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Abstract

Using a proprietary dataset of 667 companies around the world that experienced white-collar crime we investigate what drives punishment of perpetrators of crime. We find a significantly lower propensity to punish crime in our sample, where most crimes are not reported to the regulator, relative to samples in studies investigating punishment of perpetrators in cases investigated by U.S. regulatory authorities. Punishment severity is significantly lower for senior executives, for perpetrators of crimes that do not directly steal from the company and at smaller companies. While economic reasons could explain these associations we show that gender and frequency of crimes moderate the relation between punishment severity and seniority. Male senior executives and senior executives in organizations with widespread crime are treated more leniently compared to senior female perpetrators or compared to senior perpetrators in organizations with isolated cases of crime. These results suggest that agency problems could partly explain punishment severity.

Keywords: white-collar crime, gender, fraud, penalties, corruption

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1. Introduction

Studies of white-collar crime conclude that it has a significant economic impact.[1] The Federal Bureau of Investigation estimates that it costs the U.S. more than $300 billion per year, far exceeding losses from personal property crimes.[2] In addition, white-collar crime can destroy shareholder value at host companies, as demonstrated by the experiences of Enron, Worldcom, Adelphia, Siemens, and Volkswagen and documented in prior studies (see Karpoff and Lott 1993; Dechow, Sloan and Sweeney 1996; Alexander 1999; U.S. General Accounting Office 2002; and Karpoff, Lee, and Martin 2008a).

What is less clear is how punishments are meted out to perpetrators of white-collar crime. Prior research on this topic has examined punishments for U.S. perpetrators following SEC or Department of Justice enforcement actions. Early findings were inconsistent (see Feroz, Park and Pastena 1991; Desai, Hogan and Wilkins 2006; Beneish 1999; Agrawal, Jaffe and Karpoff 1999).[3] But, as noted by Karpoff, Lee and Martin (2008), these studies focused on top management at affected companies and were unable to identify the particular individuals involved in misconduct. By examining actual perpetrators, Karpoff et. al. (2008) documented that 93% were fired. These findings shape our

[1] The earliest definition of white-collar crime, provided by Sutherland (1940), was "crime committed by a person of respectability and high social status in the course of his occupation." Today, the term typically refers to “non-violent crimes committed in commercial situations for financial gain (Cornell University Law School)” and includes antitrust violations, fraud, insider trading, tax evasion, corruption, and economic espionage.

[2] See Cornell Law School (2016).

[3] These studies examine executive turnover for companies where there have been SEC investigations in accounting irregularities or restatements. Srinivasan (2005) examines turnover among audit committee directors following restatements, and finds evidence of higher rates of turnover at both the affected firm and at other firms where they hold directorships.

understanding of how corporate policies to combat and deter crime are enforced, and the effectiveness of corporate governance.[4]

However, Karpoff et. al. (2008) examine only cases where misconduct is prosecuted and publicly reported. It might not be surprising that the perpetrators of these crimes are typically fired given the regulatory and legal scrutiny. What is less clear is whether companies are equally likely to dismiss employees whose crimes do not become public, or are not even reported to regulatory authorities. In addition, the earlier research focuses on crimes investigated by U.S. legal institutions, which are rated as more effective and having a lower tolerance for white-collar crime than in many other parts of the world (LaPorta, Lopez-de-Silanes and Shleifer 2008; Healy and Serafeim 2016). It is unclear whether the findings hold for crimes committed in other jurisdictions.

