d}{dt} SL_n = O_n - A_n \tag{4.12}$$

Incoming material is stored as work in process W_n which rate is modeled as the difference between the arriving product rate A_n and the production rate P_n. It represents the materials which is currently in production and is initialized with the desired work in process $\widehat{W_n}$.

$$\frac{d}{dt} W_n = A_n - P_n \tag{4.13}$$

The production rate P_n describes the production output of echelon *n* and is only based on the size of the WIP stock W_n and the fixed production time $\tau_n(P)$. In this production model is assumed that manufacturing time is independent of the utilization rate. Besides, is assumed that there are no capacity limitations.

$$P_n = \frac{W_n}{\tau_n(P)} \tag{4.14}$$

The inventory of echelon *n*, S_n, represents the finished goods (FG) inventory and its rate depends on the delivery rate (D_n) and the production rate (P_n). It is initialized with the desired inventory level $\hat{S}_n$.

$$\frac{d}{dt} S_n = P_n - D_n \tag{4.15}$$

4.1.3 Delivery

In the delivery sector incoming and fulfilled orders are handled. A backlog, to keep track of orders, is calculated as the cumulative difference between the incoming customer order rate (O_{n-1}) and the actual delivery rate (D_n). It is initialized with a multiplication of the incoming customer order rate and the delivery time. There only exists a backlog if demand cannot be met.

$$\frac{d}{dt} B_n = O_{n-1} - D_n \tag{4.16}$$

The order delivery rate D_n is the rate of product that is actually shipped out in response to the incoming customer orders. To calculate D_n, we first define the desired delivery rate $\widehat{D}_n$, which is equal to the current backlog divided by the expected delivery delay $\tau_n(D)$,

$$\widehat{D}_n = \frac{B_n}{\tau_n(D)}. \tag{4.17}$$

The maximum delivery rate of echelon *n,* $\max(D)_n$ depends on the ability of the company to physically prepare the products for shipment and is modeled as the minimum time to fill orders $\tau_n(I)$.

$$max(D)_n = \frac{S_n}{\tau_n(I)} \tag{4.18}$$

The delivery ratio (R_n) is calculated as the proportion of outstanding orders that can be shipped from stock.

$$R_n = \min\left\{1, \frac{max(D)_n}{\widehat{D}_n}\right\} \tag{4.19}$$

Finally, the actual delivery rate is equal to the desired delivery rate $\widehat{D}_n$ multiplied by the delivery ratio R_n. If the stock level is too low to satisfy all orders immediately the actual delivery rate is smaller than desired. If there is sufficient stock to satisfy all demand the actual delivery rate D_n will be equal to the desired delivery rate.

$$D_n = \widehat{D}_n * R_n \tag{4.20}$$

Alternatively, equations 17 to 20 can be combined and the order fulfilment rate can be defined as:

$$D_n = \min\left\{\frac{B_n}{\tau_n(D)}, \frac{S_n}{\tau_n(I)}\right\}. \tag{4.21}$$

4.1.4 Trader behavior

Traders act as third parties in a supply chain by buying material from echelon n when the expectation of the price is low and selling the same material to echelon n-1 when the expectation of the price is high (Stuijts, 2014). This is modeled by introducing a second exogenous input into the model namely: price. It is based on the forward buying principle introduced in chapter 2: traders increase their desired inventory level (buy) when the price is expected to be low compared to the normal price, and decrease their desired inventory (sell) when the price is high compared to the normal price.

Traders are added into the model as a new echelon (n=4, see section 4.2) that is in between two existing ones. Their buying behavior is incorporated in the model by adding a speculation factor (*SF*) to formula (4.4):

$$\hat{S}_4 = (\hat{C}_4 * SF) * F_4 = \widehat{C_{adjusted}} * F_4 \tag{4.22}$$

__Table 1__ Speculation factors

$\frac{d}{dt}$**PRICE** \ $\left(\frac{d}{dt}\right)^2$ ***PRICE***	<	=	>
=	SF 1	SF else	SF 2
>	SF 3	SF else	SF 4
<	SF 5	SF else	SF 6

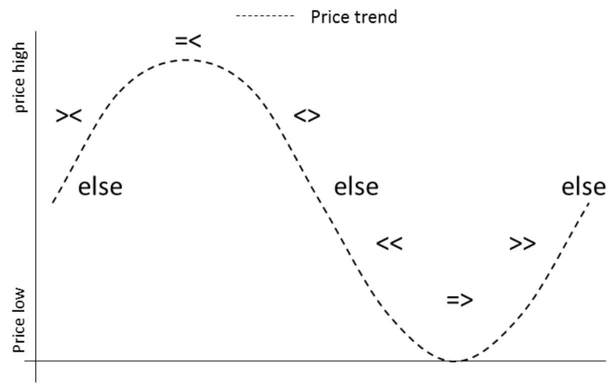


__Figure 8__ Relation between price and SF factors

The speculation factor is a variable based on the first and second derivative of price (Table 1). With the first and second derivative one can define whether the price reached a peak or a trough. Figure 8 shows how the speculation factors relate to the price trend. When the first derivative is zero (=) and the second is larger than zero (>) the price is in a through implying forward buying behavior and thus a high desired inventory coverage. When the first derivative is zero (=) and the second smaller than zero (<) the price is in a peak implying traders want to sell and thus lower their desired inventory coverage. Between a trough and a peak the price is continuously rising (>>, ><), traders are lowering their desired inventory because it is getting more attractive to sell. The opposite is expected to happen when the price is between a peak and a through, thus decreasing (<>, <<).

Traders are modeled as a whole new echelon with the same structure as in figure 7 only the area in the dotted box is adapted to figure 9.

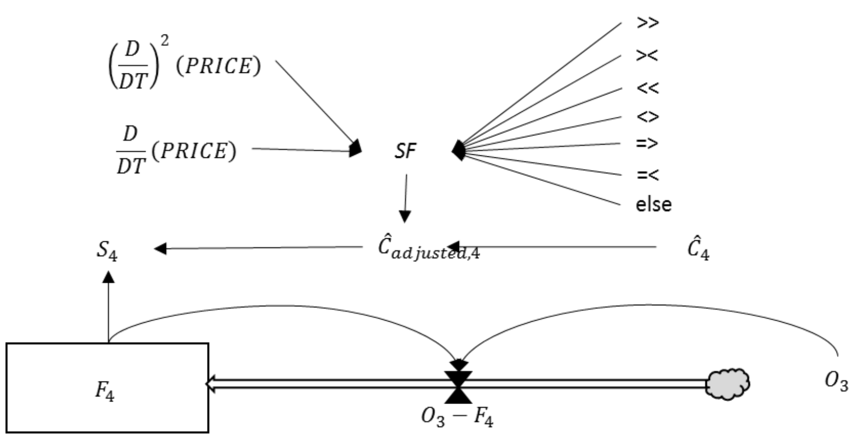


__Figure 9__ Trader extension

***Table 2** Model parameters*

Parameter	Description	Dimensions	Source
A_n	Product arrival rate of echelon n	Units/week	Endogenous
B_n	Backlog at echelon n	Units	Endogenous
D_n	Delivery rate of echelon n	Units/week	Endogenous
F_n	Sales forecast of echelon n	Units/week	Endogenous
L_n	Lead time of incoming products from echelon n+1	Weeks	Endogenous
O_n	Orders placed by echelon n	Units/week	Endogenous
P_n	Production rate of echelon n	Units/Week	Endogenous
S_n	Inventory of echelon n	Units	Endogenous
SL_n	Supply line of echelon n	Units	Endogenous
R_n	Delivery ratio of echelon n	Dimensionless	Endogenous
W_n	Work in progress stock of echelon n	Units	Endogenous
$\theta_{n,m}$	Volume share of product which goes from echelon n to n-1, m	Dimensionless	Set based on interviews
$\widehat{D_n}$	Desired delivery rate of echelon n	Units/Weeks	Endogenous
$\widehat{S_n}$	Desired inventory level of echelon n	Units	Endogenous
$\widehat{SL_n}$	Supply line size of echelon n	Units	Endogenous
$\widehat{W_n}$	Desired work in progress level of echelon n	Units	Endogenous
$O_n(S)$	Inventory adjustment of echelon n	Units/week	Endogenous
$O_n(SL)$	Supply line adjustment of echelon n	Units/week	Endogenous
$O_n(W)$	Work in progress adjustment of echelon n	Units/week	Endogenous
$C_{\widehat{adjusted}}$	Desired inventory coverage of trader echelon	Weeks	Endogenous
$\widehat{C_n}$	Desired inventory coverage of echelon n	Weeks	Estimated to fit past data
$\tau_n(D)$	Delivery delay of echelon n	Weeks	Estimated to fit past data
$\tau_n(F)$	Forecast adjustment time of echelon n	Weeks	Estimated to fit past data
$\tau_n(I)$	Minimum time to fill orders	Weeks	Estimated to fit past data
$\tau_n(P)$	Production time of echelon n	Weeks	Estimated to fit past data
$\tau_n(S)$	Inventory adjustment time of echelon n	Weeks	Estimated to fit past data
$\tau_n(SL)$	Supply line adjustment time of echelon n	Weeks	Estimated to fit past data
$\tau_n(T)$	Transportation time of product from echelon n+1 to n	Weeks	Estimated to fit past data
$\tau_n(W)$	Work in progress adjustment time of echelon n	Weeks	Estimated to fit past data

4.2 Supply chain model

The supply chain model is constructed by connecting individual echelons creating two distinct flows (Udenio, 2013): an information flow that travels upstream (orders), and a material flow that travels downstream (deliveries). The information flow of the supply chain starts with the order of a finished product, end market demand, creating a demand signal, which travels through each echelon to the most upstream one. For this study four different echelons are connected as represented in figure 10. Only 10% of all material flows through the distributor echelon.

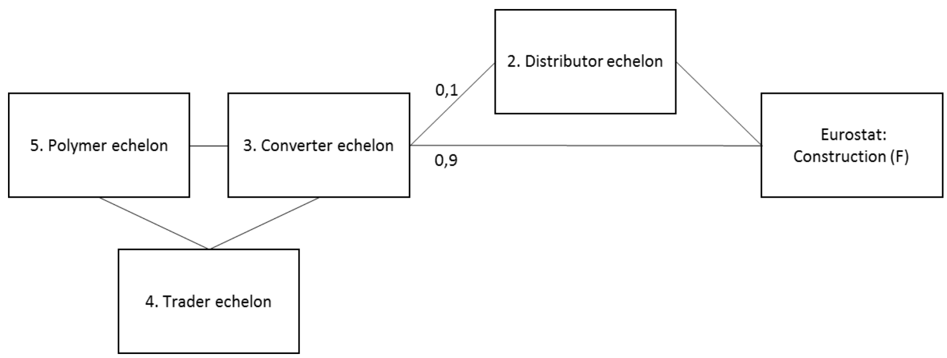


Figure 10 *supply chain structure*

4.2.1 Data collection

The model uses two exogenous time series as input: End market demand data, and price development data. Monthly EU27 sales data available in Eurostat is used as a proxy for end market demand. The series used for this study is the construction index. The data is normalized with the average of 2010 = 100. To achieve the desired granularity for the use of system dynamic software, due to the continuous time component, weekly data is estimated through a cubic spline interpolation. This implicates continues production, which is reasonable in the process industry.

As explained in section 3.1 trader influence is based on the first and second derivative of the price. The industry segment in this research is part of the polypropylene business and therefore monthly non normalized values for “POLYPROPYLENE ICIS LOW in Europe DOMESTIC FD EU” provided by ICIS are used. For the same reasoning as above weekly data is estimated through cubic spline interpolation, and hereafter derivatives are calculated.

4.2.2 Parameterization

Supply chain dynamics are captured by modeling the operational and behavioral parameters of each individual echelon. Operational parameters describe the daily operations of a firm (e.g. production times, target stocks etc.), while behavioral parameters are defined as the relationship between internal variables, implicit or explicit managerial decisions (e.g. inventory adjustment time etc.).

Both sets of parameters are estimated through full model calibration, and are presented in tables 3 and 4. Calibration is the process of estimating parameters to obtain a fit between modeled and observed behavior (Olivia, 2003). The upside of calibrating parameters is that it can be used as a validation test for the model structure, on the other hand calibration algorithms nowadays are so powerful that there is a chance that observed behavior is replicated through a set of unrealistic parameter combinations, and thus generate the right behavior for the wrong reasons. To minimize this chance parameters are calibrated within a boundary which is based on expert interviews, historical data, and/or literature reviews.

The calibration uses the EU27 end market demand data as input data and historical industry sales data as a proxy for upstream demand. The historical sales is a fraction of industry PP demand. Each year AMI consulting reports the amount of PP pipe demand in the market. This number is used to determine the fraction of PP pipe in the total PP market. This fraction is consequently applied to each month in the corresponding year, thus assuming that the fraction of PP pipe as part of the total PP demand is constant over a year. Furthermore the majority of big players in the industry report to AMI, indicating it is safe to use their data.

A time span of 13 months is used (see section 4.2.4), and the calibration is performed within the system dynamics software through a modified Powell-Brent algorithm (Brent, 2002). As in Udenio (2014) "the cumulative sum of squared errors between the estimated demand and the historical industry sales data is calculated per run and the combination of parameters that minimizes this error is then chosen." Formally, the minimization corresponds to:

$$\min_{Y} \sum_{t=1}^{k} (O_{(N-1)}(t) - \widetilde{D}_N(t))^2 \qquad (4.23)$$

Where *Y* is the set of calibration parameters, and $\widetilde{D}_N(t)$ is the historical sales data for time *t* at echelon *N* (the most upstream echelon).

Table 3 *Operational parameters*

Parameter	*value*	*lower*	*upper*	*Parameter*	*value*	*lower*	*upper*
$\tau_2(\mathrm{D})$	1.25	0.25	1.25	$\tau_4(\mathrm{D})$	0.75	0.75	1.25
$\tau_2(\mathrm{I})$	0.75	0.75	1.25	$\tau_4(\mathrm{I})$	0.75	0.75	1.25
$\tau_2(\mathrm{P})$	0.50	0.50	2.50	$\tau_4(\mathrm{P})$	0.02	0.00	2.50
$\tau_2(\mathrm{T})$	0.20	0.20	1.20	$\tau_4(\mathrm{T})$	0.20	0.20	1.20
$\widehat{\mathrm{C}_2}$	3.00	1.00	3.00	$\widehat{\mathrm{C}_4}$	12*	12	12
$\tau_3(\mathrm{D})$	0.75	0.75	1.25	$\tau_5(\mathrm{D})$	0.46	0.25	0.75
$\tau_3(\mathrm{I})$	0.88	0.75	1.25	$\tau_5(\mathrm{I})$	0.27	0.25	0.75
$\tau_3(\mathrm{P})$	1.55	1.50	2.50	$\tau_5(\mathrm{P})$	2.25	2.00	4.00
$\tau_{3,\mathrm{supplier}}(\mathrm{T})$	0.23	0.20	1.20	$\tau_5(\mathrm{T})$	1.25	0.75	1.25
$\tau_{3,\mathrm{trader}}(\mathrm{T})$	1.20	0.20	1.20	$\widehat{\mathrm{C}_5}$	6.00	3.00	6.00
$\widehat{\mathrm{C}_3}$	1.94	1.00	3.00				

Table 4 *Behavioral parameters*

Parameter	*value*	*lower*	*upper*	*Parameter*	*value*	*lower*	*upper*
$\tau_2(\mathrm{F})$	124.81	75.0	125	$\tau_4(\mathrm{F})$	75	75	125
$\tau_2(\mathrm{S})$	1.00	1.00	10.0	$\tau_4(\mathrm{S})$	8.27	1	10
$\tau_2(\mathrm{SL})$	1249.99	750	1250	$\tau_4(\mathrm{SL})$	21.88	5.00	25.0
$\tau_2(\mathrm{W})$	250.11	250	750	$\tau_4(\mathrm{W})$	544.66	250	750
$\tau_3(\mathrm{F})$	82.58	75.0	125	$\tau_5(\mathrm{F})$	5.00	5.00	15.0
$\tau_3(\mathrm{S})$	5.00	5.00	15.0	$\tau_5(\mathrm{S})$	5.00	5.00	15.0
$\tau_3(\mathrm{SL})$	1033.72	750	1250	$\tau_5(\mathrm{SL})$	1249.96	750	1250
$\tau_3(\mathrm{W})$	1230.68	750	1250	$\tau_5(\mathrm{W})$	1248.82	750	1250

Table 3 shows the calibrated operational parameters. As can be seen some are calibrated on their boundary suggesting widening the boundaries would result in a better model fit. Since the boundaries in the system represent the realistic boundaries as given by interviews and/or literature these are not changed to see to what extent they improve the model fit. We checked the sensitivity of the model outcome to the change of the operational parameters that are calibrated on their boundary. The parameters are changed within their boundary to see if it will worsen the fit. Figures 11, and 12 in show that the model outcome is sensitive to changes in $\tau_{3,\mathrm{trader}}(\mathrm{T})$ and $\tau_3(\mathrm{D})$, it did not show large sensitivity to the other operational parameters. It shows we should be especially careful with the transportation time of the trader. Table 4 also shows values calibrated on their boundary, yet here it is more difficult to pinpoint whether the boundaries represent an absolute minimum or maximum. When the behavioral parameters are on their upper boundary and this boundary is already high there is no need to flex it. For example the supply line adjustment time of echelon 2 ($\tau_2(\mathrm{SL})$) already represents an adjustment time of 1250 weeks, which is already really smooth. Increasing this parameter would pose no change to the model outcomes, the same counts for the other parameters with large values ($\tau_5(\mathrm{SL})$; $\tau_5(\mathrm{W})$; $\tau_2(\mathrm{F})$; etc).

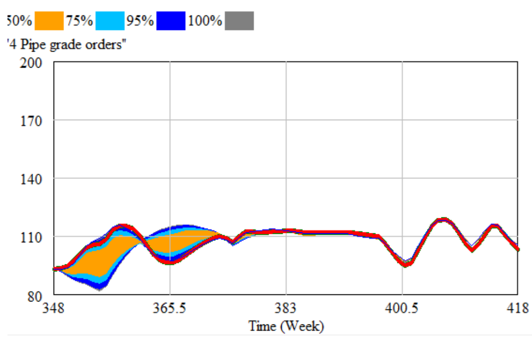


Figure 11 *Sensitivity graph* $\tau_{3.trader}(T)$

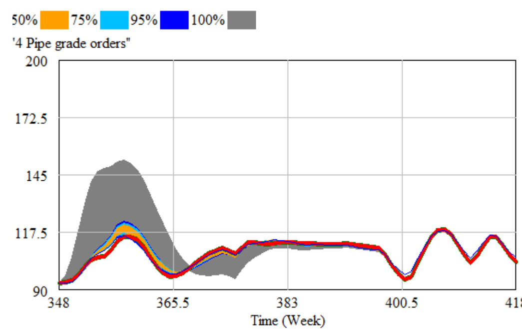


Figure 12 *Sensitivity graph* $\tau_3(D)$

Trader and speculation parameters are also calibrated to see if calibrated behavior matches expected behavior. A confirmation of this behavior will strengthen confidence in the model structure. The trader parameters represent the buying behavior of the converters. This is expected to be the opposite of the traders stocking behavior, which is represented by the speculation parameters. Recall that traders want to sell the majority of the product when the price is highest. They do this by selling the price just below the market price, hence converters buy from traders when the price is high and buy from the polymer supplier when the price is low. A high trader fraction means that converters buy more from traders than from the polymer suppliers. Expected values are in line with Stuijts (2014) and are based on expert interviews. These are shown together with the calibrated values in table 5 and figure 13.

