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Diploma thesis on:

Quantitative approach to short-term financial planning

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Declaration of authorship

I hereby declare that I have written this thesis on my own. I also declare that I have mentioned all used sources and cited them in accordance with established academic standards.

Prague, May 9, 2012 ……

Lukáš Voráček

Acknowledgement

First of all, I would like to thank to doc. Ing. Jiří Hnilica, Ph.D. for his guidance and cooperation. I also want to express my thanks to my colleagues from POS Media for their help. Especially I must thank to Filip Rudolf, my boss and the company's CFO, for enabling me to work with sensitive company data and for his valuable advices. Finally, the greatest thanks go to my family for their never-ending support during my studies.

Title of the thesis

Quantitative approach to short-term financial planning

Abstract

The aim of this study is to certify the legitimacy of employing quantitative methods in the day-to-day business practice. The task is approached as a case study of a real-life financial planning process. I work with the financial data of POS Media Czech Republic (a media company providing point-of-sale advertising solutions). My intention is to simulate the projection of a pro forma income statement with the use of quantitative methods. More specifically, I am applying time series prediction techniques in order to forecast POS Media's sales. The goal is, first, to demonstrate that quantitative techniques can be handled even with limited statistical background and, second, to discuss the relevancy of the obtained results.

In the methodical part of my thesis I deal with the theoretical aspects of financial planning. I further describe various methods of sales forecasting (qualitative vs. quantitative). Special emphasis is put on time series prediction methods.

In the application part I provide a short description of POS Media and its business. I use time series decomposition techniques to predict POS Media's sales in 2012. Consequently, I outline the rest of the pro forma income statement.

Keywords

financial planning, quantitative methods, pro forma income statement, sales forecasting, time series prediction, time series decomposition

Contents

Introduction, goals and motivation

Financial planning is a vital part of corporate financial management. It is believed that a solid financial plan is the real backbone of a successful business. Running a company without it legitimates any worries that such company will sooner or later lose its financial grip. Following a financial road map helps the management guide their day-to-day business decisions. Comparing projected numbers to actual results yields important information about a company's overall health and efficiency. It is almost impossible to predict a company's future cash position without other financial variables being planned in advance. Significant discrepancies between the financial plan and the reality can raise a warning finger about additional capital requirements (before it is too late). There are many other aspects of why financial planning is so important – all in all, proper planning means fewer surprises down the line.

There are several ways how the financial planning process can be approached – starting with a simple rule of thumb, going over erudite expert judgments and ending with very sophisticated methods based on artificial intelligence. On a more general level, two major financial planning streams can be distinguished – qualitative and quantitative. It is apparent from the title of my thesis that I predominantly engage in the latter approach.

During my Master's studies I attended two courses that inspired me to deal with quantitative methods in business/finance and to choose such a topic for my final thesis. First of them was the compulsory Corporate Finance course at my home university. Apart from that professor Hnilica covered the essence of corporate finance he also managed to enrich his lectures by interesting (mostly numerical) applications. In this sense the most influential for me was his presentation on simulation and modeling techniques used in financial planning. The other course, Analyzing Data in Business Decisions, I took at my host university in Vienna. It was taught by professor Nell and its main purpose was to involve the audience of non-statisticians into statistical methods and their use (and misuse) in the everyday business decision-making. Professor Nell, himself not being an expert on

statistics, showed us that even the people with the greatest hate of exact sciences can quite simply make use of them during their executive carriers.

This is where I slowly come to the actual topic of my thesis and all the reasoning behind my selection. I wanted to try myself that as neither a mathematician nor a statistician I can engage in quantitative techniques during a real business case. I was lucky enough that at the same time I wrote this thesis I worked as Financial Controller in POS Media, an international retail media group providing full-service point-of-sale solutions. At my position I was directly involved in the planning process. The company's management was so kind and supportive that I was allowed to use the financial data of the Czech subsidiary in order to re-predict its expected results in 2012.

To summarize the goals of my thesis, I want to verify that even with limited theoretical background I am able to apply quantitative methods in the financial planning process. Further I aim to assess to what extent the employment of quantitative methods is relevant for ordinary business practice and what added value it brings to the company.

In the theoretical part of my thesis I go through the whole process of business planning. I describe its elements, requisites and forms. I clarify why a high-quality sales forecast is a "must-have" of a credible financial plan. I further distinguish between the qualitative and the quantitative approach to sales forecasting and describe the particular techniques within each group. Special emphasis is put on time series prediction methods due to the fact that they play the key role in my case study.

The application part starts with a general description of POS Media and its Czech subsidiary. This is because I feel that it is necessary to properly understand the business essence before going deeper into the financial aspects. For the planning itself I use five-year historical financial data. The cornerstone of the application part is the 2012 sales forecast constructed using time series decomposition methods. After the revenue prediction is obtained, I deal with the projection of selected cost items in order to finish the estimate of the 2012 financial result.

1 Methodological part

1.1 Corporate financial planning

In this initial part of my thesis I would like to address corporate financial planning in general. I start with a definition of corporate financial planning and its incorporation into the whole business planning process. Afterwards, I differentiate financial plans in terms of time horizons they cover and describe basic features of each one. Finally, I present what a typical financial plan formally contains as well as the methods used during the budgeting process. Considering the topic of my thesis, the emphasis is put on budgeting short-term income statements.

Financial planning is a very broad concept that can be defined in various ways. One of the definitions is presented by Brealey, Myers and Marcus.[1] They describe corporate financial planning as: *"... the process of determining a company's financial goals and needs for the future and the means to achieve them."* As the definition suggests, financial planning is just one fragment of complex corporate planning processes.

1.1.1 Strategic, tactical and operating plans

Corporate planning hierarchy can be divided into three basic levels – strategic, tactical and operating. They differ in their time horizons, depth of detail and essentially also in their content.

The top level comprises of strategic planning. Strategic plans leans on two basic areas. On one hand, it is a definition of priorities, long-term goals, intension and notions about where the company should be heading in the future (in other words, definition of vision, mission and values of the company). On the other hand, it is an analysis of the external environment and its expected future development. Probably the most popular conceptual

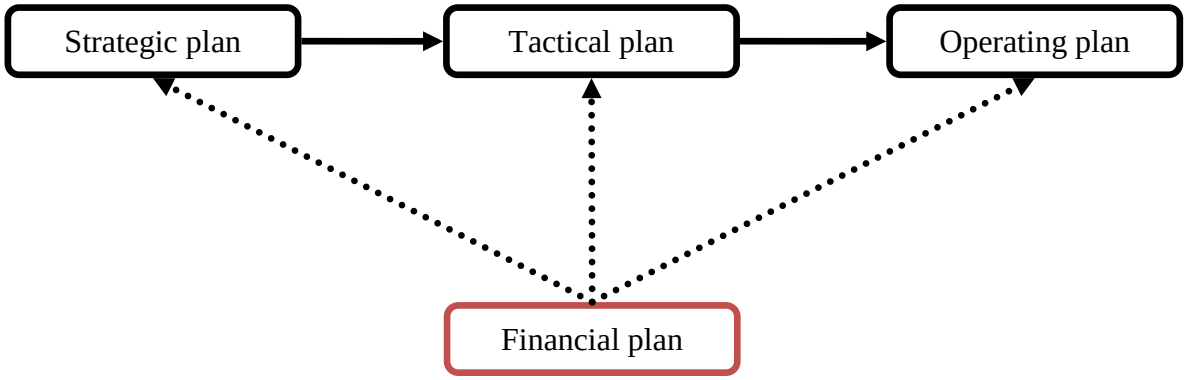
[1] BREALEY, A. Richard; MYERS, C. Stewart; MARCUS, J. Alan: *Fundamentals of Corporate Finance,* McGraw-Hill, London, 2008, ISBN 978-0073363493 – p.82

framework for examining the external environment is the Porter's five forces analysis. Most typically, strategic plans are created with a five-year and longer outlook.

Tactical plans outline key initiatives that need to be taken in order to achieve the overall strategy. They are created for a period of one to five years.

Operating plans provide very detailed implementation guidance based on the stated corporate strategy and tactics. The most common time horizon for operating plans is one year.[2]

Figure 1: Levels of corporate planning



Source: own production

As already mentioned, financial planning is a crucial part of the entire planning chain. In the matter of fact it supports, complements and interacts with each of the discussed planning phases (Figure 1). This logic implies that there must be several financial plans in place, each created for different time period.

1.1.2 Time classification of financial plans

With regards to what has been mentioned above, it is quite intuitive that financial plans can be also segmented into three main categories. According to the time horizon of their interest we distinguish among long-, medium- and short-term financial plans.

Long-term financial plans have strategic character which explicitly reflects the stage of the company's life cycle. Their time frame usually exceeds five years. In contrast to medium-

[2] HILLIER, David; ROSS, A. Stephen; WESTERFIELD, W. Randolph; JAFFE, Jaffrey; JORDAN, D. Bradford: *Corporate finance*, McGraw-Hill, London, 2010, ISBN 978-0077121150

and short-term plans, long-term financial plans do not engage in projecting cash receipts and outlays. Instead they rather aim at the question of the company's capital requirements. Their ultimate role is to support the realization of the company's entrepreneurial intention. Factual content of long-term financial plans consists primarily of optimizing the proportion of long-term debt and equity. All strategic and investment prospects must also be a part of long-term financial plans.

Medium-term financial plans are typically created for time periods of one to five years. They constitute a notional bridge between long- and short-term financial plans and as such they translate goals and expectations of strategic financial plans into a more tangible level.

Short-term financial plans, in most cases, cover a period of one year. It is not rare that the time horizon is even shorter (semiannual or quarterly). Planning itself is typically carried out per month. Short-term financial planning mainly focuses on two elements, which at the first sight can seem to be contradictory. On the one hand, it should guarantee sufficient liquidity to the target company. On the other hand, it strives to assure optimal economic profitability. It is one of the most difficult tasks of a financial manager to find a way how to successfully combine these two tendencies during the short-term planning process. The core of a short-term plan is comprised by a budgeted income statement, which is subsequently utilized as a point of departure for other parts of the financial plan (budgeted balance sheets, cash flow statements, calculations of capital requirements etc.). As already mentioned, projection of short-term income statements will be the central point of my thesis.

1.1.3 Factual form of financial plans

Each financial plan is based on a set of budgeted (also often called "pro forma") financial statements and on their subsequent analysis (ratio analysis, calculation of capital requirements etc.). When we speak about pro forma financial statements we usually mean the following (basic) ones:

- Income statement
- Balance sheet

- Cash flow statement

Financial managers prepare and use pro forma statements in four main ways:[3]

1. By looking at projected statements, it can be assessed whether the firm's projected performance is in line with its own general targets and with investors' expectations. For example, if the projected financial statements indicate that the forecasted return on equity is well below the industry average, managers should investigate the cause and then seek for proper countermeasures.
2. Pro forma statements can be subject to extensive "what-if" analysis in order to estimate the effect of proposed operating changes.
3. Pro forma statements anticipate the company's future financing needs.
4. Projected financial statements represent the main means of estimating future free cash flows, which determine the company's overall value.

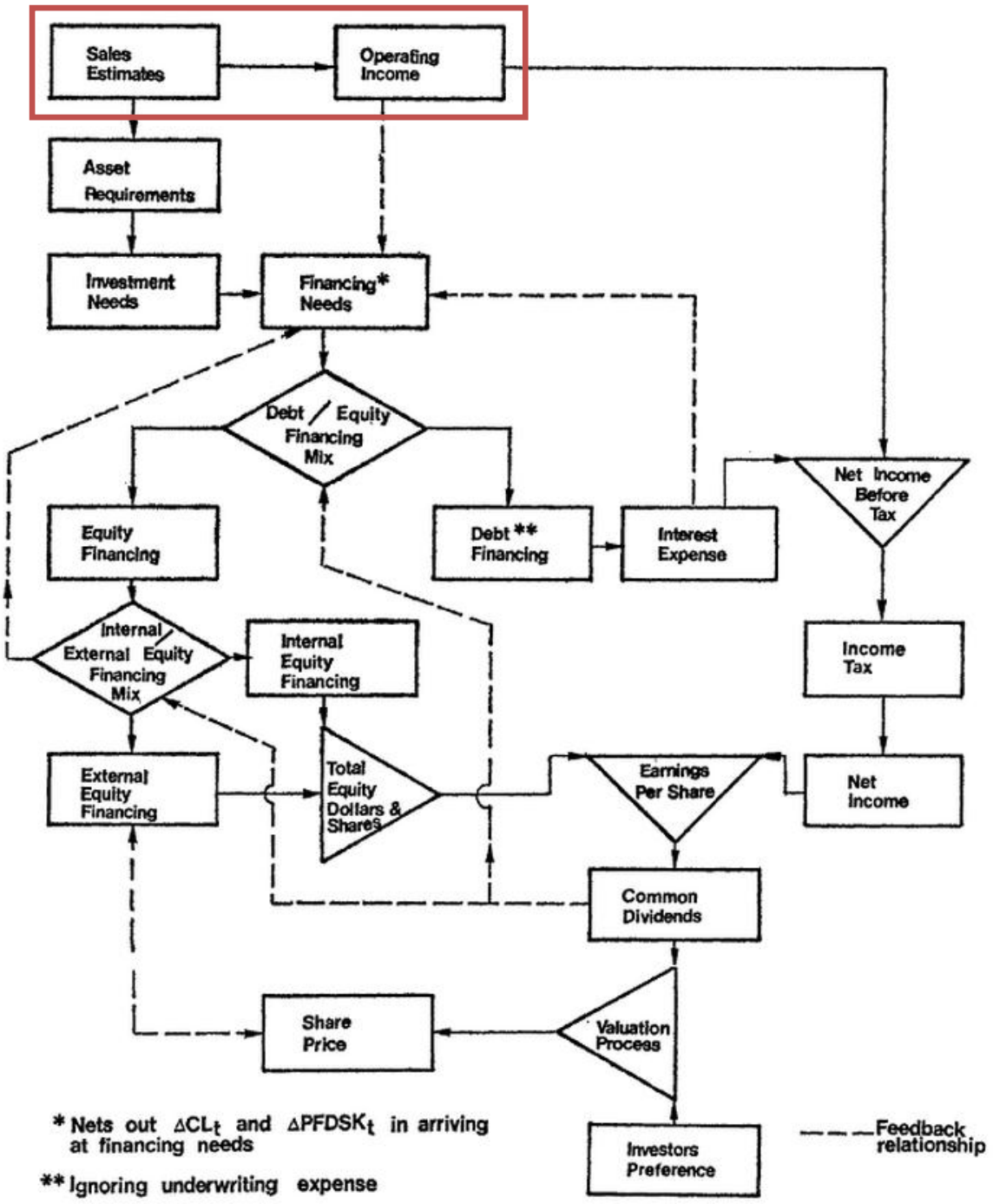
Financial planning is a very comprehensive process that consists of various mutually interconnected sub-elements. This complexity can be illustrated by Figure 1.

As can be seen from the flow chart, the whole financial planning procedure starts with estimating future sales. Indeed, a sales forecast is the most critical part of every financial plan. Even if the most sophisticated and complicated methods are used within the planning process, without a reliable sales forecast it is like building a skyscraper on a pile of mud. That is why the major part of my thesis is devoted to sales forecasting. My ambition is to approach sales forecasting with quantitative methods. Theoretical background on the subject of sales forecasting is provided in chapter 1.2.

The scope of my analysis is actually very narrow compared to the intricacy of financial planning as demonstrated in Figure 1. The work aims at short-term financial planning, the most important part of which, in my belief, is a pro forma income statement (typically a projection of 12 months). My area of focus (depicted by the red rectangle in Figure 1) is therefore limited to pro forma income statement preparation – to be more exact, only its operating part. In the next section I address the topic of pro forma income statements in deeper detail.

[3] HILLIER, David; ROSS, A. Stephen; WESTERFIELD, W. Randolph; JAFFE, Jaffrey; JORDAN, D. Bradford: *Corporate finance*, McGraw-Hill, London, 2010, ISBN 978-0077121150

Figure 2: Flow chart of a typical financial planning model



Source: WARREN, M. James; SHELTON, P. John: *A Simultaneous Equation Approach to Financial Planning*, 1971

1.1.4 Budgeting an income statement

Income statement is nothing else than an overview of how a company's revenue (also known as the "top line") is transformed into its net income (the "bottom line"). All items it records are recognized during a specific period. Thus we can claim income statements to

have a "flow" nature (in contrast to balance sheets which always represents a single moment in time).

This is a typical generic form of an income statement:[4]

Sales

– Cost of goods sold (COGS)

= Gross income

– Operating expenses

= Operating income

– Depreciation and amortization

= Earnings before interest and taxes (EBIT)

– Interest expenses

= Earnings before taxes (EBT)

– Taxes

= Net income

It is clear that preparation of every pro forma income statement starts with outlining the future sales. As already said, I thoroughly elaborate on sales forecasting further in the text. For now it is assumed that the sales forecast is already done.

There are three complementary approaches to projecting income statement items:

- Percent-of-sales method
- Budgeted expense method
- Bridge method

1.1.4.1 Percent-of-sales method

The most common method of preparing a pro forma income statement is the percent-of-sales method.[5] The basic assumption of this method is that many items on the income statement are expected to increase (decrease) proportionally with sales. Each income statement item can then be assigned a ratio (most commonly on historical basis) describing its relation to sales. The expected future value of an income statement item can then be

[4] HILLIER, David; ROSS, A. Stephen; WESTERFIELD, W. Randolph; JAFFE, Jaffrey; JORDAN, D. Bradford: *Corporate finance*, McGraw-Hill, London, 2010, ISBN 978-0077121150

[5] BERK, Jonathan; DEMARZO, Peter: *Corporate finance*, Pearson, London, 2006, ISBN 978-0321416803

found as a multiple of the forecasted sales amount (for the relevant period) and its "to-sales" ratio.

Assuming all costs to be variable is very unrealistic. Using percent-to-sales method universally for all income statement items would most probably result either in understating (when sales are increasing) or overstating (when sales are decreasing) the profit. The character of each cost items must therefore be thoroughly examined before a decision to apply percent-to-sales method is made. Typical example of an item budgeted as percent-to-sales is cost of goods sold (COGS). COGS will very probably vary directly with sales (if this is not the case, it is likely that something is wrong). Generally, all direct costs can be determined as a percentage of sales.

Good way of approaching the percent-of-sales method is to look at the past patterns in expense-to-sales ratios. Going further to the past (not only considering the last-year income statement) enables one to discover trends in relative magnitudes of each expense item.

However simple and handy this method can be, it has one major shortcoming: it fails to account for differences in expense patterns that may exist from year to year. This fact must be considered by the preparation of each financial plan.

1.1.4.2 Budgeted expense method

Budgeted expense method is a vague term denoting a rather individual consideration of each expense item and its predicted value. Generally, it is used for there where the application of percent-of-sales method would be inappropriate (fixed costs or costs with special nature).[6]

Typical example of an expense item that cannot be budgeted using the percent-of-sales method is the personnel costs (abstracted from performance bonuses). This is because salaries rather depend on HR strategies and labor market projections than on current revenue.

[6] FRIDSON, S. Martin; ALVAREZ, Fernando: *Financial Statement Analysis: A Practitioner's Guide*, John Wiley & Sons, London, 2006, ISBN 978-0471409175

1.1.4.3 Bridge method

The last method reflects the intimate interconnection of income statements and balance sheets. For our purposes it means that it is impossible to predict some of the income statement items without having a solid projection of certain balance sheet items. There are several principal "bridges" between the two statements standardly used in financial planning:[7]

- Net income less Dividends = change in Retained earnings
- Interest expenses = Interest rate times Interest bearing debt
- Depreciation and amortization ~ value, age and nature of Fixed assets

Referring to the generic income statement form presented above, we can immediately identify two items the forecast of which needs "bridging" with the balance sheet: depreciation/amortization and interest expenses.

[7] SMITH, L. Richard; SMITH, Kilholm Janet: *Entrepreneurial Finance*, Wiley, Hoboken, 2004, ISBN 0-471-23072-3

1.2 Sales forecasting

As discussed before, proper sales forecast is a real stepping stone of the whole financial planning process. Without a solid idea of what the future sales are going to be, no company is able to set up any financial plan. According to Mentzer and Moon[8], a sales forecast is defined as: *"... a best guess about customer demand for a company's goods or services, during a particular time horizon, given a set of assumptions about the environment."* Although it can sound easily, sales forecasting is a very complex process. Many factors (internal as well as external) have to be taken into account when conducting a sales forecast.

Almost every sales forecast starts with, more or less detailed, look at the past. Quite logically, the longer history of a company, the better conditions for producing high-quality sales predictions. This historic sales pattern in combination with future expectations (about the company, its customers, the industry and the whole economy) build up a basic foothold of sales forecasting.

There are many methods (and combinations of them) used for sales forecasting. In general, these can be divided into two major categories – qualitative and quantitative.

1.2.1 Qualitative approach to sales forecasting[9]

Qualitative methods of sales forecasting are of a subjective nature. They are procedures that turn opinions, personal judgments and intuition of involved expert groups (company executives, marketing/sales/finance managers, external experts etc.) into formal sales forecasts. Qualitative techniques are employed especially in situations when there is no historical data available (or when its quality is too poor to be used for forecasting).

The biggest advantage of qualitative forecasting methods is their pure future-orientation. In contrast to quantitative forecasting (which are discussed in section 1.2.2), qualitative

[8] MENTZER, John; MOON, Mark: *Sales Forecasting Management: A Demand Management Approach*, Sage Publications, London, 2004, ISBN 978-1412905718 – p.34

[9] Compiled according to: MENTZER, John; MOON, Mark: *Sales Forecasting Management: A Demand Management Approach*, Sage Publications, London, 2004, ISBN 978-1412905718

techniques have the potential to predict changes in future demand patterns. Qualitative methods can also make an extensive use of the existing human experience. By nature, this cannot be achieved using the quantitative approach (mainly due to the inherent limitations in the depth of information that can be conveyed by a quantitative data format).

The disadvantage of qualitative forecasting, on the other hand, results mainly from the bias that can be involved in the forecast. There are various sources of the potential bias. Primarily, it is the limited ability of a forecaster to process all relevant information, as well as his/her limited capability of acquiring it. It is a general human tendency to make use of such information that is already available or of such that one has been exposed to in the near past.

There are some other pitfalls concerning the qualitative prediction techniques. The quality of the forecast can be significantly influenced by internal political factors of a company. Moods and/or emotions also play an important role. Last but not least, the qualitative approach to sales forecasting proves to be relatively expensive and time-intensive.

