Online Appendix 1: Violations and Agencies

no.	Violation	Agency
1	Accounting fraud or deficiencies	Securities and Exchange Commission; U.S. Attorney; Justice Department; Commodity Futures Trading Commission.
2	Agribusiness violation	Grain Inspection, Packers & Stockyards Administration
3	Americans with Disabilities Act	Justice Department
4	Anti-money-laundering deficiencies	Treasury Department Financial Crimes Enforcement Network,U.S. Attorney; Justice Department; Federal Reserve; Securities and Exchange Commission.
5	Aviation consumer protection violation	Transportation Department Aviation Consumer Protection Division
6	Aviation safety violation	Federal Aviation Administration; U.S. Attorney.
7	Banking violation	Federal Aviation Administration; Justice Department; Federal Deposit Insurance Corporation; Federal Reserve; Office of the Comptroller of the Currency; Consumer Financial Protection Bureau; U.S. Attorney.
8	Benefit plan administrator violation	Employee Benefits Security Administration
8	Child labor or youth employment violation	Labor Department Wage and Hour Division
10	Civil contempt	Justice Department
11	Consumer protection violation	Federal Trade Commission; Consumer Financial Protection Bureau; Consumer Product Safety Commission; U.S. Attorney.
12	Controlled Substances Act violation	Justice Department; U.S. Attorney; Drug Enforcement Administration.
13	Data submission deficiencies	Commodity Futures Trading Commission; Securities and Exchange Commission.
14	Discriminatory practices	Justice Department; Housing and Urban Development Department; Transportation Department Aviation Consumer Protection Division; U.S. Attorney.
15	Drug or medical equipment safety violation	Justice Department; U.S. Attorney; Food and Drug Administration.
16	Economic sanction violation	Office of Foreign Assets Control; Justice Department; Office of Foreign Assets Controls.
17	Employment discrimination	Office of Federal Contract Compliance Programs; Equal Employment Opportunity Commission; Justice Department.
18	Energy conservation violation	Energy Department Office of General Counsel
19	Energy market manipulation	Commodity Futures Trading Commission; Federal Energy Regulatory Commission.
20	Energy market violation	Federal Energy Regulatory Commission
21	Environmental violation	Pipeline and Hazardous Materials Safety Administration; Environmental Protection Agency; U.S. Attorney; Bureau of Safety and Environmental Enforcement; Justice Department ; Environmental Protection Agency.
22	Excise tax violation	Alcohol and Tobacco Tax and Trade Bureau
23	Export control violation	Bureau of Industry and Security; State Department Directorate of Defense Trade Controls; U.S. Attorney; Justice Department; National Security Division; Office of Foreign Assets Control.
24	False claims act	Justice Department; U.S. Attorney; Food and Drug Administration.
25	Family and Medical Leave Act	Labor Department Wage and Hour Division
26	Federal leasing royalty violation	Interior Department Office of Natural Resources Revenue; U.S. Attorney

Online Appendix 1 (cont.)

no.	Violation	Agency
27	Financial institution supervision failures	Securities and Exchange Commission; Commodity Futures Trading Commission.
28	Food safety violation	Food and Drug Administration; Justice Department
29	Foreign corrupt practices act	Securities and Exchange Commission; Justice Department.
30	Foreign exchange market manipulation	Justice Department; Federal Reserve; Commodity Futures Trading Commission.
31	Fraud	U.S. Attorney; Justice Department.
32	Fuel economy (CAFE) violation	National Highway Traffic Safety Administration
33	HHS civil monetary penalties	Health & Human Services Department Office of Inspector General
34	Illicit political contributions	Securities and Exchange Commission
35	Interest rate benchmark manipulation	Commodity Futures Trading Commission; Justice Department; Federal Reserve.
36	Investor protection violation	Securities and Exchange Commission
37	Kickbacks and bribery	U.S. Attorney; Housing and Urban Development Department; Justice Department; Securities and Exchange Commission.
38	Labor relations violation	National Labor Relations Board
39	Maritime violation	Federal Maritime Commission
40	Medicare Program violation	Centers for Medicare & Medicaid Services
41	Medicare Parts C and D Enforcement Action	Centers for Medicare & Medicaid Services
42	Mining violation	U.S. Attorney
43	Mortgage abuses	Federal Trade Commission; Justice Department; Housing and Urban Development Department; U.S. Attorney; Federal Reserve; Consumer Financial Protection Bureau
44	Motor vehicle safety violation	Federal Motor Carrier Safety Administration; National Highway Traffic Safety Administration; Justice Department.
45	Nuclear safety violation	Nuclear Regulatory Commission; Energy Department Office of Enforcement.
46	Nursing home violation	Centers for Medicare & Medicaid Services
47	Off-label or unapproved promotion of medical products	Justice Department; Food and Drug Administration; U.S. Attorney.
48	Offshore drilling violation	Bureau of Safety and Environmental Enforcement
49	Payday lending violation	Consumer Financial Protection Bureau
50	Pipeline safety violation	Pipeline and Hazardous Materials Safety Administration
51	Premerger notification violation	Justice Department
52	Price-fixing or anti-competitive practices	Justice Department; Securities and Exchange Commission; U.S. Attorney.
53	Privacy violation	Federal Trade Commission; U.S. Attorney.
54	Product safety violation	Consumer Product Safety Commission
55	Railroad safety violation	Federal Railroad Administration
56	Securities issuance or trading violation	Commodity Futures Trading Commission; U.S. Attorney; Securities and Exchange Commission.
57	Service members civil relief act	Justice Department; Office of the Comptroller of the Currency.
58	Student loan abuses	Justice Department; Consumer Financial Protection Bureau.
59	Tax violations	Justice Department; U.S. Attorney; Securities and Exchange Commission.
60	Telecommunications violation	Federal Communications Commission; U.S. Attorney.
61	Tobacco litigation	Justice Department
62	Toxic securities abuses	Securities and Exchange Commission; Justice Department; Fannie Mae; Freddie Mac; National Credit Union Administration; Federal Housing Finance Agency; Federal Deposit Insurance Corporation; U.S. Attorney.

