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Detecting fraud beyond cooked books: Forensic economics, psychology and accounting toolkit

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The article focuses on the advantages and disadvantages of various methods enabling to uncover fraudulent and dishonest behavior of organizations' stakeholders — employees, managers and costumers. Based on illustrative studies, it further shows how these tools can be used in empirical fraud risk management. A comprehensive approach that is absent in most organizations and management science literature.

Forensic accounting research of financial data, as well as laboratory and field research of individual and organizational factors by economists and psychologists, are bringing us increasingly detailed knowledge of organizational misdeeds. The field of corporate and behavioral ethics uncovers the causes of individual and organizational misconduct, describes its nature and calculates the consequences of illegal behavior on the market value of firms, and suggests tools for restricting fraudulent behavior and corporate non-compliance. However, much of the evidence about corporate misconduct comes from descriptive case studies, which are dependent on a specific context and are not necessarily suitable for generalization. Alternatively, they describe the misconduct on the level of firms or sectors, which is knowledge important for regulators or prosecuting attorneys, but they do not directly offer tools for measuring the extent of a fraud inside of an organization, or the dishonesty of its customers or clients.

On the other hand, behavioral ethics and moral psychology use laboratory experiments (although with usually student populations), which can precisely identify the causal forces that influence individual fraudulent behavior. Nevertheless, they cannot be used as indicators of dishonesty in real organizations (or they have weak external validity). A significant methodological contribution was made with the introduction of randomized field experiments and other methods that uncover dishonest behavior directly in organizations.

This article supplies an interdisciplinary and multilevel overview of methods how to identify (not only) organizational misdeeds, the pros and cons of the use of each individual method, and the limitations and strengths of their results based on cherry-picked current studies. It avoids a deeper discussion of what is individual or organizational misconduct, unethical behavior or dishonesty and which factors establish or determine them. It applies the approach utilized in forensic economics to uncover the "hiding behavior". Thus, it supposes that if people want to conceal their activity, they exhibit somewhat unethical behavior (naturally not every time, as Eric Zitzewitz wrote: "Motivations for hiding behavior vary—in many of the [instances] . . . the behavior in question is very likely illegal. In other cases, behavior may be a violation of contract terms. In still others, it may be a violation of ethical norms. In each case, there may be significant controversy as to which side of the line on which behavior falls.").

The discussed methods include analyses of existing archival data and data-mining, observational studies, randomized field experiments and audit studies, lexical text analysis and analysis of speech or voice, and integrity testing (overt integrity tests and personality-oriented tests). For an overview, see Table 1. These methods of empirical fraud risk management exhibit various levels of inaccuracy. Moreover, dishonest behavior is rather rare, and usually, there are many other ("honest") explanations of the behavior in question, which are difficult to exclude. Depending on the character and level of detail of the dataset, the methods allow identification of dishonesty on the level of an individual or a group.

ANALYSIS OF EXISTING ARCHIVAL DATA

The simplest tool is a direct observation of dishonesty in existing data. Firms do not always use their opportunities to analyze data they already own to reveal whether their employees, contractors or clients cheat. However, some

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Table 1 An overview of empirical fraud risk management (EFRM)

Tools of EFRM	Showcase study	Benefits	Disadvantages
I. Analysis of existing archival data	Levitt (2006) analyzed consumption of bagels and payments to a lockbox based on an honor system and found that purchasers of donuts pay less than the full price.	The firm owns (or can easily obtain) data suitable for discovering whether dishonest behavior occurs.	Usually only identifies general factors or groups associated with cheating (discrimination legal challenges). It may be difficult to identify its causes.
Data-mining	Bhattacharyya, et al. (2011) could identify fraudulent credit card transactions with the accuracy of 99.4%, using a few transaction attributes.	Real-time, “online” identification of cheating; can reveal unexpected correlates of dishonest behavior.	Necessity of frequent data collection or obtaining it from many sources, and of having indisputable cases of fraud for calibrating the algorithm.
“Red-flag” correlations	Grieser, et al. (2016) found that an involvement of employees on an extramarital dating site correlates with investigation of their firms for fraud and corruption.	It may be possible to obtain cheap data on people or firms and to discover unexpected correlates of dishonest behavior.	Usually only identifies general factors or groups associated with cheating (discrimination legal challenges). It may be difficult to identify its causes.
II. Observational studies	In insurance claim investigations, Warren and Schweitzer (2018) found that claimant interviews by skilled experts are the most important step in determining whether claims are denied.	Targeted data collection (e.g. GPS in company cars); may lead to dissuasion from dishonest behavior. The firm owns or can easily obtain data to discover whether cheating occurs.	People behave differently if knowing they are surveilled (Hawthorne effects). Carries a risk of loss of trust in the firm if revealed that it tests people of interest with regard to cheating.
III. Randomized field experiments	Nagin, et al. (2002) found that a substantial proportion of employees did not respond to manipulations in the monitoring rate.	Enables accurate identification of the circumstances of dishonest behavior.	There is necessity of random assignment of manipulation to treatment and control groups, which is not feasible in many situations and/or organizations. Also carries a risk of loss of trust in the firm if revealed that it tests people of interest with regard to cheating.
Audit studies	Azar, et al. (2013) tested whether restaurant customers return excessive change and found that most do not.	Enables accurate identification of the circumstances of dishonest behavior.	There is necessity of random assignment of manipulation to treatment and control groups, which is not feasible in many situations and/or organizations. Also carries a risk of loss of trust in the firm if revealed that it tests people of interest with regard to cheating.