There are several qualitative techniques and tools that will be shortly described:

- Expert evaluation techniques
- Jury of executive opinion
- Delphi method
- Sales force composite

1.2.1.1 Expert evaluation techniques

This method exploits knowledge and experience of experts (in the relevant filed). The usual approach is to combine inputs from various sources (internal and external) in order to prevent biases.

1.2.1.2 Jury of executive opinion

This technique describes a situation when executives from various company departments meet to produce forecasts. By doing this a company is able to make use of joint experience and knowledge of its top-level managers. A survey conducted by Mentzer and Moon[10]

[10] MENTZER, John; MOON, Mark: *Sales Forecasting Management: A Demand Management Approach*, Sage Publications, London, 2004, ISBN 978-1412905718

showed that one of the most widespread uses of the jury of executive opinion is in a so called “consensus forecasting process”. Typically, after quantitative sales forecasts are generated, the consensus forecasting committee meets in order to assess the potential need of adjusting the predicted numbers (eventually decide how they should be adjusted).

1.2.1.3 Delphi method

Named after the mythological cradle of many prophecies, Delphi method represents a forecasting technique which, alike the jury of executive opinion, relies on a panel of experts. The main difference between those two approaches is that Delphi is strictly structured. A typical Delphi-forecasting session proceeds as follows:

1. Each panel member writes down his/her forecast and all the reasoning behind it.
2. All opinions are collected and returned to the panel, but without the identification of the authors of each forecast.
3. After hearing all the other’s opinions, each panel member either decides to retain his/her original forecast or to modify it. In the latter case, he/she again submits the adjusted forecast.

The procedure loops as many times as necessary. The aim is to narrow the range of different forecasts. One big advantage of Delphi method is that its participants usually do not meet face to face and their opinions are anonymous. This fact helps to mitigate potential bias factors resulting for example from a strong position of a leader within the group.

1.2.1.4 Sales force composite

Sales force composite is a method of producing forecasts using the experience of the company’s salespeople. The logic behind this method is to use the opinions of people that are closest to the customer. Indeed, it is the salespeople that are in every-day contact with the customers and as such they are expected to reliably assess the possible future demand patterns. There is one major concern resulting from the sales force generating the sales forecasts though. It is a common practice that the sales employees are awarded according to the extent to which they manage to meet their sales targets. Those targets usually go hand in hand with the sales forecasts.

1.2.2 Quantitative approach to sales forecasting

Quantitative sales forecasts are those that employ mathematic and statistical techniques. The future demand is estimated as a function of the past data. Thus the underlying assumption of the quantitative approach is that the future sales will follow the historical patterns. There are several crucial questions asked during quantitative sales forecasting: How did the historical sales look like? What was their (absolute) value? Which pattern did they follow and how did they develop over time? What conclusion can be drawn from what we learnt about the past? And ultimately, how can this conclusion be used to predict future sales? It is clear, by the definition, that quantitative sales forecasting is very much data-intensive. Conducting any quantitative forecast with lack of historical data simply makes no sense.

Although it can sound paradoxical the biggest advantage of the quantitative sales forecasting methods is that, as a matter of fact, they are very easy to apply. While the qualitative techniques are ambiguous, judgmental and intensive in terms of the brain power employed, the qualitative forecasting (in its narrowest sense) is quite straightforward. This becomes most obvious when we take the example of the time series analysis (a principal quantitative forecasting method). Behind all the sophisticated statistics (which nowadays is handled by computers anyway), there is a very simple logic hidden. Namely, look at the past, suppress all other influencing factors and prolong the past trends into the future. It is an exact science – there is no place for ambiguity and if yes it can be precisely delineated. Of course, this to some extent is exaggerated and nothing is just black and white (as I demonstrate further in the text).

Next advantage of quantitative forecasting approach is that it is relatively inexpensive. If we abstract from the costs of data collection (which can prove to be very costly), the analysis itself can be done by a single person. There is no need to steal precious time of the top-management or to contract various experts.

Probably the most critical stumbling block of the quantitative approach to sales forecasting is its primary prerequisite, namely that all conclusions are based solely on historic data. This brings in substantial risk of the forecast being completely out of reality. Quantitative

methods should therefore be used just in case we expect the historic sales patter to retain its basic characteristics also in the future. This often does not need to be the case. The use of purely quantitative methods should therefore be subject to deeper consideration in beforehand.

There is also one tricky thing about quantitative forecasting. The analysis itself can be done quite mechanically, without much of the human judgment needed. But as I mentioned earlier in the text, there is nothing that simple in the real world. In fact, personal judgment is very important also for the quantitative forecasting approach. Before any analysis can be done a decision about what data will be used must be made. There is a lot of subjective thinking exercised when deciding what data are to be processed during the quantitative analyses, as well as whether any modifications should be made to the data before the analyses are performed.

Ever trickier is what comes after the analysis. Getting nice tables and graphs from a statistical package is not the end of our endeavours. More on the contrary, this is the point when the real work starts. Results must be interpreted and used in drawing our conclusion on what sales we expect in the future. This is a critical part of the business, since there is a significant danger of misinterpreting the outcomes of our analysis. Such misinterpretation (or even misuse) of the results typically has a disastrous impact on the whole budgeting process.

Here is a list of the most important quantitative forecasting techniques (they are described further in the text):

- Naïve approach
- Time series prediction techniques
    - Graphical analysis
    - Time series decomposition
    - Box-Jenkins methodology
- Casual (explanatory) techniques
    - Simple regression analysis
    - Multiple regression analysis
- Alternative (experimental) techniques

- Probabilistic forecasting (Monte Carlo simulation)
- Artificial intelligence methods

1.2.2.1 Naïve approach

Naïve approach towards forecasting is nothing else than a statement that the forecast for any period equals the previous period's actual result. This primitive approach cannot be considered a proper technique and I am mentioning it just in order to be exhaustive. Despite the naïve approach having not much use in the real corporate world, it can still be viewed as a cost-effectiveness benchmark for the other methods.

1.2.2.2 Time series prediction techniques

The time series prediction techniques are used and developed to identify patterns in historical data that repeat over time.[11] These patterns are subsequently prolonged into the future to outline a sales forecast. There are many methods of time series prediction. Since this topic forms the core part of my thesis I decided to leave the discussion about time series in this part of the text and to dedicate a special chapter to theorize about what time series are and how they can be used in short-term corporate budgeting.

1.2.2.3 Casual (explanatory) techniques

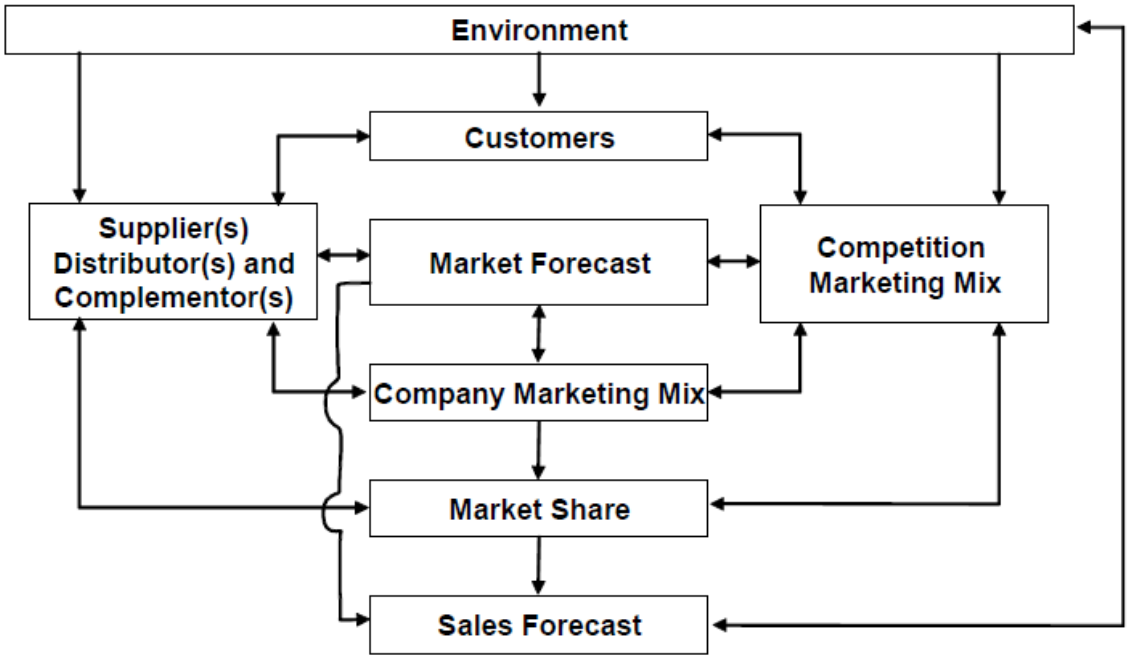
Casual techniques provide information on how various external factors are related to fluctuations of the observed variable (sales in our case). Therefore they are often called "explanatory" techniques.[12] Instead of extrapolating the sales directly, which we basically do during time series analyses, we can rather forecast the variables that cause the sales to vary. Going from the very top, this begins with environmental factors (e.g. population, gross domestic product, legal system etc.). The environment further affects the behavior of all market subjects with which the observed company interacts during its daily business (customers, competitors, suppliers, distributors etc.). Their actions provide inputs necessary to forecast the market and, subsequently, to come up with the expected market

[11] MENTZER, John; MOON, Mark: *Sales Forecasting Management: A Demand Management Approach*, Sage Publications, London, 2004, ISBN 978-1412905718

[12] MAKRIDAKIS, Spyros; WHEELWRIGHT, Steven; HYNDMAN, Rob: *Forecasting: Methods and applications*, John Wiley & Sons, New York, 1998, ISBN 0471532339

share of the target company. The product of the market forecast and the market share forecast yields the desired sales forecast.

Figure 3: Causal approach to sales forecasting



Source: BAKER, Michael: *Sales Forecasting (The IEBM Encyclopedia of Marketing)*, 1999

Casual approach can substantially improve the forecast's accuracy (compared to the time series prediction methods), but only on precondition that certain requirements are met. Above all, there must be a good understanding about how each component (independent variable) relates to the sales. If there is a high uncertainty about any of the elements, it might be (and usually is) more accurate to extrapolate the sales directly.[13]

The primary advantage of the explanatory forecasting techniques is that they provide a clear clue for decision making. After the casual relationship between the dependent variable (sales) and its explanatory factors is found, the company knows what to aim at to improve its performance. Of course, some of the elements can be changed (e.g. adjustments in the marketing mix), but some are completely out of reach (external economic factors as e.g. the purchasing power of customers). Using casual methods

[13] BAKER, Michael: *Sales Forecasting (The IEBM Encyclopedia of Marketing)*, 1999 [on-line] [retrieved 2012-3-23]

forecasts can be prepared to assess the potential changes by other decision makers such as the competitors. Such forecasts can allow the firm to develop various contingency plans.

On the other hand, the causal approach is more expensive than sales extrapolation and, as already mentioned, it is often difficult to arrive at an explanatory model of reasonable quality.

In the following part of the text I will focus on the regression analysis, which constitutes the heart of the casual forecasting techniques. Regression analysis is a statistical method which enables us to identify (and also measure) one-way relationships of independent (explanatory) and dependent variables. In practice, this relationship is most of the times considered to be linear (we speak about linear regression). In such case there is the assumption that the dependent variable is a linear combination of its parameters (explanatory variables). According to how many explanatory variables the model includes we distinguish between simple and multiple regression analysis.

1.2.2.3.1 Simple regression analysis[14]

Regression analysis in its simplest form examines only two variables – one is independent and one is dependent. When performing a regression analysis our main effort is to find a mathematical function that, as much accurately as possible, expresses the relationship between the two variables. This hypothetical mathematical function is called the "regression function". Typical process of conduction a regression analysis looks like this (of course, it must be clear first which explanatory variable will be used):

1. All available information about the character of the relationship between the two variables is assessed.
2. Regression function type is chosen (as already mentioned, in practice there is prevailing tendency to use linear functions).
3. Function parameters are set.
4. Suitability of the model is examined.

While the first two steps (the most critical part of the whole analysis) are fully in hands of the analyst, steps 3 and 4 are pure statistics. A theoretical function is sought for which it

[14] Compiled according to: HINDLS Richard; HRONOVÁ Stanislava; SEGER Jan; FISCHER Jakub: *Statistika pro ekonomy*, Professional Publishing, 2007, ISBN 978-8086946436

holds that the sum of square deviation of the empirical values from the values produced by the theoretical function is minimized. This approach is called the "least square method".

The most common quality measure of the estimated regression function is so called "coefficient of determination" or "R-squared" (R^2), which proceeds from the variance analysis. R-squared, in its simplest definition form, determines how much variability we managed to explain with our theoretical regression function.

Once we have the desired regression model (with sufficiently high R^2) we are able to estimate average values of the dependent variable allowing for the changes in the independent variable. Making such estimates within the interval of our initial measurement is called "interpolation". Since we primarily focus on regression as a technique for predicting sales we need to go beyond this interval. In this case we speak about "extrapolation".

For more detailed theoretical background on regression analysis, please refer to relevant literature.[15]

1.2.2.3.2 Multiple regression analysis

In most cases a two-variable model is not sufficient for explaining a satisfactory amount of the variance. The relations are usually much more complicated and require employing additional parameters. Although the model then becomes more complex the basic principles still hold and are the same as in the case of simple regression.

So called "parsimony principle" should be taken into account when making the decision about the number of parameters used. Parsimony principle says that regression should remain as simple as possible and an additional variable should be added only in case it brings substantial value for the model.

Conducting a multiple regression analysis we must also be really careful in respect to the potential mutual relationship between the explanatory variables (so called "multicollinearity").

[15] For example: HINDLS Richard; HRONOVÁ Stanislava; SEGER Jan; FISCHER Jakub: *Statistika pro ekonomy*, Professional Publishing, 2007, ISBN 978-8086946436

1.2.2.4 Alternative (experimental) techniques

In the corporate world (and not only there) the importance of efficient forecasting has been sharply increasing. In the chase for more and more accurate forecasts this field is subject to continuous development. The more complex the business environment becomes, the greater is the demand for alternative forecasting methods. In the following text I mention some of them.

1.2.2.4.1 Probabilistic forecasting (Monte Carlo simulation)

In contrast to single-valued forecasts, probabilistic forecasts take uncertainty into account. Probability is assigned to each of different outcomes. The result of the forecast then takes a form of a probability distribution function with all its descriptive characteristics.[16] A typical representative of the probabilistic methods, ever more often used in business planning (e.g. corporate budgeting, sales forecasting), is the Monte Carlo simulation.

Named after the capital of Monaco, Monte Carlo (in its purest form) is nothing else than a roulette-like random number generator. It is based upon a random selection of numbers from defined statistical distributions. During the simulation a random number is drawn many times (typically several thousand times) and is subsequently applied in the constructed model. This model is actually very similar to a regression function (and indeed, its components are usually sought with the use of the regression analysis). The fundamental difference between the two is that during the Monte Carlo simulation each "independent variable" is assigned a statistical distribution. The outcome is again a statistical distribution of the target quantity (in our context sales). Statistical significance of the obtained result is assured by the central limit theorem.[17] [18]

Monte Carlo simulation technique has formally existed since the early 1940s. That time it was used by the team of physicists (lead by John von Neumann) during the Project Manhattan (development of the first nuclear bomb). Monte Carlo methods were first introduced to finance in 1968 by David B. Hertz. In his Harvard Business Review article

[16] RANJAN, Roopesh: *Combining and Evaluating Probabilistic Forecasts*, 2009 [on-line] [retrieved 2012-3-24]

[17] central limit theorem states that the mean of a sufficiently large number of independent random variables will be approximately normally distributed

[18] PENGELLY, Jonathan: *Monte Carlo Methods*, 2002 [on-line] [retrieved 2012-3-24]

he pioneered the application of Monte Carlo simulation in corporate finance and risk modeling.[19]

Monte Carlo is quite a straightforward tool for including randomness into forecasting models. Thanks to widely available software (e.g. Crystal Ball – MS Excel add-on developed by Oracle) it is also relatively easy to handle by non-statisticians. Next advantage of Monte Carlo simulation is the possibility of defining correlations and other interdependencies of its parameters.

As already anticipated, the most critical part of the whole simulation is the right selection of the parameters' distributions. Wrong decision about the distributions used implies bad results of the forecast ("garbage in, garbage out"). Generally, it holds that the choice of each statistical distribution should not be made before adequate discussions with experts. Of course, this can prove to be quite costly. Thus the basic principle of Monte Carlo can quite easily turn to be its main disadvantage.

1.2.2.4.2 Artificial intelligence methods[20]

The basic effort of the artificial intelligence methods is to eliminate the urge of human interventions into the data analysis (or at least to minimize it). Without any need of a complicated statistical examination, artificial intelligence offers a viable way of creating a data set model. It is because these methods proceed directly from the data presented. With use of sophisticated algorithms they then strive to turn the raw data into a general data model. In other words, with use of the artificial intelligence we are able to solve even such problems that we do not fully understand.

Majority of artificial intelligence methods is universal enough in order to be used e.g. for time series analyses and subsequently for their forecasting. Considering the scope of my thesis I do not go too deep into artificial intelligence methods. I just briefly describe its typical representative, i.e. artificial neural networks.

No doubt that the human brain is the most perfect information processing tool known to the mankind. Artificial neural networks try to imitate its massively parallel structure of

[19] HERTZ, B. David: *Investment policies that pay off (Harvard Business Review)*, 1968 [on-line] [retrieved 2012-3-24]

[20] Compiled according to: KRÖSE, Ben; VAN DER SMAGT, Patrick: *An introduction to neural networks*, 1996 [on-line] [retrieved 2012-3-24]

simple processing units (neurons). Just as the human brain, artificial neural networks operate by creating mutual interconnections between the "neurons". These neurons may either be physically constructed or virtually simulated by computers. Each neuron receives wide variety of input signals. Consequently, based on an internal weighting system, it produces a single output signal. This signal is typically sent as the input to another neuron. The weighting system is absolutely crucial in the whole process. All neurons typically start out with randomized weights. This means that their "memory" is empty and they must "learn" to be able to solve the assigned problems. Neurons can either learn on their own (they are exposed to large amounts of data and they try to discover general patterns) or they are "trained" by the humans. In the latter case the analyst (also called "the teacher") evaluates whether the outcome is correct. If yes, the neural weightings that produced this particular output are accentuated. Vice versa, weightings responsible for incorrect outputs are degraded.

In the economic world, artificial neuron networks can find their use in areas such as bond rating, credit scoring, target marketing, or time series forecasting.[21]

The ultimate advantage of the artificial neural networks it that, in contrast to linear techniques, they are able to detect complex relationships between dependent and independent variables. Artificial neural networks are also very successful in finding all possible interactions between explanatory variables. Even if implemented on a single computer, their parallel architecture allows the artificial neural networks to process large amounts of data very efficiently. On the top of that, there is almost zero statistical knowledge demand on the analyst.

The biggest disadvantage of this approach, on the other hand, originates from its "black-box" nature. There is almost no transparency during the process of parameter determination. This fact implies substantial difficulty of assessing inherent forecast errors.

[21] HANSEN, John; NELSON, Robert: *Forecasting and Recombining Time-Series Components by Using Neural Networks*, 2003 [on-line] [retrieved 2012-3-24]

1.3 Time series prediction techniques

Time series are the main foundation for the practical part of my thesis where I engage in time series prediction in order to forecast sales. I therefore deal with this subject separately in the following text. I start with brief general description of time series. Then I present the basic methods of time series analysis and prediction.

1.3.1 Time series in general

Time series is a notion that can be defined as a set of observed values of a numerical statistical character *x* that is ordered in a naturally coherent time sequence:[22]

$$x_1, x_2, x_3, \dots, x_n \text{ eventually } x_t, t = 1, 2, \dots, n$$

where:

- n … length of time series
- x_t … observation in time period t

The time distance between two adjacent observations x_i is usually constant. Nevertheless, constant time distances between observations are not strictly imperative.

According to whether a random element is present in the time series or not, it is distinguished between deterministic and stochastic time series.[23] We speak about time series as deterministic when they that can be unambiguously (mathematically) determined. Such time series do not incorporate a random component and can be precisely predicted based on the knowledge of their past pattern. On the contrary, stochastic time series include, to certain extent, elements of randomness. Effectively, stochastic time series result from realization of a random process.[24] Predictions of stochastic time series are therefore much more difficult than those of deterministic time series. Unfortunately, almost all economic time series are of a stochastic character.

[22] HINDLS Richard; HRONOVÁ Stanislava; SEGER Jan; FISCHER Jakub: *Statistika pro ekonomy*, Professional Publishing, 2007, ISBN 978-8086946436
[23] TSAY; S. Ruey: *Analysis of Financial Time Series*, John Wiley & Sons, 2002, ISBN 0-471-41544-8
[24] ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

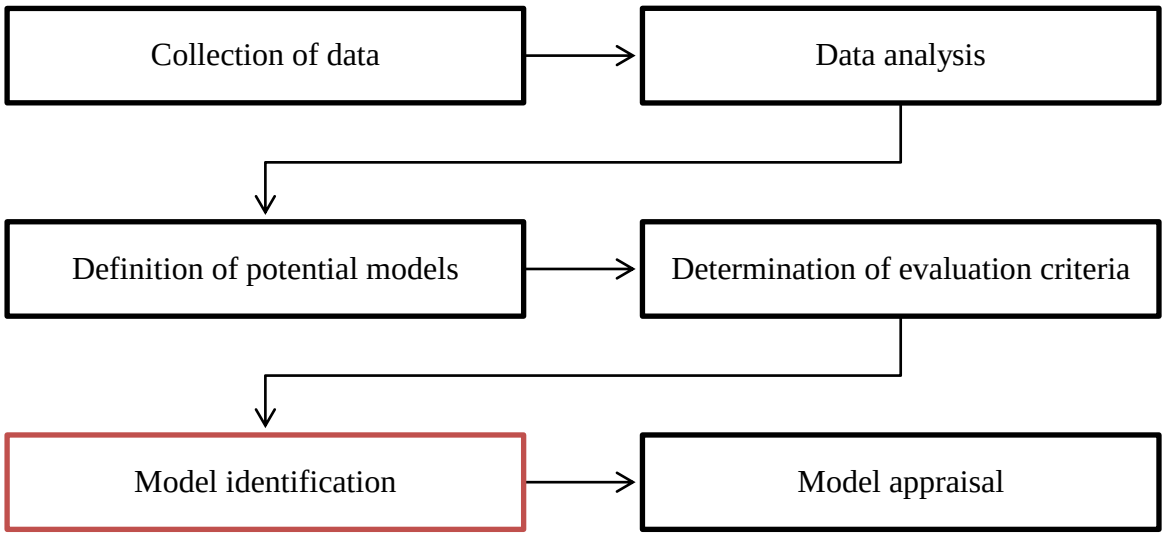
1.3.2 Prediction of time series

Prediction of time series is nothing else than determination of its future values based on the values measured in the past. It is distinguished between two types of predictions – predictions ex-post (interpolation) and ex-ante (extrapolation).[25] Prediction models as such are constructed to find out the future values of time series – predictions ex-ante. Ex-post predictions (predictions of already known values) are typically applied in order to verify the suitability of the selected prediction models.