Online Appendix 1 (cont.)

no.	Violation	Agency
63	Uniformed Services Employment and Reemployment Rights Act	Justice Department.
64	Wage and hour violation	Labor Department Wage and Hour Division; Labor Commissioner's Office; Department of Workplace Standards; Department of Labor & Industry; Attorney General's Office.
65	Work visa violations	U.S. Attorney; Justice Department.
66	Workplace safety or health violation	Occupational Safety & Health Administration; Mine Safety & Health Administration; U.S. Attorney.
67	Workplace whistleblower retaliation	Occupational Safety & Health Administration

Online Appendix 2: Discussions and Descriptive Evidence of Misconduct Word Indices

Table 2 in the paper provides some examples among the top 100 words that receive the highest weights in calculating our misconduct word indices for the pros, cons, and advice comment sections. Our methodology appears to pick up three primary types of words for each violation outcomes. First, some words speak relatively directly to potential misconduct risk (e.g. *'discrimination', 'uneth(ical)', 'integrity', 'crisis', 'trouble', 'danger', 'harass'*). Second, our methodology also gives weight to words about important features of firms' operating and control environments such as pay (e.g. *'pay', 'money', 'paycheck', 'raise'*); scheduling (e.g. *'schedule', 'overtime', 'overwork', 'shift'*); task difficulty (e.g. *'difficult', 'can't', 'unable', 'strive', 'tough'*); and other management practices and behavioral norms (e.g. '*evaluate'*, *'communicate', 'push'*, *'control'*, *'preach'*, *'measure'*, *'force'*). Third, our methodology selects words related to employees' impressions and feelings about their work environment (e.g. '*discouraging'*, *'disrespect'*, *'comradery'*, *'hostile'*). Finally, some relatively highly weighted words are more generic but commonly used when writing about the features noted above (e.g. *'aspect'*, *'workplace'*, *'corporate'*, *'among'*).

Several features about these words are worth noting. First, our methodology appears to select intuitive words that are plausibly related to misconduct risk. Some of these are relatively direct (e.g. *'uneth(ical)'*, *'discrimination'*, *'safety'*, *'slave'*, *'harass'*, *steal', 'hazard'*). Others are less direct but reflective of broader firm features that might contribute to misconduct risk such as lack of support from management (associated with words like *'unable'* and *'difficult'*) or potentially aggressive management styles and operating environments (associated with words like *'push'*, *'control'*, *'preach'*, *'measure'*, and *'force'*). Second, some of the words that are highly weighted by our methodology need not be viewed as negative *per se*. We rely on the idea that certain words showing up relatively more frequently in employees' comments signal an increase in the underlying risk of misconduct. For example, increasing frequency of words like *'supervisor'*, *'schedule'*, or *'pay'*, in the cons section may reflect increasing concerns about these particular aspects of organizations that employees might otherwise view positively. Further, depending on their job positions, experiences, or personal preferences, employees may neither hold negative views about firm features that could potentially contribute to misconduct nor connect these features with specific acts of misconduct.

