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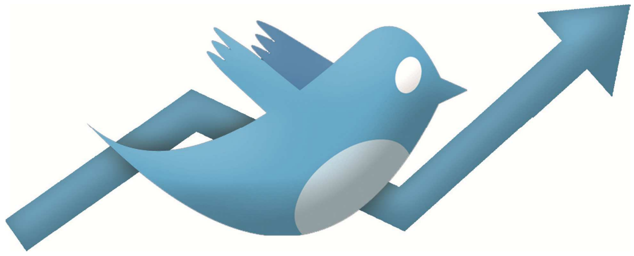

Thesis

Twitter as driver of stock price

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i. Executive summary

The goal of this research is to examine the dynamic relationship of Twitter and stock price, by examining the effects for the ten most valuable brands according Interbrand (2010): Coca-Cola, IBM, Microsoft, Google, McDonald's, Intel, Nokia, Disney, Toyota and Cisco. A VAR modelling approach captures the short and long term effects of Twitter to stock price and stock price to Twitter.

Effects were found for 5 of the 10 brand. For Coca-Cola and Toyota, the number of brand sentiment tweets drives stock price. For Microsoft and Disney the brand sentiment index (sentiment extracted from Twitter) drives stock price. For Nokia this relation is twisted, the stock price drives the number of brand sentiments tweets, the brand sentiment index and the number of followers.

Twitter does not instantaneously have an effect, investor reactions grow over time. On average, it takes 2 till 4 days before the impact peaks. The effect dies out 1 till 6 days after the peak day.

ii. Acknowledgement

Combining the contents of the master BA Marketing Research of the University of Groningen and the master Strategic Marketing Management of BI Norwegian Business School, I am among the first students to accomplish the thesis in the Double Degree Marketing.

I would like to give special thanks to Associate Professor Bendik Samuelsen and Assistant Professor Auke Hunneman for their valuable assistance. Both supervisors have helped me to accomplish my ambitious goals of using advanced modelling practices in my thesis with their comments and suggestion. Further, I would like to thank Associate Professor Jaap Wieringa for offering me final feedback on the methodology part. For the opportunity to learn from two marketing perspectives, I would like to thank both the University of Groningen and BI Norwegian Business School.

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1. Introduction

The popularity of social media rises. Already 77 of the Fortune 100 companies, in the United States, have a Twitter account and the number of followers of these corporate Twitter accounts doubled last year (The Realtime report, 2011). However, despite the popularity of Twitter and other social media, marketers have little insight in the effectiveness of social networks. Almost half of companies do not measure the results of social media, since they do not know how to measure the results. Hence, most of the companies operate on their feeling, without any structural performance targets (Marketing Online, 2011). Therefore, a need exist for a valuable metrics to measure the effectiveness of social media investments.

Due to the openness of online communication, opportunities exist for developing a good metrics. Online communication results in an extensive database of free information. Online databases save all messages sent through Twitter. This information makes it possible to track consumer communication over time, which was hard before since consumer communication was offline in face-to-face conversations (Rust, Zeithaml and Lemon, 2000). Further, due to the short messages on Twitter, tweets, the possibility exist to extract sentiment from these tweets, which is a good proxy of satisfaction. The main advantage of online sentiment over indices like the American Consumer Satisfaction Index (ACSI) is the daily measurement. Moreover, the cost of measuring sentiment online is significantly lower than the cost of satisfaction surveys who are used to come up with satisfaction indices normally.

The ultimate goal of any marketing expenditure should be to increase the value of the firm (Hanssens et al. 2009). Recent research has shown that sentiment expressed through Twitter predicts stock price fluctuations (Bollen, Mao and Zeng, 2011; Zhang, Fuehres and Gloor, 2010). Bollen, Mao and Zeng (2011) found that the mood on Twitter shifted the Dow Jones Industrial Average (DJIA) three or four days later. The most important mood for the shift of the DJIA was calmness of the public. Zhang, Fuehres and Gloor (2010) find similar results. When people express a lot of hope, fear, and worry the Dow Jones goes down the next day. However, the research of Bollen, Mao and Zeng (2011) and Zhang, Fuehres and Gloor (2010) provide only aggregate measures of sentiment, which is encouraging, but conclusions on individual stock fluctuations lack.

The objective of this research is capturing the dynamic relationships among Twitter and stock price fluctuations on a brand level. The research incorporates both the importance of the relation of marketing spending to firm value and the benefit of Twitter data.

This results in the following research question:

What is the dynamic relationship between, measured by the number followers, tweets and brand sentiment, and stock price?

Like Bollen, Mao and Zeng (2011) and Zhang, Fuehres and Gloor (2010) I make a relationship between Twitter sentiment and stock price. In contrast to previous research, this analysis is on a brand level. Further, I add additional valuable Twitter variables, like the number of followers and the number of tweets sent by the brand. Moreover, this research links marketing and finance literature, which improves understanding of the marketing finance interface and helps businesses to value investment into social media platforms. Twitter gives insights in stock price fluctuations, which businesses, investors, and other stakeholder's value. Lastly, new research opportunities arise in the field of social media. This research is among the first studies to quantify the impact of Twitter to stock value.

The next section starts with a background of Twitter, followed by a conceptual framework of the relationship between Twitter and stock price. After I describe the research methodology, and I give a description of the Twitter and financial data used, to end with results, managerial implication and conclusions.

2. Literature review

2.1 Twitter

Twitter is an online social network used by millions of people around the world to stay connected with friend, family and colleagues. The purpose of this social network is letting users talk about daily activities and seek or share information in form of news and personal experiences (Hennig-Thurau et al. 2004). Communication happens through short messages. These messages, so called tweets, consist of maximal 140 characters and users send them with the use of computers and mobile phones. Since messages are short, communication is fast, one of the main advantages of Twitter (Java et al. 2007). The tweets are open to any Twitter user, unless a user indicates that he or she prefers to hide his or her profile (Huberman, Romero and Wu, 2008). Tweets express opinions about different topics, like daily life, current events, news stories, brands and other consumer interests (Java et al. 2007). These opinions can give interesting insights in the market (Go, Huang and Bhayani, 2009). According to Jansen et al. (2009) 19% of the tweets contain a message of a brand. From these branded tweets, 20% contain some expression of sentiment. Of these sentiment tweets, 50% are positive and 33% are negative. Starbucks, Google and BBC are the most popular brands where Twitter users talk about (Brand republic, 2009). Users express brand sentiment through Twitter for desire of social interaction, economic incentives, for concerns of other consumers, and for potential ego enhancements (Hennig-Thurau et al. 2004). The motive to express positive word-of-mouth differs from negative word-of-mouth (WOM). Altruism, product involvement, self-enhancement and helping the company explains positive WOM, while altruism, anxiety reduction, vengeance and advice seeking explains negative WOM (Hennig-Thurau et al. 2004). Altruism in positive sense is to do something for others without anticipating any reward in return. The altruism in negative sense is to prevent others from experiencing the problems they encountered. Vengeance is to revenge the company for a negative consumption experience. Sentiment expressed in either positive or negative way is useful for consumers who want to explore user evaluations of products before purchase. Moreover, this sentiment is interesting for companies to monitor the public sentiment of their brands (Go, Huang and Bhayani, 2009).

As Twitter user, you can declare people who you would be interested in following. That relation does not have to be reciprocal, this in contrast to other social media platforms (Huberman, Romero and Wu, 2008), which makes some Twitter relations one-way relations (Java et al. 2007). This is one of the main powers of Twitter; it is possible to be ‘friends’ with idols and brands you like. The most popular Twitter accounts, measured by the number of followers, are @ladygaga and @justinbieber with more than nine million followers, followed by @BarackObama and @britneyspears with more than seven million followers (Twittercounter, 2011). The most popular followed brands are @Twitter with nearly five million followers and @google with more than 3 million followers (Twittercounter, 2011). The main reason to follow a brand is liking the brand (45.4%) (Kullin, 2010).Other reasons to follow a brand are to receive promotions (24.9%); to get access to exclusive information (24.9%); to be among the first to get info about the company (21.5%); because I am a customer of the company (21.0%); to be part of a group with similar interests (20.5%); because it is entertaining (20.3%); because I work for the company (7.1%); because someone asked me to (6.9%).

Twitter accounts with many followers are more active in communication, sending tweets, than accounts with smaller number of followers (Huberman, Romero and Wu, 2008). However, the number of tweets sent saturates after a certain period, although the number of followers might increase. Businesses on Twitter mostly share information about science, technology and possibly world news (Wu et al. 2011). Furthermore, more and more companies use their public Twitter account to update investors. According to research of IR web report (2010) more than 150 public companies announced their earnings on Twitter. Like DSM on April 27th, 2011:

Figure 1 Tweet of DSM

A website who collects financial information from Twitter is www.StockTwits.com. Twitter messages are short, which allows investors to receive stock information from various sources in limited time. Furthermore, Twitter expresses real-time information, which investors value.

2.2 Link of Twitter to stock price

Recent research has shown that sentiment expressed through Twitter predicts stock price fluctuations (Bollen, Mao and Zeng, 2011; Zhang, Fuehres and Gloor, 2010). Bollen, Mao and Zeng (2011) explains these findings on basis of behavioural economic theories. The mood of societies affects collective decision making, including decision making of investors. The mood on Twitter shifts the Dow Jones Industrial Average (DJIA) three or four days later. The most important mood for the shift of the DJIA is calmness of the public. Bollen, Mao and Zeng (2011) found an accuracy of 87,6% in predicting the daily up and closing values of the DJIA. Zhang, Fuehres and Gloor (2010) find similar results. When people express a lot of hope, fear, and worry the Dow Jones goes down the next day. In contrast, when people have less hope, fear, and worry, the Dow Jones goes up.

According to efficient market hypothesis, stock prices always capture all publicly available information (Brealey, Myers and Marcus, 2004). The price of the stock rapidly and accurately reflects many types of news, such as earnings and dividend announcements, plans to issue additional stock or repurchase of existing stock, so that making superior returns by buying or selling after the announcements is impossible (Brealey, Myers and Marcus, 2004). This makes that publicly available news drives stock price. Investors look back to what has happened recent periods and then assume that that is representative for what may occur in the future (Brealey, Myers and Marcus, 2004). However, this simple analysis of investors does not work, since stock prices wander randomly. Therefore, investors gauge a firm's business prospect by studying the financial and trade press, the company's financial accounts, the president's annuals statement and other items of news (Brealey, Myers and Marcus, 2004). The Internet increased the availability and speed of financial information and decreased the cost of information (Bogan, 2008). Twitter is one of these Internet tools for investors to generate earlier financial insides, to benefit immediate changes of the stock price.

Investors spread their investment advice through Twitter as well. Website like www.StockTwits.com collect this financial information expressed on Twitter. Moreover, short messages communicate financial news on Twitter, which allows investors to receive stock information from various sources in limited time.

Twitter is a source of word of mouth (WOM), where investors can collect information of consumers, brands and other investors. The opinion of consumers on Twitter refers to consumer satisfaction. Consumers express positive WOM when they are extremely satisfied and they express negative WOM in case of dissatisfaction (Anderson, 1998). Previous research already proved the effect of the American Consumer Satisfaction Index (ACSI) on stock price (Fornell et al. 2006). Firms that do well by their customers receive a reward in the form of more business from customers and more capital from investors. Buyers financially reward sellers that satisfy them and punish those that do not. Customer satisfaction decreases the number of complaints and rises customer loyalty (Bolton, 1998). Increased customer loyalty may increase usage levels, secure future revenues, reduce the cost of future transactions and lower price elasticity, which all result in stable expectations of investors and rising stock prices (Fornell et al. 2006). The logic of Srivastava, Shervani and Fahey (1998) explains the link between customer satisfaction and stock returns. In this logic, four major determinants identify the company's market value. First, the acceleration of cash flows, affected by the speed of buyer response to marketing efforts, since the persuasion of a satisfied customer takes less effort (Fornell et al. 2006). Second, an increase in customer satisfaction leads to significant cash flow growth. 1% increase in customer satisfaction leads to a 7% increase in cash flow (Gruca and Rego, 2005). Third, high customer satisfaction reduces risk associated with cash flows (Gruca and Rego, 2005). The reduction of the variability in cash flows results in a decrease of the cost of capital and an increase in stock price. Fourth, satisfaction increases the residual value of business, measured as a function of size, loyalty, and quality of the customer base (Fornell et al. 2006).

As already mentioned, Twitter is a source of word of mouth (WOM), electronic word of mouth (eWOM). One of the most recent studies linking eWOM to stock price changes is of Luo (2007; 2009). Negative feelings, expressed through

WOM, influence consumer information processing, repurchase loyalty and damage customer equity. This subsequently leads to reduced cash flows (Luo and Homburg, 2007; Srivastava, Shervani and Fahey, 1998) and decreasing stock prices. According to the brand equity theory, unfavourable experience and negative recommendations results in loss of corporate image, which results in loss of shareholders trust and decreasing stock prices (Keller 2003; Luo and Bhattacharya, 2006).

Consumers express WOM and satisfaction through Twitter. Further, Twitter is a tool for a brand to improve business-consumer and business-investor relations. In other words, the brand tries to improve the loyalty. The number of followers and tweets of the brand measure the success of the loyalty improvements of the brand's Twitter account (Thomases, 2010). Improved loyalty drives retention and CLV, which in the end drives market value (Rust, Zeithaml and Lemon, 2004).

Besides the relation of Twitter to stock price, the opposite relation of stock price to Twitter may hold as well. The ability for a company to invest in more marketing actions increases, by an increase in cash flows due to changing stock prices. The additional marketing helps to keep the buzz around a brand high (Luo, 2009). Further, in case of high or low stock performance, managers are triggered to change future actions in advertising, product innovations, and branding, this in the end influence customer experience and brand sentiment in the future (Benner, 2007; Markovitch, Steckel and Yeung, 2005). To conclude, "success breeds success" (Subrahmanyam and Titman, 2001), favourable information of the stock market might result in more positive news of the brand on Twitter.

To incorporate dynamic relationship of Twitter and stock price, I constructed the following conceptual model (figure 2). The model displays the effect of the history of Twitter to stock price and the effect of the history of stock price to Twitter.

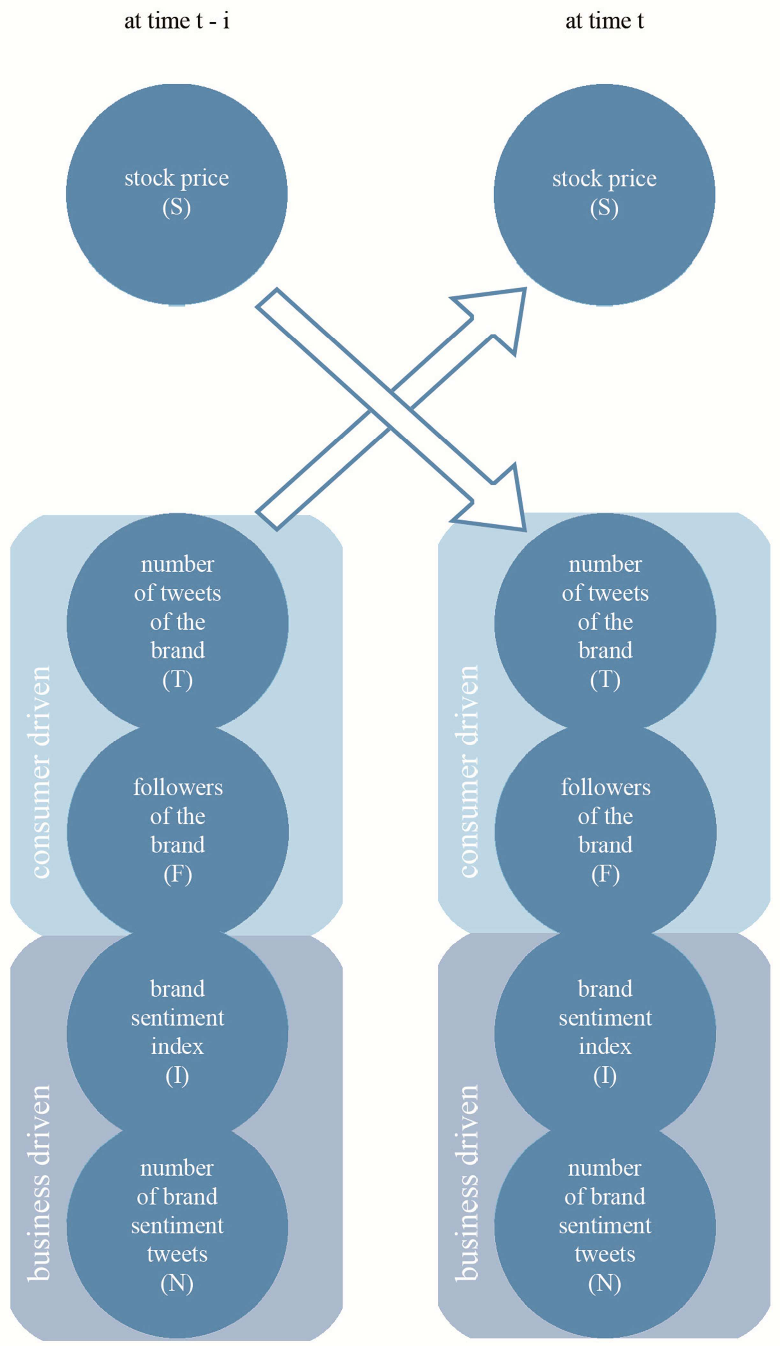


Figure 2 Conceptual model

2.2.1 Brand sentiment tweets and stock price

WOM is more effective than traditional marketing tools like personal selling and advertising, which makes WOM an important topic in marketing (Gruen, Osmonbekov and Czaplewski, 2006). Currently, the Internet is the main source for WOM, in literature often referred as electronic WOM (eWOM) (Hennig-Thurau et al. 2004).

Tweets with brand sentiment are an easy and cost-effective opportunity to measure word of mouth (Godes and Mayzlin, 2004). Further, Twitter gives the opportunity to observe consumers brand conversations in an online community. Messages on Twitter are short, which makes counting of WOM volume easier. Further, consumers send tweets either before or after purchases, while in the past WOM was a proxy for future sales only.