1.3.2.1 Prediction model selection

Prediction of time series is nothing else than seeking for a transmission function that transfers time series past values (inputs) into predicted values (outputs). When looking for such a function (model) it is usually proceed according to the scheme shown in Figure 4.

Figure 4: Time series prediction model selection process



Source: own production according to ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, 2002

After a comprehensive analysis of the time series data a set of potential models is determined. Next step is to define a criterion according to which these potential models are prioritized (eventually immediately rejected). In case of prediction models such criterion is

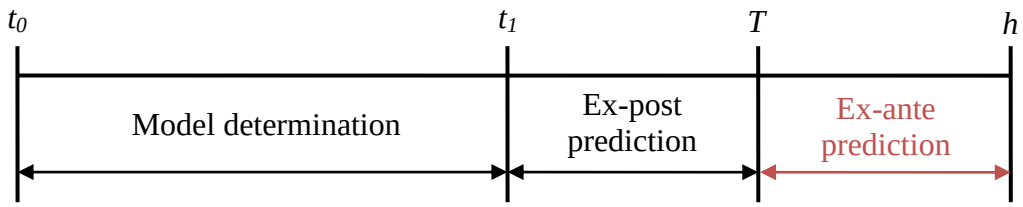
[25] ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

almost exclusively based on the deviation of the predicted and the real values.[26] Logically, a model which best fulfills this criterion is used for the prediction. Appraisal of prediction models is discussed the next chapter.

1.3.2.2 Appraisal of selected prediction models

When looking for suitable prediction models a time series is generally split into two parts (Figure 5).[27] Its entire length (T) is divided into two sub-series. The first (usually longer) data set ($t_1 - t_0$) is used for the actual identification of the model parameters. The second data set ($T - t_1$) serves for assessing the model's quality – prediction ex-post. If appraised as suitable for the specific time series, the model can subsequently be used for predicting its future values – prediction ex-ante. The range of prediction is determined by the length of the so called "prediction horizon" (h).

Figure 5: Time series split during prediction model determination



Source: own production according to TSAY, S. Ruey: *Analysis of Financial Time Series*, 2002

There is plenty of possible model evaluation criteria (usually of a statistical nature) used during the ex-post predictions. I describe the most commonly used ones:[28]

- Mean Absolute Deviation (MAD)
- Mean Square Error (MSE)
- Mean Absolute Percent Error (MAPE)
- Pearson's coefficient of correlation (r)
- Theil's coefficient of inequality (U)

[26] TSAY, S. Ruey: *Analysis of Financial Time Series*, John Wiley & Sons, 2002, ISBN 0-471-41544-8
[27] ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7
[28] Compiled according to: FOKA, Amalia: *Time Series Prediction Using Evolving Polynomial Neural Networks* (dissertation), 1999 [on-line] [retrieved 2012-4-3]

- Theil's decomposition of MSE
- Autocorrelation tests

1.3.2.2.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the prediction accuracy as average absolute value of deviations between the real and the predicted values.

$$MAE = \frac{\sum|x(t) - \hat{x}(t)|}{N}$$

where:

- *x(t)* ... real value
- $\hat{x}(t)$ ... predicted value

1.3.2.2.2 Mean Square Error (MSE)

Mean Square Error (MSE) works on analogous principle as MAE. The only difference lies in squaring the deviations (instead of simply calculating their absolute values). Main consequence of this non-linearity is that larger deviations are captured with a much greater weight.

$$MSE = \frac{\sum(x(t) - \hat{x}(t))^2}{N}$$

In order to make it easier to interpret Root Mean Square Error (RMSE) is often used instead of MSE. The advantage of RMSE is that it is measured in the same units as the original time series.

$$RMSE = \sqrt{MSE}$$

1.3.2.2.3 Mean Absolute Percent Error (MAPE)

The main benefit of Mean Absolute Percent Error (MAPE) is its dimensionlessness. MAPE is therefore a suitable measure for comparing prediction accuracy of different models.

$$MAPE = \frac{\sum \frac{|x(t) - \hat{x}(t)|}{x(t)}}{N} \cdot 100(\%)$$

1.3.2.2.4 Pearson's coefficient of correlation (*r*)

Pearson's coefficient of correlation (*r*) bases on the graphical analysis. Both real and predicted values are outlined in a diagnostic plot of *x(t)* versus $\hat{x}(t)$. In the ideal case both the real and the predicted values should lie on the I. and III. quadrants axis (45° line). Pearson's coefficient of correlation is calculated as deviation of the values from this line.

$$r = \frac{SS_{x\hat{x}}}{\sqrt{SS_{xx} \cdot SS_{\hat{x}\hat{x}}}}$$

$$SS_{xx} = \sum (x - \bar{x})^2$$

$$SS_{\hat{x}\hat{x}} = \sum (\hat{x} - \bar{\hat{x}})^2$$

$$SS_{x\hat{x}} = (x - \bar{x})(\hat{x} - \bar{\hat{x}})$$

where:

- $\bar{x}$ … mean of real values
- $\bar{\hat{x}}$ … mean of predicted values

Coefficient *r* takes values from the interval (-1, 1). For easier assessment of the result r^2 is often used instead of *r*. Values of r^2 belong to the interval (0, 1). The closer r^2 is to 1, the better is the prediction.

1.3.2.2.5 Theil's coefficient of inequality (*U*)

Theil's coefficient of inequality (*U*) measures the model's prediction accuracy in relation to the so called "no-change" (NC) model. NC model assumes time series to have relatively stable values from one period another. Following this assumption, the current value of a time series is also used as the next period's forecast, i.e. *x(t +1) = x(t)*. NC model is therefore nothing else than a simple shift of a time series in time.

The most straightforward way of arriving at U is:

$$U = \frac{\sqrt{MSE(model)}}{\sqrt{MSE(NC\ model)}}$$

If *U* equals 0 our model predicts perfectly (its MSE is zero). For values of *U* equal to 1 (or close to 1) the model predicts about as accurately as the NC model. *U* being greater than 1 means that the model predicts worse than the NC model. Analogously, if *U* is less than 1 our model predicts better than the NC model.

1.3.2.2.6 Theil's decomposition of MSE

MSE can be decomposed in the following way:

$$MSE = (\bar{\hat{x}} - \bar{x})^2 + (s'_{\hat{x}} - r s'_x)^2 + (1 - r^2) {s'_x}^2$$

$${s'_x}^2 = \sqrt{\frac{\sum (x(t) - \bar{x}(t))^2}{N}}$$

$$s'_{\hat{x}} = \sqrt{\frac{\sum (x(t) - \bar{\hat{x}}(t))^2}{N}}$$

If we divide the whole decomposed form of MSE by MSE, we get the following expression:

$$1 = \frac{(\bar{\hat{x}} - \bar{x})^2}{MSE} + \frac{(s'_{\hat{x}} - r s'_x)^2}{MSE} + \frac{(1 - r^2) {s'_x}^2}{MSE} = U_M + U_R + U_D$$

Each of the three quantities U_M, U_R and U_D can now be interpreted as a component of MSE. U_M is the part of MSE caused by systematic error of the prediction model. U_R signalizes how much of MSE is brought about by the regression line deviating from the I. and III. quadrants axis. U_D, the remaining component of MSE, is caused by random elements and cannot be controlled.

1.3.2.2.7 Autocorrelation tests

Autocorrelation tests verify the model's compliance with one of the basic requirements of residues – whether its random element is not correlated (i.e. whether the relative rate of dependence observed in the residues' development is not too large).[29] We must assure that the model captures most of the dependence in the input data. Ideally, residues should then have purely random character.

One of the most common tools of identifying possible autocorrelations is the Durbin-Watson test. It tests the null hypothesis that the autocorrelation of residues is zero against the alternative hypothesis about the presence of autocorrelation.

[29] ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

1.3.3 Basic methods of time series analysis

In this section I describe the most common statistical methods used for time series analysis:

- Graphical analysis
- Time series decomposition
- Box-Jenkins methodology

1.3.3.1 Graphical analysis

Although this method seems to be quite simple compared to the other (more sophisticated) methods of time series analysis, plotting a time series to a chart should be the first logical step. When examining a time series in its graphical expression it often becomes more apparent which other analysis techniques might be used. At the same time one can acquire a basic overview of the time series' character and adjust his/her expectations and demands placed on the final model.

Typically, the graphical analysis is complemented by determination of fundamental statistical parameters (mean, dynamics, variance etc.).

1.3.3.2 Time series decomposition[30]

Time series decomposition is a statistical method that deconstructs a time series into the following notional components:

- Trend component (T_t)
- Seasonal component (S_t)
- Cyclical component (C_t)
- Irregular component (ε_t)

Time series Y_t can then be expressed as:

$$Y_t = T_t + C_t + S_t + \varepsilon_t \ \ldots \text{ adaptive model}$$

$$Y_t = T_t \cdot C_t \cdot S_t \cdot \varepsilon_t \ \ldots \text{ multiplicative model}$$

It is not essential (even not ordinary) that each time series includes all four components.

[30] Compiled according to ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

Trend component (T_t) captures long-term behavioral changes in a time series. It results from factors that influence the time series on a long-term basis (e.g. market conditions). The trend can be described (in the whole length of a time series) by a mathematical function. Such a function can be found for example with help of the least square method.

Seasonal component (*St*) of a time series describes its periodical changes that occur repeatedly within certain time span. Seasonality can typically be observed in quarterly and annual data.

Cyclical component (*Ct*) expresses long-term (longer than seasonal) oscillations of a time series along its trend. Cycles occur in longer than one-year periods. In shorter time series cyclicality may not even be identifiable. Therefore it is often (not quite correctly) included in the trend.

Irregular component (ε_t), also called the "noise", is formed by random time series' fluctuations. In contrast to all preceding components, irregular part is non-systematic. It comprises all effects that influence development of a time series and that cannot be detected and described in a systematic way.

Practical application of the time series decomposition has the following main reasons:

- When analyzing all its components separately, such features of the examined time series can be revealed that may not be observable at the first glance.
- Time series can be adjusted for seasonality, which enables making comparisons of several time series at the same time.
- Time series can be adjusted for trends, which enables better modeling of seasonality (its character becomes more obvious).
- Decomposition facilitates making more accurate prediction of time series' future values. It is because all components can be predicted separately and afterwards summed (adaptive model) or multiplied (multiplicative model) in order to arrive at the desired prediction.

1.3.3.3 Box-Jenkins methodology[31]

In contrast to time the series decomposition, Box-Jenkins methodology accentuates almost solely the irregular component. It arrives from an assumption that the irregular component is comprised of correlated elements (random variables). Regression and correlation analysis therefore stands in the core of Box-Jenkins methodology.[32]

Box-Jenkins methods are generally considered to be more flexible and adaptable than the decomposition techniques. They react more promptly on changes in the time series' character.

During Box-Jenkins analysis, a time series is perceived as a realization of a stochastic process (i.e. a chronologically ordered series of random variables). Stationarity of this stochastic process is the basic prerequisite for application of Box-Jenkins. Stochastic process can be regarded as strictly stationary if its probabilistic behavior is invariable towards the time shifts (lags). Assumption of stationarity assures that all values of the examined process can be considered as conditional random selection from a statistical distribution. Such values then oscillate around an implicit mean value and have the same variance.

The following basic stationary processes can be named: Autoregressive process (AR), Moving average process (MA), Integrated process (I) and their combinations (ARMA, ARIMA).

For more theory on Box-Jenkins methodology, please refer to relevant literature.[33]

[31] Compiled according to ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

[32] FOKA, Amalia: *Time Series Prediction Using Evolving Polynomial Neural Networks* (dissertation), 1999 [on-line] [retrieved 2012-4-3]

[33] For example: TSAY, S. Ruey: *Analysis of Financial Time Series*, John Wiley & Sons, 2002, ISBN 0-471-41544-8 or ARTL, Josef; ARTLOVÁ, Markéta; RUBLIKOVÁ, Eva: *Analýza ekonomických časových řad s příklady*, VŠE, 2002, ISBN 80-245-0307-7

2 Application part

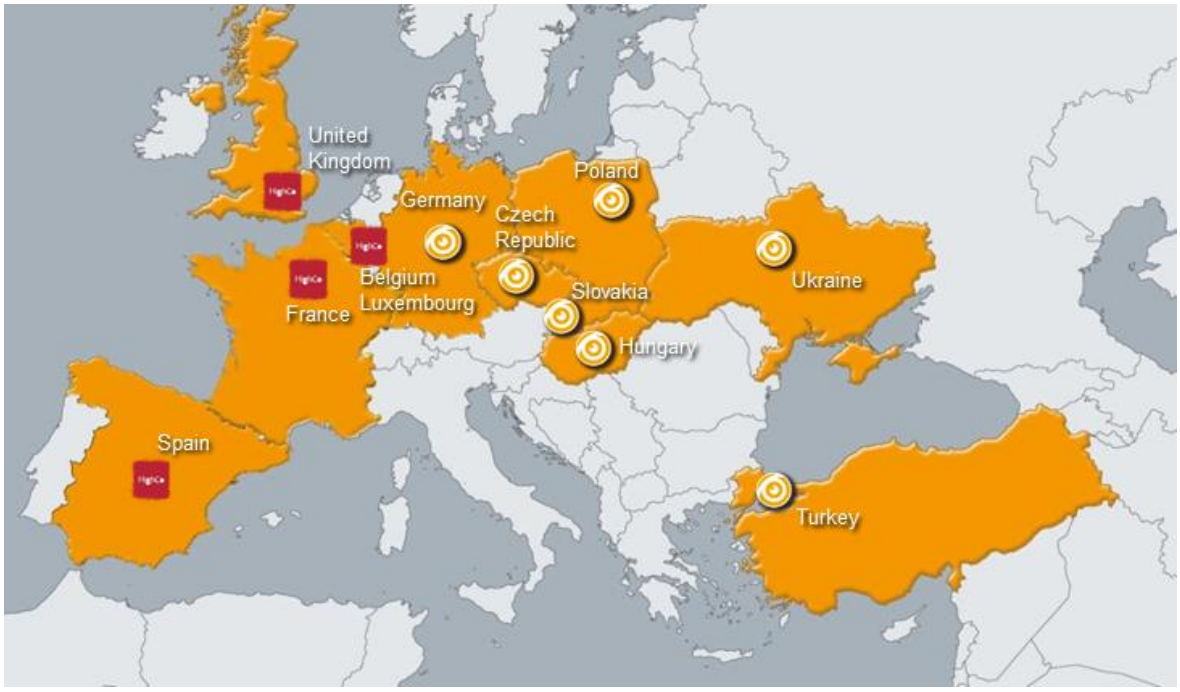
2.1 General description of POS Media

Before any financial planning can start, it is absolutely crucial to have a sound idea about the business field. I am therefore opening the practical part with the description of the target company, POS Media, and its industry.

2.1.1 POS Media Group

POS Media is the leading European media group providing point-of-sale advertising solutions. It is headquartered in Prague where it was also founded in 1998. Nowadays it is active in 11 European countries (Figure 6). POS Media has become the exclusive partner of major European retail chains and acts on behalf of the key advertisers (clients) in each of its territories.

Figure 6: Geographical presence of POS Media



Source: POS Media

2.1.2 Business model, products and clients

Among all its other activities, POS Media predominantly focuses on in-store (supermarkets, hypermarkets) point-of-sale advertising. With most of the retail chains POS Media cooperates on exclusive basis. It means that whenever a client company wants to launch any advertising campaign within the particular store, it is referred to POS Media. POS Media then not only rents the advertising space, but is able to cover a complete set of services accompanying the campaign. These include general consultancy on the campaign concept (when, where, how), campaign planning, advertising material production (graphic processing, printing etc.), installation/de-installation, follow-up activities etc.

Figure 7: Examples of in-store media carriers

Source: POS Media

There are many places where an advertisement can be placed within a store. Figure 7 shows some of the basic in-store point-of-sale media sites (also called “media carriers” or simply “carriers”).

Pallet Design (upper left) is one of the most creative ways of highlighting secondary placements (displays) and attracting customers to the client's products.

Shelf Stopper (upper right) is used to "beat" competitive products in the shelves. In order to help the consumers not to lose orientation among large numbers of different products, Shelf Stopper should communicate where the section with a specific product is. It can also carry additional information (e.g. price reductions). It is easy to install and very versatile, thus suitable for most locations and types of stores.

Shopping Trolley Advertisement (lower left) allows the client company to highlight its brand and products throughout the store. It is placed in the front part of shopping trolleys so that the customers have it directly in their line of sight. It can also be used to direct the customers to a specific product in the store.

Entrance Gate Advertisement (lower right) is a highly visible and creative solution for various types of in-store campaigns. It allows for a large visual with a very strong impact on the customers as they enter the store.

POS Media cooperates with top FMCG companies including e.g. Nestlé, Procter&Gamble, Unilever, PepsiCo, Kraft Foods, InBev, Coca Cola, L'Oreal, Danone or Heineken. Various non-FMCG clients also take advantage of POS Media services. Such clients most typically operate in the automotive industry (e.g. Volkswagen Group, Ford, Renault), telecommunications (e.g. Vodafone, Orange, Telefonica O2) or financial services (e.g. MasterCard, Visa). The clients approach POS Media either directly or via media agencies. POS media works with the majority of the top European media groups.

2.1.3 Industry

POS Media participates in a very dynamic industry. On one hand, point-of-sale advertising is still a niche segment. This fact is also obvious from the budget proportions that companies spend on point-of-sale advertising compared to the more traditional ways (TV, press, radio, outdoor etc.). On the other hand, advertisers focus on more selective and effective ways of attracting the target demographic and point-of-sale advertising thus becomes increasingly important.

In-store advertising influences the customers in the most sensitive phase of their shopping process, i.e. when they are willing to create or change their preferences. So even though the CPT (cost-per-thousand)[34] is generally higher in case of point-of-sale advertising (compared to e.g. TV), it largely capitalizes on its effectiveness and immediacy.

By its nature, the point-of-sale advertising sector is very closely related to the development in the whole retail (in-store) industry. The retail environment is then characterized by several key features:

- High grade of competition
- Dominance in the consumers "share-of-wallet"
- Strong concentration of sales
- Dependence on macroeconomic factors
- Noticeable seasonality

Historically, retail has always been a very competitive economic sector. There are many players in the field, all of them offering almost identical products. Since the final price for the consumers becomes one of the very few differentiation tools, competitive battles usually take place on the pricing level.

Retail industry absorbs most of the consumers' outlays. Statistics show that approximately two thirds of all household expenses (in the Czech Republic, roughly 100 000 CZK per a family member) flow through retail.[35]

There is a very strong concentration in the retailing sector. During the last years, the (FMCG) market share of TOP-10 retailers has been even more than 70%.[36] Strong international retailing chains dominate the industry.

Expenses for the final consumption account approximately for 75% of the gross domestic product (GDP).[37] It is therefore clear that the performance of the economy as a whole obviously has a great impact on the retailing industry. Profits of retailers are generally

[34] CPT (cost-per-thousand) = average price paid by advertisers paid for addressing 1000 potential customers with their message

[35] CIMLER, Petr; ZADRAŽILOVÁ, Dana: *Retail Management*, Management Press, 2007, ISBN 978-8072611676

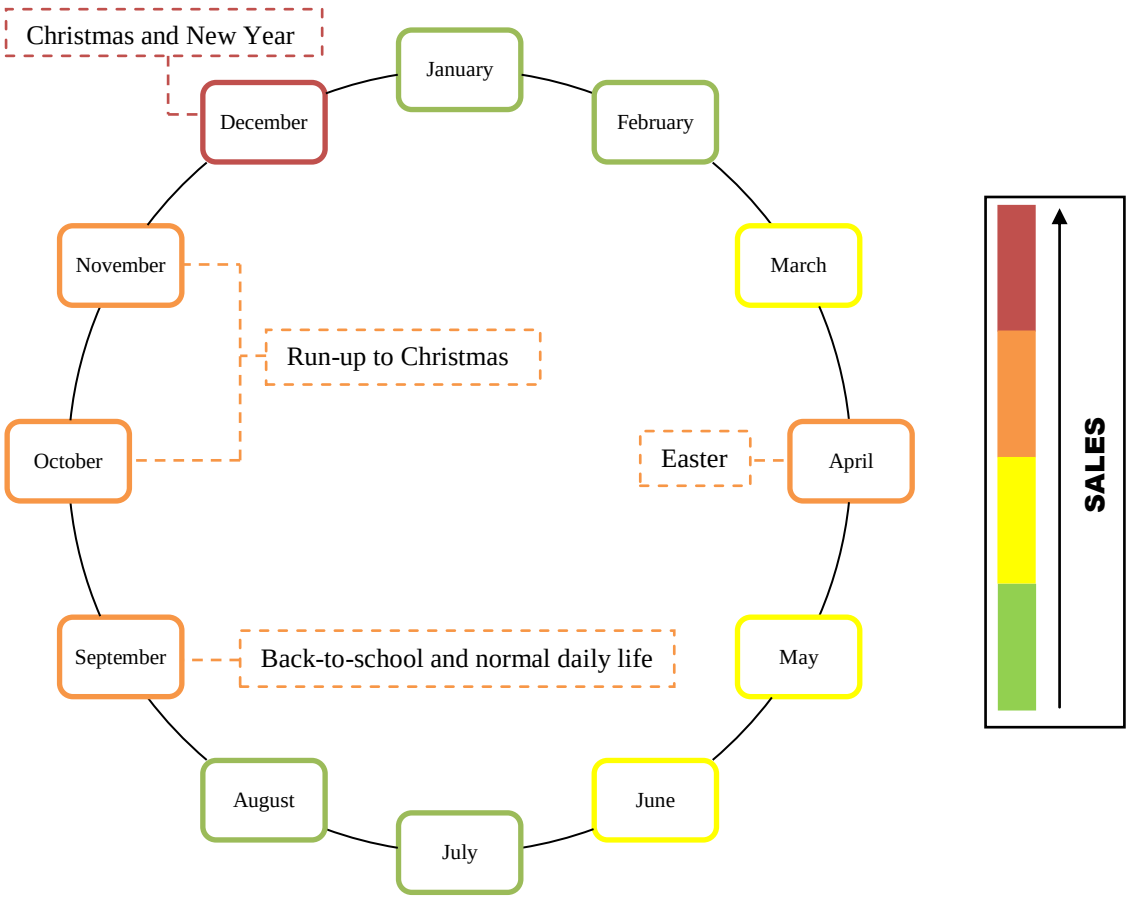
[36] CIMLER, Petr; ZADRAŽILOVÁ, Dana: *Retail Management*, Management Press, 2007, ISBN 978-8072611676

[37] BARTA, Vladimír; PÁTÍK, Ladislav; POSTLER, Milan: *Retail Marketing*, Management Press, 2009, ISBN 978-8072612079

assumed to have a very close correlation with the overall state of the economy. When making any judgments about the future estimated performance of the retail sector, it is advisable to look for trends in the main macroeconomic factors: GDP growth, inflation, consumer confidence, personal income and interest rates. From an investment perspective, the sector is generally expected to track broader stock market indices.