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Table 1 (*Continued*)

Tools of EFRM	Showcase study	Benefits	Disadvantages
Lab-in-the-field experiments	Cohn, et al. (2014) used a coin flipping task to find out that making bankers' identity more salient leads to an increase in their dishonest behavior.	"Lab tasks" may be simple behavioral markers correlating with real-world deception.	People behave differently if knowing they are surveilled (Hawthorne effects). "Lab tasks" do not necessarily have ecological validity, may be considered "just games". Carries a risk of loss of trust in the firm if revealed that it tests people of interest with regard to cheating.
IV. Lexicographical text analysis	Holton (2009) analyzed chat in discussion groups and detected disgruntled employee communications through automated text mining techniques.	Can reveal unexpected correlates of dishonest behavior.	Necessity of frequent data collection or obtaining it from many sources, and of having indisputable cases of fraud for calibrating the algorithm.
Analysis of speech and voice	Hobson, et al. (2012) used speech samples of CEOs during earnings conference calls and found that vocal dissonance markers are associated with the likelihood of irregularity restatements.	Real-time, "online" identification of cheating; can reveal unexpected correlates of dishonest behavior.	Necessity of frequent data collection or obtaining it from many sources, and of having indisputable cases of fraud for calibrating the algorithm.
V. Integrity testing (Overt integrity tests and Personality-oriented tests)	Nei, et al. (2018) found out that executives who are more conscientious, professional, and rule following, and less attention seeking are characterized by high integrity and accountability.	Relatively easy to use personality and other questionnaires in employee recruitment. Long-term data to compare the results with.	People may realize the purpose of testing and cheat the tests. Usually only identifies general factors or groups associated with cheating (discrimination legal challenges). It may be difficult to identify its causes. Impossible to submit to customers/ clients.

must do so, such as the Dutch company Candyman. It delivers a box of sweets to its clients — firms. Each employee of the client can take the candy and pay by putting money in a box of coins. The box is open so that people can get change. Marco Haan and Peter Kooreman analyzed the Candyman data and showed that already within a few weeks, employees paid much less than the recommended price and their willingness to pay gradually decreased. Similarly, Steven Levitt analyzed the consumption of bagels and donuts and payments to a lockbox based on a similar honor system in various firms and bureaus. He found that purchasers of donuts pay less than the full price and that payment rates fall in response to an increase in the prices. The lowest payment rates were observed in the telecommunications and, paradoxically, in nonprofit sectors (avionics and government have the highest payment rates).

Sometimes, simply re-checking existing data is enough to detect fraud. When a study compared historical and current data in a database of Thomson Financial, it found that the news giant cheated in its statistics. Its database I/B/E/S contains not only investment ratings of tens of thousands of firms' stocks, but also financial analysts' recommendations about their prices' movement and whether to buy, keep or sell them. These long-term records are used for future stock market predictions, and analysts and their investment firms are evaluated (and rewarded) accordingly. However, a severe conflict of interest exists, since analysts and their employers are not only among I/B/E/S clients but also constitute its data sources. Depending on the time when a client of I/B/E/S saw the data between 2000 and 2007, they could find different data in up to 22% of cases (e.g. out of 332,145 records from 2003, a whole 57,770 differed the following years). Inconsistent data could have certainly been the result of a mistake or software error. However, the errors had a strange pattern — mostly data from the largest investment firms differ, and recommendations to buy or those that did not adhere to the consensus of other analysts were erased. Recommendations to sell were added, and predictions of analysts who'd remained on their posts were anonymized. (It is not an accident that Lehman Brothers, whose crash in 2008 started the great recession, were among the first ones to push Thomson Financial to no longer make their data public.)