Moreover, tweets are an improved measure of WOM, since information is easier to track, freely available and WOM is measure endogenously. Although this offers opportunities, research on the volume of WOM. Most research focuses on the effects of either the volume of positive or negative WOM, which combines measures of volume and valence. Positive WOM involves favourable experience and recommendations of buying certain products, while negative brand WOM refers to unfavourable experience and recommendations of not buying certain products (Luo, 2009). Positive WOM is very effective in generating sales, awareness, and loyalty (Luo, 2009). While, negative WOM studies reveal an increase in retention costs, higher defection rates and lower profits. This explains the negative effect of negative WOM on the net present value of the film (Goldenberg et al. 2007). Further, negative WOM has negative long-term effect on cash flows, stock returns and stock volatilities (Luo, 2009). Luo (2009) researched the impact of negative WOM in the airline industry. He found significantly different effects for low-cost airlines and non-low cost airlines. The impact of negative WOM was more punitive for the low-cost airlines; an increase of 1% in negative WOM resulted in a decrease of stock returns of 0.003% for the low-cost airlines in comparison to a decrease of 0.001% for other airlines. WOM does not instantaneously have an effect, investor reactions grow over time (Luo, 2009).

Although research of volume of WOM lacks, the expectation is that the rise in number of brand sentiment tweet is a sign for improved customer service, increased customer retention, brand loyalty and an improved brand image. Besides these, the number of tweets with a brand sentiment could be sign of viral activity (Thomases, 2010). Further, awareness increases when volume rises, which lead to higher sales, this in the end could lead to higher stock prices (Godes and Mayzlin, 2004). Therefore, I hypothesize that the number of brand sentiment tweet has a positive effect on stock price. Thus:

H1a The number of tweets with a brand sentiment is positively related to stock price.

This relationship may hold the other way around as well, since the ability for a company to invest in additional marketing actions improves with an increase in cash flows. These extra investments will keep the buzz around a brand high (Luo, 2009). Further, tweets are an endogenous WOM measure. This means that tweets could be a proxy for future sales and an outcome of past sales. Therefore, I expect brand sentiment tweets to be a driver of stock price and stock price a driver of future brand sentiment tweets. Thus:

H1b Stock price is positively related to number of tweets with a brand sentiment.

2.2.2 Brand sentiment index and stock price

Secondly, brand sentiment index of Twitter is a good proxy for satisfaction. The definition of sentiment on Twitter according the website www.twittersentiment.appspot.com is a personal positive or negative feeling (Go, Huang and Bhayani, 2009). The American Customer Satisfaction index (ACSI) measures the overall satisfaction of total purchases of all consumption experiences of all customers, this result in an estimation of a customer satisfaction index (Fornell et al. 1996). Similar to the ACSI, the brand sentiment index of Twitter contains the percentage positive feelings of consumed goods and services as well.

The brand sentiment index measures on a daily basis and data is freely available, while the ACSI measures on a yearly basis with help of expensive surveys. To assort similarity of ACSI and the Twitter brand sentiment index, I take a sample of both the high and low performing brands of four industries: food stores, Internet retail industry, airlines and automobiles. Table 1 presents the results of the comparison.

Table 1 ACSI and Brand sentiment index compared

	ACSI value*	Brand sentiment index**
Food stores:		
Starbucks	78	63
McDonald's	67	51
Internet retail industry:		
Amazon.com	87	70
eBay	81	59
Airlines:		
Southwest Airlines	79	53
American Airlines	63	40
United Airlines	60	31
Automobiles:		
BMW	86	59
Toyota	84	51
Ford	82	62

* The ASCI value of 2010 to be found on theacsi.org ** The brand sentiment index of Twitter measures the percentage of positive sentiment messages of all brand sentiment tweets. The sentiment on Twitter over the year 2010, January 1st to December 31st, to be found on twittersentiment.appspot.com.

Table 1 reports comparable findings for the order in most satisfactory brands for three out of four selected industries. Starbucks scores are higher in comparison to McDonald's, for both the ACSI and the brand sentiment index. Further, Amazon.com scores above the satisfaction rate of eBay and Southwest Airlines scores above American Airlines and United Airlines. For the automobile sector, the satisfaction scores differ. Ford received more positive sentiment on Twitter, comparing to BMW and Toyota, while the expectation was, based on the ACSI, that BMW would receive most positive sentiment followed by Toyota. However, the automobile market has had difficulties in 2010. Toyota had to recall cars several times (BusinessWeek, 2010), which resulted in more negative sentiment on Twitter and a lower brand sentiment index. An explanation for Ford scoring higher than BMW in the brand sentiment index measure lacks. Concluding, three out of four industries show similar ratings for the ACSI and the brand sentiment index that supports the assumption that brand sentiment index is a proxy for the ACSI.

Satisfaction is an important driver of financial performance. Researchers studied the link between financial performance and satisfaction extensively and all come to the same conclusion. Highly satisfied customers are willing to pay a price premium and they are less price sensitive (Homburg, Koschate and Hoyer, 2005; Stock, 2005). Further, satisfaction increases the efficiency of advertising and promotion investments, since customer satisfaction induces free WOM, which reduces marketing costs (Luo and Homburg, 2007). Consumer satisfaction results in customer behaviour patterns, like loyalty and repurchase, who positively affect business results (Keiningham, Perkins-Munn and Evans, 2003; Seiders et al. 2005). To conclude, these positive business outcomes make to assume a link between satisfaction and market value. Table 2 summarizes the most important studies relating satisfaction and financial value.

Table 2 Literature review satisfaction and financial value

Study	Data	Results
Anderson, Fornell and Mazvancheryl (2004)	200 Fortune 500 firms in 40 industries during 1994-97 with ACSI, 1-100 scale	1 % change in ACSI -> 1.016% change in Tobin's q or $275 million in firm value.
Ittner and Larcker (1998)	140 firms and ACSI index	One unit increase in ACSI -> $240 million increase in market value of equity.
Fornell et al. (2006)	ACSI and Compustat data from 1994-2002. In total 601 observations	1% change in ACSI -> 4.6% change in market value of equity. Further. a decrease in risk is found.
Gruca and Rego (2005)	ACSI and Compustat data from 1994-2002 for 105 firms in 23 industries	1% point increase in ACSI -> 7% points increase in cash flow in the next year and 4 reduction in variability.
Luo and Bhattacharya (2006)	ACSI and Compustat data for 452 firm-year observations across 113 Fortune 500 firms for the 2001–2004 periods.	1% change in ACSI -> 0.22% increase in Tobin's q and 0.19% increase in stock return.
Luo and Homburg (2007)	Center for Research in Security Prices (CRSP), Compustat and ACSI for the airline industry from 1999-2006.	1% change in ACSI -> -0.038% change in stock value gap and -0.329 change in risk volatility.

First, based on research of 200 Fortune 500 firms in 40 industries, Anderson, Fornell and Mazvancheryl (2004) found that an 1% change in ACSI results in a 1.016% change in shareholder value as measured in Tobin's q. The Tobin's q is the ratio of market value to the replacement costs of current assets. If a firm uses its resources effective, a firm creates a market value greater than the replacement cost of its assets, this is a sign for increased shareholder value in the future. A firm without the ability to create additional value above its assets has a Tobin's q equal to 1. Second, the research of Luo and Bhattacharya (2006) report an increase of only 0.22% in Tobin's q in case of 1% increase in ACSI, while this research also used a sample of the Fortune 500. Ittner and Larcker (1998) find an increase of $250 million in market value of equity in case of 1% point change in the ACSI, this is comparable with the increase of $275 million found by Anderson, Fornell and Mazvancheryl (2004). Fornell et al. (2006) reports an elasticity of 4.6% of the ACSI to market value of equity, based on 601 observations. Further, research shows a decrease of stock value gap, reduction of stock volatility, increase in cash flow and increase in stock returns in case of an increase in customer satisfaction (Fornell et al. 2006; Gruca and Rego, 2005; Luo and Bhattacharya, 2006; Luo and Homburg, 2007). Moreover, a positive relationship exists between satisfaction and market value, which assumes a similar relationship of brand sentiment index and market value.

Thus:
H2a The brand sentiment index is positively related to stock price.

However, an opposite effect might hold as well between both variables. High or low stock performance triggers managers to change actions in advertising, product innovations, and branding, this in the end influences customer experience and brand sentiment in the future (Benner, 2007; Markovitch, Steckel and Yeung, 2005). Lower returns can lead to decreased cash flow, which results in budget constraints in R&D and advertising in following periods (Subrahmanyam and Titman 2001; Minton and Schrand, 1999). Current cash flows constraint future marketing investments, resulting in less customer service, decrease of satisfaction and a decrease of the brand sentiment index on Twitter (Luo, 2007).

H2b Stock price is positively related to the brand sentiment index.

2.2.3 Followers/Tweets of the brand and stock price

A Twitter account can help a brand stimulating loyalty and retention (Thomases, 2010). There exist four ways to stimulate loyalty and retention (Thomases, 2010). First, a Twitter account helps to build brand awareness, by letting the market know you exist, by informing stakeholders and by strengthen market perceptions. Second, the Twitter account gives opportunities for an active customer-brand relationship. A consumer can tweet a brand and the brand can tweet the consumer back by using the @ function (i.e.@CocaCola). Third, the opportunity exists to provide direct customer service through the Twitter account. A consumer can share the problem with the brand in a 140-character message and the consumer can receive a quick, satisfying and equally brief solution back. An example of a brand that provides good customer service is Jet Blue Airways (see figure 3).

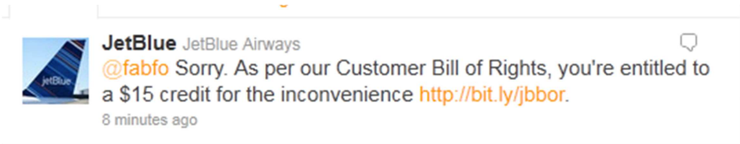


Figure 3 Service Tweet of Jet Blue Airways

Fourth, Twitter offers free promotion opportunities. A brand can remind followers about rewards, discount cards, coupons and other deals. The number of followers and number of tweets sent by the brand measures the success of the Twitter (Thomases, 2010).

Concluding, Twitter aids to improve loyalty and retention among customers. Customers who show attitudinal loyalty towards a brand expect to display positive behaviour. Moreover, loyal customers spend more money, cost less to serve, have greater propensity to generate WOM and are willing to pay a premium price (Reichheld, Markey and Hopton, 2000). Further, loyal consumers are less likely to support competitive marketing actions (Sheth and Parvatiyar, 1995). Verhoef, Franses and Hoekstra (2002) found a positive relationship between commitment and the number of services purchased. Moreover, loyalty is an important driver for retention and CLV, which links positively to market value (Rust, Zeithaml and Lemon, 2004). Therefore, a positive relationship expects to hold between followers and tweets of the brand to market value.

H3a The number of followers is positively related to stock price.

And

H4a The number of tweets sent by the brand is positively related to stock price.

A similar positive relationship expects to hold between stock price to followers and tweets. As mentioned, high or low stock performance triggers managers to change actions (Benner, 2007; Markovitch, Steckel and Yeung, 2005). Lower returns lead to decreased cash flow, resulting in budget constraints in R&D and advertising in following periods (Subrahmanyam and Titman 2001; Minton and Schrand, 1999). These constraints future marketing investments and leads to less customer service (Luo, 2007). A decrease in marketing investment reduces the popularity of the brand and results in a decrease in the rise of followers of the brand.

Thus:

H3b Stock price is positively related to the number of followers of the brand.

Further, a decrease in customer service would mean a decrease in number of tweets sent by the brand.

Thus:

H4b Stock price is positively related to the number of tweets sent by the brand.

3. Methodology

To the test the hypotheses, I research all dynamic interactions of the Twitter variables to stock prices. The modelling framework gives a visual representation of all the dynamic relations (figure 5). Table 3 gives a description of the variables in figure 5.

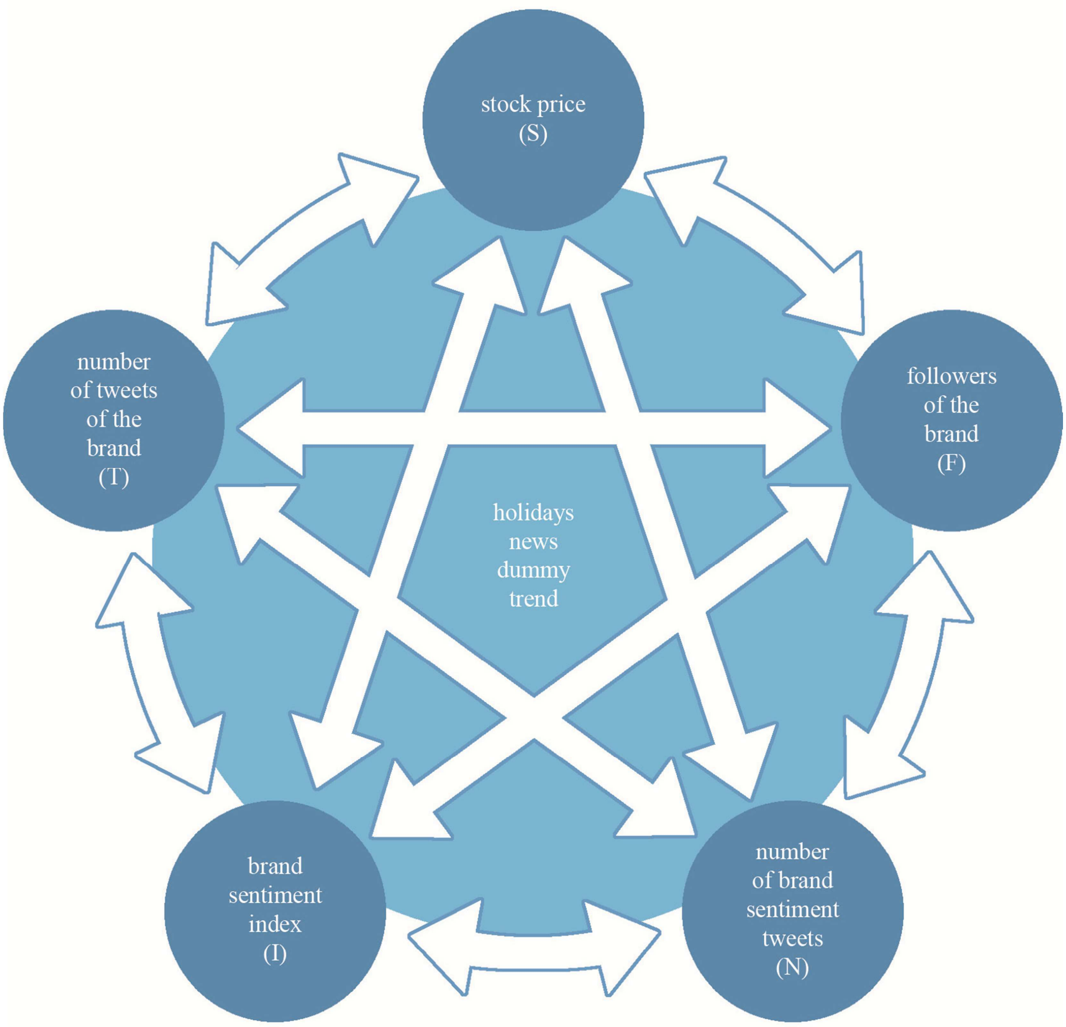


Figure 4 Modelling framework

Table 3 Description of the conceptual variables

Conceptual variable	VAR variable	Endogeneity	Description	Time frequency	Data source
Stock price	S_{it}	Endogenous	Firm's daily closing value on the US stock market (Nasdaq or Dow Jones)	Daily (January 1st of 2010 - February 28th of 2011)	www.yahoo.com/finance
Number of brand sentiment tweets	N_{it}	Endogenous	Consumer tweets with a personal positive or negative feeling, Sentiment is extracted with machine learning algorithms, where emoticons are used as noisy labels (Go, Huang and Bhayani, 2009)	Daily (January 1st of 2010 - February 28th of 2011)	http://Twitter sentiment.appspot.com/
Brand sentiment index	I_{it}	Endogenous	The percentage positive tweets of the total number of brand sentiment tweets. Sent by consumers.	Daily (January 1st of 2010 - February 28th of 2011)	http://Twitter sentiment.appspot.com/
Followers	F_{it}	Endogenous	Cumulative measure of the number of followers of the brand's Twitter account of the brand.	Daily (January 1st of 2010 - February 28th of 2011)	www.Twitter counter.com
Tweets	T_{it}	Endogenous	Cumulative measure of the number of tweets sent by the brand's Twitter account.	Daily (January 1st of 2010 - February 28th of 2011)	www.Twitter counter.com
Holidays	$holiday_{it}$	Exogenous	Holidays in the United States will be taken into account as dummy variables (1 for a holiday and 0 for normal days) .	Daily (January 1st of 2010 - February 28th of 2011)	www.timeand date.com
News	$news_{it}$	Exogenous	This variable has the value 1 on the day of news and value 0 in case of no news. On average 7 to 9 news events are incorporated per brand.	Daily (January 1st of 2010 - February 28th of 2011)	www.google.com/trends

Dummy	$dummy_{it}$	Exogenous	A seasonal dummy to omit the difference in measurement of the brand sentiment index and the number of brand sentiment tweets in different periods. The dummy has the value 1 from January 1st 2010 to May 31st 2010.	Daily (January 1st of 2010 - February 28th of 2011)
Trend	$trend_{it}$	Exogenous	A time trend to omit the trend in trend stationary variables.	Daily (January 1st of 2010 - February 28th of 2011)

All the data in the model has a daily measurement, which gives the suggestion to use a time series model. The vector autoregressive (VAR) model is the most appropriate. This model has several advantages over alternative models. First, VAR is a time-series method simultaneously estimates a system of equations (Luo, 2009), this allows using multiple endogenous variables. The dark blue circles on the outside of the modelling framework represent the endogenous variables (figure 4). The endogenous variables in the model are stock price, brand sentiment index, number of brand sentiment tweets, number of tweets of the brand and number of followers of the brand. Second, the model allows for both direct and feedback effects. The direct and feedback effect capture the dynamic relations among the Twitter variables and stock price. The double arrows in the modelling framework are the direct and feedback effects.