Retail is one of the most seasonal industries. Holiday spending and other seasonal factors usually mean substantial swings in the financial results from one quarter to another. Generally there are several revenue peaks throughout the year (Figure 8).

Figure 8: Seasonality of the retail industry



Source: own production

The most obvious peak is naturally in December. Christmas time and the preparations for the New Year's Eve make the consumers shop a lot. In fact, it is not unusual for many retail businesses to see their sales rise by more than one-third above the normal monthly

sales in December.[38] This giant sales peek is typically followed by an abrupt chill-out in January and February. In March the retail sales start to revive again to reach their local maximum before and during the Easter time. This usually occurs in April (depending on when Easter comes in a given year). The spring season is usually characterized by slightly below-average sales levels. Another low season comes during the summer holiday. This low season is interrupted by the back-to-school term in September when people come back to their "normal" lives after enjoying the days-off. October and November are often called as the "run-up for Christmas" period. Sales grow continuously during these two months and they culminate in December.

2.1.4 POS Media Czech Republic

During my analysis I concentrate solely on POS Media Czech Republic. There are several reasons why I decided for the Czech subsidiary. Above all, it is the oldest member of POS Media Group with the longest history. Therefore I was able to obtain high-quality financial data that go relatively deep into the past. Secondly, the Czech Republic is a quite stable market, which is one of the main prerequisites of employing quantitative methods in short-term financial planning. Finally, since I know them personally, I was free to approach any of my colleagues with my queries. Indeed, these consultations helped me immensely during the work on my thesis.

As I said, POS Media Czech Republic is the oldest POS Media subsidiary. It was founded in 1998. Back then the company was called IMIGe Czech Republic (rebranded to POS Media in 2008).

The Czech in-store retail market is very developed and relatively extensive. For illustration, the relative number of hypermarkets is one of the highest in Europe (approximately 250 in total).[39] This precondition makes the Czech Republic an ideal place for deployment of point-of-sale solutions.

[38] DUNNE, Patrick; LUSCH, F. Robert: *Introduction to Retailing*, South Western College, 2010, ISBN 978-0538755078

[39] CIMLER, Petr; ZADRAŽILOVÁ, Dana: *Retail Management*, Management Press, 2007, ISBN 978-8072611676

POS Media Czech Republic is a clear market leader in its sector. It is the exclusive provider of point-of-sale services in three of TOP-5 Czech retail chains[40] – Tesco, Ahold and Makro. In large volumes it also cooperates with Interspar. POS Media Czech Republic therefore covers a great majority of the market.

Apart from the in-store segment, which definitely is its dominant focus, POS Media Czech Republic also services great number of schools (universities and secondary schools) and some of the petrol station networks. Figure 9 illustrates how such advertising can look like. Bulletin Board (left) is a standard school carrier which can usually be found in corridors all over the building. Nozzle (right) is the most typical carrier of petrol stations.

Figure 9: Examples of media carriers at schools and petrol stations

Source: POS Media

2.1.5 Financial planning process

Each subsidiary of POS Media Group, including POS Media Czech Republic, has its own financial plan. Financial planning in POS Media prevalently takes the form of short-term financial plans, the dominant part of which is comprised by pro forma income statements. These short-term plans typically cover one calendar year (January-December) and are divided into 12 months. Plans for the upcoming period are usually finalized in November and are updated ("reforecasted") regularly after each quarter.

In general, a lot of emphasis is put on the yearly planning process. This has several reasons. First, short-term financial plans are drawn in order to materialize operational plans

[40] http://www.incoma.cz/

of each subsidiary. Observing the development of the crucial financial indicators and their comparison with the planned values enables the management of POS Media to identify potential traps on the way towards accomplishing the operational plan.

Second, the yearly financial plan constitutes a binding profit target for all subsidiaries. Confrontation of the real results with the planned values makes up a crucial part of each country manager's remuneration scheme.

Last but not least, it is because of strict official reporting requirements. POS Media Group is almost half-owned by a French media group HighCo. HighCo's shares are quoted on the Paris Stock Exchange, which has considerable reporting consequences for POS Media. Results of each subsidiary have to be reported monthly. They are compared with the annual financial budgets (pro forma income statements). This comparison takes place on actual month's as well as on year-to-date (cumulative) basis. Yearly plans are released at the end December and updated regularly during the season.

As already mentioned, prevailing part of the short-term financial planning process in POS Media primarily accounts for projecting pro forma income statements. It is because the character of POS Media's business does not require detailed observation (and planning) of balance sheet items. POS Media as a service provider (in contrast to manufacturing companies or retailers) holds almost zero inventory. As a result, there is not much need to, for example, plan the level of working capital. Projection of balance sheet items is therefore narrowed to just those ones that have direct impact on the operating result (most typically fixed assets/depreciation) – as discussed in section 1.1.4.3.

Regarding the planning process as such, major emphasis is logically put on proper sales forecast – the rest of income statement is mostly planned with use of the percent-of-sales method, eventually based on other factual circumstances. Selected sales prediction method is partially dependent on the specific subsidiary. Common feature throughout the company is that the sales forecasts are rather judgmental in their nature (see section 1.2 for discussion about judgmental vs. quantitative approach to sales forecasting). Revenue is planned from different aspects. Projection are drawn by retail chain, by segment, by salesperson, sometimes even by customer. Forecast is further allowed for expected development in the retail industry. Adjustments are done for expected slumps or booms.

During my experiment, I would like to contrast to this judgmental planning approach. Therefore I use purely quantitative methods for sales forecasting.

2.1.5.1 POS Media income statement

In POS Media, income statements (actual as well as pro forma ones) have a standardized format across all subsidiaries. Regardless of the local accounting specifics (legal requirements, chart of account structure etc.), income statements are unified in a universal management accounts form. Results are monitored on the level of so called "Responsible EBIT", i.e. operational result that excludes costs that stand out of reach of local decision-making power. Since, for example, the currency movements hedging policy is fully centralized (local management cannot influence it), foreign exchange gains and losses are excluded from Responsible EBIT.

This section provides detailed description of all Responsible EBIT items.

2.1.5.1.1 Revenue

The top line of Responsible EBIT is naturally made up by the revenue from the company's principal activity, i.e. from provision of point-of-sale advertising solutions and all complementary services. Two main revenue groups are distinguished – Revenue Advertisement and Revenue Operation.

Revenue Advertisement incorporates the turnover from provision of media space and from all services that accompany a campaign (planning, supervision, installation/de-installation etc.). If a rebate or discount is provided to a client, it is recorded as minus Revenue Advertisement.

Revenue Operations stands for the physical production of the specific media, i.e. mainly for processing of the graphic design and printing.

2.1.5.1.2 Sales & Marketing Direct Costs

Sales & Marketing Direct Costs is a category that comprises all expenses directly related to the selling process. The difference between Revenue and Sales & Marketing Direct Costs produces **Commercial Margin**.

Sales Personal Costs account for salaries of the Sales staff and all other relevant personal expenses of the sales department (health insurance, social insurance, personal income tax,

reimbursements, refunds etc.). Bonuses and commissions of the sales team are also included here.

Agency Bonuses represent agency discounts provided to media agencies that serve as intermediaries between POS Media and the final clients. Such discounts are typically derived from the amount of services a particular media agency buys from POS Media.

Consultancy & Training is a line that records spending for professional training of the sales team.

Sales Travel Costs stand for travel expenses of the Sales team – more specifically costs connected to the company cars (fuel, maintenance, fees), refunds to the Sales employees for use of their private cars, expenses for business trips (accommodation, alimentation, pocket money) etc.

Other Sales Costs incorporate all other expenses that can be directly allocated to the sales process, i.e. for example telecommunications costs, gifts for customers, meetings with customers (entertainment, food, accommodation, rentals) etc.

Marketing Personal Costs cover all payroll expenses for the Marketing staff.

Marketing & PR Costs comprise direct marketing and PR expenditures, i.e. all expenses related to the product, brand (trademark), service promotion etc. Activities relevant to the Group brand are excluded. Market research and business development, especially new market segments acquisitions, are also included in this category.

Bad Debts & Revenue Write-offs mean accounts receivable classified as uncollectible according to the company's financial guidelines. It includes partial adjustments (lowering the value of receivables) as well as full write-offs (in case of the debtor's bankruptcy). Only the revenue captured in the top line of the Responsible EBIT statement, that is revenue from the company's main business, can be depreciated in this category.

2.1.5.1.3 Operations Direct Costs

Operations Direct Costs is a crucial cost category for POS Media. While Sales & Marketing Direct Costs covered the selling process expenditures, this cost class incorporates all direct expenses that relate to the product itself. In terms of volume, Operations Direct Costs account for the most significant cost category that imminently

influences the final profit. If we deduct Operations Direct Costs from Commercial Margin we get **Operational Margin**.

Operations Personal Costs stand for payroll expenditures for the Operations staff. Operations department coordinates the factual facet of the provided services, i.e. media production, installation/de-installation, campaign supervision etc.

Installation is a cost category that comprises all expenditures related to the activity of installation and de-installation of media carriers. Installations are typically handled by external companies and freelancers.

Field Marketing accounts for the costs that emerge when a campaign is accompanied by active field promotion – typically in form of hostesses. In such case, POS Media needs to hire the hostesses and the corresponding expenses are recorded within this category.

Freight & Transport is a line that includes mainly the expenditures for external transport services that are utilized in order to get all media carriers to their destination points.

Operations Travel Costs represent travel expenses of the Operations team, analogue of Sales Travel Costs.

Maintenance & Cleaning are costs connected with preserving the serviceability of the media carriers.

Energy means all energy (electricity, fuel, gas etc.) consumed by the installation/de-installation of the media carriers as well as during their stay in the stores (e.g. electricity for LCD panels).

Material Costs are costs incurred due to the physical production of the advertisement. Typically all printing expenses are contained within this category. Material Costs form the cardinal cost counterpart to Revenue Operation.

Carriers account for newly purchased and installed media carriers that are below the limits for capitalization and depreciation ("petty property") and as such are recorded as an instant expenditure in the accounting period.

3rd Party Rents in the most important cost category for POS Media. This is the line where the rent of advertising space from the retailers (eventually petrol stations or schools) is recorded. In general, 3rd Party Rents eat up more than a half of the Responsible EBIT

margin. Together with Installation costs, 3rd Party Rents constitute the main counterpart to Revenue Advertisement.

2.1.5.1.4 Overhead Costs

In general, Overhead Costs represent all expenses that cannot be directly allocated to the output sold. This category thus covers a wide range of mostly administrative costs.

Overhead Personal Costs include payrolls of the Overhead staff (country manager, finance department, support functions etc.).

Premises pose a very wide scale of expenses relevant to the company's premises, i.e. rent, repairs, cleaning, maintenance, real estate taxes, water, waste removal, power, heat, moving expenses, security services, fire preventing measures etc.

IT Costs account for tangible (low-value long-term tangible IT equipment plus relevant services) as well as intangible (software licenses) expenditures on IT infrastructure.

Telecommunications represent all regular payments to operators and internet providers.

Postage & Stationery is a category that includes postage expenditures (postal charges, messenger and delivery services) and purchases of various stationery and office equipment.

Car Fleet stands for expenses for cars without direct allocation to a particular department or shared by more than one department (e.g. the country manager's car or cars used by the Overhead staff). It includes rental and leas expenses, fuel, car repairs and maintenance, car material and services etc.

Travel & Entertainment covers the company's multi-departmental travel and entertainment expenses, i.e. representation costs, refreshment cost, travel expenditures not directly related to Sales (Sales Direct Costs), or Operations (Operations Direct Costs).

Legal & Business Services represent payments to lawyers and other forms of consulting services.

Accountancy & Audit Fees are expenditures for external accounting services and for the statutory yearly audit.

Bank Charges stand for various bank fees (for bank statement draw-up, reports, disclosures etc.). Of course, interest expenses are excluded.

2.1.5.1.5 Other Revenue

Other Revenue is a category dedicated to the extraordinary revenue that stands beyond the company's principal business. It mainly includes the revenue from selling of fixed assets (their market value), recovery of damages and refunds for insurance, warranties and/or contract penalties.

2.1.5.1.6 Other Costs

Other Costs prevalently contain the residual value of sold fixed assets.

2.1.5.1.7 Depreciation & Amortization

Depreciation & Amortization constitute the last item in the Responsible EBIT statement. It includes accounting depreciation and amortization of assets designated for depreciating according to the company's financial guidelines.

2.2 Pro forma income statement construction

I this section I get to the core of my thesis, i.e. construction of the pro forma income statement of POS Media Czech Republic. The projection is drawn up for the calendar year 2012. Although the actual results for the first quarter were already known at the time of my analysis, I decided to ignore this fact and not to reflect the data during the planning process. The 2012 pro forma income statement is thus created from scratch. Confronting the actual results of January, February and March with the predicted values helps me to assess the relevancy of my plan.

Apart from standard software tools (e.g. MS Excel), Statgraphics was abundantly used during my analysis. Statgraphics is a statistics package initially released in 1980.[41] Its interface can there give impression of an old-fashioned application. On the other hand, development of Statgraphics still continues (the most up-to-date release is version 16 from October 2009). All in all, Statgraphics proved to be an easy-to-handle tool that fully satisfied my needs.

2.2.1 Sales forecast

As also the structure of the theoretical part already indicates, the most attention is devoted to sales forecasting. Time series decomposition is used during the sales forecasting process.

2.2.1.1 Available data set

For purposes of my analysis I use monthly revenue data of the past five years (2007, 2008, 2009, 2010 and 2011). The data was extracted directly from the company's information system SAP Business One (SBO).

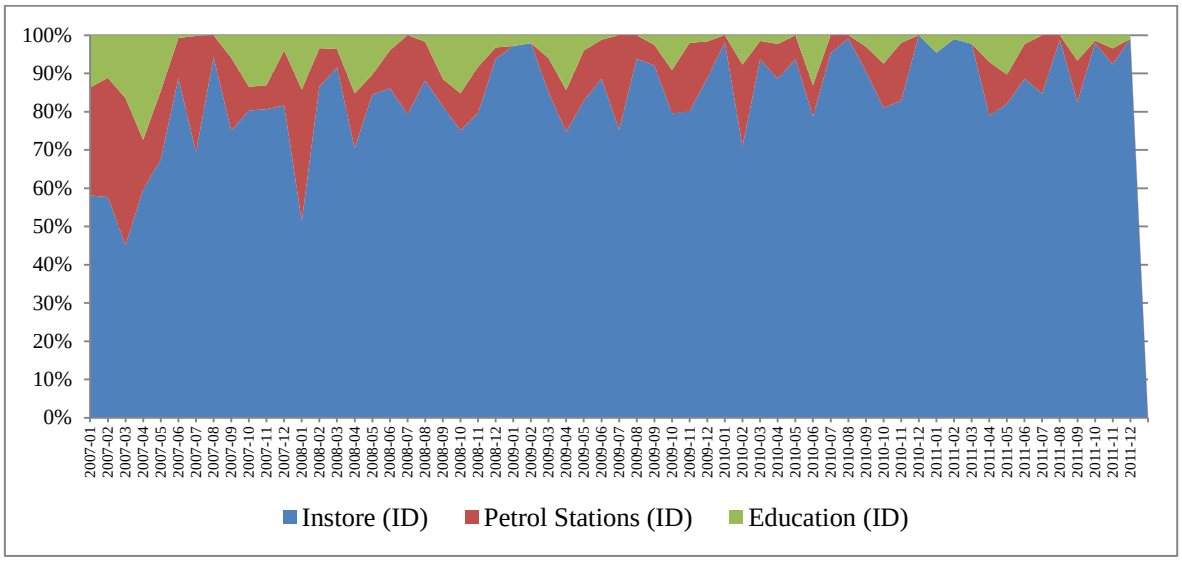
Following the basic accounting principles, SBO records revenue on the posting date (PD), which is the date when an invoice is issued. Since the posting date can be dependent on various subjective factors as for example on agreement with clients, I first needed to

[41] http://www.statgraphics.com/

"normalize" the time distribution of sales. Otherwise there would be a danger of missing the right seasonality pattern because the posting date sometimes does not reflect the true time reality. The most unbiased criteria for division of sales in time seems to be the date when the campaign was physically installed – installation date (ID). In order to transpose the sales in compliance with the installation date, I had to combine the accounting data together with the Sales data. In POS Media sales data are gathered in the form of so called "Monthly Sales Report" (MSR). MSR contains exhaustive information about the realized campaigns (e.g. which brand was advertised, where, for how long, which carriers were use and in what quantities etc.) – including the desired installation date. In the following charts (Figure 11, Figure 13, Figure 15), I show sales sorted by the posting date in grey. At the end, the scale of difference between the two views proved to be quite significant.

Sales were split according to the "Network" where they were realized. POS Media Czech Republic services the following three Networks – Instore, Petrol Stations, Education (as discussed in 2.1.4). Looking at the proportions of these three networks within total sales (Figure 10), we can immediately conclude that Instore accounts for the dominant part of the total turnover of POS Media Czech Republic.

Figure 10: Proportions of the single Networks on the total sales (%)



Source: POS Media

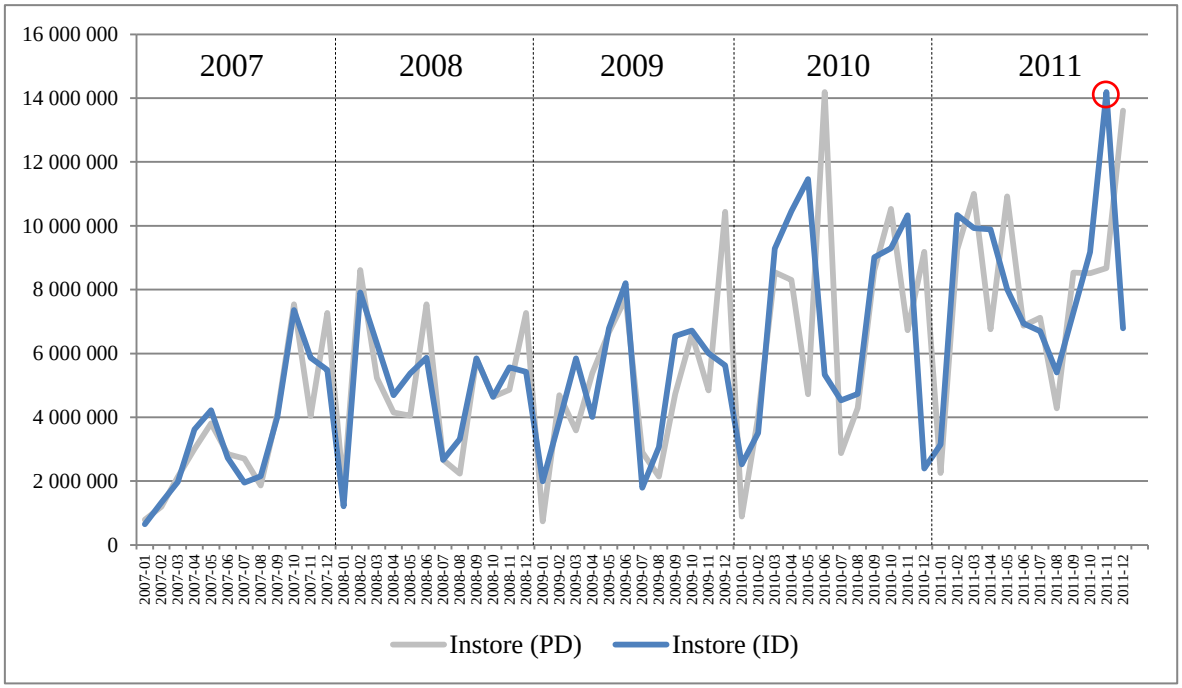
2.2.1.2 Graphical analysis

First step of examining the sales data is simply plotting them in charts. Doing so, I try to optically identify the main features of the time series.

2.2.1.2.1 Instore sales

Just for recapitulation, Instore sales denote all revenue generated by provision of point-of-sale media solutions in retail chains (mainly Tesco and Ahold). Figure 11 depicts the time series of Instore sales from 2007 to 2011.

