Internet Appendix for
"The Power of Voice: Managerial Affective States and Future Firm Performance"*

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A.1 Literature on Detecting Emotion in Voice

In this section, we provide an overview of the literature on detecting emotion in voice. This overview is not intended to be an exhaustive survey of the literature on emotions. Rather it is meant to provide an interested reader with a reasonable starting point to appreciate the vast emotion literature. Juslin and Scherer (2008) provide an easy to digest summary of the theory and methods related to analyzing vocal markers of affect. As they mention, the basic assumption underpinning speech emotion analysis is that there exists a set of objectively measurable parameters that reflect the affective state a person is currently experiencing. Finding the precise set of parameters from voice that will robustly identify various emotions in real world settings is difficult and still evolving. Not surprisingly, clear identification of the voice profile that marks a particular affective state would be useful in a wide variety of applications, from robot/human interactions to customer service in call centers, credibility assessment in security settings and patient diagnosis in healthcare.

The process of identifying emotion from voice first requires the researcher to obtain or create a speech corpus. The speech corpus provides the samples from which voice parameters, or acoustic features of the speech signal, are extracted. Speech samples analyzed in the literature come generally from three sources: emotion portrayals by professional actors, natural vocal expressions, and experimentally evoked affect expressions. Researchers face trade offs when selecting among these three sources. Professional actor portrayals of emotion lack ecological validity, but provide experimental control. Natural vocal expressions are ecologically valid, but it is difficult to know the precise emotion felt by the speaker. Experimentally evoked affect expressions have some aspects of both - experimental control and ecological validity. However, experimentally inducing a detectable level of emotion can be difficult. Ververidis and Kotropoulos (2006) provide one of the more recent surveys of available speech data collections for studying emotions (see Douglas-Cowie, Campbell, Cowie and Roach 2003 for an earlier survey). Few speech databases are publicly available, which prevents researchers from replicating published results. One exception is the Berlin Database of emotional speech (see Xiao, Dellandrea, Dou and Chen 2005), which is a collection of speech samples spoken in German by professional actors.

Once speech samples are obtained from whatever source, voice features must be extracted. Common acoustic features receiving attention in the literature include fundamental frequency, jitter, and shimmer, among others (Owren and Bachorowski 2007). However, the complete set of acoustic features that might be useful for detecting emotion in voice is still being uncovered. Recent work by Yang and Lugger (2010)

* Citation format: Mayew, William J., and Mohan Venkatachalam, 2010, Internet Appendix to "The Power of Voice: Managerial Affective States and Future Firm Performance," *Journal of Finance* ***, http://www.afajof.org/supplements.asp. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

uses music theory to introduce a new set of harmony features for detecting emotion in voice. Procedurally, to extract acoustic features, many researchers rely on the Praat acoustics program. After a speech file is uploaded into Praat, a researcher then makes choices with respect to segmenting the file and as well as choosing the acoustic features for extraction. Owren (2008) introduces a set of Praat add-on scripts that extract commonly studied acoustic features and place them into machine readable datasets.

Upon extracting the acoustic features of interest, researchers then develop recognition models that combine acoustic features in particular ways so as to identify the emotional content of a given speech sample. Research is ongoing to uncover the most accurate recognition model. Wu, Yeh and Chuang (2009) review some of the existing recognition models, the acoustic features used, and introduce a recognition model of their own. As Ververidis and Kotropoulos (2006) point out, comparing classification rates across various classification models in the literature is difficult due to variation in the speech corpus used and experimental methods employed.

Ongoing research focuses on generating new speech databases, identifying new acoustic features that mark emotions, comparing the predictive ability of existing recognition models, developing new recognition models by combining existing acoustic features in new ways and/or some combination of the aforementioned. For example, in the call center setting, Morrison, Wang and Silva 2007 examine two speech sample databases and introduce two new classification models. Koolagudi, Maity, Kumar, Chakrabarti and Rao (2009) develop a speech database from professional actors in the Telugu language and test a recognition model using this new speech database.