This study re-examines punishments that companies mete out to perpetrators of white-collar crime. Unlike earlier studies, it employs proprietary data from a survey of companies on white-collar crime. The survey collects information on the incidence of economic crime at the company during the prior twelve months, as well as information on the most serious crime committed and the punishment of the perpetrator. By examining responses to crimes discovered by the company itself, but where the company may opt to not report the crime to regulators, the dataset allows us to test the generalizability of earlier findings and document drivers of organizational actions taken against perpetrators. In addition, since the sample includes non-U.S. companies, with some from countries where

[4] Public policy debate has also examined whether and when companies should be punished for economic crimes, in addition to punishment at the level of the individual perpetrator(s). See Atkins (2005), arlen and Carney (1992), Polinsky and Shavell (1993) and Arlen and Kraakman (1997). In addition, considerable research has been devoted to understanding factors that induce perpetrators to commit crimes (see Soltes, 2016 for a discussion of this literature).

regulatory enforcement is weak, it allows us to extend prior research. While our dataset has advantages, it also has drawbacks that limit the generalizability of our findings and rely on truthful reporting of survey participants. Therefore, we caveat our results alerting the readers to the limitations of the data in our discussion.

We observe considerable variation across companies in the punishment of perpetrators of crimes. The sample companies fire the perpetrator in 78% of the cases and pursue legal action against perpetrators in 40% of the cases. Only 17% of our sample firms report the detected crimes to regulators. For these cases, the probability of dismissal is 87%, close to the 93% estimate in Karpoff et. al. (2008), and the probability of legal action is 56%. In the remaining cases where the crime is not reported, the probability of dismissal is 76% and the probability of legal action is 37%.

Tests of variation in punishment rates across countries show that the rate of dismissal for U.S. perpetrators is 94%, similar to that of Karpoff et. al. (2008), and the rate of legal action is 34%, versus 77% and 40% respectively for non-U.S. perpetrators. Surprisingly, there is little difference across low and high corruption countries in dismissal rates (77% and 80% respectively) or in rates of legal action for perpetrators (43% versus 38%).

We examine two models of behavior that potentially explain variation in company responses to white-collar crime. Under the economic model, managers trade off the economic costs and benefits to shareholders of various potential punishment decisions. For example, dismissing a perpetrator sends a signal to other employees that illegal activity can be detected and is not tolerated, potentially deterring future wrongdoing. However, if the perpetrator is highly productive relative to a replacement, short-term performance may deteriorate. Pursuing legal action against a perpetrator (in addition to dismissal) sends an even stronger signal to employees that the company is committed to punishing perpetrators, but also increases the risk that the crime will be publicized, potentially damaging the firm's business relations and reputation, and leading to legal actions and regulatory actions that may be especially costly if outsiders overreact to the reported crime.

Under the second model, which we term the agency model, executives' decisions on how to punish perpetrators are based on their own self-interest. Executives may reduce punishments for perpetrators who are close colleagues and friends. Alternatively, executives' punishment decisions may be driven by their concerns about any personal loss of reputation that arises if a crime is publicized within or outside the company. For example, if the perpetrator was hired or promoted by another senior executive, publicizing the crime could damage the superior's reputation.

To provide evidence on how these models of behavior influence punishment meted out to perpetrators of white-collar crime, we examine the relation between punishment decisions and perpetrator, transaction and company factors. We find that punishment severity is related to the personal characteristics of perpetrators. For example, punishments are less severe for senior perpetrators, consistent with both the economic and agency model predictions. The costs of replacing productive employees and media and regulatory scrutiny should their crimes become public are both likely to be higher for senior perpetrators. Their punishments could also be driven by agency costs, since senior perpetrators are likely to have personal relationships with top management and the board. Reduced punishments could therefore reflect personal connections or senior executives' desire to deal with the incident quietly to reduce the risk of damaging their own reputations should crimes of close senior colleagues become public.

At the transaction level, we find that punishments are less severe if the perpetrators' crimes could be rationalized as being for the benefit of the firm (e.g. industrial espionage), rather than where he/she has directly misappropriated money from the company itself. This finding suggests that senior executives responsible for punishing illegal acts consider those directly against the company to warrant the harshest penalties.

Finally, firm characteristics are related to punishment severity. Larger firms typically pursue more aggressive punishments of perpetrators. If the costs of monitoring and control are higher at such firms, their tougher punishments may reflect perceived benefits of sending a strong formal signal to employees that such behavior is not tolerated.

The finding that punishments are less severe for senior executives is consistent with the predictions of both the economic and agency models. Distinguishing between them is challenging. Senior executives who determine punishments are likely to justify their decisions on economic grounds, even if self-interest is at stake.

