

Text Mining

An Aspiring and Innovative Technique to Measure Emotions

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Text Mining: An Aspiring and Innovative Technique to Measure Emotions

An Investigation of Changes in Affective Status and Linguistic Style in the Enron Corpus

Master Thesis

Maastricht University

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I6026996

Track:

Finance

Assignment:

Master Thesis

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Date:

January 22nd 2016

Abstract

This Thesis investigates a new measurement technique for emotions. Text mining is used to measure changes in affective content, as well as, in linguistic style in the Enron corpus. LIWC 2007 measures the percentage amount of words that belong to categories associated with emotions and linguistic style. We found a sharp decrease in the intensity of affective content and found little evidence for an emotional dependence on the stock price. Both findings are strongly depended on the frequency used. Two different approaches are conducted for the analysis of linguistic style and both lead to different results. Whereas the first approach shows constancy in the LSM score over the whole time period, the second method fails to find a constant or increasing LSM score. Overall, the new measurement technique is successful in measuring changes in emotions and linguistic style and could lead to stronger results, especially for the LSM score, when a longer time period is considered.

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1. Introduction

With most of the decisions made, might it be a decision of either high or less importance, people tend to think that they judge and choose in a conscious, wise and rational manner. Unfortunately, in the majority of the cases this is not the reality. Most of the decision-making processes trigger a conflict between intuition and logic. What do you eat or drink? What do you believe in? Who do you fall in love with? How much risks are you willing to take when making financial decisions? Thus, researchers try to shed light on the conflict that takes place in everyone's mind, in order to understand how far it affects the decision-making process. This helps to understand why and in which particular situations a person makes intuitive decisions rather than logical ones. After 30 years of research on the topic of affective content on decision-making, it has turned out that people behave in an irrational way and are likely to be influenced by emotions that lead them to intuitive decision-making. Daniel Kahnemann, one of the leading scientists in the field of decision-making, gives one of many examples, which is associated with cab drivers in the United States. On a sunny day the demand for cabs is much lower than on rainy days, such that on rainy days the cab drivers can earn higher profits. However, cab drivers tend to finish their job earlier on rainy days than they do on sunny days, which seems to be irrational from a value based perspective as they would increase their return behaving differently. From a value maximizing perspective, a cab driver should work longer on rainy days. However, this is not the case due to the fact that most cab drivers in the United States have a daily target that they want to reach and once they hit the target they stop working and go home. They view as being below the target as a loss and being above the target as a gain and they are more concerned about preventing the loss than about achieving a higher gain. From a profit maximizing perspective, this kind of behavior does not make sense, as one would assume that cab drivers work longer on rainy days and take their leisure on sunny ones (Jettpace, 2013). Another example is that people, when asked which word is more likely to be observed, a word starting with the letter "r" or a word with an "r" on the third position, tend to answer that the first possibility is true. This is because it is easier for individuals to think of words that start with the letter "r" even though there are almost three times as many words with an "r" on the third position. This kind of bias is known as the availability heuristic in assessing probabilities and frequencies (Fiske, Gilbert

& Lindzey, 2010). Both examples mentioned reveal that there is a discrepancy between logic and intuition in the decision making of people.

One element of intuitive decision-making is emotions, which play a key role during the decision process, and therefore, it is highly important to gain a deeper understanding of how emotions affect this process. However, existing research on emotions is scarce and current research techniques have large shortcomings that might lead to biased results. Former experiments asked participants to engage in several, unrelated studies, in which their temporary emotional state has been manipulated by either showing cheerful or depressing movies (Andrade, 2005) or by giving positive or negative performance feedback (Barone, Miniard, and Romeo, 2000). To observe the depended measure of interest, a second study has been conducted directly after manipulation took place. However, this procedure is difficult to be applied outside the lab because it often creates potential cofounds and the resulting affective state dissipates quickly. Another approach is to ask participants to recall their affective experience and to document it. Nonetheless, this approach has also essential drawbacks, such as the need of high participant motivation, as well as an underestimation in the intensity of experienced emotions (Cohen, Pham, and Andrade 2008). Therefore, both approaches are weak in terms of measuring emotions, leading to the need of a new measurement technique. In this study we are going to apply text mining in order to measure emotions and we are going to test if this technique is suited better than the techniques that are used so far. Text mining is a tool that is similar to data mining. However, the difference is that text mining involves the process of structuring a large amount of a specific data, namely text.

The definitional approaches to text mining vary considerably. Structured data is managed with the use of database systems. Text data, however, is managed with the use of search engines, where keywords are enquired due to the lack of structure. In order to increase the effectiveness and efficiency of search engines, a great process has been established within the information retrieval, in the fields, such as text clustering, text categorization and text summarization. The primary goal of text mining is information retrieval, which has traditionally focused on providing easy access to information rather than on the analysis. While the goal of access to information is to connect the right information at the right time with the right user, text-mining tools, such as LIWC 2007, have the additional capability to

help the user to analyze information in order to gain a deeper understanding of the problem at hand by discovering interesting patterns, trends or outliers. (Seidel, 2013)

In this study we are going to use LIWC 2007 to analyze the Enron corpus that is free available in the Internet. It is a data set of the email correspondence of Enron's employees, which was written from 1998 until 2002, amounting to four gigabyte of text. We use the sent folders of the cleaned version and sort them on a weekly, as well as on a daily basis, such that all emails written during each week (day) are included in one single text document. Then we run each text file through LIWC 2007 in order to get the linguistic output, which we need for our further analysis. The overall purpose of this study is to use a newly and innovative measurement for emotions and to test how reliable it is when analyzing the Enron corpus.

Enron was established in 1985 by Kenneth Lay, the CEO of Houston Natural Gas, by acquiring InterNorth and changing the two merged companies into Enron Corporation. In the 1980's the States Congress of the United States passed legislations allowing a deregulation of the sale of natural gas, and in the 1990's a deregulation of the sale of Energy. This led to a new era in the energy market, which Enron benefitted considerably from. Enron's primary operations were the distribution of natural gas and electricity in the United States and the sale of pipelines and power plants worldwide. Even though the operations mentioned before were Enron's core businesses, most of the companies growth came from non-energy related operations, such as derivative trading, risk management, Internet bandwidth and the distribution of TV-quality movies via Internet. Nonetheless, Enron experienced a huge downturn, starting in early 2000, as the costs of new investments made could not be recovered. In addition, the losses made could not longer be hidden from the investors as they realized that most of Enron's former growth was due to accounting tricks rather than real growth, which would have ensured an inflow of real capital. On December 2nd 2002, Enron filed for Chapter 11 bankruptcy protection, which was the largest bankruptcy in history at that time (McLean & Elkind, 2013). We are going to use the dataset of email correspondence in order to measure changes in affective status. As time passes towards bankruptcy, we should observe a change in affective content towards negative emotions. Thus, our first hypothesis is the following:

Hypothesis 1: The magnitude of affective content changes towards negative emotions as time passes by towards bankruptcy.

This implies that there has to be a decrease in words used, which are associated with positive emotions and an increase in words used, which are associated with negative emotions. Therefore, Hypothesis 1 is divided further into the following hypotheses:

Hypothesis 1a: The use of words associated with positive emotions decreases as time passes by towards bankruptcy.

Hypothesis 1b: The use of words associated with negative emotions increases as time passes by towards bankruptcy.

On August 23rd in 2000, Enron's stock experienced its all time high and steadily decreased afterwards. The mood of Enron's employees is closely linked to Enron's stock price, thus, we should first observe a change in the magnitude in affective content towards positive emotions and, after the stock price peaks, a change in the magnitude towards negative emotions. Therefore, we hypothesize the following:

Hypothesis 2: The intensity of affective content is higher the year before Enron's stock hits it's all time high and lower the year after.

Hypothesis 2a: The use of words associated with positive emotions is higher the year before Enron's stock hits it's all time high and lower the year after.

Hypothesis 2b: The use of words associated with negative emotions is lower the year before Enron's stock hits it's all time high and higher the year after.

In order to find the relation between the intensity of affective content with the stock price, we are going to run a regression, where the measure for the intensity of affective content is the depended variable and the stock price, as well as other indices and commodities, that are related to Enron's business, are the independent variables. As will be explained in more detail in Section 2, there was an obsession on the stock price by Enron's employees, which was influenced by stock price charts that were visible everywhere on screens throughout the headquarter in Houston. Therefore, we hypothesize that there has to be a positive relation between the intensity of affective content and the stock price.

Hypothesis 3: There is a positive relation between Enron's stock and the intensity of affective content.

Besides the measure for affective content, LIWC 2007 gives us the possibility to analyze changes in linguistic style over time. Prior research suggests that the writing style of people becomes more similar in the course of time because people mimic each other in order to increase the sense of belonging. According to this, we should observe an increase in the score of Linguistic Style Match (LSM) when time passes by.

Hypothesis 4a: The LSM measure increases from 1999 until 2002.

However, it is also likely that we observe the LSM score to be constant over this period as the time period we consider only includes the final years of Enron's existence. This would imply that the adjustments in linguistic style occurred earlier in time. Therefore, Hypothesis 4b is the following.

Hypothesis 4b: The LSM measure stays constant from 1999 until 2002.

We find evidence, that supports Hypothesis 1, 1a and 1b, showing that the magnitude of affective content changes towards negative emotions and consequently, leads to a decrease in the use of words associated with positive emotions and an increase in words associated with negative emotions. Additionally, we find support for Hypothesis 2, 2a and 2b, which imply that we find indirect evidence for the existence of a positive relation between the stock price and the intensity of affective content. However, we find contradicting results when using daily frequency and, therefore, depending on the frequency we also find inconsistent results with Hypothesis 2, 2a and 2b. Moreover, we find mixing evidence for Hypothesis 3 as it also depends on the frequency that is used. When using weekly frequencies, the results are inconsistent with Hypothesis 3 but are consistent when using daily frequency. A further discussion on the distinctive findings when choosing different frequencies is given in Section 5. When turning our analysis on the linguistic style of written mails, we find that overall the LSM scores are extremely high and quite similar over the time period considered when using Formula 2. Those results are in line with Hypothesis 4b, meaning that the LSM score stays constant over time. However, when using Formula 3, we obtain a different picture where the LSM score increases from 1999 until 2000, stays constant from 2000 until 2001 and decreases in the last year. This finding contradicts Hypothesis 4b as the LSM score varies over the three years considered and, additionally, we find no support for Hypothesis 4a

because the LSM score only increases from 1999 until 2000 and for the rest it stays constant or decreases. Therefore, we find mixed evidence as the second formula leads to LSM scores, that are not constant over time and do not show a clear trend. However, when using Formula 2, we do find a constant LSM score.

Considering all results, we find evidence that supports most of our hypotheses mentioned above, especially for changes in affective content. Therefore, we can conclude that the new approach for measuring emotions works well but for measuring the LSM score of a company, a longer time period needs to be considered to gain a clearer picture and a better understanding of trends in linguistic style. Thus, further analyses with the use of improved text mining procedures are a promising field that can shed new light on the topic of decision-making, as well as, on changes in linguistic style in a corporation.

In the following, we are going to support our hypotheses with former research that has been conducted on the topics of emotions and linguistic style. Furthermore, we are going to discuss Enron's history and its obsession on the stock price in more detail. Section 3 is going to deal with the methodology of the analysis that we conducted in this study and Section 4 is going to analyze the resulting outputs. Section 5 is going to provide a more profound discussion on the results, as well as, on the shortcomings of the methodology used and the consequences of those on our outcome. Lastly, Section 6 is going to summarize all the results, discuss academic and managerial implications and finally draw a conclusion of this study.

2. Literature Review

2.1. Enron

Within 15 years Enron has become the nations' seventh biggest company in revenue and was seen as a paradigm, how an American company has to be run, how the culture has to be established and how creativity is used in order to capture opportunities. Enron's image before bankruptcy was remarkably positive as becomes evident when considering the statement by an utility industry analyst at Deutsche Bank called Edward Tirello, who named Enron as,

“The industry standard for excellence” and as the Financial Times wrote in the late 90’s, “Enron is the one to emulate” (McLean & Elkind, 2013).

2.1.1. Enron before 1990

Enron was formed in 1985 due to a merger between HNG (Houston Natural Gas), a utility company and InterNorth, a gas pipeline company (Internorth of Omaha). Kenneth Lay served as the CEO of HNG and even though InterNorth was three times the size of HNG, Ken Lay became the CEO of the two merged companies. The name of the two merged companies became Enron and the headquarter has been shifted from Omaha to Houston. From a business perspective, the two companies were a promising combination with a pipeline network of 37,500 miles, a market value of \$12 billion and possession of the largest gas-distribution system in the United States, that reached from the southern border to the northern one and from the east coast to the west coast. Additionally, the new-formed company had access to the three fastest growing gas markets in the country, namely, California, Texas, and Florida. (McLean & Elkind, 2003)

However, in the late 80’s, after the merger took place, the new-formed company had financial trouble in meeting their obligations as deregulation did not took place as fast as expected by Kenneth Lay. He operated on the theory: “get big fast”, which was creating even bigger problems for Enron in the first glance. In 1978, the Congress increased the regulated price that would be paid to producers, creating an increase in supply by exploration companies. Unfortunately, the demand for natural gas was extremely sensitive to price changes, thus industrial customers switched to coal or fuel oil as prices rose. Why did it create such an immense problem for Enron? As Lay believed that deregulation in the gas industry was inevitable in the near future, consequently leading to the believe that prices for gas will decrease and create an increase in demand, Enron signed “take or pay” contracts instead of long-term deals with their producers. Now, Enron was obliged to pay for the gas at the new higher rates even if they did not need it. There was a surplus of gas in the market but no demand for it, prompting prices to plunge to levels that nobody had ever imagined, creating more than \$1 billion in take-or-pay liabilities. Consequently, Enron reported a loss of \$14 million for its first year. (McLean & Elkind, 2013, pp. 9-14)

Due to Rich Kinder, the number two executive behind Kenneth Lay, things settled down at Enron in 1988. Kinder started to cut costs to a minimum and helped Enron to negotiate its way out of the take-or-pay contracts with remarkable little financial pain such that Enron was generating positive cash flows at the end of 1988 (\$109 million) (McLean & Elkind, 2013, p. 27).

2.1.2. Enron after 1990

In June 1990, Jeff Skilling, a former consultant at McKinsey, joined Enron and became chairman and CEO of Enron Finance, a new division that was created exclusively for the purpose to put a revolutionary idea Skilling's from theory into reality. He called it the "Gas Bank". The initial purpose was to diminish the level of risk for every player involved in natural gas transactions, which led to a reshaping of the whole industry. The basic idea was that in the "Gas Bank", where three different kind of parties were involved, the producers would contract to sell their gas to Enron on the one hand, thus acting as depositors, and on the other hand, the gas customers would contract to buy the gas from Enron, therefore, acting as the borrowers. Enron (the bank) acted as a market maker in the natural gas industry, capturing the profits between the price Enron promised to sell and the price it paid to acquire the gas. In addition, Enron was the first company that began trading the contracts in the same way as oil-future contracts were traded. This put the company at the very center of the newly emerging market and in an informational advantage compared to their competitors, as Enron had unique information on demand and supply creating "an immense network of physical assets, as well as the ability to tie all the moving pieces together and provide physical delivery on the gas itself" (McLean & Elkind, 2013, p. 38). There was another major change in Enron due to Jeff Skilling that should have immense consequences on the company and much what happened later at Enron could be seen as a consequence of this change. (McLean & Elkind, 2013, chapter 3)

Jeff Skilling replaced the accounting method at Enron from historical-cost-accounting to mark-to-market accounting. The differences between the two accounting types are that for the former one "the value on the books reflects the initial assumption over the life of the deal" (McLean & Elkind, 2013, p. 39), no matter if the economic situation changes. The latter one takes differences in the economy into account by adjusting the value for fluctuations in the market. Even though this sounds superior to the conventional accounting method at the first

glance, after mentioning the second major difference, it becomes clear that mark-to-market accounting is susceptible to abuse. Where in historical-cost-accounting one can only book the revenues from a contract as they come through the door, mark-to-market accounting gives one the possibility to book the entire estimated value for the whole timespan on the day the contract is signed. As the value for gas can not be determined as precisely as the price of a share of stock, there was a lot of freedom in valuing these contracts and, thus, in abusing this particular accounting treatment. “Over the years, Enron extended mark-to-market accounting well beyond natural gas to other areas where the value was even more subjective and abuse even more tempting” (McLean & Elkind, 2013, p. 40). Surely, this led to a large discrepancy between the profits, that Enron was reporting and the cash it had to run the business. All the worse, reporting the entire value of the deals upfront, generated a rapid growth in Enron’s earnings and the stock rocked upwards. Originating a constant annual growth of 15 per cent and beating the previous quarter, as promised to Wall Street, was practically impossible with honest and ethical business. Surprisingly, Enron made it possible to manipulate their accountings on an extremely large scale and to hide losses and unethical practices for a very long time period even though it was one of the biggest companies in the United States with immense media attention, as well as, with a high amount of other parties involved in Enron’s businesses. The following section is going to describe Enron’s culture and the resulting stock obsession. (McLean & Elkind, 2013)

2.1.3. Enron’s Culture & Enron’s Stock Obsession

As it has been mentioned already, Jeff Skilling had the unique opportunity to put his ideas into reality and took action by creating the Gas Bank, as well as, changing the accounting treatment at Enron. Moreover, he had a clear vision of how a corporation has to be built and how it has to function, how the treatment among employees should work and how the compensation scheme should look like. The culture that Skilling wanted to establish was a Darwinian one, where intelligence and creativity were of bigger importance than real life experiences and management skills. Young graduates should be free to chase their ideas and to make them alive, backed with company millions in hand with fabulous rewards for generating profits. However, there was no room for failing and who did fail was directly laid off. In Skilling’s newly established world the greatest motivations were greed and money. “I’ve thought about this a lot, and all that matters is money. You buy loyalty with money. This touchy-feely stuff isn’t as important as money. That’s what drives performance” as Jeff

Skilling once told Terry Thorn, a former Enron executive (McLean & Elkind, 2013, p. 55). Changing Enron's culture meant also to hire new employees that fit best in the newly established culture. These were MBA's or executives with mostly one singular narrow talent or "Guys with spikes" as Skilling used to say. As long as they had the talent that skilling needed, their shortcomings and team ability was of low importance. Surprisingly, a lack in the capacity in teamwork was exactly what Skilling was looking for. "Jeff always believed pitting three people against each other would be the quickest way to assure the best ideas bubbled to the top. He wanted them to fight", a former trading executive once said (McLean & Elkind, 2013, p. 56). However, this created a mismatch between the creation and implementation of new ideas and the resulting maintenance of these projects. Consequently, this led to corporate infighting between the originators and the traders. The former ones had the pressure to come up with new deals that were generating money increasingly on paper without creating any real cash flows. As mark-to-market accounting was the practice in Enron, the originators did not care what would happen after the deal was completed. By the time it was clear that the deal had become unprofitable, the originators already received their bonuses and moved on. As a former executive Amanda Martin put it: "People became deal machines. All you had to do was bring them in the door". Making it worse "the corporate culture was such that you never say no to a deal and you didn't want to be seen as someone saying no to a deal", as a former employee in the corporate finance department once mentioned (McLean & Elkind, 2013, p. 116). However, with every new deal completed, the burden for meeting demand increased for the traders because they were responsible for hedging the price risk and long after the originators received their compensation, the traders still had to bear the risk that the project becomes unprofitable. This created tension between the two divisions but as Skilling believed in creative tension, this problem was not perceived as one (McLean & Elkind, 2013, p. 62). (McLean & Elkind, 2013)

Even though Skilling thought he was acting in the firm's best interest and believed that the culture he established put Enron into a competitive advantage, he created a dysfunctional enterprise and turned Enron into a "chaotic, destructive and free-for-all" workplace (McLean & Elkind, 2013, p. 56), that was dominated by "corporate killers" as one executive reveals, where "you always had to look out for someone stabbing you in the back because the prize was so high" (McLean & Elkind, 2013, p. 121). It became a culture of excess where nothing was too over-the-top (McLean & Elkind, 2013, p. 122). Furthermore, the use of perquisites increased where "people began spending money as if every day has been Christmas".