Researchers who wish to measure emotions from speech samples face the challenge of selecting from a vast literature both the specific acoustic features and the recognition model that will best identify a given emotion. Both of these choices are necessarily ad-hoc to a large degree because no standard set of acoustic features or recognition models has emerged as universally applicable (Schuller, 2010). Additionally, for researchers interested in analyzing natural vocal expressions from real life speech samples, extracting emotion specific acoustic features is difficult due to noise emanating from two sources. First, speech samples extracted from natural environments may contain extraneous sounds. Additionally, acoustic features may vary across speech samples in a cross section of speakers due to variation is the speaking mechanism of the speaker (this is commonly not a problem in speech samples collected from professional actors where the same actor repeats a common utterance under different emotions). Thus, removing extraneous sounds and normalizing natural speech samples to remove speaker specific effects are important considerations.

Notwithstanding the lack of consensus in terms of acoustic features and models for identifying emotions, commercial enterprises have developed tools for measuring emotion in voice. Accenture holds a 2007 patent (US Patent No. 7,222,075 B2) to a voice based emotion analyzer based on early research by Petrushin (1999). However, Accenture does not commercially sell or license a related software product. Advanced Generation Interface, Inc (AGI, Inc) holds a 2008 patent (US Patent No. 7,340,393 B2) to a Sensibility Technology development kit called the ST2.0 voice emotion analysis system which attempts to classify speech segments into various emotional categories based on research by Mitsuyoshi, Ren and Li 2006. Commercial availability of this development kit began in 2010. Both of these products use internal classification models based on proprietary combinations of various acoustic features of the speech signal, such as fundamental frequency, to identify emotions. The purpose of these products is to directly measure emotions, which could then be used in applications such as call centers, robotics and video games.

Nemesysco, Ltd holds a 2003 patent (US Patent No. 6,638,217 B1) to an apparatus for detecting emotions from speech. Nemesysco offers commercial products based on what it calls Layered Voice Analysis

(LVA), but does not divulge the specific vocal parameters extracted from the speech signal nor how such parameters are combined to generate the software output. The original Nemesysco products were designed for lie detection by first extracting various parameters from speech, classifying various emotions, and then combining emotion measures and other voice parameters to generate a deception indicator. The LVA technology now underpins a variety of software products for a various of commercial purposes. We discuss research that uses and evaluates LVA based software products in the next section.

A.2 Research Utilizing Layered Voice Analysis (LVA)

Early academic research on LVA focused on LVA's ability to detect deception from speech samples, with no studies finding support for LVA's built-in deception indicator working at better than chance levels. More recent research investigates the predictive ability and construct validity of some of the more primitive emotion variables offered by the LVA software with some success. In this section, we provide an extensive listing of research investigating LVA (in reverse chronological order), accompanied by a description that briefly summarizes the key insights of each study. The descriptions provided are not intended to be comprehensive summaries, but rather to enable a reader to easily ascertain the particular LVA based product utilized, the particular LVA variables of interest (base layer variables are referred to as raw variables, the subsequent layer variables that remove speaker specific characteristics are referred to as first grade variables, and conclusion layer variables are referred to as algorithmic variables), and the main empirical results.

Han and Nunes (2010) uses the LVA based QA5 software variable called embarrassment. The paper validates this LVA embarrassment measure experimentally by showing voice segments when describing a packet of oatmeal (a low embarrassment product) exhibit lower embarrassment scores than subjects describing a packet of condoms (a high embarrassment product). The paper also examines determinants of embarrassment as a function of brand status signals.

Elkins and Burgoon (2010) uses a comprehensive set of LVA 6.50 first grade and algorithmic variables in a repeated measures deception experiment. Statistical analysis provides evidence consistent with the LVA software capturing latent constructs of conflicting thoughts, thinking, emotional cognitive effort and emotional fear. Several of the vocal features captured by the software discriminate between truthful and deceptive responses and between responses to neutral and charged questions.