Third, the model captures both carryover and cross-effects (Luo, 2009). The VAR model creates a function of each endogenous variables based on its own lag(s), and the lag(s) of other endogenous variables in the model (Hill, Grith and Lim, 2007). The own lag(s) represent the carryover effects and the lag(s) of other variables represent the cross-effects. In this research, the cross-effects are the most important. Fourth, the VAR model estimates both short and long-term effects (Luo, 2009). Fifth, besides endogenous variables, the opportunity exists to add exogenous variables to the VAR model (Luo, 2009). The exogenous variables appear in the middle of the conceptual model: news, holiday, seasonal dummy and a time trend. First, the news; I assume that consumers tweet more and more positive in case of positive news. In case of negative news, I expect an increase in the number of brand sentiment tweets and a decrease in the brand sentiment index. For each brand, the VAR model considers six to eight different news facts. Further, the VAR model incorporates holidays. Holidays are special days like Christmas, New Year and Easter. Since people spend less time behind computer, the number of tweets expects to decrease during special holidays. Moreover, I add a seasonal dummy to omit the difference in measurement of the brand sentiment index and the number of brand sentiment tweets in different periods. Lastly, the added time trend deletes the effect of the trend in the trend stationary variables.

Mathematical specification of the model:

$$\begin{bmatrix} F_{it} \\ I_{it} \\ N_{it} \\ T_{it} \\ S_{it} \end{bmatrix} = \begin{bmatrix} \alpha_{i1} \\ \alpha_{i2} \\ \alpha_{i3} \\ \alpha_{i4} \\ \alpha_{i5} \end{bmatrix} + \sum_{j=1}^{Ki} \begin{bmatrix} \beta_{i11}^{j} & \beta_{i12}^{j} & \beta_{i13}^{j} & \beta_{i14}^{j} & \beta_{i15}^{j} \\ \beta_{i21}^{j} & \beta_{i22}^{j} & \beta_{i23}^{j} & \beta_{i24}^{j} & \beta_{i25}^{j} \\ \beta_{i31}^{j} & \beta_{i32}^{j} & \beta_{i33}^{j} & \beta_{i34}^{j} & \beta_{i35}^{j} \\ \beta_{i41}^{j} & \beta_{i42}^{j} & \beta_{i43}^{j} & \beta_{i44}^{j} & \beta_{i45}^{j} \\ \beta_{i51}^{j} & \beta_{i52}^{j} & \beta_{i53}^{j} & \beta_{i54}^{j} & \beta_{i55}^{j} \end{bmatrix} \begin{bmatrix} F_{it-j} \\ I_{it-j} \\ N_{it-j} \\ T_{it-j} \\ S_{it-j} \end{bmatrix} + \begin{bmatrix} \gamma_{i11} & \gamma_{i12} & \gamma_{i13} & \gamma_{i14} \\ \gamma_{i21} & \gamma_{i22} & \gamma_{i23} & \gamma_{i124} \\ \gamma_{i31} & \gamma_{i32} & \gamma_{i33} & \gamma_{i34} \\ \gamma_{i41} & \gamma_{i42} & \gamma_{i43} & \gamma_{i44} \\ \gamma_{i51} & \gamma_{i52} & \gamma_{i53} & \gamma_{i54} \end{bmatrix} \begin{bmatrix} dummy_{it} \\ holiday_{it} \\ news_{it} \\ trend_{it} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Fit} \\ \varepsilon_{Iit} \\ \varepsilon_{Nit} \\ \varepsilon_{Tit} \\ \varepsilon_{Sit} \end{bmatrix} \quad (1)$$

Where: F=number of followers of the brand, I=brand sentiment index, N=number of brand sentiment tweets, T=number of tweets of the brand, S=stock price, t=time, K=lag length, i=brand and ε=white-noise residuals. All parameters are brand-specific, indicated by i. The parameters estimates differ per brand, since the response of consumers and investors expects to vary (Leeflang et al. 2000).

As can be seen from equation (1), the main disadvantage of the VAR model is the high number of parameter estimates. An extensive dataset is necessary to maintain degrees of freedom to estimate a valuable model (Luo, 2009). The description of the beta's in the vector is as follows: β_{i15}, β_{i25}, β_{i35}, β_{i45} are the feedback effect of stock price on followers, brand sentiment index, brand sentiment tweets and tweets of the brand. The direct effects of followers on stock price is β_{i51}, for index β_{i52}, for brand sentiment tweets β_{i53} and for tweets sent by the brand β_{i54}. The carryover effects are β_{i11}, β_{i22}, β_{i33}, β_{i44}, β_{i55}. An example of a cross effect between tweets sent by the brand and stock price are β_{i54}, β_{i45} (Luo, 2009).

Further, the intercepts are $\alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_{i4}, \alpha_{i5}$. Furthermore, the vector of γ represents the effect of these exogenous variables and lastly, the vector of ε captures the measurement error.

Five different equations derive from equation (1):

$$F_{it} = \alpha_{i1} + \sum_{j=1}^{Ki} \beta_{i11}^{j} F_{it-j} + \sum_{j=1}^{Ki} \beta_{i12}^{j} I_{it-j} + \sum_{j=1}^{Ki} \beta_{i13}^{j} N_{it-j} + \sum_{j=1}^{Ki} \beta_{i14}^{j} T_{it-j} + \sum_{j=1}^{Ki} \beta_{i15}^{j} S_{it-j} + \gamma_{i11} dummy_{it} + \gamma_{i12} holiday_{it} + \gamma_{i13} news_{it} + \gamma_{i14} trend_{it} + \varepsilon_{Fit} \quad (2)$$

$$I_{it} = \alpha_{i2} + \sum_{j=1}^{Ki} \beta_{i21}^{j} F_{it-j} + \sum_{j=1}^{Ki} \beta_{i22}^{j} I_{it-j} + \sum_{j=1}^{Ki} \beta_{i23}^{j} N_{it-j} + \sum_{j=1}^{Ki} \beta_{i24}^{j} T_{it-j} + \sum_{j=1}^{Ki} \beta_{i25}^{j} S_{it-j} + \gamma_{i21} dummy_{it} + \gamma_{i22} holiday_{it} + \gamma_{i23} news_{it} + \gamma_{i24} trend_{it} + \varepsilon_{Iit} \quad (3)$$

$$N_{it} = \alpha_{i3} + \sum_{j=1}^{Ki} \beta_{i31}^{j} F_{it-j} + \sum_{j=1}^{Ki} \beta_{i32}^{j} I_{it-j} + \sum_{j=1}^{Ki} \beta_{i33}^{j} N_{it-j} + \sum_{j=1}^{Ki} \beta_{i34}^{j} T_{it-j} + \sum_{j=1}^{Ki} \beta_{i35}^{j} S_{it-j} + \gamma_{i31} dummy_{it} + \gamma_{i32} holiday_{it} + \gamma_{i33} news_{it} + \gamma_{i34} trend_{it} + \varepsilon_{Nit} \quad (4)$$

$$T_{it} = \alpha_{i4} + \sum_{j=1}^{Ki} \beta_{i41}^{j} F_{it-j} + \sum_{j=1}^{Ki} \beta_{i42}^{j} I_{it-j} + \sum_{j=1}^{Ki} \beta_{i43}^{j} N_{it-j} + \sum_{j=1}^{Ki} \beta_{i44}^{j} T_{it-j} + \sum_{j=1}^{Ki} \beta_{i45}^{j} S_{it-j} + \gamma_{i41} dummy_{it} + \gamma_{i42} holiday_{it} + \gamma_{i43} news_{it} + \gamma_{i44} trend_{it} + \varepsilon_{Tit} \quad (5)$$

$$S_{it} = \alpha_{i5} + \sum_{j=1}^{Ki} \beta_{i51}^{j} F_{it-j} + \sum_{j=1}^{Ki} \beta_{i52}^{j} I_{it-j} + \sum_{j=1}^{Ki} \beta_{i53}^{j} N_{it-j} + \sum_{j=1}^{Ki} \beta_{i54}^{j} T_{it-j} + \sum_{j=1}^{Ki} \beta_{i55}^{j} S_{it-j} + \gamma_{i51} dummy_{it} + \gamma_{i52} holiday_{it} + \gamma_{i53} news_{it} + \gamma_{i54} trend_{it} + \varepsilon_{Sit} \quad (6)$$

Equation (6) is the most important, since it tests hypothesis H1a, H2a, H3a and H4a. β_{i15} in equation (2) answers hypothesis H3b; β_{i25} in equation (3) answers hypothesis H2b; β_{i35} answers hypothesis H1b; β_{i45} answers hypothesis H4b.

The steps in the VAR estimation process are the following. First, I estimate all time-series properties of all variables (Pauwels, 2004), with the Dickey Fuller unit root test and cointegration tests. After performing a Granger Causality test to obtain insights in which variables is leading which variable (Pauwels, 2010), I continue estimating the VAR model. I base the optimal number of lags on different information criteria like the Akaike information criteria (AIC), Schwartz criteria (SC) and the Hannan-Quinn criteria (HQC), since combining different criteria increase the success rate of choosing the optimal lag length substantially (Hatemi and Hacker, 2009). After choosing the optimal VAR model, the interpretation of the results starts, with the help of the Impulse response function. Impulse response functions (IRF) capture the long-term, accumulative effect of an unexpected shock of one endogenous variable to another endogenous variable (Luo, 2009). The impulse in eViews is the increase of one standard deviation (ε) (Pauwels, 2010). For instance, one-standard deviation increase to stock price yields an immediate increase of the brand sentiment index of 0.004. Since stock price has a standard deviation of 0.420, one point increase in stock price results in an immediate increase in brand sentiment index of 0.004/0.420=0.011% point.

The IRF estimates both the short and the long-term impact of a shock. The IRF incorporates a period of 30 days in its calculation. The statistical significance of each impulse response values by two-standard deviations (Leeflang et al. 2000). The IRF converge to zero in a stationary scenario or stabilizes at non-zero level in an evolving scenario (Nijs et al. 2001). The IRF graph reports the development of a reaction to a shock. The graph tells for example how many days it takes before the effect to a shock peaks (wear-in) and how many days it takes before the effect to shock dies out (wear-out) (Pauwels, 2004).

Since the outcome of the IRFs of equation (1) is in unit instead of elasticity's, comparison among brands is difficult. Elasticity's would allow for comparison across the different brand specific models. The log-transformed VAR model has parameters interpretable as elasticity's (Leeflang et al. 2000). Another advantage of this model is the reduction of the impact of outliers and reduction of the variance of trending time series. However, the IRF of the log-transformed model will contain log-transformed effects, which makes interpretation complicated (Wieringa and Horvath, 2005). Therefore, I will interpret the elasticity's directly from the parameter estimation of VAR (7), instead of using the IRF estimates.

The log transformation of equation (1) is as follows:

$$\begin{bmatrix} \log F_{it} \\ \log I_{it} \\ \log N_{it} \\ \log T_{it} \\ \log S_{it} \end{bmatrix} = \begin{bmatrix} \log \alpha_{i1} \\ \log \alpha_{i2} \\ \log \alpha_{i3} \\ \log \alpha_{i4} \\ \log \alpha_{i5} \end{bmatrix} + \sum_{j=1}^{Ki} \begin{bmatrix} \beta_{i11}^{j} & \beta_{i12}^{j} & \beta_{i13}^{j} & \beta_{i14}^{j} & \beta_{i15}^{j} \\ \beta_{i21}^{j} & \beta_{i22}^{j} & \beta_{i23}^{j} & \beta_{i24}^{j} & \beta_{i25}^{j} \\ \beta_{i31}^{j} & \beta_{i32}^{j} & \beta_{i33}^{j} & \beta_{i34}^{j} & \beta_{i35}^{j} \\ \beta_{i41}^{j} & \beta_{i42}^{j} & \beta_{i43}^{j} & \beta_{i44}^{j} & \beta_{i45}^{j} \\ \beta_{i51}^{j} & \beta_{i52}^{j} & \beta_{i53}^{j} & \beta_{i54}^{j} & \beta_{i55}^{j} \end{bmatrix} \begin{bmatrix} \log F_{it-j} \\ \log I_{it-j} \\ \log N_{it-j} \\ \log T_{it-j} \\ \log S_{it-j} \end{bmatrix} + \begin{bmatrix} \log \gamma_{i11} & \log \gamma_{i12} & \log \gamma_{i13} & \log \gamma_{i14} \\ \log \gamma_{i21} & \log \gamma_{i22} & \log \gamma_{i23} & \log \gamma_{i124} \\ \log \gamma_{i31} & \log \gamma_{i32} & \log \gamma_{i33} & \log \gamma_{i34} \\ \log \gamma_{i41} & \log \gamma_{i42} & \log \gamma_{i43} & \log \gamma_{i44} \\ \log \gamma_{i51} & \log \gamma_{i52} & \log \gamma_{i53} & \log \gamma_{i54} \end{bmatrix} \begin{bmatrix} dummy_{it} \\ holiday_{it} \\ news_{it} \\ trend_{it} \end{bmatrix} + \begin{bmatrix} \log \varepsilon_{Fit} \\ \log \varepsilon_{Iit} \\ \log \varepsilon_{Nit} \\ \log \varepsilon_{Tit} \\ \log \varepsilon_{Sit} \end{bmatrix} \quad (7)$$

The elasticity for the number of followers to stock price is given by β_{i51}, the elasticity of brand sentiment index to stock price by β_{i52}, elasticity of number of brand sentiment tweets to stock price by β_{i53}, elasticity of number of tweets sent by the brand to stock price by β_{i54}. And the elasticity's of stock price to respectively number of followers, brand sentiment index, number of brand sentiment tweets and number of tweets sent by the brand are β_{i15}, β_{i25}, β_{i35}, β_{i45}.

4. Data analysis

4.1 Data description

The database consists of Twitter and financial data of 10 popular brands. I collected data from January 1st of 2010 until February 28th of 2011, a total of 424 days. For an explanation of the variables and overview of the data, see table 3 and 4. The website twittersentiment.appspot.com provides daily data on the number of brand sentiment tweets and the brand sentiment index. The site measures on a daily basis the positive and negative tweets on different topics, like brands. By adding the number of negative and positive tweets, the variable number of brand tweets arises. The brand sentiment index is the number of positive tweets divided by the number of brand sentiment tweets. The website www.twittercounter.com provides the number of followers of Twitter accounts and the number of tweets sent by these accounts. All Twitter data has a daily measurement. This in comparison to stock price, since the weekend has no trading days, stock price has only measurements from Monday to Friday. The data from Twitter captures valuable information during weekends, since the number of re-tweets is 40% less during weekends (Zhang, Fuehres and Gloor, 2010). This speculates that tweets sent during the weekends are more original. In order to retain the information of Twitter during the weekend, I fill the gaps in the stock price data. Moreover, the VAR technique needs a large amount of data points, which strengthen the option to fill the missing values of the stock price variable. I will fill the gaps with the help of the cubic smoothing spline technique in MATLAB.

The stock price (S(t)) is measured at time t=1,2,3..T, which gives the following smoothing spline estimate as the function of h(t), that minimizes (Sood, James and Tellis, 2009):

$$\sum_{t=1}^{T}(S(t)-h(t))^2+\lambda\int(h''(s))^2\,ds(8)$$

The smoothing parameter h regulates the trade-off between smoothness and goodness of fit of the smoothed curve for stock price (S) (Brumback and Rice, 1998). The first squared error term in the equation (8), forces h(t) to provide a close fit to the observed data, while the second integrated second-derivative term penalizes the curve in h(t). The tuning parameter λ determines the relative importance of the two components in the fitting procedure (Sood, James and Tellis, 2009).

I fill the gaps in the original data set with the new estimated data of the smoothing spline. As seen from figure 5 the smoothing spline effectively fits the data, since the smoothing spline estimate fit is close to the original values of the NYSE of Coca-Cola.

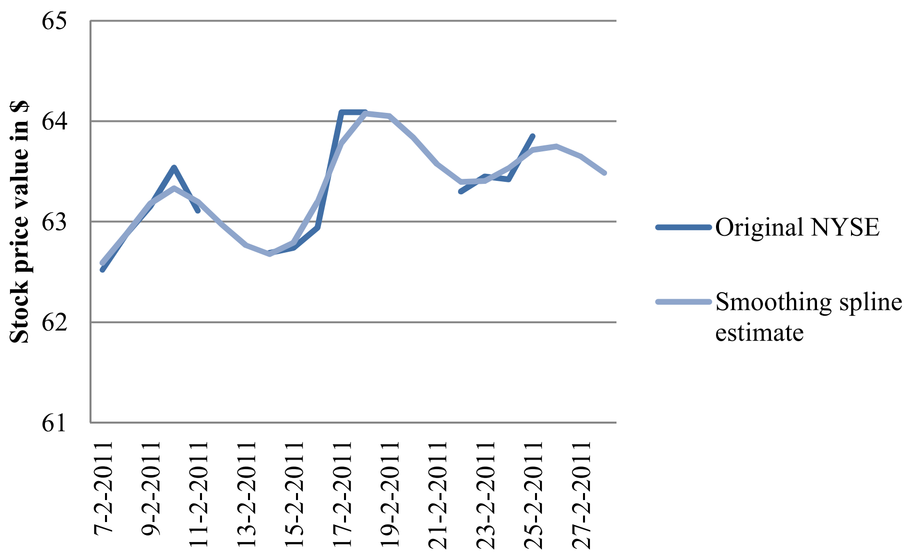


Figure 5 Example Coca-Cola smoothing spline

Besides the endogenous variables, I add several exogenous variables to the VAR model, like news and holidays. The main news events are from www.google.com/trends. I measure the news facts with a dummy variable (1 for news and 0 for no news). Further, I take the holidays in the United States into account as dummy variables (1 for a holiday and 0 for normal days) (www.timeanddate.com).

I collected data for the ten best global brands in the Interbrand top 100. The chosen brands need to conform the following requirements.

1. First, the brand name should consist of three or more characters in the brand name. When the brand name consists of only two letters, the problem could arise that more abbreviations exist with these letter combinations. This rule applies to long brand names we as well, since consumers have the tendency to shorten the brands down to only two letters. I.e. Hewlett-Packard to HP.
2. Second, a brand should have one meaning. When a brand has multiple meanings, difficulties exist in arising the real sentiment to the brand. I.e. Apple (a brand and a fruit).
3. Third, the brand should be on the American stock exchange (NYSE, NASDAQ), since the sentiment arises from English tweets only. Further, the stock should have the same brand name as the brand. i.e. Gillette is part of Procter & Gamble this makes the relation between product brand and parent brand unexpected.
4. The brand should be known and talked about.
5. Enough data should be available in the Twitter sentiment database. At least from January 1st of 2010 to February 28th of 2011.