Table 5 *Expected and calibrated trader fractions*

	Price Movement	***Expected***	***Calibrated***
Trader =<	*top*	*0.95*	*0.86*
Trader =>	*through*	*0.05*	*0.25*
Trader >>	*Increasing rise*	*0.25*	*0.00*
Trader ><	*Decreasing rise*	*0.65*	*1.00*
Trader <<	*Increasing decline*	*0.85*	*0.40*
Trader <>	*Decreasing decline*	*0.20*	*0.12*
Trader else	*inflection point*	*0.50*	*0.16*

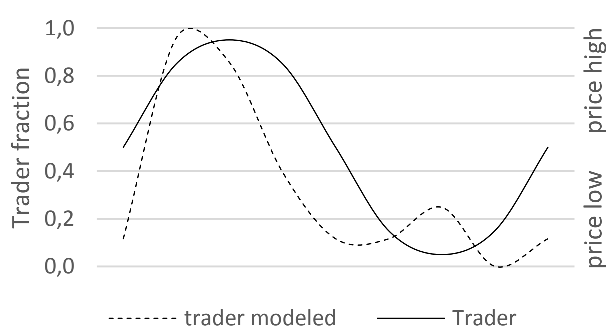


Figure 13 *Expected vs. calibrated trader fractions*

From these can be concluded that for the PP pipe segment converters seem to react very fast to the price changes. This implies that converters quickly buy from traders when the price is increasing, and when the price is declining they quickly switch back to buying from the polymer suppliers. A possible explanation is that converters want to minimize the risk of missing the top, and therefore show proactive buying behavior. When the price is declining they tend to stick to the suppliers, an explanation for this could be to keep the buyer-supplier relationship intact. In a make to stock environment suppliers sell their material when it is available, but also forecast on past buying behavior by customers. Converters might be afraid that they lose their 'credit' with the supplier if they buy too much from traders.

Table 6 and figure 14 show the expected value, which are the direct opposite of the trader fractions, and calibrated speculation fractions by which traders alter their desired stock position. The expected values for the trader stocking behavior are also based on expert interviews.

Table 6 *Expected and calibrated speculation fractions*

	Price Movement	*Expect.*	*Calibr.*
Speculation =<	*top*	*0.05*	*0.19*
Speculation =>	*through*	*0.95*	*0.65*
Speculation >>	*Increasing rise*	*0.65*	*0.52*
Speculation ><	*Decreasing rise*	*0.35*	*0.48*
Speculation <<	*Increasing decline*	*0.15*	*0.20*
Speculation <>	*Decreasing decline*	*0.80*	*0.66*
Speculation else	*inflection point*	*0.50*	*0.38*

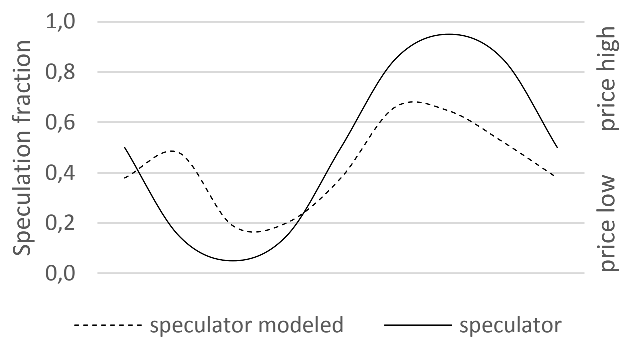


Figure 14 *Expected vs. calibrated speculation fractions*

Overall the traders follow expected movement: they increase their stock when the price is low and decrease (sell) when the price is high, only do no not buy and sell as much as expected. An explanation is that traders are probably more risk averse than expected. Though less money can be made this way, their risk of having too much or too few material is lower. Overall the behavior of the converters and traders is mostly in line with expectation and therefore strengthens confidence in the model.

4.2.3 Model robustness

In this section we assess whether the multiple echelon supply chain model is correctly derived from the single echelon model. We do this by performing a sensitivity analyses which checks whether it acts to changes to certain parameters as expected, while keeping others constant. The analyses is done by performing a Monte Carlo simulation with 2,000 runs changing the selected parameters within the set boundaries following a random uniform distribution. The confidence bounds in the figure show that the values of the simulation are within those bounds with the given confidence level, and the starting situation is given by the red line. Both figures 13 and 14 display the orders arriving at the polymer echelon. First is investigated how the industry demand level at the fifth echelon reacts to changes in the distributor fraction in the third echelon. We recall that only 10% percent of products flow through the distributor echelon, as it concerns a percentage of demand the boundaries are [0,1]. Expected is larger variability in upstream demand due to the larger amount of demand information traveling upstream in the chain (Lee et al., 1997). Figure 15 shows the upstream demand of pipe orders (echelon 5), as can be seen the confidence bounds show higher variability in the demand confirming the expected model behavior. This also shows that is very important to get the distributor fraction right as it has high influence on the outcomes of the model.

Second the change of forecast adjustment time of the fifth echelon on the industry demand level at the fifth echelon is investigated. Smaller adjustment times represent a faster and steeper reaction to changes in orders, thus is expected that decreasing this parameter will increase the amplitude of the tops and troughs, and fasten the response to changes in demand. The boundaries are set as [0,5] allowing to see an increase in variability at the peak and troughs since this parameter is calibrated at 5. Figure 16 again confirms expected behavior, furthermore increasing confidence in the model structure.

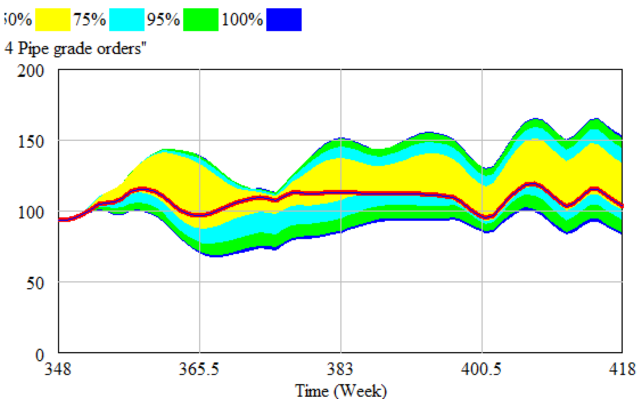


Figure 15 Sensitivity graph change in distributor fraction

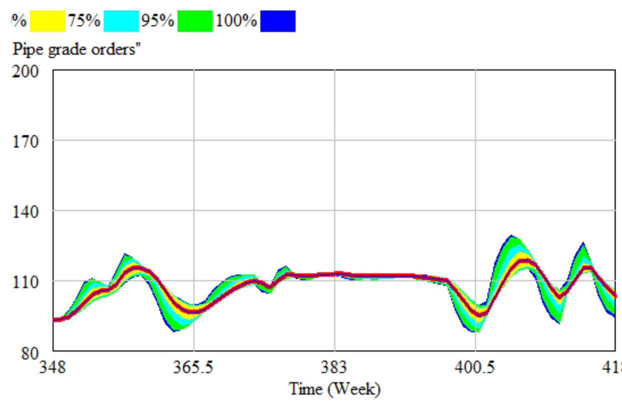


Figure 16 Sensitivity graph change in forecast adjustment time

4.2.4 Results and Validation

Calibration period & historical fit

Different calibration periods yield different model fits. To test which calibration period yields the best model fit it is calibrated using twelve different time spans and subsequently three months are forecasted. To statistically determine historical fit a selection of the appropriate summary statistics for evaluating the historical fit of system dynamics models by Sterman (1984) is used. The selection consists of the coefficient of determination (R^2) to assess the goodness of fit, Root mean square error (RMSE) to compare the different calibration horizons, and Theil's inequality statistics to determine the source of the error. Theil's inequality statistics decompose the mean squared error into three fractions representing: bias (U_m), variation component (U_s), and a correlation component (U_c). A low U_m indicates small deviation between the actual mean and model mean, a low U_s indicates a similar relation between variances, and thus a high U_c indicates a unsystematic error which is desired.

Theil's inequality statistics:

$$U_m = \frac{(\overline{X_m} - \overline{X_d})^2}{MSE} \tag{4.24}$$

$$U_s = \frac{(\sigma_m - \sigma_o)^2}{MSE} \tag{4.25}$$

Coefficient of determination:

$$R^2 = \left(\frac{1}{n}\sum \frac{(X_o - \overline{X_o})(X_m - \overline{X_m})}{\sigma_o \sigma_m}\right)^2 \tag{4.27}$$

Root mean squared error:

$U_c = \frac{2(1-\sqrt{R^2})\sigma_o\sigma_m}{MSE}$ (4.26) $RMSE = \sqrt{\frac{1}{n}\sum(X_m - X_o)^2}$ (4.28)

$With\ o = observed\ value, m = modeled\ value, and\ n = \#\ values$

Table 7 shows the statistics for the three month/thirteen week forecast given the calibration period of indicated months. Overall goodness of fit measures (R^2) are acceptable given the number of observations. The most desirable calibration horizon is thirteen months. Although it does not have the highest value of R^2 it beats the twelve and fifteen month calibration in terms of Theil's statistics, which indicate a more desirable unsystematic error in the modeled values. A 13 month calibration likely gives the best forecast because the cyclical behavior of the whole year is captured. This exercise also shows that a very small calibration period yields a very bad forecast indicating that the model needs sufficient memory to give a more accurate forecast.

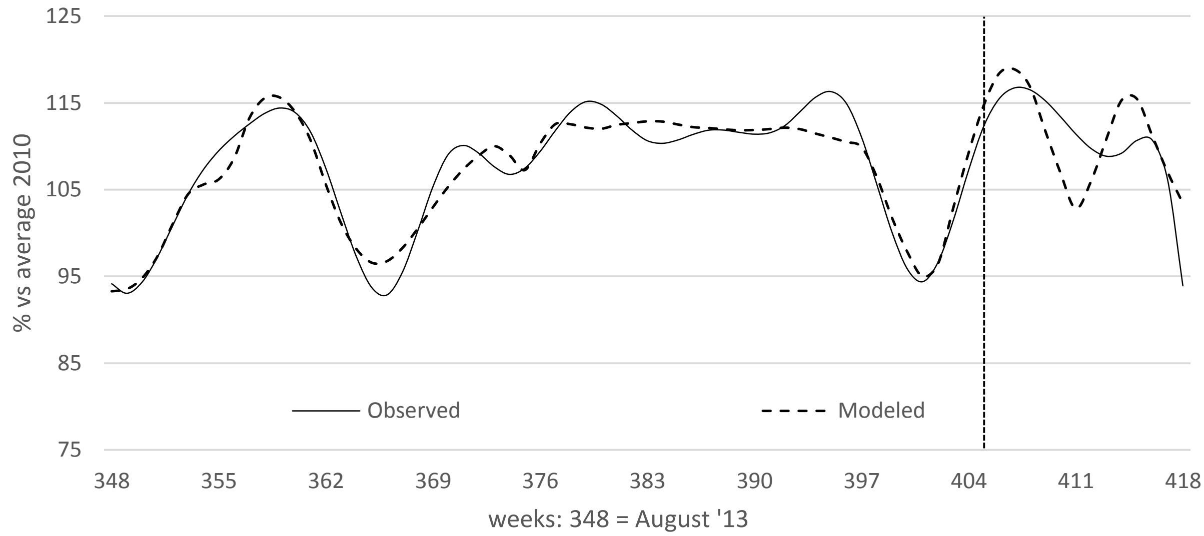
Table 7 *Statistics on calibration horizon*

Months	**24**	**20**	**16**	**15**	**14**	**13**	**12**	**11**	**10**	**8**	**6**	**4**
R^2	0,169	0,343	0,366	0,410	0,367	***0,383***	0,400	0,346	0,344	0,354	0,040	0,099
$RMSE$	5,261	4,719	5,029	4,630	4,922	***4,892***	5,036	6,025	6,108	5,945	20,909	5,575
U_m	0,001	0,001	0,087	0,087	0,126	***0,012***	0,063	0,072	0,288	0,192	0,792	0,035
U_s	0,488	0,130	0,545	0,208	0,142	***0,007***	0,001	0,033	0,001	0,003	0,022	0,589
U_c	0,511	0,869	0,368	0,704	0,732	***0,981***	0,937	0,895	0,711	0,804	0,186	0,376

Model output & validation

The model is calibrated with a calibration horizon from august 2013 (week 348) to September 2014 (week 404) and the last three months of 2014 are forecasted. The validation is done over the whole time horizon (August 2013-December 2014). Figure 17 shows the visual fit of the modeled on the historical output. The statistical fit of the model was measured over the full horizon (August 2013 – December 2014). Next to the clear visual fit, the model shows a relatively low RMSE value compared with Theil's statistics and a high value for the determination coefficient. Together with the previous sensitivity analyses and assessment of the trader parameters, these statistics give confidence that the model is valid and structurally sound. The supply chain model also performs well compared to previous models by Stuijts (2014), Brandstädter (2013), and Corbijn (2013) which respectively report a R^2 of 0.85, 0.83, and 0.67.

Although the model gives a good fit there are a few spots where it misses real behavior. This is around weeks 394, 411, 415. While the miss of week 394 is difficult to explain a possible explanation for weeks 411 and 415 is given by the low stock and forecast adjustment times of the fifth echelon. These show too fast and steep response to the respectively declining and rising trend in the demand. Parameters are calibrated to fit the whole horizon, and then set constant. The calibration includes the steep dips in demand around weeks 348, 366, and 400 for which probably tight adjustment times are required, while for the rest of the time horizon the variability is less severe and the adjustment parameters don't need to be as tight as calibrated.



	R^2	$RMSE$	U_m	U_s	U_c
Model	0,841	2,763	0,000	0,031	0,969

Figure 17 *Visual and statistical fit system dynamics model*

The demand troughs are around August and December which are respectively summer holidays and a very cold month in most European countries, in both these situation the pipe market experiences demand drops due to a hold in the construction market. The adjustment times are thus necessary to capture the seasonality present in the pipe market.

4.3 Conclusion

This chapter investigated how the variability of the upstream industry demand for polypropylene pipe was influenced by traders, and if a model could be built that could predict industry demand. The modeling process showed that adjusting the single echelon model to a multi echelon model including a trader echelon taken the pipe's supply chain into account resulted in a good fit. We notice that the trades acted less severely than expected but had considerable influence on demand variability. Next it is interesting to see that converters buy the majority of their material from traders just before the price goes into a peak, and also quickly switch back to supplier when the price is declining again.

The model performance over the second half of 2013 and 2014 indicated a R^2 of 84.1% and a low RMSE of 2.763. These together with Theil's inequality statistics which showed that the majority of the error is distributed in the covariance show that the model can be used to predict industry demand. Furthermore the model nicely captures the seasonal dips in demand.

Further elaboration and discussion of research question A can be found in chapter 8.

5. Factors influencing firm demand

This chapter describes the different factors influencing the demand arriving at SABIC. Section 5.1 discusses how the different concepts from the literature are applied to fit the research. In section 5.2 the data is discussed and section 5.3, 5.4, and 5.5 respectively discuss the analyses of short, balanced, and long market. For each of these market conditions the influence of SABIC's supply position and price setting on their market share is investigated. Finally section 5.6 will wrap up with a conclusion.

5.1 Supply position and price deviation

The concepts of demand and supply discussed in section 2.6 can be translated such that they are relevant for this research. Since SABIC is a player in the market their market share is represented by a subset of customers consuming their product. Each of these customers has a different utility for SABIC's product, which results in a different reaction to a certain asked price. Recall that for commodities the law of one price exists since the quality of the product is the same among players. Deviating from the market price would result in lower sales, but taking the utility of each customer in mind the effect deviating from the market price is expected not the same for every player in the market.

The supply is made out of the available inventory and production during a month. Since SABIC is a player in the market expected it is that customers will react to SABIC's supply position (SABIC's available supply as part of the supply available in the industry). Due to events like turnovers and temporary shut downs of production factories their part of the total industry supply is not always the same, this means that their position in the market will change.

The remainder of the chapter investigates how SABIC's supply position and price setting will affect their market share given the overall market setting trying to provide an answer for research questions B & C. The market is either set short when industry demand is greater than industry supply, balanced when industry demand and industry supply are about the same, and long when industry supply is greater than industry demand.

5.2 Data

Data is collected from FIDES on industry demand (equal to the historical sales in chapter 4.2.2), end month stock for PP and production for PP for EU27. To determine SABIC's market share and supply position, sales, production and end month stock for the grades that are dedicated to PP pipe are collected. Three variables were constructed from this: SABIC's market share (SABIC sales PP Pipe/Industry demand PP Pipe), inventory position (SABIC end month stock PP Pipe/Industry end month stock PP), and production position (SABIC production PP pipe/Industry production PP). We are thus assuming that industry PP pipe stock and production move with the industry stock and production of PP. Production in the process industry goes in production cycles, when the total production decreasing suppliers usually decrease in every batch. Because both production and demand of PP Pipe to a large extend move in line with production and demand of PP, the stocks of PP pipe will also move along stocks of PP. Hence these assumptions are reasonable.

To assess the influence of deviating from the market price the "POLYPROPYLENE ICIS LOW in Europe DOMESTIC FD EU" as proxy for the market price and SABIC's selling price are selected. ICIS is a firm which is continuously in contact with all the players in the market, the given price is thus a benchmark of the whole industry and since the market price can never be measured precisely the ICIS price is a reasonable proxy. Furthermore the market prices of all derivatives of PP follow and are close to the market price of PP, which makes the “POLYPROPYLENE ICIS LOW in Europe DOMESTIC FD EU” a suitable proxy for the PP pipe market price. The ‘price deviation’ variable is constructed by calculating the percentage difference between SABIC’s selling price and the market price.

To reduce the demand uncertainty SABIC, next to selling their product on the spot market, has contracts with some customers. These contracts are based on price and volume agreements, and because of these agreements this data will not represent a free moving market. The data has been split into sales that were made in the spot market and sales that were made in the contracted market. In terms of selling price this split was only available from 2009 on a monthly basis. Data is taken from 2009 to 2014 resulting in a sample size of 72.

Split into market conditions

To be able to assess how the different factors (position in the market, price deviation) affect SABIC’s market share the sample has to be split into different sub samples. Figure 18 shows a scatterplot with industry end month stock as a proxy for industry supply on the horizontal axis and industry demand on the vertical axis. Stocks represents the availability of product during the month, when end month stocks are high, stocks during the month are usually also high, and therefore it is a reasonable proxy. Points on the solid line represent a balanced market, points to the right of this line represent the long market where supply is higher than demand, and points to the left represent the short market where demand is greater than supply.

Recall that the process industry is a very capital expensive industry and production facilities are aimed to run as much as possible. This make-to-stock feature of the process industry makes the market in 46 of the cases long and in 26 of the cases short. Yet due to demand uncertainty players in the industry keep some degree of safety stock to diminish the chance of lost sales. We assume that the zone with a width of a standard deviation of the difference between supply and demand in the sample is considered a balanced market, see figure 18 for a visual representation. The balanced market thus represents a market where supply is greater than demand but this excess supply represent a safety stock margin which companies don’t want to deplete.