Elkins (2010) examines whether LVA 6.50 first grade and algorithmic variables help detect deception in a repeated measures experiment. Using the built-in algorithmic variables, Elkins does not detect deception at better than chance levels (consistent with other research such as Harnsberger et al. 2009). However, relaxing the use of the built-in algorithmic variables and instead using the software's more primitive layer variables, Elkins documents statistical discrimination between truth and deception (consistent with findings in Brown et al. 2003).

Konopka, Duffecy and Hur (2010) investigate whether Layered Voice Analysis is a valid screening tool for the identification of post traumatic stress disorder (PTSD). The authors classify Vietnam era veterans as having (not having) PTSD if they were (were not) diagnosed with PTSD previously or scored 50 or greater (43 or lower) on the military version of the PTSD Checklist. Verbal responses to PTSD checklist questions are separately obtained for each subject, from which LVA’s first grade global stress metric is derived. The authors then estimate a logistic regression of the dichotomous PTSD classification variable on the LVA global stress metric and find that the LVA global stress metric is a statistically significant predictor of PTSD. Results are most pronounced for the earlier portions of the speech sample (i.e. answers to the early questions).

Hobson, Mayew and Venkatachalam (2010) incentivizes misreporting by subjects performing an experimental task resulting, thereby creating an endogenous sample of misreporters and truth-tellers. They subsequently capture voice segments of the experimental subjects by conducting an interview using pre-scripted questions regarding the subjects' reported score on the task. Moral code reminders are provided prior to the interview to elicit cognitive dissonance in misreporting subjects. In debriefing, subjects admit to whether they misreported or not, and this admission serves as the dependent variable. The paper uses the first grade LVA variable, Cognition Level, from Ex-Sense Pro R version 4.3.9 that is purported to measure cognitive dissonance in a subject's voice. This voice based metric of cognitive dissonance is then used to statistically predict those subjects who admit to misreporting after the experiment (which are the very subjects who should feel cognitively dissonant when speaking). The results suggest that the LVA Cognition Level variable is able classify individuals as misreporters or truth-tellers at better than chance levels.

Lacerda (2009) reviews the available public patent information on the LVA technology and concludes that LVA technology cannot work because it does not extract relevant information from the speech signal. The paper shows real world hit rate data from LVA usage by the UK's Department of Work and Pensions. Overall areas under the ROC curve are 0.65 overall and reach values as high as 0.73.

Harnsberger, Hollien, Martin and Hollien (2009) use LVA 6.50 and investigate whether the raw value JQ metric can detect experimentally induced stress from electric shocks and whether LVA algorithmic deception markers can identify false statements. Each measure does not detect at better than chance levels. These results are based on findings from a March 17, 2006 study by Hollien and Harnsberger sponsored by the United States Department of Defense (DoD) Counterintelligence Field Activity (CIFA) agency entitled "Voice Stress Analyzer Instrumentation Evaluation."

Adler (2009) uses LVA 6.50 in a sex offender setting where the polygraph is considered an effective tool for detecting deception and investigates whether algorithmic deception markers in LVA can detect deceptive statements by actual sex offenders at levels comparable to polygraph. Conclusions reached regarding truth and deception in speech based on LVA does not statistically differ from polygraph conclusions.

Eriksson and Lacerda (2007) discuss lie detection capabilities of voice stress analysis (VSA) and layered voice analysis (LVA) technology by focusing on findings from two papers (Damphousse et al. (2007), Hollien and Harnsberger (2006)) that find no support for either technology to detect deception at better than chance levels. Study also briefly reviews patent information for LVA and dismisses the technology as non-scientific.

Damphousse, Pointon, Upchurch and Moore (2007) conduct a study funded by grant 2005-IJ-CX-0047 from the U.S. Department of Justice and uses LVA 6.50. Utilizing a field setting, the paper asks jail arrestees monosyllable yes/no questions regarding drug use, and subsequently administers drug tests to determine ground truth for question responses. Then, using algorithmic LVA conclusion variables derived from speech samples, the authors classify subject answers as deceptive or not. Study concludes that LVA algorithmic conclusion variables utilized cannot detect deception at better than chance levels.

