Tone at the Bottom: Measuring Corporate Misconduct Risk from the Text of Employee Reviews

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Background

- Numerous cases of corporate misconduct have emerged globally and caused large losses for firms, their stakeholders, and even broader society.
- Misconduct is deeply rooted in the operating and control environment of their organization according to the accounting literature (Heese 2020; Chen 2012).
- However, due to information asymmetry, external stakeholders cannot easily obtain inside information on firms.
- An incentive-compatible mechanism is essential for employees to share their inside information(a by-product of their normal work) with outsiders.

Motivation

- Many employees lack incentives to use whistleblowing complaints
 due to the lack of incentive-compatible mechanism and the information
 revealed by employees is backward-looking.
- The emergence of social websites(Glassdoor, 看准网) provides employees with platforms to talk about their firms which are likely to function as a more **incentive-compatible** mechanism:
 - > Share **general** observations and experiences & **Not oriented** specifically toward detecting misconduct & **Anonymity.**
 - Users may describe misconduct that have yet to become widespread or externally observable.
 - ➤ Most employees may instead possess more general information about **control and operating** practices in their firms which contribute to misconduct risk.

An introduction to the Glassdoor

- Glassdoor website is a leader in this firm review segment and the rich amount of reviews make it a useful source for examining employee inside information:
 - ➤ When sharing their reviews, employees are asked to **rate** their firms on several different dimensions
 - > Provide commentary about the **pros** and **cons** of their firms as well as their **advice** to the management team.
- Evidence indicates that the outlook ratings can also predict stock returns (Green et al. 2019).
 - > The ratings are **homogenous** for all the firms on Glassdoor.
 - > The ratings are noisy due to the individual-belief heterogeneity.
 - Does not contain specific information about why employees chose to give a particular rating.

Research Framework

 Develop text-based measures of employees' inside information about misconduct risk (MW-Indexs).



Cons

$$E(W_{jit} \mid x_{it}, v_{it+1})$$

$$= e^{\alpha_j + \beta_j x_{it} + \phi_j v_{it+1} + \varepsilon_{it}}$$

Advice



 Use these indices along with machine learning techniques to predict future violations. Predicting one year ahead Misconduct

Predicting Serial Violator Transitions in long horizon

Predicting Criminal Violator Transitions

Information in employee comments as a leading indicator of whistleblower complaints

Research Conclusion

- Our results suggest that these text-based measures have potentially useful properties for measuring misconduct risk.
- The MW-Indexs are not simply proxies for more readily available firm ratings. Most importantly, they are useful in predicting misconduct beyond other readily observable characteristics such as firm size, performance, press coverage, industry risk, and prior violations.
- Further, our text-based measures of employee inside information appear to be most useful when predicting longer-term misconduct risk, particularly in samples of firms with little prior misconduct history.
- Finally, we find that our measures are leading indicators of the more intermediate risk outcome of employee whistleblower complaints.

Research Contributions

- Most prior studies focus on how to detect accounting fraud and misreporting (e.g. Dechow et al. 2011; Purda and Skillicorn 2015), there is limited evidence about how to assess and control the risks of other forms of corporate misconduct.
- Prior research has examined market and firm characteristics as determinants of misconduct. We focus instead on understanding and extract the information that employees themselves have about broader misconduct risk in their firms.
- Our study also complements the emerging literature on whistleblowers, highlighting the possibility of obtaining broader and timelier employee information from the detailed text of external reviews.
- Our findings also have practical implications in light of the considerable financial, legal, and reputational risks that can arise due to corporate misconduct.

Sample selection

- First, we collect data on employee comments from the Glassdoor.
 - ➤ Leave out firms that received less than **ten reviews** during 2008.06-2016.12.
 - Leave out firms not **listed in the U.S.** market.
- Second, we obtain firm's fundamental data (e.g. size, capital structure, profitability) from Compustat and press coverage data (e.g. number of media articles and news sentiment relating to each firm) from Ravenpack.2.
 - Leave out firm-year observations that have **any missing** values in the merged firm variables.
- Our final sample consists of 13,363 firm-year observations representing 1,478 unique firms during the period 2008-2017.