To provide further insight into the two explanations, we examine the interactions between seniority and two variables: gender and number of crimes detected at the firm during the last year. Prior research finds that women executives are often seen as outsiders in informal male social networks (see Kanter 1977; Brass 1985; Ibarra 1992; Blair-Loy 2001; Groysberg 2010). Women perpetrators are therefore less likely to have close personal relationships with male executives who determine their punishment. If weaker punishments for senior executives are driven by bias and personal relationships, rather than economic costs and benefits, we predict that such effects are less likely to be observed for senior women. Consistent with the agency explanation, we find that the lower punishments for senior perpetrators are restricted to male executives. For senior women executives, no such effect is found. Executives who mete out punishments are therefore willing to reduce the penalty for crimes committed by senior male colleagues, but not by senior women colleagues. In fact, we find a positive relation between punishment severity and seniority for women but a negative relation for men.

The interaction between seniority and the number of economic crimes detected at the firm during the prior year also has differential predictions under the economic and agency models. Discovery of multiple crimes at a company suggests that the problem cannot be attributed to just one "bad apple." As a result, management at these firms faces pressure to send a strong signal to employees that compliance is taken seriously and to settle on tough punishments, particularly for senior perpetrators. In contrast, agency considerations are likely to lead senior managers to settle on weaker punishments for senior perpetrators when there have been multiple crimes detected, reducing their risk of increased job insecurity and loss of reputation should the crimes become public knowledge. We find a negative interaction between perpetrator seniority and the number of crimes detected, indicating that firms with multiple crimes are even more lenient towards senior perpetrators, consistent with management self-interest driving seniority punishments.

In summary, punishments of white-collar crime are systematically related to perpetrator, transaction, and company characteristics. Our evidence on punishments at large firms is consistent with management at these firms perceiving that there are economic benefits from setting tougher penalties for perpetrators to deter future crime. However, it appears that not all punishment decisions are driven by economic considerations. Our findings that senior male executives receive lighter punishments than female peers, and that senior executives receive even lighter punishments when the firm has detected multiple crimes during the past year suggest that not all the decisions are taken with shareholders' interests in mind – the self-interest of host company executives is also an important consideration.

The remainder of the paper is organized as follows. Section 2 discusses the motivation, and Section 3 examines the survey used in this study and reports summary data. Section 4 describes our tests and results, and Section 5 reports our conclusions.

2. Motivation

Many business leaders and corporate boards recognize the importance of creating a culture of zero tolerance towards employees who fail to comply with local laws. As a result, their companies have adopted codes of conduct to communicate to employees that misconduct is unacceptable and will be punished. In recent years, companies' public discussion of commitment to compliance has focused on corruption. For example, Marilyn Hewson, Chairman and CEO of Lockheed Martin wrote to all company employees: "We have zero tolerance for corruption and an expectation that anyone who acts on behalf of the Corporation adheres to all applicable anti-corruption laws. … We would rather lose business than operate in a manner contrary to our core values."[5] ING Groep N.V.'s Values Statement states: "ING has a zero tolerance towards bribery and corruption, regardless of the identity or position of the originator or recipient of the bribe."[6] Even in countries where corruption is common, many companies and business leaders publicly argue for zero tolerance. The CEO of MTN Nigeria, for example, observed: "As we maintain our

[5] See http://www.lockheedmartin.com/us/who-we-are/ethics/1209-hewson.html

[6] See http://www.ing.com/About-us/Compliance/Zero-Tolerance-Bribery-Statement.html

leadership position in Nigerian telecommunications, we are committed to also leading the way in zero tolerance for corrupt practices."[7]

In addition, organizations created to combat corruption argue for zero tolerance. For example, CEOs of members of the World Economic Forum's Partnering Against Corruption Initiative (PACI), launched at Davos in 2004 by business leaders from the construction, engineering, energy, metals and mining industries, pledged to "set the 'tone at the top' through a visible and active leadership commitment to zero tolerance of corruption in all its forms."[8]

Finally, audit firms typically recommend that their clients adopt a zero tolerance tone towards economic crime. PwC recommends that its clients: "Should show 'zero tolerance' towards fraud and set the right tone, by dealing with the fraudster officially and by involving outside authorities."[9]

Despite these public stands on compliance, it is unclear how companies actually implement their policies in punishing employees found to have committed white-collar crimes. The types of punishments that can be imposed vary widely, ranging from internal reprimand without dismissal, dismissal, and legal action (with or without dismissal).