Hundreds of dealmakers were flying first class around the globe staying at luxury hotels and even junior executive had the authority to hire expensive consultancy. Consequently, these led to an immense increase of costs that no one took care off. Bob Schorr, a company veteran, who worked as a gas marketing executive, illustrates how far beyond rationality company spending went: “If you met your earnings target, you’d get your bonus, even if you spent twice your budget for expenses. If you are told to make \$25 million, it doesn’t matter how much it cost you to make that \$25 million” (McLean & Elkind, 2013, p. 119). (McLean & Elkind, 2013)

During the Skilling era, next to the deal closing desire, the stock became Enron’s obsession. A constant update of the share price was given in the headquarters lobby that could be observed on the stock ticker. In the elevators CNBC was broadcasted on TV monitors, such that the stock price was everywhere omnipresent. Skilling’s mood was strongly depended on Enron’s share price. “The stock price was his report card. When it rose, he was exultant; when it dropped, he was glum. Whenever Skilling was on the road, he would call several times a day just to check on how the stock was performing,” says a former aid (McLean & Elkind, 2013, p. 125). Consequently, Skilling was basing his business decisions entirely on the resulting effect on Enron’s valuation. However, Skilling was not the only one obsessed by the stock price. As the share price was omnipresent at Enron and on average, employees kept more than half of their 401(k) retirement holdings in Enron’s shares, practically everyone was highly concerned about the stock price. Therefore, it was for each employee and executive of great importance to meet its quarterly earning targets, which again led to a bigger incentive to abuse the accountings and to act in an unethical manner (McLean & Elkind, 2013, p. 125). Thus, we believe to observe a positive relation between the stock price of Enron and intensity of affective content as a decrease in the measurement relates to a stronger magnitude towards negative emotions that might be, amongst other things, due to a decrease in the stock price. (McLean & Elkind, 2013)

In the next section, we are going to take a closer look at Enron’s two new business opportunities, which were supposed to recover the losses experienced in the years before. Those losses were hidden with the help of creative accounting, opportunistic valuation by mark-to-market accounting, by delaying recorded losses to the next quarter and by backdating data with the support of legally independent entities (called LJM1, LJM2, and later Raptor 1,2,3 and 4), which actually were not independent at any moment as the CEO of

these entities was Andy Fastow, Enron's CFO. By stretching and bending the rules to Enron's favor, employees did not feel guilty for misleading other stakeholders but rather they saw their actions as creative. "Budget shortfalls weren't just business issues, they were accounting issues. There was an absolute conviction at Enron that clever accounting could alter the business reality", claimed a former accountant at Enron (McLean & Elkind, 2013, p. 142). The question at stake is how long will it last until everything will collapse? (McLean & Elkind, 2013)

2.1.4. The Big Enchilada and the Big Fall

All accounting practices that Enron underwent were not meant forever and were supposed to function as a sort of bridge until Skilling's new big idea or as he called it, "the big enchilada" kicked in. In 1997, Jeff Skilling became President and the Chief Operating Officer for Enron and became simultaneously the most important person in the company next to Kenneth Lay. Skilling was betting on two big opportunities, which were the "Enron Energy Service" (EES) and the "Broadband business" pushing both with billions of dollars to make them work. (McLean & Elkind, 2013)

The aim of EES was to capture the retail side of the Energy market by providing electricity, gas and energy management directly to the customers. In order for EES to succeed, it was essential to deregulate the energy market in the United States. Since Kenneth Lay had close ties to regulators, Jeff Skilling and Ken Lay were convinced that they were able to make it happen. Unexpectedly, the utility owners had closer ties to regulators, which were close enough to withstand the enormous amount of money Enron was spending for government affairs that amounted in an annual spending of \$37 million in 1999. A senior member of the Enron government staff claimed: "Jeff (Skilling) thought you could throw money and buy people and they did what you told them to do" (McLean & Elkind, 2013, p. 173). Even though it was much harder to push deregulation through the energy business than it was expected, Kenneth Lay and Jeff Skilling convinced some states to open up. For electricity, New Hampshire and Pennsylvania approved limited pilot programs and for gas, Ohio gave it an attempt. California even deregulated the whole energy market in 1998, such that Enron was finally allowed to sell power directly to companies and households. However, this was not enough to cover all EES's costs. Enron expected to start making profits at the tail end of their contracts since they assumed that half of the U.S. retail market would be opened by

2001. In fact, only a quarter of the market had opened up and the deregulation effort had come to stagnation. Along with the problem caused by deregulation, there has been a much bigger issue, namely, that Enron was not as good at executing deals as at making the deals. According to David DeMauro, a Californian State administrator, EES never got it right from the very first month that the contract went into effect. Further, “There was no situation, where the bills were either on time or correct. We probably went five or six month without paying Enron at all, which summed up to around \$40 million in accounts payable” (McLean & Elkind, 2013, p. 183). Nonetheless, it was crucial to execute the deals appropriately when being an energy provider at the retail side and, especially, when trying to convince the regulatory body of the advantages of deregulation which was immensely important for the project to become profitable. Unluckily, Enron’s approach was: “Let’s sell it and we will figure out everything else later” as Glenn Dickson, a back office manager, recalls it (McLean & Elkind, 2013, p. 184). (McLean & Elkind, 2013, Chapter 12)

The Broadband business had nothing to do with energy. It was Enron’s venture to become a high tech company by laying a fiberoptic network over the whole country to move Internet data in high speed. After spending billions of dollars to build those networks, Enron’s executives hoped to trade bandwidth, or putting it differently, to trade the capacity on the fiber optic networks just like natural gas and electricity. In addition, they wanted to distribute TV-quality movies and other video content rapidly at a reasonable price. However, there were many problems involved with the ventures mentioned above, especially, in the limited time of two years of development. Take trading first, Enron wanted to enable customers to buy only the capacity they needed and only at the time when needed, however, a real time switching of broadband capacity is practically impossible as this would mean to send workers out to change connections by hand. Another issue was that the telecommunication companies were the owners of the existing networks, were not interested in hooking up into Enron’s systems as it would reduce their own profits. Further, Enron needed to develop a set-top box that was supposed to cost \$500 a piece, which led to high expenses without any promise to capture those costs because Enron would compete with the cable-television industry, which already had wires and boxes in millions households in the United States. (McLean & Elkind, 2013, pp. 286-287). (McLean & Elkind, 2013)

Attempting only one of “the big Enchiladas”, without any previous experience, was an enormous effort that required an extraordinary commitment to talent, time and resources.

Both ventures had tremendous obstacles that had to be overcome, aligned with huge costs that had to be incurred in order to bring those businesses into reality. The broadband division made a loss of around \$500 million in 2000 (McLean & Elkind, 2013, p. 287) whereas Enron Energy Service made losses of \$119 million in 1998 and \$65 million in 1999 (McLean & Elkind, 2013, p. 179). Again, instead of concentrating on building the business, Enron started to play accounting games but this time on much greater scale. Those games went well as long as the market was bullish since most of the losses were transferred to the “legally in depended” entities that were backed up with Enron’s rising stock. Nonetheless, the overall market started to decline and Enron ran into problems, as the “legally in-depended” entities could not be longer backed by an increasing stock price. This led to a closer investigation of Enron’s finances by various investors and journalists and, therefore, they started to find indications of wrong disclosure in Enron’s financial statements. This increased the skepticism about the company and the amount of investors that started to shorten Enron’s stock, as well as, the amount of journalist and analysts that started to write negative reports on Enron, leading to a further decrease in the stock price. After Enron’s all time high in August 2000 at \$90.56 a share (McLean & Elkind, 2013, p. 318) it dropped to \$16.41 (October 24th, 2001) a share in only one year (McLean & Elkind, 2013, p. 377). It became apparent that most of Enron’s earnings were due to capital sales and accounting creativity and not due to operating income. At Enron, it was bookable accounting profits, not cash coming in the door. On October 24th Enron realized that it had no cash to cover its obligations. After the deal with Dynergy, which was an acquisition of Enron, did not work out, Enron got downgraded deep into junk-company territory on November 28th. The downgrading led to a violation in Enron’s debt contracts and triggered further \$3.9 billion in debt that was due immediately. At that day Enron’s share dropped to 61 cents a share. On December 2nd, Enron’s lawyers filed the largest bankruptcy case in the history of the United States, with a total outstanding debt of \$38 billion, both on and off the balance sheet (McLean & Elkind, 2013, p. 405). As there was a large downturn for Enron in most of the time period covered in the dataset, we believe that there will be a decrease in the measure of affective content in the course of time with a break point surrounding the 23rd of August in 2000 and, thus, leading to Hypothesis 1 and 2. (McLean & Elkind, 2013)

The next part is going to focus on the latest findings in the field of behavioral finance and on the role of emotions on the decision-making, as well as, on changes in linguistic style during various forms of conversations between two or more parties.

2.2. Emotions

Emotions and their relation to rationality have been of big interest in the past hundreds years and fascinated many philosophers and classical writers. However, only in the last 30 years, the subject of emotions has become popular in the scientific world, in fields, such as economics, psychology, sociology and history, to mention only a few of them. Scholarly papers on emotions doubled from 2004 to 2007 and again from 2007 to 2011 and nowadays, most scientist belief that emotions are the key drivers on a person's essential decisions (Lerner, Li, Valdesolo, Kassam, 2015). The relation of emotions and rationality cannot be explained with just one study that gives the best and only answer but rather a study can provide a fractional answer on the overall picture. There is also the fact that empirical evidence on the relation between emotions and rationality are partially inconsistence. Thus, all studies conducted so far should be considered in conjunction to provide a clearer understanding of the topic and, therefore, this section provides an overview of the empirical findings that have emerged in the past 30 years.

Before dealing with emotions itself, it is necessary to mention three different types or concepts of rationality in order to understand the outcomes of research on emotions. The first concept of rationality relates to logic and infers that a person is rational if her belief, choice, decision, action, as well as judgment obey certain standard of logic. One example is transitive preferences in choices, meaning that if a person prefers a product A over B and prefers product B over C, than in terms of logical rationality, she should also prefer product A over C. The second concept, which is a person's judgment on different choices depending on the question if it maximizes someone's individual utility, relates to material rationality. Hence, an individual is material rational when a choice of action is consistent with someone's goals or objections and aligns someone's self interest. The third type can be referred to as "ecological rational" meaning that someone's behavior and choices on action may be purely due to consistency with social objectives and norms, moral standards and evolutionary purposes and not because of logical or material perception. The following part deals with emotions, the relation to rationality and consequently, explaining the implication of the empirical findings of the last 30 years. (Pham, 2007)

According to Bodenhausen (1993), two types of emotions can be distinguished, namely, integral emotional responses and incidental emotional states. The former ones are emotions that are the outcome of real, anticipated or imagined characteristics of the target object

whereas the latter ones are emotional states that or not caused by the target object but are still carried over to the target.

2.2.1. Integral Emotional Responses

Integral emotions are feelings which arise from judgment and choice close at hand, either conscious or non-conscious, that strongly shapes the decision making of an individual, as well as, a group of individuals (Greene & Haidt, 2002). If a person is anxious about the potential outcome of a risk choice, she might ignore the more lucrative option and might choose the safer one. Thus, taking the risk creates a negative feeling and makes the risky choice undesirable, which infers that integral emotional responses are used as proxies in the valuation process that can take different properties under different circumstances (Damasio, 1994). Those are mentioned below.

- **Speed and processing efficiency:** From an ecological view, speed and processing efficiency provide a fast and resource efficient evaluation of value, requiring less processing time. This is essential for decision making under time constraints or with a high cognitive load. Empirical findings show that individuals' decisions, which are based on integral affective responses, are realized faster than those based on descriptive inputs. (Pham et al., 2001)
- **Extremity and polarization:** Reactions on risk seem to be more extreme when risk is mentioned in an emotion-provoking manner. Sinaceur, Heath, & Cole (2005) found that newspaper articles with the label "Mad Cow disease" led to greater decreases in beef consumption than articles using less emotional labels, such as "Creutzfeldt-Jakob disease". However, it is not clear if the decrease in beef consumption is ecological, material or logical irrational and extremity, as well as, polarization should be viewed as a by-product of affective responses that redirects and motivates action and behavior. (Pham, 2007)
- **Myopia:** As it is more difficult to imagine an emotional experience further in the future, rewards and punishments have a greater effect in the present than delayed ones. Therefore, "affective rules of valuation seem to be geared to the present" (Pham, 2004).
- **Concreteness and scale insensitivity:** Affective decisions under uncertainty rely on discrete images of options that an individual can choose from, which do not

incorporate probabilities and continuous quantitative information as “they involve discrete prototypical representations of the target”. However, individuals tend to be sensitive to the possibility or the deviation from certainty. Thus, people are not sensitive to scale, which contradicts logical rationality. Lazarus (1991) argues that integral emotions evaluate value categorically in terms of their significance for well-being. (Pham, 2007)

- **Reference-dependence:** Emotional valuation is rather based on the relation to other objects than on the focal point considered in isolation. In a study by Hsee, Zhang, Yu, and Xi (2003) participants were asked to decide on either a job offer in company A, that offers a small office space where a comparable employee has an office space of the same size or on a job offer in company B, that offers a larger office where a comparable employee has an even larger office space, holding compensation and workload constant. When asked to make a choice between the two jobs, people tend to choose the job offer in company B. However, when asked in which of the companies they would be happier, participants tended to choose the job offer for company A. Hence, when a person is asked to make a cold choice, she focuses on the objective personal payoff. However, she changes her answer when she takes into account social comparisons with their fellow colleague, that is, she is reference dependent when asked to make a more affective valuation. This seems to be logically irrational but materially and ecologically rational. When considering the well-being of participants in the long run, they probably would be better off working in a company where they are treated equally, supporting the norm of justice. (Pham, 2007)
- **Interpersonal consistency:** Assessments based on integral emotions tend to be made in a way that they fit in conjunction with beliefs of others, meaning that individuals put a greater emphasis on judgments, that are consensual rather than subjective. Different findings suggest that that physical attractiveness or the taste of music is judged on the shared perception of people surrounding an individual (Langlois et al., 2000; Peretz, Gagnon, and Bouchard, 1998). (Pham, 2007)
- **Intrapersonal consistency:** Judgments based on affective integral responses do not only rely on interpersonal consistency but also on intrapersonal consistency over time, as well as, over choices. For high-involvement products, Darke, Chattopadhyay, and Ashworth (2006) found that a utility-based assessment about the product benefits is less predictive in the long-term satisfaction than integral emotional responses and

further, Lee and Ariely (2006) discovered that the transitivity of choices between goods increases when the reliance on emotions in the decision-making is enhanced. (Pham, 2007)

Integral emotions have various effects on the decision-making and take different forms of proxies in the valuation process by biasing or benefiting the decision making of an individual. An example of an integral affect bias in the decision making is a person that is afraid to fly and chooses to drive instead even though the mortality rate to be involved in a car accident is much higher (Gigerenzer, 2004). Further, Loewenstein et al (2001) found that especially intense and expressive emotions can override a rational course of action. Nevertheless, integral affect can also be a beneficial guide as anticipation of regret can inhibit excessive risk taking (Loomes and Sugden, 1982). Going one step further, a perspective on the overall society, it seems that integral emotions have an important role in the regulation of social and moral behavior with a mostly beneficial role. Anger, for example, supports the respond to injustice (Solomon, 1993) or guilt and shame arises when someone has violated certain norms whereas pride comes into play when someone has fulfilled those norms (Ortony, Clore, and Collins, 1988). Therefore, anticipation of emotional responses fulfills an ecological function in enhancing behavior that is morally and socially accepted. This leads to the fact that emotional responses are not just consequences of moral and social appraisals but also carry information to inform others about those appraisals. All in all, it seems that affective responses, as well as, their anticipation produce a socially desirable outcome that overrides someone's material self- interest. (Pham, 2007)

2.2.2. Incidental Emotional States

Many studies have discovered that incidental emotional states unconsciously carry over from one situation to another and trigger decisions that should be unrelated to the emotional state by a normative perspective (i.e. Loewenstein & Lerner, 2003; Pham, 2007). For example, Schwarz and Clore (1983) found that individuals wrongly reflected their personal feeling about their life due to weather-induced moods, meaning that participants that got surveyed on a sunny day documented a higher life satisfaction than participants surveyed on a rainy day. This might be an explanation for the above average performance of the stock market on sunny days. Hirshleifer and Shumway (2003) found that this is due to a misinterpretation of good mood as optimism and bad mood as pessimism about the stock market. Furthermore,

the misinterpretation of incidental emotional states seem to depend on the perceived representativeness of the affective state with respect to the target as the carryover disappears when individuals are made aware of the real source of their emotional state. (Pham, 2007)

The influence of affective states is a function of their valance, the intensity of the state and the appraisal content, which mostly, except for sadness, goes along with an impairment of working memory capacity (Darke, 1988), leading to deficits in the ability of reasoning by individuals. As Pham (2007) stresses out in his paper, a wide range of studies concentrating on anxiety found that anxious participants, perhaps partially driven by the involvement of the cognitive domain of worry, tend...