Archival data can be analyzed by many perspectives to reveal concealed dishonest behavior and to react to it, e.g. a Swedish study found that during important sports events, the absence of employees increases. Companies could announce the option of home office before such events, or on the contrary, announce more severe oversight on absences.

Data-Mining

Archival analyses of big data samples use statistical data mining techniques. In financial fraud detection there are especially regression, clustering, outlier detection, and visualization. They are tools for detecting discrepancies in the financial information of the company and its stock price, its financial statements, and its operating behavior. Other tools utilized especially in bank fraud and insurance fraud include computational tools as self-organizing maps, neural networks, and Bayesian belief networks and other business intelligence and forensic accounting technologies.

All the above-mentioned data-mining tools can be characterized by searching for unusual patterns in variables of interest in databases and uncovering non-explicit information indicating the possibility of fraudulent behavior (see also section Lexicographical Text Analysis and Analysis of Speech and Voice). Finding patterns identifying the risks of cheating also enables highlighting suspicious transactions in real-time available data. The accuracy (ratio of all successfully classified samples to unsuccessful ones) of different methods is estimated to range from 20 to 99.6%. A study using logistic regression could identify fraudulent credit card transactions with an accuracy of 99.4%, using a few primary attributes of these transactions (transaction type, merchant name, merchant country etc.) and derived attributes (number of transactions with a specific merchant type over a month, average spending per day over a month, total amount spent with a credit card on the day). Evolving computational technology and empirical strategies for data-mining enable firms to identify more and more attributes that serve as "red flags" for dishonest behavior.

Most of the data-mining tools are being used in financial and insurance sectors, since firms from other sectors lack suitable datasets (i.e. data obtained with high frequency and from multiple sources, and precisely identified cases of fraud in the past for calibration) for reliable use of data-mining tools for uncovering fraud likelihood — respectively, their accuracy would be low. However, with continued digitization, more companies will be able to use these tools to detect dishonest behavior.

Indirect dishonesty attributes (Red flags)

Another approach in archival analyses is using indirect dishonesty attributes, i.e. a strong correlation of hidden dishonest behavior with idiosyncratic behavior about which external data exists ("red flag" correlations). A study examined the question of whether there is a relation between willingness to transgress norms in personal life and higher dishonesty on the level of organizations. Its authors utilized a data leak from AshleyMadison.com, an online dating site focused on extramarital relationships. They confirmed that higher involvement of employees on this dating site correlates with an investigation of their firms for accounting discrepancies or frauds. Financial analysts also suspected these firms of corruption. Another example can be drawn from a similar study which tested whether expensive sports cars are primarily bought by risk-seeking managers who could be more inclined toward dishonesty. Authors analyzed over 50,000 American hedge funds with available data about their performance, portfolio or size, and about their managers. Then they utilized American automobile databases where insurance companies and car dealers insert data about new car sales. Authors managed to connect sales of nearly 2000 cars with approximately a thousand hedge fund managers. Consequently, they compared how owners of expensive sports cars on one hand and family minivans on the other hand performed. They found that sports car owners more frequently closed their funds because of regulation breaks or criminal charges.

Such correlative "red flags" may not only work for individual managers but also whole firms. An analysis of 9616 yearly general meetings of 2342 American companies between 2006 and 2010 showed that firms suddenly organizing their shareholder meetings in locations far from their headquarters manifest significantly worse revenues and profits, which reflect in the subsequent drop in their stock prices. The finding shows that managers possess information about the company's bad performance and choose a more distant shareholder meeting location in an attempt to delay the news getting out. Many shareholders, reporters and other interested parties do not attend meetings in far locations. Executives are not confronted with uncomfortable questions and do not have to disclose any looming problems. The meeting goes according to their scenario. What is most surprising is that shareholders have not yet discovered this diversion, since the stock value doesn't fluctuate significantly when the company announces the unusual location and time of the shareholder meeting.

An apparent advantage of archival data analysis is the existence of relevant data (or very low costs of obtaining them for analysis) that can be used to find if and under what circumstances cheating occurs. It's up to a given organization whether to analyze its data to discover whether dishonest behavior is prevalent and eventually, what personality and situational data correlate with it.

OBSERVATIONAL STUDIES

Another simple tool is made when an organization or an individual decides to create data about potentially fraudulent behavior by recording or observing, be it illegal parking or bribery. Another possibility is to compare data drawn from two independent sources and examine if frauds occur, e.g. utilizing the independent measurement of GPS proves that taxi drivers overestimate the distance traveled. Sometimes it may be necessary to obtain new data verifying a potential fraud in already existing data. Ginger Zhe Jin and Andrew Kato purchased baseball cards on eBay and had them professionally graded by experts. They found that some buyers are misled by fraudulent claims of quality.