The brands that meet these conditions are Coca-Cola, IBM, Microsoft, Google, McDonald's, Intel, Nokia, Disney, Toyota and Cisco. The variety of the brands is wide, from food to electronics and from service to product. The variety of brands gives stronger results. I estimate equation (1) and equation (8) for these ten brands with five endogenous variables: stock price fluctuations, number of brand sentiment tweets, brand sentiment index, number of followers and the number of tweets sent by the brand. Table 4 summarizes of the endogenous variables for the brands. Nine out of ten brands have an active Twitter account. IBM is the only brand without active Twitter account. Further, Disney only started to use its Twitter actively on 24th of May. Since data of the first months of both the tweets of the brand and followers of Disney lacks, I do not incorporate the Twitter account of Disney in the VAR estimations. The popularity of the different Twitter accounts varies. The highest stock value is for Google with a price of $613, the business has the highest number of followers as well. However, no direct relation exists among the popularity of the Twitter account and the stock value. IBM for example has the second highest value on the stock exchange ($160) without any Twitter account.

Table 4 Brands and average values of endogenous variables

	Brand & Industry	Twitter account	Followers** (F)	Tweets** (T)	Brand sentiment index (I)	Value on the stock exchange** (S)
1 (1*)	Coca-Cola Beverages	@CocaCola (2009-02-10)	231,986	25,023	68%	$63,46 (NYSE)
2 (2*)	IBM Business services	-	-	-	59%	$161,88 (NYSE)
3 (3*)	Microsoft Computer software	@Microsoft (2009-09-14)	59,499	1,037	44%	$26,58 (Nasdaq)
4 (4*)	Google Internet services	@google (2009-03-26)	2,816,938	2,214	60%	$613,40 (Nasdaq)
5 (6*)	McDonald's Restaurants	@McDonalds (2009-09-02)	89,196	4,624	50%	$75,68 (NYSE)
6 (7*)	Intel Electronics	@intel (2007-03-29)	37,479	1,218	54%	$21,47 (Nasdaq)
7 (8*)	Nokia Electronics	@nokia (2009-03-16)	62,610	1,576	55%	$8,63 (NYSE)
8 (9*)	Disney Media	@Disney (2010-08-20)	275,598	174	72%	$43,74 (NYSE)
9 (11*)	Toyota Automotive	@Toyota (2008-03-25)	35,958	2,087	56%	$93,30 (NYSE)
10 (14*)	Cisco Business services	@ciscosystems (2008-08-06)	50,618	3,432	56%	$8,63 (Nasdaq)

* Place in the Interbrand top 100 (2010) **On February 28th, 2011

4.2 Unit root tests

To determine whether to incorporate the endogenous variables in level or differences, I conduct Augmented Dicky Fuller (ADF) unit root tests. The danger exists of obtaining apparently significant regression results from unrelated data by using non-stationary data in regression (Hill, Grith and Lim, 2007). A time series is stationary if its mean and variance are constant over time, and if the covariance between two values from the series depends only on the length of time separating the two values (Hill, Grith and Lim, 2007).

The unit root test incorporates an intercept, since all endogenous variables expect to be unequal to zero. The ADF unit root test result show that the number of followers (F), stock price (S) and the number of tweets (T) sent by the brand are non-stationary for all ten brands (see table 5 and 6). I incorporate these evolving variables in first-differences. The results of the unit root test of the linear and the log-transformed data are similar. The number of brand sentiment tweets (N) are stationary for nine out of ten brands. This endogenous variable is trend stationary for Toyota. The brand sentiment index is stationary for six out of ten brands and trend stationary for the other four brands. For the brands with trend stationary variable the deterministic-time trend, will capture the impact of trends.

Table 5 Unit root test first five brands

Variable	Coca-Cola	IBM	Microsoft	Google	McDonald's
F	Non-stationary	-	Non-stationary	Non-stationary	Non-stationary
S	Non-stationary	Non-stationary	Non-stationary	Non-stationary	Non-stationary
T	Non-stationary	-	Non-stationary	Non-stationary	Non-stationary
N	Stationary	Stationary	Stationary	Stationary	Stationary
I	Stationary	Stationary	Trend stationary	Stationary	Trend stationary

Table 6 Unit root test last five brands

Variable	Intel	Nokia	Disney	Toyota	Cisco
F	Non stationary	Non stationary		Non stationary	Non stationary
S	Non stationary	Non stationary	Non stationary	Non stationary	Non stationary
T	Non stationary	Non stationary		Non stationary	Non stationary
N	Stationary	Stationary	Stationary	Trend stationary	Stationary
I	Trend stationary	Stationary	Stationary	Stationary	Trend stationary

In case of unit root $\Delta X_t = X_t - X_{(t-1)}$ replaces X_t. This gives the following adjustment to the VAR model (1):

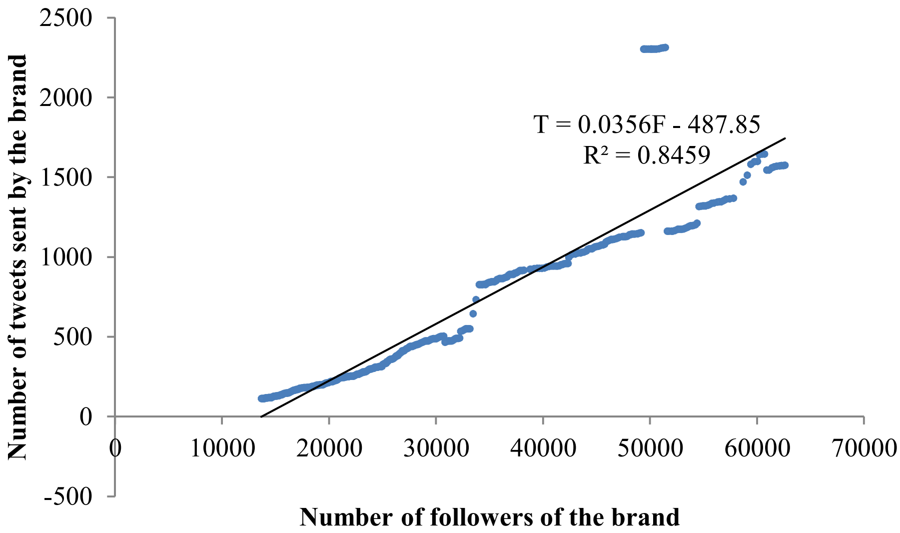
$$\begin{bmatrix} \Delta F_{it} \\ I_{it} \\ N_{it} \\ \Delta T_{it} \\ \Delta S_{it} \end{bmatrix} = \begin{bmatrix} \alpha_{i1} \\ \alpha_{i2} \\ \alpha_{i3} \\ \alpha_{i4} \\ \alpha_{i5} \end{bmatrix} + \sum_{j=1}^{Ki} \begin{bmatrix} \beta_{i11}^j & \beta_{i12}^j & \beta_{i13}^j & \beta_{i14}^j & \beta_{i15}^j \\ \beta_{i21}^j & \beta_{i22}^j & \beta_{i23}^j & \beta_{i24}^j & \beta_{i25}^j \\ \beta_{i31}^j & \beta_{i32}^j & \beta_{i33}^j & \beta_{i34}^j & \beta_{i35}^j \\ \beta_{i41}^j & \beta_{i42}^j & \beta_{i43}^j & \beta_{i44}^j & \beta_{i45}^j \\ \beta_{i51}^j & \beta_{i52}^j & \beta_{i53}^j & \beta_{i54}^j & \beta_{i55}^j \end{bmatrix} \begin{bmatrix} \Delta F_{it-j} \\ I_{it-j} \\ N_{it-j} \\ \Delta T_{it-j} \\ \Delta S_{it-j} \end{bmatrix} + \begin{bmatrix} \gamma_{i11} & \gamma_{i12} & \gamma_{i13} & \gamma_{i14} \\ \gamma_{i21} & \gamma_{i22} & \gamma_{i23} & \gamma_{i124} \\ \gamma_{i31} & \gamma_{i32} & \gamma_{i33} & \gamma_{i34} \\ \gamma_{i41} & \gamma_{i42} & \gamma_{i43} & \gamma_{i44} \\ \gamma_{i51} & \gamma_{i52} & \gamma_{i53} & \gamma_{i54} \end{bmatrix} \begin{bmatrix} dummy_{it} \\ holiday_{it} \\ news_{it} \\ trend_{it} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Fit} \\ \varepsilon_{Iit} \\ \varepsilon_{Nit} \\ \varepsilon_{Tit} \\ \varepsilon_{Sit} \end{bmatrix} \quad (9)$$

And the adjustments to the log equation (7):

$$\begin{bmatrix} \Delta \log F_{it} \\ \log I_{it} \\ \log N_{it} \\ \Delta \log T_{it} \\ \Delta \log S_{it} \end{bmatrix} = \begin{bmatrix} \log \alpha_{i1} \\ \log \alpha_{i2} \\ \log \alpha_{i3} \\ \log \alpha_{i4} \\ \log \alpha_{i5} \end{bmatrix} + \sum_{j=1}^{Ki} \begin{bmatrix} \beta_{i11}^j & \beta_{i12}^j & \beta_{i13}^j & \beta_{i14}^j & \beta_{i15}^j \\ \beta_{i21}^j & \beta_{i22}^j & \beta_{i23}^j & \beta_{i24}^j & \beta_{i25}^j \\ \beta_{i31}^j & \beta_{i32}^j & \beta_{i33}^j & \beta_{i34}^j & \beta_{i35}^j \\ \beta_{i41}^j & \beta_{i42}^j & \beta_{i43}^j & \beta_{i44}^j & \beta_{i45}^j \\ \beta_{i51}^j & \beta_{i52}^j & \beta_{i53}^j & \beta_{i54}^j & \beta_{i55}^j \end{bmatrix} \begin{bmatrix} \Delta \log F_{it-j} \\ \log I_{it-j} \\ \log N_{it-j} \\ \Delta \log T_{it-j} \\ \Delta \log S_{it-j} \end{bmatrix} + \begin{bmatrix} \log \gamma_{i11} & \log \gamma_{i12} & \log \gamma_{i13} & \log \gamma_{i14} \\ \log \gamma_{i21} & \log \gamma_{i22} & \log \gamma_{i23} & \log \gamma_{i124} \\ \log \gamma_{i31} & \log \gamma_{i32} & \log \gamma_{i33} & \log \gamma_{i34} \\ \log \gamma_{i41} & \log \gamma_{i42} & \log \gamma_{i43} & \log \gamma_{i44} \\ \log \gamma_{i51} & \log \gamma_{i52} & \log \gamma_{i53} & \log \gamma_{i54} \end{bmatrix} \begin{bmatrix} dummy_{it} \\ holiday_{it} \\ news_{it} \\ trend_{it} \end{bmatrix} + \begin{bmatrix} \log \varepsilon_{Fit} \\ \log \varepsilon_{Iit} \\ \log \varepsilon_{Nit} \\ \log \varepsilon_{Tit} \\ \log \varepsilon_{Sit} \end{bmatrix} \quad (10)$$

For all brands, the number of followers and the number of tweets sent by the brand are non-stationary or evolving, which might be a signal of cointegration. As known from previous research, Twitter accounts who receive attention from more followers will post more than Twitter accounts with less attention (Huberman, Romero and Wu, 2008). Therefore, Twitter accounts with more followers are more actively sending tweets in comparison to Twitter accounts with a smaller number of followers, as seen in figure 6 of the brand Nokia. Knowing one variable gives the idea of the location of the other variable (Pauwels, 2010). The number of tweets sent by Nokia are around 3.5% the number of followers of Nokia.

Figure 6 Number of tweets sent by the brand vs. number of followers of the brand (Nokia)



Cointegration exists among the number of followers (F) and the number of tweets sent by the brand (T), when the residuals of equation (11) are stationary (Hill, Grith and Lim, 2006):

$$F_{it} = \alpha_{i1} + \beta_1 T_{it} + \varepsilon_{Fit} (11)$$

For the brands Nokia and Intel residuals of equation (11) are stationary, which means that cointegration exist for those two brands. However, the test does not specify whether the number of followers is driving the number of tweets sent by the brand or whether the number of tweets sent by the brand drives the number of followers. The Granger Causality gives more insights in the direction of this relation (Pauwels, 2010).

4.3 Granger Causality

In the Granger Causality, I test whether one variable causes another variable (Hill, Grith and Lim, 2007). The test compares the forecast of i.e. S based on its own past:

$$S(t) = S(t-1) + S(t-2) + S(t-3)(12)$$

To the forecast including the past of another variable i.e. I:

$$S(t) = S(t-1) + S(t-2) + S(t-3) + I(t-1) + I(t-2) + I(t-3)(13)$$

If adding an additional variable significantly improves the forecast fit, the test concludes that I Granger causes S. The test does not consider an immediate but a delayed effect (Pauwels, 2010). The Granger Causality makes it possible to test for mutual causality as well. So I could Granger cause S and S could on the same time Granger cause I. Disadvantage of the Granger Causality test is that the test gives no suggestion of the direction of the relationship (positive or negative).

In the following section I sum up all the significant effects (p-value<0,1) of the Granger Causality test for all ten brand with 1 and 3 lags. A double arrow means mutual causality.

4.3.1 Coca-Cola

For Coca-Cola the Granger Causality test finds multiple significant results relating to stock price (figure 7). In the three lags solution the number of brand sentiment tweets and the brand sentiment index improve the estimation fit of stock price. Further, a causal relationship exists between the number of followers of the brand and the number of tweets sent by the brand. Moreover, a significant causal relationship exists between the number of brand sentiment tweets and the brand sentiment index.

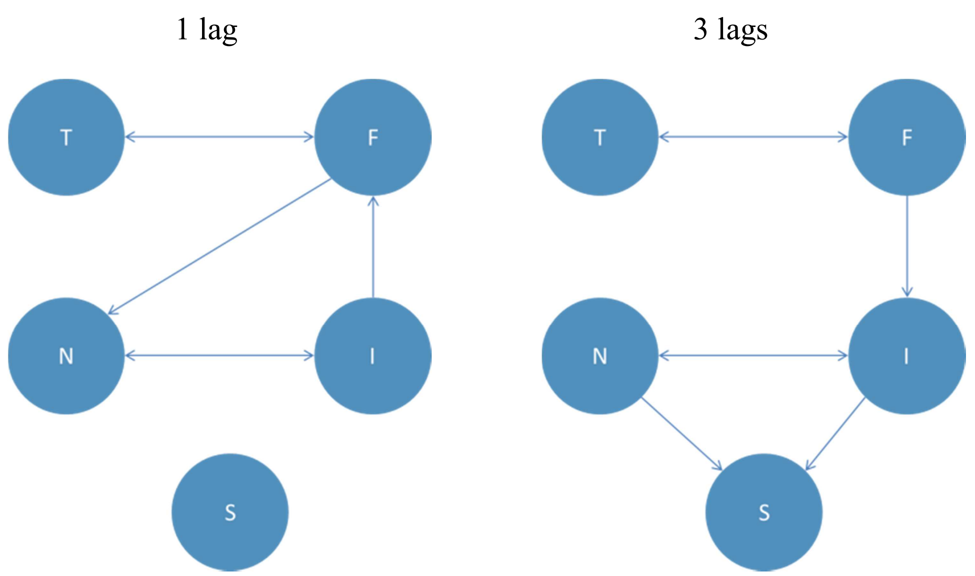


Figure 7 Granger Causality model Coca-Cola (arrows are significant with p-value <0,1)

4.3.2 IBM

For IBM the Granger Causality tests find no significant results relating to stock price (figure 8). In the three lags solution, the number of brand sentiment tweets Granger cause brand sentiment index.

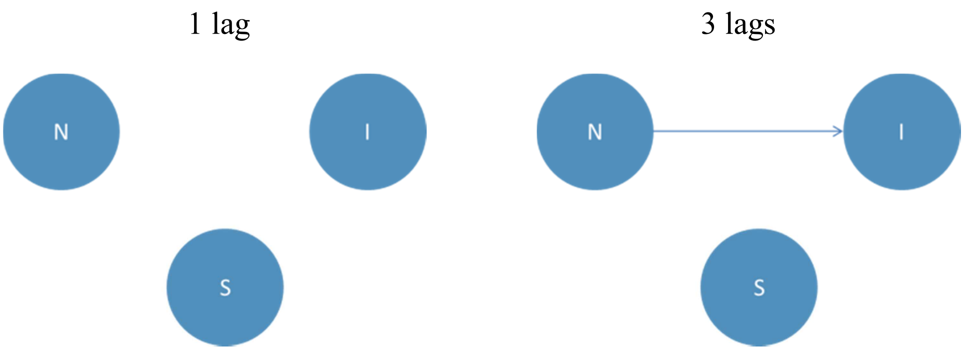


Figure 8 Granger Causality model IBM (arrows are significant with p-value <0,1)

4.3.3 Microsoft

For Microsoft the Granger Causality test finds no causal relations towards stock price (figure 9). However, the test reports causal relations between number of followers of the brand and the number of tweets sent by the brand. Further, a causal relationship exists between the number of followers of the brand and the number of brand sentiment tweets.

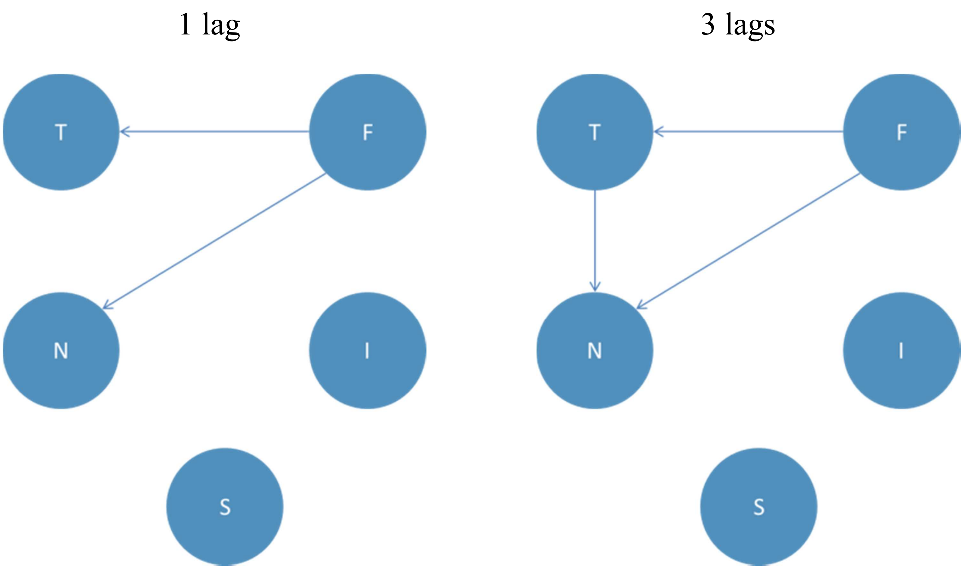


Figure 9 Granger Causality model Microsoft (arrows are significant with p-value<0,1)

4.3.4 Google

In the one lag solution, the Granger Causality test finds a significant relationship between the brand sentiment index and stock price (figure 10). Further, significant causal relations exist among the number of brand sentiment tweets and tweets sent by the brand; the number of brand sentiment tweets and followers; the brand sentiment index and the tweets sent by the brand.