“...(a) to have lower ability to recall information and organize this information in memory (Mueller, 1977, 1978), (b) take longer to verify the validity of logical inferences (Darke, 1988b), (c) scan alternatives in a more haphazard fashion (Keinan, 1987), (d) select an option without considering every alternative (Keinan, 1987), (e) commit more errors in geo- metric and semantic analogical problems (Keinan, 1987; Leon & Revelle, 1985), and (f) process persuasion arguments less thoroughly (Sanbonmatsu & Kardes, 1988)”.

However, intense states of emotions also have beneficial aspects on judgment because they enhance the dependence on diagnostic information respective to non-diagnostic information. Moderate affective states shape the reasoning, judgment and, thus, the decision making of individuals as well. Pham (2007) states that ...

“...compared to neutral moods, good moods have been found to lead individuals to (a) categorize objects more broadly (Isen & Daubman, 1984; Isen, Niedenthal, & Cantor, 1992), (b) generate more creative answers in response-generation tasks (Greene & Noice, 1988; Hirt, Melton, McDonald, & Harackiewicz, 1996), (c) perform better in problem-solving tasks that require ingenuity (Greene & Noice, 1988; Isen, Daubman, & Nowicki, 1987), and (d) solve multiattribute decision problems more efficiently (Isen & Means, 1983)”.

Nonetheless, positive moods also lead to over optimism and a higher reliance on judgmental

heuristics. Therefore, as Pham (2007) continues, positive moods affect individual's reasoning on the decision-making in diverse ways by either promoting logically less preferable effects, like a less data driven and thorough mode of processing that is more top-down driven, or by promoting more preferable effects, like a problem solving procedure that is more creative and flexible. Furthermore, negative moods, in this case sadness, mirror the effects for positive moods described above as they decrease the dependence on judgmental heuristics and increase the vigilance of the information processing. Hence, persistent with logical rationality, sadness leads to a more data driven and analytical form of reasoning as this is necessary to solve a problematic situation that has created the emotional state of sadness. It is important to mention that anger and disgust differ to sadness in a way that they do not share the uncertain element of sadness, that promotes the systematic evaluation in the decision-making, but lead to a broader evaluation with an increase reliance on heuristics. However, they also share common characteristics like the effect on risk seeking since a strong negative emotional state decreases risk averseness and increases risk taking for potential gains, as well as, losses because the immediate goal of feeling better becomes superior (Tice, Bratslavsky, and Baumeister, 2001). This characteristic is, however, not shared with anxiety or fear. It is related to an uncertain situation of low control leading to higher risk averseness. As a result, the effect of emotional states cannot be just arranged by the valance but it is important to consider the level of arousal that is associated with the emotion, as well as, a function of the appraisal content (Lerner and Keltner, 2001).

The next section is going to combine all the findings above into a emotion-imbued choice (EIC) model proposed by Lerner, Li, Valdesolo and Kassam (2015) in order to get a clearer understanding of how all different aspects of emotions influence peoples' decision-making.

2.2.3. Decision-Making Model

The model in Figure 1, which is presented below, accounts for traditional inputs referring to logical rational choices and for affective inputs referring to the findings mentioned above. The Emotion Imbued Choice (EIC) model is a visual illustration of a choice process affected by emotions, which assumes that the decision maker has only a one-time choice between the options and has no opportunity to seek for additional alternatives, as well as, information on the options. Furthermore, the model does not include actual outcomes and resulting feelings,

which arise because of the decision made. Also, reflexive behavior is excluded, such as, sneezing after inhaling dust or the kicking leg when a doctor conducts the knee-jerk reaction test. However, it does include expected visceral influences, which form the decision process, as well as, emotions that a person considers up front before making the decision. Therefore, it is important to note that the EIC model does not try to explain all human behavior but rather tries to illustrate conscious and non-conscious decision-making of humans. Firstly, we are going to discuss the solid lines representing rational choice models taking into account expected utility theory. The decision maker evaluates her options by estimating the utility of the expected outcome for each option as it is represented by line A. Additionally, she takes into account the characteristics of the option (line C), such as, the probability of occurrence and the characteristics of herself (the decision maker) like personal preferences influencing behavior toward risk (line B). All three aspects influence the overall evaluation leading to a rational best option that is chosen by the decision maker (line D). (Lerner, Li, Valdesolo and Kassam, 2015)

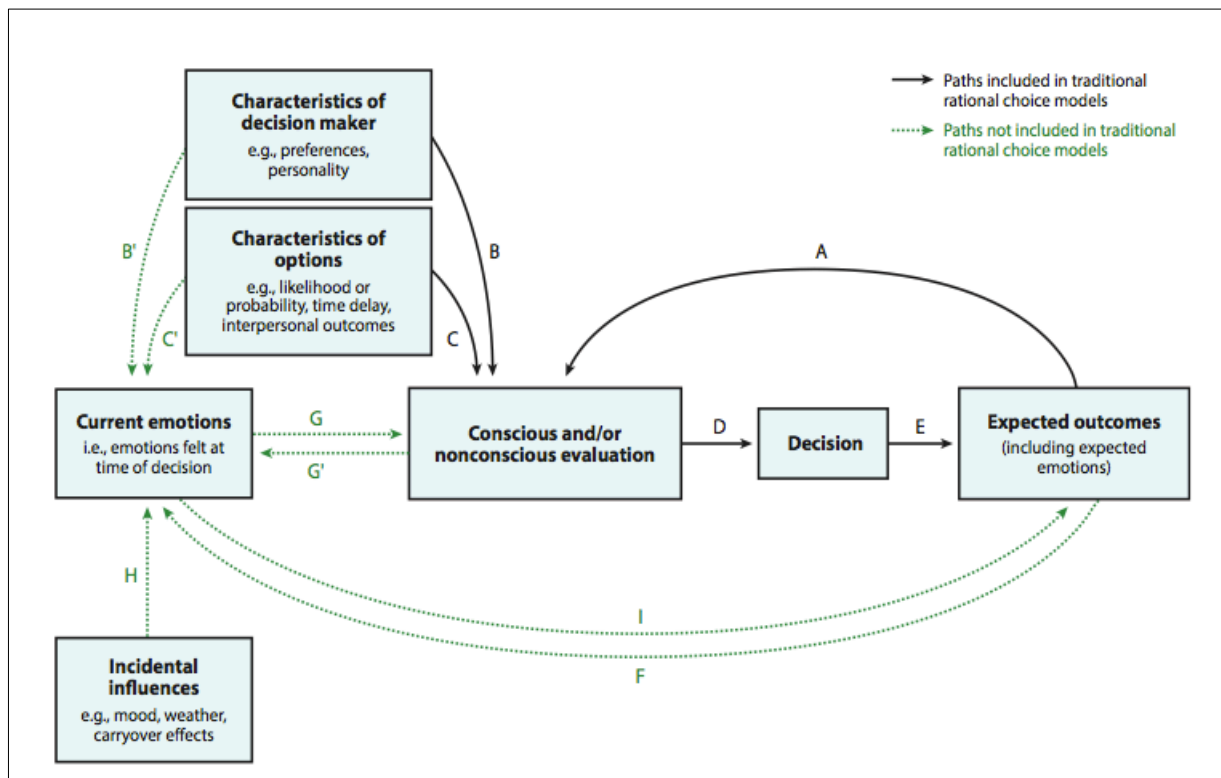
Next, we are going to add emotions to the decision-making process, that can be divided into expected emotions and emotions that are felt at the time when the decision is made. Even though predicted affective responses to the outcome are evaluated much like utility and, thus, are persistent with the concept of somatic markers¹ (both illustrated by line A), they differ in a way that the EIC model allows for constructed rather than stable preferences. Current emotions that are felt at the time the decision takes place are illustrated in green dotted lines and are outside the scope of logical rational choices model presented above. Five potential sources of current emotions can be observed in Figure 1. Line B' represents the influence of characteristics of the decision maker that can infer to a baseline level of current emotions. Those can be chronic disorder, such as, anxiety or depression. Further, characteristics of the option can directly affect the current emotional state by increasing anxiety if the probabilities are uncertain and are represented by line C'. Predicting emotions that occur if someone

¹ Somatic makers hypothesis states that “emotional responses evoke by objects are stored with memory representations of these objects as somatic markers of these objects’ value” (Pham, 2007). However, some people do not seem to learn from previous experiences and, therefore, they tend to choose courses of action that elicit unfavourable consequences. This is due to emotion-based biasing signals, which occur from the body that are integrated in higher brain regions, in particular the ventromedial prefrontal cortex. This brain region regulates the decision-making in situations of complexity. Evidence for the somatic makers hypothesis is mostly based on the Iowa Gambling Task (Damasio, 1994) Nevertheless, Pham (2007) argues that more recent findings by Shiv, Lowenstein, Bechara, Damasio (2005) show that the original findings by Damasio (1994) are not conclusive about the general material rationality or irrationality of integral affect as a proxy for value. Rather it depends on the correlation that is under researcher’s control, namely, between the emotional responses to the target and its criterion value.

chooses an option also have an influence on current emotions and are noted as line F. This might be the case if a person fears a decision because she anticipates a painful shock with the outcome of that choice. (Lerner, Li, Valdesolo and Kassam, 2015)

Figure 1

The Emotion-Imbued Choice Model by Lerner, Li, Valdesolo & Kassam (2014)



Line G' deals with the fact that evaluation can have a direct effect on the current emotion of an individual by causing frustration due to nearly equivalent outcomes of the decision options. The potential sources of current emotions mentioned above refer to integral emotions. Rozin et al. (1986) discovered that once integral emotions attach themselves to the decision target, it is difficult to detach them again. Besides the sources mentioned before, the last source of current affect is incidental emotions that are not related to the event but also have an influence on the decision-making. This can be the state of mood that is influenced by external events, such as, weather or news on the television. Those are illustrated by line H. The assessment of the potential outcomes is directly affected by current emotions and represented by line G. As described above, current emotions determine how rational a person decides on the inputs that are evaluated. For example, sadness decreases the reliance on

heuristics or increases the vigilance of the information processing. Therefore, the content of thought, debt of thought and content of implicit goals influence the evaluation of options in the decision-making process. Finally, as Loewenstein et al. (2003) stress out and as being illustrated by line I, current emotions can indirectly affect the decision-making by altering the predicted utility for possible outcomes. For example, sadness can lower the expectation of outcomes, such that, all options seem less rewarding. (Lerner, Li, Valdesolo and Kassam, 2015)

2.3. Linguistic Style

Former perceptions about shared views, that occur in conversations, in order to synchronize with others, assumed that those shared perceptions are dependent from conversational content (Giles and Coupland, 1991). However, Ireland and Pennebaker (2010) suggest that, regardless of content, the synchronization with others may be an unconscious outcome of linguistic style match (LSM) referring to the synchronized use of function words, including personal pronouns, impersonal pronouns, prepositions, adverbs, articles, conjunctions, auxiliary verbs, negations and quantifiers. The distinction between content words, which are the basic information that is conveyed, and language style, which is the way content is conveyed, are important in a sense that both types are processed differently in different brain regions. The Wernicke's area is linked to the use of content words whereas Broca's area is linked to the use of style words (Miller, 1995). Further, Ireland and Pennebaker (2010), as well as, Chung and Pennebaker (2007) argue that a high LSM during a conversation between two parties expresses a form of psychological synchrony, that decreases social distance and, thus, enhances perceptions of common social identity. This is in accordance with Fayard and DeSanctis (2010). They refer to "language games" where members of an online text based platform comply to the overall style in a forum in order to demonstrate their association with the group. The importance of function words and, therefore, the need for consideration of LSM is supported by Bird, Franklin, and Howard (2002), who found that on average 55 per cent of English speaking people daily word usage are function words, yet, there are approximately only 500 of these words.

Ludwig, Ruyter, Friedman, Brügger, Wetzels and Pfann (2013) investigate the influence of affective content on customer book reviews on Amazon, as well as, the impact of changes in

linguistic style properties. They find that not only positive changes in affective cues but also ...

“... an increasing congruence with the product interest group’s typical linguistic style directly and conjointly increase conversion rates ... as it influences the perceived representativeness of the sender and influences the effectiveness of affective content conveyed in reviews.”

People put greater trust in reviews but also in communicators that have greater similarities with one self and, hence, their opinion seems to be more representative, competent and qualified than reviews or communicators with lesser similarities (Brown, Grzeskowiak, and Dev, 2008). However, people also tend to mimic one another by changing personality when they are part of a dyad that is in conjunction with Giles and Coupland’s (1991) communication accommodation theory (CAT), which states that people change their speaking style in order to create a positive image. Zajonc, Adelman, Murphy and Niedenthal (1987) found that married couples’ facial expressions become more congruent over time and Ireland and Pennebaker (2010) discovered that the degree in LSM on a first date can predict the intention and stability of the relationship. Taylor and Thomas (2008) investigated the relationship between LSM and negotiation outcomes on hostage negotiations. Their results show that higher aggregated levels of LSM lead to a higher probability of successful outcome and they observe a dramatic fluctuation of LSM during unsuccessful negotiations. Huffaker, Swaab and Diermeier (2011) investigated negotiations in online-based settings and observed an increased agreement between coalition partners due to higher LSM.

LSM is not only important in a bilateral communication between two parties but also in the communication inside a group enhancing the functioning of the collective. Ludwig, Ruyter, Mahr, Wetzels, Brüggem, and Ruyck (2014) find that higher LSM in computer-mediated communication positively affects the community identification and, subsequently, enhances participants’ quality and quantity of participation and, therefore, increases cooperative behavior and enhances group’s overall performance. Another study by Elsbach and Bhattacharya (2001), as well as, by Herring (2001), find that the level of identification of employees to an organization is not stable but fluctuates and evolves over time. Therefore, we are going to test three years of Enron’s email communication for changes in LSM to see if LSM increases or if it stays constant over time. In addition, we are going to investigate the change in affective status and examine changes in affective content that are due to decreasing

or increasing stock prices. The next section is going to focus on the research design and an analysis and a discussion about the outcomes will follow.

3. Research Design

For the purpose of this study we are going to use text mining, which is a process of structuring a large amount of text and deriving patterns within the structured data in order to evaluate and interpret the output. Thus, different from search engines, text-mining programs are more focused on a profound analysis of text data to extract the knowledge of the outcome and to support the decision-making. Text-mining software can be used for many applications, such as, information retrieval, document clustering, information extraction, natural language processing, concept extraction and web mining. In this study we are going to use a language processing software to analyze four-gigabyte text data of the Enron corpus. In the following we present different software solutions for text mining purposes, as well as, the mechanisms of LIWC 2007. A description of the Enron corpus follows, as well as, an explanation of how the raw data has been prepared such that it could be analyzed by LIWC 2007. In addition, we are going to present the formulas to analyze the resulting output of LIWC 2007 for changes in affective content and LSM. Furthermore, the procedure is presented, that is used to analyze the relation of changes in affective content to the stock price of Enron, as well as, to other commodities and indices. (Seidel, 2013)

3.1. Software Tools

Atlas.ti 7: This is the most sophisticated program and has already been released in 1993. It is used by major organizations and corporations, such as, Microsoft, the United Nations, the World Bank, Google and Yahoo. Users comment that it is very user friendly and that the program is being improved and revised on a yearly basis. It handles multimedia data like videos, audios, slides, PDF-files and gives the possibility to link the data to quantitative surveys, that are being imported from excel. Coded data can be exported to SPSS for quantitative analysis and the primary strength of the program is the theoretical model building capability. Sets of training videos are available on the webpage, as

well as, web seminars are offered twice a month. The program costs 505€ for a single user license and 75€ for a two year license for students. (ATLAS.ti: The Qualitative Data Analysis & Research Software, n.d.)

Dedoose: Dedoose is a web based cross-platform qualitative software, that is used on a cloud and is only accessible online. It is very useful when working in a team because it gives the possibility to share the data among each other. Dedoose is a collaborative software that analyzes qualitative and mixed-methods research by making use of texts, audios, photos, videos and spreadsheets. It can be used for data management, excerpting, coding and for multiple perspective analyses of different media. The software is free for one month and afterwards it costs 12,95 € per month. Similar to Atlas, Dedoose offers video guidelines on its webpage. (A cross-platform app for analyzing qualitative and mixed methods research with text, photos, audio, videos, spreadsheet data and so much more, n.d.)

Wordij: This is a cross platform text based tool to analyze frequency of words and word pairs to determine statistical differences between text documents. Thus, it has the ability to compare two texts in a short time, to tell what is unique about each text or what they have in common. Wordij also has the ability to visualize the outcomes by creating semantic word networks where the nodes are words and the links are the relationships between these words. In addition, it has a built in ability to conduct an analysis of Lexis-Nexis newspaper articles, which is the largest electronic database for legal and public records in the world and includes a proper noun extraction. The software is free for academic use and can be downloaded after having shared personal information on the website. With the download comes an extensive documentation file that explains how the software is used. Especially, the document “WORDij_At_a_Glance.doc” provides a good overview of the capabilities of the program and explains what the requirements of the input files are, as well as, what the outcome files mean. (WORDij Semantic Network Tools, n.d.)

Condor: This is a social network analysis tool, which has the ability to work with many different data sets, such as, email, Twitter, Facebook, Wikipedia and more.

Condor has a built in set of analytical tools that investigate network structures, as well as, their content. The results are visualized in a dynamic and static format. Condor's webpage offers a set of tutorial videos explaining how to install Condor, MySQL and how to use the software. It runs on Windows, Mac and on Amazon Web Services and is free for academic use. (GalaxyAdvisors, n.d.)

LIWC 2007: Linguistic Inquiry and Word Count is a text analysis software that is used in this study. It is easy to install and to use. The software calculates the degree to which people use different categories of words across a wide range of texts, such as, emails, speeches, poems or whole books. LIWC has the ability to determine the degree of positive and negative emotions, function words and 70 additional language dimensions any text uses. For example, the anger scale is made up of 184 anger-related words and the submitted text is screened for those words. In addition, the program counts the number of words that match the predefined dictionary. (Ludwig, de Ruyter, Friedman, Brügger, Wetzels, and Pfann, 2013) According to Slatcher and Pennebaker (2006), LIWC dictionaries offer strong, reliable convergence between the dimensions they extract and the content ratings performed by human coders. The price of the full version is 108,17€ and 30€ for the light version. The input has to be either a word document or a text file. (LIWC | Linguistic Inquiry and Word Count, n.d.)