Dependent Variable: Corporate misconduct

- We obtain data on corporate misconduct from Violation Tracker:
 - ➤ Banking, consumer protection, wage and hour, unfair labor practice and other cases initiated by 43 **federal regulatory** agencies.
 - ➤ We extract all 26,934 violation cases committed by public U.S. firms over the period of 2008 and 2017.

Variable	Description	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Outcome Variables						
Violation	Indicator for the presence of any violation	0.28	0.45	0	0	1
ViolationHV	Indicator for the presence of any 'high-visibility' violation directly related to workers or consumers (e.g. safety, health, employment, wages, hours, and labor relations; product/service safety, consumer protection, etc)	0.23	0.42	0	0	1
#Violations	Total number of violations	1.39	8.42	0	0	3
#ViolationsHV	Total number of 'high-visibility' violations directly related to workers or consumers (e.g. safety, health, employment, wages, hours, and labor relations; product/service safety, consumer protection, etc)	1.15	8.26	0	0	2
Penalty	Penalties imposed by the relevant regulatory or legal authorities	\$15,800,000	\$361,000,000	0	0	\$300,000

- First, we eliminate any non-English words, numbers, stop words.
- Second, we replace each word with its root using the Porter stemming algorithm (Porter 1980) and the Natural Language Toolkit (Loper and Bird 2002) to reduce redundancies.
- Third, we drop words that are used in more than 50% reviews or less than five reviews.
- This final step leaves us with our vocabulary of 11,772 unique words for our sample firms.

Variable	Description	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Glassdoor Data	•		•		•	
Rating	Average overall Glassdoor rating	3.13	0.66	2.30	3.14	4.00
Number of Reviews	Number of employee reviews on Glassdoor	79.55	288.77	2	15	158
Number of Words	Total number of words across Glassdoor employee reviews	5,318	16,872	114	1,154	11,241
Press Variables			-	-		
Coverage	Natural log of (1 + the number of relevant articles appearing in major press outlets)	2.17	2.91	0	0	6.65
Sentiment	Aggregate sentiment of press articles written on a firm in a given year	0.01	0.02	0	0	0.02

- $E(W_{jit} \mid x_{it}, v_{it+1}) = e^{\alpha_j + \beta_j x_{it} + \phi_j v_{it+1} + \varepsilon_{it}}, \quad t \in [2008, 2011]$
- x_{it} is a vector of controls for firm i in year t (Glassdoor ratings, contemporaneous violations, size, leverage, ROA, press coverage, news sentiment, and firm and year indicators)
- MW-Index = $\phi_1 \frac{W_{1it}}{\sum W_{it}} + \phi_2 \frac{W_{2it}}{\sum W_{it}} + \dots + \phi_{11,772} \frac{W_{11,772it}}{\sum W_{it}}$, $\sum W_{it} = \sum_{j=1}^{11,772} W_{jit}$
- Note that rather than doing one regression with 35,316 independent regressors (11,772 relative word frequencies × 3 review categories) which would be inefficient and computationally intensive.
- The approach we outline above allows us to aggregate highdimensional word counts into low-dimensional summary indices while preserving the underlying information about misconduct risk contained in the text of Glassdoor reviews.

$$E(W_{jit} \mid x_{it}, v_{it+1}) = e^{\alpha_j + \beta_j x_{it} + \phi_j v_{it+1} + \varepsilon_{it}}, \quad t \in [2008, 2011]$$