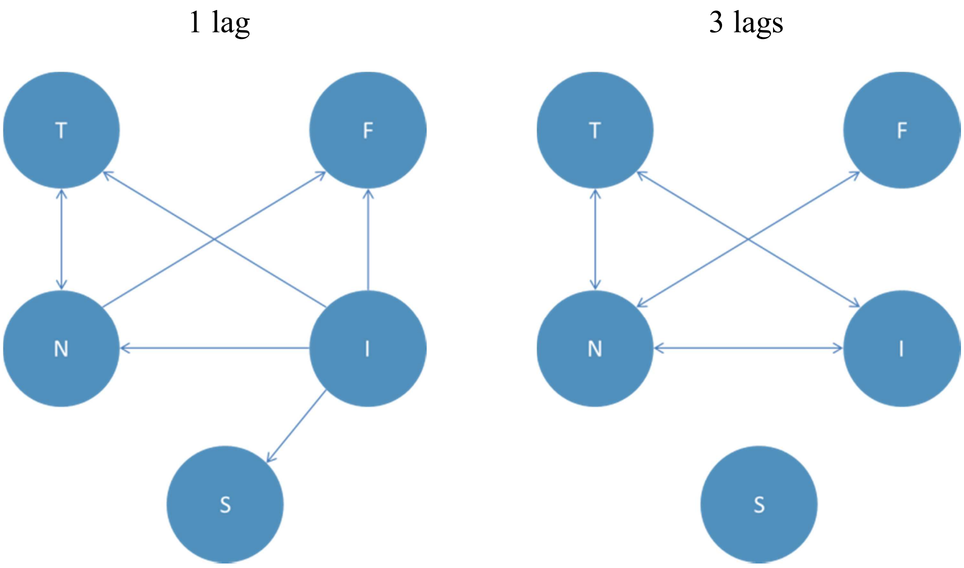


Figure 10 Granger Causality model Google (arrows are significant with p-value<0,1)

4.3.5 McDonald's

For McDonald's the Granger Causality test reports no significant causal relations related to stock price. However, multiple causal relations exist among the Twitter variables (figure 11), like between the number of brand sentiment tweets and followers; number of tweets sent by the brand and followers.

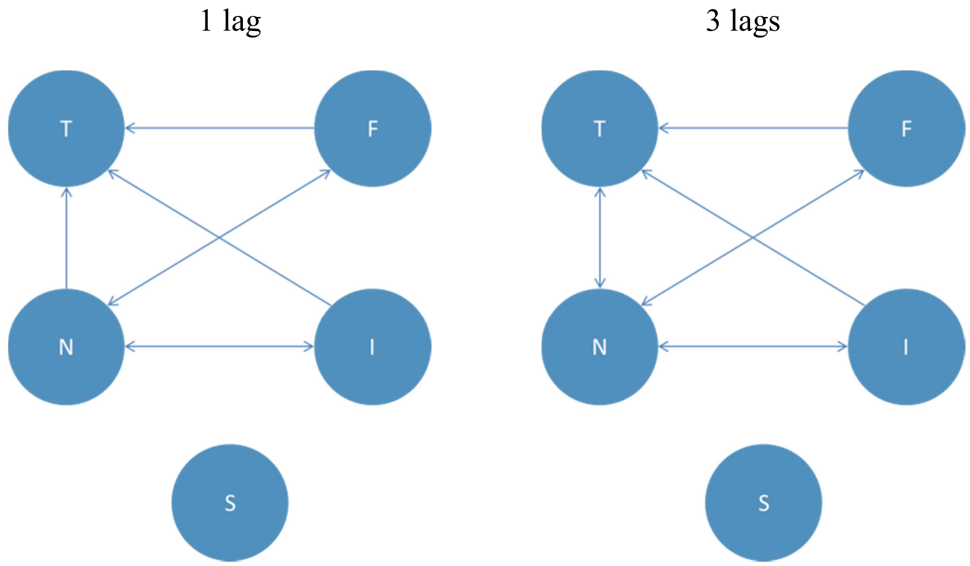


Figure 11 Granger Causality model McDonald's (arrows are significant with p-value<0,1)

4.3.6 Intel

For Intel the Granger Causality tests gives multiple significant results related to stock price (figure 12). In the one lag solution, the brand sentiment index Granger causes stock price. In the three lag solution, the stock price Granger causes the number of brand sentiment tweets. For Intel cointegration exist among the number of followers and the number of tweets sent by the brand. As seen in figure 11, the one lagged solution, the number of followers of the brand drives the number of tweets sent by the brand.

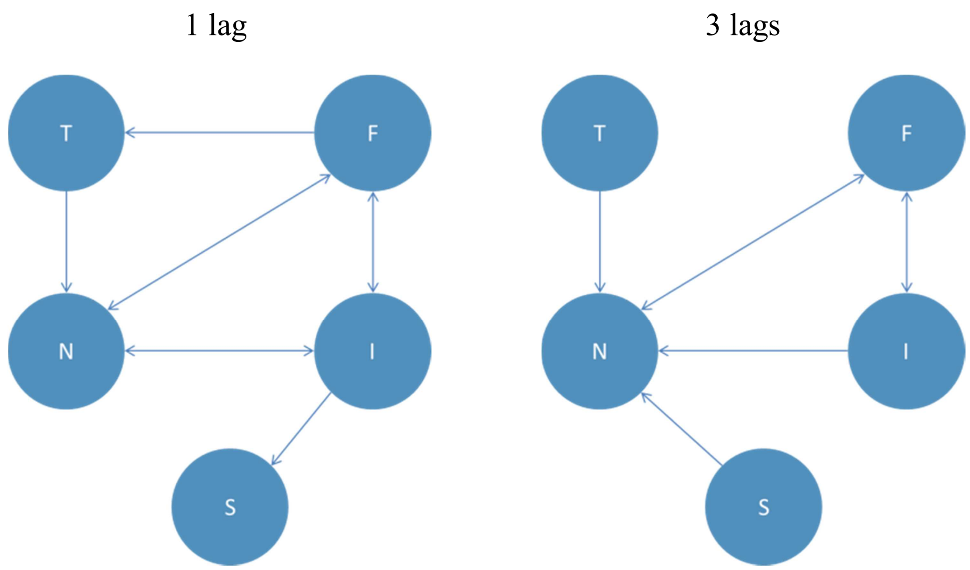


Figure 12 Granger Causality model Intel (arrows are significant with p-value<0,1)

4.3.7 Nokia

For Nokia the brand sentiment index Granger causes stock price with one lag (figure 13). In the three lags solution the Granger Causality test finds a reciprocal relationship between the number of brand sentiment tweets and stock price. Similar to Intel, the number of followers drives the number of tweets sent by the brand. Further, multiple causal relations exist among the Twitter variables.

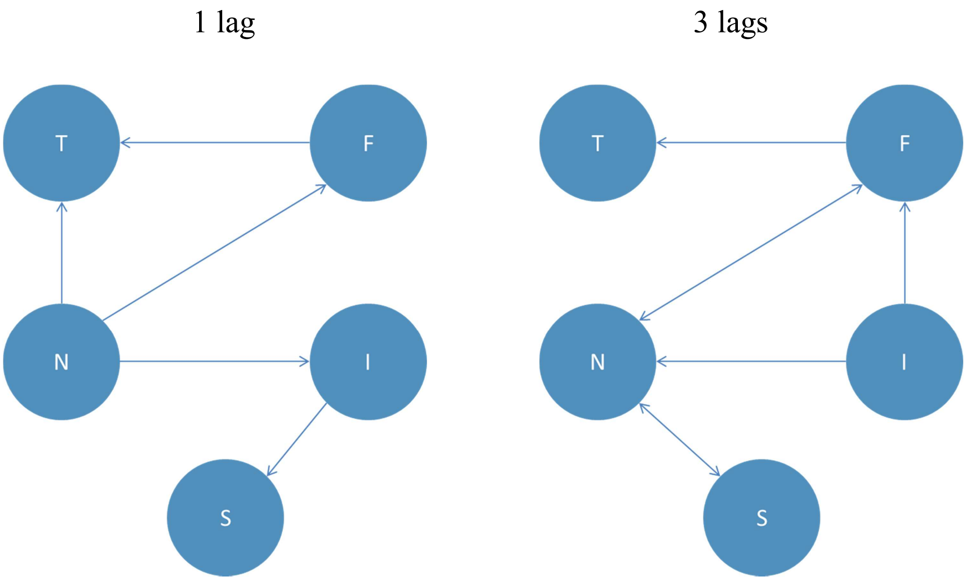


Figure 13 Granger Causality model Nokia (arrows are significant with p-value<0,1)

4.3.8 Disney

In figure 14 reports several significant causal relations for Disney. The brand sentiment index Granger causes the stock price and a reciprocal relationship exist between the brand sentiment index and the number of brand sentiment tweets.

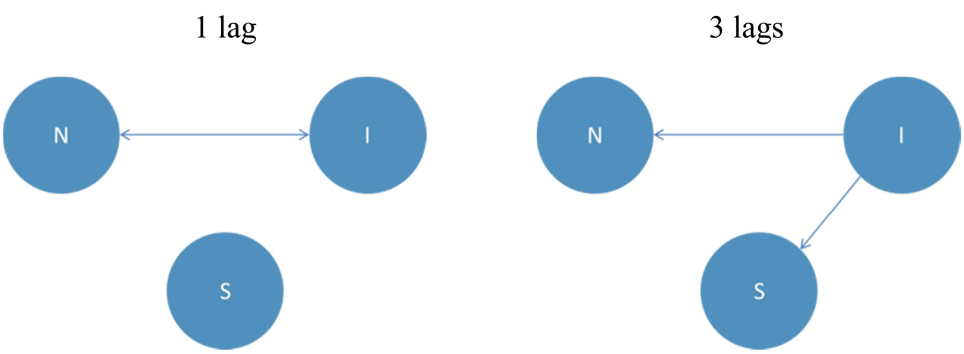


Figure 14 Granger Causality model Disney (arrows are significant with p-value<0,1)

4.3.9 Toyota

For Toyota multiple Granger causal relations exist among the Twitter variables and stock price (figure 15). In the first lag option followers has a causal relationship towards stock price, in the three lags solutions the relation followers - stock price is reciprocal. Further, the stock price Granger cause the number of brand sentiment tweets. Besides the relation to stock price, the test reports multiple significant relationships between the Twitter variables.

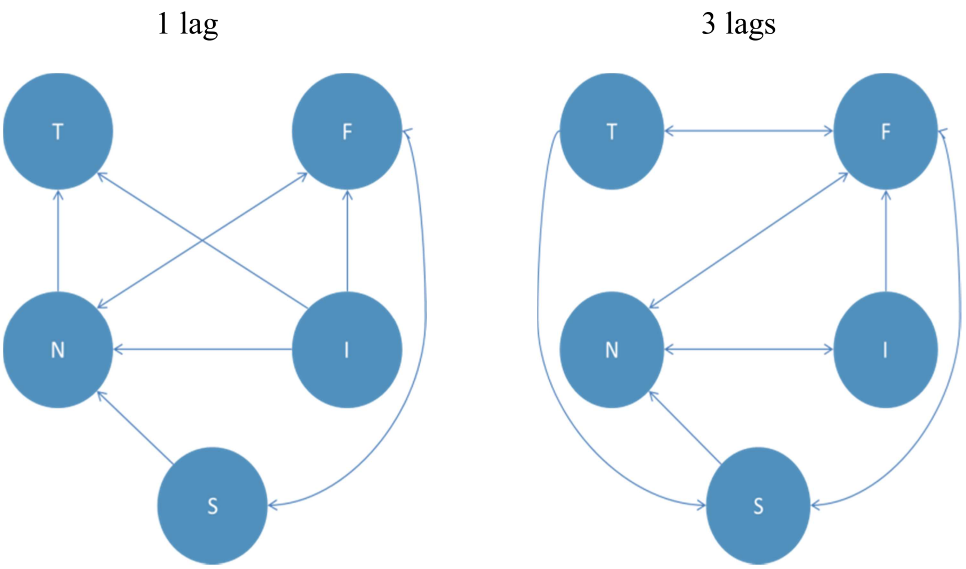


Figure 15 Granger Causality model Toyota (arrows are significant with p-value<0,1)

4.3.10 Cisco

For Cisco the stock price Granger cause the brand sentiment index (figure 16). In the model with three lags, this relation has turned; the brand sentiment index Granger cause the stock price. Further, multiple relationships exist between the Twitter variables.

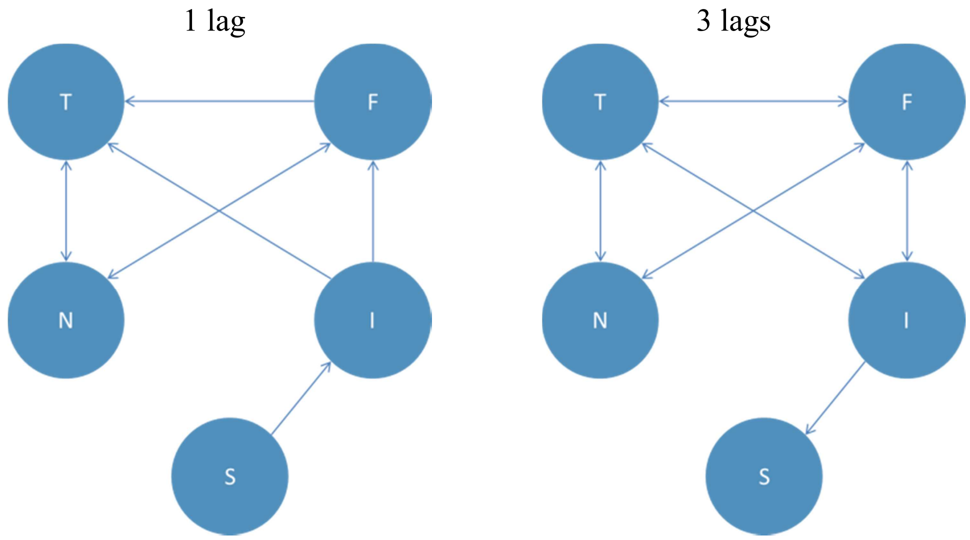


Figure 16 Granger Causality model Cisco (arrows are significant with p-value<0,1)

4.4 VAR estimations

For the first brand, Coca-Cola, I will describe the VAR estimation procedure in more detail. I only report the most important results for the other brands. Coca-Cola is the highest valued brand according the Interbrand top 100. The brand promises fun, freedom, spirit and refreshment all over the world. Coca-Cola adapted to social media quickly, which shows in the numbers. The brand has 11 million fans on Facebook and more than 200,000 followers on Twitter (Interbrand, 2011).

The VAR estimation starts with estimating equation (9). The Akaike information criteria (AIC), Schwartz criteria (SC) and the Hannan-Quinn criteria (HQC) determine the optimal number of lags for this equation (see table 7). The AIC suggest a three lags model. However, this model has heteroskedasticity in the residuals, since the variance of the parameter estimates differs, which makes this VAR unstable (Hill, Grith and Lim, 2007) (VAR Residual Heteroskedasticity test, without cross terms: Chi Square 556.7; p-value 0.98). Reducing the number of lagged variables helps to overcome heteroskedasticity. The information criteria SC and HQ support this, since these information criteria suggest a one lagged model. This one lagged model has no problem with heteroskedasticity (VAR Residual Heteroskedasticity test, without cross terms: Chi Square 415.4; p-value 0.00). Further, this VAR estimation is stable, since the AR root graph reports roots with an absolute value less than one. The residuals have a normal distribution.

Table 7 Lag length information criteria

Lag	AIC	SC	HQ
0	36,047	36,629	36,277
1	35,332	**36,158***	**35,659***
2	35,242	36,309	35,664
3	**35,237***	36,548	35,755
4	35,308	36,861	35,922
5	35,335	37,130	36,045

* lowest score

Since the number of estimated parameters of the one lagged VAR model is high, I only report the results related to the hypotheses. For testing H1a, H2a, H3a and H4a the results of the Twitter variables to stock price are the most important. Equation (14) reports the parameter estimates related to these hypotheses:

$$\Delta S_{1t} = \underset{(0.20)}{0.189} + \underset{(0.00)}{0.000}\Delta F_{1t-1} - \underset{(0.28)}{0.269} I_{1t-1} + \underset{(0.00)**}{0.001} N_{1t-1} + \underset{(0.00)}{0.000}\Delta T_{1t-1} + \ldots\ldots \quad (14)$$

standard deviation in between ( ) ** significant at p<0,05

As seen, the parameter estimates are small. The only significant coefficient with the expected sign is for the number of brand sentiment tweets (N). When the number of brand sentiment tweets increase with 1, the stock price increases with 0.001 the day after. This assumes that H1a holds for Coca-Cola. The adjusted R-square of this equation is 0.058. The adjusted R-square of the stock price equation without the Twitter variables is 0.054. Therefore, adding the Twitter variables improves the explanation of the variance of stock price.

For H1b, H2b, H3b and H4b the effect of stock price to Twitter are important. β^1_{115}, β^1_{125}, β^1_{135} and β^1_{145} measure the effect of the stock price to followers, brand sentiment index, number of brand sentiment tweets and number of tweets sent by the brand. Table 7 reports these parameter estimates. None of the parameter estimates is significant, this assumes that no relation exist from stock price to Twitter for Coca-Cola.