Two models of managerial behavior are used to examine variation in punishments. First, executives charged with deciding on punishments weigh the economic costs and benefits to the organization of possible punishments, including any loss to company reputation and future business should the violation become public, the cost of replacing the

[7] "Clean Business is Good Business. The Business Case against Corruption." A joint Publication by the International Chamber of Commerce, Transparency International, the United Nations Global Compact and the World Economic Forum.
[8] See *http://www.weforum.org/en/initiatives/index.htm*
[9] See PwC (2011).

perpetrators (some of whom may be key contributors), and the benefit of signaling to employees that illicit behavior is not tolerated. Alternatively, punishment decisions are driven by management self-interest, either because top managers have personal relationships with perpetrators and/or fear that they may be blamed for weak oversight.

An Illustrative Case

The case of the largest waste management company in Norway, Norsk Gjenvinning (NG), illustrates how these factors influence punishment decisions. After acquiring NG in 2011 and replacing its CEO, private equity firm Altor discovered extensive cases of earlier crimes, including theft of company assets, illegally dumping hazardous waste, and accounting fraud (Serafeim and Gombos 2015). While many inside the organization knew about these practices, prior to the change in ownership, no one was willing to take action. Economic considerations undoubtedly played a role. Many of the perpetrators had close ties to valuable customers and were viewed as "breadwinners" who would be costly to replace. Also, there was concern that if the crimes became public, the firm could be excluded from public tenders for household waste collection for municipalities for 12 years, destroying a business that represented 35% of total sales. In addition, many of the perpetrators were close colleagues of senior managers, whose reputations were likely to be tarnished should the crimes become public.[10]

The new CEO at NG observed that although many employees did not want to participate in the criminal activities, they saw that they were tolerated prior to the buyout. As a result, motivation and productivity at the firm deteriorated (Serafeim and Gombos

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[10] Findings from a recent study by Groysberg, Lin and Serafeim (2015) show that employees at companies subject to scandal face reputational loss for years after the crimes were publicized. Former executives at their sample of scandal firms received lower compensation than peers years after the scandal, even if they were never implicated.

2015). The investigation of the crimes by the new owners led to the dismissal of more than 50% of line managers and legal action was pursued against some (Serafeim and Gombos 2015). In addition, many other senior managers departed voluntarily. The immediate effects of these actions confirmed the economic costs of dismissing the perpetrators and seeking legal action against the most egregious. Many of the dismissed employees took valuable customers with them and the extensive press coverage damaged the company's reputation, reducing short-term revenues. However, over time, as the employee base changed employee morale, productivity and profitability started increasing while violations of compliance regulations dramatically decreased.

In summary, the severity of punishment for white-collar crime is likely to reflect both economic considerations and managerial self-interest. To further understand these effects for our sample firms, we examine the relation between punishment decisions and a variety of transaction, perpetrator, and company factors for which data is available.

Perpetrator Factors

The seniority of the perpetrator is likely to be relevant to the severity of punishment, although a priori it is unclear whether more senior perpetrators will be punished more or less severely. Given the responsibility of senior executives to lead by example, it may be desirable for senior perpetrators to receive harsher penalties than junior colleagues. By setting an example of high profile perpetrators, the company sends a powerful message to other employees on compliance standards, potentially deterring others from future wrongdoing. Fragale et al. (2009) find, analyzing data from laboratory experiments, observers attribute greater intentionality to the actions of high status perpetrators than the identical actions of low status perpetrators, and as a result they recommend more severe punishment for high status perpetrators.