With this assumption the sample is divided as follows: 26 observations in the short market, 18 observations in the balanced market, and 28 observations in the long market.

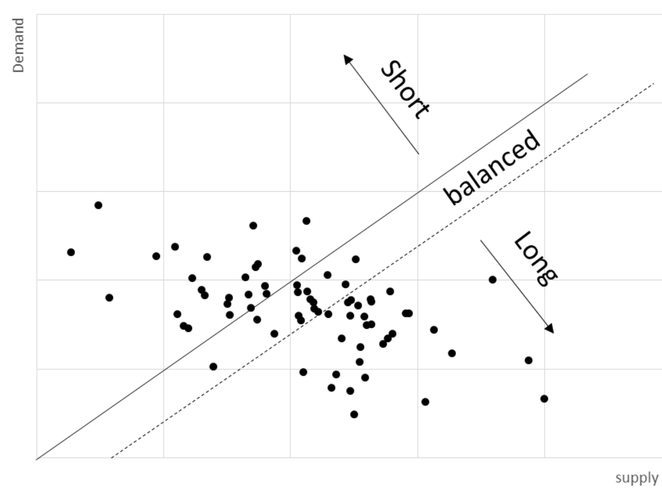


Figure 18 *market circumstances*

5.3 Short market

In a short market the demand for the commodities is higher than the supply. Having a strong inventory position in such a market means having a better capability to supply. When one can supply more than their competitors and there is an excess of demand we expect it leads to a higher market share. This leads to the first hypotheses:

S.1 There exists a significant positive relation between SABIC's inventory position and their market share in a short market.

The same analogy goes for the production position. When SABIC has a strong production positions it means that during the month on average they produced more than their competitors. Production goes into stocks, hence it adds availability to the market. We therefore expect that a stronger production position leads to a higher market share. The second hypotheses is drafted as follows:

S.2 There exists a positive relation between SABIC's production position and their market share in a short market.

SABIC, as every company in the industry, tries to maximize their margin. Since feedstock cost are the main component of their total cost, they try to keep the difference between their selling price and feedstock price as high as possible. Since a very large part of the cost price of PP Pipe consist of the feedstock, the market price of PP moves in line with the feedstock price. Price setting which does not follow this trend calls suspicion at the customer. Combining this with the fact that there is no real difference in product quality among suppliers, customers tend to move toward another supplier when the prices deviate too much from the market price. Yet in a short market we expect price sensitivity to be negligible since production at the customers also cannot stop. Expected is that an increase in price does not have any effect on their market share. We thus hypothesize that:

S.3 There exists no significant relation between deviating from the market price and SABIC's market share in a short market.

5.3.1 Analysis

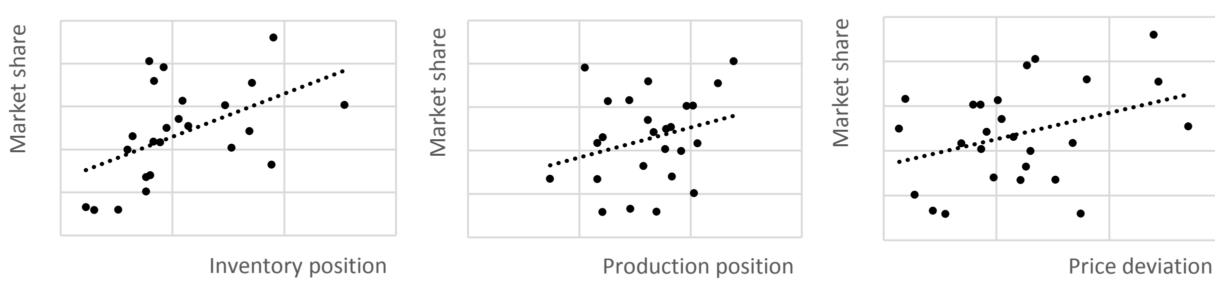


Figure 19 *Scatterplot of SABIC's market share vs. inventory position, production position and price deviation in a short market*

The scatterplots in figure 19 suggest a linear relation for inventory position and price deviation, but no linear relation between the production position and SABIC's market share seems to be present. For assessing the above hypothesis we use linear regression to test whether and to what extent inventory position, and price deviation have influence on SABIC's market share and a correlation analyses to check the influence of the production position. Linear regression relies on several assumptions which will be discussed during the analyses. One of them is the assumption of normal distributed data for small sample sizes. A sample size of 26 is considered to be small, and hence normality testing is required.

Inventory position

We first look into the data of the inventory position, firstly the data is checked for the presence of outliers as they might disproportionally influence the outcomes of the analyses. Standardized z-scores are calculated for each observation. Hair et al. (2009) recommend a cutoff point of 2.5 for samples smaller than 80, months with an absolute standardized z-score greater than 2.5 are denoted as outliers. For the inventory position variable 1 observation (-2.5) has an absolute z-score greater than 2.5, no clear explanation can be given why this was the case this month. The observation is removed from the sample and reduces the sample size to 25.

To test for normality we look at a normal probability plot and perform a goodness of fit test. The Kolmogorov-Smirnov and Shapiro-Wilk tests are the two most commonly used goodness-of-fit tests. The latter one is more appropriate for small sample sizes (n<50) (Hair et al., 2009), and will therefore be used in this analyses. The normal probability plot shows normality when the plotted points are on or really close to the linear line. Appendix I, figure I-1 shows the plot for the inventory position, from this can be seen that they point almost perfectly fit the linear line indicating that the sample is normal distributed. To confirm this a Shapiro-Wilk test is performed. It tests the null hypothesis that the actual distribution of the observed data is equal to the normal distribution. As the value of the Shapiro-Wilk statistic is not interpretable, the p-value is used to indicate how likely a normal distribution is (Hair et al., 2009). A significance level of 1% is recommended to avoid too strict rejections of normality. If the p-value is lower than the significance level, the null hypothesis is rejected. For the inventory position the Shapiro-Wilk statistic has a value of $W = 0.938$, with p-value = 0.187. Since 0.187>0.01 the null hypothesis is not rejected and we can conclude that the data is likely to be normally distributed.

The linear model constructed uses SABIC's market share (MS_i) as the dependent variable and inventory position (IP_i) as the independent variable The linear model to be fitted is as follows, where β_0 and β_1 are estimated through ordinary least squares:

$$MS_i = \beta_0 + \beta_1 * IP_i + \varepsilon_i \tag{5.1}$$

Two other assumption underlying linear regression are the absence of auto-correlation and the assumption of homoscedasticity. Auto correlation exists when the error term are not independent from each other, or in other words when the predicted values are not independent of each other. This can be tested with the Durbin-Watson test, where d is tested against its lower (d_L) and upper bound (d_U) which are dependent on the sample size.

$$d = \frac{\sum_{i=2}^{n}(\varepsilon_i - \varepsilon_{i-1})^2}{\sum_{i=1}^{n}(\varepsilon_i)^2} \tag{5.2}$$

If d<d_L it suggest there is autocorrelation, if d>d_U there is no sign of auto correlation and if d_L< d <d_U the test is inconclusive. For this regression d=1.063, d_L=1.055 and d_U=1.210. Hence d is between the lower and upper criterion. The test for significant autocorrelation is inconclusive, there might be some autocorrelation but since it is not at a significant level we continue the analyses. Homoscedasticity tells whether the variance of the residuals is equal among the regression line. This is checked by interpreting the scatterplot of standardized residuals and predicted values (Appendix I, figure I-2), indicating this is met.

The null hypothesis to be tested is whether β_1 is equal to zero, where the alternative hypothesis suggests it is not zero. The test statistic and rejection criterion are based on t-distribution. The value for estimated coefficient ($\widehat{\beta_1}$), t-statistic, and the p-value are generated by using the Excel data analyzer: $\widehat{\beta_1} = 1.111$; with t=2.400, and p-value=0.025. All values can also be found in table I-1, appendix I along with the remainder of the analysis. The null hypothesis is rejected for both a 10% and a 5% significance level and $\widehat{\beta_1}$ > 0, we can thus conclude that SABIC's inventory position has significant positive relation on their market share. This confirms hypothesis 5.1.

Production position

Interpreting the scatterplot of the production position in figure 19 there seems to be no linear relation between the operating position and SABIC's market share. We therefore first perform a correlation analyses to check whether there is any dependence between the two variables before going along with performing a linear regression. Pearson correlation is the most commonly used statistic to test for dependence, and is especially sensitive to linear relations. The correlation coefficient is computed as:

$$\rho_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{\frac{1}{n} * \sum_{i=1}^{n}((x_i - \bar{x}) * (y_i - \bar{y}))}{\sigma_x \sigma_y} \tag{5.3}$$

The correlation coefficient can range between [-1,1] with 1 indicating a perfect increasing linear relationship and -1 indicating a perfect decreasing linear relationship. When the coefficient is 0 it means there is no dependency between variables. To test whether the coefficient is significantly deviating from 0 we use a one tailed t-test, because we are looking for a unidirectional effect of SABIC's production position (*PrP*) on their market share. Where t is defined as:

$$t = \frac{\rho_{x,y}}{\sqrt{(1 - \rho_{x,y}2)/(n-2)}} \tag{5.4}$$

First we remove outliers from the sample using the same steps as before. One observation for the operating rate has an absolute z-score of 2.7, the production position was 2.9% of the industry average. No clear explanation can be given for the high value, so it is removed from the sample. We continue with a sample size of n=25. The correlation coefficient and t-statistic are calculated resulting in: $\rho_{PrP,MS} = 0.254$ and $t = 1.259$. The t statistic is significant with 95% confidence when it is greater than 1.708. Since 0.727 < 1.708 we conclude that there is no significant correlation between SABIC's production position and their market share, indicating that the two variables are independent of each other. We therefore reject hypothesis S.2.

Price deviation

Figure 19 suggest a linear relation between deviating from the market price and SABIC's market share. The same procedure as with the inventory position is followed to test hypothesis 5.3. None of the observations had an absolute standardized z-score greater than 2.5, so no outliers are present. Figure I-3, appendix I suggest the data is normal. The outcomes of the Shapiro-Wilk test are W=0.953 with a p-value=0.344, since 0.344>0.01 the null hypothesis, suggesting that the observed data is equal to the normal distribution, cannot be rejected and hence the assumption of normal distributed data can be maintained.

The following linear model is tested, and the outcomes of the analysis can be found in appendix I, table I-3

$$MS_i = \beta_0 + \beta_1 * PD_i + \varepsilon_i \tag{5.5}$$

The assumptions of auto-correlation and homoscedasticity are respectively checked with the Durbin-Watson test and the interpretation of the scatterplot of standardized residuals and predicted Y value. The Durbin-Watson test gives d=1.190 with a lower and upper limit of respectively 1.077 and 1.220, the test is again inconclusive and since it is not significant we continue the analyses. The scatterplot in appendix I, figure I-4 shows variances are equal amongst predictions, hence both assumptions are met.

The values for $\widehat{\beta_1}$, t-statistic, the p-value are respectively 0.587, 1.860 and 0.075. The null hypothesis that $\beta_1 = 0$ cannot be rejected with a 5% significance level but can be rejected with a 10% significance level. Depending on the desired confidence level we find partial support for the hypothesis S.3 but the positive relation in combination with the near significance of β_1 gives reason to further investigate this effect.

Interaction

A possible explanation could be that a strong inventory position in combination with higher prices leads to a higher market share. The reasoning behind this is when there is more demand than supply in the market and SABIC has a strong inventory position they know they can ask higher prices because the customers has only limited place to go to. This suggests a moderation effect of the inventory position on the relationship between price deviation and market share. To investigate this we introduce two different interaction effect:

1. Interaction between the inventory position and the price deviation (IP*PD), where both variables are kept continuous. Because a straight multiplication of IP and PD will likely result in multicollinearity (a high correlation of two or more independent variables), the variables IP and PD are first mean centered before they are multiplied.
2. Interaction between the inventory position and the price deviation (IP*PD), where IP is turned into a categorical variable with 0 when IP is low and 1 where IP is high. To distinct between low and high all variables which had a value greater than the mean are labeled high (1) and all below mean are consequently labeled low (0)

The multiple regression model which is investigated is the same for both interaction terms and is as follows:

$$MS_i = \beta_0 + \beta_1 * PD_i + \beta_2 * IP_i + \beta_3 * (PD * IP)_i + \varepsilon_i \tag{5.6}$$

Multiple regression analyses hold the same assumptions as simple linear regression only one also has to check for multicollinearity. This is checked by interpreting the Variance Inflation Factors (VIF) for each variable. According to Hair et al. (2009) a VIF > 5 indicates multicollinearity. The VIF for PD, IP, and IP*PD are respectively 1.469, 1.056, and 1.442 hence the assumption is maintained. The test for normal distributed data is the same as for the previous regressions and is therefore also maintained.

The regression outcomes of the interaction between two continuous variables are presented in table I-3 appendix I. To conclude whether there is any moderation the null hypothesis that β_3 is equal to zero has to be rejected we therefore look at the t-statistic and p-value of the interaction coefficient. The t-statistic = 0.314 with a corresponding p-value of 0.756, hence we cannot reject the null hypotheses. The regression outcomes of the interaction between PD and IP, where IP is categorical is presented in table I-4, appendix I. the values for the estimated coefficient $\widehat{\beta_3}$, t-statistic, and p-value of the interaction are respectively -0.03, -0.050, and 0.961, hence we can conclude that neither two interactions terms have any significant effect. We therefore conclude that there is no moderation of the inventory position on the relation between price deviation and the market share.

Multiple regression

Next to investigating the individual differences we investigate whether multiple factors can explain more variance in the model. We start with including all variables into the regression make use of the backwards elimination method to get to the final model. Insignificant variables are removed from the model until all remaining variable coefficients are significant. Since the production position did not show any linear relation with the market share it is excluded. All outliers from the variables are removed from the sample, therefore the regression will be performed with 25 observations. The regression model tested is as follows:

$$MS_i = \beta_0 + \beta_1 * PD_i + \beta_2 * IP_i + \varepsilon_i \qquad (5.7)$$

The VIF values for PD and IP are both 1.051 so the assumption of no multicollinearity is maintained. A look at the scatterplot between standardized residuals and predicted Y variables in figure I-6, appendix I shows that the residuals have equal variance amongst predictions, and hence the assumption of homoscedasticity is also maintained.

The regression outcomes can be found in appendix I, table I-4. Both $\widehat{\beta_1}$ (p-value = 0.073) and $\widehat{\beta_2}$ (p-value = 0.052) are significant with a significance level of 10%. Together the variables have an R^2 of 0.311, which means that together they explain 31.1% of the variance in the dependent variable.

5.3.2 Conclusion and interpretation

Table 8 gives a summary of the findings in the short market. The significant β_1 for the inventory position has a value of 1.111 this indicates that for every 100% increase of their Inventory position their market share will increase with 111.1%. The R^2 is 0.20 implies that 20% of the variance of the market share can be explained by the inventory position, this is a considerable amount since the model has only 1 predictor. Since hypothesis S.1 can be confirmed we can safely say that it is a considerable advantage of have ample stock when the market is short

Table 8 *Summary statistics short market*

	R^2	Adj. R^2	Sign. F	n	*i*	β_i	*t Stat*	*P-value*	*Corr.*	*p-value*	*Hypothesis?*
IP	0.200	0.166	0.025	25	0. Intercept	0.157	2.323	0.029			S.1: Confirm
					1. IP	1.111	2.401	0.025	N/A	N/A	
PrP	N/A	N/A	N/A	25		N/A	N/A	N/A			S.2: Reject
					PrP	N/A	N/A	N/A	0.254	1.259	
PD	0.126	0.090	0.075	26	0. Intercept	0.284	13.350	0.000			S.3: partly Confirm
					1. PD	0.587	1.860	0.075	N/A	N/A	
Mult.	0.311	0.248	0.017	25	0. Intercept	0.148	2.306	0.031			
					1. PD	0.585	1.880	0.073			
					2. IP	0.924	2.052	0.052	N/A	N/A	

No significant relation could be found between SABIC's production position and the market share. Because product is scarce in a short market, customers are eager to buy quickly. A possible explanation is that it is more important to have stocks in place so SABIC can react quickly to the needs of the customer and later on replenish inventory with production. A strong production position is than only contributes to a fast replenishment instead of extra sales.

The direct effect of deviating from the price has an almost significant effect on the market share in the positive direction. We expected to see a non-significant effect, so we investigated possible interaction effects. These proposed interaction effects between the inventory position and price deviation were non-significant, so we exclude the moderation effect of the inventory position on the relation between price deviation and market share as an explanation. Another likely explanation comes from a business management perspective. They constantly try to increase margin, especially in a short market they can push the limits since there is ample demand. When this price increase did not yield in loss of sales yet, the data will show a positive relation.

The multiple regression showed that including both the inventory position and the price deviating variable had more explanatory power than the variables separately. The magnitude of the effect of IP reduces in the joint model indicating that it still might be that price deviation and inventory position are in some way related to each other.

5.4 Balanced market

In a balanced market demand more or less equals supply, we expect the same relations as in the short market but to a lesser extent. A strong inventory position still enables a company to supply more than their competitors. When both supply and demand are in line, switching between suppliers might be difficult for customers because there is no excess supply. Yet our definition of a balanced market suggest that there is excess supply in the safety stock suggesting some room for customers to switch between suppliers. Suppliers are willing to supply and decrease in safety stock to some extend to increase sales. We hypothesize that having a stronger inventory position is still of significant positive relation yet the effect is less strong than in a short market:

B.1 There exists a positive relation between SABIC's inventory position and their market share in a balanced market, but the effect is less strong than in a short market.

The expectations regarding the production position are in line with those of the inventory position, we thus hypothesize that:

B.2 There exists a positive relation between SABIC's production position and their market share in a balanced market, but the effect is less strong than in a short market.

Because there is room for customers to switch between suppliers, deviating from the market price is expected to have more negative influence on sales. It is difficult to assess whether this effect is already significant in a balanced market since suppliers are still keen on keeping stock on optimal (safety stock) levels. Still when there is room to switch, customers are expected to seize that opportunity. We therefore hypothesize that deviating from the market price has a significant negative relation with SABIC's market share:

B.3 There exists a significant negative relation between deviating from the market price and SABIC's market share in a balanced market.

5.4.1 Analysis

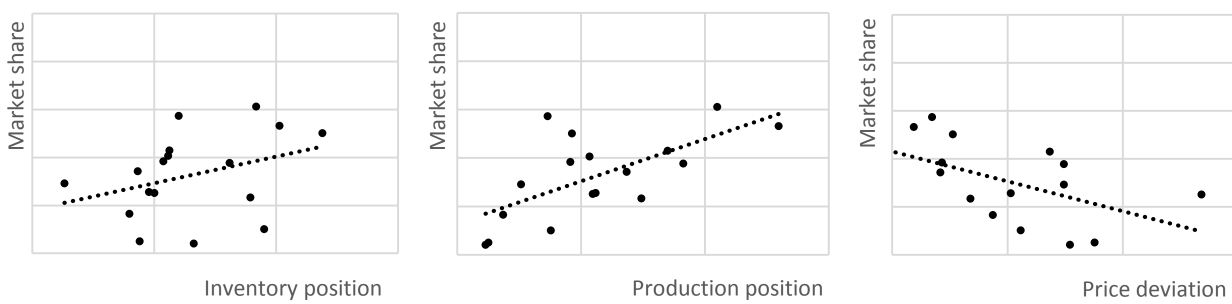


Figure 20 *Scatterplot of SABIC's market share vs. inventory position, production and price deviation in a balanced market*

The scatterplots in figure 20 suggest that all dependent variables have a linear relations with the market share. We therefore will perform a linear regression to test the possible effect and significance of the relations in order to reject of confirm hypothesis 5.4, 5.5, and 5.6. In this sample there seems to be an unnatural high value of the market share. Interpreting the z-scores confirms this, the observation has a z-score of 3.24 with a value for the market share of around 50%. The observation is the first month of 2009, the market was probably still in recess due the financial crisis, and somehow SABIC did not see a decline in their own sales yet. The observation can heavily interfere with the outcomes of the analysis and will therefore be removed from the sample. We continue the analyses with a sample size of n=17.