Figure 11: Instore sales 2007-2011 by month (CZK)



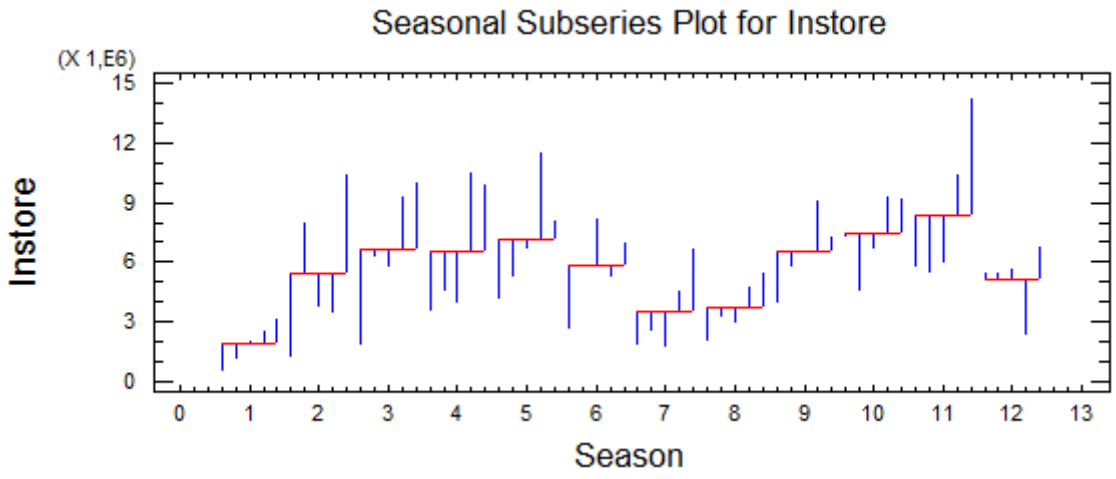
Source: POS Media

From the chart we can draw several basic remarks. First of all, it is obvious that the observed time series is quite volatile. This volatility can be justified by the strong seasonal character of sales (the topic of sales seasonality will be extensively studied in the succeeding text). Some hints of potential seasonality can be identified by the naked eye. In January of each year the sales tend to reach their yearly bottoms. They start to grow up in the next couple of months and fall down sharply during the summer holiday period. Revival of sales comes in September and their boost continues until Christmas. POS Media Czech Republic apparently tends to experience two major strong Instore seasons within a

calendar year – one of them connected with Easter, the other one related to the pre-Christmas shopping. The clients obviously do not underestimate the preparations for both those periods and invest heavily in point-of-sale advertising.

Figure 12 provides a closer look at the seasonality of the Instore sales. Red horizontal lines account for each month's average values. Blue vertical lines illustrate deviations of the actual values from the average in each of the five observed periods. The chart supports my assumption about the seasonality character of the Instore sales.

Figure 12: Seasonal plot for the Instore sales (mil. CZK)



Source: Statgraphics

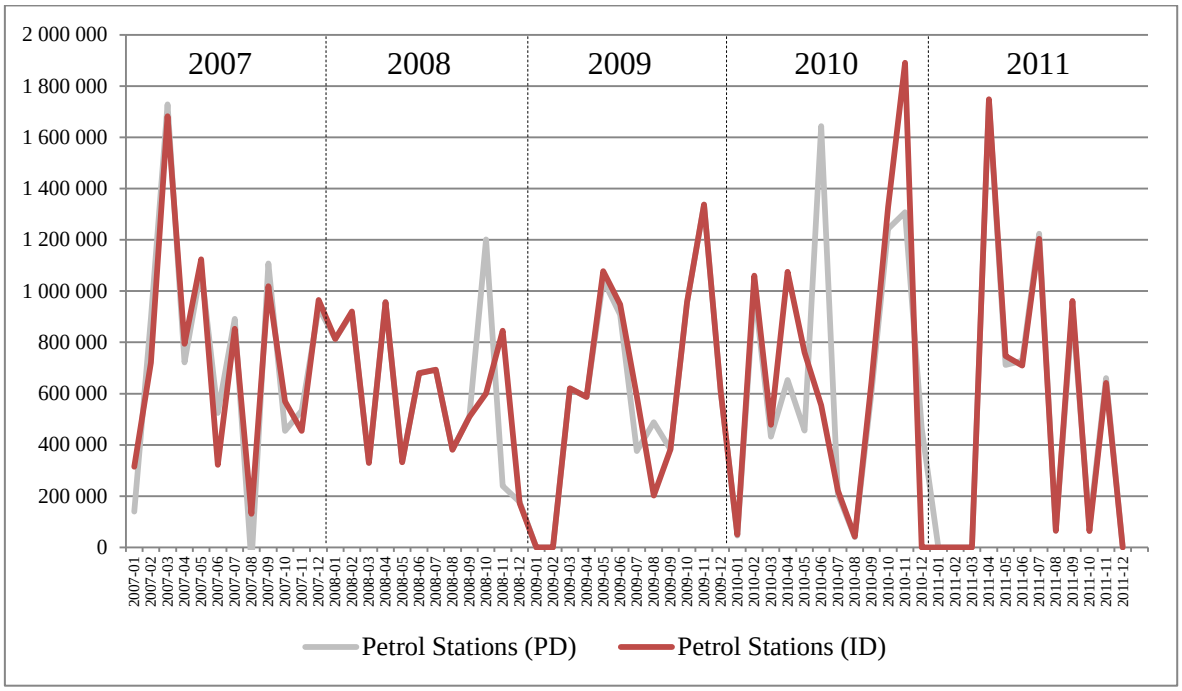
Next what can be done during the graphical analysis is the search for potential outliers.[42] One such suspicious point evidently appears at the very end of the Instore sales time series – November 2011 (circled red in Figure 11). At this moment it is not sure whether it indeed is an outlier. Some further investigation is needed.

2.2.1.2.2 Petrol Stations sales

In absolute measure (as can be seen from Figure 10), Petrol Stations sales are rather minor in scale compared to Instore. It is because this business itself is not as intensive as the point-of-sale advertising. On top of that, POS Media Czech Republic services just some of the petrol stations chains. The Petrol Stations sales time series is portrayed in Figure 13.

[42] Time series outliers are data points that do not follow the general (historical) pattern of regular variation seen in the data sequence.

Figure 13: Petrol Stations sales 2007-2011 by month (CZK)

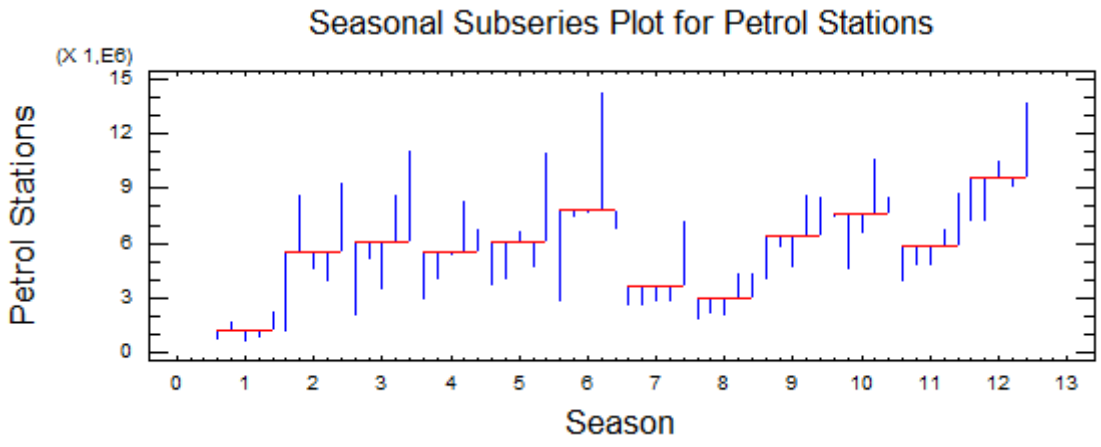


Source: POS Media

Brief look at the chart indicates considerable volatility in the time series. This can be credited to the low volume of the Petrol Stations business – there are even months with no sales realized at all. Statistical laws of large number cannot be fully utilized.

Although Figure 14 implies some presence of seasonality (weak January and summer holidays, strong spring and Christmas run-up), drawing any conclusion about its character would be very courageous at the moment.

Figure 14: Seasonal plot for the Petrol Stations sales (mil. CZK)



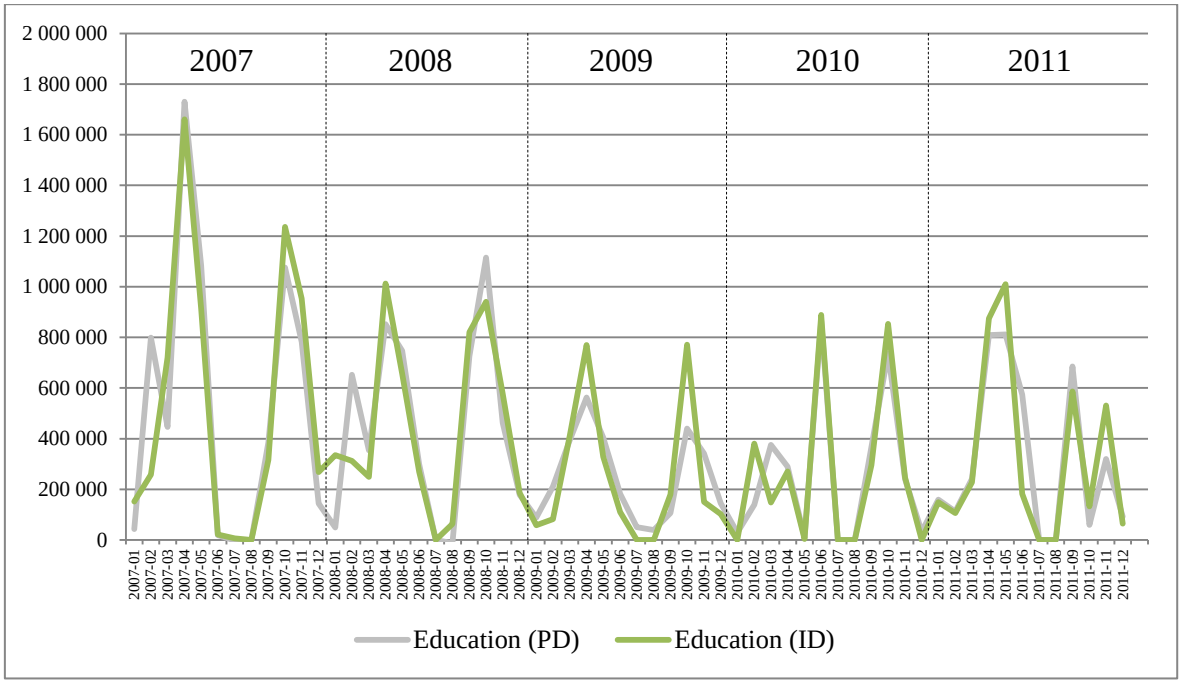
Source: Statgraphics

We also should be skeptical about the possibility of finding a solid prediction model for such a time series.

2.2.1.2.3 Education sales

Education network is a notion that accounts for selling advertisement solutions in secondary schools and at universities. In term of sales volumes, it is very similar to Petrol Stations. Figure 15 shows the time series for Education sales.

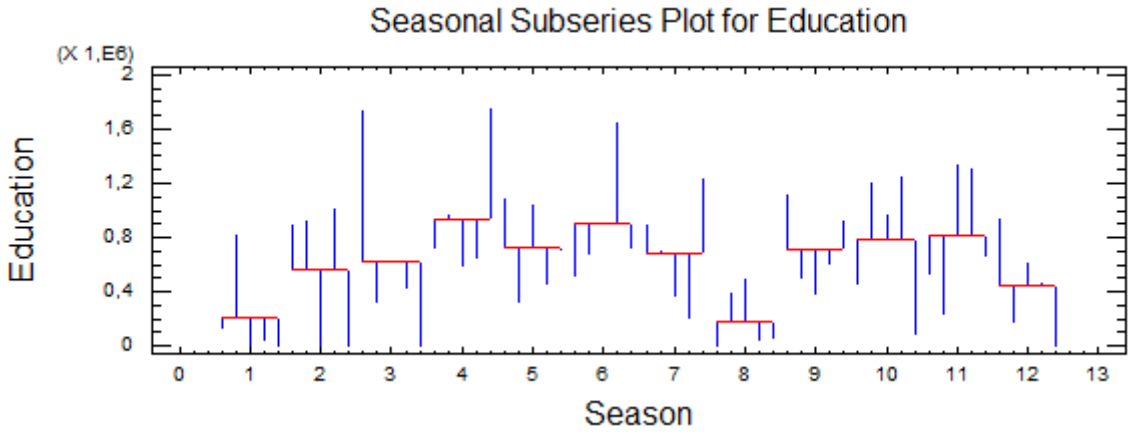
Figure 15: Education sales 2007-2011 by month (CZK)



Source: POS Media

Again there is not much that can be concluded about the seasonality nature of the Education sales. Since the advertising takes place in schools two obviously "dead" seasons are during the holidays (January and summer holidays). This proposition is visually confirmed by Figure 16. Some hints of tendency to copy the same seasonality pattern as the Instore sales are vaguely noticeable. Despite this fact, any strong verdict based just on chart analysis can lead to critical managerial mistakes.

Figure 16: Seasonal plot for the Education sales (mil. CZK)



Source: Statgraphics

From the same reasons as by the preceding time series, applying quantitative approach to Education sales forecast has just negligible chance of success. One way of solving this issue could be not to split the sales data per Network. This I wanted to avoid in order not to "spoil" the Instore data with data from other sectors that do not necessarily need to possess analogous characteristics and features. From this point on, I dedicate the whole quantitative analysis only to the Instore sales. Judgmental approach needs to be employed to predict the Petrol Stations and the Education sales.

2.2.1.3 Identification of outliers

As premised, there is a suspicion that the Instore sales data series can include outliers. Specifically, the November 2011 data entry was visually identified as the most probable candidate for an outlying value.

A simple technique based on the assumption of normally distributed samples is used to detect outliers. Since there is little chance that an object (value) from a normally distributed sample will occur in the tails of the distribution, an observation that lies beyond the area of mean ±3 standard deviations is often considered to be an outlier.[43] This presumption is very strong though. Even if such value occurs within a data set, it should be subject to further analysis before definitively excluding it from the sample.

[43] CHEMICK, R. Michael; DOWNING, J. Darryl; PIKE, H. David: *Detecting Outliers in Time Series Data*, 1982 [on-line] [retrieved 2012-4-7]

First the Instore sales time series must be tested in order to determine whether it can be adequately modeled by a normal distribution. Figure 17 shows the results of several normality tests.

Figure 17: Tests for normality of the Instore sales data sample

```
Tests for Normality
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Computed Chi-Square goodness-of-fit statistic = 22,6667
P-Value = 0,16042

Shapiro-Wilks W statistic = 0,966115
P-Value = 0,20595

Z score for skewness = 1,18034
P-Value = 0,237864

Z score for kurtosis = 0,158636
P-Value = 0,87395
```
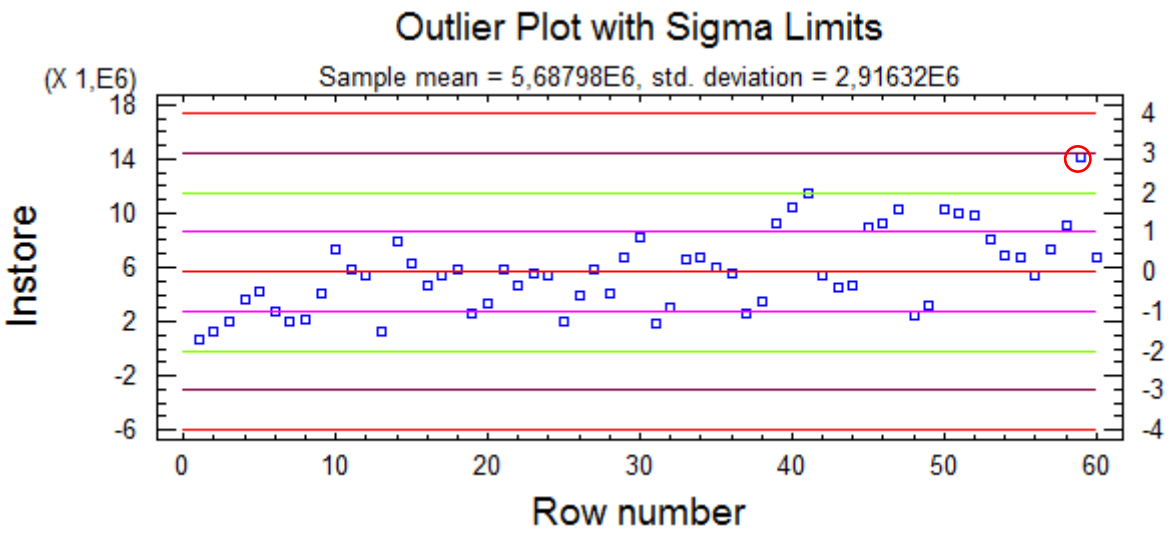

Source: Statgraphics

The lowest P-value amongst the tests performed equals 0,16042. Therefore the idea that the sample comes from a normal distribution cannot be rejected (on 5% significance level).

Figure 18: Outlier plot for the Instore sales data sample (mil. CZK)



Source: Statgraphics

My suspicion proved to be justified. According to Figure 18 the most extreme value indeed is that in November 2011 (2,914 standard deviations from the mean).

Because the value lies almost exactly at the threshold, it would be wrong to immediately declare it to be an outlier. However, such a marginal result should at least trigger some further investigation.

In my case I went to SBO and searched for any abnormal invoicing in November 2011. I found out two aspects that probably caused such exceptionally high revenue. First, there was an invoice issued to Tesco Stores SK. Formally, this was the revenue of POS Media Slovakia and was reinvoiced accordingly. Second, POS Media Czech Republic managed a hostess campaign for Tesco Stores CZ. Such service (dedicated provision and supervision of hostesses without also selling the media) is not a part of the standard service portfolio of POS Media Czech Republic. Since it probably was a one-time activity, I further adjusted the November sales for this invoice. Total adjustment was minus 1 456 000 CZK.

2.2.1.4 Further time series adjustments

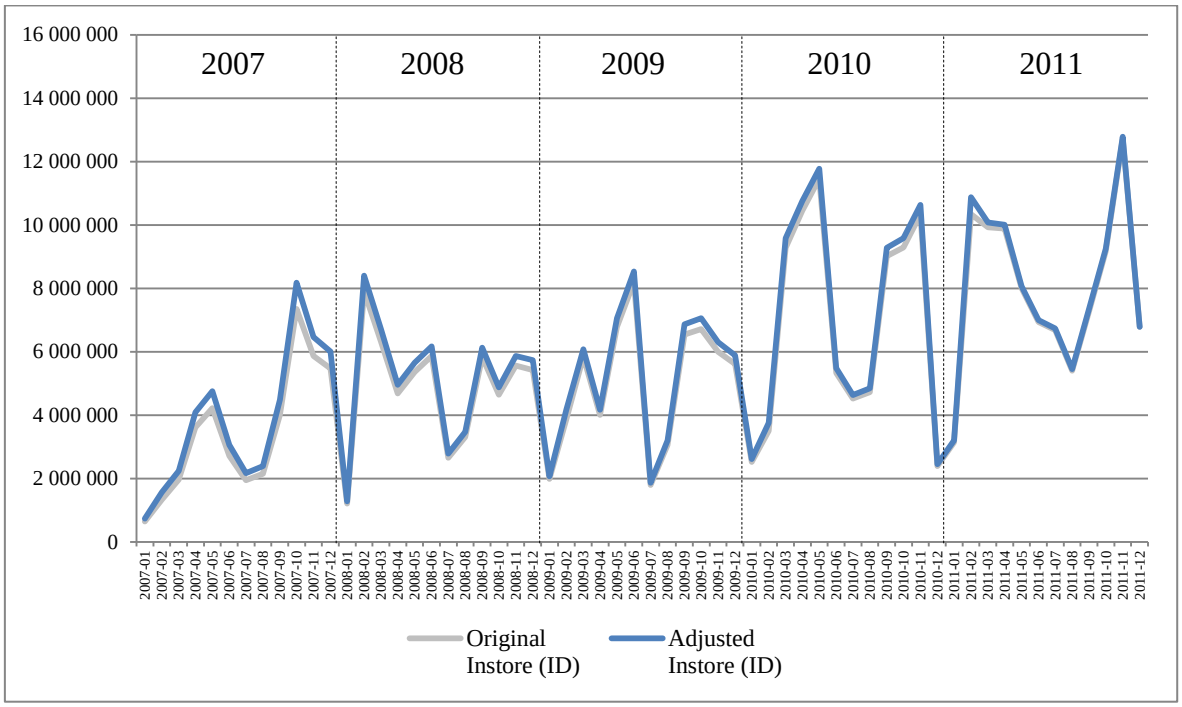
There are some other adjustments to be done. It makes no sense to adapt the time series for the number of working days in each month since it has no effect on in-store advertising. I also decided not to normalize all months to the same day-count basis (typically 30). My reasoning is that it would be counterproductive since my aim is to extrapolate the time series with the same "irregular" distribution of days within each month.

What should certainly be done is to convert the time series to constant prices (adjust it for inflation). Even though in the Czech Republic the prices have been quite stable in the last years, this modification should be done in order to avoid potential biases. Of course, this implicates that incorporating the prediction of inflation rates for 2012 would be necessary to finish the sales forecast. My approach to inflation adjustment is maybe quite unusual – I convert all monthly sales to the price level of December 2011. Doing so, I am able to comfortably use the latest (December) inflation rate forecast.

Next, rather minor, adjustment is to account for leap years. Since 2012 is a leap year I decided to inflate Februaries 2007, 2009, 2010 and 2011 as they were leap as well.

Final (adjusted) version of the Instore sales time series is shown in Figure 19 (for details on the whole adjustment procedure please refer to Appendix 1).

Figure 19: Adjusted time series of the Instore sales (CZK)



Source: own production

2.2.1.5 Modeling of seasonality

In section 2.2.1.2.1 an assumption was made, that the Instore sales time series is quite clearly seasonal – some estimates about the seasonality character were pronounced. In the following text I try to prove this speculation on a statistical basis.

First we need to decide which model of time series decomposition to use – additive or multiplicative (see 1.3.3.2). In general, additive decomposition is used if the variability of the time series remains more or less constant in time. If this is not the case, we need to go for the multiplicative model.

In order to find out the dynamics of the Instore sales variability, I split the sample by years and determine the variability of the single sub-series separately. Once I arrived at the descriptive statistics of each sample (Figure 20), I needed to find a comparable measure of their variabilities. I decided to go for simplicity and calculate coefficients of variation[44] for the corresponding sub-series. I arrived at the following results: 0,58; 0,37; 0,40; 0,49 and 0,32 for the sub-series 2007, 2008, 2009, 2010 and 2011 respectively. This signalizes that

[44] Coefficient of variation is defined as ratio of the standard deviation to the mean. It is a dimensionless measure of dispersion which allows comparing variability across diverse samples.

the variability of the observed data set changes in time. Thus the multiplicative method appears to be more suitable for the decomposition of the Instore sales time series.