An illustrative example of an observational study from the retail sector is a study by Dylan Glover and colleagues, who analyzed productivity (e.g. shirking) of shopkeepers of French majority and minority populations (of North African or Sub-Saharan African origin) depending on the presence of a manager who was or was not biased against minorities. They measured managers' bias toward minorities with the Implicit Association Test, which correlates well with real-world discriminatory behavior. The study found that minority shopkeepers have more absences, spend less time at work and scan fewer items if they happen to work under a biased manager. On the contrary, if they work under a non-biased manager, they are half as likely to be absent and serve 9% more customers than majority shopkeepers.

It is apparent that observational studies can provide detailed data and a range of observational variables can be used, such as witnesses, physical evidence or chronologies conducted by skilled experts used in the insurance industry. Even simple observation of people or listening to their arguments can help in revealing dishonesty; i.e. liars make a more negative impression and are tenser.

RANDOMIZED FIELD EXPERIMENTS, AUDIT STUDIES, AND LAB-IN-THE-FIELD EXPERIMENTS

Randomized experiments (A/B testing) reveal how a group exposed to a specific treatment (be it an intensity of supervision, a form of operational management, working conditions etc.) behaves compared to the control group with the treatment absent. For instance, Daniel Nagin and colleagues conducted a double-blind field experiment to observe the effect of experimentally-induced variations in monitoring on employee opportunism. Many employees acted dishonestly; nevertheless, a substantial proportion of employees did not respond to manipulations in the monitoring rate. In general, field experiments can quantify the extent of organizational misconduct very accurately. Another example can be the gradual implementation of technology for automatic billing of orders in restaurants, which helped to uncover the rate of deceptions of waiters and waitresses.

Another similar tool is mystery shopping or audit studies, in which the characteristics of the customers or nature of the business vary, with the intention to uncover how employees (be it car mechanics, sales clerks or estate agents) cheat their customers. It is also possible to explore which groups of customers cheat most; e.g., Ofer Azar and colleagues tested whether restaurant patrons return excessive change. They found that most customers do not return excessive change. On the other hand, the greater its value, the greater was also the probability that the client will return the change. Regular patrons and women behaved more honestly.

Lab-in-the-field experiments apply standardized laboratory tasks and games in the natural environment of the studied population. These kinds of experiments thus enables to observe the decisions of employees, managers or customers and to compare them to results attained in purely laboratory studies, usually conducted on students. A typical example is a banker study that used a coin flipping task. In this task, participants guess in several rounds which side of a coin comes up in a flip and report whether their guess was correct or not. Correct guesses are rewarded financially. Since only the participant sees the coin, he or she can lie and report a greater success rate (than the theoretical 50%). The study found that making the banker identity more salient leads to an increase in dishonesty (bankers reported 58.2% success rate). A similar study found that incentive-based compensation increases dishonest behavior among professional internal auditors (members of the German Institute for Internal Audit). The study used the so-called real effort task, in which participants identify incorrectly added sets of numbers and they are rewarded based on different compensation schemes.

Firms are often unwilling to conduct field experiments aimed at stakeholders' dishonest behavior, because knowing that the company tests dishonesty tendency in clients, employees and managers can lead to the loss of trust and loyalty. Moreover, experiments are usually conducted using between-subjects analysis, which only enables to discover general factors or groups associated with cheating, not to identify specific transgressions.

LEXICOGRAPHICAL TEXT ANALYSIS AND ANALYSIS OF SPEECH AND VOICE

Text analysis can reveal patterns which correlate with fraud. For example, deceptive language uses more activation language, words, imagery, pleasantness, group references, and less lexical diversity than non-deceptive language. Fraudulent financial disclosures thus appear credible while communicating less in actual content. Gerard Hoberg and Craig Lewis based on firms' disclosures to the U. S. Securities and Exchange Commission have found that fraudulent verbal disclosure contains fewer details explaining the sources of the firm's performance while disclosing more information about positive aspects of firm performance.

In the case of retail business, a study found out that 5% of product reviews on a retailer's website are submitted by customers with no record of ever purchasing the product they are reviewing. These reviews are more negative than other reviews. They are also more likely to contain linguistic cues associated with deception (liars in general express more negative emotions, they distance themselves more from events and express fewer sensory-perceptual words).