Features	Any Violations	Violations - HV	Serial Violators	Criminal Violators
pay	pay, money, salaried, receive, rate, hourly	pay, money, salaried, paycheck, receive, hourly	pension, wage, raise, salaried, receive, pay, earn, hourly	cash
work schedule	week, vacation, Saturday, schedul, holiday, hour, flexible, time, shift, everyday	overtime, overwork, week, schedul, shift, thanksgiving, Saturday, time, flexible, vacation, holiday, everyday	overtime, shift, week, schedul, everyday, flexible, time	
organization (re)structure				merger, reorganization, decentralize
discrimination	discrimination, women, femal	discrimination, women, femal	women, white, male	
managerial practices and behavioral norms	ask, apply, slave, push, praise, favoritism, recognize, speak, require, reinforce, boss, request, preach, teach, respond, collaboration, supervisor, order, communicate, mentor, guarantee	apply, allow, beat, establish, favoritism, call, subordinate, praise, tell, teach, slave, promise, preach, control, supervisor, rotating, score,	check, force, pick, select, establish, praise, assign, wait, appreciation, plan, preach, boss, award, order, supervisor, upper, transfer, review, assist, assign, serve, review, rotate, protect	assess, approval, arrange, align, acquire, compete, collaboration, committee, constrain, measure, restrict, strategy, meritocracy, telecommute, outsource, prohibit, integrate, evaluate, press, navigate, mentorship, identify
career-related decisions	advance, hire, ladder	advance, retire, employ, promote, ladder	advance, promotion, eliminate, ladder	layoff
task difficulty and motivation	ability, achieve, can, capable, dedicate, duty, incompetent, motivation, strive, task, rough,	cant, difficult, busy, task, motivation, rough, unable, excess, extra	difficult, can't, extra, excess	tough, massive, capability, commit
problem/risk	trouble, crap, lazy, rule, leg(al)/leg(itimate), break, safety	steal, hurt, idiot, lazy, trouble, hazard, harass, complain, safety, hurt, danger, break, downside, steal, backward	complain, decline, discipline, dirty, insurance, uneth(ical), wast(e), safety, principle, health, issue, harass, hazard, rule clean, break, forget, hurt, dirty, complain, leg(al)/leg(itimate)	uneth(ical), transparent, lost, harm, bureaucrat, compliance, crisis, worrying, legal, risk, downturn, exposure, integrity, opaque, closure, bureaucracy, underperform

- While many pairwise correlations are negative and statistically significant, there are relatively modest correlations between overall ratings and our primary misconduct word indices.
- This is in part by design as we controlled for ratings in estimating the underlying word weightings for these indices.
- More intuitively, high values of these indices and related increases in violation-associated words need not necessarily occur only when employees are dissatisfied with their firms.

Table 3: Correlations between Text Measures and Ratings

	Rating	(1)	(2)
(1) MW_Index - Pros	-0.18*		
$(2) MW_Index - Cons$	-0.13*	0.43*	
(3) MW_Index - Advice	-0.16*	0.31*	0.41*

Note: Table 3 shows correlations between weighted misconduct word indices and overall ratings. * denotes significance at the p < 0.10 level.

1. Predict one year ahead Misconduct

- We estimate gradient boosted regression trees and split firms in our sample into training (80%) and test sets (20%) during the 2012 to 2017.
- While prior violations and firm size are the most influential individual predictors in both cases, our misconduct word indices contribute both individually and collectively to prediction performance.

Table 4: Performance and Variable Influence for Violation Prediction Models

	Prediction Performance in Test Sample			Influence Statistics for Full Model									
						MW Index -							
Outcome	Pseud	do-R ²	AU	C	Lagged Outcome	Pros	Cons	Advice	Rating	Size	Leverage	ROA	Press Variables
	<u>Full</u> Model ^a	No Indices	Full Model ^b	No Indices		9.	2%		_				
Violation Violation –	29.2%	27.3%	85.0%	83.5%	44.0%	3.6%	3.6%	2.0%	1.9%	27.2%	3.1%	3.3%	2.1%
High Visibility	26.1%	23.5%	84.1%	82.1%	37.3%	6.9%	4.4%	2.8%	2.7%	22.4%	4.2%	4.2%	3.1%