Inventory position

The z-scores for the inventory position are calculated and none of the observations has an absolute z-score greater than 2.5. No observation will be removed from the sample. The normality plot in Appendix II, figure II-1 suggest normal distributed data which is confirmed by the Shapiro-Wilk test (W=0.958; p-value=0.563).

The linear model to be tested is the same as formula (29) only now in the balanced market. The assumption of autocorrelation is not violated since d=1.18>1.102 which is the upper limit given a sample size of n=17. The interpretation of the scatterplot presented in appendix II, figure II-2 suggest there is no sign of heteroscedasticity, so we can conclude that the assumption regarding the residuals (error terms) are met.

The outcome of the analysis can be found in the table II-1, appendix II. The important statistics regarding hypothesis b.1 will be discussed. $\widehat{\beta_1} = 0.901$, t-statistic = 1.410 with a p-value of 0.179. This means that the null hypothesis suggesting that $\beta_1 = 0$ cannot be rejected for both a 5% and 10% significance level. We thus have to reject hypothesis B.1.

Production position

The assessment of outliers gave no z-score greater than 2.5, hence the normality test is run with 17 observations. The normal probability plot can be found in appendix II, figure II-3, the plot suggest normality. To test for significance again a Shapiro-Wilk test is executed, the results of the test are *W*=0.956 with a p-value of 0.545. With a significance of 0.01, the normality hypothesis cannot be rejected and such the assumption of normality is met.

The linear model that is tested has SABIC's market share (MS) as predictor variable and their production position (PrP) as independent variable:

$$MS_i = \beta_0 + \beta_1 * PrP_i + \varepsilon_i \tag{5.8}$$

The scatterplot of the standardized residuals vs. predicted Y, which can be found in appendix II, figure II-4, suggest that the variance among predicted values of equal and shows no seasonal pattern. The value for the Durbin-Watson test is d=1.610, and the lower and upper bound are 0.873 and 1.102. This indicated that both the assumption of homoscedasticity and auto-correlation are met.

The regression outcomes are presented in table II-2, appendix II. The estimated coefficient $\widehat{\beta_1}$ has a value of 0.871 and the corresponding t-statistic of 3.713 has a p-value of 0.002. Hence with a both a significance level of 10%, 5%, and 1% the null hypothesis that suggest that β_1 is zero is rejected. Since $\widehat{\beta_1}$ one is positive we can accept hypothesis B.2: '*There exists a positive relation between SABIC's production position and their market share in a balanced market, but the effect is less strong than in a short market'.*

Price deviation

When assessing there was no z-score above 2.5 of below -2.5, yet when we look at the scatterplot in figure II-5, appendix II there is clearly one observation deviation from the pattern suggested by the other observations. Hair et al. (2009) mentions that using standardized values to detect outliers will not always filter out all outliers. Also the opposite can happen when the z-scores suggest outliers when they are actually not. Yet given the first reason by Hair et al. and the clear deviation from the pattern the other observations suggest the observation with a value for price deviation = 0.124 and market share = 0.353 is removed from the sample. We continue the analyses with 16 observations. Given the normal probability plot presented in figure II-6, appendix II the data is normally distributed. This is confirmed by the outcomes of the Shapiro-Wilk test which gives a value W=0.962 and a corresponding p-value of 0.695.

The linear model which is tested is the same as formula 33 only now for a balanced market. The Durbin-Watson test has a value of 1.435 with a lower and upper bound of respectively 0.844 and 1.086, thus the assumption for autocorrelation is met. The assumption regarding equal variances of residuals can be confirmed looking at the scatterplot presented in figure II-7, appendix II.

The outcomes of the regression can be found in table II-3, appendix II. The estimated coefficient $\widehat{\beta_1}$ has a value of -0.623 and the corresponding t-statistic of 2.441 has a p-value of 0.029. Hence with a both a significance level of 10% and 5% the null hypothesis that suggest that β_1 is zero is rejected. Hence hypotheses B.3 is accepted.

Multiple regression

The same procedure as in the short market is followed. All variables IP, PrP, and PD are included resulting in the following regression model:

$$MS_i = \beta_0 + \beta_1 * IP_i + \beta_2 * PrP_i + \beta_3 * PD_i + \varepsilon_i \tag{5.9}$$

The Regression outcomes of the model can be found in table II-4 appendix II. The VIF value for IP is 1.257, for PrP 1.423, and for PD 1.231 hence there is no sign of multicollinearity. The regression outcomes can be found in table II-5, appendix II. The estimated beta of IP is insignificant (t-stat =-0.366, p-value= 0.720) and the variable is therefore removed from the regression. The new regression includes only PrP and PD and is given by formula 5.10, the outcomes can be found in table II-x, appendix II.

$$MS_i = \beta_0 + \beta_1 * PrP_i + \beta_2 * PD_i + \varepsilon_i \tag{5.10}$$

The interpretation the scatterplot in figure II-8 appendix II shows no pattern and such the assumption of homoscedasticity is maintained. The values for $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are respectively 0.627 and -0.477. Given the p-values for PrP (0.032) and PD (0.057) they are both significant at 10% significance and PrP is also significant at 5%. The variance explained in the dependent variable is 51.4% which is relatively high for a model with two independent variables and 16 observations/variable.

5.3.2 Conclusion and interpretation

Table 9 *Summary statistics balanced market*

	R^2	Adj. R^2	Sign. F	n	*i*	$\boldsymbol{\beta_i}$	*t Stat*	*P-value*	*Hypothesis?*
IP	0.117	0.058	0.179	17	0. Intercept	0.172	2.187	0.045	B.1: Reject
					1. IP	0.921	1.409	0.179	
PrP	0.479	0.444	0.002	17	0. Intercept	0.136	3.419	0.004	B.2: Confirm
					1. PrP	0.912	3.713	0.002	
PD	0.299	0.248	0.029	16	0. Intercept	0.308	19.985	0.000	B.3: Confirm
					1. PD	-0.623	-2.441	0.029	
Mult.	0.514	0.439	0.009	16	0. Intercept	0.205	4.548	0.001	
					1. PrP	0.627	2.400	0,032	
					2. PD	-0.477	-2.088	0.057	

Table 9 shows the summary statistics for the balanced market. Hypothesis B.1 could not be confirmed, indicating that there is no effect between the inventory position and the market share in the balanced market. We already expected a smaller effect, but still a significant one. Most likely we overestimated the effect of a strong inventory position, keeping stock around optimal and thus keeping safety stock levels healthy apparently outweighs the value of increased sales when the market is balanced.

Opposite to the short market we found a significant effect for the production position in the balanced market. Adding 100% to the production position increases sales with 91.2%, and the model explains 47.9% of the variation in the dependent variable. Although we expected an effect less strong than in the short market, we confirm hypothesis B.2. Hypothesis B.3 is also confirmed: there exists a highly significant negative relation between deviating from the price and the market share. The magnitude is such that deviation 100% from the market price results in a loss of 62.3% market share. Also the variance explained by the model is pretty high (29.9%).

It is interesting to see that in the balanced market a strong production position accounts for more sales while in the short market extra sales are accounted by a stronger stock position. It seems that when the demand is very high SABIC does not mind decreasing in stock, probably because they can ask a high price because they have the capability to supply. In the balanced market customers are already really sensitive to price changes, and suppliers seem to be keen on keeping safety stock levels healthy. Extra sales are thus only possible when the production is on average higher than the market.

5.5 Long market

In a long market supply exceeds demand so there is a lot of room for customers to switch between suppliers and to find the best deal among them. This means that a stronger inventory positions compared to competitors has no influence what so ever since everyone in the market has high inventories and wants to sell. We thus expect that the inventory position is of no significance in the long market:

L.1 There exists no significant relation between SABIC's inventory position and their market share in a long market.

A stronger production position in the long market implies that during the month on average SABIC produced more than their competitors while there is no demand for it. They likely end up not selling the product and increase their stock. We hypothesize that:

L.2 There exists no significant relation between SABIC's production position and their market share in a long market.

As mentioned above in a long market there is a lot of room for customers look for the best deal available. Too high stock positions are also not favorable for suppliers since there are considerable cost of keeping stock. This already drives the market price down, deviating from this price will likely have severe consequences in terms of sales since it is very easy for customers to switch between suppliers. We therefore hypothesize that:

L.3 There exists a significant negative relation between deviating from the market price and SABIC's market share in a long market, which is stronger than in a balanced market.

5.3.1 Analysis

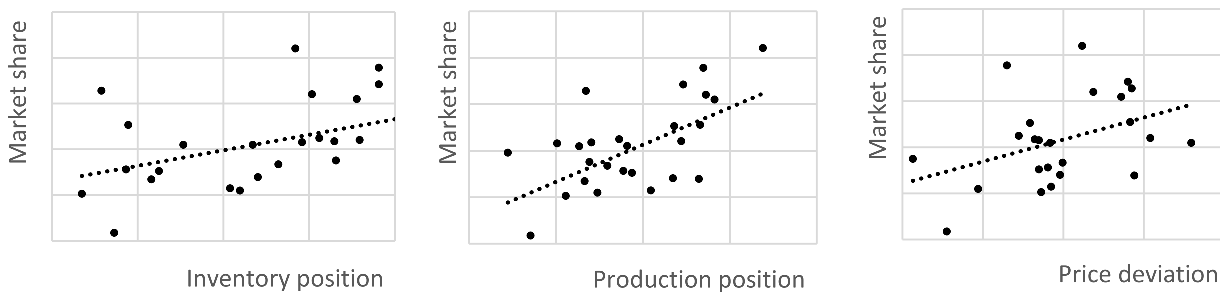


Figure 21 *Scatterplot of SABIC's market share vs. inventory position, production position and price deviation in a long market*

As in the data for the balanced market there is 1 observation in the long market which also has an extremely high market share (54%) probably due to the same reasons as described earlier. This observation is therefore removed from the sample, reducing the sample size to n=27. Furthermore all scatterplots in figure 21 suggest a possible linear relation. Therefore for all three the dependent variables a linear regression will be executed in order to assess the hypotheses L.1, L.2, and L.3.

Inventory position

First z-scores are calculated to make an assessment of the outliers. No observations had an absolute z-score greater than 2.5 so the sample size remains 27. Both the normal probability plot shown in figure III-1, appendix III and the Shapiro-Wilk test (W=0.955, p-value=0.371) indicate normal distributed data. The assumption that the dependent variable is normal distributed is thus met.

The linear model tested for the long market is the same as for the short and balanced market. An interpretation of the scatterplot in figure III-2 appendix III between the standardized residuals and predicted Y value indicates homoscedasticity and the Durbin-Watson test gives a value of d=1.741. The lower and upper bound for a sample size of n=27 are respectively 1.088 and 1.232. Since 1.741 > 1.232 there is no autocorrelation present. Hence both assumption regarding the residuals are met.

The outcomes of the analyses can be found in table III-1, appendix III. The statistic relevant to verify or reject the hypotheses are $\widehat{\beta_1} = 0.838$, t-statistic = 2.130 with a p-value of 0.043. This indicates that there is a positive relationship between SABIC's inventory position and their market share in the long market, which is against expectations. This might be explained by possible mediation through price deviation. A mediation effect entails that the independent variable is not directly influencing the dependent variable but is mediated through another variable, hence the independent variable is influencing the mediator which on its turn influences the dependent variable.

It could be that when SABIC has a strong inventory position they want to decrease in stock and try to achieve this by pushing sales into the market. A possible way to do this is by lowering the price of their product. Another possibility is that not the inventory position but the production position is responsible for the increase in market share. To investigate these the following mediation models in figure 22 and 23 are tested.

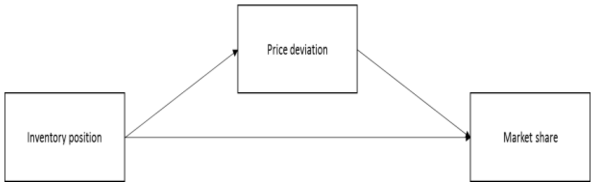


Figure 22 *Mediation model 1*

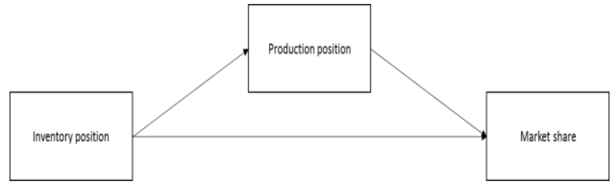


Figure 23 *Mediation model 2*

Baron and Kenny's (1986) steps for mediation are used to test for mediation. These consist of three steps, the first step is to regress the dependent variable on the independent variable to confirm that the independent variable is a significant predictor of the dependent variable. The second step is to regress the mediator on the independent variable to establish if there is any association of the mediator with the independent variable. If this is not the case the mediator could not possibly mediate anything (Baron, Kenny, 1986). The final step is to regress the dependent variable on both the independent variable and the mediator, when the effect (coefficient) of the independent variable decreases or becomes insignificant, one can confirm mediation.

First mediation model 1: Step 1 is already performed in the analyses of the inventory position above. Step 2 is done by performing a linear regression with price deviation as the dependent variable (mediator) and the inventory position as the independent variable. This regression output can be found in table III-2 appendix III. The test shows that the coefficient of the inventory position ($\widehat{\beta_1}$) is highly insignificant (t-statistic=0.256, p-value=0.801), we can thus abort the test at step 2 concluding that there is no mediation effect between the inventory position and their market share by SABIC's price setting.

Second the mediation of production position: it seems counter intuitive for the production position to be the mediating variable but since in the inventory positions concerns end-month stock, and it can be that this is high because the production was high. Baron and Kenny's steps for mediation are repeated. Step 2 tests the following linear model:

$$PrP_i = \beta_0 + \beta_1 * IP_i + \varepsilon_i \tag{5.11}$$

The regression outcomes can be found in table III-3 appendix III. The estimated coefficient has values for t-statistic = 3.353 and p-value = 0.003, confirming an association between the independent variable (IP) and the mediator (PrP). Step 3 involves a multiple regression as in formula (5.7) but now with IP and PrP as independent variables.

The outcomes of the regression are shown in table III-4 appendix III. As can be seen the coefficient for IP has become insignificant (t-stat=0.525, p-value=0.604) and all the variance is explained by the production position. We can thus conclude that a high end month stock position is mediated by the production position and confirm hypotheses L.1.

Production position

The z-scores regarding the production position indicate no outliers, the sample size remains n=27. The normal probability plot in figure III-3 appendix III shows some fluctuation around the trend line but it still looks acceptable. The Shapiro-Wilk test confirms this given W=0.977 and corresponding p-value of 0.772. The same model as in the balanced market (34) is run and residuals are tested for auto correlation and homoscedasticity. The Durbin-Watson test gives a value for d of 1.607, the bound given a sample size of 27 are 1.088 and 1.232. Since 1.607 > 1.232 the sample model shows nog sign of autocorrelation. The interpretation of the scatterplot in figure III-4 appendix III shows that the residuals have equal variances thus also the assumptions of homoscedasticity is met.

The outcomes of the regression can be found in table III-5, appendix III The estimated coefficient $\widehat{\beta_1}$ has a value of 0.666 and the corresponding t-statistic of 3.171 has a p-value of 0.004. Hence with a both a significance level of 10% and 5% the null hypothesis that suggest that β_1 is zero is rejected. This indicates that there is a significant relation between the operating rate and the market share in the long market, and hypothesis L.2 has to be rejected.

Price deviation

Deviating from the market price is expected to have the largest effect in the long market. To perform a linear regression we first look at the standardized values again to check for outliers. There are two observations with a z-score greater than 2.5. One has z-score of 2.96 and a value of 19% deviation in the positive direction of the market price, the corresponding market share is around average of the sample. There is no clear explanation for this observation and is therefore removed from the sample. The second observation has a z-score of 3.67 with a corresponding value of +22.8% deviation, the market share was way below average. This observation marks a month where prices were declining but SABIC did not decline accordingly, and is thus showing exactly the behavior that we are trying to explain. For this reason we keep the observation in the sample. The remaining sample size consists of 26 observations. The normality plot in figure III-5 appendix III along with the Shapiro-Wilk test (W=0.625, p-value=0.000<0.001) now show non normal data due to one observation. This is caused by the outlier left in the sample, for this reason the observation is still taken out. The new normality plot in figure III-6, appendix III given the sample of 25 observations shows normal distributed data, this is confirmed by the Shapiro-Wilk test which has a value of W=0.962 and a corresponding p-value=0.437, hence we will continue with this data set.

The model of (5.5) is run to obtain the residuals and predicted Y values. The interpretation of the scatterplot in figure III-7 appendix III shows no real pattern and we can thus conclude that the assumption of homoscedasticity is met. The Durbin-Watson test gives a value for d of 1.652 since the upper bound for a sample of 25 is 1.210 the sample shows no auto correlation. Both assumptions regarding the residuals are met and we can safely perform the linear regression.

The outcomes of the regression can be found in table III-6 appendix III. The estimated coefficient $\widehat{\beta_1}$ has a value of 0.838 which indicates a positive relation between deviating from the price and SABIC's market share in the long market. This is entirely against expectations since we expected a strong negative relation between deviating from the price and the market share. Yet the t-statistic has a value of 1.517 and the corresponding p-value=0.143 indicating no significance for both a 5% and 10% significance level. This means no significant relation can be found between deviating from the price in the long market and SABIC's market share, and we therefore reject hypothesis L.3.

To find a possible explanation for this behavior, the sample in the long market is separated by looking into absolute values of the market demand and market supply. It might be that different behavior is seen when absolute demand levels are low then when they are high. The sample is split into four parts: when supply is low and demand is low, supply low and demand high, supply high and demand low, and finally supply high and demand high. Since the observations per section are really low, regression analyses nor are any other statistical tests are feasible. Therefore an interpretation of the scatterplots is given as a guideline for further research.

Figure 24 displays the scatterplot for the different combinations of supply and demand in the long market. It seems neither only supply nor demand levels are responsible for the positive relation between PD and the market share but when they are both low and both high this is noticed. The observation in high-high and low-low are closer to a balanced market than low-high and high-low, this makes the observed behavior even stranger since we found a strong negative relation between PD and SABIC's market share in the balanced market.

In the absence of a clear indication we expect that there are some supplier-consumer relations playing a role why a positive relation between PD and MS is observed, because suppliers can only differentiate themselves with either price or service.