Figure 20: Descriptive statistics of the Instore sales sub-series

Summary Statistics

	Instore 2007	Instore 2008	Instore 2009
Count	12	12	12
Average	3,84875E6	5,17415E6	5,27552E6
Variance	4,95459E12	3,59308E12	4,5538E12
Standard deviation	2,22589E6	1,89554E6	2,13396E6
Minimum	742438,0	1,29164E6	1,87584E6
Maximum	8,1822E6	8,40198E6	8,53186E6
Range	7,43976E6	7,11034E6	6,65602E6
Stnd. skewness	0,785813	-0,844303	-0,503791
Stnd. kurtosis	-0,304904	0,464374	-0,699368

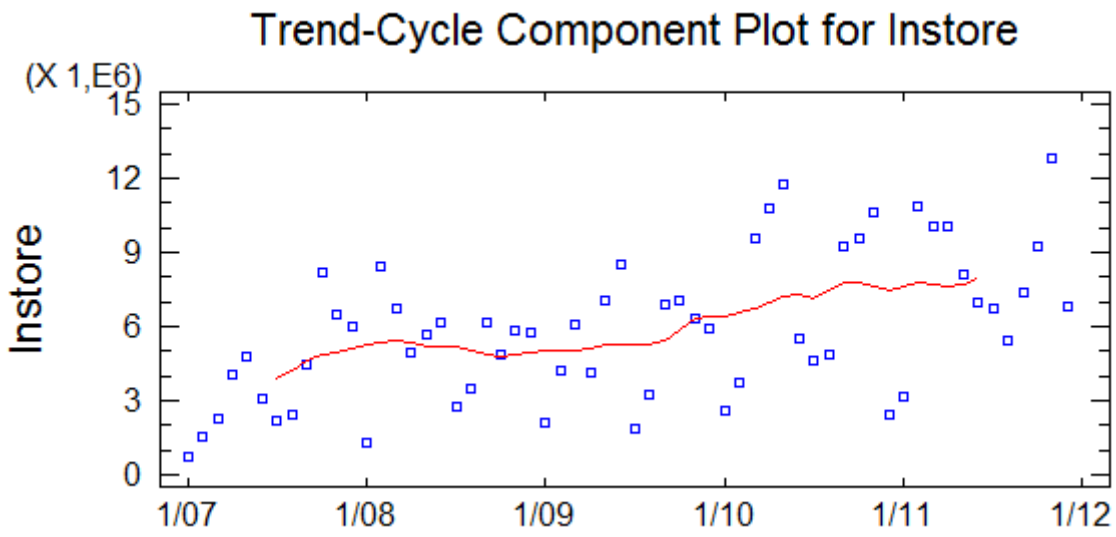
	Instore 2010	Instore 2011
Count	12	12
Average	7,11968E6	8,13647E6
Variance	1,19541E13	6,80923E12
Standard deviation	3,45746E6	2,60945E6
Minimum	2,45385E6	3,20062E6
Maximum	1,17805E7	1,27842E7
Range	9,32669E6	9,58353E6
Stnd. skewness	-0,108613	-0,0887266
Stnd. kurtosis	-1,30792	0,0464488

Source: Statgraphics

The outcome of the multiplicative seasonal decomposition is shown in Appendix 2. In the "Trend-Cycle" column we can find centered moving averages (length 12) of the original time series (column "Data"). The moving averages stand for an estimate of the trend-cycle time series component – graphically expressed in Figure 21. This estimate has to be considered to be only tentative and as such it is not suitable for forecasting. By definition, the series of moving averages is shorter by the first and the last 6 values. Thus it would be even necessary to predict the last values of the time series, which are actually already known. Trend components are therefore typically predicted from seasonally adjusted time series. Based on such a seasonally adjusted data set, a suitable trend model is determined and its parameters are estimated. Once we have such a fitting model, we can project the

trend forecast. Finally, the prediction of the original (seasonal) time series is achieved by multiplying the trend forecast by its seasonality indices (multiplicative decomposition).

Figure 21: Trend-cycle component plot for the Instore sales time series (mil. CZK)



Source: Statgraphics

In the "Seasonality" column (still Appendix 2), we can see estimates of the seasonal component. They were attained as ratios of the original time series values to the corresponding centered moving averages. This implicates that, in contrast to the trend-cycle component, the seasonal component is not measured in the same units as the original time series (property of multiplicative decomposition).

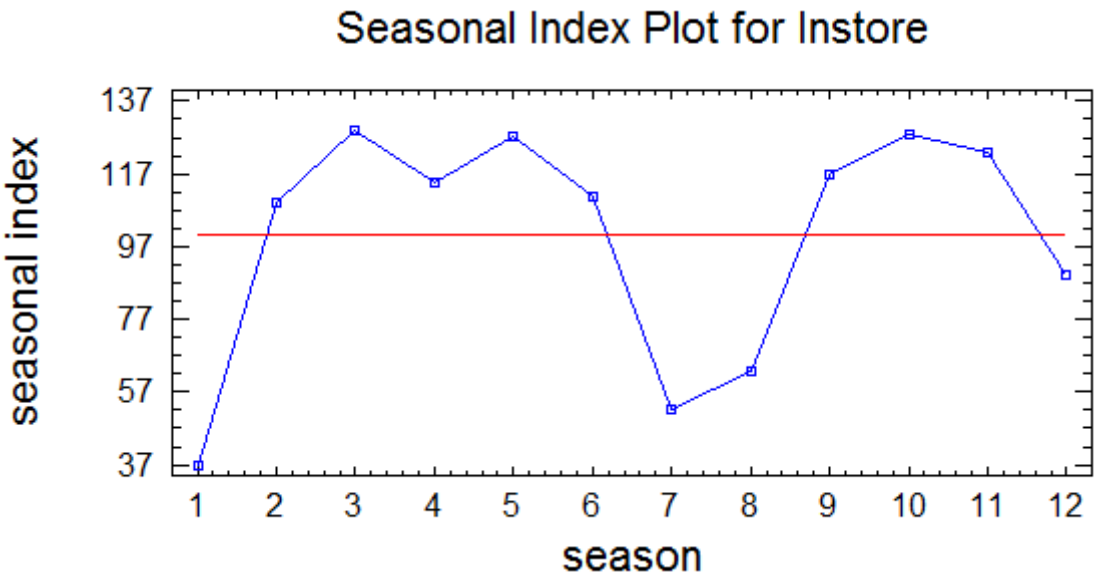
Seasonality indices (i.e. the projection of seasonal fluctuations) are determined ex-post by averaging the values from the "Seasonality" column. The seasonality indices are depicted in Figure 22. An average month is scaled so that it equals to 100 (red horizontal line). The indices range from a low of 37,0305 in January to a high of 128,982 in March. This indicates that there is a seasonal swing from 37,0305% of average to 128,982% of average throughout the course of one complete cycle. This acknowledges the hypothesis about seasonality uttered above, i.e.:

- Yearly bottom comes in January, which is generally rather a month of clearance sales and discounts than of point-of-sale advertising.

- Revival of sales starts immediately in February and the high spring season lasts up to May/June.
- Summer holidays (July, August) mean a "death" season for point-of-sales advertising.
- The "back-to-school" period starts up another boom of sales that continues until Christmas.

Interestingly enough, periods of Easter and Christmas (April and December), which act as the main accelerators for both upswing seasons, do not represent absolute peaks. Sales in December are even below average. This can be logically reasoned by the fact that the advertisers try to reach their customers upfront in order to assure their purchase decisions in the exposed periods. In this sense, the seasonality of POS Media sales precedes the seasonality of the whole retail industry (Figure 8), even though it follows the same pattern. Exact values of the monthly seasonality indices can be found in Appendix 3.

Figure 22: Seasonal index plot for the Instore sales time series (%)

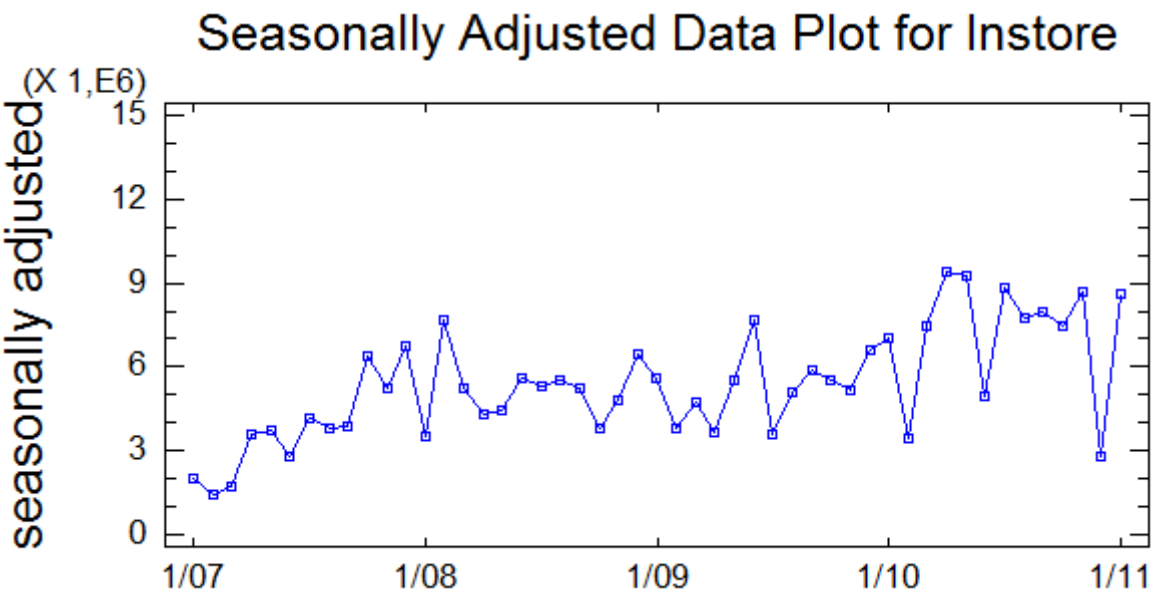


Source: Statgraphics

In the "Irregular" column (Appendix 2) we can find residues, i.e. percentage estimates of the irregular component. They are calculated as ratios of the original time series values to the multiple of the centered moving averages and the seasonal indices.

Finally, in the "Seasonally Adjusted" column we have the values of the seasonally adjusted time series. They were obtained as ratios of the original time series values to the respective seasonal indices. This seasonally adjusted time series is shown in Figure 23 and can be perceived as an estimate for the trend-irregular component.

Figure 23: Seasonally adjusted data plot for the Instore sales time series (mil. CZK)



Source: Statgraphics

2.2.1.6 Trend modeling and forecasting

In this part of my thesis I come to the core of the forecast. I try to find an appropriate trend model for the Instore sales time series. This time series was already seasonally adjusted in the previous section. Based on the visual analysis of the time series' shape, it can be assumed that even a very simple linear modeling method might quite fairly capture its trend. Nevertheless, I also decided to apply methods of exponential smoothing (linear and nonlinear).

2.2.1.6.1 Applied models

Altogether, I apply the following trend modeling methods:

A. Random walk with drift
B. Linear trend
C. Brown's linear exponential smoothing

D. Holt's linear exponential smoothing

E. Brown's quadratic exponential smoothing

Random walk is used for stochastic trend modeling. It does not try to directly predict the level of the series at each period. Instead, it predicts the change that occurs between two periods. At the same time, it assumes that from one period to the next, the time series merely takes a random "step" away from its last recorded position. I use this method rather for completeness and out of curiosity. I do not expect random walk to capture the trend in such a way that could be used for predictions.

Linear trend modeling is nothing else than describing the trend with a suitable straight line. In other words it assumes that the best forecast for future data is given by a linear regression line fit to all previous data.

Brown's linear exponential smoothing with the "smoothing constant" α (acquiring values between 0 and 1) can be applied for prediction of such non-seasonal[45] time series the course of which can be decomposed into local linear trends. This model assumes that the best forecast for future data is given by a linear trend estimated by exponentially weighting all previous data values.

Holt's linear exponential smoothing is a smoothing process similar to the previous one. It has two smoothing constants – α for the adaptive level estimates and β for the adaptive slope estimates.

Brown's quadratic exponential smoothing can be defined analogously to its linear version. This time, it is assumed that the series has a quadratic trend.

2.2.1.6.2 Model appraisal

In order to find the models' parameters and to appraise the models, the time series was split into two parts (see 1.3.2.2) – the first four years of data were used for actual determination of the models' parameters while the last year is utilized as a validation sample for the ex-post prediction.

[45] Exponential smoothing does not generally bring satisfactory outcomes for seasonal time series. Therefore the adjustment for seasonality has to be carried out in advance. Winter's exponential smoothing is the only exponential smoothing method that is appropriate for modeling of seasonal time series.

Comparison of the single models in terms of their quality and explanatory power can be found in Figure 24. In the upper part we can see the parameters that came out of the statistical analysis (optimal α and β constants for all three exponential smoothing methods were automatically set by the computer).

Figure 24: Appraisal for trend models of the Instore sales time series

```
Models
------
(A) Random walk with drift
(B) Linear trend = 3,20605E6 + 86117,7 t
(C) Brown's linear exp. smoothing with alpha = 0,1487
(D) Holt's linear exp. smoothing with alpha = 0,1348 and beta = 0,051
(E) Brown's quadratic exp. smoothing with alpha = 0,095

Model  RMSE         RUNS  RUNM  AUTO  MEAN  VAR
-----------------------------------------------
(A)    2,08768E6     OK    *     *     OK    OK
(B)    1,57044E6     OK    OK    OK    OK    OK
(C)    1,74553E6     OK    OK    OK    OK    OK
(D)    1,66163E6     OK    OK    OK    OK    OK
(E)    1,79022E6     OK    OK    OK    OK    OK

Validation Period
Model  RMSE         MAE          MAPE
---------------------------------------
(A)    2,08768E6    1,53169E6    31,3256
(B)    1,57044E6    1,17599E6    18,233
(C)    1,74553E6    1,29881E6    22,1542
(D)    1,66163E6    1,25321E6    20,0635
(E)    1,79022E6    1,35753E6    22,375

Key:
RMSE = Root Mean Squared Error
RUNS = Test for excessive runs up and down
RUNM = Test for excessive runs above and below median
AUTO = Box-Pierce test for excessive autocorrelation
MEAN = Test for difference in mean 1st half to 2nd half
VAR = Test for difference in variance 1st half to 2nd half
```

Source: Statgraphics

Before we can start comparing the models it is necessary to assure that all models pass the tests run on the residuals (middle part of Figure 24) to determine whether each model is actually adequate for the data. An "OK" means that the model passes the test. A "star" means that it fails on 5% significance level. As we can see, the random walk model fails the test for excessive runs above and below median and the test for excessive

autocorrelation. There is a well-founded suspicion that it the random walk model misinterprets the trend. I therefore decided to exclude it from further appraisals.

Looking at the error statistics (bottom part of Figure 24), it can be claimed that the simplicity wins because the linear trend model seems to produce the least errors during the ex-post prediction (RMSE = 1 570 440; MAE = 1 175 990; MAPE = 18,23%).

2.2.1.6.3 Linear trend modeling

Once we have found the most suitable model, the analysis should be run once again – this time using the full five-year time series just for the model determination. This is expected to make the model more accurate for our purposes.

Figure 25 shows the model's summary. As can be seen, the linear trend has statistically significant parameter (the constant and the slope) estimates on 5% significance level. The model is described by the following linear function:

$$y_t = 3087766 + 93349{,}6t$$

Figure 25: Linear trend model forecast summary for the Instore sales time series

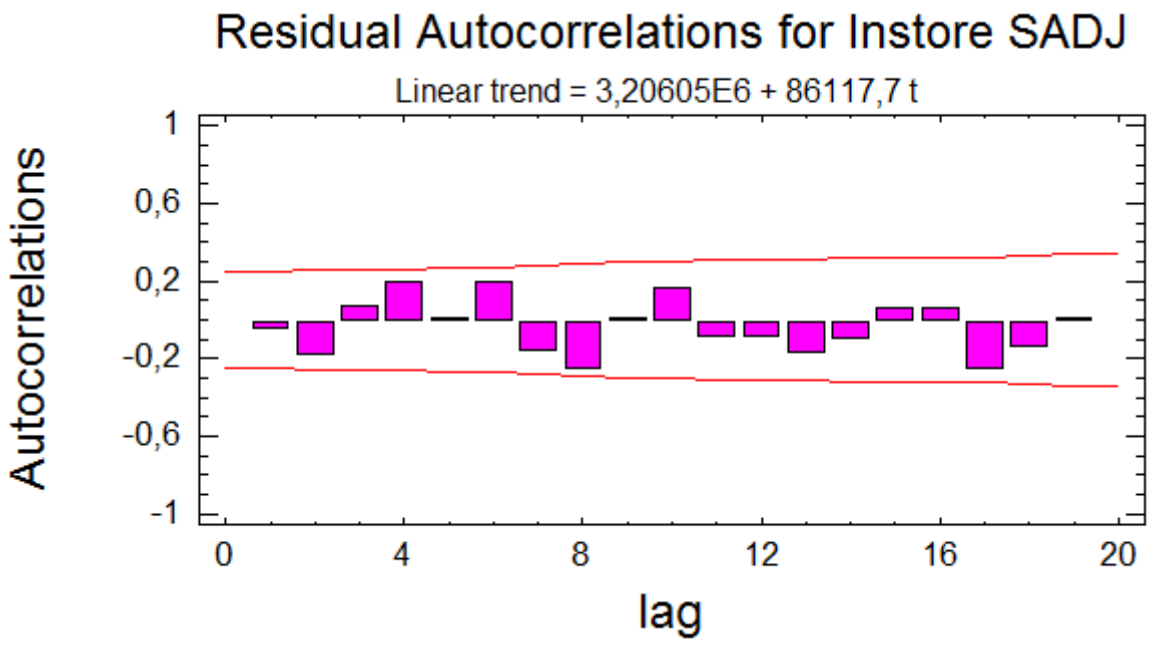
```
Forecast Summary
----------------
Forecast model selected: Linear trend = 3,08776E6 + 93349,6 t
Number of forecasts generated: 12
Number of periods withheld for validation: 0

                        Trend Model Summary
Parameter           Estimate        Stnd. Error     t          P-value
-----------------------------------------------------------------------
Constant            3,08776E6       432710,0        7,13585    0,000000
Slope               93349,6         12337,2         7,56654    0,000000
-----------------------------------------------------------------------
```

Source: Statgraphics

Now we need to further investigate whether the linear trend really models the trend in a proper way, i.e. whether it captures a significant portion of the trend component. In order to do this, the model must be more thoroughly checked for possible presence of autocorrelation. Figure 26 depicts estimated autocorrelations among the residuals at various lags (*k*). The autocorrelation coefficient measures the correlation among the residuals at time *t* and time *t-k*. The red lines represent 95% probability limits (confidence interval) around the point where the autocorrelation coefficient equals 0. Looking at the

chart, it is clear that at all the lags the estimated autocorrelation coefficients lie within the probability limits. It implies that none of the autocorrelations coefficients are statistically significant, which means that the irregular component may well be completely random (near to white noise).

Figure 26: Residual autocorrelations plot for the linear model of the Instore sales time series



Source: Statgraphics

For further appraisal of the linear model, it would also be useful to calculate two other quality indicators – namely the Durbin-Watson statistic (to double-check our conclusion about the residual autocorrelation) and the coefficient of determination (to see how much variability we managed to explain with the linear trend line).

Figure 27: Cut-out from regression analysis of the Instore sales time series

```
Regression Analysis
----------------------------------------------------------------------
Dependent variable: Instore SADJ
----------------------------------------------------------------------
R-squared = 59,6757 percent
Durbin-Watson statistic = 2,0896 (P=0,3140)
```

Source: Statgraphics

In order to obtain these statistics I performed a simple regression analysis with time as the independent variable and with the (seasonally adjusted) time series data points as the dependent variable. Its results are shown in Figure 27.

The Durbin-Watson statistic being greater than 2 definitively rules out the eventuality of autocorrelated residues. The R-squared statistic indicates that the model as fitted explains 59,68% of the variability in the time series. At the first glance, this can be rather disappointing. On the other hand, we must consider the fact that there are many transformations that may have been applied to the time series before it was used as a dependent variable in the regression model – I am speaking mainly about the seasonality adjustments and all the modifications carried out in 2.2.1.4. If the dependent variable in the regression model has already been transformed in some way, it is possible that much of the variance has already been explained merely by the choice of an appropriate transformation.[46]

2.2.1.6.4 Forecasted values

In this section I finally come to the desired forecast of the Instore sales for the year 2012. The linear trend line is plotted in Figure 28. Its extrapolated part forms the forecast. The red lines stand for 95% confidence interval of the prediction. The exact values of the linear model are captured in Appendix 4. The forecasted values can be found in Appendix 5.

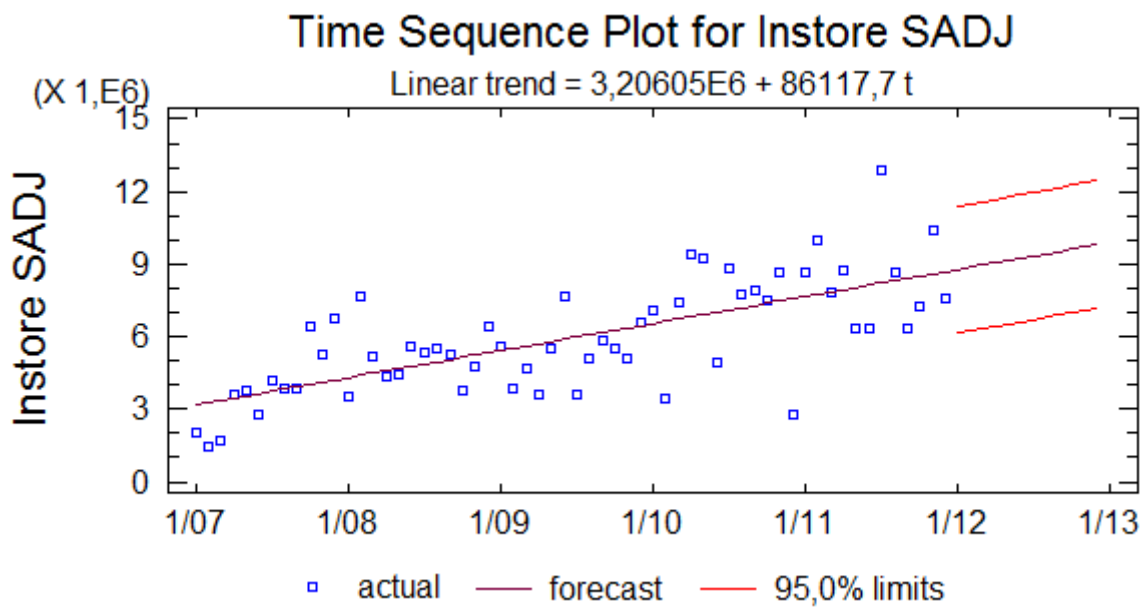
In order to arrive at the complete Instore sales forecast we need to re-introduce seasonality in the extrapolated trend. This is done by a simple multiplication of the values obtained by the trend extrapolation (Appendix 5) and the seasonality indices (Appendix 3).