These features can be seen when looking at specific reviews. For example, consider the following comment taken from the 'cons' section of an employee review of Wells Fargo in 2012 prior to widespread public knowledge of the underlying misconduct in its sales practices:

> *'**Pay** was too low and incentives/bonus are a kick in the head even if qualify for it. District managers and up are only email reachable and the micro management is ridiculous. The reporting by peers to management is **unethical**. Everyone lies about their numbers **hourly/daily/weekly** and monthly hoping for walk in traffic to meet those numbers. The leads they expect you to call are **crap** unless you have all the seniority then you get the top leads. Make sure you work in a branch with three or less bankers anymore and it is a Shark Tank.'*

The bold words above appear in the top 100 highly weighted words in our Misconduct Word Indices. This comment points out the underlying problem in Wells Fargo's practices, even though it was made a year before the LA Times exposé of Wells Fargo's fraudulent behaviors and four years before the company was fined by various regulators. Similar patterns can also be found in shorter reviews. For example:

> *'Branches are open **Saturdays** for a few **hours**. High sales goals. Even tellers are **responsible** for sales.'*

> *'Personally, none. However, I am aware that some sales goals are **difficult** to **achieve**.'*

Some words that are highly weighted in our method, such as *'Saturday'* and *'hour'* (other examples including *'Thanksgiving'* and *'holiday'*), are not intuitive *per se*.[1] However, if employees *in aggregate* systematically bring up such words, it could be indicative of scheduling practices in relatively high-pressure organizational cultures where employees are expected to work longer hours during unusual times. Some other words, such as *'responsible'*, are somewhat intuitive but not directly related to misconduct. Depending on the context of different reviews, employees who are in different positions are likely to face different task pressures and organizational objectives (e.g., an employee in one business unit of a high-pressure firm may feel highly *responsible* for sales and another for cost performance). Therefore, words like *'responsible'* are likely to discriminate violation versus non-violation firm-years better than more specific words such as *'teller'* or *'sales'*. That is, these less direct words picked up by our methodology may relate to the broader issues in firms' operating environments and thus be predictive of misconduct risk.

Interestingly, although these reviews reveal the aggressive sales culture in Wells Fargo, which is widely viewed as having led to its consumer protection violations, none of these employees directly connects the features they mention with the culture of Wells Fargo. In fact, all of them gave a rating of four or five (out of five) for the "Culture Values" of Wells Fargo. The third employee mentioned above did not even view the organization as having any cons, even though its *'sales goals are **difficult** to **achieve**'*. Further, employees appreciate the pros of working in Wells Fargo, including *'**room** for career **advancement**'*, *'**clean** work environment'*, and '***paid** banking **holidays**'*. With both the pros and cons they experienced, these employees gave Wells Fargo a high overall rating (four or five out of five). While only meant for descriptive purposes, these patterns are consistent with our arguments that employees may not consciously connect their observations or experiences with misconduct risk. Consequently, the ratings they give to their firms could be overly aggregate and less informative than the written comments.

Third, our methodology seems to pick up different words for different types of violation outcomes. In particular, for violations that are highly visible to employees, such as violations relating to employment discrimination, wages and hours, and consumer protection, our indices tend to pick up words about daily practices (e.g. *'favoritism'*, *'discrimination'*, *'schedule'*, *'pay'*, *'praise'*, *'harass'*, *'safety'*, etc.) as well as employees' feelings about their daily work (e.g. *'hostile'*, *'miser(able)'*, *'discouraging'*, etc.). In comparison, for criminal violations, our indices tend to pick up more words relating to broader organizational features, such as *'bureaucracy'*, *'transparent'*, *'opaque'*, *'meritocracy'*, *'strategy/strategic'*, *'downturn'*, *'underperform'*, *'crisis'*, and *'compliance'*. This difference is interesting, showing that the risk of different types of violations may be embedded in different firm features captured by employees' comments posted on Glassdoor.