Table 8 Parameter estimates stock price to Twitter variables equation (9)

	ΔF	I	N	ΔT
Parameter estimates	β^1_{115}	β^1_{125}	β^1_{135}	β^1_{145}
ΔS(-1)	-47.72	0.01	1.83	-4.30
	(84.86)	(0.08)	(4.63)	(11.60)
Adjusted R-square	0.15	0.54	0.40	0.04
F-test	5.60	31.78	18.53	2.00

standard deviation in between ( ) ** significant at p<0.05

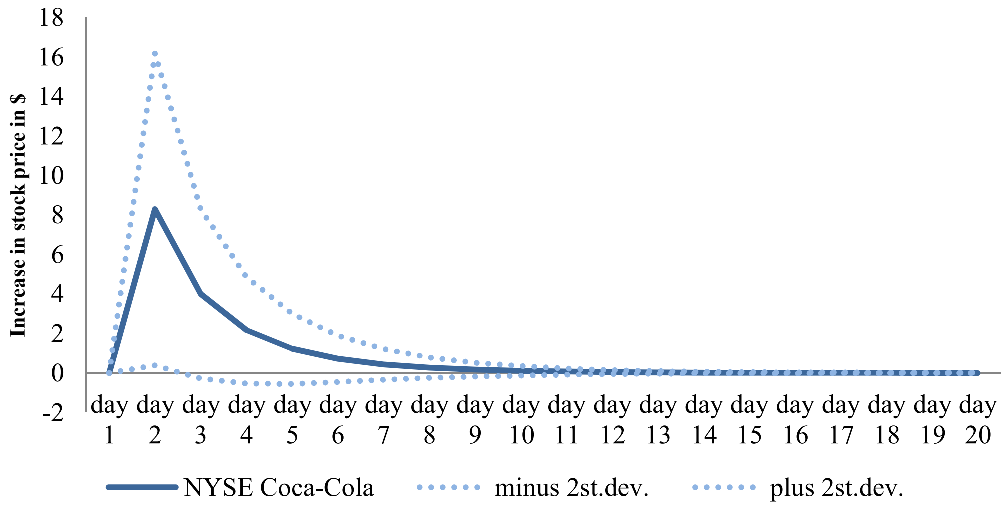
After estimating the VAR model, I use the parameter estimates to build impulse response functions (IRF). The IRF gives insights in short and long-term effect of a shock in the Twitter variables to stock price and to a shock in stock price to the Twitter variables (Pauwels, 2010). Table 9 states the effects of a shock in the Twitter variables to stock price. The only shock resulting in an effect is of the number of brand sentiment tweets to stock price. An additional 100 brand sentiment tweets sent results in an temporary increase of $8.29 in stock price. The effect peaks two days after the shock and dies out three days after the shock (figure 17).

Table 9 Results IRF immediate and long term effects

Relations	Immediate	Long term*	Wear-in	Wear-out
Effect of 100 additional tweets with a brand sentiment to stock price	$0.00	$8.29	2 days	3 days
Effect of increase of stock price with $1 to number of brand sentiment tweets	0.00	0.00		
Effect of increase of the brand sentiment index with 10% points to stock price	$0.00	$0.00		
Effect of increase of stock price with $1 to brand sentiment index	0.00%	0.00%		
Effect of 100 additional followers to stock price	$0.00	$0.00		
Effect of increase of the stock price with $1 to the number of followers	0.00	0.00		
Effect of one additional tweet of the brand to stock price	$0.00	$0.00		
Effect of a stock price increase with $1 to number of tweet sent by the brand	0.00	0.00		

* total effect, summed over 30 days

Figure 17 IRF of 100 additional brand sentiment tweets to stock price.



Besides the VAR model in levels, I estimate a log transformed VAR model. Similar lag length criteria's as for the previous model determine the number of lags for the log transformed model. The one lag model is the most appropriate for this equation. The parameters in the log transformed VAR model are interpretable as elasticity's. Equation (15) reports the elasticity's of the Twitter variables to stock price, which are important for hypotheses H1a, H2a, H3a and H4a:

$$\Delta \log S_{1t} = -0.012 - \underset{(0.00)}{0.070}\Delta \log F_{1t-1} - \underset{(0.10)}{0.004}\log I_{1t-1} + \underset{(0.00)}{0.002}\log N_{1t-1} + \underset{(0.00)**}{0.059}\Delta \log T_{1t-1} + \ldots\ldots (15)$$
$$(0.63)$$

standard deviation in between ( ) ** significant at p<0.05

Similar to equation (14), the only significant parameter estimate found is of the number of brand sentiment tweets. When the number of brand sentiment tweets rise with 1% the stock price rises the day after with 0.002% .The adjusted R-square of these equation is 0.063. The adjusted R-square of the equation without the Twitter variables is 0.060. Hence, adding additional variables increases the explanation of the log transformed stock price.

Table 10 reports the output of the effect of stock price on the Twitter variables, this is important for H1b, H2b, H3b and H4b. The only significant parameter is of stock price to followers of the brand. This suggests that when the stock price of Coca-Cola rises with 1% the number of followers decrease with 0.05% the day after.

Table 10 Parameter estimates stock price to Twitter variables equation (10)

	ΔlogF	logI	logN	ΔlogT
Parameter estimates	β^{1}_{115}	β^{1}_{125}	β^{1}_{135}	β^{1}_{145}
ΔlogS (-1)	-0.08 (0.04)**	0.93 (0.66)	0.97 (1.60)	-0.05 (0.04)
Adjusted R square	0.32	0.52	0.52	0.12
F-test	13.21	29.21	29.13	4.73

Standard deviation in between ( ) ** significant at p<0.05

5. Results

In total, I estimated 10 VAR models and 10 log transformed VAR model. The R-square of these models varied from 0.08 to 0.83. I discuss the results in the same order of the hypotheses, starting with the relationship of the number of brand sentiment tweets and stock prices and ending with the relationship of tweets sent by the brand and stock price.

5.1 Results number of tweets with a brand sentiment and stock price

Table 11 reports the impulse response function of a shock of 100 additional brand sentiment tweets to stock price and table 12 reports the elasticity's of the number of brand sentiment tweets to stock price. The parameter estimates of the log transformed VAR model are directly interpretable as elasticity's (Leeflang et al. 2000).

Table 11 IRF number of tweets with a brand sentiment to stock price

Brand	Immediate effect of shock of 100 tweets with a brand sentiment	Long term effect of shock of 100 tweets with a brand sentiment*	Wear-in	Wear-out
Coca-Cola (NYSE)	$0.00	$8.29	2 days	3 days
IBM (NYSE)	$0.00	$0.00		
Microsoft (Nasdaq)	$0.00	$0.00		
Google (Nasdaq)	$0.00	$0.00		
McDonald's (NYSE)	$0.00	$0.00		
Intel (Nasdaq)	$0.00	$0.00		
Nokia (NYSE)	$0.00	$0.00		
Disney (NYSE)	$0.00	$0.00		
Toyota (NYSE)	$0.00	$14.41	3 days	10 days
Cisco (Nasdaq)	$0.00	$0.00		

* total effect, summed over 30 days

Table 12 Elasticity's number of brand sentiment tweets to stock price (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	**0.0028 (0.001)****		
IBM (NYSE)	-0.0007 (0.001)	0.0005 (0.001)	
Microsoft (Nasdaq)	-0.0011 (0.002)	0.0003 (0.002)	0.0015 (0.002)
Google (Nasdaq)	0.0004 (0.003)	-0.0018 (0.004)	0.0042 (0.003)
McDonald's (NYSE)	-0.0022 (0.002)	0.0024 (0.003)	0.0010 (0.002)
Intel (Nasdaq)	-0.0006 (0.002)		
Nokia (NYSE)	-0.0045 (0.004)	0.0025 (0.004)	
Disney (NYSE)	-0.0002 (0.003)	-0.0018 (0.003)	0.0032 (0.003)
Toyota (NYSE)	0.0010 (0.001)		
Cisco (Nasdaq)	0.0033 (0.003)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

As can be concluded from these results, the stock market does not instantaneously react to an increase in the number of brand sentiment tweets. The investor's reaction grows over time for Coca-Cola and Toyota. For Coca-Cola, the effect of stock price peaks two days after the shock in brand sentiment tweets. It takes one additional day before the effect dies out. The total long-term effect to Coca-Cola stocks is $8.29, in case of an increase 100 brand sentiment tweets. In other words, 1% increase in the number of brand sentiment tweets results in a 0.003% increase in stock price one day later. This result is comparable with the results of Luo (2009), who reports long-term elasticity's varying from 0.001% to 0.003%.

For Toyota, the effect to stock price peaks three days after a change in brand sentiment tweets. Seven additional days later the effect dies out. The shock of 100 additional brand sentiment tweets results in a temporary increase of stock price of $14.41for Toyota.

Table 13 reports the of the impulse response functions for a shock of 1$ in stock price to the number of brand sentiment tweets and table 14 reports the elasticity's of the stock price to the number of brands sentiment tweets.

Table 13 IRF stock price to the number of tweets with a brand sentiment

Brand	Immediate unit effect $1 shock in stock price	Long term unit effect $1 shock in stock price*	Wear-in	Wear-out
Coca-Cola (NYSE)	0.00	0.00		
IBM (NYSE)	0.00	0.00		
Microsoft (Nasdaq)	0.00	0.00		
Google (Nasdaq)	0.00	0.00		
McDonald's (NYSE)	0.00	0.00		
Intel (Nasdaq)	0.00	0.00		
Nokia (NYSE)	0.00	0.08	4 days	7 days
Disney (NYSE)	0.00	0.00		
Toyota (NYSE)	0.00	-0.22	2 days	10 days
Cisco (Nasdaq)	0.00	0.00		

* total effect, summed over 30 days

Table 14 Elasticity's number of stock price to brand sentiment tweets (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	0.9651 (1.609)		
IBM (NYSE)	-3.4938 (2.265)	-0.1945 (2.261)	
Microsoft (Nasdaq)	2.0572 (1.359)	1.0868 (1.333)	-0.7973 (1.339)
Google (Nasdaq)	-1.0600 (0.840)	-0.1520 (0.831)	-0.3250 (0.837)
McDonald's (NYSE)	-0.4091 (1.116)	0.563 (1.134)	-0.0159 (1.113)
Intel (Nasdaq)	-1.4127 (1.289)		
Nokia (NYSE)	0.2413 (0.512)	**0.9416** **(0.511)***	
Disney (NYSE)	0.229 (0.910)	0.4937 (0.889)	**1.9838** **(0.890) ** **
Toyota (NYSE)	-1.6522 (1.263)		
Cisco (Nasdaq)	0.2673 (0.847)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

The only brand reporting a positive relationship between stock price to the number of brand sentiment tweets is Nokia. An 1% increase in stock price results in an increase of the number of brand sentiment tweets of 0.94% two days later. In other words, a $12 increase in stock price results in a temporary raise of one brand sentiment tweet. The effect to the number of brand sentiment tweets peaks 4 days after the shock in stock price. It takes 3 days more before the effect dies out. For Disney an 1% increase in stock price results in an increase of brand sentiment tweets of 1.98% three days after. In contrast to Nokia and Disney, Toyota reports a negative effect of an increase in stock price to the number of brand sentiment tweets. A decrease of $5 in stock price leads to a temporary increase of one brand sentiment tweet. The effect to the number of brand sentiment tweets peaks 2 days after a shock in stock price. It takes 8 days more before the effect dies out.

5.2 Results brand sentiment index and stock price

Table 15 reports the IRF for a shock in the brand sentiment index to stock price. Table 16 reports the elasticity's of the brand sentiment index to stock price.

Table 15 IRF brand sentiment index to stock price

Brand	Immediate effect of 10% points increase in the brand sentiment index	Long term effect of 10% points increase in the brand sentiment index*	Wear-in	Wear-out
Coca-Cola (NYSE)	$0.000	$0.000		
IBM (NYSE)	$0.000	$0.000		
Microsoft (Nasdaq)	$0.000	$0.015	4 days	8 days
Google (Nasdaq)	$0.000	$0.000		
McDonald's (NYSE)	$0.000	$0.000		
Intel (Nasdaq)	$0.000	$0.000		
Nokia (NYSE)	$0.000	$0.000		
Disney (NYSE)	$0.000	$0.001	5 days	6 days
Toyota (NYSE)	$0.000	$0.000		
Cisco (Nasdaq)	$0.000	$0.000		

* total effect, summed over 30 days

Table 16 Elasticity's brand sentiment index to stock price (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	-0.0040		
	(0.003)		
IBM (NYSE)	0.0009	-0.0005	
	(0.003)	(0.003)	
Microsoft (Nasdaq)	0.0006	-0.0030	**0.0102**
	(0.004)	(0.005)	**(0.004)****
Google (Nasdaq)	0.0031	-0.0129	0.0143
	(0.011)	(0.013)	(0.010)
McDonald's (NYSE)	0.0015	0.0012	0.0050
	(0.007)	(0.007)	(0.007)
Intel (Nasdaq)	**0.0082**		
	(0.003)**		
Nokia (NYSE)	0.0116	0.0041	
	(0.010)	(0.009)	
Disney (NYSE)	-0.0004	**-0.0275**	**0.0388**
	(0.013)	**(0.015)***	**(0.013)*****
Toyota (NYSE)	0.0044		
	(0.003)		
Cisco (Nasdaq)	0.0067		
	(0.005)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

As seen from table 15 the relationship between the number of brand sentiment tweets and stock price, the stock market does not react directly to changes in the brand sentiment index. For Microsoft, the effect to the stock price peaks 4 days after the shock in the brand sentiment index. The peak of the stock price of Disney is 5 days after the shock in the brand sentiment index. The effect of the brand sentiment index on stock price is small for both brands. For Microsft, a 10% points increase of the brand sentiment index, increases the stock price temporarily with $0.015. In other words, an 1% increase in the brand sentiment index results in an increase of the stock price of 0.01% three days later. For Disney, an increase of 1% in the brand sentiment index results in a decrease of the stock price of 0.027% two days later. In addition, an increase of the brand sentiment index of 1% results in an increase of the stock price of 0.039% three days later. This results in an overall positive effect as in the IRF, an increase of 10% points of the brand sentiment index of Disney results in a stock price temporary increase of $0.001. For Nokia, an 1% increase in brand sentiment index results in an increase of the stock price of 0.008% 1 day later. The significant elasticity's found, are lower than the reported elasticity of the research of Fornell et al. (2006). Fornell et al. (2006) reports an elasticity of 0.046 of the ASCI to market value.

Besides the effect of the brand sentiment index on stock price, I also study the opposite effect of the stock price on brand sentiment index. Table 17 reports the IRF of a $1 shock in stock price to the brand sentiment index and table 18 reports the elasticity's of stock price to brand sentiment index.

Table 17 IRF stock price to brand sentiment index

Brand	Immediate unit effect $1 shock in stock price	Long term unit effect $1 shock in stock price*		
Coca-Cola (NYSE)	0.00	0.00		
IBM (NYSE)	0.00	0.00		
Microsoft (Nasdaq)	0.00	0.00		
Google (Nasdaq)	0.00	0.00		
McDonald's (NYSE)	0.00	0.00		
Intel (Nasdaq)	0.00	0.00		
Nokia (NYSE)	6.89	6.89	1 day	2 days
Disney (NYSE)	0.00	0.00		
Toyota (NYSE)	0.00	0.00		
Cisco (Nasdaq)	0.00	0.00		

* total effect, summed over 30 days

Table 18 Elasticity's stock price to brand sentiment index (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	0.9303 (0.658)		
IBM (NYSE)	0.0250 (0.895)	-1.2583 (0.893)	
Microsoft (Nasdaq)	0.3224 (0.554)	0.3819 (0.543)	-0.0871 (0.546)
Google (Nasdaq)	-0.0276 (0.231)	-0.0141 (0.228)	**0.4079** **(0.230)***
McDonald's (NYSE)	-0.2797 (0.376)	0.0280 (0.382)	-0.0816 (0.374)
Intel (Nasdaq)	0.5765 (0.674)		
Nokia (NYSE)	-0.0237 (0.238)	0.0286 (0.237)	
Disney (NYSE)	-0.1104 (0.185)	0.0025 (0.181)	-0.1931 (0.181)
Toyota (NYSE)	-0.2093 (0.730)		
Cisco (Nasdaq)	**0.9956** **(0.415)****		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

Brands that with a significant relation between the brand sentiment index and stock price are Nokia, Google and Cisco. For Nokia, an increase of stock price of $1 results in a temporary increase of the brand sentiment index of 6.89% points. The effect on the brand sentiment index peaks one day after a shock in stock price. The effect dies out one day later. Further, for Google an increase of the stock price of 1% results in an increase of the brand sentiment index of 0.41% three days later. For Cisco an increase of stock price of 1% results in an increase of the brand sentiment index of 0.99% one day later.

5.3 Result of followers and stock price

Table 19 reports the IRF of the number of followers to stock price and table 20 reports the elasticity's of followers on stock price.

Table 19 IRF number of followers to stock price

Brand	Immediate effect of 100 extra followers	Long effect of 100 extra followers*	Cumulative unit effect	Cumulative elasticity
Coca-Cola (NYSE)	$0.00	$0.00		
Microsoft (Nasdaq)	$0.00	$0.00		
Google (Nasdaq)	$0.00	$0.00		
McDonald's (NYSE)	$0.00	$0.00		
Intel (Nasdaq)	$0.00	$0.00		
Nokia (NYSE)	$0.00	$0.00		
Toyota (NYSE)	$0.00	$10.28	2 days	3 days
Cisco (Nasdaq)	$0.00	$0.00		

* total effect, summed over 30 days

Table 20 Elasticity's number of followers of the brand to stock price (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	-0.0703 (0.104)		
Microsoft (Nasdaq)	-0.0128 (0.015)	0.0178 (0.016)	-0.0208 (0.017)
Google (Nasdaq)	0.7582 (1.328)	**-3.0862 (1.240)****	0.0212 (1.286)
McDonald's (NYSE)	-0.0040 (0.115)	-0.1022 (0.110)	0.0663 (0.112)
Intel (Nasdaq)	-0.1364 (0.306)		
Nokia (NYSE)	-0.9459 (0.617)	0.3960 (0.561)	
Toyota (NYSE)	**0.8832 (0.338)** ***		
Cisco (Nasdaq)	-1.6107 (1.180)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

Brands that have a significant relationship between the number of followers and stock price are Google and Toyota. An increase of 1% in Toyota followers leads to an increase of the stock price of 0.88% one day later. In other words, 100 extra followers results in a temporary increase of Toyota's stock price of $10.28. The effect to stock price peaks two days after the shock in the number of followers and dies out one day later.

In contrast to Toyota, Google reports a negative significant elasticity. If the number of Google followers increase with 1% the stock price decreases two days later with 3.08%.

Besides the effect of number of followers to stock price, I study the effect of stock price on followers. Table 21 reports the IRF of stock price to an increase in the number of followers and table 22 reports the elasticity's of stock price to followers.

