Content analysis of business communication: Introducing a German dictionary

Online-Appendix

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Table 12: Literature summary

This table extends the overview of content-analysis studies from Kearney and Liu (2014).

Research	Narrative	Time	Language	Content analysis methodology	Measure	Key Findings
Boukus and Rosenberg (2006)	Federal Open Market Committee minutes	1987-2005	English	Topic Modelling (LSA)	Topics	The authors identify the topics of Federal Open Market Committee minutes and find those topics to be correlated with current and future economic conditions.
Cicon et al. (2012)	Corporate Governance Codes	1998-2007	English	Topic Modelling (LSA)	Topics	The authors identify the topics of the corporate governance codes of 23 EU nations and find new insights regarding their thematic content, variability, and convergence.
Larcker and Zakolyukina (2012)	Earnings conference calls	2003-2007	English	Dictionary-based (LIWC)	Several	The authors show that the textual sentiment is indicative of financial misreporting.
Ammann et al. (2014)	Newspaper articles	1989-2011	German	Word-count index	-	Using word count indices, the authors find that newspaper articles provide valuable information for predicting future market returns.
Bao and Datta (2014)	Annual reports (10-K)	2006-2010	English	Topic Modelling (LDA)	Topics	Introducing LDA learning methods into the field of financial accounting, the authors measure distinct risk types in annual reports.
Buehlmaier and Whited (2014)	Annual reports (10-K)	1994-2010	English	Machine-Learning (Naïve Bayes)	-	The authors build measure of financial constraints from the tone of annual reports and find more financially constrained firms to have higher stock returns.
Chen et al. (2014)	Online comments	2005-2012	English	Dictionary-based (LM)	Negativity	The authors measure the textual sentiment of online commentaries and it to predict future stock returns and earnings surprises.
Tirunillai and Tellis (2014)	Costumer reviews	2005-2009	English	Topic Modelling (LDA)	Topics	The authors find customer reviews to be rich in marketing meaning which can be gauged by LDA.
Allee and Deangelis (2015)	Earnings conference calls	2004-2014	English	Dictionary-based (LM)	Positivity Negativity	Tone dispersion within earnings conference calls is associated with current performance and future performance, managers' financial re-porting decisions, and managers' incentives and actions to manage perceptions.
Arslan-Ayaydin et al. (2015)	Earnings press releases	2004-2012	English	Dictionary-based (HENRY)	Rel. positivity	Managers inflate the positive tone of earnings press releases when the managerial portfolio value is more closely tied to the firm's stock price.
Davis et al. (2015)	Earnings conference calls	2002-2009	English	Dictionary-based (DICTION, HENRY, LM)	Rel. positivity	The tone of earnings conference calls is influenced by manager-specific tendencies to be optimistic or pessimistic.