Sommers, Brown, Ryan and Senter (2007) use Vericator, a precursor software to LVA 6.50, to measure algorithmic variables for existence of deception, excitement and stress in subject speech samples. Undergraduate student subjects in low (high) stress conditions answered questions regarding whether they took a small item (witnessed a possible theft). While algorithmic variables for detecting deception did not work at better than chance levels, algorithmic variables for existence of stress and excitement did work at better than chance levels.

Salganik, DeVries, Intrater and Sheizaf (2006) use LVA 6.50 and examine whether the raw value JQ LVA metric increases as task difficulty increases. The paper finds statistically significant increases in average JQ values as experimental task difficulty increases. One co-author, A. DeVries, is an employee of Nemesysco, the software developer.

Gamer, Rill, Vossel and Godert (2006) use TrusterPro (a precursor software to Vericator and LVA 6.50) to measure 4 algorithmic variables for the existence of deception: No Deception Indicated, Inconclusive, Inconclusive Plus, and Deception Indicated. These algorithmic variables are measured for one voice segment of each subject saying the monosyllable word "No" in response to multiple choice questions in a Guilty Actions Test. 30 (30) subjects in a treatment (control) condition were sent to a mock crime scene (room) where they would steal money from a wallet (memorize poster contents). Results reveal that guilty subjects in the treatment condition have higher (lower) frequencies of the algorithmic variables Deception Indicated (No Deception Indicated), but the results are not statistically different in a two tailed test of significance at the 5% level (p-values were 0.14 and 0.36, respectively). Tests of significant differences between treatment and control groups on other algorithmic, raw and first grade variables are not statistically different at the 5% level. Significant differences are observed, however, between treatment and control groups on 4 different psychophysiological measures including electrodermal responses, respiration, relative arterial blood pressure, and heart rate. Logistic regression reveals over 90% hit rate for psychophysiological variables. LVA voice based variables are not analyzed via logistic regression.

Sommers (2006) uses Vericator, a precursor software to LVA 6.50. The paper does not provide details of any specific analysis performed and essentially summarizes and repeats findings from Sommers et al. (2007) and Brown et al. (2003).