William Mayew and Mohan Venkatachalam showed that the emotional tone of the voice of managers during earnings conference calls is predictive of the firm's financial performance. Similar study used speech samples of CEOs during earnings conference calls and found that vocal dissonance markers are associated with the likelihood of irregularity restatements. Methods combining features across categories (based on financial numbers, linguistic behavior, and non-verbal vocal cues) have demonstrated the best potential for

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detecting financial fraud. Another study used data from several Vault.com and Yahoo! discussion groups (intra-company communications off of the companies' networks) and detected disgruntled employee communications through automated text mining techniques. The study concludes: "Once identified, patterns signaling fraud risk events, such as expression of intent to seek retribution for inadequate pay, could have their persons ("boss"), entities ("department"), dissatisfaction objects ("salary"), dissatisfaction expressions ("loathe," an expression of high intensity), and other attributes tagged . . . Using this procedure, we could potentially locate messages expressing intent to seek retribution for perceived low compensation, for instance. Disgruntled communication events that prove especially valuable for fraud prediction would be assigned higher fraud risk scores within a fraud detection and deterrence system."

Lexicographical text analysis and analysis of speech and voice technically constitute data-mining conducted on human communication. Increasingly advanced algorithms used on the increasing volume of digitized communication may facilitate fine-tuned detection of cheating in the near future.

INTEGRITY TESTING (OVERT INTEGRITY TESTS AND PERSONALITY-ORIENTED TESTS)

Integrity testing is a large class of structured interviews, questionnaires and other personality tests which measure the moral attitudes of employees or managers, their theft attitudes, perceived ease of fraud, endorsement of common rationalizations for fraud or dishonesty, etc. The most employed tests, The Reid Report, Stanton Survey, and PSI Honesty Scale, are identified as overt measures of integrity. Alternatively, the questioner tries to (directly or indirectly) gain admissions of theft and other counterproductive work behaviors (or "CWBs", i.e. theft, rule-breaking, absence, and poor work habits). As Saul Fine and colleagues state: "Overt integrity taps individuals' attitudes and opinions toward CWBs, such that the perceived frequency of CWBs (i.e., "projectiveness"), leniencies toward offenders (i.e., "punitiveness"), justifications for CWBs, and admissions of past involvement in CWB, reflect low overt integrity and a higher risk for future engagement in CWB".

There a lot of personality characteristics correlating with moral (dis)integrity identified in the literature (by personality-based, i.e. covert tests). People characterized by conscientiousness, agreeableness, and emotional stability cheat less; on the other hand, the impact of age, gender or race tends to be negligible. A study found out that in the managerial class, executives who are more conscientious, professional, and rule-following, and less attention seeking are characterized by high integrity and accountability.

There are several methodological objections against integrity testing: respondents may know or realize what is being tested and not answer truthfully (some of the questions read: "Do you believe a person who has taken merchandise from his company just a few times should be given another chance? . . . Did any fellow employee ever show you how you could cheat your company out of money? . . . If you got merchandise by accident from a vending machine, would you put the money in the machine anyway?"). Alternatively, dishonest people may not confess to their cheating (or dishones tendencies), and the found absence of correlation between a personality trait and dishonesty will be false. Nevertheless, overt integrity tests' validity for predicting CWB in a variety of professions ranges between .26 and .32.

CONCLUSION

Cheating, dishonest and deceptive behavior bear indisputable costs. Corporate scandals not only lower or destroy a firm's value for its shareholders and undermine (otherwise) a productive and ethical company culture, but also weaken trust in the market or government. Similarly, stealing and cheating customers do not merely weaken moral norms, but also decrease the motivation of employees.

Cheating is, by definition concealed, so the striving for its detection and elimination is an ongoing struggle between rule-breakers and rule-enforcers. This article has demonstrated that firms' stakeholders who want to identify dishonest behavior of managers, employees or customers have a wide range of tools and methods at their disposal nowadays. However, many companies do not seem to take advantage of such opportunities. Of course, dishonest behavior (transgressing moral values, social norms or laws) is being supported in some firms if it leads to immediate profit or more effective functioning of the organization. Although for stakeholders, it would be most beneficial to use the tools outlined in this article in such firms, the motivation to implement them will likely meet with the unwillingness of employees or managers.

Discussed tools of empirical fraud risk management have varying requirements in terms of cost, time, data collection or analysis, but they have quite a high accuracy in dishonesty detection. On the other hand, greater effort in cheating detection is not only positive. Clients and customers do not appreciate being surveilled and audited closely (unless the firm does protect them from becoming a victim of deception). There is also a risk of blaming an innocent, which would harm the firm's reputation. Also, as stated above, some tools require data collection regarding employees' behavior, and such increased oversight may lead to weakening their loyalty toward the firm. It can be imagined that data collection and analysis would, in the end, cost more than the damage caused by cheating.

CONFLICT OF INTEREST

The author declares that he has no conflict of interest.

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