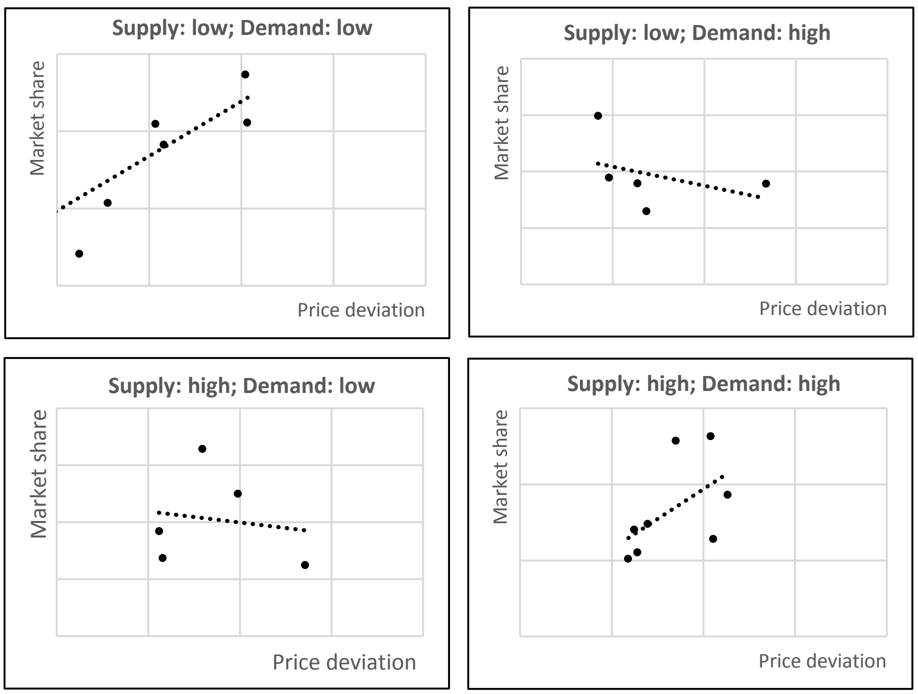


Figure 24 *scatterplots price deviation long market*

Multiple regression

The starting model of the regression is the same as model (5.9) in the balanced market. Table III-7 appendix III shows that only the production position is significant (t-statistic = 2.575; p-value = 0.018). IP has the highest level of insignificance with a t-statistic of 0.678, and corresponding p-value of 0.505. IP is therefore removed from the regression which reduces the new model to the model of (5.10). The regression outcomes including the PrP and PD are shown in table III-8 appendix III, the table shows that again only the coefficient for PrP is significant (t-statistic = 3.615; p-value = 0.002). Removing PD from the model reduces the regression to the simple linear regression discussed in the production position section of this chapter.

5.4.2 Conclusions and interpretation

Table 10 *Summary statistics long market*

	R^2	Adj. R^2	Sign. F	n	*i*	β_i	*t Stat*	*P-value*	*Hypothesis?*
IP	0.154	0.120	0.043	27	0. Intercept	0.194	3.806	0.001	L.1: Confirm
					1. IP	0.838	2.130	0.043	
PrP	0.287	0.258	0.004	27	0. Intercept	0.194	5.517	0.000	L.2: Reject
					1. PrP	0.653	3.171	0.004	
PD	0.091	0.051	0.143	25	0. Intercept	0.276	12.573	0.000	L.3: Reject
					1. PD	0.838	1.517	0.143	

Opposite to what was expected we found a significant positive relation between SABIC's inventory position and their market share. The R^2 indicates that 15.4% of the variance in the dependent variable can be explained by their inventory position if it is seen as a direct effect. Mediation analysis could not prove that there exists any mediation effect between the inventory position, price deviation and the market share, but it showed a mediation effect between the inventory position, production position and the market share. This means that when the end-month stock is high, PrP is high, and this is what causes the higher market share. Hence we conclude that in the long market when you produce more, the inventory position increases, but also your market share increases (so extra production goes partly into the stocks and partly into sales. Since we found a full mediation effect hypothesis L.1 "*There exists no significant relation between SABIC's inventory position and their market share in a long market"* can be confirmed.

Because we found a strong significant relation between PrP and SABIC's market share hypothesis L.2 has to be rejected. In the balanced market we also saw a significant positive relation. We recognize that it might be that higher sales can also lead to higher production, expert interview even confirm that sometimes when sales are good during a month production is increased, yet this does not happen often. Also production sequences, and production budgets for each grade are determined once a year so there is not a lot of flexibility.

We expected a strong negative relation between deviating from the market price and SABIC's market share in the long market, yet we could find no support for the hypothesis. Also the direction the regression is showing is in the positive direction which makes it even stranger. Remarkable is that in a balanced market the effect is heavily present, even when it is easier for customers to switch between customers in the long market. The reason why customers are not sensitive to price change in the long market is unclear and is interesting to investigate in the future.

5.6 Conclusions

In the previous chapter we found that we can fairly accurately predict industry demand movement. During an S&OP these market movements are discussed. To provide more guidance in the S&OP we investigated which market factors influence SABIC's market share. For this we looked into their supply position in the market and their price setting compared to the market price. We distinguish three market configuration and hypothesized each factor to be of different influence in these different markets.

We found that in a short market, where industry demand is greater than industry supply, a strong inventory position in the market enables SABIC to increase their market share. Surprisingly we also found a positive relation between deviating from the market price and their market share, meaning that in a short market there is room for SABIC to increase their margins without a loss of sales. A multiple regression analyses showed that both the inventory position and price deviation had significant influence on SABIC market share and together explain 31.1% of the variance.

In the balanced market we found that a strong production position enabled SABIC to increase their market share, confirming hypotheses B.2. The expected negative relation between deviating from the market price and their market share is also found, and is a big impact. Deviating 1% from the market price results in a 0.47% decrease in their market share. The multiple regression eventually showed that both the production position and price deviation are included and have a relatively high R^2 of 51.4%

In the long market SABIC's inventory position initially showed to have a positive influence on their market share, yet after mediation analyses this effect is fully mediated by their production position. Thus a strong production position accounts for a larger market share but not all is converted into sales which results in higher inventory levels as well. Surprisingly we did not find a significant relation between price deviation and the market share, the relation (although not significant) was even in the positive direction. We could not find a clear explanation, but expect that supplier-customer relations play a role in this. Finally a multiple regression analyses did not find any significant influences of the inventory position and price deviation together with the production position. On its own the production position has an R^2 of 28.7% and if SABIC strengthen their position relative to the market with 1% their expected increase in market share is 0.65%.

6. S&OP Implementation

This chapter goes into the development of an S&OP tool that can be used to financially motivate sales and supply decisions. The findings from chapters will 4 and 5 be used to determine sales, supply and production decisions for 1-3 months and optimize the earnings over this period. First the model variables will be discussed, second in section 6.2 the model set up is described, and the following sections present the results and conclusions.

6.1 Model variables

During an S&OP process decisions upon pushing sales into the market or purposefully building up stock to cover events in the future are made. Chapter 5 showed that the inventory position, production position, and price setting are of different influence in different market settings. The industry demand forecast from chapter 4 together with industry supply and industry production input from the Market Intelligence department gives a prediction of the market setting and enables SABIC to make more founded volume push or inventory ramp up decisions. Moreover price setting can now be taken into account when deciding upon agreed sales, agreed production and agreed inventory levels. This enables us to build an optimization model that maximizes revenue/profit over the S&OP time span of three months.

6.1.1 Input

Listed in table 11 are the required input variables for the model developed in this chapter. The previous chapter gave a thorough analysis of the factors influencing SABIC's market share. We looked at how SABIC's supply position (inventory and production position) in the market and their price setting affected their share of the industry demand. The industry demand forecast of the system dynamics model derived in chapter 4 serves as main input for the model by providing a three month forecast for the industry demand.

The market intelligence department makes a three month forecast for industry inventory, industry production and market prices every month. These serve as input to determine SABIC's inventory position, production position, and price setting targets.

Production capacity, optimal inventory and the price limit are parameters needed to subject the model to several constraints in order to keep the results realistic. Finally the chapter 5 provides regression equations for the different market settings (short, balanced, long), the regression coefficients determined in the analyses serve as input to determine SABIC's potential market share.

6.1.2 Output

Both decision variables and output are also listed in table 11. SABIC can only decide on the amount they produce, how much inventory they want to end up with and their selling price. Together with the market input parameters these determine the expected market share. The objective function is to either maximize revenue or profit; it does this by maximizing the product between market share and the selling price, and when optimized towards profit is also takes some general logistic cost into account.

The main assumption of the model is that SABIC's market share is not related to the absolute values of industry demand and industry supply. So for instance high values of industry demand do not lead to a higher market share. Figure 25 and 26 illustrate that the market share is to a large extend equally distributed among the absolute value of demand and supply, hence the assumption is reasonable. This inherently means that we assume independence between the industry demand model developed in chapter 4 and the market share models in chapter 5.

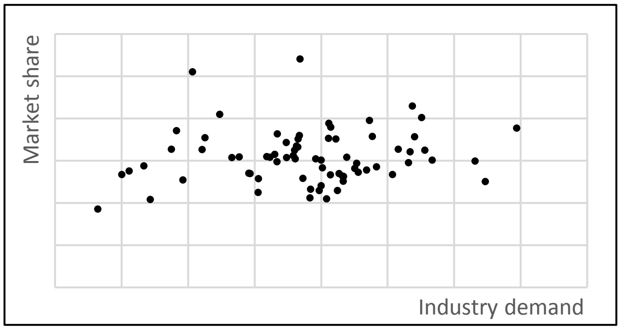


Figure 25 *scatterplot industry demand vs. market share*

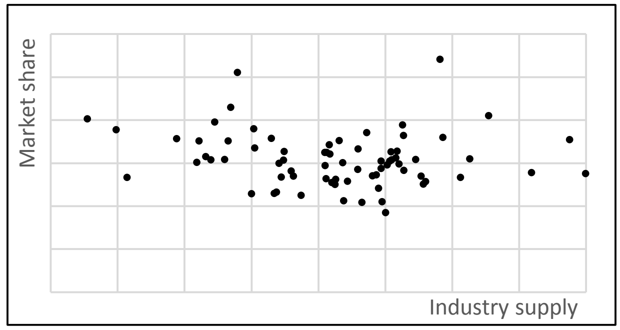


Figure 26 *scatterplot industry supply vs. market share*

6.2 Model derivation

From the section 1.2 we learned that during each month SABIC has a sales and operations planning (S&OP) meeting to discuss coming three months in terms of supply and demand. To recall, this tactical planning process has the goal to maximize the utilization of the production plants while keeping stock levels close to optimal levels. The outcomes of each meeting are agreed figures on sales, production and inventory for the next three months. Grimson and Pyke (2007) indicate that the next step in S&OP maturity is to optimize profit. While the motivation of SABIC's S&OP has a financial perspective, the main goal remains to balance supply and demand in order to keep inventory levels on optimum.

6.2.1 Revenue model

The goal of the model is to either optimize the revenue or the profit for the next three months. SABIC's revenue is determined by their selling price in month *i* (p_i^S) and their sales orders in month *i* (o_i^S).

$$R = p_i^S * o_i^S \tag{6.1}$$

SABIC's selling price is determined by how much they choose to deviate from the market price (p_i^M) in month i, and their sales are a share of the total sales in the market (o_i^M). Thus ($p_i^S * o_i^S$) can be rewritten as:

$$(p_i^S * o_i^S) = \left(p_i^M * \left(1 + \frac{p_i^S - p_i^M}{p_i^M}\right)\right) * \left(o_i^M * \frac{o_i^S}{o_i^M}\right) \tag{6.2}$$

Chapter 5 showed that SABIC's market share is significantly influenced by several market factors. We use the regression models to determine their market share in month i by changing the inventory position in month *i* (IP_i), production position in month *i* (PrP_i), and how much they deviate from the market price in month *i* (PD_i). The influence of these parameters, determined by the regression coefficient (β^j), differs under different market configurations *j* (short; balanced; long) and is determined by multiple regression analyses conducted in the previous chapter:

$$\frac{o_i^S}{o_i^M} = \beta_0^j + \beta_1^j * IP_i + \beta_2^j * PrP_i + \beta_3^j * PD_i$$

$$= \beta_0^j + \beta_1^j * \frac{s_i^S}{s_i^M} + \beta_2^j * \frac{m_i^S}{m_i^M} + \beta_3^j * \frac{(p_i^S - p_i^M)}{p_i^M} \tag{6.3}$$

Formula (6.3) shows that, following the logic of chapter 5, SABIC's inventory position is determined by their stock (s_i^S) and the market stock (s_i^M), and their production position by their production (m_i^S) and the market production (m_i^M). Price deviation is defined as the percentage change from the market price.

The model will decide on SABIC's stock, SABIC's production, and selling price, and it will determine the expected sales endogenously. These decision variables are subjected to several constraints. First optimal inventory levels (s^*) are determined each year per grade to ensure desired customers service levels. It is not allowed to reduce inventory to less than 85% of optimal stock to ensure customer service levels remain healthy:

$$s_i^S \geq 0.85 * s^* \tag{6.4}$$

Second, during month *i* it is not allowed to produce more than the supply budget for *i*, these budget figures are a target set at the beginning of each year for the remainder of that year. The budget is further referred to as the production capacity (m_i^C):

$$m_i^S \leq m_i^C \tag{6.5}$$

Third, price setting below the market price is subjected to a price (p_i^{lim}) set by senior management:

$$p_i^S \geq p_i^{lim} \tag{6.6}$$

Fourth, stock levels have to be in balance with sales and production levels. This means the end stock of month *i* is a result of previous month's stock plus production minus sales. The analyses in chapter 5 is based on spot sales in Western Europe (WE), yet production and stock is not solely dedicated to the spot market in WE. We therefore have to account for this "sales gap", co nsisting of contracted sales and export sales, in order to balance the equation. This is done by introducing a sales gap parameter (o_i^{gap}):

$$s_i^S = s_{i-1}^S + m_i^S - (o_i^S + o_i^{gap}) \tag{6.7}$$

And finally to ensure validity of the regression equations IP, PrP, and PD are bounded by the minimum and maximum values of the observations used in the regression analyses of chapter 5, in each market configuration *j*:

$$IP_{MIN}^j \leq \frac{s_i^S}{s_i^M} \leq IP_{MAX}^j \tag{6.8}$$

$$PrP_{MIN}^j \leq \frac{m_i^S}{m_i^M} \leq PrP_{MAX}^j \tag{6.9}$$

$$PD_{MIN}^{j} \leq \frac{(p_i^S - p_i^M)}{p_i^M} \leq PD_{MAX}^{j} \tag{6.10}$$

The goal of the model is to optimize revenue over a three month time span, it can be written as follows:

$$\begin{aligned} \max R(p_i^S, s_i^S, m_i^S) \\ = \max\left(\sum_{i=i}^{i+2}\left(\left(p_i^M * \left(1 + \frac{p_i^S - p_i^M}{p_i^M}\right)\right)\right.\right. \\ \left.\left.* \left(o_i^M * \left(\beta_0^j + \frac{\beta_1^j}{s_i^M} * s_i^S + \frac{\beta_2^j}{m_i^M} * m_i^S + \frac{\beta_3^j}{p_i^M} * (p_i^S - p_i^M)\right)\right)\right)\right) \end{aligned}$$

$$s.t. \tag{6.11}$$

$s_i^S \geq 0.85 * s^*$

$m_i^S \leq m_i^C$

$p_i^S \geq p_i^{lim}$

$s_i^S = s_{i-1}^S + m_i^S - (o_i^S + o_i^{gap})$

$$IP_{MIN}^{j} \leq \frac{s_i^S}{s_i^M} \leq IP_{MAX}^{j}$$

$$PrP_{MIN}^{j} \leq \frac{m_i^S}{m_i^M} \leq PrP_{MAX}^{j}$$

$$PD_{MIN}^{j} \leq \frac{(p_i^S - p_i^M)}{p_i^M} \leq PD_{MAX}^{j}$$

6.2.2 Profit model

The profit model adds a cost component that consists of three parts. First the cost price (c_i) which is equal to the feedstock price (C3 price), second cost for holding inventory which is equal to the amount of inventory (s_i^S) times the weighted average cost of capital (*r*) times the cost price of the product, and finally a penalty (s^{pen}) when the inventory exceeds 115% of optimal inventory (s^*). Since the production plants run 24 hours a day and the grades are produced in batches the cost of producing an extra ton in negligible and therefore not in the model. The cost term is as follows:

$$Cost = (o_i^S + s_i^S * r) * c_i + \max\left(0, (s_i^S - 1.15 * s^*\ ) * s^{pen}\right) \tag{6.12}$$

The profit model is subjected to the same constraints as the revenue model, and therefore the final profit model is equal to the model of (6.8) only the objective function is extended by subtracting formula (6.12).

Table 11 *NLP model variables*

Decision variables		Input		Output	
p_i^S	Selling price month *i*	p_i^M	Market price month *i*	o_i^S	SABIC sales month *i*
s_i^S	SABIC inventory month *i*	s_i^M	Market inventory month *i*	R	Revenue
m_i^S	SABIC production month *i*	m_i^M	Market production month *i*	P	Profit
		o_i^M	Market demand month *i*		
		m_i^C	Production capacity month *i*		
		s^*	Optimal inventory level		
		p_i^{lim}	Price limit month *i*		
		β_0^j	Regression intercept		
		β_1^j	Coefficient inventory position in market *j*		
		β_2^j	Coefficient production position in market *j*		
		β_3^j	Coefficient price deviation in market *j*		
		r	Weighted average cost of capital		
		s^{pen}	Inventory penalty		
		c_i	Cost price month *i*		

6.3 Model validation

In order to validate the model we check if the model can replicate historical sales. Historical data is used for the input parameters industry demand, industry stock, industry production, and market price. Actual production, inventory and sales prices are used for the decision variables, thus the model is not yet used as an optimization tool.

The model is validated over 2014. From figure 27 we learn that the model outcomes nicely replicates the trend. Unfortunately it systematically overestimates the demand at SABIC, but lies within the 90% confidence bounds. The error between the modeled sales and actual sales is on average 29.2% with a minimum of 4.4% and a maximum of 48.0%. The overestimation is a result of the regression analyses. We noticed that overall sales declined from 2009 to 2014 with 2014 having the lowest sales, yet the analyses is done over a timespan from 2009-2014. This likely resulted in higher intercept coefficients.

It has an acceptable R^2 of 0.601%, but considering the overestimation one should be careful with predicting future values. Yet since the modeled trend is following the trend of the actual sales, the regression coefficients have the right impact. Therefore the model can be used to optimize S&OP input given the market circumstances, but again one should be careful with the absolute outcomes of expected sales.