LIWC 2015: After having started to conduct the study and having purchased LIWC 2007, a later version of LIWC has been released. In contrast to the former version, PDF, RTF and CSV files can be analyzed. Furthermore, the analysis can be done directly in excel and includes a function to built dictionaries easily. Additionally, LIWC 2015 is considerably more big data friendly and runs on LIWC 2015 dictionaries, that use a more precise counting metric than LIWC 2007 dictionaries do. However, the variations for the word count, words per sentences, affective content and functions words are very small and can be neglected. (Comparing LIWC2015 and LIWC2007, n.d.)

3.2. Enron Corpus

The Enron Corpus is the only extensive data set of real emails that are publicly available. This is due to privacy concerns. Nevertheless, during its investigations the Federal Energy Regulatory Commission published a dataset of emails from 150 users that are mostly senior managers of Enron. The corpus contains 500.000 messages and gives many researches the possibility to use the corpus for a wide array of studies. However, the dataset has many integrity problems as it is not well structured, many messages are multiple times available, many invalid email addresses are existent and many attachments are included. Therefore, Melinda Gervasio, a senior computer scientist at the SRI, removed all attachments and deleted some messages due to requests of former Enron employees. Furthermore, she converted invalid emails in the form of user@enron.com when it was possible to specify the recipient and in no_address@enron.com when that was not possible. (Enron Email Dataset, n.d.)

Jitesh Shetty and Jafar Adibi cleaned the data further and put it in a MySQL 4 database. They cleaned the dataset by removing duplicate emails, folders like “discussion_threads”, “all documents” as a computer generated them and messages that were returned due to a transaction failure. Invalid email addresses were converted to “no.address@enron.com” and mails where the recipients were not disclosed, were changed into “undisclosed-reipients@enron.com”. The cleaned Enron email dataset contains 252,759 messages from 151 employees distributed in around 3000 user-defined folders. Further improvements have been achieved by Arne Hendrik Schulz, who recoded the dataset in order to enable the import into MySQL 5 and updated the dataset with the position of former employees. In addition, he tackled the problem of multiple emails by one person by updating all addresses to a unique one. A detailed description of the tables and data frames can be found in Appendix I (Schulz, n.d.).

Anyhow, the dataset published by Arne Hendrik Schulz still needs to be recoded manually in order to set it in a format that enables us to import text documents into LIWC 2007. Thus, we write a PHP code to create text documents from the database in weekly frequency (daily frequency) containing all emails written during each week (day) in order to analyze the

overall change of affective status and LSM. In addition, the code creates separate text documents sorted by message id and contains all emails written during each week. The code including the description can be found in Appendix IIa and Appendix IIb. Finally, after having recoded the dataset for the purpose of this study, it is now possible to run the dataset through LIWC 2007.

3.3. Change in Affective Content

The formula for the intensity of affective content is chosen from a prior study with the title “More than words: The influence of affective content and linguistic style matches on online reviews on conversation rates” by Stephan Ludwig, Ko de Ruyter, Mike Friedman, Elisabeth C. Brüggem, Martin Wetzels and Gerard Pfann (2013) and is changed conforming to this study. It can be found below and gives an overall picture of the emotional intensity of negative and positive affective content for each week from week 44 in 1998 to week 28 in 2002.

$$AC = \frac{\sum PA_B - \sum NA_B}{\sum N_B} + \frac{\left[\frac{\sum PA_S - \sum NA_S}{\sum N_S} \right]}{2}$$

where $\sum PA_B$ is the sum of positive affective content words (PA) in the body part of an email, $\sum NA_B$ is the sum of negative affective content words in the body and $\sum N_B$ is the sum of all words used in the body. The second part of the formula has the same variable as the first one except that the subscript (S) denotes the subject of an email. It is divided by two as the subject is not the main part of an email. The outcome can only take values from 1 to -1 and positive (negative) values mean that the magnitude of positive (negative) emotional words is greater than of negative (positive) emotional words.

Additionally, we calculate the affective content separately for the body part, as well as, for the subject part of an email in order to observe if separating both parts lead to different results. In a further method, we calculate the intensity of affective content by dividing the body part by two. This gives us the opportunity to investigate the impact of the subject on the emotional content and gives evidence that the outcome is not influenced by the choice of dividing the subject part as in Formula 1. Further, it is necessary to limit the time span being

considered from week 19 in 1999 until week 28 in 2002 when taking into account the subject because the word count for each week is less than 100 before week 19 in 1999 and, thus, it could bias the results. We choose the Wilkinson signed rank test in order to analyze the statistical significance of changes. For all outputs of LIWC 2007, as well as, for the intensity of affective content, we test if the differences of means between two time periods are statistically different from zero.

As it has already been mentioned, during Skilling's era the stock became Enron's obsession. Since the share price was omnipresent at Enron and on average, employees kept more than half of their 401(k) retirement holdings in Enron's shares, practically everyone was concerned about the stock price. Therefore, we pick week 34 in 2000 where Enron's stock price experienced its all time high and the two weeks around that week to calculate the average for the resulting five weeks. Next, we index the weekly data for one year before (starting from two weeks before week 34 in 2000) and one year after (starting from two weeks after week 34 in 2000) the all time high with the average score calculated before. Thus, the timespan surrounding the week of Enron's all time high is our baseline and is equal to one. A value higher than one indicates a higher score for a variable of interest during a specific time period and a value below one indicates a lower score. Using this method we can observe if the intensity of affective content increased before Enron's all time high and decreased after as predicted by our hypothesis. Additionally, we are going to use daily data and split the year before and after into quarterly time periods. The Wilcoxon signed rank test is used to test if the resulting scores differ significantly to one.

Next, we want to investigate if fluctuations in the stock price explain the affective change that is observed in the email communication of Enron's employees. Therefore, we are going to regress the intensity of affective content (dependent variable) against Enron's stock price return on investment in an OLS model. In addition, we regress against the Henry Hub natural gas price return, WTI and Brent crude oil price returns and against the returns of S&P 500 composite and the S&P 500 Energy index. The rationale to test the relation between the natural gas price and affective content is that it includes Enron's primary market and, therefore, a change in the natural gas price should have a link to the mood of the employees. We included the WTI and Brent spot price return of crude oil because the oil price has an effect on the market Enron is operating in because oil is a substitute to natural gas. Additionally, Enron was active in oil trading. We regress on the S&P 500 and the S&P 500

Energy index since those indices reflect the conditions of the overall market, and the energy market, in the United States. The prices are downloaded from DataStream and cover the timespan from 12.05.1999 until 10.07.2002. We calculate the return on investment for each independent variable by dividing the price at t by the price at $t-1$ and take the natural logarithm of the outcome.

3.4. Change in Linguistic Style

Similar as the method for intensity of affective content, the formula for LSM is chosen from “More than words: The influence of affective content and linguistic style matches on online reviews on conversation rates” by Stephan Ludwig, Ko de Ruyter, Mike Friedman, Elisabeth C. Brüggem, Martin Wetzels and Gerard Pfann (2013) and changed conforming to this study. We calculate separate LSM scores for every function word category to derive the difference in usage intensity of a particular LIWC category (e.g. personal pronouns) between the mails written in week (day) t and the average usage intensity of the same category in all mails. However, LIWC 2007 gives the percentage usage of each category for each text file. Therefore, it is necessary to calculate the absolute value for each category by multiplying the obtained percentage of every function category by its respective word count in that specific week (day). Table 1 shows all nine categories of function words that we use to calculate the LSM score including examples and the amount of words that fall into each category. The formula for calculating the LSM score is the following.

$$(2) \quad LSM_{Mt} = 1 - \left| \frac{\frac{M_t}{N_t - \mu M_T}}{\mu N_T} \right|$$

where LSM_{Mt} is the similarity in the usage intensity of the function word category M between a week (day) and the overall sample. M_t refers to the count of all words that fall into category M during time t . N_t denotes the total words written during time t and μM_T is the average count of the words that fall into category M in the overall sample. μN_T is the average of words used in the complete sampling. The time period is from week 1 in 1999 until week 28 in 2002.

Table 1
Categories of Function Words

In column one, all nine categories that fall into the classification of Function Words are shown. The second column shows the abbreviations for all categories as displayed in the output of LIWC 2007 and column three presents examples of words that fall into each category. The last column shows how many words are included in the dictionary for each type of Function words.

Category	Abbrev	Examples	Words in category
Personal pronoun	ppron	I, them, her	70
Impersonal pronoun	ipron	It, it's, those	46
Articles	article	A, an, the	3
Auxiliary verbs	auxverb	Am, will, have	144
Adverbs	adverb	Very, really, quickly	69
Prepositions	prep	To, with, above	60
Conjunctions	conj	And, but, whereas	28
Negations	negate	No, not, never	57
Quantifiers	quant	Few, many, much	89

After calculating the LSM score for each category M , we are going to take the average of all nine LIWC categories in a particular week (day) in order to receive the overall LSM score for each week (day). The composite LSM score is bounded between zero and one where higher numbers present a greater linguistic and stylistic similarity between a week (day) t and the over all sample style. This methodology is in line with Ireland and Pennebaker (2010). Furthermore, we are going to investigate the differences for each LIWC category separately. This might provide us with additional information on the changes of linguistic and stylized similarity. Again, we choose the Wilkinson signed rank test in order to analyze the statistical significance of changes.

Moreover, we are going to make use of another methodology for calculating LSM that is in line Niederhoffer & Pennebaker (2002) to find out how synchronized Enron's employees are in email correspondence over the course of time. The Formula, which represents the LSM score between two time periods for each function word category M , is shown below.

$$LSM_M = 1 - \frac{|M_t - M_{t+1}|}{M_t + M_{t+1} + 0.0001}$$

where M_t is the percentage of total words in time t that fall into category M and M_{t+1} is the percentage of M in time $t+1$. In the denominator, the number 0.0001 is added to prevent empty sets. Finally, we average all nine LIWC category scores to provide a composite measure of function word similarity between two time periods. For both methods and for all outputs of LIWC 2007, as well as, for the LSM measures, we test if the differences of means between two time periods are statistically different from zero by using the Wilcoxon signed rank test.

4. Results

This section is going to deal with the analysis of the results obtained from the methodology mentioned in the section before. Firstly, we are going to discuss the outcome for the change in affective status, as well as, the results on regressing the measure for affective content on Enron's stock price and, secondly, we are going to cover the results for the LSM approach.

4.1. Analysis of the Change in Affective Content

On December 2nd 2001, Enron filed for Chapter 11 bankruptcy protection, which was the largest bankruptcy in U.S. history at that time and on August 23rd 2000 Enron's stock reached its all time high. As the Enron corpus covers the time period 1999 until 2002 including both events mentioned above, we are going to reveal changes in emotions on Enron's employees that might be caused by those events. We expect to observe a decrease in the intensity of affective content from the end of 2000 onward and, therefore, an increase (decrease) in the words used that are associated with negative (positive) emotions. Furthermore, we expect the intensity for affective content to be higher the year before Enron's stock hits its all time high and lower the year after. Consequently, we predict that the use of words associated with positive (negative) emotions is higher (lower) the year before Enron's stock hits its all time high and lower (higher) the year after.

4.1.1. Graphical Illustration

In order to get a first impression of the resulting output of LIWC 2007, we are going to consider Figure 2 below. Panel A presents the percentage of affective content for each week in the body part, which is represented by the blue line, as well as, the mean of the whole period, that is represented by the red line. As can be seen, affective content is more volatile during the first year and becomes less volatile during 2000 and the first half of 2001. However, in the second half of 2001 there is an increase in affective content observable, which is followed by a decrease in early 2002. The increase might be caused by many reasons that go beyond the scope of this study and that is why we are careful in interpreting the figures below. Anyhow, when looking at big events that happened at Enron, the increase coincides with Skilling resignation as CEO in August 14th 2001. The figures for the subject part look similar to the ones presented in Figure 2 and can be found in Appendix III.

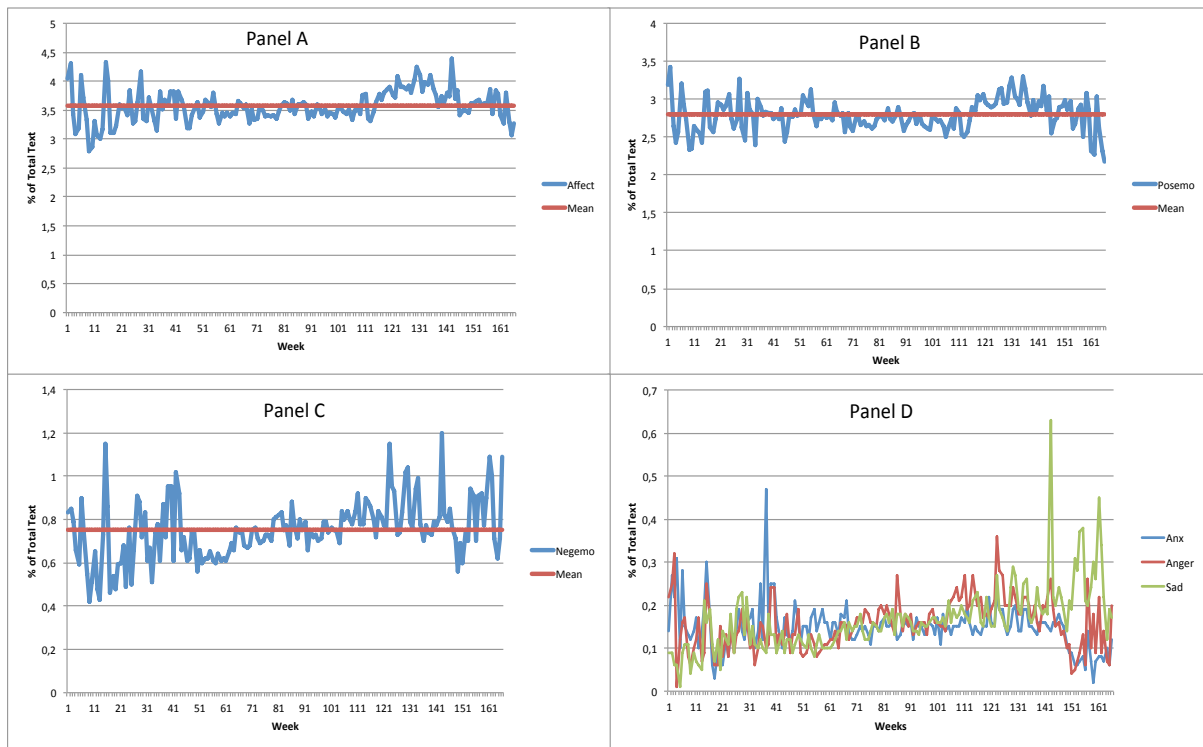
Panel B of Figure 2 shows one part of affective content that is attributed to positive emotions. The pattern for positive emotions seems to mimic the one for affective content in panel A. The increase in the use of words associated with positive emotions before 2002 is contradicting to Hypothesis 1a, which states that positive emotions should decrease after 2000, especially, when considering the stock price of Enron that was decreasing since mid-august 2000. One explanation is that we observe only an increase in positive emotions because affective content increased as well over the time period, which leads to a proportional upward shift that is observed in panel B and, thus, it might be that the relative change is actually non existing. Therefore, it is important to make further investigations on the magnitude of positive and negative emotions on total affective content by using the measure for intensity obtained from Formula 1. Consistent with Hypothesis 1a, we observe a decrease from 2002 onwards, however, it has to be mentioned that also the volatility increased during this time. Panel C shows affective content, which is associated with negative emotions. Similar to Panel A and B, the volatility is highest during 1999 and 2002 whereas it is lowest during 2000 and most of 2001. Overall, we observe an increase in the use of words that are associated with negative emotions. During the first half of the time period considered, the percentage of negative emotional words is mostly below the average amount and between the years 2000 and 2001 the percentage of negative emotional words become higher than the average. This is consistent with Hypothesis 1b, which states that there should be an increase in negative emotions in the email correspondence of Enron as it comes closer

to bankruptcy. Another question is if this increase is associated with the decrease in share price as the all time high in August 2000 occurred directly before the level of negative emotions exceeded the mean. We are going to deal with that question in the next section.

Figure 2

Graphical Illustration of Changes in Affective Content from 1999 until 2002

The data is retrieved from the output of LIWC 2007. The Time period starts in week 19 in 1999 and ends in week 28 in 2002. Panel A presents the percentage of affective content for each week in the body part. Panel B presents the percentage amount of positive words for each week in the body part and Panel C shows the percentage amount of negative words for each week in the body part. The red line represents the mean of the whole period. Panel D shows the percentage amount of words related to anxiety (blue line), anger (red line) and sadness (green line) for the body part.



Panel D illustrates the graphs for anxiety, anger and sadness, which are further distinctions of negative emotions into three different dimensions. It can be observed that there is an overall increase of all three dimensions until the end of 2001 and that from 2002 onwards, the amount of words associated with anxiety and anger decreased sharply whereas words associated with sadness seem to increase and outgo the other ones. Thus, it might be that the increase in negative emotions is due to an increase in sadness rather than in anxiety and anger. In order to check if the differences in affective content including positive and negative emotions have any statistical relevance, we are going to separate the whole time period into

four years, from 1999 until 2002, and test the significance in changes between these years. Further, we are going to investigate differences in the year before Enron's all time high with the year after and finally we are going to regress the measure for affective content with Enron's stock price, as well as, on other commodities and indices.

4.1.2. Statistical Relevance of Changes in Affective Content

Panel A of Table 2 shows changes in affective content and in its subcategories for the body part of the emails written for each year whereas Panel B of Table 2 shows the results for the subject part. For both, the body and the subject, the highest word count is in year 2001 with an average of 365.445 words written during one week in the body part and an average of 6.903 words written during one week in the subject part. 1998 is the year with the lowest amount of written emails in our sample as the average amount of words written in one week is 1,820 for the body part and 34 words for the subject. Especially, the average number of words written in the subject part is extremely low, causing the values for negative emotions to be zero. Thus, we are going to exclude year 1998 and start our sample from week 19, in 1999 as from this point of time the word count for both is always higher than 100 for each week. Panel A of Table 2 shows that, besides anxiety, none of the changes between 1999 and 2000 are significant. Anxiety, which is marginally significant at the ten per cent level, increases slightly.