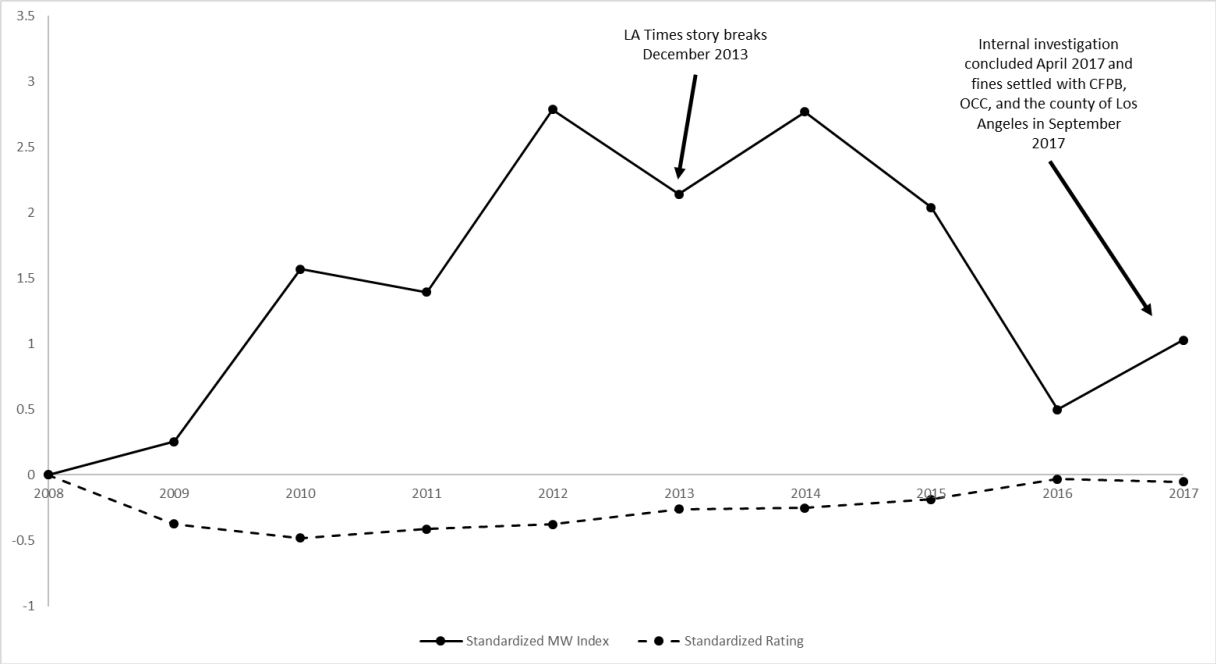
Of course, not all of the top words in our index are obviously intuitive, which may reflect the difficulty of predicting violations with underlying text in employee reviews. Whether or not our text-based measures of employee inside information are predictive of future misconduct is the central question in our paper.

We also consider descriptive patterns in these measures for firms known to have engaged in misconduct over particular periods. The figure below shows an aggregate summary measure of our underlying misconduct word indices for Wells Fargo during 2008-2017, a period in which misconduct in its sales practices was reported to be widespread throughout the organization (Srinivasan et al. 2017). The summary measure is simply the sum of the three *MW_Index* measures for the pros, cons, and advice sections of Glassdoor reviews. To facilitate comparability with aggregate ratings, and to explore trends in this metric, we standardize this index by subtracting its value in 2008 and dividing by its within-firm standard deviation. Our summary index for Wells Fargo grows relatively steadily through 2013 by 2-2.5 standard deviations from its baseline value in 2008 and declines dramatically after 2013 and through 2017. This overall trend in our measure appears to track well with the periods in which reporting suggested that Wells Fargo was engaged in increasingly fraudulent sales practices (2008-2013) and when it was subsequently engaged in broad organizational changes aimed at reducing the risk of misconduct in its sales practices (2013-2017).[2]

[1] For example, some employees indicate that they are expected to '*work all **holidays** even if the branches are closed including **Thanksgiving***'.

[2] In December 2013, the Los Angeles Times published the first major exposé on potentially widespread fraudulent sales and account opening practices at Wells Fargo (Reckard 2013). The LA Times article is broadly credited with bringing public awareness as

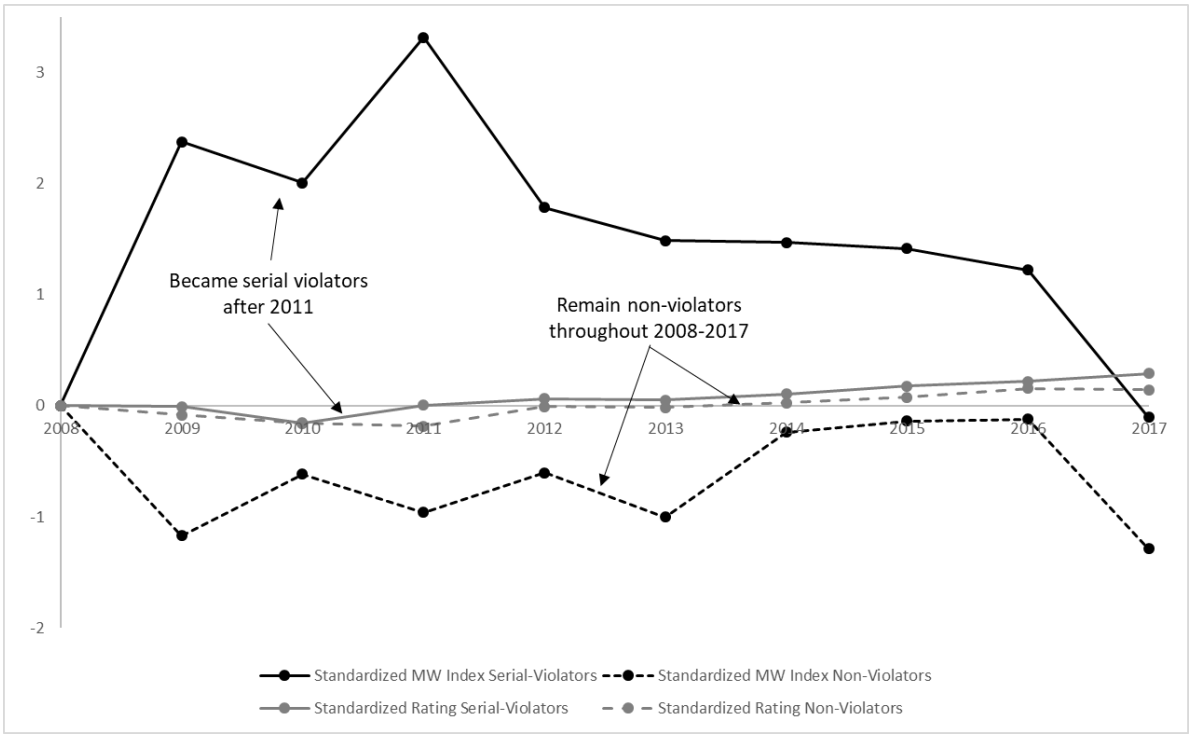
Figure OA 1: Misconduct Word Index and Glassdoor Ratings during a Period of Known Widespread Misconduct in Sales Practices at Wells Fargo