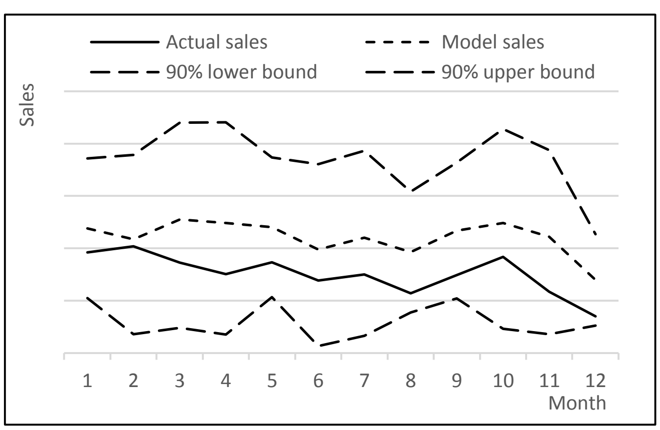


Figure 27 *actual sales vs. modelled sales*

6.4 Model solving

Since the described models in section 6.2 are both non-linear they cannot be solved using linear programming. The generalized reduced gradient (GRG2) algorithm in the excel solver is a powerful non-linear solver and commonly used for optimization problems. This algorithm is very robust and reliable, but takes in general more time than other non-linear optimization algorithms (Biegler, 2008). Due to the large solution space non-linear problems are much more complex than linear problems, the solution found by the algorithm is not guaranteed to be a global optimum but could also be a local optimum. To increase the probability that the found optimum is also the global minimum, the multistart option is set on 100. This option lets the GRG engine automatically run the optimization problem from different starting points. The first starting point has to be set manually and the GRG engine subsequently chooses the next starting points by making incremental changes to the previous starting point and then checks whether the solution improves. The first starting point is always set at $\left(p_i^S, s_i^S, m_i^S\right) = (0{,}0{,}0)$.

The values for the input parameters are based on historical output and S&OP managers and can be found in appendix IV. Given the input parameters we let the model solve $\left(p_i^S, s_i^S, m_i^S\right)$ for $i = 1\ to\ 12$ with $i = 1$ is January 2014 and $i = 12$ is December 2014. We optimize the model from both a revenue and profit perspective.

The following sections present the model outcomes and how the decision variables influence these. Both endogenous and exogenous outcomes are presented relative to actual results such that these can be compared and recommendations can be given.

6.4.1 Profit and revenue

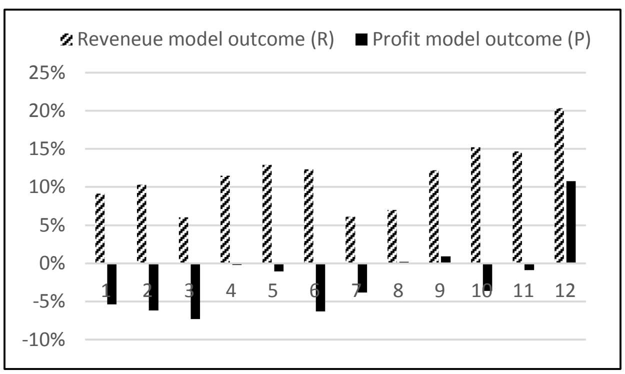


Figure 28 *Modeled revenue relative to actual revenue*

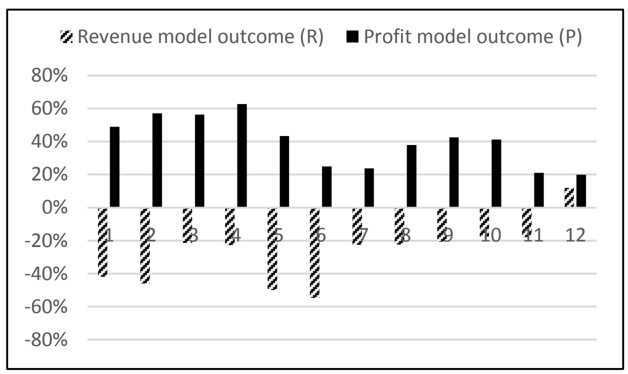


Figure 29 *Modeled profit relative to actual profit*

Figure 28 shows the revenue when modeled relative to the actual revenue. Revenue optimization yields on average 11% higher revenues then actual with a maximum of 20%, when optimized towards profit the revenues are on average 2% lower than actual. Figure 29 shows that the higher revenues are completely offset by the cost since optimizing towards revenue accounts for 27% lower profits. This can be explained by the amount of inventory held and will be discussed in section 6.4.3.

Figure 29 shows that profit optimization on the other hand lead on average to 40% higher profits with a maximum of 63%, in none of the cases the modeled profit was lower than actual profit. The difference between actual and modeled profit can be explained by a combination of the decision variables: Inventory is kept low, and expected sales generated by a strong inventory position are slightly offset by asking a higher price than the market. Together these boost revenue while keeping cost low.

Although revenue optimization yields higher revenues, profits are not desirable. The opposite is seen when optimized towards profit, hence it is important to take cost into consideration.

NOTE: The modeled profit and revenue might both be inflated since the model optimizes 3 months, consequently expected sales in each month are always sold while the sales per month in reality were lower.

6.4.2 Decision variables: Production, Inventory & Sales price

This paragraph shows how the figures in the following section should interpreted. The model optimizes one S&OP cycle. Each cycle consists of three months, the first month in the cycle is called i, the second i+1, and the last i+2. Figure 30 shows an example figure. If we now take for instance June, the red line (i+2) represents the value for June when the model was optimized in March, the green line (i+1) represents the value for June when it was optimized in April, and the grey line (i) represents the value for June when it was optimized in May. So the values for i, i+1, and i+2 do not represent the next three months when the model was optimized in June, but the values for June when it had a certain position in the cycle. The outcomes for a cycle can also be seen: the S&OP optimization outcomes in May can be seen by looking into i in June, i+1 in July, and i+2 in August.

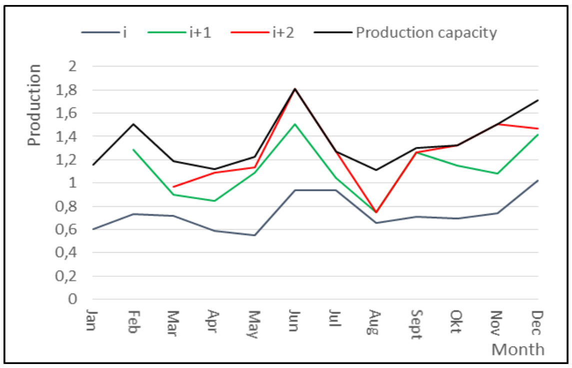


***Figure 30** Example graph*

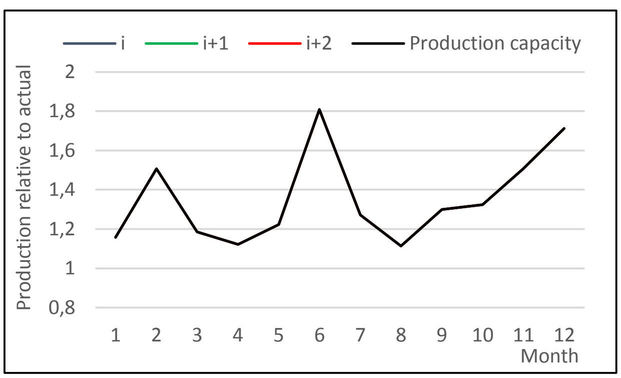


***Figure 31** Modeled production relative to actual production*

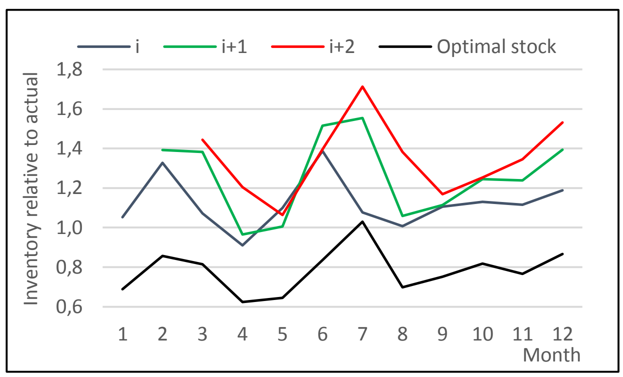


***Figure 32** Modeled inventory relative to actual inventory*

Figure 31 and 32 respectively visualize the values of the production and inventory relative to the actual values when optimized towards revenue. In 2014 all months where either balanced or long. Recall that a strong production position enables SABIC to increase their market share. Figure 31 shows that regardless of the position in the cycle the production set equal to the production capacity, and when the production increased relative to the actual production, revenues relative to actual increased as well. Not all the production can be converted into sales, If we take a look at i in January, i+1 in February, and i+2 in March (the cycle run in December) in figure 31 we see that the inventory keeps rising in every month, this is the same for every cycle. In every month inventory is both above actual and optimal, averaging 24% above actual and 58% above optimal. Both cost components in the profit model consist of inventory related cost, this explains why the revenue model performs so badly in terms of profit.

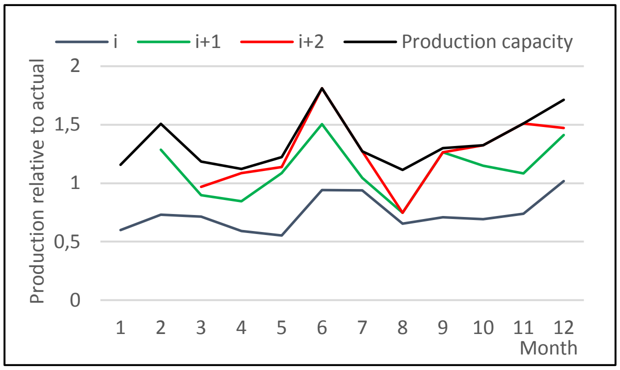


Figure 33 Modeled production relative to actual production

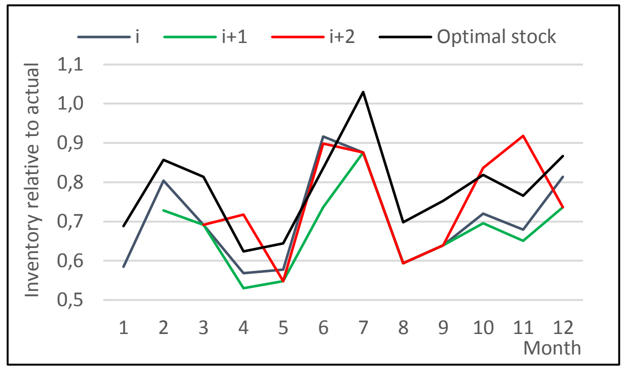


Figure 34 Modeled inventory relative to actual inventory

When the model is optimized towards profit we see the opposite. Figure 34 shows Inventory levels are all the time lower than actual and in most of the cases even lower than optimal. By keeping inventory levels low, cost in model are reduced. On average modeled inventory is only 70% of actual inventory, this translates in 30% lower inventory related cost.

Figure 34 also shows that only in July optimal inventory was higher than actual inventory. Actual inventory was on average 130.1% of optimal, this means that every month stock penalties occur. Figure 33 shows that initially production is kept low while in the following months in the cycle production is increased and approaches the production capacity. This leads to higher expected sales and an increase of revenue in the last two months of the cycle. The combination of overall low inventory levels and high sales in the last two months of the cycle account for the difference in profit between the model and actual.

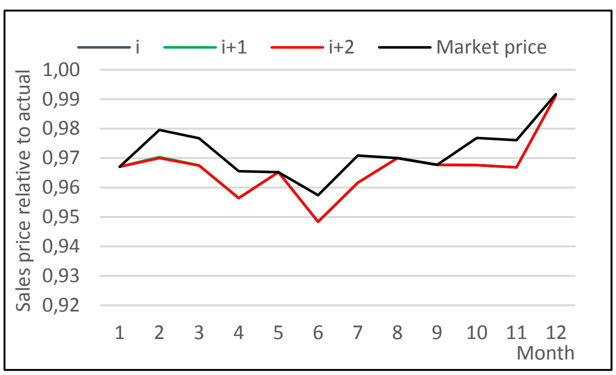


Figure 35 Modeled selling price relative to actual selling price

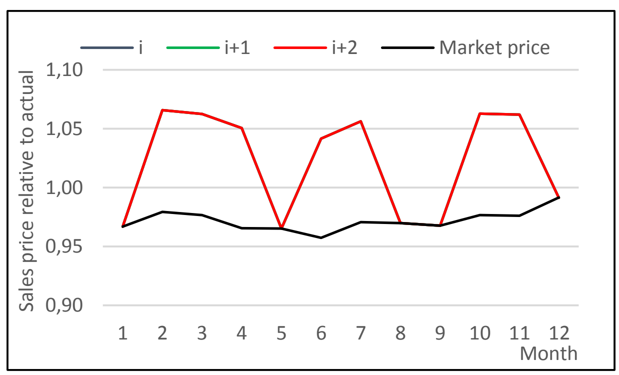


Figure 36 Modeled selling price relative to actual selling price

Figure 35 and 36 respectively show the modeled sales price when optimized towards revenue and modeled sales price when optimized towards profit. In the long market it is not allowed to deviate from the market price since there was no significant effect found. In the balanced market a strong negative effect between deviating from the market price and SABIC's market share was found.

When the model is optimized towards revenue the sales price is set beneath the market price, again to increase sales. The opposite is seen when optimized towards profit, the sales price is set above the market price. Figure 35 shows that in the same months the production is also increased. A higher sales price slightly offsets sales generated by a stronger production position, yet the extra value gained per product outweighs the extra inventory cost.

6.4.3 Sales

Figure 37 and 38 respectively shows the sales in month i when optimized towards revenue and towards profit. The revenue model cuts prices and increases production with the sole purpose of increasing sales, it does not take inventory into account. Figure 35 shows that the profit model generates expected sales much more in line with the actual sales but we know from the previous section that these have a higher profit margin. This is achieved by keeping inventory and production low and exploit price effects.

Expected sales when in month i+1 or i+2 are depicted in figure IV-1 and IV-2, appendix IV. Optimizing towards revenue yields the same value as when a month is predicted in the beginning of the S&OP cycle. When optimized towards profit the expected sales for month i+1 and i+2 are higher. When going into a new S&OP cycle realized end month stock of month i gets available. If this is higher than expected the profit model optimizes such that inventory levels are low to avoid extra cost, it does this by decreasing production and sales are adjusted accordingly.

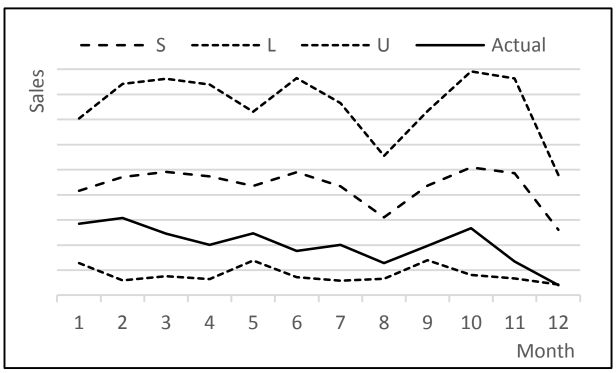


Figure 37 *Modeled sales vs actual sales*

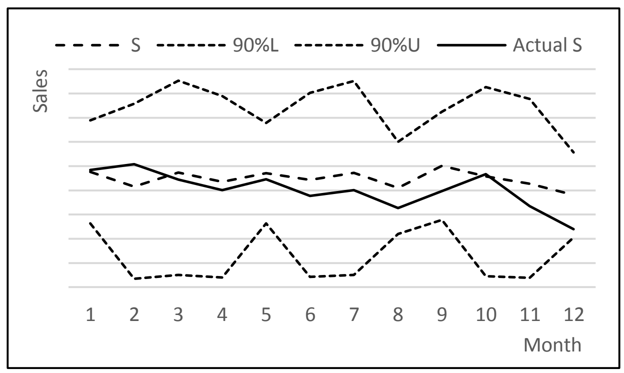


Figure 38 *Modeled sales vs actual sales*

Note that the sales lie within the 90% confidence bounds also presented in figures 37 and 38. These are at their largest point plus and minus 83% of the sales. This marks one of the main limitations to the model.

6.5 Conclusion and discussion

This chapter went into the development of an optimization tool that can be used to financially optimize the S&OP. The industry demand forecast model from chapter 4 and market share model(s) from chapter 5 are combined in order to choose optimal values for price, inventory and production given a set of market conditions. Both a revenue and a profit model where explored.

The revenue model yields unsatisfactory results. Since the revenue is a product of price and volume the model optimizes such that sales are as high as possible. It does this producing as much as possible and cuts prices to further increase expected sales. This constant ‘push mode’ increases inventory to undesirable high levels because not all production can be sold. Although expected revenues were a lot higher than actual revenues these were completely offset by logistic cost resulting in on average 27% lower profits.

The profit model on the other hand yields interesting results. Expected sales for month *i* are in line with actual sales but while keeping inventory low, production and price influences were exploited to increase profits. The expected profits are on average 40% higher with a peak to 62%. So by making different decision SABIC could have increased profit. Though due to several limitations the model should not be used as a replacement of the current process but as a guidance tool to compare with their current input. This is elaborated more in chapter 7.

The results of the model can be inflated or deflated since the model because of some limitations. First, the model relies on the multiple regression models derived in chapter 5. These were derived with small datasets, which resulted in 1) large confidence bounds, and 2) fairly low R^2 statistics (between 28.8% - 51.4%).

Second, market input parameters form limitation to the model outcomes. While chapter 4 gives a fairly accurate industry demand forecast, the industry inventory, industry production, and market prices required to determine the inventory position, production position and price deviation parameters still have to be forecasted in absence of a scientific model by the Market Intelligence department. Further elaboration on this will follow in section 8.2.

7. Managerial insights

In this chapter we reflect upon the findings of the research and indicate the practical relevance. The first two points can be generalized to all managers European producers of polypropylene based pipe products, while the latter point is specifically tailored towards SABIC.

i. Insights concerning the industry demand model

This study showed that a system dynamics model previously developed within SABIC to forecast the demand of polyethylene based stretch film can be generalized and used to forecast other commodities as well. This research specifically focused on polypropylene based pipe commodity market. The influence of so-called traders on the demand level is investigated following the research of Stuijts (2014). Traders exploit price dynamics by attempting to buy product from polymer producers when the price is low and sell to the converters when the price is high. This behavior disturbs the real demand signal creating an additive bullwhip through the forward buying principle (Lee et al. 1997). The research confirmed that traders influence the industry demand level but they are more risk averse than expected. This is probably a consequence of the buying behavior of the converters. We found that they respond really quickly to changes in price: when the price is going up they quickly start to buy from traders but even before the price settles in peak, they start buying from the polymer producers again.

The model uses only end market demand and price as exogenous variables to predict industry demand at the polymer echelon. It proves to give an accurate forecast for a 1-3 month period, and can therefore be used as valuable input in the monthly S&OP process. It is important to keep track of changes in end market demand since these can account for structural changes in the supply chain. Moreover it is important that managers can foresee the extra demand variability caused by changes in price. SABIC is not a price leader in the pipe market, which makes them unable to influence the market price. Figure 39 shows that the market price in 2014 was far from stable. To interpret the demand signals caused by price dynamics SABIC has to make a prediction about the price direction. In the light of this we recommend use of the model as a scenario testing and forecasting tool to see how industry demand reacts to certain realistic changes in the market price.