Gamache et al. (2015)	Annual reports (Letters to shareholders)	1997-2006	English	Dictionary-based (own dictionary)	CEO regulatory focus	The authors show that CEO regulatory focus has an influence on the acquisition behavior of the firm.
Giorgi and Weber (2015)	Analyst reports	1989-2012	English	Topic Modelling (LDA)	Topics	The authors tested the relationships between analysts' framing repertoires and professional investors' evaluations of analysts. They find that investors appreciate analysts with framing repertoires that resonate with their needs.
Kaplan and Vakili (2015)	Journal articles		English	Topic Modelling (LDA)	Topics	The authors develop a text-based measure of novel ideas in patents using topic modeling to identify those patents that originate new topics in a body of knowledge.
Loughran and McDonald (2015)	Annual reports (10-K)	1994-2012	English	Dictionary-based (DICTION, LM)	Positivity Negativity Rel. positivity	General language dictionaries like Diction inappropriate for gauging the tone of financial disclosures.
Wang et al. (2015)	Journal articles	1974-2014	English	Topic Modelling (LDA)	Topics	The authors use a topic modeling procedure to uncover 16 topics that have been featured in the Journal of Consumer Research since its inception and to show the trends in topics over time.
Ammann and Schaub (2016)	Online comments	2013-2014	German	Dictionary-based (Ad-hoc, SENTIWS, LIWC)	Positivity Negativity	The authors analyse data from an online social trading network, where traders publish their trading strategies for followers to comment on and invest in. They find that online investors adjust their trading behavior to the commentaries' sentiment, but the commentaries does not seem to have predictive power for the trading strategies' future performance.
Antons et al. (2016)	Journal articles	1984-2013	English	Topic Modelling (LDA)	Topics	The authors provide a map of the topic landscape in the Journal of Product Innovation Management. Further, they identify articles per innovation management topic that are most strongly associated with the respective topic to provide a fast and efficient way to dive into a topic.
Bochkay et al. (2016)	Earnings conference calls	2006-2013	English	Dictionary-based (Ad-hoc)	linguistic extremity	Investors respond strongly to extreme language, resulting in higher abnormal trading volume and stock returns.
Boudt and Thewissen (2016)	CEO Letters	2000-2011	English	Dictionary-based (DICTION, LM)	Positive Negative Net positivity	CEOs present negative and positive words strategically in CEO letters in order to prompt a more positive perception by the reader.
Debortoli et al. (2016)	Customer reviews	2012-2016	English	Topic Modelling (LDA)	Topics	The authors provide a tutorial for information system researchers on text mining using topic modelling.

Eickhoff and Muntermann (2016a)	Analyst reports, Earnings conference calls	2000-2015	English	Topic Modelling (LDA)	Topics	As the amount of potential useful business communication is steadily growing, the authors provide a structural approach to reduce information overload.
Eickhoff and Muntermann (2016b)	Analyst reports, Earnings conference calls	2000-2015	English	Topic Modelling (LDA)	Topics	The authors use LDA to investigate financial analysts' information processing behavior. They find that analyst reports written in a short period after a conference call show a significant topic-uptake from conference call events.
Feuerriegel et al. (2016)	Ad-hoc announcements	2004-2011	German	Topic Modelling (LDA)	Topics	Using Latent Dirichlet Allocation, the authors analyse the effects of topics found in German regulated ad-hoc announcements on stock market returns. The authors find that some topics have no resulting effect on abnormal returns of stocks, whereas other topics, such as drug testing, exhibit a large effect.
González et al. (2016)	Annual reports	2010-2013	Spanish and Portuguese	Dictionary-based (LM)	Uncertainty	For a sample of firms in the six largest Latin America countries, the authors look at the textual sentiment of annual reports. They can show that uncertainty is negatively associated with firm valuation and financial performance.
Henry and Leone (2016)	Earnings press releases	2004-2012	English	Dictionary-based (HENRY, DICTION, HARVARD, LM) Machine-Learning (Naïve Bayes)	Rel. positivity	Dictionary based measures of textual sentiment based on domain-specific wordlists are better in predicting market reactions to earnings announcements compared to general language wordlists. Dictionary based measures of textual sentiment are as powerful as the Naive Bayesian machine-learning methodology.
Heston and Sinha (2016)	News articles	2003-2010	English	Machine-Learning (Thomson Reuters sentiment engine)	Negativity Positivity Net positivity	Daily news predicts stock returns for 1 to 2 days and weekly news predicts stock returns for one quarter. Thereby, positive news articles increase stock returns quickly and negative articles have a long-delayed reaction.
Hillert et al. (2016)	Mutual fund shareholder letters	2006-2012	English	Dictionary-based (LM, HARVARD)	Negativity	Negative tone in funds' shareholder letters lead to lower fund inflows. Thereby, shareholder letter tone has no predictive power for future fund performance.
Mengelkamp et al. (2016)	Twitter messages	2013	German	Dictionary-based (Ad-hoc, SENTIWS)	Negativity Positivity	Textual sentiment in Twitter messages contains evidence concerning the financial stability of companies. The authors' constructed ad-hoc dictionary performs superior compared to the general German language dictionary SENTIWS.