While Wells Fargo serves as a single illustrative example, a similar general pattern emerges when we consider a broader sample of firms that undergo a substantial change in realized misconduct risk. Figure 2 shows a summary misconduct word index with the same underlying calculation as in the Wells Fargo example above for two subsamples of firms, both of which had no violations during the period 2008-2011. 'Non-violators' are those firms that also had no violations during 2012-2017. 'Serial-violators' are those firms that went on to have violations in at least two of the years during the period 2012-2017. Firms that transition to serial violator status show a large relative increase in our index through 2012 with a relative decrease during the period in which enforcement actions eventually took place. This represents a clear divergence from the pattern seen in firms that continue to remain non-violators, where our index shows a downward trend through 2012. While we have less direct information on this set of firms than on the widely publicized case of Wells Fargo, the pattern suggests that our measure is tracking well with periods where misconduct risk is high, and it clearly discriminates between firms with higher and lower future realized misconduct risk.

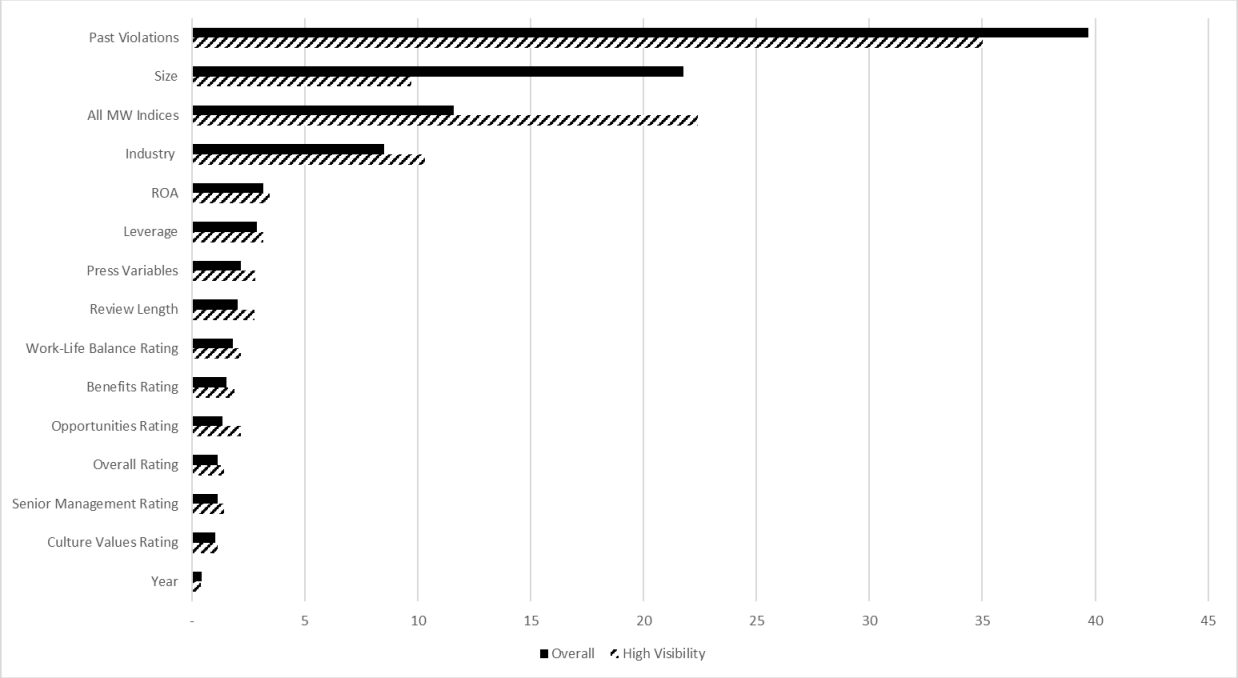
well as legal, regulatory, and political scrutiny to the bank for its sales practices. Subsequently, Wells Fargo engaged in several actions aimed at mitigating misconduct risk in its sales practices. These actions included, among others: reducing sales goals, conducting a detailed internal investigation led by an outside law firm, and firing employees, middle and senior management, and even the CEO (Srinivasan et al. 2017).