The amount of affective content rises between 2000 and 2001 and decreases slightly the year after. Both changes are significant at a five per cent level. When considering the changes in positive and negative emotions, we can see a statistical marginal decrease of 2,12 percent for positive emotions between 2001 and 2002 and a significant increase in negative emotions between the years 2000 and 2001 of 12,36 percent, which is affected by an increase in anger and sadness. Despite the fact that the change in negative emotions between 2001 and 2002 is insignificant, the changes for anxiety, anger and sadness, which are shown in Panel A, remain significant. As can be seen in Figure 2, we observe a decrease in the first two dimensions of negative emotions whereas the amount of words written, related to sadness, increases. Here, one drawback of LIWC 2007 becomes apparent. Even though we observe no change in negative emotions, we do observe changes in the dimensions of negative emotions that equal each other out and, thus, lead to the misleading outcome when only the valance is considered.

This implies a need for subcategories for positive emotional words, as well as, for more dimension in both emotional sub-categories.

Table 2
Changes in Affective Content from 1999 until 2002

The Table shows the yearly average Word Count (given in absolute value) and yearly average percentage of total word count for affective content, positive emotions, negative emotions, and words associated with anxiety, anger and sadness (given in percent) from week 19 in 1999 until week 28 in 2002. The last column shows the average amount for the total time period. Output is retrieved from LIWC 2007. Panel A displays the output for the body part and Panel B shows the output for the subject part of Enron's mails. Panel C presents the intensity of affective content by using Formula 1 for the calculation. The intensity for affective content for Panel A and Panel B is calculated by using only the first part of Formula 1. This means that the sum of negative affective content words is subtracted from the sum of positive affective content words and the result is divided by the sum of all words used. The Wilcoxon signed rank test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

Avg. Weekly data (Body)								
Panel A	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	22204		263627		787896		186777	365445
affect in %	3,47	0,048	3,51	0,154***	3,67	-0,061**	3,61	3,569
posemo in %	2,78	-0,004	2,77	0,061	2,83	-0,060*	2,77	2,792
negemo in %	0,67	0,048	0,72	0,089***	0,81	0,008	0,81	0,752
anx in %	0,15	0,011*	0,16	-0,004	0,16	-0,049***	0,11	0,148
anger in %	0,13	0,014	0,14	0,051***	0,20	-0,058***	0,14	0,156
sad in %	0,12	0,013	0,13	0,053***	0,18	0,069***	0,25	0,164
AC in %	2,11	-0,052	2,05	-0,028	2,03	-0,068	1,96	2,040
N	34		52		52		28	166

Avg. Weekly data (Subject)								
Panel B	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	360		5479		14133		3863	6903
affect in %	3,93	0,419*	4,35	-0,515***	3,84	-0,353	3,49	3,98
posemo in %	3,37	0,232	3,60	-0,613***	2,99	-0,543***	2,45	3,20
negemo in %	0,40	0,341	0,74	0,092***	0,83	0,192*	1,02	0,77
anx in %	0,12	0,134	0,25	-0,062	0,19	-0,135**	0,05	0,17
anger in %	0,10	0,048	0,15	0,069***	0,22	-0,136	0,08	0,15
sad in %	0,05	0,084	0,13	0,0556**	0,19	0,254	0,44	0,19
AC in %	3,02	-0,157	2,87	-0,705***	2,16	-0,735***	1,43	2,43
N	34		52		52		28	166

Avg. Weekly data (Body + Subject)								
Panel C	1999	2000	2001	2002	Whole Period			
AC in %	3,62	-0,130	3,49	-0,380***	3,11	-0,435**	2,67	3,26
N	34	52	52	28	166			

The changes in the intensity for affective content or, to put it differently, the changes in the magnitude of positive and negative emotions in affective content are all insignificant. However, Panel B shows different results. When taking the subject part of written emails into consideration, we do observe a significant decrease in the intensity of affective content of 50,17 percent from 2000 until 2002 and, thus, a large shift in the magnitude towards words associated with negative emotions. Furthermore, Panel B shows a significant decrease in positive emotions of 32,11 percent from 2000 until 2002 and an increase of 37,83 percent in negative emotional words, where the difference between 2001 and 2002 is only marginally significant. The outputs for the subcategories for negative affect look similar to Panel A. The only difference can be found in column seven where the changes for anger and sadness are insignificant. Panel C shows the output for the intensity of affective content taking the body part, as well as, the subject part into account. Note that in the calculation in Panel A and B, we only use the first part of Formula 1, without the second fraction. The results are similar but the changes are lower than in Panel B as the intensity of affective content decreases by 23,5 percent over the last two years.

We observe a decrease in positive emotions and an increase in negative emotions during the time period from 2000 to 2002, leading to a shift in the magnitude towards negative emotions. Nevertheless, we should keep in mind that the magnitude of positive emotions is always larger during the whole period since the measure for affective content is always positive. In addition to the findings above, we are also concerned about the question whether it is possible to measure the impact of the stock price on the feelings of Enron's employees. Therefore, we pick week 34 in 2000, when Enron's stock price experienced its all time high and the two weeks around that week to calculate the average for the resulting five weeks. Next, we index the weekly data for one year before (starting from two weeks before week 34 in 2000) and one year after (starting from two weeks after week 34 in 2000) the all time high with the average score, which we calculated in the preceding sentence. Thus, the timespan surrounding the week of Enron's all time high is our baseline and is equal to one. An outcome below one, for the year before or the year after, indicates a decrease in the variable of interest compared to the base period and an outcome above one indicates an increase. We expect, for the year before (after), the measure for positive emotions and the intensity of affective content to be higher (lower) than the year after (before) and for negative emotions including anxiety, anger and sadness to be lower (higher).

Table 3

Changes in Affective Content One Year Before & One Year After Enron's All Time High Using Weekly Frequency

The table shows scores for affective content that are indexed on the average score of week 32 until week 36 in 2000. Column one shows the measures for affective content and column two presents the indexed weekly data for one year before (starting at week 31 in 2000) Enron stock hit its all time high and column four presents the indexed weekly data for one year after (starting at week 37 in 2000). Thus, the timespan surrounding the week of Enron's all time high is our baseline and is equal to one. Column three and five show the respective t-statistic resulting from the Wilcoxon signed rank test, which is used to test if the indexed scores are significantly different from one. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

Avg. Weekly data (Body)				
Panel A	Before	t- stat.	After	t- stat.
affect	1,032***	-2,678	1,042***	-4,991
posemo	1,045***	-4,117	1,023***	-2,815
negemo	0,981	-1,531	1,111***	-5,649
anx	1,083	-0,994	1,075***	-3,121
anger	0,852***	-3,712	1,288***	-5,653
sad	0,880***	-2,955	1,163***	-5,312
AC	1,052***	-3,37	0,971***	-2,878
N	52		52	

Avg. Weekly data (Subject)				
Panel B	Before	t- stat.	After	t- stat.
affect	1,040	-0,592	0,919***	-4,235
posemo	1,085	-1,384	0,899***	-4,599
negemo	0,912***	-3,124	1,005	-0,084
anx	2,399***	-3,878	1,195**	-2,008
anger	1,069	-0,36	1,487***	-3,89
sad	0,602***	-4,229	0,844***	-3,216
AC	1,153**	-2,359	0,869***	-4,481
N	52		52	

Avg. Weekly data (Body + Subject)				
Panel C	Before	t- stat.	After	t- stat.
AC	1,093***	-3,306	0,936***	-4,572
N	52		52	

Panel A of Table 3 displays the results obtained for the body part and Panel B of Table 3 shows the ones for the subject part. In the body part, we observe that the amount of words, associated with positive emotions, is higher for the year before and after, when comparing it to the occasion of Enron's all time high. No statistically significant difference for negative

emotions can be found in the year before but in the year after there is a significant increase of 11 percent compared to the base period. Further, the measures for anger and sadness related words are lower by 15 and 12 percent respectively in the year before whereas in the year after there is an increase in anxiety, anger and sadness. In addition, Panel A shows that the measure for the intensity of affective content is significantly higher by the year before and significantly lower the year after the all time high. Panel B indicates a significantly lower amount of words associated with positive emotions for the year after and a significantly lower amount of negative emotions for the year before the occasion of interest. The outcomes for anxiety in the year before show an extremely high value, which is not surprising, as in the subject for 1999 the measures for anxiety, anger and sadness lack data and, therefore, we are not going to interpret these results. Finally, in line with Hypothesis 2, Panel A, B and C show that the value for affective content is larger before the week of Enron's all time high and decreases afterwards such that the intensity for affective content decreases relative to the base week. This is caused by an increase in words related to negative emotions and also due to a decrease in words related to positive emotions. Thus, we find support for Hypothesis 2, as well as, for Hypothesis 2a and 2b.

We are going to investigate further the emotional content around Enron's all time high. To do so, we are going to split the year before and after into four quarters. However, when using weekly data we would only have a maximum of 16 observations for each quarter and, therefore, we are going to use daily data to run this test. One major drawback when using daily data is that we do not have continuous data as emails are not consequently written on each day and the amount written changes heavily from day to day. Due to data constraints we only use the body part.

Table 4 shows the results obtained. Besides a significant decrease in the quarter directly after the baseline period, all other quarters are insignificant for affective content. For positive emotions all results are insignificant, thus, we conclude that there is no change in positive emotions over the time period when using daily frequency. However, the results for negative emotions are all significant at a one percent level. Surprisingly, we find that before and after Enron's all time high the use of words associated with negative emotions is lower than during the baseline period. This contradicts what we have expected.

Table 4

Changes in Affective Content One Year Before & One Year After Enron's All Time High Using Daily Frequency

The table shows scores for affective content that are indexed on the average score of week 32 until week 36 in 2000. Only the body part is represented in the table, as the data is lacking for the subject part when using daily frequency. Column one shows the measures for affective content and columns two to five present the indexed daily data for one, two, three and four quarters before (starting at week 31 in 2000) Enron stock hit its all time high. Columns six to nine present the indexed daily data for one, two, three and four quarters after (starting at week 37 in 2000) Enron stock hit its all time high. Thus, the timespan surrounding the week of Enron's all time high is our baseline and is equal to one. In the brackets the respective t-statistic, resulting from the Wilcoxon signed rank test that is used to test if the indexed scores are significantly different from one, are shown. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	Before				After			
	Q4	Q3	Q2	Q1	Q1	Q2	Q3	Q4
affect	1,012 (-0,142)	0,992 (-0,021)	1,000 (-0,134)	1,005 (-0,014)	0,930*** (-3,072)	0,984 (-1,061)	0,998 (-0,658)	0,956 (-1,538)
posemo	1,034 (-1,574)	1,001 (-1,030)	1,025 (-1,625)	1,030 (-1,196)	0,960 (-1,256)	1,020 (-0,915)	1,020 (-0,368)	0,976 (-0,390)
negemo	0,925*** (-2,615)	0,933*** (-2,967)	0,906*** (-3,430)	0,913*** (-2,891)	0,825*** (-5,133)	0,861*** (-3,595)	0,915*** (-3,499)	0,883*** (-3,801)
anx	1,156 (-0,807)	1,191** (-2,456)	1,138* (-1,838)	1,074 (-0,874)	1,088 (-0,614)	1,084 (-0,225)	1,095 (-1,258)	1,072 (-0,483)
anger	0,922*** (-3,218)	0,877*** (-3,235)	0,861** (-2,480)	0,903** (-2,490)	0,655*** (-5,809)	0,792*** (-3,971)	0,920** (-2,192)	0,753*** (-5,447)
sad	0,818*** (-3,639)	0,939 (-0,599)	0,824*** (-3,440)	1,067 (-0,186)	0,852*** (-3,989)	0,867** (-2,584)	1,053 (-0,686)	0,974** (-2,006)
AC	1,080*** (-2,737)	1,040** (-2,076)	1,075*** (-2,729)	1,080** (-2,060)	1,017 (-0,980)	1,086** (-2,517)	1,064* (-1,720)	1,015 (-1,523)
N	79	88	84	89	90	82	90	92

The results for anxiety are only significant at a five percent level for three quarters before the baseline and during this quarter the score for anxiety is higher by 19,1 per cent. For anger, the results are significant in every quarter and are similar to the results of negative emotions, peaking during the baseline period and declining sharply afterwards. Similar conclusion can be drawn for sadness, however, quarter one and three before the baseline period and quarters three after the baseline period are not statistically significant. Finally, when considering the measure for affective content, we observe that the score is lowest directly after Enron's all time high, which implies that the magnitude towards negative words is highest during this period. Furthermore, for the quarters in the year after, the statistical significance is lower,

which we interpret as weak evidence that the measure for affective content is proportionally lower the year after, when comparing it to the year before. However, it is still higher for the second and third quarter in the year after than it is during the baseline period.

The results in Table 4 are not consistent with Hypothesis 2, 2a and 2b. Thus, when using daily data we find contradicting results when comparing it to Table 3, where we used weekly frequency. To find such large differences in the results when using different frequencies is surprising. This concern will be further discussed in Section 5. Overall, we find results that are consistent with Hypothesis 2, 2a and 2b for weekly frequency and inconsistent results for daily frequency. Further, the results in Table 3 are only indirect indications for a link between the shift towards negative emotions measured in the email correspondents of Enron's employees and the influence of the stock price on that shift. Therefore, we are going to regress the measure for affective content on the return of Enron's stock price, as well as, on the returns of the Henry Hub index for natural gas, WTI crude oil, Brent crude oil, S&P 500 composite and S&P 500 energy index. We expect positive relations between the measure for affective content and the return on Enron's stock price or on the other commodities and indices. Additionally, we regress the measure on affective content on the lag returns since we assume that the information conveyed by the stock, commodities or indices need one or two days to be incorporated in the emails written.

Table 5 below displays the results obtained from the OLS regression. Panel A shows the results for weekly data and Panel B for daily data. When considering Panel A, we can observe that the coefficients for the return on Enron's stock are negative and insignificant which leads us to the suggestion that there is no relation between the stock price and changes in the magnitude in affective content. This is inconsistent with Hypothesis 3. Nonetheless, we find a positive relation between the intensity for affective content and the return of the index for natural gas, as well as, for the lagged return, that are statistically significant at a five per cent level. Further, we find a marginal significant and positive coefficient for the twice-lagged return on S&P 500 composite and, therefore, we find only weak evidence on a positive relation when weekly frequency is applied. Panel B presents the results for daily frequency and, similar to Table 3 and 4, we find mixed results when using different frequencies. Now we do find a positive relation between the lagged return on Enron's stock price and the intensity of affective content, that is significant at a five per cent level and is consistent with Hypothesis 3. Furthermore, we find marginal significant results for the lagged

return on natural gas and the twice lagged return on WTI crude oil and S&P 500 composite whereas the coefficient for natural gas is positive and, surprisingly, the coefficients for the latter two are negative which can have various reasons. Firstly, for all columns the r-squared is extremely low, meaning that only a small portion is explained by the regressions, which leads to the conjecture that the results obtained in Table 5 might be due to coincidence. Secondly, taking the second lag of the returns might lead to over assessment, which causes the measure to be unreliable as it might be influenced by other factors that play a role between the day of the release of the specific price information and the two days after.

All in all, in Table 2 we find evidence that supports Hypothesis 1, 1a and 1b. We find a sharp decrease of 23,5 percent in the intensity of affective content over the last two years. In Table 3 we find evidence that supports Hypothesis 2, 2a and 2b. However, in Table 4 we find contradicting results when using daily frequency, which are inconsistent with Hypothesis 2, 2a and 2b. In addition, we also find mixed evidence on Hypothesis 3 that depends on the frequencies used. When using weekly frequencies, as shown in Panel A of Table 5, the results are inconsistent with Hypothesis 3 but are consistent when using daily frequency as shown in Panel B of Table 5. A further discussion on the distinctive findings, when choosing different frequencies, is given in Section 5. Next, we are going to investigate changes in linguistic style by using two different methods to obtain the LSM score.

Table 5

The Relation Between the Intensity of Affective Content & the Return of Enron's Stock Price & Other Commodities/ Indices

The table presents results of the OLS regression where the intensity of affective content is the depended variable and the returns on Enron's stock price, the Henry Hub index for natural gas, WTI crude oil, Brent crude oil, S&P 500 composite and S&P 500 energy index are the independent variables. The return on investment is calculated for each independent variable by dividing the price at t by the price at t-1 and taking the natural logarithm of the outcome. The prices are downloaded from DataStream and cover the timespan from 12.05.1999 until 10.07.2002. Panel A shows the outcome using weekly frequency and the time period is from 19.05.1999 until 10.07.2002 whereas Panel B shows the outcome using daily frequency and the time period is from 02.06.1999 until 30.04.2002. In the brackets, below the coefficients, the respective t-statistic is given. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

Panel A	(1)			(2)			(3)			(4)			(5)			(6)		
	Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2	
Enron	0,002 (0,71)	-0,0003 (-0,12)	-0,001 (-0,21)															
Natural Gas				0,011** (2,04)	0,015** (2,94)	0,003 (0,48)												
WTI							0,005 (0,49)	-0,002 (-0,21)	-0,006 (-0,67)									
Brent										-0,004 (-0,46)	0,001 (0,06)	0,009 (1,03)						
S&P Comp													0,015 (0,71)	0,017 (0,876)	0,033* (1,70)			
S&P Energy																0,025 (1,47)	0,005 (0,29)	-0,01 (-0,58)
R-squared	0,003	0	0	0,025	0,05	0,001	0,001	0	0,003	0,001	0	0,007	0,003	0,005	0,018	0,013	0,001	0,002
N	165	164	163	165	164	163	165	164	163	165	164	163	165	164	163	165	164	163

Panel B	(1)			(2)			(3)			(4)			(5)			(6)		
	Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2		Lag1	Lag2	
Enron	-0,002 (-0,72)	0,005** (2,26)	0,001 (0,242)															
Natural Gas				-0,003 (-0,56)	0,009* (1,83)	-0,008 (-1,55)												
WTI							0,007 (0,84)	0 (-0,04)	-0,016* (-1,84)									
Brent										0,009 (0,97)	-0,005 (-0,52)	-0,014 (-1,60)						
S&P Comp													0,017 (0,92)	0,013 (0,72)	-0,036** (-1,96)			
S&P Energy																-0,006 (-0,37)	0,012 (0,79)	-0,024 (-1,54)
R-squared	0,001	0,007	0	0	0,005	0,003	0,001	0	0,005	0,001	0	0,004	0,001	0,001	0,006	0	0,001	0,003
N	712	692	672	712	692	672	712	692	672	712	692	672	712	692	672	712	692	672

4.2. Analysis of the Change in Linguistic Style

In this section we are going to deal with the change in linguistic style during the period from 1999 to 2002. In the first part of this section, we are going to investigate changes in the raw data, obtained from LIWC 2007, and the outcome of the LSM score using the first method (Formula 2) that is described in the methodology. The second part is going to show the outcome using the second method (Formula 3). We have two different expectations of how the LSM score changes from 1999 until 2002. Either, we observe an increase in the LSM score during this period since the writing style of Enron's employees becomes more similar as time passes by because people mimic each other in order to increase the sense of belonging or we observe the LSM score to be constant over this period as the period we consider only includes the final years of Enron's existence. This implies that the adjustments in linguistic style might have occurred earlier in time.