Since the Instore sales time series was equalized in terms of the price level (section 2.2.1.4), inflationary prediction should be now plugged in so that we also take the rise in prices into consideration. There are various sources of inflation forecasts. POS Media, as an important corporate client of ING Bank, disposes of reports written by the bank's analysts. One part of such reports is also the periodical forecast of fundamental macroeconomic indicators, including the inflation. According to the ING Economic

[46] FOKA, Amalia: *Time Series Prediction Using Evolving Polynomial Neural Networks* (dissertation), 1999 [on-line] [retrieved 2012-4-3]

Forecast[47], the average monthly rate of inflation will be 2,3% in 2012. Inflating the prediction thus means nothing else than multiplying each month's revenue by 1,023.

Figure 28: Linear trend model and the forecast of the Instore sales time series (mil. CZK)



Source: Statgraphics

2.2.1.7 Finalizing the sales forecast

By now the quantitative revenue forecasting is over. Using the time series decomposition method I obtained the yearly forecast for the Instore sales. Since the potential employment of quantitative methods for the remaining components of POS Media revenue (Petrol Stations and Education sales) was ruled out in sections 2.2.1.2.2 and 2.2.1.2.3, we still have to draw some estimates for these sales.

As described in section 2.1.5.1.1, the Responsible EBIT statement distinguishes between two kinds of revenue – Revenue Advertisement and Revenue Operations. We therefore also need to split the sales forecast between those two parts.

2.2.1.7.1 Petrol Stations sales

When forecasting the Petrol Stations sales we should first have a look at the historical seasonality in this segment. From Figure 14 in section 2.2.1.2.2 it can be seen that January,

[47] ING: *ING Economic Forecast (9 December 2011)*, 2011 [on-line] [cit. 2010-4-14]

July, and August are very week seasons. In order to preserve the principle of cautiousness, I plan zero Petrol Stations sales in January and only minimum sales during the summer holidays. Since the Petrol Stations data sample is too sparse to base any further forecast on its historic values, I decided to abandon any other quantitative projections and set out the way of judgmental forecasting. More specifically, I interviewed the Sales Director of POS Media Czech Republic as well as the Account Manager responsible for the Petrol Stations segment. Based on their evaluation, I completed my forecast as shown in Figure 30.

2.2.1.7.2 Education sales

By the Education sales I proceeded exactly the same way. The seasonality chart (Figure 16) testifies the logical conclusion that there is very low turnover realized during the holiday period (December, January, July, August). That is why I project zero sales during those months. The rest of the year is, just as the Petrol Stations sales, planned in compliance with my interview with the Sales department. The Education sales forecast is again depicted in Figure 30.

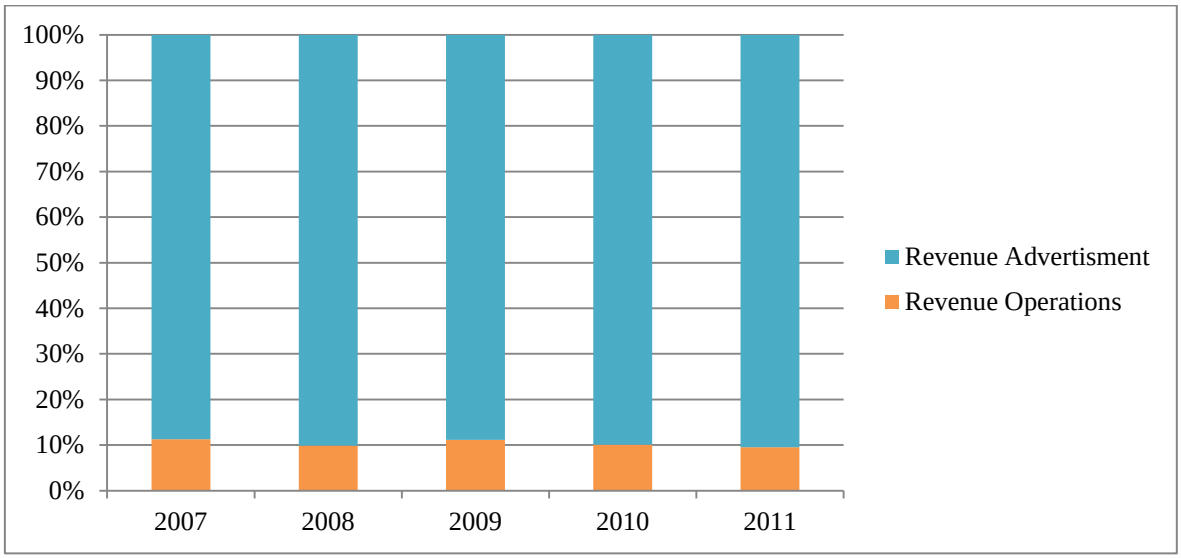
2.2.1.7.3 Revenue Advertisement vs. Revenue Operations

Once we have finished the forecast of total sales for 2012 (sum of Instore, Petrol Stations and Education), it is necessary to find the right split proportion between Revenue Advertisement and Revenue Operations.

Both two categories go hand in hand – if there is no advertisement service sold, there is also no need to print the carriers, there is nothing to install in the stores, there is nothing to supervise etc. And of course, the opposite is true as well. Following this simple logic, I try to find a fix ratio that I intend to apply to the total sales.

Figure 29 shows the past annual proportions of both components to total sales. As can be seen from the chart, the ratio has historically been very stable, oscillating around nine-to-one in favor of Revenue Advertisement. I decided to use the proportion of 88,4% vs. 11,6% which is the long-term average.

Figure 29: Historical proportions of Revenue Advertisement and Revenue Operations to total sales (%)

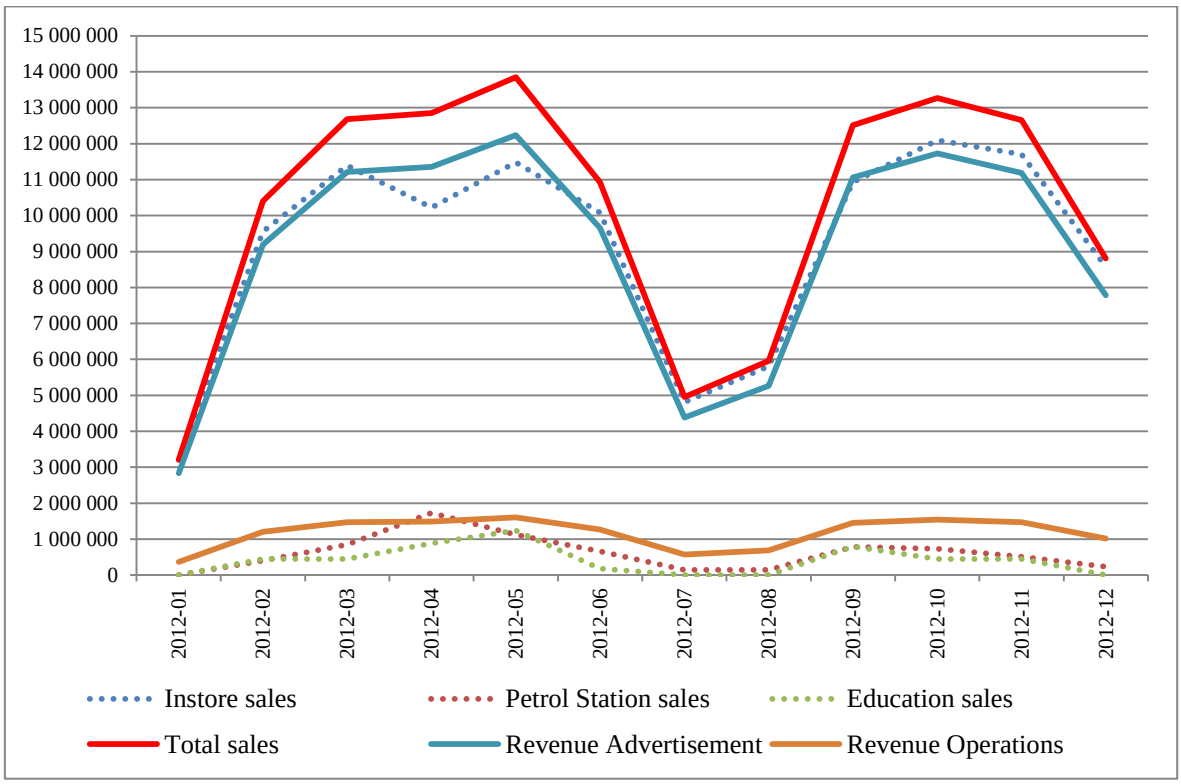


Source: POS Media

2.2.1.7.4 Sales forecast for 2012

At this point the sales forecast is definitively finalized. The course of the forecasted sales is depicted in Figure 30. The exact values of the prediction can be found in Appendix 6.

Figure 30: Sales forecast for 2012 (CZK)



Source: own production

2.2.2 Completing the pro forma income statement

The top line of the pro forma income statement is known. Thus the core of the planning process can be declared as done. Now this is the time when all the remaining (cost) items described in section 2.1.5.1 should be planned.

In my opinion, going line by line is pointless and completely out of scope of my thesis. Without conveying deeper context of the company's daily business (the description of which often contains information of a rather confidential character), it is impossible to provide logical reasoning about the specific amount planned for each cost item. Some of the expenses have fixed budgets throughout the year, some of them heavily depend on the company's current procurement/sourcing strategy etc. Therefore I decided to devote the final part of my thesis only to the prediction of those cost items that are to some extent variable, i.e. that they tend to develop according to the level of generated output in the observed period.

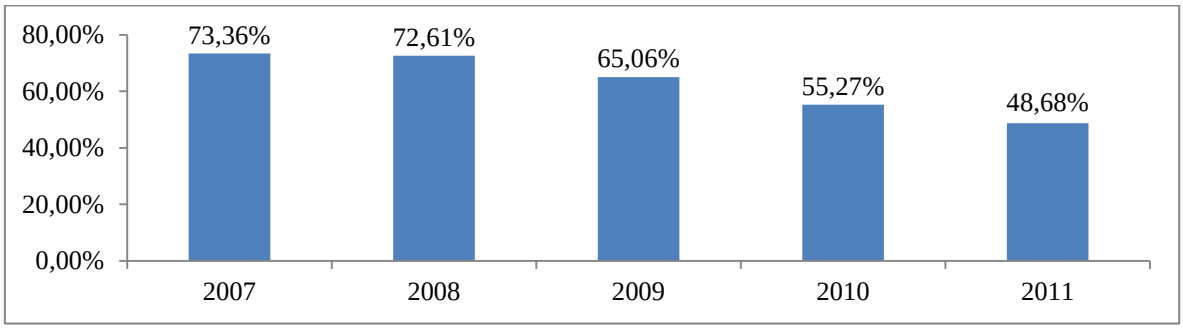
My decision has two basic reasons. First, forecasting of such expenses does not require thorough understanding of the internal policies – the percent-of-sales method (or its variation) is prevalently applied. Second, the projection of variable costs accentuates the necessity of having a credible sales forecast. As can be seen in the following text, it is the variable costs that consume the major part of POS Media's profit margin. Having a solid projection of such costs is the basic precondition of an accurate profit forecast.

2.2.2.1 Agency Bonuses

Agency Bonuses are strongly reliant on the level of sales realized through media agencies. We should therefore investigate historical proportions of the revenue rendered by the media agencies versus those sold directly to the final clients.

As can be seen from Figure 31, the share of media agencies in the total revenue diminishes over time. This is a sign of the company's maturity – it cooperates with more customers directly and diversifies beyond the influence of big media agencies. Revenue realized directly is naturally more profitable since no additional bonus (contractual quantity discount) needs to be awarded.

Figure 31: Historical ratios of sales realized through media agencies (%)



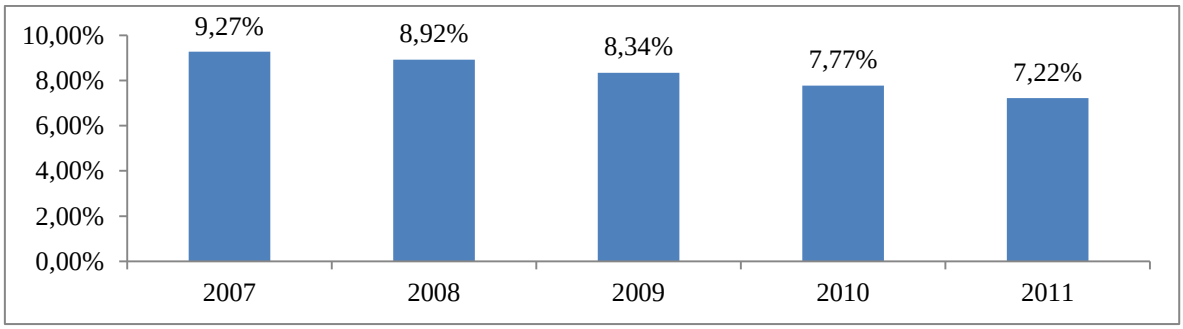
Source: POS Media

The target for 2012 level is 55% of the output sold directly. An average media agency bonus is approximately 20% of the campaign volume (both the media price and the production). This cost item is planned accordingly.

2.2.2.2 Installation

Installation is a typical representative of variable costs. If there is no campaign sold, there are also no expenditures for installation services. The Installation fee (direct counterpart of the Installation cost) is usually invoiced to the client as a separate item within Revenue Advertisement (see section 2.1.5.1.1). It is therefore crucial to investigate historical percentage relationship between Installation and Revenue Advertisement (Figure 32).

Figure 32: Historical ratios of Installation to Revenue Advertisement (%)



Source: POS Media

From the chart it is clear that POS Media is successful in extending its profit margin in the field of Installation fees/Installation costs. In other words, the proportion of Installation to Revenue Advertisement has been declining continuously. Evidently, POS Media has either

managed to make the whole installation process more efficient or it has got in a stronger bargaining position towards its contractors. Most likely it is the combination of both. Nevertheless, important information for our cost projection is that the target ratio could be somewhere around 7% in 2012 (anticipating just a subtle improvement).

2.2.2.3 Field Marketing

By its character, Field Marketing is a cost item that (although it is direct) does not depend on the whole portion of Revenue (or Revenue Advertisement, as the case may be). Since Field Marketing predominantly contains expenditures for hostesses, we must first find out which part of the sales was historically made by campaigns accompanied by hostesses (such campaigns are often called "Promo Actions").

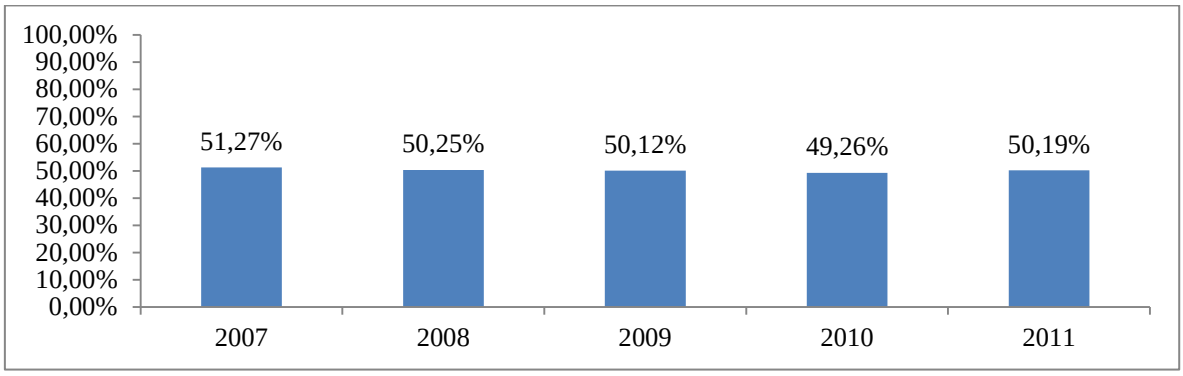
The main stumbling block is that such campaigns were not sold before 2011. In this respect, we do not much of the history at our disposal. In 2011 Promo Actions made the total volume of 9 796 209 CZK which accounts for 10,15% of Revenue Advertisement. There is no further comparison available so we have to assess the 2012 Promo Actions target level in the same value, i.e. approximately 10% of Revenue Advertisement. My conclusion was confirmed by the Sales department as they anticipate roughly the same proportion as in 2011.

Next step is to find out what costs were incurred by earning the already mentioned 9 796 209 CZK of revenue. Field Marketing costs in 2011 amounted to 31,42% of the Promo Actions revenue. Thus 31,5% is also my target cost ratio for 2012.

2.2.2.4 Material Costs

Material Costs should have direct relation to Revenue Operations. This assumption is proved by Figure 33 which shows that the ratio of Material Costs and Revenue Operations has been very stable over time – it oscillates around 50%. It is therefore reasonable to presume that this percentage will be preserved also in 2012.

Figure 33: Historical ratios of Material Costs to Revenue Operations (%)



Source: POS Media

2.2.2.5 3rd Party Rents

3rd Party Rents is the last cost item the projection of which is addressed in my thesis. As already mentioned before, it is the most significant expense of POS Media as it consumes more than a half of its Responsible EBIT margin. Saying this it is clear that special attention should be paid to 3rd Party Rents forecasting.

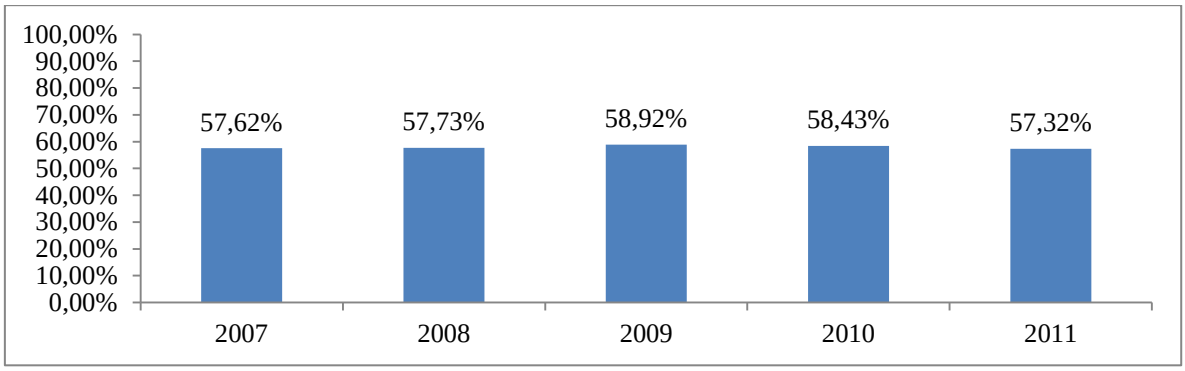
In reality the prediction process indeed is quite complicated. 3rd Party Rents are projected on two levels. First level is the per segment projection (Instore, Petrol Stations, Education). Within Instore it is further projected by specific retail chains. POS Media has different kinds of contract with its partner retail chains – some of them are exclusive, some of them are not (see section 2.1.4). The institute of minimum guarantees (expressed as monetary value of realized campaigns) is often introduced in the contracts. This means that even if POS Media does not manage to sell the estimated volume of campaigns in the particular retail chain, it still has to pay the guaranteed sum as the media rent.

Going in such a deep detail would require releasing a lot of confidential information about the POS Media's business. I strongly believe that omitting such thorough forecasting analysis does not prevent me from fulfilling the goals of my thesis. From the preceding reasons I decided to apply the percent-to-sales methods also to the prediction of 3rd Party Rents.

Typically, rents are paid from the net media income (i.e. Revenue Advertisement). It is therefore reasonable to compare historical 3rd Party Rents in relation to Revenue Advertisement (not to the whole portion of total sales). As can be seen from Figure 34, this

ratio has been very stable in the past five years so in the end the percent-of-sales method seems to be a good forecasting proxy. I predict 3rd Party Rents as 58% of Revenue Advertisement in 2012.

Figure 34: Historical ratios of 3rd Party Rents to Revenue Advertisement (%)



Source: POS Media

Conclusion

The complete pro forma income statement for 2012 is shown in Appendix 7 (I used the standardized company template).[48] As can be seen, the target Responsible EBIT is slightly less than 8,5 million CZK. In the weakest months (January, July, August) a negative operating income is planned since it is assumed that the low sales will not outweigh the fixed costs. On the other hand, during the strong season – spring (March, April, May), back-to-school (September) and run-up for Christmas (October, November) – the average monthly operating income climbs up well above 1 million CZK.

For the purposes of my thesis the exact predicted Responsible EBIT values are not of such a high significance (also because they depend on the cost items the projection of which was skipped in my analysis).

What is more important, I managed to prove to myself that even with minimum upfront statistical knowledge I was able to apply the time series prediction methods (and obtain meaningful results) during the financial planning process. From this experience I can conclude that management teams of virtually every company can utilize quantitative methods without any particular need of them being statistical or mathematical experts. Even though I engaged in financial planning, I dare to declare that the same conclusion holds for other managerial disciplines as well.

Another question is to what extent the quantitative methods are appropriate for supporting day-to-day business decisions. Is it a tool that really brings value to the company? Do not they rather make managers run substantial risk of misjudging the situation? Before I discuss this dilemma, I come back to my application first.

At the time I am writing these lines POS Media Czech Republic has already know the results of the whole first quarter of 2012. Therefore I am free to compare the actual results with what I have forecasted. Without bringing out the exact figures I must sadly concede that my financial plan substantially overestimated the realized sales.

[48] The items the prediction of which was addressed are highlighted in red.

From the beginning of the year almost all FMCG producers have drastically restrict their marketing spending. This restriction often came as an order from their international headquarters in an effort to respond to the bad expectations about the demand development in the European retail market (rising unemployment and risk of general downsizing, planned higher taxation, depreciation of Euro etc.).

Such situation is very similar to what the market experienced in 2008 as a consequence of the world financial crisis. At that time the negative impact on the POS Media sales was not so severe (refer back to Figure 21) – at least not to the extent that would prevent us from modeling the sales by a linear trend. With the selected model there was no chance of anticipating such a sudden slump.