Figure OA 2: Misconduct Word Index for Firms that Transitioned from Non-Violator Status (2008-2012) to Serial Violator Status (2012-2017)



Online Appendix 3: Further Analysis of Multiple Glassdoor Rating Categories

This figure shows influence statistics for the prediction model estimated in Table 4 in the paper, including review length and multiple Glassdoor rating categories for *Culture-Values, Senior Management, Opportunities, Benefits,* and *Work-Life Balance*. The graph shows the sum of the influence statistics from our prediction models across all MW-Indices, across all industries, across all press variables, and across all years respectively. That is, 'All MW Indices' in the figure refers to the sum of influence statistics for *MW_Index – Pros*, *MW_Index – Cons,* and *MW_Index – Advice*. Similarly, 'Industry' and 'Year' refers to the sum of influence statistics across all included industry and year fixed effects respectively. 'Overall' and 'High Visibility' refer to results from the model predicting any violation (*Violation*) and high visibility violations (*ViolationHV*) respectively.



Consistent with disaggregate ratings adding little incremental value in our prediction models relative to the overall rating (as shown above), employees do not appear to differentiate individual review categories very strongly in their overall evaluations. As the table below shows that the correlations between the overall rating and the other ratings categories are very strong ($p<0.01$ in all cases).

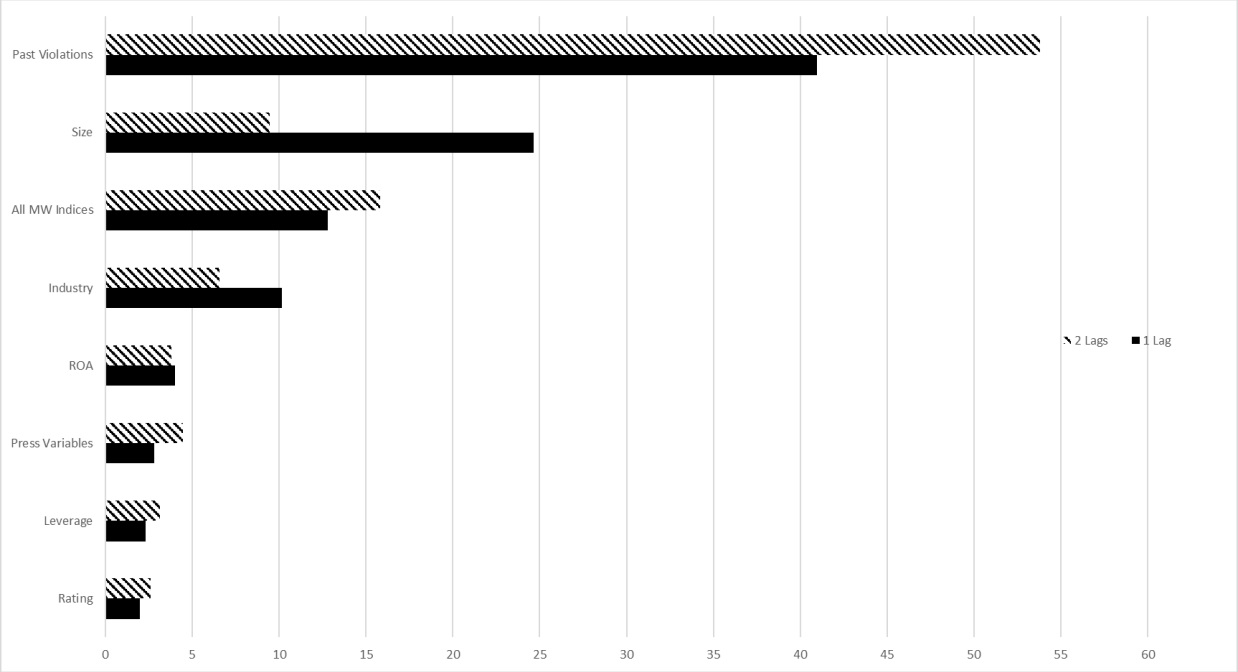
	Overall Rating
Culture Values Rating	0.83
Senior Management Rating	0.84
Work-Life Balance Rating	0.68
Benefit Rating	0.66
Opportunities Rating	0.80

In contrast, our misconduct word indices are more differentiated from, and only modestly negatively correlated with, each of these ratings categories ($p<0.01$ in all cases) suggesting they are picking up different information for purposes of measuring misconduct risk.