Bannier et al. (2017)	CEO Speeches	2008-2016	German	Dictionary-based (SENTIWS, LIWC, BPW)	Negative Rel. positivity	Textual sentiment in CEO speeches held at the companies' annual general meetings is significantly related to stock market reactions following the annual general meeting.
Dzieliński et al. (2017)	Earnings conference calls	2003-2015	English	Dictionary-based (LM)	Uncertain	Investors respond less and more slowly with managers' use of uncertain language in earnings conference calls.
Ertugrul et al. (2017)	Annual reports (10-K)	1995-2013	English	Dictionary-based (LM)	Uncertain Modal words	Firms with less readable more uncertain words in their annual reports have stricter loan contract terms and greater future stock price crash risk.
Huang et al. (2017)	Analyst reports, Corporate disclosures	2003-2012	English	Topic Modelling (LDA)	Topics	Using LDA, the authors compare the topics of earnings conference calls and subsequent analyst reports. Doing so, they are able to analyse the value added by the analysts.
Lee and Kang (2017)	Journal articles	1997-2016	English	Topic Modelling (LDA)	Topics	The authors identify and analyse technology and innovation management research topics using topic modeling based on the articles published in 11 major journals in the field of technology and innovation management.
Renault (2017)	Online comments	2012-2016	English	Dictionary-based (Ad-hoc, LM, HARVARD); Machine-Learning (naïve Bayes, maximum entropy, support vector machines)	Positivity Negativity	The authors generate an ad-hoc dictionary in their analysis of social media messages' effect on intraday stock returns. The authors compare their ad-hoc dictionaries to the LM and HARVARD dictionaries as well as to machine-learning approaches. They find their ad-hoc dictionary to be better in explaining intraday stock price reactions than common dictionaries and to be competitive with complex machine learning approaches.
Antons and Breidbach (2018)	Journal articles	1986-2016	English	Topic Modelling (LDA)	Topics	The authors identify and analyse 69 distinct research topics in the body of service innovation and service design research.

Table 13: Adjustments to the sample of quarterly and annual reports

This table lists word combinations that were controlled for throughout our analysis using annual and quarterly reports. While the bag-of-words model generally assumes word independence, the evaluation of quarterly and annual reports obliges us to control for certain combinations of words. A company's „GAINS AND LOSSES“ or „PROFITS AND LOSSES“ are frequently mentioned without negative or positive connotation in quarterly or annual reports. This would, in comparison to the German documents where the equivalent „GEWINN- UND VERLUSTRECHNUNG“ is not included in the BPW dictionary, lead to a more extreme assessment of the English documents' positivity and negativity. Thus, we identify 40 combinations of the words „GAIN(S)“ and „LOSSE(S)“ as well as „PROFIT(S)“ and „LOSSE(S)“ and exclude them from the equivalence analyses. Likewise, the terms „IMPAIRMENT LOSS“ and „IMPAIRMENT LOSSES“ would account for two negative words while the German counterparts „WERTMINDERUNGSVERLUST“ and „WERTMINDERUNGSVERLUSTE“ would only account for one negative word. As this would also lead to an overestimation of the English documents' negativity compared to their German counterparts, we counted „IMPAIRMENT LOSS“ and „IMPAIRMENT LOSSES“ each as one negative word for our equivalence analyses. Note that we also controlled for different number of spaces between the combinations.

GAINS & LOSSES	PROFITS & LOSSES	LOSSES & GAINS	LOSSES & PROFITS
GAINS/LOSSES	PROFITS/LOSSES	LOSSES/GAINS	LOSSES/PROFITS
GAINS (LOSSES)	PROFITS (LOSSES)	LOSSES (GAINS)	LOSSES (PROFITS)
GAINS AND LOSSES	PROFITS AND LOSSES	LOSSES AND GAINS	LOSSES AND PROFITS
GAINS OR LOSSES	PROFITS OR LOSSES	LOSSES OR GAINS	LOSSES OR PROFITS
GAIN & LOSS	PROFIT & LOSS	LOSS & GAIN	LOSS & PROFIT
GAIN/LOSS	PROFIT/LOSS	LOSS/GAIN	LOSS/PROFIT
GAIN (LOSS)	PROFIT (LOSS)	LOSS (GAIN)	LOSS (PROFIT)
GAIN AND LOSS	PROFIT AND LOSS	LOSS AND GAIN	LOSS AND PROFIT
GAIN OR LOSS	PROFIT OR LOSS	LOSS OR GAIN	LOSS OR PROFIT