4.2.1. LSM Using Formula 2

When considering Table 6, we are first going to pay attention to the last row, which indicates the results for the LSM score. The outcome on the changes are significant for the years 2000 until 2002, nonetheless, they are extremely small such that we consider these changes equal to zero. Thus, the first method for the LSM measure indicates the linguistic style match to be practically equal to one over the whole time period, meaning that all the e-mails written during this period have basically the same linguistic style. This is consistent with Hypothesis 4b. One additional explanation for this finding is that we are investigating cooperative email correspondence, which might be written more formally and, thus, follow a formal business standard in writing style. Section 5 is going to elaborate on this issue when comparing the emails contained in the Enron corpus to different texts. Nevertheless, in this section we are going to investigate the changes on each category of function words that lead together to the LSM measure. Table 6 shows that, from 1999 to 2000, there is a decrease in the average scores of articles, auxiliary verbs, adverbs, prepositions and quantifiers, that are significant at a five percent level with the biggest decrease in the use of prepositions. Decreases for impersonal pronouns and negations are only marginal. The column, that indicates the year from 2000 to 2001, shows a decrease in personal pronouns by 20,63 percent, which is the largest change of all subcategories. During this period of time, impersonal pronouns,

auxiliary verbs, adverbs, prepositions and conjunctions are decreasing as well whereas articles and negations increase slightly. All changes are significant at least at a five percent level. Column seven shows the results for changes from 2001 to 2002. It can be observed that the use of personal pronouns increases significantly from 4 percent to 4,49 percent. The use of conjunction and negation words also increases significantly at a one percent level but with a lower magnitude. Furthermore, the use of articles decreases slightly and, as it is the case for every year, the use of prepositions decreases further.

Table 6
Changes in Linguistic Style Using Formula 2

The table shows the output that is obtained from LIWC 2007 for separate function word categories, as well as, the outcome of the total LSM score using Formula 2. The time period is from week 1 in 1999 until week 28 in 2002. Differences and the corresponding significance are shown in columns three, five and seven. The last column shows the average amount for the total time period. The Wilcoxon signed rank test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	Avg. Weekly data (Body)							
	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	16932		263627		787896		186777	330377
ppron in %	5,10	-0,065	5,04	-1,040***	4,00	0,490***	4,49	4,68
ipron in %	3,40	-0,217*	3,18	-0,170**	3,01	-0,041	2,97	3,16
article in %	6,19	-0,395***	5,80	0,109**	5,91	-0,300***	5,61	5,91
auxverb in %	6,68	-0,356***	6,33	-0,638***	5,69	0,235	5,92	6,19
adverb in %	2,29	-0,290***	2,01	-0,150***	1,86	-0,076	1,78	2,01
preps in %	13,01	-0,540***	12,47	-0,492***	11,98	-0,741***	11,24	12,30
conj in %	4,30	-0,085	4,22	-0,109***	4,11	0,162***	4,27	4,22
negate in %	0,66	-0,055*	0,60	0,028**	0,63	0,087***	0,72	0,64
quant in %	2,07	-0,122**	1,95	0,001	1,95	-0,061	1,89	1,97
LSM	0,99999914	6,908E-07***	0,99999983	2,958E-08***	0,99999986	-3,972E-07***	0,99999946	0,999999584
N	52		52		52		28	184

Overall, those differences do not clearly show a pattern and, especially, do not show an increase in LSM during the considered period of time. Even though we do find an increase in LSM during the first two years and a decrease for the last year, those changes are not economical significant because they are extremely low. Therefore, Table 6 leads to the conclusion that there is neither a clear decrease nor a clear increase in linguistic style visible. This is consistent with Hypothesis 4b, which states that the LSM score is going to be constant from 1999 until 2002. Anyhow, we are going to use a second method to calculate the change in LSM, which is shown in the next section.

4.2.2. LSM Using Formula 3

In this section we are going to investigate the change in linguistic style by using Formula 3. Figure 3 gives a first impression that Formula 3 might lead to different results than Formula 2 as the total LSM score fluctuates between 0,93 and 1. This means that the score differs now at one decimal place behind the comma. Furthermore, Panel A of Figure 3 shows that the total LSM score seems to be quite large over the whole period and that a clear trend towards a higher LSM score is not existent. However, the LSM total score seems to be more volatile than in the section before.

Figure 3

Graphical Illustrations of Changes in Linguistic Style from 1999 until 2002

All scores are calculated by using Formula 3. Panel A represents changes in the total LSM score. Panel B, C and D show the separate LSM scores for personal pronouns, prepositions and negations respectively. Note that for Panel A the values on the y-axis begin with 0,6. The time period is from week 1 in 1999 until week 28 in 2002.

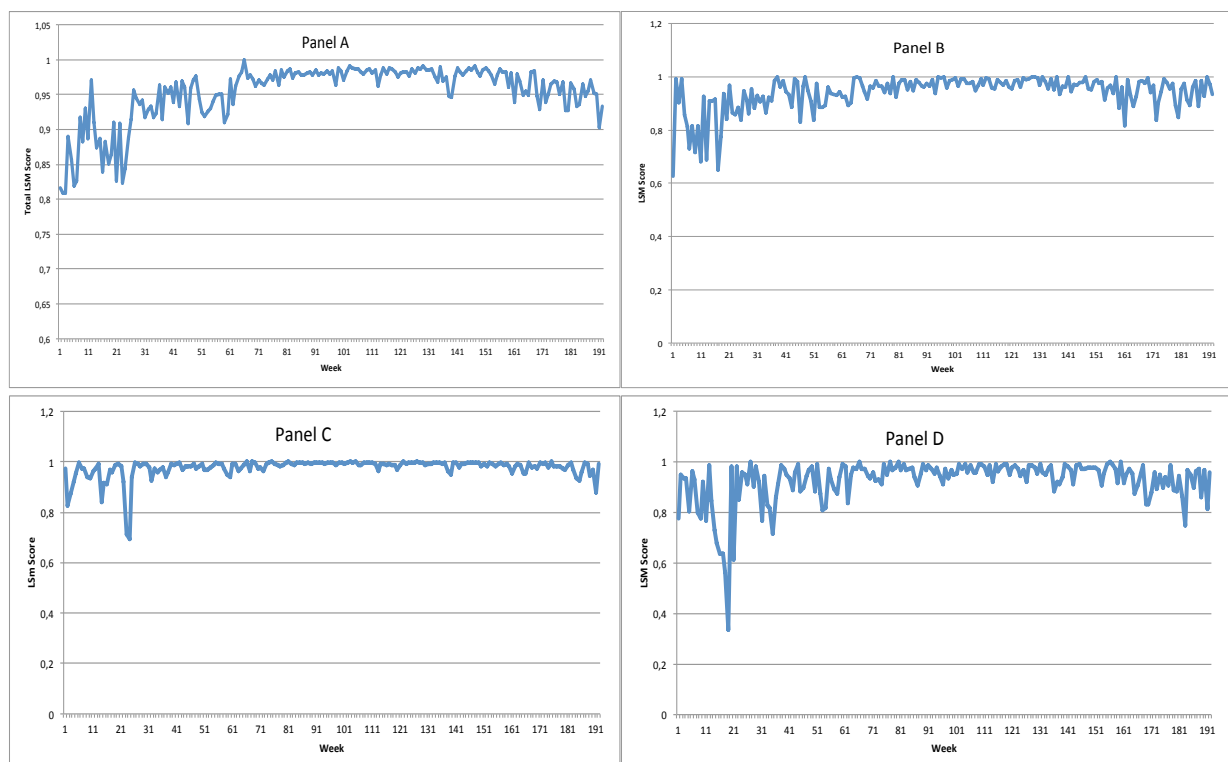


Table 7 shows the separate LSM scores and the total LSM score for the years 1999, 2000, 2001 and 2002, as well as, the differences between those years including their statistical significance. Column three of Table 7 shows a significant increase from 1999 to 2000 for all subcategories of function words, as well as, for the total LSM score. The increase for the total

LSM score is 6,19 percent over the year, which is in line with Hypothesis 4a. However, there is practically no change from 2000 to 2001 as it is shown in column five of Table 6. The total LSM score stays identical and the use of impersonal pronouns decreases slightly but significantly at a five percent level. There is a marginal significant increase for quantifier words but it is minimal as well. All other scores are insignificant and, therefore, we conclude that from 2000 until 2001 there is no change in LSM. This is in line with Hypothesis 4b. Column seven of Table 6 shows a highly significant decrease for all scores, besides impersonal pronouns and articles for which the differences are insignificant. The Total LSM score decreases by 2,66 percent and is lower than the increase from 1999 until 2000. This is also true for the separate LSM scores.

Table 7
Changes in Linguistic Style Using Formula 3

The table shows the separate LSM scores for each function word category, as well as, the outcome of the total LSM score using Formula 3. The time period is from week 1 in 1999 until week 28 in 2002. Differences and the corresponding significance are shown in columns three, five and seven. The last column shows the average amount for the total time period. The Wilcoxon signed rank test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	16932		263627		787896		186777	330377
ppron	0,898	0,070***	0,968	-0,001	0,967	-0,021**	0,946	0,944
ipron	0,922	0,060***	0,982	-0,009**	0,974	-0,014	0,960	0,959
article	0,935	0,049***	0,984	-0,004	0,980	-0,020	0,960	0,965
auxverb	0,939	0,043***	0,982	0,002	0,984	-0,023***	0,961	0,967
adverb	0,914	0,059***	0,973	0,004	0,978	-0,030***	0,948	0,954
preps	0,958	0,033***	0,991	-0,002	0,989	-0,017***	0,972	0,978
conj	0,947	0,036***	0,983	0,002	0,984	-0,024***	0,961	0,970
negate	0,867	0,095***	0,962	0,002	0,964	-0,055***	0,910	0,928
quant	0,908	0,069***	0,977	0,005*	0,983	-0,034***	0,948	0,955
Total LSM	0,921	0,057***	0,978	0,000	0,978	-0,026***	0,952	0,958
N	52		52		52		28	184

All in all, Table 7 has a different outcome than Table 6 has. Firstly, we observe an increase in LSM scores from 1999 until 2000. Secondly, the scores remain constant over the next year and, finally, from 2001 until 2002, all scores experience a significant decrease besides impersonal pronouns and articles. However, those decreases are smaller in nature than the increases observed in column three. Thus, we find mixed evidence when considering each year independently where column three is consistent with Hypothesis 4a, column five is

consistent with Hypothesis 4b and column seven is inconsistent with both. However, when taking the whole period of time into consideration, we can conclude that from 1999 until 2002 there is an increase in total LSM of about 3,58 percent. Nonetheless, this increase is not consistent over the whole period and, therefore, Table 7 gives only weak evidence for Hypothesis 4a, which states that the total LSM score increases from 1999 until 2002. In addition, we do not find the LSM score to be constant and, therefore, the outcome of Table 7 also contradicts Hypothesis 4b. When considering both tables, we conclude that the linguistic style is already similar in the email correspondence of Enron's employees and if there is an increase in the similarity in linguistic style, it is small and inconsistent over time. Therefore, we argue that we fail to find valid support for Hypothesis 4a and that we find only consistent results for Hypothesis 4b when using Formula 2 to calculate the LSM score. Especially, in Table 6 the LSM score stays relatively constant on a high score level over the period of time, meaning that, if at all, the convergence in linguistic style must have happened earlier in time. Table 7 shows results that are in line with the findings of Elsbach and Bhattacharya (2001), as well as, Herring (2001) since we find support that the level of identification of employees to Enron is not stable but fluctuates over time. Even though both Formulas lead to different results, they have one outcome in common, which is a statistical significant decrease in the LSM score during the last year of Enron's existence. However, only in Table 7 the decrease is economically significant. This might be caused by the fact that the sense of belonging declines during depressed times, which leads to less mimicking behavior of Enron's employees. All the results that we obtained for the LSM score do not provide us with a clear picture or a clear tendency towards a certain magnitude. Thus, for further research it is necessary to investigate a longer time period than it is the case for this study. The next section is going to discuss the outcome about affective content and linguistic style in more depth and, especially, how the methodology, that we used, affects the results.

5. Discussion

In this section we are going to discuss the shortcomings of the analysis and the effects, which it has on the results. We are going to start this section with a comparison between the text used in this study and other types of texts. Secondly, we are going to examine the significance test of this thesis, meaning that we are going to investigate if the Wilcoxon

signed rank test is the proper test to use and if not what consequences it has on the outcome. Thirdly, we are going to deal with the methodology used to conduct the intensity of affective content and, finally, we are going to discuss possible shortcomings in the methodology for the LSM approach.

5.1. Comparison of Different Types of Text

Table 8 below shows the LIWC 2007 outcome for different types of text, which are all mails written by Enron's employees from 1999 until 2002, Kenneth Lay's email declaring that Jeff Skilling is going to resign his engagement as CEO at Enron, a circular letter on Enron's top management (both are taken from the Enron corpus), an acceptance speech of a CEO award, a customer review of a hotel customer in Amsterdam, a movie review written by Susan Wlosacayna and, lastly, my own thesis. The full texts of each type mentioned before can be found in Appendix IV. Panel B of Table 8 displays examples for the categories that are investigated and Panel A shows the relative amount of words used for each category and for each text being analyzed. Clearly, function words is the category with the most words in each text ranging from 40 percent to nearly 64 percent of total words used. The Enron corpus is the lower boundary of the range and, thus, the analyzed mails use on average fewer function words. Most are used in the customer review and the acceptance speech. Social words range from 4,82 percent up to 10,88 percent. The mails analyzed, including the mail written by Kenneth Lay and the circular letter for the top management, use the most social words in our sample. When considering cognitive words, we observe that the two mails, which are taken from the Enron Corpus, as well as, my own thesis, include the most words in this category while the other ones range around 13 percent. Column three, four and five show the output for affective content, positive emotions and negative emotions respectively. The acceptance speech includes most affective content in the text with 12 percent of the total words written. This is mostly due to the high load coming from positive emotions. Kenneth Lay uses an exceptional high amount of emotional words as well when comparing it to the average amount of 3,55 percent in the whole dataset. Furthermore, we observe that the composition of affective content, which consists of positive and negative emotions, differs extremely from the types of text, as well as, from the different mails, that are included in the corpus. Our research investigates the linguistic pattern of a set of over 200,000 mails written. Finding a unique pattern by combining all mails of a whole company over four years is only possible

for extremely pronounced patterns. Further research on a single person or a smaller group of people by using an advanced dictionary, that includes more subcategories, can shed new light on the topic and discover patterns, which are not found in this research. For example, it would be interesting to investigate if it is possible to measure the effect of the stock price on the emotional status of Jeff Skilling instead of on the whole company as he was the person that infected the company with the emotional dependence on the stock price. However, the corpus, that we used for our research, does not include enough mails written by Jeff Skilling or others in the top management team that are consistent over time and, thus, do not allow us to analyze their mails separately.

Table 8
Comparison of Different Types of Text

The table shows the output that is obtained from LIWC 2007 on six different categories for seven different types of text. Row two and three (Ken Lay & Circular Letter) display emails that are taken from the Enron corpus. All scores represent the percentage amount of the full text being analyzed. Examples for each word category can be found below.

	Social words	Affective Words	Positive Emotions	Negative Emotions	Cognitive Words	Function words
Enron Corpus	7,40	3,55	2,78	0,75	12,64	40,08
Ken Lay	9.62	7.22	4.81	2.06	17.53	56.36
Circular Letter	10.88	3.06	3.06	0.00	20.75	47.96
Acceptance Speech	4.82	12.05	11.45	0.60	13.25	63.25
Costumer Review	6.92	3.08	0.77	1.54	12.31	63.85
Movie Review	4.76	5.44	2.72	2.72	12.93	48.30
Own Thesis	4.92	4.44	2.18	1.58	18.53	49.35

Examples for each category:

Social words: Mate, talk, they, child
Affective Words: Happy, cried, abandon
Positive Emotions: Love, nice, sweet
Negative Emotions: Hurt, ugly, nasty
Cognitive Words: cause, know, ought
Function words: We, those, the, it

5.2. Wilcoxon Signed Rank Test & Stationarity of the Dataset

For the purpose of this study, we use the Wilcoxon signed rank test, which is the nonparametric statistical hypothesis test equivalent to the dependent t-test that is used in order to compare two related or matched samples, as well as, time series data on a single sample. It tests whether the population mean rank is statistical different. One advantage of a nonparametric test is that it does not assume normality in the data. However, also the Wilcoxon signed rank test has assumptions that have to be taken into consideration when

using this method. Firstly, the depended variable has to be measured at an ordinal or continuous level. Secondly, the independent variables are supposed to consist of two related or matched samples. Lastly, the Wilcoxon signed rank test assumes a symmetrical distribution of the differences between the two related groups. Especially, the last assumption is not always true in our dataset and that is why we conducted another method to calculate the statistical significance, namely, the sign test. It does not assume a symmetrical distribution of differences, however, the statistical power of the sign test is lower than the one of the Wilcoxon signed rank test. The results can be found in Appendix V. Overall, the outcome stays the same even though some variables have a lower statistical significance. Thus, we conclude that the Wilcoxon signed rank test is appropriate to use for the purpose of this study as the first two assumptions are met and when controlling for the concern of symmetry, our results remain nearly the same. (Sheskin, 2003)

Another obstacle that is important to deal with when working with time series data is to investigate if the dataset is stationary. Therefore, we conduct a unit root test on each single time series using the Augmented Dickey-Fuller test and, additionally, we take the autocorrelation function into account. Both methods are conducted in Eviews. The results of the Augmented Dickey-Fuller unit root test show that the data seem to be non-stationary when we do not include a trend or intercept but are stationary when we include them. When we change the data into the first difference, the Augmented Dickey-Fuller unit root test shows that the data is stationary and, therefore, we conduct the same tests as in Section 3 by using the first difference. However, none of the differences is significant for the change in affective content, as well as, for the LSM scores. Next, we use the autocorrelation function to see if there is any trend in our dataset. The autocorrelation function indicates no trend and despite of the mixed findings in the Augmented Dickey-Fuller unit root test, we conclude that our data has no stationary problems. Next, we are going to discuss the validity of the outcomes for the change in affective content, as well as, for the LSM approach.