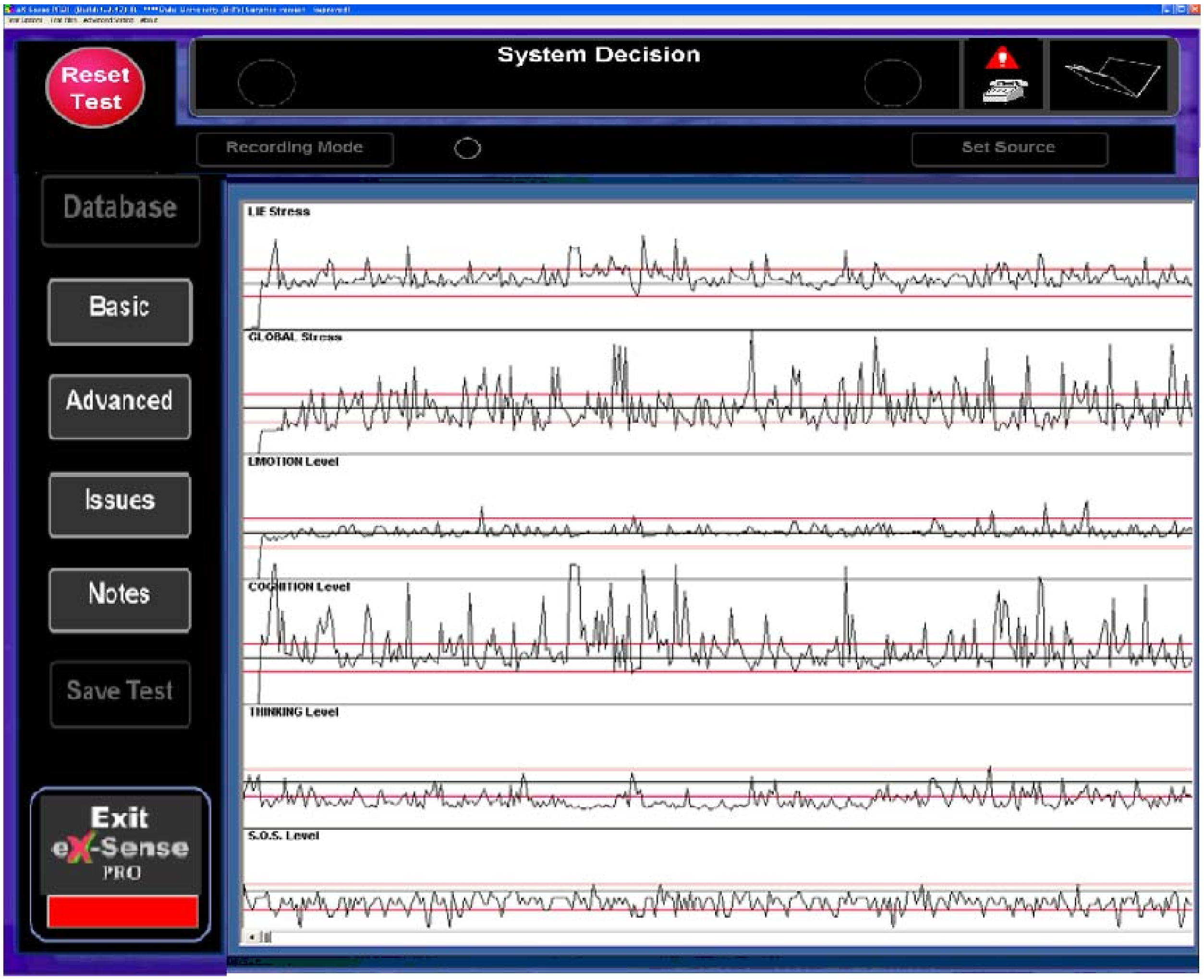
Palmatier (2005) refers to LVA as an advanced digital voice analysis (ADVA) tool, and uses Vericator to assess how well the software could, relative to a polygraph and a computer voice stress analyzer (CVSA), distinguish between a treatment group of deceivers and a control group of truth tellers. Actual interrogations by a state police polygraph unit of 36 deceptive subjects (as determined by subsequent admission of crimes) and 41 truthful subjects (as determined by admission of guilt of the crime by a different party) are analyzed by each of the 3 tools. Monosyllable answers are provided by interrogated subjects answering 13 questions, with the resulting polygraph data being sent to a trained polygraph evaluator, and the resulting voice data being sent to both a trained CVSA evaluator and a trained Vericator evaluator. The polygraph, CVSA and Vericator evaluators did not know whether each subject was a truth teller or deceiver. The classifications provided by all three evaluators are then compared with known outcomes for each subject. Vericator successfully classifies 81% (71%) of truthful (deceptive) subjects, which is similar to the polygraph. CVSA does perform better than chance. Actual parameters from each tool utilized by the trained evaluators is not provided, so it is unclear how much the results are impacted by the training of the user of the tool versus the tool itself.

Brown, Senter, and Ryan (2003) send smuggler and non-smuggler experimental participants through a mock security checkpoint where each is asked a set of security questions. Responses to questions are analyzed with Vericator, a precursor software to LVA 6.50. Algorithmic conclusion variables do not detect smugglers from non-smugglers at better than chance levels. However, logistic regression analysis using base level raw values instead of algorithmic variables greatly improved detection capabilities.

Heddad, Walter, Ratley and Smith (2002) is funded by grant 98-LB-VX-A013 from the U.S. Department of Justice and conducted by representatives of the Air Force Research Laboratory and ACS Defense, Inc. The study analyzes 48 voice segments from polygraph interrogations of two suspects who were both ultimately convicted of murder. Ground truth stress for each utterance is determined either from the polygraph or from subsequent court proceedings. Algorithmic variables for deception and stress as measured via Vericator correctly identify the existence of relevant stress in all 48 instances.

A.3 Ex-Sense Pro R version 4.3.9 Screen Shot

The following screen shot graphically depicts Excitement Level and Cognition Level values. These values are extracted for the construction of *PAFF* and *NAFF*, respectively.