Table 14: Additional analyses

This table includes additional robustness checks to our main analyses. It presents summary statistics for the quarterly and annual reports' shares of sentimental words with respect to the dictionary by Loughran and McDonald (2011) for the English versions of the reports and with respect to the BPW dictionary for the German versions of the reports. Further, this table shows simple pairwise correlations, Spearman rank correlations and intra-class correlations (ICC[3,2]) after Shrout and Fleiss (1979) between the English and German textual sentiment with respect to the negative, positive and uncertain wordlists dictionary by Loughran and McDonald (2011) and our adapted dictionary, respectively. Panel A, presents our main analysis, making no exception from the word independence assumption described as described in Table 13. Panel B, presents our main analysis not using pruning or stop-word filtering. In panel C, we use a subsample of only professionally translated reports, whereby we identify professionally translated reports by manually reviewing the reports with respect for the disclosure of the usage of external professional translation, proofreading, or text-production services. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	English LM					German BPW							
	Mean [%]	Median [%]	SD [%]	Min [%]	Max [%]	Mean [%]	Median [%]	SD [%]	Min [%]	Max [%]	Pairwise Corr.	Spearman Corr.	ICC[3,2]
Panel A: No exception from the word independence assumption.													
NEG	1.58	1.47	0.57	0.34	3.84	1.40	1.31	0.47	0.16	3.30	0.779***	0.779***	0.863***
POS	1.27	1.25	0.29	0.40	2.53	1.15	1.14	0.31	0.00	2.37	0.676***	0.680***	0.806***
Panel B: No pruning, no stop-word filtering													
NEG	1.20	1.13	0.46	0.25	3.15	1.27	1.20	0.43	0.12	3.04	0.779***	0.783***	0.874***
POS	1.04	1.03	0.28	0.29	2.43	1.08	1.06	0.31	0.00	2.82	0.635***	0.718***	0.774***
UNC	0.98	0.92	0.38	0.29	2.97	0.93	0.93	0.24	0.21	1.90	0.753***	0.762***	0.807***
Panel C: Professionally translated reports (N=382)													
NEG	1.26	1.22	0.45	0.47	2.77	1.27	1.22	0.36	0.51	3.30	0.774***	0.779***	0.862***
POS	1.18	1.17	0.29	0.34	2.08	1.19	1.17	0.26	0.48	2.03	0.760***	0.711***	0.860***
UNC	1.11	1.03	0.47	0.46	3.25	1.05	1.04	0.28	0.41	2.08	0.869***	0.864***	0.865***

Table 15: English vs German textual sentiment in the quarterly and annual reports (Different versions of our dictionary)