5.3. Affective Content

In Section 4 we find statistical significant changes in affective content during the period 1999 until 2002. However, we find different results depending on the frequency used when analyzing weekly and daily frequency. For daily frequency it is not possible to take the

subjects into account, as the word count is extremely small in most of the time period considered. This leads to the fact that the emotional content, that is shown in LIWC 2007, especially, when differentiating between positive and negative emotions, often takes the value zero and, therefore, it leads to misleading results. This means that when calculating the measure for affective content, we can only use the first part of formula 1 which might be the reason for different results. Further, when using daily frequency, the data is not continuous as on many days no mails were written during the time period and, more important, the amount written differs extremely from day to day. Thus, the rational behind using weekly frequency is that it assures that we obtain continuous data that it does not differ as much as the data for daily frequency. When considering the different results in table 3 and 4, we conclude that the results in table 3 are more accurate because weekly frequency is more precise. However, the outcome in table 5 is only consistent with Hypothesis 3 when using daily frequency. Here, we argue that it seems to be more applicable to consider Panel B (daily frequency) instead of Panel A (weekly frequency) because one major advantage outweighs the obstacles mentioned above, namely, daily data takes into account daily changes in the stock price, which is lost when using weekly frequency and, therefore, leads to an insignificant outcome. Thus, when looking at differences, weekly data is more applicable and when regressing the changes on affective content on the stock price and other commodities and indices, daily data is more applicable as a lower frequency fails to take into account daily changes in prices. Anyhow, the result in Table 5 have a low r squared and, hence, one has to be careful when interpreting those numbers as it is very likely that the outcome is a result by chance. Therefore, an extended time period might lead to better results but the Enron corpus is the only dataset covering such an extending amount of mails that is freely available.

Next, we are going to investigate if the outcome changes when we change the second part of Formula 1. The rational behind dividing the subject part by two is that the body part is of greater importance and, thus, the effect of the subject has to be smaller on the intensity of affective content. Yet, it might be the case that it has an influence on our results when we do not divide any part of Formula 1 by two or if we divide the body part by two. Therefore, we rerun our test for Table 2 by using different procedures for calculating the intensity. The results can be found in Appendix VI and they show that the overall results are not changed. However, dividing the subject part by two (original results) leads to the lowest outcomes for the intensity of affective content.

Finally, Table 2 points out that there is a need for subcategories for positive emotional words, as well as, for more subcategories in both emotional categories (positive and negative). Further, Loughran and McDonald (2013) state in their study “ IPO first-day returns, offer price revision, volatility and form S-1 language” that results in positive words can be misleading because many negative phrases are wrapped into positive words as for example: “Our new business strategy is not successful”. This might be one reason why we find a higher amount of positive emotional words compared to negative ones. Despite this fact, we find evidence for Hypothesis 1b and 2b, which state that negative emotional words increase. This supports Hypothesis 1 and 2 even if the hypothesis, that includes positive emotions, is excluded.

5.4. Linguistic Style Match

We have used two different approaches to calculate the LSM score and have concluded that both approaches lead to different results. Whereas Formula 2 leads to results that are consistent with Hypothesis 4b, Formula 3 leads to results, which are inconsistent with Hypothesis 4a and 4b. The rationale behind it is that we only observe the last four years of Enron’s existence, excluding the 15 years before. This means that if there was a convergence in the writing style of Enron’s employees, because people mimic each other in order to increase the sense of belonging, then it must have happened in the years before. This calls for a longer time period that needs to be taken into consideration. It becomes especially evident when considering Table 7 where we observe fluctuations in the trend of the LSM score from year to year. It might be that the fluctuations, which we found over the short term, disappear over the long term, or vice versa, that the fluctuations become more pronounced.

All in all, our data is robust in the sense that it is stationary and the data does not have a symmetry problem that biases our results when using the Wilcoxon signed rank test. However, when conducting the regression, as well as, the LSM approach, it becomes obvious that a longer time period would be beneficial in order to have a stronger support for our hypotheses. Further, there is a need for an improved dictionary, that includes more subcategories for negative and, especially, for positive emotions.

6. Conclusion

This study was set out to explore the concept of a new measurement technique for emotions by using text-mining software in order to analyze the Enron corpus on affective content. The need for a new measurement for emotions becomes obvious when considering methods that have been conducted so far to analyze emotions on the decision-making of individuals. In Section 1, we show that the former approaches have large shortcomings, which might lead to biased results since they are often difficult to be applied outside the lab. They often create potential confounds, the resulting affective state dissipates quickly, there is a necessity of high participant motivation, as well as, an underestimation in the intensity of experienced emotions by participants is possible (Cohen, Pham, and Andrade 2008). Therefore, we use an innovative approach of analyzing written text on affective content to see if we are able to observe changes in affective content as it has been expected in the hypotheses.

Firstly, in our study we find that negative emotions increase significantly from 2000 until 2002 by 12,05 percent for the body part and 37,83 percent for the subject part. Positive emotions stay the same for the body part but decrease significantly by 31,94 percent in the subject part and, most important, the measure for the magnitude in affective content including the body and the subject part decreases significantly by 23,5 percent. Thus, in Table 2 of Section 4 we find support for Hypothesis 1, 1a and 1b. In line with Hypothesis 2, Panel A, B and C of Table 3 show that the intensity for affective content is larger before the week of Enron's all time high and decreases afterwards such that the value for affective content decreases afterwards relative to the base week. This is caused by an increase in words related to negative emotions and also due to a decrease in words related to positive emotions. Thus, we find support for Hypothesis 2, 2a and 2b, which indirectly support Hypothesis 3, meaning that there is a positive relation between the intensity for affective content and Enron's stock price. However, when using daily frequency, the results in Table 4 are conflicting to the ones in Table 3 but the data, which uses daily frequency is less precise as the data is not consistent over the whole time period and the amount written fluctuates from day to day, which affects the outcome of our analysis for affective content. Nevertheless, the outcome in Table 5 is only consistent with Hypothesis 3 when using daily frequency. Here, we argue that it seems to be more applicable to consider Panel B (daily frequency) instead of Panel A (weekly frequency) because, despite the disadvantages, daily data takes into account daily changes in

the stock price, which is lost when using weekly frequency. Hence, the advantage of daily frequency is that it takes into account daily changes of the stock price and outweighs the limitations for daily frequency.

By finding expected results, as well as, limitations that have to be overcome, we can provide a baseline for further research in the field of behavioral economics in financial decision-making that is influenced by emotions. As discussed before, affective content plays a key role in the decision-making of human beings. Thus, it is important to discover measurement techniques on emotions in order to analyze how changes in affective content influence the behavior of people. This is especially true when it comes to pension plan decisions because the trend is going towards Defined-Contribution plans. The duty to meet one's monetary needs in the retirement stage shifts therefore from the employer to the employee. From the perspective of a pension fund, this creates a need to find the best possible long-term investment for each customer (employee) such that every individual makes well-informed decisions upon their long-term savings, which fits her best. A deeper understanding of emotions on the decision-making and on the preferences of choices can therefore be value-adding by minimizing longevity risk (Post and Hanewald, 2013), caused by self-control issues, or incorrect prediction of future emotions (projection biases) (Knoll, 2010). Hence, text-mining techniques can be used to measure emotions of customers during email correspondence and identify how emotions differ according to diverse dimensions of heterogeneity. This gives pension funds the capability to treat their customers in a different and more precise manner by mirroring or priming certain emotions.

Moreover, in our study we use LIWC 2007 as the text mining software and we observe that there is a need for more categories in both, the measurement for positive and negative emotions. Therefore, it is important to study specific dimensions of emotions. Measuring only the valence would lead to biased results because different negative emotions, such as anxiety, anger and sadness cause different outcomes on the decision making of an individual.

Furthermore, this study goes beyond the use of text-mining software on affective content by analyzing the linguistic style of Enron's employees between 1999 and 2002. We use two different approaches to calculate the LSM score and find that both formulas lead to different results. However, Formula 3 leads to results that seem to be better for the purpose of further analysis because the changes in LSM are more pronounced in this method. Further research

needs to examine which method fits best for the purpose of its study because our results on both formulas may only be applicable for the Enron corpus. Nonetheless, in Table 6, we found indications that the LSM score stays constant over the time period considered. Formula 2 does not show a clear pattern for the subcategories of function words and the LSM measure changes statistically significant but not economically significant. The results for Formula 3 are shown in Table 7 and indicate an increase in the score from 1999 until 2000, no change in the score for the year after and a decrease from 2001 until 2002. Even though the increase in the first year is higher than the decrease in the last year, we conclude that our findings are not in line with Hypothesis 4a and Hypothesis 4b, meaning that the LSM score stays not constant over time and, even though, there is an increase in the similarity in linguistic style, it is small and inconsistent over time. Thus, all the results obtained for the LSM score do not provide us with clear tendency towards a certain magnitude and therefore calls for a longer time period that should be taken into consideration. However, freely available datasets of email correspondences are limited and the Enron corpus is already the most extensive dataset that is freely accessible.

As a final remark, we conclude that using text mining software in order to measure emotions and linguistic style is a newly, innovative and promising field in the future. This study is laying the groundwork for further analysis in this area and it becomes obvious that improvements have to be made in the approaches that we have used so far. For example, future research should take the dimensions of emotions more intensively into account. In this study we observe three different dimensions of negative emotions but none for positive emotions. For both, we suggest a further development of dimensions that are measured by the text-mining software. As the new version, LIWC 2015, is now able to create an own dictionary that analyzes text, this software can be used in future studies to develop stronger dictionaries in the field of emotions. Taking into account the growing importance in data mining, and thus also in text mining, over the last decade, it seems surprising that there are only few studies using this technique on emotions. We hope that this academic work can raise attention for further analysis and development in this area, as the implications for academia, as well as, for the industry can be extremely beneficial. From an academic perspective, further studies on emotions can shed new light on non-rational behavior that people exhibit when making financial decisions. From an industrial or managerial perspective, the use of text-mining techniques bundled with the knowledge obtained from

research on emotions can enhance customer service and boost long-term decisions made by pension fund customers.

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8. Appendices

Appendix I

A detailed description of the tables and data frames created by Arne Hendrik Schulz. This is the dataset (MySQL 5.0 dump) that has been used for further analysis.

1.1.1 Employeelist

- **eid:** Employee-ID
- **firstName:** First name
- **lastName:** Last name
- **Email_id:** Email address (primary). This one can be found in the other tables/dataframes and is useful for matching.
- **Email2:** Additionally E-Mail-Address that was replace by the primary one.
- **Email3:** See above
- **Email4:** See above
- **folder:** The user's folder in the original data dump.
- **status:** Last position of the employee. "N/A"s could not be found out.

1.1.2 Message

- **mid:** Message-ID. Refers to the rows in recipientinfo and referenceinfo.
- **sender:** Email address (updated)
- **date:** Date.
- **message_id:** Internal message-ID from the mailserver.
- **subject:** Email subject
- **body:** Email body. Can be truncated in the R-Version!
- **folder:** Exact folder of the e-mail including subfolders.

1.1.3 Recipientinfo

(Note: If an E-Mail is sent to multiple recipients, there is a new row for every recipient!)

- **rid:** Reference-ID
- **mid:** Message-ID from the message-table/-dataframe

- **rtype:** Shows if the reciever got the mail normally (“to”), as a carbon copy (“cc”) or a blind carbon copy (“bcc”).
- **rvalue:** The recipient’s email address.

1.1.4 Referenceinfo

- **rfile:** referenceinfo-ID
- **mid:** Message-ID
- **reference:** Contains the whole email with shortend headers.

Appendix II A

Below one can find the script that is used to clean the dataset and to create text files for weekly frequencies, such that the data can be analyzed by LIWC 2007.

```
<?php

// Specify Database, Server, User and Password for the Enron database:

$servername = "localhost";
$username = "root";
$password = "";
$dbname = "enron";
$targetPath = 'C:\Users\Public\Enron\';

// Create database connection:

$conn = new mysqli($servername, $username, $password, $dbname);

// Check if connection could be established correctly:

if ($conn->connect_error) {
    die("Connection failed: " . $conn->connect_error);
}

// SQL Statement, select the date, body and subject from the message table sorted
ascending by date:

$sql = "SELECT date , body, subject FROM `message` ORDER BY `date` ASC";

// Fire the SQL Statement:

$result = $conn->query($sql);

// If the result from the Statement is not empty:

if ($result->num_rows > 0) {

    // Get every message; make folder for subject and body for each year:

    // Make a file for every week

    while($row = $result->fetch_assoc()) {

        $Year = date('Y',strtotime($row['date']));
        $Week = date('W',strtotime($row['date']));
```

```

    $Path = $TargetPath . $Year . '\\' . $Week;

//If one of the paths folders does not exist, create the folder
    if (!file_exists($Path)) {
        mkdir($Path, 0777, true);
    }

// Put files in body path, with week filename

    file_put_contents($Path . '\\' . "Body.txt", $row['body'], FILE_APPEND |
    LOCK_EX);

    file_put_contents($Path . '\\' . "Body.txt", '
', FILE_APPEND | LOCK_EX);

// Put files in subject path, with week filename

    file_put_contents($Path . '\\' . "Subject.txt", $row['subject'], FILE_APPEND |
    LOCK_EX);

    file_put_contents($Path . '\\' . "Subject.txt", '
', FILE_APPEND | LOCK_EX);
    }

} else {
    echo "0 results";
}

//Close the Connection:

$conn->close();

?>

```

Appendix II B

Below one can find the script that is used to clean the dataset and to create text files for daily frequencies, as well as, for each messenger ID on a weekly frequency in order to prepare the data for further analysis with LIWC 2007.

```
<?php
```

```
// Specify Database, Server, User and Password for the Enron database:
```

```
$servername = "localhost";  
$username = "root";  
$password = "";  
$dbname = "enron";  
$TargetPath = 'C:\Users\Public\Enron';
```

```
// Create database connection:
```

```
$conn = new mysqli($servername, $username, $password, $dbname);
```

```
// Check if connection could be established correctly:
```

```
if ($conn->connect_error) {  
    die("Connection failed: " . $conn->connect_error);  
}
```

```
// SQL Statement, select the date, body and subject from the message table sorted  
ascending by date:
```

```
$sql = "SELECT sender, date , body, subject FROM `message` ORDER BY `date` ASC";
```

```
// Fire the SQL Statement:
```

```
$result = $conn->query($sql);
```

```
// If the result from the Statement is not empty:
```

```
if ($result->num_rows > 0) {
```

```
    // Get every message; make folder for sender and subject/body folders:
```

```
    // Make a file for every day, and for every week
```

```
    while($row = $result->fetch_assoc()) {  
        $Sender = $row['sender'];  
        $Year = date('Y',strtotime($row['date']));  
        $Month = date('m',strtotime($row['date']));  
        $Week = date('W',strtotime($row['date']));
```

```

$Day = date('d',strtotime($row['date']));
$BodyPath = $TargetPath . DIRECTORY_SEPARATOR . 'Body' ;
$SubjectPath = $TargetPath . DIRECTORY_SEPARATOR . 'Subject' ;
$SenderPath = $TargetPath . DIRECTORY_SEPARATOR . $row['sender'];

$SenderPathBody = $TargetPath . DIRECTORY_SEPARATOR .
$row['sender'] . DIRECTORY_SEPARATOR . 'Body';

$SenderPathSubject = $TargetPath . DIRECTORY_SEPARATOR .
$row['sender'] . DIRECTORY_SEPARATOR . 'Subject';;

```

//If one of the paths folders does not exist, create the folder

```

if (!file_exists($BodyPath)) {
    mkdir($BodyPath, 0777, true);
}

if (!file_exists($SubjectPath)) {
    mkdir($SubjectPath, 0777, true);
}

if (!file_exists($SenderPath)) {
    mkdir($SenderPath, 0777, true);
}

if (!file_exists($SenderPathBody)) {
    mkdir($SenderPathBody, 0777, true);
}

if (!file_exists($SenderPathSubject)) {
    mkdir($SenderPathSubject, 0777, true);
}

```

// Put Files in Body Path, with day-month-year name, so 1 per day:

```

file_put_contents($BodyPath . DIRECTORY_SEPARATOR . $Day . '-' .
$Month . '-' . $Year . ".txt", $row['body'], FILE_APPEND | LOCK_EX);

file_put_contents($BodyPath . DIRECTORY_SEPARATOR . $Day . '-' .
$Month . '-' . $Year . ".txt", '
', FILE_APPEND | LOCK_EX);

```

// Put Files in Subject Path, with day-month-year name, so 1 per day:

```

file_put_contents($SubjectPath . DIRECTORY_SEPARATOR . $Day . '-' .
$Month . '-' . $Year . ".txt", $row['subject'], FILE_APPEND | LOCK_EX);

```

```

        file_put_contents($SubjectPath . DIRECTORY_SEPARATOR . $Day . '-' .
$Month . '-' . $Year . ".txt", '

        ', FILE_APPEND | LOCK_EX);

        // Put Files in sender/body, with week-year filename

        file_put_contents($SenderPathBody . DIRECTORY_SEPARATOR . $Week
. '-' . $Year . ".txt", $row['body'], FILE_APPEND | LOCK_EX);

        file_put_contents($SenderPathBody . DIRECTORY_SEPARATOR . $Week .
'-' . $Year . ".txt", '

        ', FILE_APPEND | LOCK_EX);

        // Put Files in sender/subject, with week-year filename
        file_put_contents($SenderPathSubject . DIRECTORY_SEPARATOR .
$Week . '-' . $Year . ".txt", $row['subject'], FILE_APPEND | LOCK_EX);

        file_put_contents($SenderPathSubject . DIRECTORY_SEPARATOR .
$Week . '-' . $Year . ".txt", '

        ', FILE_APPEND | LOCK_EX);
    }

} else {
    echo "0 results";
}

//Close the Connection:

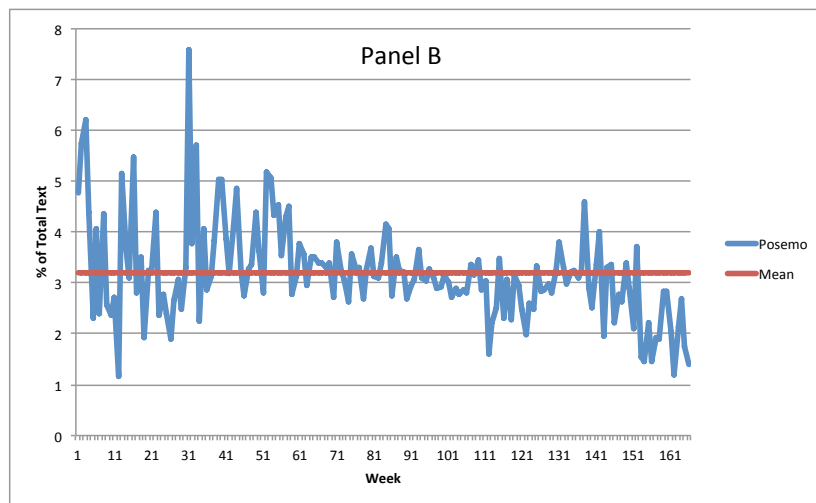
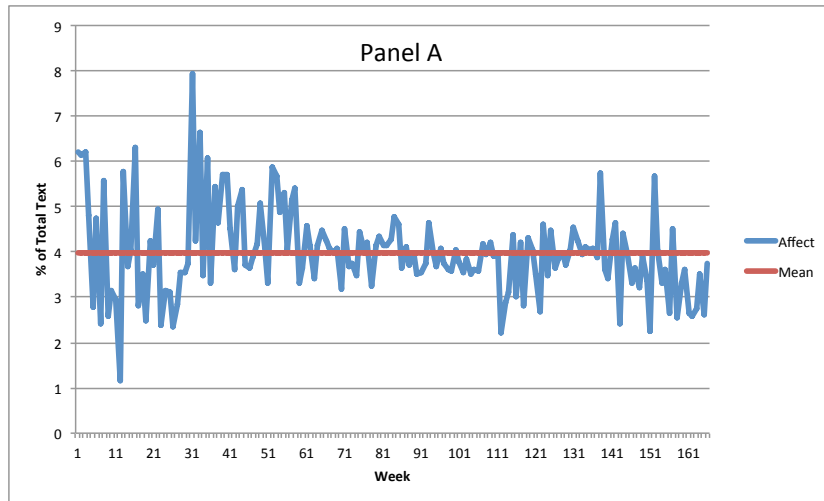
$conn->close();

?>

```

Appendix III

Figures representing the relative amount of (a) affective content, (b) positive emotions, (c) negative emotions for the subject part from week 1 in 1999 until week 28 in 2002. Graphs for anxiety, anger and sadness are not included due to data constraints.