14.1%

1. Predict one year ahead Misconduct

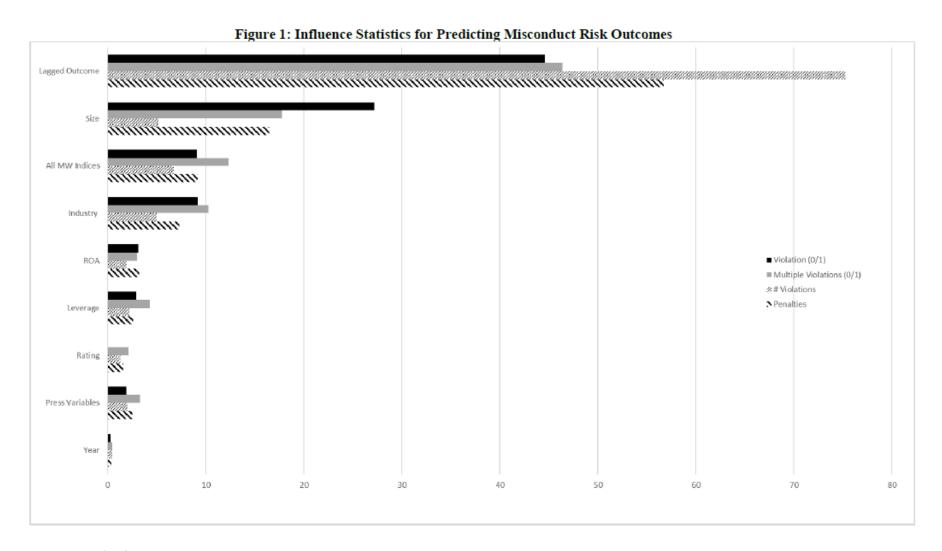
- our misconduct word indices are individually and collectively influential in our predictive models beyond other readily observable firm characteristics.
- For every outcome, inclusion of these measures also increases out-of-sample prediction performance based on the pseudo-R2.

Table 5: Prediction Performance and Variable Influence for Different Violation Outcomes

		erformance in Sample		Influence Statistics							
				MW Index							
			Lagged								Press
Outcome	Pseud	do-R ²	Outcome	Pros	Cons	Advice	Rating	Size	Leverage	ROA	. Variables
	Full Model ^a	No Indices			6.9%						
#Violations	52.4%	50.9%	75.5%	1.9%	3.5%	1.5%	1.4%	5.1%	2.1%	2.0%	1.9%
MultipleViolations	30.0%	28.0%	45.4%	2.6%	6.0%	4.1%	2.1%	17.9%	4.3%	3.1%	3.5%
Penalty	34.3%	33.1%	60.7%	3.1%	3.9%	1.7%	1.0%	16.7%	2.3%	2.6%	1.7%

8.7%

1. Predict one year ahead Misconduct



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2. Predict Serial Violator Transitions

- Our misconduct word indices are meant to capture underlying risk factors which may be present multiple years prior to actual violation enforcement actions.
- So we collapse our data down to two longer window time periods, 2008-2011 and 2012-2017, and focus on the set of firms which had either no violations or no more than one year with violations in the first period.
- $E(W_{ji} \mid x_i, v_{i+1}) = e^{\alpha_j + \beta_j x_i + \phi_j v_i + \varepsilon_i}, t \in [2008, 2011]$
- Transitions to serial violator status may due to failures in organizational control systems or shifts in culture, which should be picked up by our text-based measures.
- There are less prior violation history to draw on in making an inference about these firms' misconduct risk, and employee comments may be particularly informative.

2. Predict Serial Violator Transitions

- We use an 80% (20%) train (test) sample split for these little violation firms and use the same GBRT to predict transitions to serial violator status in the period 2012-2017.
- Collectively, they have the second largest influence of any variable in the model accounting for 21.0% and 22.1% of the improvement in prediction performance

Table 6: Predictive Performance and Variable Influence for Serial Violator Transition Models

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	Prediction	on Perform	ance in Te	est Sample	Influence Statistics for Full Model								
							MW Inde:	x-					
Outcome	Pseu	do-R²	A	IUC	Lagged Outcome	Pros	Cons	Advice	Rating	Size	Leverage	ROA	Press Variables
	Full Model ^a	No Indices	Full Model ^b	No Indices			21%)					
Serial Violator Serial Violator -	21.0%	18.0%	83.2%	79.9%	24.5%	9.8%	6.6% 22.1	4.6% 9/ 0	4.9%	13.2%	6.0%	3.9%	7.3%
High Visibility	19.9%	16.9%	79.3%	75.2%	27.8%	8.3%	10.6%	3.2%	5.0%	8.8%	7.2%	4.9%	5.0%
Criminal Violator	24.6%	19.7%	92.2%	90.3%	4.7%	8.1%	4.8%	4.2%	6.6%	18.6%	5.5%	11.1%	15.2%

3. Predict Criminal Violator Transitions

- Criminal violations are a salient outcome that can carry significant legal, financial and reputation risk for firms.
- We reconstruct our misconduct word indices in the same manner described above, except in the case we regress word frequencies (over the whole first period) on criminal violator status.