Table 21 IRF stock price to followers

Brand	Immediate effect of $1 shock in stock price	Long term effect of $1 shock in stock price	Wear-in	Wear-out
Coca-Cola (NYSE)	0.00	0.00		
Microsoft (Nasdaq)	0.00	0.00		
Google (Nasdaq)	0.00	0.00		
McDonald's (NYSE)	0.00	0.00		
Intel (Nasdaq)	0.00	0.00		
Nokia (NYSE)	0.00	0.05	4 days	8 days
Toyota (NYSE)	0.00	-0.10	3 days	9 days
Cisco (Nasdaq)	0.00	0.00		

* total effect, summed over 30 days

Table 22 Elasticity's stock price to number of followers of the brand (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	**-0.0802 (0.036) ****		
Microsoft (Nasdaq)	0.0591 (0.164)	0.1621 (0.161)	-0.0742 (0.162)
Google (Nasdaq)	0.0013 (0.002)	-0.0026 (0.002)	-0.0005 (0.002)
McDonald's (NYSE)	0.0107 (0.023)	0.0278 (0.023)	-0.0160 (0.023)
Intel (Nasdaq)	-0.0028 (0.008)		
Nokia (NYSE)	-0.0013 (0.004)	-0.0064 (0.004)	
Toyota (NYSE)	0.0015 (0.009)		
Cisco (Nasdaq)	-0.0014 (0.002)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

Nokia, Toyota and Coca-Cola report significant relationships between stock price and the number of followers. For Nokia, if the stock price increases with $1, the number of followers temporary increase with 0,05. So in case of a daily increase of $20 in stock price Nokia's Twitter account adds one follower. However, this seems not likely to happen. In contrast to Nokia, a negative effect of stock price to the number of followers in found for Toyota. If the stock price decreases with $1 the number of followers increases with 0.1. So, an increase of $10 in stock price results in one additional follower for Toyota. Coca-Cola shows a negative relationship as well. A decrease of 1% in stock price results in an increase of the number of followers of 0.08%.

5.4 Results of tweets and stock price

Table 23 reports the elasticity's of number of tweets sent by the brand to stock price.

Table 23 Elasticity's number tweets sent by the brand to stock price (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	0.0591 (0.094)		
Microsoft (Nasdaq)	0.0114 (0.012)	-0.0006 (0.011)	0.0022 (0.010)
Google (Nasdaq)	-0.3595 (0.358)	0.3738 (0.355)	**-0.5886 (0.354)***
McDonald's (NYSE)	0.0053 (0.063)	0.0645 (0.063)	0.0148 (0.062)
Intel (Nasdaq)	0.0076 (0.056)		
Nokia (NYSE)	0.0022 (0.018)	-0.0072 (0.018)	
Toyota (NYSE)	0.0758 (0.138)		
Cisco (Nasdaq)	0.0209 (0.646)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

The only brand reporting a significant relationship between the number of tweets sent by the brand and stock price is Google. For Google, if the number of tweets sent by the brand increases with 1% the stock price decreases with 0.59% three days later. The IRF shows no effects between the number of tweets sent by the brand to stock price.

Table 24 and 25 report the opposite relationships, for the ten brands, of stock price to number of tweets sent by the brand. Table 25 reports the IRF of stock price to the number of tweets sent by the brand and table 26 reports the elasticity's of stock price to number of tweets sent by the brand.

Table 24 IRF stock price to number of tweets sent by the brand

Brand	Immediate unit effect of $1 shock in stock price	Long term unit effect of $ 1shock in stock price*	Wear-in	Wear-out
Coca-Cola (NYSE)	0.00	0.00		
Microsoft (Nasdaq)	0.00	-0.08	3 days	4 days
Google (Nasdaq)	0.00	0.00		
McDonald's (NYSE)	0.00	0.00		
Intel (Nasdaq)	0.00	0.00		
Nokia (NYSE)	0.00	0.00		
Toyota (NYSE)	0.00	0.00		
Cisco (Nasdaq)	0.00	0.00		

* Total effect, summed over 30 days

Table 25 Elasticity's stock price to number of tweets sent by the brand (based on VAR estimation in logs)

Brand	Elasticity lag 1	Elasticity lag 2	Elasticity lag 3
Coca-Cola (NYSE)	-0.0599 (0.041)		
Microsoft (Nasdaq)	0.3040 (0.189)	**-0.4060** **(0.186)** **	0.0622 (0.187)
Google (Nasdaq)	0.0104 (0.007)	-0.0032 (0.007)	0.0047 (0.007)
McDonald's (NYSE)	0.0397 (0.042)	0.0240 (0.042)	0.0605 (0.041)
Intel (Nasdaq)	0.0159 (0.044)		
Nokia (NYSE)	0.0274 (0.130)	-0.0115 (0.129)	
Toyota (NYSE)	0.0048 (0.020)		
Cisco (Nasdaq)	0.0007 (0.004)		

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

Microsoft shows the only significant relation of stock price to number of tweet sent by the brand. If the stock price of Microsoft increases with 1% the number of tweets sent by the brand decrease with 0.4%, In other words, a $1 increase of the stock price results in a temporary decrease of 0.08 tweets sent by the brand. Therefore, before observing an effect a decrease of one tweet, the stock price of Microsoft should at least increase with $12.5. The effect on the number of tweets sent by the brand peaks 3 days after a shock in stock price and dies out one day later.

5.5 Summary of the results

Table 27 summarizes the results of the hypotheses testing. Acceptance of a hypothesis for a brand depends on the results of the IRF. Interpreting the results correctly from the log transformed model is difficult, due to the high number of parameter estimates and possible multicollinearity among the variables (Pauwels, 2004). IRF analyses the dynamic behaviour of the VAR by simulating the over-time impact of a change to one variable on the system of equations (Wieringa and Horvath, 2005). This makes that the results of the IRF outweigh the results of the log transformed VAR model.

The first assumed relationship between Twitter and stock price. More Internet attention works as a signal effect of improved cash flows in the future. H1a assumed a positive relation of the number of brand sentiment tweets and stock price. Coca-Cola and Toyota support this hypothesis. For Coca-Cola, if the number of brand sentiment tweets increase with 1%, the stock price increase with 0.003% one day later. For Toyota 100 more tweets about a brand results in an increase in stock price of $14.41, which levels out in 10 days. H2a assumes a positive relationship between the brand sentiment index and stock price. Microsoft and Disney support this hypothesis. For Microsoft, an increase of 10% in sentiment improved the stock price with $0,015, the effect peaks on day 4 and levels out in 8 days. For Disney, an increase in the brand sentiment index of 10% results in a temporary increase of the stock price of $0,001. H3a assumes a positive the relationship between the number of followers and stock price. Toyota is the only brand supporting this hypothesis. 100 additional followers for the Toyota brand results in a temporary increase of the stock price of $10.18. Lastly, H4a assumes a positive relation of the number of tweets sent by the brand to stock price. No brand supports this hypothesis.

Besides a relation of the Twitter variables to stock price, stock price to the Twitter was an expected relation. An increase in stock price, supported by an increase in cash flow, would result in additional budgets for marketing and additional attention on the Internet. Nokia is the only brand supporting this relation. First, H1b assumes a positive relation of stock price to the number of brand sentiment tweets. Results are small, since Nokia's stock price has to increase with more than $10, before observing an additional tweet. H2b assumes a positive effect of stock price to the brand sentiment index. A shock of $1 in Nokia's stock price results in an increase of the brand sentiment index of 6.89% points one day later. H3b assumes a positive relation of stock price to number of followers. An increase in stock price of $20 is necessary before observing an effect in the number of followers of Nokia. Lastly, H4b assumes a positive relation of stock price to number of tweets sent by the brand. No brand supports this hypothesis.

Remarkable is the variation in the results. The studied brands have different product characteristics. Processing WOM depends on these product characteristics (Sundaram and Webster, 1999). The eWOM effect is greater for experience goods than for search goods (Park and Lee, 2009). This explains that the effect of number of brand sentiment tweets to stock price is higher for Toyota ($14) in comparison to Coca-Cola ($8). Businesses that are more efficient in converting satisfaction to cash flows are in concentrated and specialized industries (Gruca and Rego, 2005). This makes that the effect for Microsoft ($0,015) is higher than for Disney ($0,001).

To conclude, support for the hypotheses is only found for some brands. This might be explained by firm and industry differences (Luo and Homburg, 2007). Business with higher market shares, like Microsoft and Disney, are more efficient in converting customer satisfaction in future cash flow growth. While business with lower market shares, like Nokia and McDonald's might fail to convert satisfaction in future cash flow growth. Moreover, brands with a focus on the business market, like IBM and Cisco, are less likely to be influenced by messages on Twitter.

Further, all the studied brands are well known brands with high brand equity. Improving the brand sentiment index of these brands might not convince investors. Improving customer satisfaction comes with a cost, which makes that excessive satisfaction does not pay off (Kumar and Reinartz, 2006). Every brand has an optimal satisfaction level, so more is not always better. It might be that the additional satisfaction does not pay off for in the eyes of the investors. Fornell et al. (2006) give three reasons why investors would react unfavourable to an increase in satisfaction. Firstly, investors might believe that a firm gives away too much surplus. Secondly, investors might feel that investments in satisfaction are unnecessary, if a firm is already ahead of competition. Thirdly, investors may think that the marginal cost of improving customer satisfaction is too high.

Moreover, consumers are not likely to change their attitude towards familiar brands (Hoyer and MacInnes, 2007). This makes that exposure to WOM communication, on for example Twitter, is not likely to produce significant changes in consumers' pre-existing brand evaluations (Sundaram and Webster, 1999) and behaviour for these popular brands.

Table 26 Summary of results H1-H4

Hypotheses	Coca-Cola	IBM*	Microsoft	Google	McDonald's	Intel	Nokia	Disney*	Toyota	Cisco
H1a The number of tweets with a brand sentiment is positively related to stock price.	✓								✓	
H1b Stock price is positively related to number of tweets with a brand sentiment.							✓			
H2a The brand sentiment index is positively related to stock price.			✓					✓		
H2b Stock price is positively related to the brand sentiment index.							✓			
H3a The number of followers is positively related to stock price.		X						X	✓	
H3b Stock price is positively related to the number of followers of the brand.		X					✓	X		
H4a The number of tweets sent by the brand is positively related to stock price.		X						X		
H4b Stock price is positively related to the number of tweets sent by the brand.		X						X		

*For IBM and Disney the number of followers and tweets are not included in the calculations

As concluded from the results, brands cannot directly influence the stock price with its Twitter account (sending more tweets i.e.). However, the brand might have an indirect effect on the stock price with its Twitter account, by influencing the number of brand sentiment tweets and the brand sentiment index. An effect of the Twitter account to the number of brand sentiment tweets and brand sentiment index is important for brands that support H1a and H2a (i.e.). Coca-Cola and Toyota support H1a, since they report a direct positive relation of the number of brand sentiment tweets to stock price. To study whether the brand influences the number of brand sentiment tweets of Coca-Cola and Toyota, I study the relationship between number of followers and the number of tweets sent by the brand on the number of brand sentiment tweets (table 27). Coca-Cola shows no significant effects of the number of followers or of the number of tweets of the brand to the number of brand sentiment tweets. For Toyota, 100 additional followers results in a temporarily increase of 41 brand sentiment tweets. 100 extra tweets of the brand results in a temporarily increase of the number of brand sentiment tweets of almost 5.

Table 27 Relation of the number of followers and number of tweets sent by the brand to number of brand sentiment tweets (Coca-Cola and Toyota)

	Coca-Cola	Toyota
	logN	logN
ΔlogF(t-1)	4.465 (3.506)	3.1816 (8.086)
ΔlogT(t-1)	-2.3357 (3.156)	-2.3021 (3.301)

() standard deviation *significant with p-value 0.1 ** significant with p-value 0.05 ***significant with p-value 0.001

	IRF	IRF
Long-term effect of the number of brand sentiment tweets to a shock of 100 extra tweets sent by the brand.*	0.00	4.78 wear-in day 1 wear-out day 2
Long-term effect of the number of brand sentiment tweets to a shock of 100 additional followers of the brand.*	0.00	40.78 wear-in day 1 wear-out day 10

* total effect, summed over 30 days

Microsoft and Disney support H2a, since they report a positive relationship between the brand sentiment index and stock price. For these brands, I study the effect of the number of followers and number of tweets sent by the brand to the brand sentiment index (table 28). Unfortunately, I cannot study this relation for Disney, since data of the first months of its Twitter account are lacking. I find no significant effects for Microsoft. This means the brands Twitter account does not influence Twitter behaviour.

Table 28 Relation of the number of followers and number of tweets sent by the brand to brand sentiment index (Microsoft and Intel)

	Microsoft
	logI
ΔlogF(t-1)	0.0015 (0.174)
ΔlogF(t-2)	0.2650 (0.181)
ΔlogF(t-3)	-0.1300 (0.198)
ΔlogT(t-1)	0.0801 (0.138)
ΔlogT(t-2)	0.1359 (0.123)
ΔlogT(t-3)	0.0165 (0.114)
	IRF
Long-term reaction of the number of brand sentiment tweets to a shock of 100 extra tweets sent by the brand.*	0.00
Long-term reaction of the number of brand sentiment index to a shock of 100 additional followers of the brand.*	0.00

* total effect, summed over 30 days

6. Conclusions and implications

6.1 Conclusion

The goal of this research was to examine the dynamic relationship between Twitter and stock price. The research focused on the ten most valuable brands according Interbrand (2010): Coca-Cola, IBM, Microsoft, Google, McDonald's, Intel, Nokia, Disney, Toyota and Cisco. I found significant effects for 5 of the 10 brands. All effects were one-sided, so either from Twitter to stock price or from stock price to Twitter. To summarize the main results were:

1) Coca-Cola and Toyota show a significant relationship of the number of brand sentiment tweets on stock price. For Coca-Cola an additional 100 brand sentiment tweets results in an temporary increase of stock price of $8 and for Toyota, an additional 100 brand sentiment tweets results in a temporary increase of the stock price of $14. An explanation for this positive relation is the increase in brand awareness, due to an increase of brand sentiment tweets. An increase in brand awareness leads to higher sales and in the end to higher stock prices (Godes and Mayzlin, 2004).
2) Microsoft and Disney show a significant relationship of the brand sentiment index on stock price. For Microsoft, an increase of 10% points in sentiment index improved the stock price temporarily with $0,015. For Disney, an increase in the brand sentiment index of 10% points results in a temporary increase of the stock price of $0,001. Increased brand sentiment index is a sign of increased in satisfaction. An increase in satisfaction leads to an increase in efficiency of advertising and promotion investments, since customer satisfaction induces free WOM. All these positive antecedents of satisfaction reduce marketing costs (Luo and Homburg, 2007). Moreover, consumer satisfaction results in customer behaviour patterns, like loyalty and repurchase, that positively affect business results (Keiningham, Perkins-Munn and Evans, 2003; Seiders et al. 2005) and stock price (Fornell et al. 2006; Luo and Bhattacharya, 2006).
3) Nokia is the only brand reporting significant relationships between stock price and Twitter. In case of a $10 increase in stock price, the number of brand sentiment tweets temporarily increase with 1. In case of a $1 increase in stock price, the brand sentiment index increases with almost

7% points. If the stock price increases with $20, the number of followers increase with one. Two lines of reasoning might explain the effect of stock price to Twitter. First, an increase in stock price and cash flow, that increases the ability for a company to invest in more marketing actions. This additional marketing helps to keep the buzz around a brand high (Luo, 2009). Second, "success breeds success" (Subrahmanyam and Titman, 2001), favourable information of the stock market might result in more positive news of the brand on Twitter

4) Twitter does not instantaneously have an effect, investor reactions grow over time. On average, it takes 2 till 4 days before the impact of the number of brand sentiment tweets and the brand sentiment index on stock price peaks. The effect dies out 1 till 6 days after the peak day. For Nokia the impact of stock price to Twitter peaks 1 to 4 days after the shock and dies out 1 to 3 days later. All the effect diminishes over time, which means that model captures the effect of forgetting (Luo, 2009).

6.2 Managerial implications

The findings offer several implications for business, investors and researchers. First, the outcome of this study offer business a possible metrics to measure the effectiveness of social media investments. For brands like Coca-Cola and Toyota, the number of brand sentiment tweets could measure the effectiveness of social media. For brands like Microsoft and Disney, the brand sentiment index could measure the effectiveness. The brand could drive the number of brand sentiment tweets and brand sentiment index by, for example, paying individuals to spread positive WOM. Or better, to motivate satisfied customers to provide positive feedback (Gelb and Sundaram, 2002). Satisfied customers could be stimulated to spread their opinion on Twitter, by offering them a chance to win prices with their opinion. Another option to stimulate the number of brand sentiment tweets and the brand sentiment index is increasing the brand activity on Twitter. The brand could send more tweets and try to communicate directly with its customers by using the @-mention (Thomases, 2010). Further, the brand could stimulate customers to follow the brand, by giving followers of the Twitter account an additional customer benefit, like a 10% discount on new collections. Toyota is a brand that succeeds with its Twitter strategy. An additional 100 tweets sent by the Toyota results in 5 extra brand sentiment tweets and an additional 100 followers results in 40 extra brand sentiment tweets.

Important is to measure whether these actions results in a higher number of brand sentiment tweets and an increased brand sentiment index. In addition, whether these improvements in Twitter measures results in additional sales and increased stock prices.

Further, Twitter offers the business the opportunity to increase understanding of the consumer, since consumer discuss openly on Twitter. The content of consumer discussions can be used to modify products and to improve advertising campaigns (Gelb and Sundaram, 2002). If the business succeeds in reflecting the needs of customers in supply, customer satisfaction will improve.

Second, the outcomes of this study offer a possible basis for decision making for financial analysts and investors (Luo, 2009). Insights acquired though Twitter sentiment can help to predict future financial prospects. Investors might sell stocks with low volume of brand sentiment tweets and low brand sentiment index and buy stocks with high volume of brand sentiment tweets and high brands sentiment index. The advantage of Twitter for investors is the speed of information and the brevity of the information. Moreover, if investors would use trade-offs like the number of brand sentiment tweets and brand sentiment index for investment decisions, firms would be encouraged to improve customer satisfaction (brand sentiment index) and stimulate WOM (number of brand sentiment tweets), which would result in more happy customers. Further, this balance of investor and customer needs, would contribute to less miss allocation of capital, quicker deflation of stock market bubbles, fewer cases of security mispricing and better functioning of markets in general (Fornell et al. 2006).

Lastly, this study shows that Twitter gives unique opportunities for research in marketing. Twitter is freely available and updated every second. Moreover, Twitter proves to be a proxy for WOM and the sentiment extracted from Twitter is comparable to satisfaction indices like the ACSI.