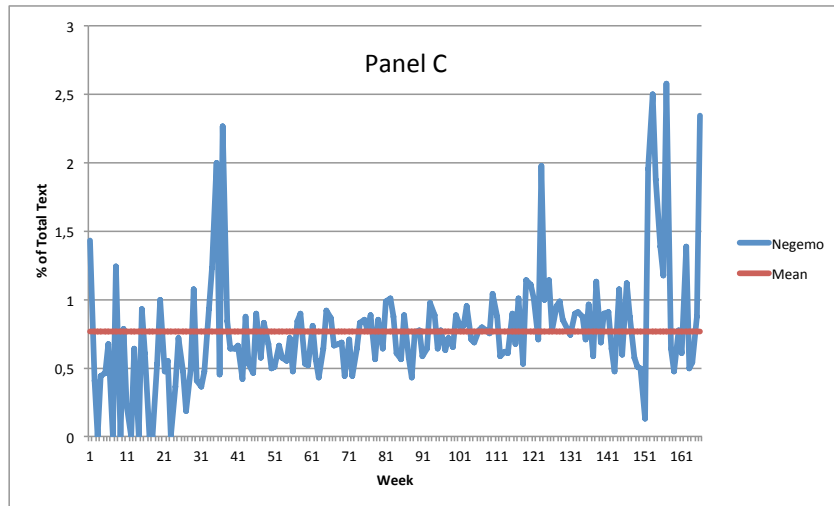


Figure 4 A representation of changes in affective content, positive emotions, negative emotions for the subject part. The data is retrieved from the output of LIWC 2007. The Time period starts in week 19 in 1999 and ends in week 28 in 2002. Panel A presents the percentage of affective content for each week in the subject part. Panel B presents the percentage amount of positive words for each week in the subject part and Panel C shows the percentage amount of negative words for each week in the subject part part. The red line represents the mean of the whole period. A graphical representation of the percentage amount of words related to anxiety, anger and sadness is not possible for the subject part due to data constraints.

Appendix IV

Full text representation of different texts analyzed in Section V including Kenneth Lay's email declaring that Jeff Skilling is going to resign his engagement as CEO at Enron, a circular letter on Enron's top management (both are taken from the Enron corpus), an acceptance speech of a CEO award, a customer review of an hotel customer in Amsterdam, as well as, a movie review.

Kenneth Lay - It is with regret that I have to announce that Jeff Skilling is leaving Enron. Today, the Board of Directors accepted his resignation as President and CEO of Enron. Jeff is resigning for personal reasons and his decision is voluntary. I regret his decision, but I accept and understand it. I have worked closely with Jeff for more than 15 years, including 11 here at Enron, and have had few, if any, professional relationships that I value more. I am pleased to say that he has agreed to enter into a consulting arrangement with the company to advise me and the Board of Directors. Now it's time to look forward. With Jeff leaving, the Board has asked me to resume the responsibilities of President and CEO in addition to my role as Chairman of the Board. I have agreed. I want to assure you that I have never felt better about the prospects for the company. All of you know that our stock price has suffered substantially over the last few months. One of my top priorities will be to restore a significant amount of the stock value we have lost as soon as possible. Our performance has never been stronger; our business model has never been more robust; our growth has never been more certain; and most importantly, we have never had a better nor deeper pool of talent throughout the company. We have the finest organization in American business today. Together, we will make Enron the world's leading company. On Thursday at 10:00 a.m. Houston time, we will hold an all employee meeting at the Hyatt. We will broadcast the meeting to our employees around the world where technically available, and I look forward to seeing many of you there.

Circular Letter - Thanks for making time to have dinner with us on Wednesday: it was great to see you. As Art mentioned, since the time we have started working with you, we have made frequent references to our operating teams about Enron accomplishments in the areas of customer excellence and employee satisfaction. More generally, we have held Enron out as an example of a highly accomplished company in all the areas Macerich is currently focusing on as an organization (operational integration, customer orientation, scalability, change leadership, and strategic focus). All of that being said, we would be extremely

appreciative of an opportunity to have either Jeff Skilling or Dave Delainey speak at either of these conferences. In any event, we are delighted that you would make an effort to see if this can be put together. Relative to upcoming Macerich events, there are two scheduled:(1) University of Notre Dame Executive Education Program, May 7 - 9 in South Bend. The curriculum is centered on change leadership and strategic thinking (officially "Enhanced Leadership and Strategy in the NewEconomy"). Attendees include our Executive Team (Art, David, Rick, Tom, Ed, and Larry Sidwell) and our Operating Team (17 SVPs). There is also around-table discussion scheduled with our Board on May 9.(2) Macerich s Company Conference, June 4 - 7 in Park Cities, Utah. The emphasis of the conference will be on our "e-Business Transformation" (more specifically on becoming wholly integrated across functional roles, customer facing, and highly scalable) and capturing value in our "ValueNetwork" (relationships we have with retailers, partners, vendors, shoppers, etc.) The attendees for this event include the same people at UND as well as our managerial professionals from the malls and our corporate offices (about 250 people, total). Let me know if you need any additional background or information.

Acceptance Speech - Dear Ladies and Gentlemen! It is a great honor for me to stand here today. I am sincerely grateful for this nomination and I am pleased to accept the CEO of the Year Award. I want to thank all who worked with me to make this event happen. I clearly realize the scale of this project and this makes me even more proud of this achievement. I want to pay a tribute to those more than two hundred CEOs from global energy companies who were nominated for this award. Particular tribute is to my potential competitors, eight other finalists. They all are devoted professionals who deserve this award just as I do. So, I want to thank them, because I am really proud to be put to the same row. You know, this award is also special to me because I turn out to be one of few CEO of the Year winners from Asia. So, there is also some national proud for my part. (Speech Guru: Free Sample Acceptance Speech: Accepting CEO of the Year Award. , n.d.)

Customer Review - I was disappointed in the size of our room it was very small. We were in the 4th floor room 4072 next to the lift. I had to request large towels in the 2nd day as there was none left in the room. I also had to request the pillows to be changed as I woke up after the first night with 5 bites on my face 1 in my shoulder and I on my arm. I told the reception I was convinced there was something in the pillows and they never had protectors on. The pillows were changed but I didn't really get anyone concerned for me even though I told

them I felt unwell and the fact my face was covered in bites sort of ruined my trip. (Booking.com: 857,036 hotels worldwide. Book your hotel now! , 2015)

Movie Review - Normally I would place most of the blame on director Jessie Nelson (“I Am Sam”) for delivering such a jumbled, toxic snow globe of a movie complete with a brewing storm, caustic quarreling and excessive caroling in an effort to undercut sentimentality. But I suspect screenwriter Steven Rogers (“Hope Floats,” “Stepmom”), is more to blame, if only for over- stuffing the plot. There are too many trite storytelling devices, such as a narrator a la “A Christmas Story” on top of flashbacks of past holiday memories with younger actors who barely look like their adult versions. That the voice belongs to Steve Martin doesn’t help a whit. There are too many characters to even attempt to care about. And there is too great of a reliance on music both yuletide and not (Sting, Nina Simone and Bob Dylan) to fill in the emotional blanks. (Wloszczyna, S., 2015)

Appendix V

Tables representing the outcome of Section VI but instead of using the Wilcoxon signed rank test, the statistical significance is conducted by using the sign test.

Table 9

Changes in Affective Content from 1999 until 2002 (Sign test)

The Table shows the yearly average Word Count (given in absolute value) and yearly average percentage of total word count for affective content, positive emotions, negative emotions, and words associated with anxiety, anger and sadness (given in percent) from week 19 in 1999 until week 28 in 2002. The last column shows the average amount for the total time period. Output is retrieved from LIWC 2007. Panel A shows the output for the body part and Panel B shows the output for the subject part of Enron's mails. Panel C presents the intensity of affective content by using Formula 1 for the calculation. The intensity for affective content for Panel A and Panel B is calculated by using only the first part of Formula 1. This means that the sum of negative affective content words is subtracted from the sum of positive affective content words and the result is divided by the sum of all words used. The Sign test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

Avg. Weekly data (Body)								
Panel A	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	22204		263627		787896		186777	365445
affect in %	3,47	0,048	3,51	0,154**	3,669	-0,061**	3,61	3,57
posemo in %	2,78	-0,004	2,77	0,061	2,834	-0,060	2,77	2,79
negemo in %	0,67	0,048	0,72	0,089***	0,807	0,008	0,81	0,75
anx in %	0,15	0,011*	0,16	-0,004	0,156	-0,049***	0,11	0,15
anger in %	0,13	0,014	0,14	0,051***	0,195	-0,058**	0,14	0,16
sad in %	0,12	0,013	0,13	0,053***	0,182	0,069***	0,25	0,16
AC in %	2,11	-0,052	2,05	-0,028	2,027	-0,068	1,96	2,04
N	34		52		52		28	166

Avg. Weekly data (Subject)								
Panel B	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	Whole Period
Word Count	360		5479		14133		3863	6903
affect in %	3,93	0,419	4,35	-0,515***	3,84	-0,353*	3,49	3,98
posemo in %	3,37	0,232	3,60	-0,613***	2,99	-0,543***	2,45	3,20
negemo in %	0,40	0,341	0,74	0,092**	0,83	0,192*	1,02	0,77
anx in %	0,12	0,134	0,25	-0,062	0,19	-0,135	0,05	0,17
anger in %	0,10	0,048	0,15	0,069**	0,22	-0,136	0,08	0,15
sad in %	0,05	0,084	0,13	0,0556*	0,19	0,254	0,44	0,19
AC in %	3,02	-0,157	2,87	-0,705***	2,16	-0,735***	1,43	2,43
N	34		52		52		28	166

Avg. Weekly data (Body + Subject)								
Panel C	1999		2000		2001		2002	Whole Period
AC in %	3,62	-0,130	3,49	-0,380***	3,11	-0,435	2,67	3,26
N	34		52		52		28	166

Table 10

Changes in Affective Content One Year Before & One Year After Enron's All Time High Using Weekly Frequency (Sign Test)

The table shows scores for affective content that are indexed on the average score of week 32 until week 36 in 2000. Column one shows the measures for affective content and column two presents the indexed weekly data for one year before (starting at week 31 in 2000) Enron stock hit its all time high and column four presents the indexed weekly data for one year after (starting at week 37 in 2000). Thus, the timespan surrounding the week of Enron's all time high is our baseline and is equal to one. Column three and five show the respective t-statistic resulting from the Sign test, which is used to test if the indexed scores are significantly different from one. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

Avg. Weekly data (Body)				
Panel A	Before	t- stat.	After	t- stat.
Word Count	99695		548763	
affect in %	1,032**	-2,357	1,042***	-4,299
posemo in %	1,045***	-4,299	1,023*	-1,803
negemo in %	0,981	-1,525	1,111***	-5,131
anx in %	1,083	-0,139	1,075***	-3,190
anger in %	0,852***	-3,744	1,288***	-5,686
sad in %	0,880***	-4,022	1,163***	-4,299
AC in %	1,052***	-3,467	0,971**	-2,080
N	52		52	

Avg. Weekly data (Subject)				
Panel B	Before	t- stat.	After	t- stat.
affect in %	1,040	-0,416	0,919***	-3,467
posemo in %	1,085	-0,139	0,899***	-4,299
negemo in %	0,912***	-2,635	1,005	-0,280
anx in %	2,399***	-2,739	1,195	-0,722
anger in %	1,069	0,000	1,487***	-2,912
sad in %	0,602***	-3,104	0,844***	-3,467
AC in %	1,153	-1,525	0,869***	-4,299
N	52		52	

Avg. Weekly data (Body + Subject)				
Panel C	Before	t- stat.	After	t- stat.
AC in %	1,093**	-2,357	0,936***	-4,299
N	52		52	

Table 11

Changes in Linguistic Style using Formula 2 (Sign test)

The table shows the output that is obtained from LIWC 2007 for separate function word categories, as well as, the outcome of the total LSM score using Formula 2. The time period is from week 1 in 1999 until week 28 in 2002. Differences and the corresponding significance are shown in columns three, five and seven. The last column shows the average amount for the total time period. The Sign test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	Avg. Weekly data (Body)							Whole Period
	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	
Word Count	16932		263627		787896		186777	330377
ppron in %	5,10	-0,065	5,04	-1,040***	4,00	0,490	4,49	4,68
ipron in %	3,40	-0,217*	3,18	-0,170***	3,01	-0,041	2,97	3,16
article in %	6,19	-0,395**	5,80	0,109**	5,91	-0,300***	5,61	5,91
auxverb in %	6,68	-0,356***	6,33	-0,638***	5,69	0,235	5,92	6,19
adverb in %	2,29	-0,290***	2,01	-0,150*	1,86	-0,076*	1,78	2,01
preps in %	13,01	-0,540***	12,47	-0,492***	11,98	-0,741***	11,24	12,30
conj in %	4,30	-0,085	4,22	-0,109***	4,11	0,162***	4,27	4,22
negate in %	0,66	-0,055	0,60	0,028*	0,63	0,087**	0,72	0,64
quant in %	2,07	-0,122*	1,95	0,001	1,95	-0,061	1,89	1,97
LSM	0,99999914	6,908E-07***	0,99999983	2,958E-08***	0,99999986	-3,972E-07	0,99999946	0,999999584
N	52		52		52		28	184

Table 12

Changes in Linguistic Style using Formula 3

The table shows the separate LSM scores for each function word category, as well as, the outcome of the total LSM score using Formula 3. The time period is from week 1 in 1999 until week 28 in 2002. Differences and the corresponding significance are shown in columns three, five and seven. The last column shows the average amount for the total time period. The Sign test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	Avg. Weekly data (Body)							Whole Period
	1999	Diff 99/00	2000	Diff 00/01	2001	Diff 01/02	2002	
Word Count	16932		263627		787896		186777	330377
ppron	0,898	0,070***	0,968	-0,001	0,967	-0,021*	0,946	0,944
ipron	0,922	0,060***	0,982	-0,009*	0,974	-0,014	0,960	0,959
article	0,935	0,049***	0,984	-0,004	0,980	-0,020	0,960	0,965
auxverb	0,939	0,043***	0,982	0,002	0,984	-0,023**	0,961	0,967
adverb	0,914	0,059***	0,973	0,004	0,978	-0,030**	0,948	0,954
preps	0,958	0,033***	0,991	-0,002	0,989	-0,017**	0,972	0,978
conj	0,947	0,036***	0,983	0,002	0,984	-0,024**	0,961	0,970
negate	0,867	0,095***	0,962	0,002	0,964	-0,055***	0,910	0,928
quant	0,908	0,069***	0,977	0,005*	0,983	-0,034***	0,948	0,955
Total LSM	0,921	0,057***	0,978	0,000	0,978	-0,026***	0,952	0,958
N	52		52		52		28	184

Appendix VI

Table 13

Comparison of Different Calculation Methods for the Intensity in Affective Content

The Table shows the differences in the results for the variable intensity in affective content, when changing the influence of each fraction on the total outcome. The time period starts in week 19 in 1999 and ends in week 28 in 2002. The Output is retrieved from LIWC 2007. The Wilcoxon signed rank test is used to test if the difference of means is significantly different from zero. The symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. N denotes the number of observations.

	Average weekly data						
	1999	Diff	2000	Diff	2001	Diff	2002
(1)	3,62	-0,130	3,49	-0,380***	3,11	-0,435***	2,67
(2)	4,08	-0,183	3,89	-0,719***	3,17	-0,769***	2,41
(3)	5,13	-0,209	4,92	-0,733***	4,19	-0,803**	3,39
N	34		52		52		28

Meaning of Columns:

- (1) Subject part is divided by two (Results of Thesis)
- (2) Body part is divided by two
- (3) Neither Subject part, nor body part is divided by two

Official statement of original paper/report/thesis

By signing this statement, I hereby acknowledge the submitted ~~paper/report~~ ^{paper/report/thesis*}, titled:

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Study programme: International Business - Finance track
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Course/skill: Master thesis
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