Table 6: Predictive Performance and Variable Influence for Serial Violator Transition Models

					I								
	Predictio	on Perform				Influ	ence Stat	istics for	Full Model				
							MW Inde:	<i>x</i> -	-				
					Lagged								Press
Outcome	Pseu	do-R²	A	UC	Outcome	Pros	Cons	Advice	Rating	Size	Leverage	ROA	Variables
	<u>Full</u>	No	<u>Full</u>	No									
	Model ^a	<u>Indices</u>	Model ^b	<u>Indices</u>									
Serial Violator	21.0%	18.0%	83.2%	79.9%	24.5%	9.8%	6.6%	4.6%	4.9%	13.2%	6.0%	3.9%	7.3%
Serial Violator -													
High Visibility	19.9%	16.9%	79.3%	75.2%	27.8%	8.3%	10.6%	3.2%	5.0%	8.8%	7.2%	4.9%	5.0%
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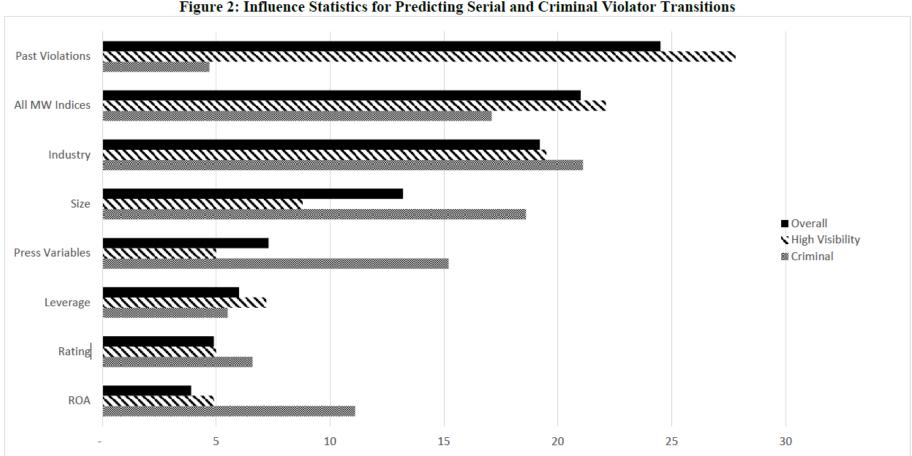


Figure 2: Influence Statistics for Predicting Serial and Criminal Violator Transitions

Note: Figure 2 graphically summarizes the influence statistics reported in Table 6.

4. A Leading Indicator of Whistleblower Complaints

 There are likely to be intermediate outcomes between the underlying risks reflected in our measures and the ultimate realizations of these risks. A primary example, as we have argued earlier, is whistleblower complaints.

Dependent Variable = Employee Complaint _t	Coefficient	Robust Std. Error	z	P>z
Employee Complaint _{t-1}	2.02***	0.11	17.91	0.00
$MW_IndexHV_{t-1} - Pros$	60.74***	16.86	3.60	0.00
$MW_IndexHV_{t-1} - Cons$	60.96***	11.03	5.53	0.00
$MW_IndexHV_{t-1} - Advice$	28.81	21.73	1.33	0.19
$Rating_{t-1}$	-0.22**	0.09	-2.53	0.01
Size _{t-1}	0.46***	0.04	12.98	0.00
Leverage _{t-1}	0.00	0.00	-1.01	0.31
ROA_{t-1}	1.49***	0.58	2.56	0.01
Coverage _{t-1}	-0.01	0.02	-0.68	0.49
Sentiment _{t-1}	2.91	3.19	0.91	0.36
Industry Fixed Effects		Yes		
Year Fixed Effects		Yes		
Psuedo R ²		37.3%		
/ <u>4</u> №11		7,255		

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Research Conclusion

- Our results suggest that these text-based measures have potentially useful properties for measuring misconduct risk.
- The MW-Indexs are not simply proxies for more readily available firm ratings. Most importantly, they are useful in predicting misconduct beyond other readily observable characteristics such as firm size, performance, press coverage, industry risk, and prior violations.
- Further, our text-based measures of employee inside information appear to be most useful when predicting longer-term misconduct risk, particularly in samples of firms with little prior misconduct history.
- Finally, we find that our measures are leading indicators of the more intermediate risk outcome of employee whistleblower complaints.

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