A.4 Robustness Tests Controlling for CEO characteristics

Table IA1

Estimation of the association between affect and contemporaneous stock returns after controlling for CEO age and tenure

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and the contemporaneous stock market reaction (*CAR(0,1))*. Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$) is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. *AGE* is CEO's age and *TENURE* is CEO's tenure at the firm. See Table 2 in the paper for detailed description for the other variables. Robust standard errors are presented in parentheses below the coefficient estimates. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted sign	***(1)***	***(2)***
Intercept	?	0.0017	0.0067
		(0.0252)	(0.0246)
PAFF	+	0.1670**	
		(0.0774)	
NAFF	-	-0.0280	
		(0.0272)	
$PAFF^{HS}$	+		0.1303*
			(0.0958)
$NAFF^{HS}$	-		-0.1523***
			(0.0440)
$PAFF^{LS}$	+		0.1517**
			(0.0817)
$NAFF^{LS}$	-		0.0443*
			(0.0317)
UE_t	+	0.8218***	0.2603
		(0.2493)	(0.2682)
LNMVE	?	0.0004	-0.0007
		(0.0015)	(0.0015)
MOM	?	0.0040	0.0012
		(0.0107)	(0.0104)
BM	?	-0.0034	-0.0003
		(0.0072)	(0.0071)
VOL	?	-0.1989	-0.2145
		(0.3438)	(0.3317)
POSWORDS	+	0.0289***	0.0236***
		(0.0072)	(0.0071)
NEGWORDS	-	-0.0454***	-0.0400***
		(0.0086)	(0.0086)
AGE	?	-0.0028	-0.0022
		(0.0003)	(0.0027)
TENURE	?	0.0001	-0.0001
		(0.0003)	(0.0002)
N		1,647	1,647
Adjusted R^2		6.25%	10.69%

Table IA2

Estimations of the association between affect and future earnings news after controlling for CEO age and tenure

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and future earnings surprises (*UE*). Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$), is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. *AGE* is CEO's age and *TENURE* is CEO's tenure at the firm. See Table 2 in the paper for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted sign	UE_{t+1} ***(1)***	UE_{t+2} ***(2)***	$UE_{t+1,t+2}$ ***(3)***
Intercept	?	0.0078**	0.0120*	0.0211*
		(0.0049)	(0.0071)	(0.0115)
$PAFF^{HS}$	+	0.0229	0.0675**	0.0744*
		(0.0230)	(0.0337)	(0.0509)
$NAFF^{HS}$	-	-0.0026	-0.0301*	-0.0426*
		(0.0129)	(0.0185)	(0.0295)
$PAFF^{LS}$	+	0.0106	0.0210	0.0214
		(0.0150)	(0.0225)	(0.0295)
$NAFF^{LS}$	-	-0.0057	-0.0124	-0.0191*
		(0.0053)	(0.0114)	(0.0118)
UE_t	+	0.4765***	0.4416***	0.7455***
		(0.1106)	(0.1531)	(0.2430)
FREV	+	0.4397***	0.2855	0.5790*
		(0.1879)	(0.2659)	(0.3914)
FDISP	-	-0.0357*	-0.0443*	-0.0824*
		(0.0163)	(0.0293)	(0.0519)
LNMVE	?	-0.0003	-0.0006	-0.0007
		(0.0003)	(0.0005)	(0.0008)
MOM	?	0.0078***	0.0091***	0.0123***
		(0.0028)	(0.0031)	(0.0047)
BM	?	-0.0074***	-0.0145***	-0.0211***
		(0.0023)	(0.0039)	(0.0061)
VOL	?	-0.1352	-0.2999**	-0.3334*
		(0.0976)	(0.1458)	(0.1942)
POSWORDS	+	-0.0020	-0.0023	-0.0029
		(0.0014)	(0.0018)	(0.0026)
NEGWORDS	-	0.0013	-0.0030	-0.0023
		(0.0015)	(0.0038)	(0.0053)
CEO AGE	?	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
CEO TENURE	?	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
N		1,647	1,146	1,146
Adjusted R^2		28.81%	17.22%	20.29%

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