Anyway, these are only the results of the first quarter. Nobody can tell with certainty that the situation will not change for better. After all, the reaction of the FMCG producers was too abrupt and too general. In the next phase the situation is likely to develop according to the specifics of the local markets. On the top of that, the marketing budgets of the POS Media's clients are only frozen – no real losses have been incurred yet. This means that there is still some probability that the funds will be released and the sales forecast will at the end be fulfilled (in annual terms).

Whether the situation turns out in either way, this finding carries a very important message. Namely that it is very naive to suppose that the future will always universally follow the past trends. At some point new elements always come into play. Although there are certain methods of dealing with sudden external shocks in quantitative forecasting (e.g. jump-diffusion models), their application is at least arguable. Sometimes there is simply nothing more appreciable than the human judgment.

My personal impression of this endeavor is that either approach (qualitative and quantitative) cannot exist without each other. Without employing human judgment quantitative forecasting itself fails to anticipate new and unique influence factors and their potential effect on the observed variable. Purely subjective techniques based exclusively on personal opinions, on the other hand, introduce substantial bias into the planning process. Sales forecasting should therefore always contain elements of both the factual basis and the judgment. The balance between these two factors is the key to improving accuracy.

Appendix

Appendix 1: Adjustments of the Instore sales time series

Period	Original Instore (ID)	CPI[49] *(2005 = 100)*	CPI[50] *(12-2011 = 1)*	Adjustment for inflation	Adjustment for leap years	Adjusted Instore (ID)
2007-01	648 300	103,3	0,8732	94 138	0	742 438
2007-02	1 333 900	103,6	0,8757	189 270	47 639	1 570 809
2007-03	1 969 227	103,9	0,8783	272 925	0	2 242 152
2007-04	3 620 075	104,6	0,8842	474 140	0	4 094 215
2007-05	4 223 207	105,0	0,8876	534 940	0	4 758 147
2007-06	2 724 489	105,3	0,8901	336 357	0	3 060 846
2007-07	1 948 762	105,8	0,8943	230 241	0	2 179 004
2007-08	2 149 996	106,1	0,8969	247 219	0	2 397 215
2007-09	4 013 998	105,8	0,8943	474 244	0	4 488 242
2007-10	7 359 139	106,4	0,8994	823 062	0	8 182 200
2007-11	5 866 797	107,4	0,9079	595 420	0	6 462 217
2007-12	5 479 364	107,9	0,9121	528 131	0	6 007 496
2008-01	1 213 024	111,1	0,9391	78 612	0	1 291 636
2008-02	7 911 921	111,4	0,9417	490 056	0	8 401 977
2008-03	6 310 534	111,3	0,9408	396 889	0	6 707 423
2008-04	4 687 509	111,7	0,9442	276 970	0	4 964 479
2008-05	5 370 383	112,2	0,9484	291 973	0	5 662 355
2008-06	5 869 577	112,4	0,9501	308 101	0	6 177 678
2008-07	2 664 562	113,0	0,9552	124 975	0	2 789 537
2008-08	3 315 234	112,9	0,9544	158 567	0	3 473 801
2008-09	5 841 330	112,7	0,9527	290 252	0	6 131 583
2008-10	4 646 104	112,7	0,9527	230 862	0	4 876 966
2008-11	5 566 878	112,1	0,9476	307 892	0	5 874 770
2008-12	5 422 288	111,8	0,9451	315 249	0	5 737 537
2009-01	1 991 466	113,5	0,9594	84 221	0	2 075 686
2009-02	3 884 747	113,6	0,9603	160 725	138 741	4 184 213
2009-03	5 846 430	113,8	0,9620	231 186	0	6 077 616
2009-04	4 008 748	113,7	0,9611	162 183	0	4 170 931
2009-05	6 787 487	113,7	0,9611	274 604	0	7 062 091
2009-06	8 200 104	113,7	0,9611	331 754	0	8 531 858
2009-07	1 796 558	113,3	0,9577	79 283	0	1 875 841
2009-08	3 065 651	113,1	0,9560	140 949	0	3 206 601
2009-09	6 543 380	112,7	0,9527	325 137	0	6 868 517
2009-10	6 718 877	112,5	0,9510	346 395	0	7 065 272
2009-11	6 001 220	112,7	0,9527	298 197	0	6 299 417
2009-12	5 619 453	112,9	0,9544	268 778	0	5 888 231
2010-01	2 528 726	114,3	0,9662	88 494	0	2 617 220
2010-02	3 509 583	114,3	0,9662	122 820	125 342	3 757 746
2010-03	9 284 789	114,6	0,9687	299 771	0	9 584 560
2010-04	10 457 718	115,0	0,9721	300 091	0	10 757 809
2010-05	11 461 879	115,1	0,9730	318 662	0	11 780 541
2010-06	5 338 207	115,1	0,9730	148 412	0	5 486 619
2010-07	4 526 331	115,5	0,9763	109 729	0	4 636 060
2010-08	4 726 455	115,2	0,9738	127 188	0	4 853 643
2010-09	9 016 628	114,9	0,9713	266 811	0	9 283 438
2010-10	9 295 727	114,7	0,9696	291 758	0	9 587 485
2010-11	10 331 434	114,9	0,9713	305 717	0	10 637 150
2010-12	2 395 775	115,5	0,9763	58 079	0	2 453 854
2011-01	3 146 513	116,3	0,9831	54 110	0	3 200 624
2011-02	10 343 432	116,4	0,9839	168 836	369 408	10 881 676
2011-03	9 926 174	116,5	0,9848	153 366	0	10 079 540
2011-04	9 887 120	116,8	0,9873	126 975	0	10 014 095
2011-05	8 009 957	117,4	0,9924	61 405	0	8 071 362
2011-06	6 939 520	117,2	0,9907	65 132	0	7 004 652
2011-07	6 692 935	117,5	0,9932	45 569	0	6 738 504
2011-08	5 402 980	117,2	0,9907	50 711	0	5 453 691
2011-09	7 287 089	117,0	0,9890	80 968	0	7 368 057
2011-10	9 176 679	117,3	0,9915	78 233	0	9 254 911
2011-11	12 730 119	117,8	0,9958	54 033	0	12 784 152
2011-12	6 786 419	118,3	1,0000	0	0	6 786 419

Source: POS Media; Czech Statistical Office

[49] CPI = Consumer Price Index
[50] Calculated as: $CPI_t \div CPI_{2011\text{-}12}$

Appendix 2: Seasonal decomposition of the Instore sales time series

Data Table for Instore

Seasonal decomposition method: Multiplicative

Period	Data	Trend-Cycle	Seasonality	Irregular	Seasonally Adjusted
1/07	742438,0				2,00494E6
2/07	1,57081E6				1,43654E6
3/07	2,24215E6				1,73834E6
4/07	4,09422E6				3,56999E6
5/07	4,75815E6				3,73401E6
6/07	3,06085E6				2,76134E6
7/07	2,179E6	3,87163E6	56,2813	107,426	4,15913E6
8/07	2,39722E6	4,17915E6	57,3613	91,5074	3,82423E6
9/07	4,48824E6	4,64983E6	96,5248	82,6642	3,84375E6
10/07	8,1822E6	4,87215E6	167,938	131,168	6,39069E6
11/07	6,46222E6	4,94608E6	130,653	106,484	5,26679E6
12/07	6,0075E6	5,11363E6	117,48	131,839	6,74174E6
1/08	1,29164E6	5,26893E6	24,5142	66,2001	3,48804E6
2/08	8,40198E6	5,33923E6	157,363	143,912	7,68378E6
3/08	6,70742E6	5,45256E6	123,014	95,3731	5,20028E6
4/08	4,96448E6	5,38331E6	92,2198	80,4119	4,32883E6
5/08	5,66236E6	5,22112E6	108,451	85,1082	4,4436E6
6/08	6,17768E6	5,18539E6	119,136	107,478	5,57318E6
7/08	2,78954E6	5,20681E6	53,5747	102,26	5,32447E6
8/08	3,4738E6	5,06374E6	68,6015	109,439	5,54169E6
9/08	6,13158E6	4,86176E6	126,119	108,008	5,25111E6
10/08	4,87697E6	4,80245E6	101,552	79,3166	3,80914E6
11/08	5,87477E6	4,82771E6	121,688	99,1777	4,78801E6
12/08	5,73754E6	4,98412E6	115,116	129,186	6,43879E6
1/09	2,07569E6	5,04415E6	41,1504	111,126	5,60535E6
2/09	4,18421E6	4,99494E6	83,769	76,6085	3,82655E6
3/09	6,07762E6	5,01451E6	121,201	93,9669	4,71199E6
4/09	4,17093E6	5,1364E6	81,2034	70,8061	3,63689E6
5/09	7,06209E6	5,24527E6	134,637	105,658	5,54206E6
6/09	8,53186E6	5,26924E6	161,918	146,074	7,697E6
7/09	1,87584E6	5,29809E6	35,406	67,5805	3,58048E6
8/09	3,2066E6	5,30288E6	60,469	96,4651	5,11543E6
9/09	6,86852E6	5,43123E6	126,463	108,304	5,88223E6
10/09	7,06527E6	5,85181E6	120,737	94,301	5,51832E6
11/09	6,29942E6	6,32287E6	99,6291	81,199	5,13411E6
12/09	5,88823E6	6,39258E6	92,1104	103,368	6,6079E6
1/10	2,61722E6	6,38071E6	41,0177	110,768	7,06775E6
2/10	3,75775E6	6,56434E6	57,2448	52,3516	3,43654E6
3/10	9,58456E6	6,73359E6	142,339	110,356	7,43092E6
4/10	1,07578E7	6,93931E6	155,027	135,178	9,38038E6
5/10	1,17805E7	7,22514E6	163,049	127,955	9,24492E6
6/10	5,48662E6	7,26278E6	75,5444	68,1522	4,94974E6
7/10	4,63606E6	7,14399E6	64,8946	123,866	8,84899E6
8/10	4,85364E6	7,46512E6	65,0176	103,721	7,74292E6
9/10	9,28344E6	7,78258E6	119,285	102,156	7,95037E6
10/10	9,58749E6	7,77222E6	123,356	96,3469	7,48829E6
11/10	1,06372E7	7,58668E6	140,208	114,272	8,66941E6
12/10	2,45385E6	7,49538E6	32,7382	36,7395	2,75377E6
1/11	3,20062E6	7,64623E6	41,8588	113,039	8,64322E6
2/11	1,08817E7	7,75884E6	140,249	128,26	9,95152E6
3/11	1,00795E7	7,70403E6	130,835	101,436	7,81468E6
4/11	1,00141E7	7,61037E6	131,585	114,737	8,73189E6
5/11	8,07136E6	7,68597E6	105,014	82,4111	6,33409E6
6/11	7,00465E6	7,95595E6	88,0429	79,4277	6,31923E6
7/11	6,7385E6				1,2862E7
8/11	5,45369E6				8,70017E6
9/11	7,36806E6				6,31003E6
10/11	9,25491E6				7,22853E6
11/11	1,27842E7				1,04192E7
12/11	6,78642E6				7,61586E6

Source: Statgraphics

Appendix 3: Seasonality indices for the Instore sales time series

Seasonal Indices for Instore

Seasonal decomposition method: Multiplicative

Season	Index
1	37,0305
2	109,347
3	128,982
4	114,684
5	127,427
6	110,847
7	52,3908
8	62,6849
9	116,767
10	128,033
11	122,697
12	89,109

Source: Statgraphics

Appendix 4: Linear model values for the Instore sales time series

Forecast Table for Instore SADJ

Model: Linear trend = 3,20605E6 + 86117,7 t

Period	Data	Forecast	Residual
1/07	2,00494E6	3,18111E6	-1,17617E6
2/07	1,43654E6	3,27445E6	-1,83791E6
3/07	1,73834E6	3,3678E6	-1,62946E6
4/07	3,56999E6	3,46115E6	108836,0
5/07	3,73401E6	3,5545E6	179506,0
6/07	2,76134E6	3,64785E6	-886513,0
7/07	4,15913E6	3,7412E6	417927,0
8/07	3,82423E6	3,83455E6	-10322,5
9/07	3,84375E6	3,9279E6	-84152,1
10/07	6,39069E6	4,02125E6	2,36944E6
11/07	5,26679E6	4,1146E6	1,15219E6
12/07	6,74174E6	4,20795E6	2,53379E6
1/08	3,48804E6	4,3013E6	-813261,0
2/08	7,68378E6	4,39465E6	3,28913E6
3/08	5,20028E6	4,488E6	712280,0
4/08	4,32883E6	4,58135E6	-252519,0
5/08	4,4436E6	4,6747E6	-231099,0
6/08	5,57318E6	4,76805E6	805131,0
7/08	5,32447E6	4,8614E6	463072,0
8/08	5,54169E6	4,95475E6	586942,0
9/08	5,25111E6	5,0481E6	203012,0
10/08	3,80914E6	5,14145E6	-1,33231E6
11/08	4,78801E6	5,2348E6	-446787,0
12/08	6,43879E6	5,32815E6	1,11064E6
1/09	5,60535E6	5,4215E6	183854,0
2/09	3,82655E6	5,51485E6	-1,6883E6
3/09	4,71199E6	5,6082E6	-896205,0
4/09	3,63689E6	5,70154E6	-2,06465E6
5/09	5,54206E6	5,79489E6	-252835,0
6/09	7,697E6	5,88824E6	1,80876E6
7/09	3,58048E6	5,98159E6	-2,40111E6
8/09	5,11543E6	6,07494E6	-959513,0
9/09	5,88223E6	6,16829E6	-286063,0
10/09	5,51832E6	6,26164E6	-743323,0
11/09	5,13411E6	6,35499E6	-1,22088E6
12/09	6,6079E6	6,44834E6	159558,0
1/10	7,06775E6	6,54169E6	526058,0
2/10	3,43654E6	6,63504E6	-3,1985E6
3/10	7,43092E6	6,72839E6	702529,0
4/10	9,38038E6	6,82174E6	2,55864E6
5/10	9,24492E6	6,91509E6	2,32983E6
6/10	4,94974E6	7,00844E6	-2,0587E6
7/10	8,84899E6	7,10179E6	1,7472E6
8/10	7,74292E6	7,19514E6	547781,0
9/10	7,95037E6	7,28849E6	661881,0
10/10	7,48829E6	7,38184E6	106452,0
11/10	8,66941E6	7,47519E6	1,19422E6
12/10	2,75377E6	7,56854E6	-4,81477E6
1/11	8,64322E6	7,66189E6	981333,0
2/11	9,95152E6	7,75524E6	2,19628E6
3/11	7,81468E6	7,84859E6	-33906,3
4/11	8,73189E6	7,94194E6	789954,0
5/11	6,33409E6	8,03529E6	-1,7012E6
6/11	6,31923E6	8,12864E6	-1,80941E6
7/11	1,2862E7	8,22198E6	4,64002E6
8/11	8,70017E6	8,31533E6	384836,0
9/11	6,31003E6	8,40868E6	-2,09865E6
10/11	7,22853E6	8,50203E6	-1,2735E6
11/11	1,04192E7	8,59538E6	1,82382E6
12/11	7,61586E6	8,68873E6	-1,07287E6

Source: Statgraphics

Appendix 5: Forecasted values for the Instore sales time series

Period	Forecast	Lower 95,0% Limit	Upper 95,0% Limit
1/12	8,45923E6	5,04659E6	1,18719E7
2/12	8,54535E6	5,12096E6	1,19697E7
3/12	8,63146E6	5,19506E6	1,20679E7
4/12	8,71758E6	5,26889E6	1,21663E7
5/12	8,8037E6	5,34245E6	1,22649E7
6/12	8,88982E6	5,41574E6	1,23639E7
7/12	8,97593E6	5,48877E6	1,24631E7
8/12	9,06205E6	5,56154E6	1,25626E7
9/12	9,14817E6	5,63405E6	1,26623E7
10/12	9,23429E6	5,7063E6	1,27623E7
11/12	9,32041E6	5,7783E6	1,28625E7
12/12	9,40652E6	5,85006E6	1,2963E7

Source: Statgraphics

Appendix 6: Sales forecast for 2012

Period	Instore sales	Petrol Station sales	Education sales	Total sales	Revenue Advertisement	Revenue Operations
2012-01	3 204 543	0	0	3 204 543	2 832 816	371 727
2012-02	9 558 998	399 475	443 861	10 402 333	9 195 663	1 206 671
2012-03	11 389 089	848 817	443 861	12 681 767	11 210 682	1 471 085
2012-04	10 227 616	1 731 390	887 722	12 846 727	11 356 507	1 490 220
2012-05	11 476 311	1 124 921	1 242 810	13 844 042	12 238 133	1 605 909
2012-06	10 080 743	665 791	177 544	10 924 078	9 656 885	1 267 193
2012-07	4 810 720	146 474	0	4 957 195	4 382 160	575 035
2012-08	5 811 189	146 474	0	5 957 663	5 266 574	691 089
2012-09	10 927 731	782 305	798 949	12 508 985	11 057 942	1 451 042
2012-10	12 094 866	732 370	443 861	13 271 097	11 731 650	1 539 447
2012-11	11 698 888	512 659	443 861	12 655 408	11 187 381	1 468 027
2012-12	8 574 843	233 027	0	8 807 870	7 786 157	1 021 713

Source: own production

	1	2	3	4	5	6	7	8	9	10	11	12
**** EBIT**	**-871 484**	**780 797**	**1 304 050**	**1 341 918**	**1 570 855**	**899 866**	**-504 506**	**-275 195**	**1 228 687**	**1 403 633**	**1 262 300**	**331 832**
**** EBITDA**	**-801 484**	**850 797**	**1 374 050**	**1 411 918**	**1 640 855**	**969 866**	**-434 506**	**-205 195**	**1 298 687**	**1 473 633**	**1 332 300**	**401 832**
**** Operational Margin**	**-264 234**	**1 388 047**	**1 911 300**	**1 949 168**	**2 178 105**	**1 507 116**	**102 394**	**332 055**	**1 835 937**	**2 010 883**	**1 869 550**	**939 082**
**** Commercial Margin**	**2 338 693**	**8 744 727**	**10 773 423**	**10 920 237**	**11 807 848**	**9 209 080**	**3 898 553**	**4 788 970**	**10 619 646**	**11 297 926**	**10 749 963**	**7 278 404**
****** Revenue**	**3 204 543**	**10 402 333**	**12 681 767**	**12 846 727**	**13 844 042**	**10 924 078**	**4 957 195**	**5 957 663**	**12 508 985**	**13 271 097**	**12 655 408**	**8 807 870**
******* Revenue Advertisement**	2 832 816	9 195 663	11 210 682	11 356 507	12 238 133	9 656 885	4 382 160	5 266 574	11 057 942	11 731 650	11 187 381	7 786 157
******* Revenue Operations**	371 727	1 206 671	1 471 085	1 490 220	1 605 909	1 267 193	575 035	691 089	1 451 042	1 539 447	1 468 027	1 021 713
****** Sales & Marketing Direct Costs**	**-865 850**	**-1 657 607**	**-1 908 344**	**-1 926 490**	**-2 036 195**	**-1 714 999**	**-1 058 641**	**-1 168 693**	**-1 889 338**	**-1 973 171**	**-1 905 445**	**-1 529 466**
******* Sales Direct Costs**	**-776 600**	**-1 568 357**	**-1 819 094**	**-1 837 240**	**-1 946 945**	**-1 625 749**	**-969 391**	**-1 079 443**	**-1 800 088**	**-1 883 921**	**-1 816 195**	**-1 392 966**
******** Sales Personal Costs**	-444 091	-588 047	-633 635	-636 935	-656 881	-598 482	-479 144	-499 153	-630 180	-645 422	-633 108	-556 157
******** Agency Bonuses**	-288 409	-936 210	-1 141 359	-1 156 205	-1 245 964	-983 167	-446 148	-536 190	-1 125 809	-1 194 399	-1 138 987	-792 708
******** Consultancy & Training**	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000
******** Sales Travel Costs**	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500
******** Other Sales Costs**	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600	-19 600
******* Marketing Direct Costs**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-68 250**	**-115 500**
******** Marketing Personal Costs**	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-47 250	-94 500
******** Marketing & PR Costs**	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000	-21 000
******* Bad Debts & Revenue Write-offs**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**	**-21 000**
****** Operations Direct Costs**	**-2 602 927**	**-7 356 679**	**-8 862 122**	**-8 971 070**	**-9 629 742**	**-7 701 964**	**-3 796 159**	**-4 456 915**	**-8 783 709**	**-9 287 043**	**-8 880 414**	**-6 339 323**
****** Operations Personal Costs**	-420 000	-420 000	-420 000	-420 000	-420 000	-420 000	-455 000	-455 000	-455 000	-455 000	-455 000	-455 000
****** Installation**	-198 297	-643 696	-784 748	-794 955	-856 669	-675 982	-306 751	-368 660	-774 056	-821 215	-783 117	-545 031
****** Field Marketing**	-89 234	-289 663	-353 136	-357 730	-385 501	-304 192	-138 038	-165 897	-348 325	-369 547	-352 402	-245 264
****** Freight & Transport**	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000
****** Maintenance & Cleaning**	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500	-10 500
****** Energy**	-7 000	-7 000	-7 000	-7 000	-7 000	-7 700	-7 700	-7 700	-7 700	-7 700	-7 700	-7 700
****** Material Costs**	-185 863	-603 335	-735 543	-745 110	-802 954	-633 597	-287 517	-345 544	-725 521	-769 724	-734 014	-510 856
****** Carriers**	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000
****** 3rd Party Rents**	-1 643 033	-5 333 484	-6 502 196	-6 586 774	-7 098 117	-5 600 994	-2 541 653	-3 054 613	-6 413 607	-6 804 357	-6 488 681	-4 515 971
**** Overhead Costs**	**-537 250**	**-537 250**	**-537 250**	**-537 250**	**-537 250**	**-537 250**	**-536 900**	**-537 250**	**-537 250**	**-537 250**	**-537 250**	**-537 250**
***** Overhead Personal Costs**	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000	-385 000
***** Premises**	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000	-56 000
***** IT Costs**	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000	-35 000
***** Telecommunications**	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000
***** Postage & Stationery**	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000	-14 000
***** Car Fleet**	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500	-17 500
***** Travel & Entertainment**	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000
***** Legal & Business Services**	-350	-350	-350	-350	-350	-350	0	-350	-350	-350	-350	-350
***** Accountancy & Audit Fees**	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000	-7 000
***** Bank Charges**	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400	-1 400
**** Other Revenue**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
**** Other Costs**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
**** Depreciation & Amortization**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**	**-70 000**

Appendix 7: Pro forma income statement for 2012 (CZK)

Source: own production; POS Media

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