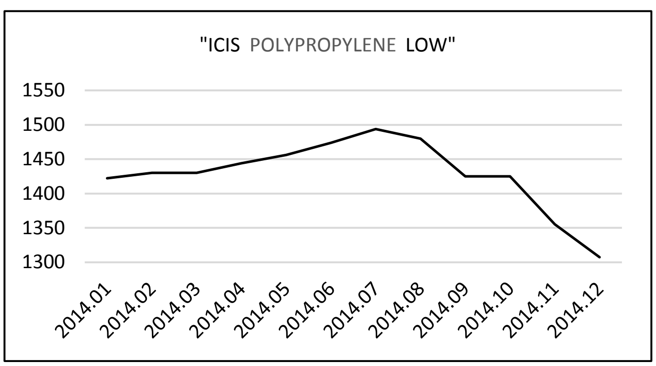


Figure 39 *ICIS polypropylene price in 2014*

ii. Insights concerning the market share model

To make the step from industry demand towards firm demand, this research investigated how SABIC's supply position in the market and their price setting decisions influence their market share. Three different market configurations where recognized: short, balanced, and long. Three notable findings are of interest. First a strong inventory position in the short market and a strong production position in the balanced market enables SABIC to have higher sales. Having ample stock in position is essential in a short market since SABIC can then quickly react to the needs of the customer. On the other hand customers do not act very quickly in the balanced and long market. This gives SABIC the time to react to the customers with their production. Second a positive price effect was found in the short market. This implies when

SABIC asks more than the market their sales are not negatively impacted. Although this relation preferably has to be confirmed for other commodities it implies that managers can set prices high before customers are distancing themselves from SABIC. Last the investigation found a strong negative relation between deviating from the market price and SABIC's market share in a balanced market.

Because demand planners often plan demand for both commodity and specialty products, price and volume settings are often not combined. Given our findings we strongly recommend to combine price and volume settings of commodity products in anticipation of or during an S&OP meeting instead on deciding sales volumes and try to sell them at the best price afterwards.

iii. Financial S&OP

Insights in the factors influencing industry demand and factors influencing SABIC market share gave way to develop an optimization tool which managers can use in their S&OP process. Once the tool is provided with the necessary market information, either by the supply chain model or the Market Intelligence department, it can set values for production, stock, and price to optimize profits or revenue. The two models have been compared to each other and to reality. When revenue is used as the goal function production is increased, and prices are cut to boost sales. It also builds big amounts of inventory which offset gained revenue with cost. The profit model shows better results: it focuses on keeping inventory low and 'waits' for strategic moments to increase price in order to increase profit margins. Expected profit is on average 40% higher than reality. Increasing profit can thus be achieved by keeping inventory low and increase prices at strategic moments in time. We showed that optimizing towards revenue yield considerably worse results than optimizing towards profit. For management it is important to take certain logistical cost into consideration and focus on increasing profit instead of focusing solely on increasing revenue.

The 90% confidence bounds on expected sales are wide, which might inflate expected profit because the model assumes that expected sales are always sold. In reality this might not be true, possibly resulting in higher inventory levels and consequently higher cost. Instead of replacing the current S&OP methods with this tool we recommended to use the tool to explore different effects of adjusting the production, inventory, and/or selling price. To increase confidence in the model outcomes regression have to be repeated every once in a while with new data observations.

As an example we show how the model can be used as exploration in Table 12. During a certain S&OP cycle SABIC has a sales forecast of 2486, 2834, and 2174 tons of product for the WE spot market which results in their proposed situation (production, inventory and sales price). The model can serve as a guideline. It overestimates these sales, but we know the influences are right so the difference in the model sales is deducted from the expectation. The market is long in month 1, and balanced in 2 and 3. In the table we see that by adjusting production, inventory, and sales price a higher profit can be obtained. Instead of solving the model managers can also enter values for production, inventory and sales price and see what the model predicts as sales and corresponding profit. Subsequently they can compare this to their initial choice.

***Table 12** example cycle (actual values have been multiplied by a fraction x due to confidentiality)*

Demand planner				Optimization model		
Production	5356	5155	4649	4113	6827	7014
inventory	5322	4893	5229	3651	4338	5736
sales price	€ 736,30	€ 729,43	€ 694,09	€ 712,50	€ 775,23	€ 737,15
model sales	3339	3481	3219	3072	3564	3476
DP expect	2486	2834	2174	2219	2916	2431
Expected profit	€ 284.276,05	€ 697.985,15	€ 743.740,64	€ 579.591,88	€ 1.108.124,39	€ 991.574,85
Total	€ 1.726.001,84			€ 2.679.291,13		

8. Conclusion and Future research

In the final chapter of this thesis we evaluate the theoretical contribution of this study. Section 8.1 presents the conclusions and limitations and future research are defined in section 8.2.

8.1 Conclusions

First the research question are answered enabling us to discuss the main motivation for the project: How can the current S&OP process be made more financially driven.

A. Can the current system dynamics model at SABIC be adjusted to predict the industry demand volatility of PP pipe products, and to what extend are price dynamics influencing trader behavior?

The system dynamics model developed in this thesis is an extension of the model developed by Stuijts (2014). The model of Stuijts looked at the supply chain of LLDPE stretch film, and is adjusted in this research to focus at PP pipe products. Since the supply chain model consist of several interlinked echelons models, the model can easily be adjusted once information about the supply chain structure is gathered. A calibration with a thirteen month horizon resulted in a good model fit with an R^2 of 84.1% and showed to nicely capture seasonal behavior. The model can subsequently be used to accurately forecast industry level demand for a 1-3 month period in every new month, hence making a rolling horizon. Trader (de)stocking behavior and converter buying behavior were also explored through calibration. Traders were expected to heavily increase their stock when prices were in a through and decrease (sell material) when prices were in a peak. The calibrated stocking effect was less severe implying that they pursue a less risky strategy. This can be explained by the buying behavior of the converters. The calibrated trader fractions in section 4.2.2 showed that converters only bought a lot of material when the price was rising but immediately start switching back to buying from the polymer suppliers when the price reaches a peak.

Micro economic theory describes that, for commodity products, an equilibrium of supply and demand result in a market price and market quantity. As such to translate industry level demand movement into firm demand we investigated how SABIC's supply position in the market affects and their price setting affect their market share.

B. How is SABIC supply position influencing demand arriving at SABIC?

SABIC's supply position is made up of their inventory position and their production position. The effect of these on SABIC's market share is investigated in three different market configurations: a short market (demand > supply), a balanced market (demand ≅ supply), and a long market (demand < supply). We found that SABIC's inventory position only had significant influence on their market share when the market was short, an increase of 1% of their inventory relative to the market increases their market share by 0.92%. In a short market it is important to have inventory already in place since customers need material fast. When stock is already there SABIC can satisfy this demand quickly before customers go to other suppliers. SABIC's production position was found to be significantly influencing their market share in the balanced and surprisingly in the long market. In a balanced market an increase of 1% of their production relative to the market increases their market share by 0.62%, in the long market this is 0.65%. We reflect on this by acknowledging it might not be a direct causal effect of production on their market share but that good sales can possibly also drive production, yet ample production increases product availability which enables SABIC to sell more as well.

C. What is the relation between price-setting and the demand at SABIC?

Commodities are subjected to the law of one price (O'Sullivan, 2003) since they are uniform in quality. This enables customers to switch easily between suppliers. The effect of price setting on demand was investigated by analyzing how deviating from the monthly set market price influenced SABIC's market share. We found a significant effect of price deviation in the short and in the balanced market. Remarkably the effect in the short market was in the positive direction, this indicates that asking more than the market price accounts for more sales. A likely explanation is that business management constantly tries to increase margins, especially in a short market managers can push the limits without losing market share since there is ample demand. In the balanced market we found a strong negative relation, asking 1% more than the market price results in a 0.47% loss of market share. There is enough product to fulfill demand so it is easy to switch between suppliers. No significant effect could be found in the long market while we expected a strong negative effect. We could not find a clear explanation but expect that either some supplier-customer relations play a role or managers do not attempt to increase their margins in the long market to prevent loss of sales.

Multiple regressions were conducted to combine the results of research questions B and C. In the short market the inventory position and price deviation together explained 31.1% of the variance in the market share (R^2=31.1%). In the balanced market the production position and price deviation result in an R^2 of 51.4%. In the long market only the production position had a significant effect and resulted in an R^2 of 28.7%. These regression equation are combined with the industry demand input from the system dynamics model to construct an optimization tool that can be used to make financially driven decisions in an S&OP.

SABIC's management mentioned that it is not always clear whether their goals is to optimize profit or optimize revenue, therefore the two have been compared. Optimizing towards revenue sets SABIC in a push mode to generate as much sales as possible. The extra revenue gained is most of the time offset by extra supply chain cost which are not taken into account. Furthermore not all production can be converted into sales, which results in undesirable high inventory levels. Optimizing towards profits resulted in more desirable levels of expected sales while keeping inventory in line with optimal levels. This highlights the importance for the supply chain managers to include several supply chain cost when deciding upon values for production, inventory and sales.

It is important not to see the models constructed in the thesis as purely forecasting tools. High commodity price volatility makes it challenging to give accurate three month forecasts for the market price, and price has a big impact on demand movement. Furthermore the regression models are constructed using small datasets resulting in wide confidence bounds, it is better to use the model to explore the impact of the different variables on the market share until more data improves the regressions.

8.2 Limitations

The research comes with several limitations. First the scope is limited to EU27, leaving imports and exports out of scope. The amount of imports depend on several factors that are difficult to capture in the system dynamics model such as exchange rates, and import duties. Import grades usually come in vast amounts and are therefore able to saturate the market with product potentially affecting the market price. Though Stuijts (2014) investigated that import do not affect the amount of production they might potentially have an effect on the demand pattern arriving at the polymer echelon. Historical sales used in this research thus might be affected. We therefore propose this as source for future research.

The biggest limitation was access and availability of accurate data. Because monthly industry demand data was only available for PP and PP Pipe only yearly we had to assume that throughout the year PP pipe demand followed the demand of PP, results might be a bit inflated or deflated due to this assumption. Furthermore to achieve the desired granularity for the system we used cubic spline interpolation to estimate weekly data points from monthly data. Interpolation is not fully able to capture intra month behavior. This poses a limitation since demand and price data is summed up over a month where in reality these occur in different moments during the month. A final limitation due to the limited availability of data is that we could not perform partial model calibration. Partial model estimation means calibrating multiple sets of a reduced number off parameters and is the preferred calibration strategy for system dynamic models. This strategy (i) reduced the risk of the structure being forced into fitting the data, and (ii) limits the chance of errors in the structure being scattered over a large amount of parameters (Olivia, 2003).

Further limitation concern the second part of the research. Because we had only monthly data, and the data set was split up into three parts to investigate the effect in a short, balanced, and long market the sample size for each set was very small (<28). This resulted large confidence intervals for the coefficients, and eventually the market share. To increase confidence in the results, and tighten confidence intervals SABIC has to keep increasing the sample with monthly data.

When investigating SABIC's price setting we assumed a constant market price for a specific month where in reality the market price is constantly adapting due to competitors reacting to each other. This might influence the relations found in the regression analyses.

Finally the input variables of the S&OP optimization model consist of industry demand, industry inventories, industry production and market prices. This research developed a forecasting tool for industry demand, but cannot be used to accurately predict industry inventory and production. Since the model needs this as an input to determine SABIC's position in the market and the state of the market influences might be over or underestimated. To overcome this further research has to be done into determining factors that influence industry stocks and production, which on its turn will also result in better industry demand forecasts.

8.2 Further Research

Beyond overcoming the limitations and the suggestions for further research in the previous section we propose the following suggestions for further research as well.

We could not find a significant relation between price setting and the market share in the long market, even though we expected the relation to be the strongest here. Our efforts to explain this effect did not result in a clear explanation. We suspect customer-supplier relations beyond contracts playing in role, such as hesitance to change from supplier when one almost always orders at a particular one. We therefore suggest investigating if, and to what extend such relations impact the relation between price and volume.

Secondly this research is scoped on commodity polymers which still make out the major part of the petrochemical industry. Yet the big players in the market are increasingly focusing on specialty polymers because bigger margins can be earned on these products. These are products produced in smaller batches and are not of equal quality among players, thus the law of one price does not apply. Together with the fact that sometimes certain certificates are needed to sell these product (i.e. plastics going into the healthcare segment) this diminishes the role of traders, which alters the price-volume dynamics investigated in this thesis. So the effect of changing the scope of this thesis to specialty polymers is proposed as a source for further research.

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Appendix I Regression analysis short market

Inventory position

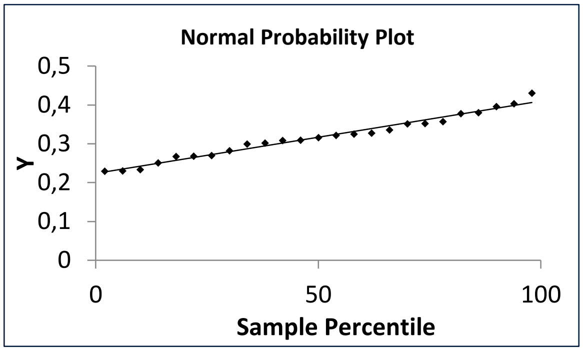

Figure I-1 *Normal probability plot inventory position short market*

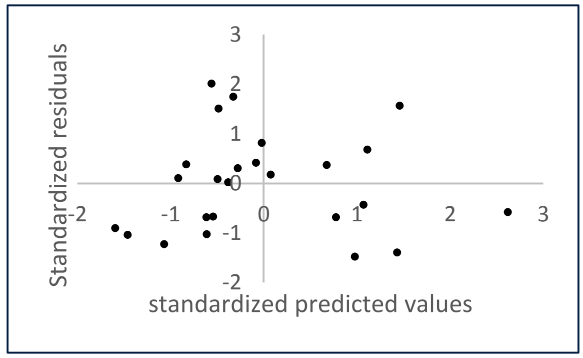

Figure I-2 *Scatterplot standardized predicted values vs standardized residuals IP*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,448
R Square	0,200
Adjusted R Square	0,166
Standard Error	0,051
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,015	0,015	5,763	0,025
Residual	23	0,059	0,003		
Total	24	0,074			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,157	0,067	2,323	0,029	0,017	0,296
IP	1,111	0,463	2,401	0,025	0,154	2,069

Table I-1 *Regression outcomes IP short market*

Price deviation

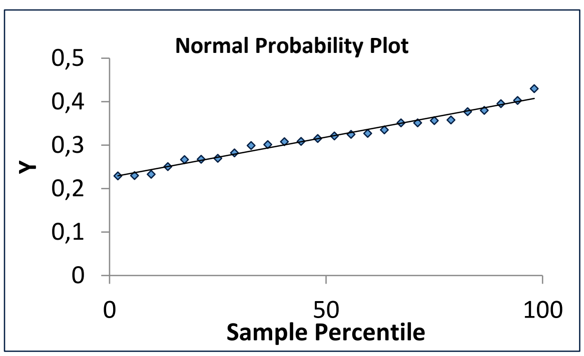

Figure I-3 *Normal probability plot price deviation short market*

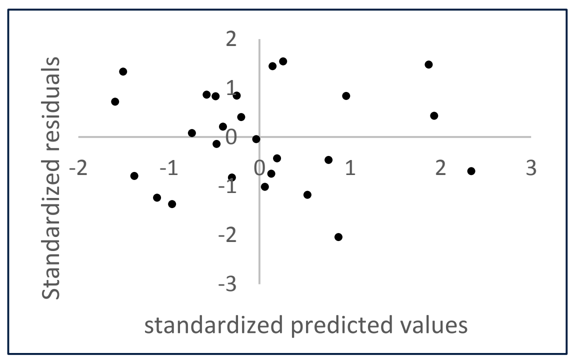

Figure I-4 *Scatterplot standardized predicted values vs standardized residuals PD*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,355
R Square	0,126
Adjusted R Square	0,090
Standard Error	0,053
Observations	26

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,010	0,010	3,460	0,075
Residual	24	0,066	0,003		
Total	25	0,076			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,284	0,021	13,350	0,000	0,240	0,327
X Variable 1	0,587	0,316	1,860	0,075	-0,064	1,239

Table I-2 *Regression outcomes PD short market*

Moderation (Interaction)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,561
R Square	0,314
Adjusted R Square	0,216
Standard Error	0,049
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regression	3	0,023	0,008	3,209	0,044
Residual	21	0,051	0,002		
Total	24	0,074			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95,0%*	*pper 95,0%*
Intercept	0,145	0,066	2,182	0,041	0,007	0,283	0,007	0,283
PD	0,568	0,323	1,763	0,093	-0,102	1,239	-0,102	1,239
IP	0,949	0,467	2,033	0,055	-0,022	1,919	-0,022	1,919
PDMC*IPMC	4,829	15,342	0,315	0,756	-27,077	36,735	-27,077	36,735

Table I-3 *Regression outcomes interaction effect*

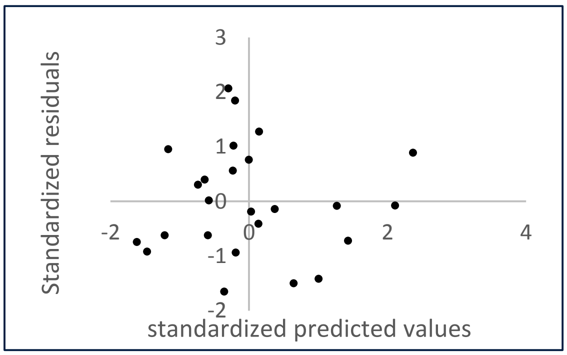

Figure I-5 *Scatterplot standardized predicted values vs standardized residuals multiple regression with interaction*

Multiple regression

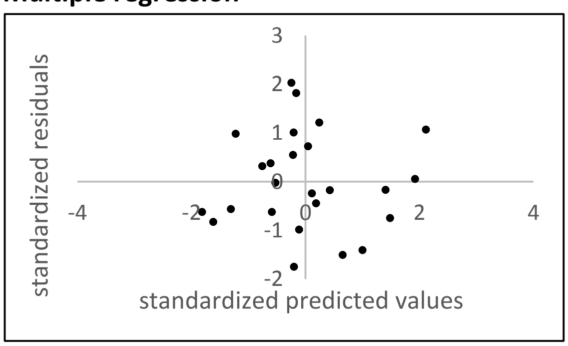

Figure I-6 *Scatterplot standardized predicted values vs standardized residuals multiple regression*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,558
R Square	0,311
Adjusted R Square	0,248
Standard Error	0,048
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0,023	0,012	4,967	0,017
Residual	22	0,051	0,002		
Total	24	0,074			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,148	0,064	2,306	0,031	0,015	0,281
PD	0,585	0,311	1,880	0,073	-0,060	1,231
IP	0,924	0,450	2,052	0,052	-0,010	1,858

Table I-3 *Multiple regression outcomes short market*

Appendix II Regression analysis balanced market

Inventory position

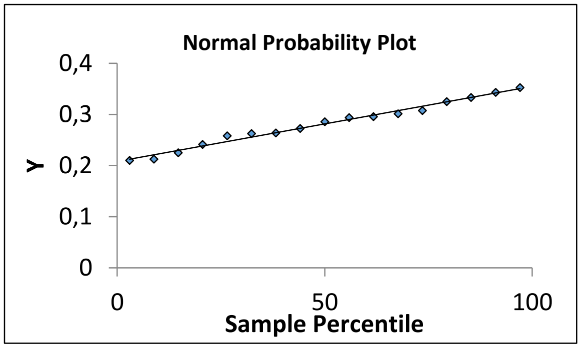

Figure II-1 *Normal probability plot IP balanced market*

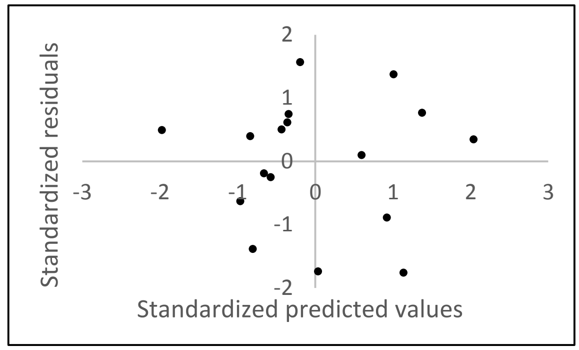

Figure II-2 *Scatterplot standardized predicted values vs standardized residuals IP balanced market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,342
R Square	0,117
Adjusted R Square	0,058
Standard Error	0,043
Observations	17