For the construction of the BPW dictionary, we start by conducting a word-by-word translation on the LM word lists, accounting for differences in inflectional morphology, lexical morphology, and compound wording between German and English afterwards. This table shows the effect of these adaptions by re-conducting our main analysis for the different developmental stages of our dictionary. It presents the numbers of words in the BPW's wordlists with respect to the developmental stage as well as summary statistics for the quarterly and annual reports' shares of sentimental words with respect to the developmental stages of our (BPW) dictionary for the German versions of the reports. Further, it shows simple pairwise correlations, Spearman rank correlations and intra-class correlations (ICC) after Shrout and Fleiss (1979) between the English and German textual sentiment with respect to the negative, positive and uncertainty wordlists by Loughran and McDonald (2011) and the versions of our adapted BPW dictionary, respectively. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		German (BPW)							
	# words in BPW	Mean [%]	Median [%]	SD [%]	Min [%]	Max [%]	Pairwise Corr.	Spearman Corr.	ICC[3,2]
Panel A: Initial dictionary									
NEG	11,746	3.11	3.02	0.65	0.48	5.85	0.656***	0.625***	0.784***
POS	2,913	3.53	3.47	0.63	0.13	5.78	0.517***	0.530***	0.573***
UNC	1,883	1.88	1.82	0.36	0.20	3.13	0.249***	0.272***	0.396***
Panel B: Dictionary including compound words									
NEG	12,031	3.21	3.11	0.69	0.48	6.04	0.676***	0.648***	0.793***
POS	2,940	3.53	3.47	0.63	0.13	5.78	0.518***	0.531***	0.573***
UNC	1,941	1.92	1.88	0.36	0.20	3.14	0.338***	0.335***	0.503***
Panel C: Final dictionary including compound words, controlling for lexical and inflectional morphology									
NEG	10,147	1.40	1.31	0.47	0.16	3.30	0.769***	0.779***	0.865***
POS	2,223	1.15	1.14	0.31	0.00	2.37	0.725***	0.734***	0.840***
UNC	1,697	1.01	1.01	0.26	0.25	2.13	0.752***	0.774***	0.811***

Table 16: Summary Statistics of the CEO speeches

This table presents summary statistics of our sample of CEO speeches uses for our analyses in Table 6.

			Words per document					Individual words per document				
	Reports	Total Words	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Panel A: Whole sample												
GER	338	1,160,453	3,433	3363	985	1,327	6,392	1,120	1,116	247	530	1,835
Panel B: Sub-sample of corresponding English and German speeches												
ENG	270	892,557	3,306	3,181	1,056	1,172	6,176	979	966	224	447	1,635
GER	270	931,213	3,449	3,343	1,047	1,327	6,392	1,126	1,114	265	530	1,835

Table 17: Test of differences of cumulative abnormal returns

This table sorts holding period excess returns following the release of annual and quarterly reports into tertiles with respect to their negativity, positivity and uncertainty as measured by our BPW dictionary. Excess returns are estimated as a firm's buy-and-hold stock return index for the 3-day time window of day -1 to day 1 minus the CDAX buy-and-hold market index return over the respective 3-day event window. Statistical significance of the differences in mean and median excess returns between the highest and lowest tertiles of textual sentiment categories are assessed by t and z test statistics, respectively. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		T1	T2	T3	T3-T1	t-Statistic	Wilcoxon rank-sum z-Statistic
Panel A: Whole sample (N=1,348)							
Negativity	Mean	0.006	0.003	0.000	-0.005	-1.778*	
	Median	0.002	0.003	-0.001	-0.003		-1.220
Positivity	Mean	0.001	0.001	0.007	0.006	2.183**	
	Median	0.001	-0.002	0.008	0.007		2.907***
Uncertainty	Mean	0.007	0.002	0.000	-0.007	-2.179**	
	Median	0.004	0.002	-0.001	-0.005		-1.942*
Panel B: Annual reports (N=351)							
Negativity	Mean	-0.001	0.000	0.005	0.006	0.918	
	Median	-0.006	0.003	0.005	0.011		1.799*
Positivity	Mean	-0.001	0.002	0.002	0.002	0.393	
	Median	0.003	-0.002	0.001	-0.002		-0.264
Uncertainty	Mean	0.005	-0.007	0.005	0.000	-0.005	
	Median	0.003	-0.009	0.007	0.004		0.407
Panel B: Quarterly reports (N=997)							
Negativity	Mean	0.009	0.002	0.000	-0.009	-2.429**	
	Median	0.004	0.002	-0.001	-0.005		-2.250**
Positivity	Mean	0.000	0.002	0.009	0.009	2.812***	
	Median	-0.002	0.000	0.009	0.011		3.811***
Uncertainty	Mean	0.009	0.002	0.001	-0.008	-2.284**	
	Median	0.008	0.001	-0.001	-0.009		-2.562**

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