However, economic considerations can offset deterrence benefits from punishing senior perpetrators of white-collar crime severely. Regulatory review, media coverage and litigation risks are likely to be more intense for crimes perpetrated by senior executives, potentially reducing host firms' reputations with key stakeholders. Executives at companies where a crime has been detected may be concerned about the risk of regulator and the public overreaction should the events become public, particularly for isolated incidents. As a result, they may decide that it would be more harmful for shareholders to pursue legal redress against senior perpetrators given the risks of public disclosure. Further since senior executives are typically more costly to replace than juniors, companies that factor costs of lost productivity and replacement into punishment analyses may be less likely to dismiss high-performing senior perpetrators.

Punishments for senior perpetrators of white-collar crime are also likely to be affected by agency considerations. Personal friendships with senior perpetrators may affect the partiality of executives charged with meting out punishments, leading them to be more lenient on peers than on junior managers. They may also be concerned about being held publicly accountable for failing to provide adequate oversight of close senior perpetrators, leading to increased media scrutiny, damage to their personal reputations and even legal actions by disaffected shareholders. Given these personal risks, it would not be surprising if senior executives avoided legal redress of senior colleagues to protect their own job security and reputations.

Transaction Factors

Crimes of larger economic magnitude are likely to be viewed more seriously and, as a result, perpetrators subjected to harsher penalties. We examine two transaction metrics that are likely to be related to the severity of punishments: the economic magnitude of the crime and whether the criminal acts inflict damage directly on the company.

Prior research on accounting misconduct subject to enforcement by the SEC or DOJ has found that the severity of harm for shareholders is correlated with the probability of dismissal (Karpoff, Lee and Martin 2008). We therefore expect that perpetrators of white-collar crimes that have larger economic consequences will receive more severe penalties. The nature of the crime may also influence the punishment. Crimes that expropriate company resources, such as asset misappropriation, are likely to be perceived especially negatively and punished more severely than crimes that are viewed as benefitting the company at the expense of external parties, or are seen as victimless. For example, corruption is often seen as helping companies to compete and generate sales in countries where laws are unenforced, albeit at the expense of taxpayers or customers. Industrial espionage may also be viewed as undertaken to benefit the company at the expense of competitors. Alternatively, insider trading is often seen as a victimless crime that does not explicitly harm the company. In such cases, the perpetrators may receive lighter punishments than where they directly profited at the company's expense.

Firm Factors

A variety of firm characteristics are expected to influence the severity of punishments for white-collar crimes. Firms that have experienced a higher incidence of white-collar crime may settle for relatively strong punishments of perpetrators to deter future crimes. The severity of the punishment clarifies the company's commitment to compliance, and puts other employees engaged in risky or illegal behavior on notice about the costs of being caught.

Punishments may vary systematically with firm size and listing status. Under the economic model, if large firms face more challenging control problems, they are likely to impose tougher penalties on white-collar perpetrators to deter future wrongdoing. Listed firms are also likely to face higher economic costs from penalizing perpetrators severely, particularly if the penalties increase the risk of public disclosure and accompanying media scrutiny and legal actions by disaffected shareholders. Finally, if agency costs are higher at large listed firms, where ownership and control are separate, executives responsible for punishing white-collar crime may opt for less severe penalties to reduce the risk of personal reputation loss should the crimes become public. Past research has found no relation between firm size and probability of dismissal (Karpoff, Lee and Martin 2008).

In summary, perpetrator punishments are expected to be associated with variables that reflect both economic analysis of costs and benefits of punishments, and management self-interest. Findings of more severe penalties for senior executives and employees at large listed companies are consistent with a cost-benefit analysis where management values sending a strong message to employees that white-collar crime is not tolerated. Findings of less severe penalties for senior executives or employees at large listed firms are consistent with both the cost-benefit and agency models. In particular, severe punishments that risk publicizing the crimes increase potential costs of regulatory and legal actions, and diminished company reputation. Of course, executives could also settle on punishments that reduce the risk of publicizing crimes to protect their own job security and reputations.