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,004	0,004	1,987	0,179
Residual	15	0,027	0,002		
Total	16	0,031			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,172	0,079	2,187	0,045	0,004	0,339
IP	0,921	0,653	1,409	0,179	-0,472	2,314

Table II-1 *Regression outcomes IP balanced market*

Production position

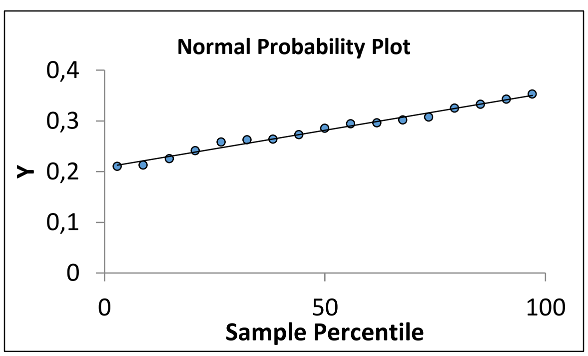

Figure II-3 *Normal probability plot PrP balanced market*

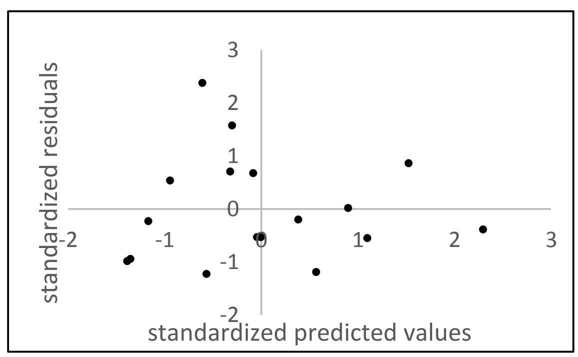

Figure II-4 *Scatterplot standardized predicted values vs standardized residuals PrP balanced market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,692
R Square	0,479
Adjusted R Square	0,444
Standard Error	0,033
Observations	17

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,015	0,015	13,786	0,002
Residual	15	0,016	0,001		
Total	16	0,031			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,136	0,040	3,419	0,004	0,051	0,221
PrP	0,912	0,246	3,713	0,002	0,389	1,436

Table II-2 *Regression outcomes PrP balanced market*

Price deviation

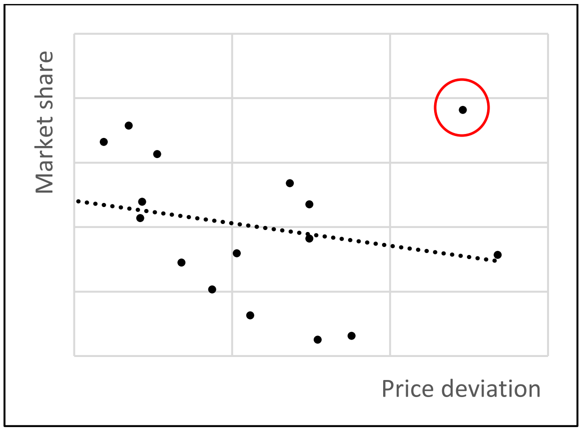

Figure II-5 *Scatterplot PD balanced market*

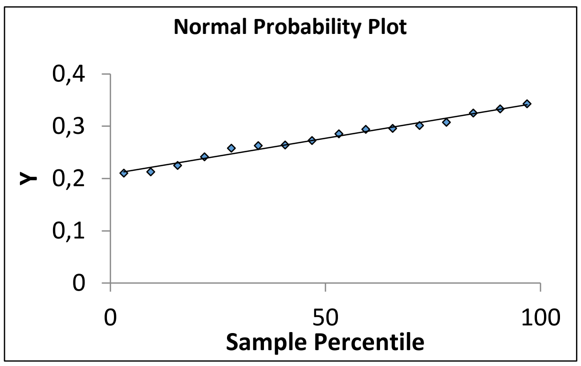

Figure II-6 *Normal probability plot PD balanced market*

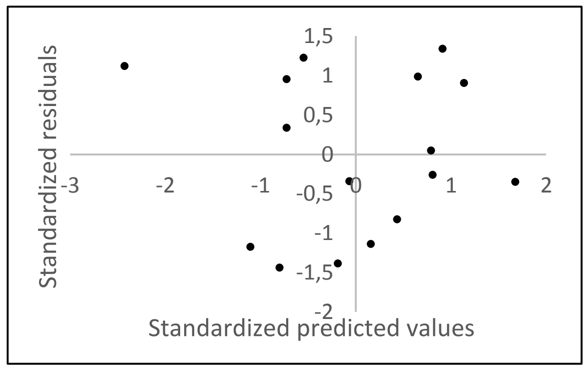

Figure II-7 *Scatterplot standardized predicted values vs standardized residuals PD balanced market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,546
R Square	0,299
Adjusted R Square	0,248
Standard Error	0,036
Observations	16

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,008	0,008	5,960	0,029
Residual	14	0,018	0,001		
Total	15	0,025			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,308	0,015	19,985	0,000	0,275	0,341
PD	-0,623	0,255	-2,441	0,029	-1,170	-0,076

Table II-3 *Regression outcomes PD balanced market*

Multiple regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,721
R Square	0,519
Adjusted R Square	0,399
Standard Error	0,032
Observations	16

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0,013	0,004	4,321	0,028
Residual	12	0,012	0,001		
Total	15	0,025			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	VIF
Intercept	0,224	0,070	3,187	0,008	0,071	0,377	
IP	-0,211	0,575	-0,366	0,721	-1,464	1,043	1,257
PrP	0,669	0,294	2,275	0,042	0,028	1,310	1,423
PD	-0,495	0,241	-2,050	0,063	-1,021	0,031	1,232

Table II-4 *Multiple regression outcomes IP, PrP, & PD balanced market*

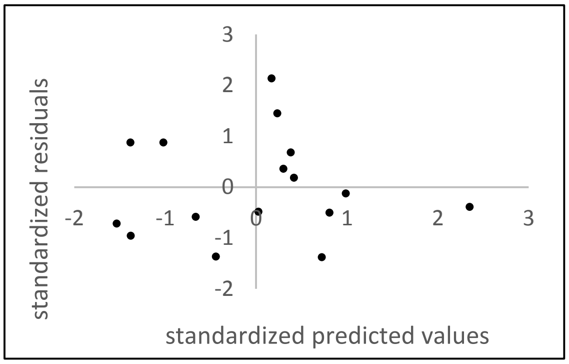

Figure II-8 *Scatterplot standardized predicted values vs standardized residuals PrP & PD balanced market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,717
R Square	0,514
Adjusted R Square	0,439
Standard Error	0,031
Observations	16

ANOVA

	df	SS	MS	F	Significance F
Regression	2	0,013	0,007	6,872	0,009
Residual	13	0,012	0,001		
Total	15	0,025			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	VIF
Intercept	0,205	0,045	4,548	0,001	0,107	0,302	
PrP	0,627	0,261	2,400	0,032	0,063	1,191	1,129
PD	-0,477	0,229	-2,088	0,057	-0,971	0,017	1,129

Table II-5 *Multiple regression outcomes PrP, & PD balanced market*

Appendix III Regression analysis long market

Inventory position

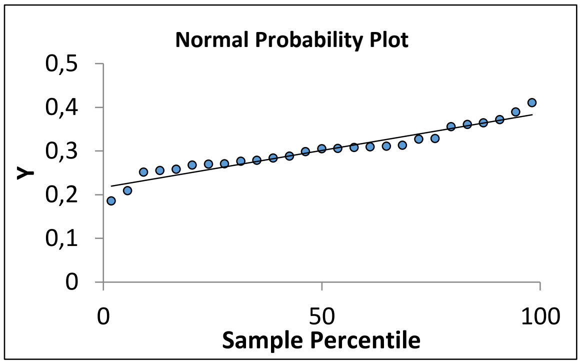

Figure III-1 *Normal probability plot IP long market*

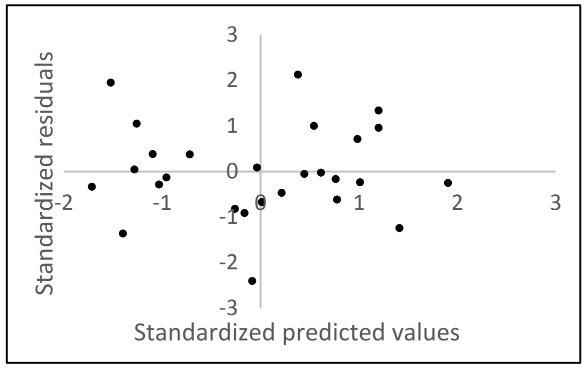

Figure III-2 *Scatterplot standardized predicted values vs standardized residuals IP long market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,392
R Square	0,154
Adjusted R Square	0,120
Standard Error	0,049
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,011	0,011	4,539	0,043
Residual	25	0,059	0,002		
Total	26	0,070			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,194	0,051	3,806	0,001	0,089	0,300
IP	0,838	0,393	2,130	0,043	0,028	1,648

Table III-1 *Regression outcomes IP long market*

Mediation model 1

Step 2: Regress price deviation (PD) on inventory position (IP)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,053
R Square	0,003
Adjusted R Square	-0,041
Standard Error	0,018
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2E-05	2E-05	0,065	0,801
Residual	23	0,007	0,000		
Total	24	0,007			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,031	0,019	1,620	0,119	-0,009	0,071
IP	0,037	0,147	0,256	0,801	-0,266	0,341

Table III-2 *Regression outcomes step 2, mediation model 1 long market*

Mediation model 2

Step 2: Regress production position (PrP) on inventory position (IP)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,557
R Square	0,310
Adjusted R Square	0,283
Standard Error	0,036
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,015	0,015	11,239	0,003
Residual	25	0,032	0,001		
Total	26	0,047			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,041	0,038	1,071	0,294	-0,037	0,118
IP	0,976	0,291	3,353	0,003	0,377	1,576

Table III-3 *Regression outcomes step 2, mediation model 2 long market*

Step 3: both PrP and IP in the regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,560
R Square	0,313
Adjusted R Square	0,256
Standard Error	0,045
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0,022	0,011	5,472	0,011
Residual	24	0,048	0,002		
Total	26	0,070			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,176	0,048	3,689	0,001	0,077	0,274
IP	0,233	0,443	0,525	0,604	-0,682	1,148
PrP	0,590	0,250	2,361	0,027	0,074	1,106

Table III-4 *Regression outcomes step 3, mediation model 2 long market*

Production position

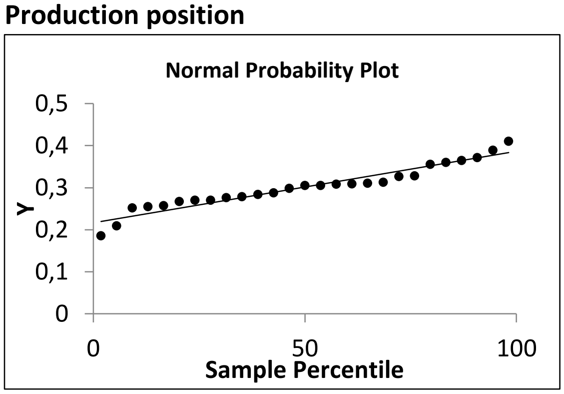

Figure III-3 *Normal probability plot PrP long market*

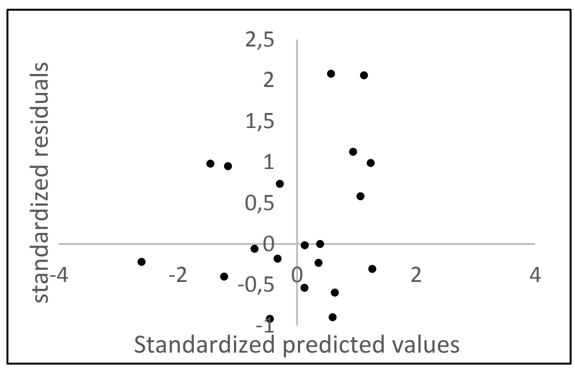

Figure III-4 *Scatterplot standardized predicted values vs standardized residuals PrP long market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,536
R Square	0,287
Adjusted R Square	0,258
Standard Error	0,045
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,020	0,020	10,055	0,004
Residual	25	0,050	0,002		
Total	26	0,070			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,194	0,035	5,517	0,000	0,121	0,266
PrP	0,653	0,206	3,171	0,004	0,229	1,077

Table III-5 *Regression outcomes PrP long market*

Price Deviation

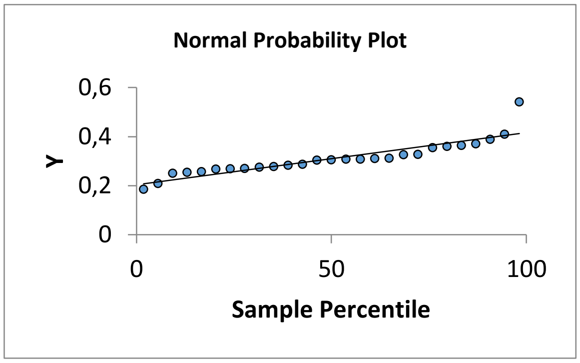

Figure III-5 *Normal probability plot PD long market (n=26)*

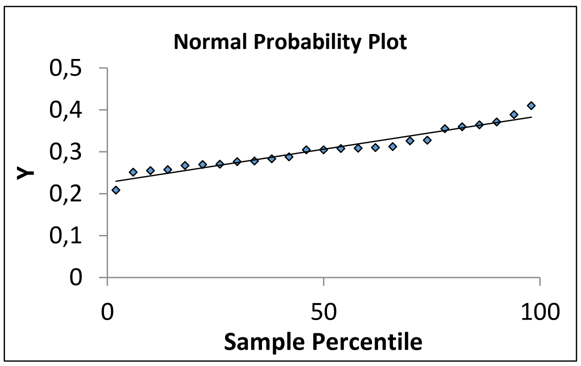

Figure III-6 *Normal probability plot PD long market (n=25)*

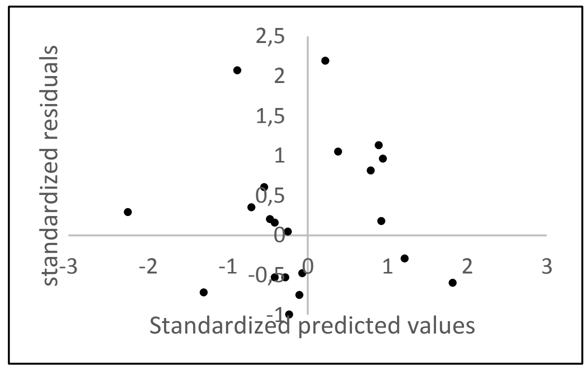

Figure III-7 *Scatterplot standardized predicted values vs standardized residuals PD long market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,302
R Square	0,091
Adjusted R Square	0,051
Standard Error	0,047
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,005	0,005	2,301	0,143
Residual	23	0,051	0,002		
Total	24	0,056			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,276	0,022	12,573	0,000	0,231	0,322
PD	0,838	0,552	1,517	0,143	-0,305	1,980

Table III-6 *Regression outcomes PD long market*

Multiple regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,665
R Square	0,442
Adjusted R Square	0,362
Standard Error	0,038
Observations	25

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0,025	0,008	5,542	0,006
Residual	21	0,031	0,001		
Total	24	0,056			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	VIF
Intercept	0,155	0,045	3,478	0,002	0,062	0,248	
IP	0,261	0,386	0,678	0,505	-0,541	1,064	1,405
PrP	0,626	0,243	2,575	0,018	0,120	1,131	1,534
PD	0,367	0,481	0,764	0,453	-0,632	1,366	1,112

Table III-7 *Multiple regression outcomes IP, PrP, & PD long market*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,655
R Square	0,430
Adjusted R Square	0,378
Standard Error	0,038
Observations	25

ANOVA

	df	SS	MS	F	Significance F
Regression	2	0,024	0,012	8,286	0,002
Residual	22	0,032	0,001		
Total	24	0,056			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	VIF
Intercept	0,175	0,033	5,294	0,000	0,107	0,244	
PrP	0,718	0,199	3,615	0,002	0,306	1,130	1,095
PD	0,320	0,470	0,682	0,502	-0,654	1,294	1,095

Table III-8 *Multiple regression outcomes PrP & PD long market*

Appendix IV S&OP Implementation

Table IV-1 *Input variables optimization models*

i	1	2	3	4	5	6
o_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
s_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
m_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
p_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
j	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
c	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
r	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
s^{pen}	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
<u>Constraints</u>						
s^*	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
p_i^{evp}	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
m_i^C	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
o_i^{GAP}						[redacted]

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i						
o_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
s_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
m_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
p_i^M	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
j	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
c	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
r	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
s^{pen}	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
<u>Constraints</u>						
s^*	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
p_i^{evp}	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
m_i^C	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
o_i^{GAP}	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

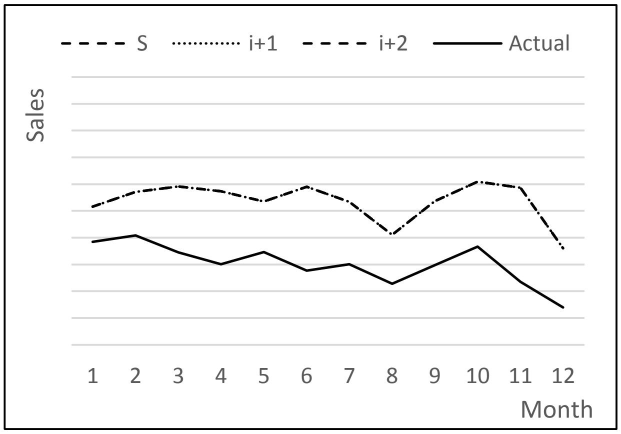

Figure IV-1 *Sales i+1; i+2 revenue model*

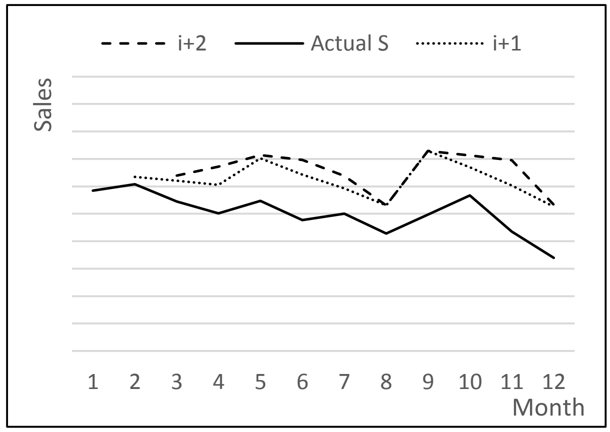

Figure IV-2 *Sales i+1; i+2 profit model*