To conclude, the results, support that investments in Twitter and stimulating WOM makes financial sense (Luo, 2009) and that in some cases Twitter indeed drives stock price.

7. Limitations

This study has various limitations. These limitations offer areas for extending and improving this study.

First, the financial value in this study was stock price, represented as the daily closing value of the stock. This variable ignores the main components of stock price: stock return, systematic risk, and idiosyncratic risk (Osinga et al. 2011). Stock return is the percentage change in a firm's value. Systematic risk is the economy wide risk that cannot be diversified away through a balanced portfolio. Idiosyncratic risk is the uncertainty about the price of a stock, which investors eliminate with through the creation of a diversified portfolio. The assumption is that the brand sentiment index and the number of brand sentiment tweet would lead to higher stock returns and lower idiosyncratic risk (Luo, 2007).

Second, this research focussed on ten well-known brands. Consumers are not likely to change their attitude towards familiar brands (Hoyer and MacInnes, 2007). More brands, also less familiar brands should be studied in order to be able to generalize any results. Further, the period including this research was short. The VAR modelling is a modelling approach that needs high volume of data. Therefore, my suggestion would be to repeat the same study over a longer period of time and with additional brands.

Third, in this research tweets receive a code with a negative or positive sentiment. However, the problem with sentiment analysis is correct identification of the sentiment (Go, Huang and Bhayani, 2009). For example, a tweet like "Apple beats Nokia :)", the sentiment is positive for Apple and negative for Nokia. However, since classification of the tweets is on overall sentiment the tweet is classified positive for both Apple and Nokia. Further, the base of the sentiment analysis is on two emotions only (positive or negative). In previous research more convincing results have been found, with the use of other emotion like calmness of the public (Bollen, Mao and Zeng, 2011), and hope fear and worry (Zhang, Fuehres and Gloor, 2010). For future research, adding additional emotions could improve the results.

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Preliminary thesis report

-Effect of brand sentiment expressed through Twitter on stock prices -

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Master of Science Strategic Marketing Management

1. Introduction

Traditional advertising is losing effectiveness; one of the major reasons for the decrease is the rise in use of the Internet and social media (Luo, 2009). Social media has increased in popularity the last years. Currently, about 127 million Americans, or three-quarters of the population, use social media, according to Nielsen Online. Of the online population, 47% visit Facebook daily which means that social media is getting close to the 55% of the people who watch TV daily. Facebook daily use easily beats out other traditional media like radio (37%) and newspapers (22%). Twitter is coming up as well with 105 million registered users and 11.4 million (6%) daily users[1].1 In social media collaboration and community are important characteristics. Social media provides constant connectivity among people. Social communication service, have the potential to impact word-of mouth branding, which can impact key elements of the company–customer relationship like brand image and brand awareness (Jansen et al. 2009). According research of Jansen et al (2009) 19% of the tweets (short message on Twitter) contain mention of a brand. Of the branding tweets, nearly 20% contained some expression of brand sentiments. Of these, more than 50% were positive and 33% were critical of the company or product. With the high number of users of social media platforms and the content where people talk about on social media should increase awareness of marketers and researchers. However, little is known about the impact of social media on the brand. In the thesis I hope to improve the knowledge of the impact of social media, with the focus on Twitter. The main findings from previous research is that Twitter sentiment effect stock prices (Bollen, Mao and Zeng, 2010; Zhang, Fuehres and Gloor, 2009). Both articles found evidence that the general mood on Twitter is a good predictor for the Dow Jones Industrial Average and NASDAQ. However, both articles are not focused on brand specific sentiment. The reasoning behind the fact that Twitter sentiment has an effect on stock prices is based on behavioural economics, which tells us that emotions can affect individual behaviour and decision-making. The emotions would express the general mood of the country and therefore affect also the mood of the investors. If we look more on a brand level this explanation would not be limited. The question should be asked: "Why do people engage in WOM?" In

[1] http://www.pamorama.net/2010/04/18/if-size-matters-social-media-is-huge-in-the-u-s/

general consumer express positive WOM when they are extremely satisfied and they express negative WOM in the case of dissatisfaction (Anderson, 1998). Previous research has proven the effect of the American Satisfaction Index (ASCI) on the stock price (Fornell et al.
2006). Firms that do well by their customers would be rewarded by more business from customers and more capital from investors. This results in higher profits with satisfied consumers. However, the main problem with the ASCI is the fact that it is measured on a yearly basis and not on a daily basis. Expression of emotion on Twitter could be a good proxy for the satisfaction levels. The advantage of using Twitter would be that satisfaction can be measured on a daily basis and the data is freely available. In the thesis I hope to find a correlation between Twitter sentiment and ASCI. Another explanation why brand emotion have an effect on stock prices can be found in customer and brand equity theories (Luo, 2009). In case of negative feelings a strong negative influence exist on consumer information processing and repurchase loyalty, which may result in damage of customer equity and customer lifetime value, which results in reduced cash flows in the future (Luo and Homburg 2007, Srivastava, Shervani and Fahey, 1998).
Furthermore, according to the brand equity theory, unfavorable experience and negative recommendations can result in loss of corporate image, which results in loss of shareholders trust (Keller 2003, Luo and Bhattacharya 2006).

The thesis will make a relation between marketing and finance literature, which will improve further understanding of the marketing finance interface. When the relationship between Twitter sentiment and stock price changes hold, marketers will have a financial reasoning for investment in positive WOM on social media platforms (Luo, 2009).

Too summarize the main research question which will be answered in the thesis is:
Does brand sentiment expressed through Twitter have an effect on stock prices?

Besides answering this question I hope to find evidence for the relation between brand sentiment and the ASCI.

To further explain the subject the preliminary thesis report will first go into depth into previous research, followed by the explanation of the concept and the methodology.

2. Literature review

Since social media is upcoming since the last years, research on this topic is lacking. Recently published studies on Twitter are general. Therefore a relation with satisfaction and WOM theory is made as well. The most recent article on Twitter is of Bollen, Mao and Zeng (2010). Bollen, Mao and Zeng (2010) find evidence for the predicted value of Twitter mood on stock prices. This is explained by behavioural economic theories. It is argued that the mood of societies affect collective decision making. The article investigates whether a correlation exist between the Dow Jones Industrial Average (DJIA) and Twitter moods. Different moods are taken from daily Twitter message: positive/negative, calm, alert, sure, vital, kind and happy. The mood on Twitter shifted the DJIA three or four days later. The most important mood was calmness of the public. Bollen, Mao and Zeng (2010) found an accuracy of 87.6% in predicting the daily up and closing values of the DJIA. This in comparison to old theories, who suggest that stock market prices are largely driven by news fact. However the old theory has only an accuracy of 50%. Similar results are found by Zhang, Fuehres and Gloor (2009). When people express a lot of hope, fear, and worry the Dow Jones goes down the next day. When people have less hope, fear, and worry, the Dow Jones goes up.

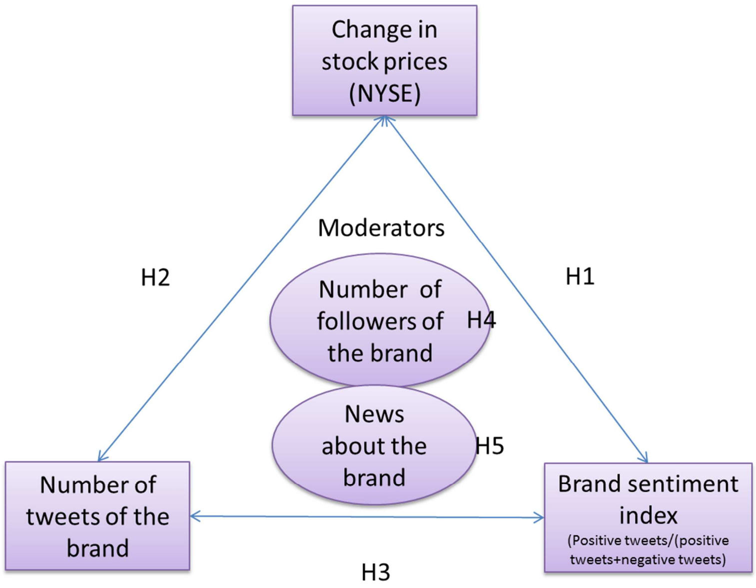
According to satisfaction literature when customers are satisfied the reward will be more business and more capital from investors (Fornell et al 2006). Both marketing and neoclassical economics see consumer utility, or satisfaction, as the standard for economic growth. Buyers financially reward sellers that satisfy them and punish those that do not. Satisfied customers express more positive WOM (Anderson, 1998), so it is expected that satisfied customers expressing their mood on for example Twitter. Customer satisfaction has a negative impact on customer complaints and a positive impact on customer loyalty and usage behaviour (Bolton 1998). Increased customer loyalty may increase usage levels, secure future revenues, reduce the cost of future transactions and lower price elasticity, which all result in stable expectations of investors and rising stock prices (Fornell et al. 2006). The link between customer satisfaction and stock returns can be found in the logic of Srivastava, Shervani and Fahey (1998). Four major determinants of a company's market value are identified is this logic. First, the acceleration of cash flows, which is affected by the speed of buyer response to marketing efforts, since it takes less effort to persuade a satisfied customer (Fornell et al. 2006). Second, the increase in cash flow. Research has shown that the increase in customer satisfaction lead to significant cash flow growth. One point in customer satisfaction leads to a 7% increase of cash flow (Gruca and Rego, 2005). Third, the reduction of risk associated with cash flows is reduced with high customer satisfaction (Gruca and Rego, 2005). If the variability in cash flows is reduced, the cost of capital goes down as well; this results in stock price growth. Fourth, the increase in the residual value of business, which is measured as a function of size, loyalty, and quality of the customer base, all of which are related to the satisfaction of this customer base (Fornell et al. 2006). The evidence found in Fornell et al. (2006) was weak. This is explained by the different reasons why investors may not react always in a positive way in case of increased satisfaction.

First, investors may react negatively to news about rising customer satisfaction if it is believed that the firm is giving away too much surplus to the buyers. Second, investors may see an improvements in customer satisfaction as unnecessary if a firm is already ahead of competition. Third, investors may think that the marginal cost of improving customer satisfaction is too high. Fourth, customer defection can have a positive effect on average customer satisfaction simply because the departing customers were the most dissatisfied. Fifth, the ACSI measures each company once a year, which creates problem with timing. If Twitter would be a good measure of satisfaction the last point could be solved.

Tweets could be seen as electronic word of mouth. By taking this approach more research could be found. One the most useful is of Luo (2007;2009). Luo makes a

relation between WOM and stock price changes. In case of negative feelings a negative influence exist on consumer information processing and repurchase loyalty, which could result in damage of customer equity and customer lifetime value. This all will results in reduced cash flows in the future (Luo and Homburg 2007, Srivastava, Shervani and Fahey, 1998). According to the brand equity theory, unfavorable experience and negative recommendations can result in loss of corporate image, which results in loss of shareholders trust (Keller 2003, Luo and Bhattacharya
2006). Luo researched the short and long term effects of consumer negative voice on stock returns. To model the long term effect a vector autoregressive (VAR) model is used. Luo (2009) argues that a focus on solely short-term effects would underestimate the power of WOM. However, in the past WOM was hard to measure since it was not written (Rust, Zeithaml and Lemon, 2000). With the increase use of the
Internet WOM can be tracked more easily. The advantage of a VAR model is that it is a flexible time-series approach that can gauge the long-term, accumulative effects of an unexpected shock in WOM and test whether such effects evolve nonmonotonically over time (Dekimpe and Hanssens 1999). So the VAR model does not only measure the short term effect but also the long-term effect. Further wear-in and wear-out effects will be measured (Luo, 2009). Another important relation Luo (2009) took into account a two-way influence between stock price changes and WOM, the feedback loop. His framework captures the direct impact of WOM on the stock market and the stock market's feedback impact on future WOM over time. This feedbackloop suggest a vicious cycle of NWOM; i.e., historical shortfalls in cash flows and underperformance in the stockmarket breed more harmful buzz in the future.

3. Hypothesis



3.1 The effect of brand sentiment index on stock price (NYSE)

Positive brand sentiment involves favorable experience and recommendations of buying certain products. Negative brand sentiment refers to unfavorable experience and recommendations of not buying certain products (Luo,2009)

Positive WOM is very effective in generating sales, awareness, and loyalty, then negative WOM would be detriment to achieving these goals (Luo,2009). It is expected that expressed brand sentiment could be related to the WOM theories.
It is expected that the positive brand sentiment index has a positive correlation with stock price. Which would mean that the stock market should react unfavourable to negative brand sentiment and favourable to positive brand sentiment.

H1a.Brand sentiment index has a positive correlation with stock price change.

Stockprices may have a feedback impact on the future brand sentiment index.
In case of high or low stock performance managers get triggered to change actions in advertising, product innovations, and branding, which in the end will influence customer experience and brand sentiment in the future (Benner 2007, Markovitch, Steckel and Yeung, 2005). Lower returns can lead to decreased cash flow which results in budget constraints in R&D and adverstising in following periods (Subrahmanyam and Titman 2001; Minton and Schrand, 1999). Current cash

flows constraint future marketing investments, which could lead to less customer service which would results in lower brand sentiment index (Luo, 2007). So it expected that the feedback effect of stock prices on brand sentiment index is in a vicious cycle.

H1b The higher the decrease (increase) in stock price change the higher the decrease (increase) in brand sentiment index.

3.2 The effect of the number of tweets of the brand on stock price

When the number of tweets with a brand mention is high this could be a sign for improved customer service, increased customer retention, brand loyalty and improved brand image. Besides these the number of tweets could be sign of viral activity (Thomases, 2010). On the other hand the number of tweets could rise because of negative attention. Therefore the relation between stock price change and number of tweets of a brand is not clear.

H2a The effect of the number of tweets of a brand is either positively or negatively correlated with the stock price change.

A similar vicious circle as with brand sentiment index and stock price is expected in the relation between number of tweets and stock price. In case of positive high attention it expected that the stock price rise. If the change in stock price is supported by increased cash flows which gives the company the ability to invest in more marketing actions who hopefully keep up the buzz (Luo, 2009). In case of negative attention the effect will result in a negative vicious circle.

H2b *The higher the decrease (increase) in stock price change the higher the decrease (increase) in the number of tweets.*

3.3 The effect of the number of tweets of the brand on the brand sentiment index

As stated in H2 it is not clear whether the effect of the number of tweets is either positive or negative. This makes the relation towards the brand index unclear as well. It is expected that the number of tweets rise when the content of the tweets are extremely positive or extremely negative (Anderson, 1998). Since the mood behind could explain the relevance of tweeting about it. Which gives evidence for the third hypothesis.

H3a Either when the brand index is extremely positive or extremely negative the number of tweets of a brand rises.

A feedback effect is added in the number of tweets and the brand sentiment index. It is expected that the number of tweets rises in case of extremely negative or extremely positive tweets.

H3b The number of tweets rise in case of extremely positive or extremely negative brand sentiment.

3.4 Moderators

It is expected that the effectiveness of the Twitter strategy of the company influences all the constructs in the model. The effectiveness of the Twitter strategy can be measured by the number of followers of the companies Twitter. The number of followers is an indicator for the relationship strength of the company with its customers (Thomases, 2010). Which leads to the fourth hypothesis,

H4 The number of followers increases the effect of the number of tweets and the brand index on stock prices.

The last moderator which will be taken into account are the news facts related to the brand. When a brand is high in attention it is expected that the buzz on the brand increases which lead to a higher number of tweets and depending on the news fact on a changes brand index. Further positive or negative news is an indicator for future cash flow changes which makes that news directly influence stock price to change.

H5 News related to the brand influences all construct of the conceptual model. The direction of the effect depends on whether the news is positive or negative.

4. Methodology

4.1 Data collection

All the data will be collected from different online sources. The number of tweets and the sentiment will be downloaded from http://twittersentiment.appspot.com/. The site stocks tweets since May 28 (2010). Twitter Sentiment is created as an academic project by three Computer Science graduate students at Stanford University. The side is currently lead by Google, Twitter and Amazon. Al the tweets are saved per day and splitted in positive, negative and neutral mood. Only the positive and negative tweets are saved and can be used for the brand sentiment index. Data will be collected for one year from May 28, 2010 till May 28, 2011.

The number of followers can be found on http://www.twittercounter.com. The side tracks the number of followers on a daily basis.

The stock price of the NYSE will be downloaded from http://finance.yahoo.com/.

News will be extracted with the help of http://www.google.com/trends. A site which gives insides in the most searched items on google. Google Trends tries to relate the search trend to news items. This variable will be taken into account as either positive or negative.

4.2 Brand selection

The brands will be selected based on the position in the ASCI. Three industries will be chosen and further analysed: “food” industry, Internet retail, airlines. In each of the industries the best and worst performer of the satisfaction index will be chosen. In order to have enough data it is important that the corporate name is the same for the products as for the business. For a business like Unilever data is lacking since it is a corporate name. Another problem is that some business names have also a different meaning like Apple and Target. Which gives the following outcome for the “food" industry: Starbucks and MacDonalds, Internet retail:

amazon.com and eBay, and airlines: Southwest Airlines and American Airlines. It would be good to analyse different industries and companies to see whether effects could be generalized or whether effects are specific for a company or industry.

4.3 Model Specifications

All the data in the model are daily measured, which gives suggestions for a times series mode. Like the Luo (2009) I will use a VAR approach. The advantage of this modeling approach is that it can model dynamic interactions among brand emotion index, number of tweets, and stock prices. VAR is a time-series method that can simultaneously estimate a system of equations. VAR has several advantages over alternative model specifications. First, it can estimate both short and long-term effects. Second, the model allows for feedback effects. The persistence modeling approach of Dekimpe and Hanssens (1999) will be used.

The persistence modeling approach starts with determining which variables should be included in the model as endogenous. To determine the endogenous variable a Granger Causality will be executed. This test can be used to determine how variables are related to each other. The second step is the unit root and cointegration test to determine in what form the endogenous variables have to be used in the model. The third step is estimating the dynamic interactions between the endogenous variables, which will be done by executing a VAR model. The methodology will be done with the use of e-views.

5. Planning

Action	Deadline
Hand in preliminary thesis report	12.01.2011
First try of company: Starbucks	24.01.2011
Discussion of report and Starbucks	24.01.2011
Improving model and further data collection	January, February, March
Literature review	March, April
Data analysis	April, May
Conclusion	June, July
End version	1.09.2011

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