	MW Index - Pros	*MW Index - Cons*	*MW Index - Advice*
Overall Rating	-0.184	-0.132	-0.156
Work-Life Balance Rating	-0.291	-0.271	-0.230
Culture Values Rating	-0.210	-0.133	-0.159
Opportunities Rating	-0.107	-0.059	-0.116
Benefits Rating	-0.139	-0.099	-0.142
Senior Management Rating	-0.179	-0.097	-0.144

Online Appendix 4: Including Additional Lags in Annual Violation Prediction Models

We analyzed additional lags of violations and other variables for our year-to-year violation predictions during our prediction sample period of 2012-2017. Introducing two lags of our misconduct word indices, overall rating, size, ROA, leverage, and press coverage/sentiment yields a test sample pseudo-R^2 of 35.0% (versus 31.5% when only one lag of each variable is included). The following figure summarizes the influence, or relative variable importance (summed over all included lags), for the models with one and two lags respectively.



Per the above figure, more violation history appears to help as test sample model fit improves and this variable becomes overall more influential in the final prediction model. Moreover, more lags of violations appears to subsume the importance of other more fixed firm characteristics like size and industry which become considerably less influential in the final model once more violation history is observed. However, crucially, this is not the case with our misconduct word indices which increase in influence as more lags are added and they move to become the second most influential variable group in the model behind lagged violations. There is little change in the overall influence of the press coverage and financial performance variables as further lags of these variables are added.

These results complement our serial violator transition analysis in showing that the relative importance of our text-based measures of misconduct risk increases when considering risk over longer time periods. This is important given the influence of lagged violations in our models. Firm status as a violator in the current year may be the single most influential predictor, but it also occurs relatively infrequently (e.g. the large majority of firms do not commit violations in any given year and fewer than half have any violations during our sample period). That is, only when misconduct risk progresses to a point that results in external enforcement actions does prior violation history become an important signal of future risk. However, it will not be a useful indicator for the majority of firms in any given time period. For most firms, understanding misconduct risk and how it might be evolving requires alternative, less easily observed information to assess. The evidence above, coupled with our analysis of serial violators in the paper, suggests that text-based measures like those we explore in this paper can be useful in this context.

Online Appendix 5: Cross-Validation Analyses for Serial and Criminal Violations

Violations, especially criminal violations, are relatively rare events, and collapsing the data into a cross-sectional sample further reduces the sample size. Therefore, a single split into training and test samples may not exhibit enough variation to both fit the models and consistently estimate out-of-sample performance. To address this issue, we conduct additional cross-validation analyses for serial and criminal violations. In particular, we follow Larcker and Zakolyukina (2012) and Witten and Frank (2005) by performing repeated cross-validation. In our case, we use repeated random 80%-20% train-test splits using 5-fold cross validation repeated 5 times. This approach proceeds as follows:

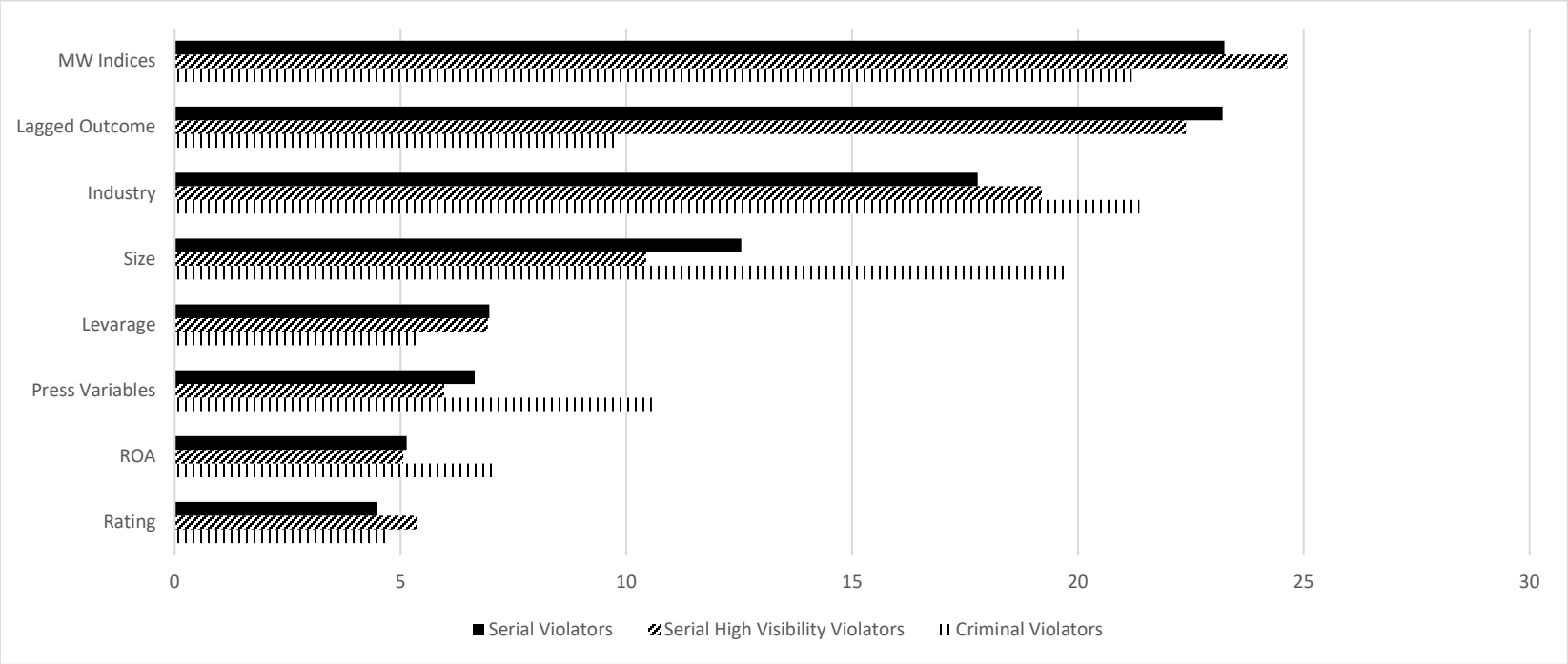
(1) the data are first split into 5 roughly equal samples (folds);
(2) the k^{th} (k = 1, ... , 5) fold is held fixed;
(3) the models both including and excluding our misconduct word indices are trained using the remaining 4 folds and ignoring the k^{th} fold; and
(4) the performance of the models are evaluated using the k^{th} fold.

In this procedure, each fold is eventually used as a test sample. We run this 5-fold cross validation procedure 5 times with the data randomly sorted in between each run to produce new folds. We then follow Larcker and Zakolyukina 2012 by comparing model performance based on the average difference in AUCs over the resulting 25 cross validation runs and testing for significant differences using the corrected resampled t-statistic (Nadeau and Bengio 2003; Bouckaert and Frank 2004). The corrected resampled t-statistic is computed as: $\frac{\bar{d}}{\sqrt{\left(\frac{1}{k}+\frac{n_2}{n_1}\right)\hat{\sigma}_d^2}}$. Here, d is the paired difference in the AUC; k=25 is the total number of cross-validation runs; and n_1=4 and n_2=1 are the respective number of folds used for training and testing in each run. Because criminal violations are extremely rare in our data (<1% of firm-years), we implement a stratified version of this cross-validation procedure for this outcome in which we maintain the proportion of criminal and non-criminal violators in each random data split to be approximately the same as in the overall sample. The results of our prediction estimates are as follows:

	Average Performance in Test Sample		***Average Influence Statistics for Full Model***									
				MW Index-								
Outcome	*AUC*		*Lagged Outcome*	*Pros*	*Cons*	*Advice*	*Rating*	*Size*	*Leverage*	*ROA*	*Press Variables*	*Industry*
	Full Model[a]	No Indices										
Serial Violator	81.7%	80.0%	23.2%	9.8%	8.5%	4.9%	4.5%	12.5%	7.0%	5.1	6.6%	17.8%
Serial Violator - High Visibility	84.2%	82.0%	22.4%	8.8%	10.1%	5.8%	5.5%	10.4%	6.9%	5.1%	6.0%	19.2%
Criminal Violator	80.7%	78.7%	9.8%	11.2%	4.9%	5.1%	4.7%	19.7%	5.5%	7.1%	10.6%	21.4%

[a] donates differences in AUCs are significant at the p<0.01 levels for the *Serial Violator* model (corrected resampled t-statistic=2.77) and for the *Serial Violator – High Visibility* model (corrected resampled t-statistic=3.40). The average difference in the AUC is not significant at conventional levels for the *Criminal Violator* model (corrected resampled t-statistic=0.61).

The following figure summarizes the average influence of the various predictors used in the model.



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