3. Sample and Data

Sample Selection and Composition

The sample comprises 3,877 firms responding to a PwC survey of global clients (see PwC, 2011) on their experiences with economic crime. The survey was carried out between June 2011 and November 2011 and requested respondents to provide information about the number of economic crime incidents detected by their firm during the prior year. It then requested more detailed information on the crime that was considered the most serious, including details on the transaction itself, how the event was detected, the seniority of the perpetrator, the punishment meted out, as well as background information on their firm. 52% of the respondents were identified as senior executives of the organization while the remaining held titles such as "Head of Internal Control", "Head of Business Unit", "Manager", or "Senior Vice President/Vice Presidents." PwC designed the survey in such a way that at every point the reader was reminded of the definitions of survey constructs to ensure cross-respondent comparability in answers. Moreover, the survey was administered in local language in each country to ensure that there was no English-speaking bias in responses.

Table 1 reports our sample selection process. From the total number of respondents, 1,303 (34%) reported that they had detected incidences of economic crime within the last twelve months. Of these, 730 respondents (56%) identified the main perpetrator as an employee of the firm. The remaining 573 (44%) are excluded from the final sample because the main perpetrator was an outsider (supplier, customer, government employee, etc.). We also exclude 14 observations with missing data on the seniority of the perpetrator and 49 with missing company data (e.g. industry, country or firm size). The final sample comprises 667 observations.

There are several strengths of the survey and the sample. First, because the respondent was able to answer anonymously, there was little incentive not to report truthfully. Second, restricting the sample to respondents that acknowledged that they had experienced economic crime avoids concerns that the results are affected by including firms that detected but did not acknowledge economic crime, or from firms that experienced economic crime but did not detect it. Including these firms in our analysis would require econometric modeling of any resulting selection biases.

However, the sample is not a random one, limiting the potential generalizability of the results. It comprises clients of a Big 4 audit firm that responded to a survey and that were subject to economic crime that was detected. The results therefore may not be generalizable to clients of smaller audit firms, to responding clients unwilling to report detecting economic crime (even anonymously), or to firms that did not detect crimes. Nonetheless, the sample is broader than those used by earlier studies because it is not limited to firms that were caught in criminal activity or to firms that received publicity or regulatory sanctions.

Tables 2 and 3 show the frequency of respondents across countries and industries respectively. A disproportionate number of firms in the final sample come from emerging market countries with weak institutions to deter economic crime. Firms from countries such as Mexico, Kenya, South Africa, and Brazil have a higher representation in our final sample than in the initial survey sample, consistent with corruption risk rankings provided by organizations such as Transparency International and the World Bank. However, there are almost an equal number of companies coming from developed markets where corruption is much less frequent, such as Spain, the UK, and the US. No single country represents more than 6.3% of the sample.

Dominant industries include financial services, retail services and manufacturing industries. However, there is a wide representation of companies across all industries with no single industry representing more than 16%.

Punishment Variable

Table 4 presents summary statistics on organizational responses to the discovery of economic crime. In 78% of the cases the organization dismisses the perpetrator. In 40% it pursues legal action, primarily civil action, against the perpetrator. The frequency of dismissal is markedly lower than that reported by Karpoff et. al. (2008), suggesting that either companies are more likely to dismiss employees when their crimes become public, or that dismissal rates in the U.S. are higher than those for other countries represented in our sample. A third explanation is that the crimes in our sample are of lower severity compared to the crimes investigated and prosecuted by regulatory authorities by the SEC and that firms' propensity to punish a perpetrator is a function of the severity of the crime. However, as we show below in all our models we fail to find evidence that punishment severity is significantly related to a measure of the direct financial cost from the crime.

Table 4 reports statistics on punishments for crimes reported to regulators and those that are unreported. Seventeen percent of the sample crimes are reported to the regulator. For these crimes, the rate of dismissal is 87%, closer to the 93% reported by Karpoff et. el. (2008), and the rate of legal action is 56%. In contrast, for crimes not reported to regulators, the rate of dismissal is 76%, and the rate of legal action is 37%. Differences in the rates of dismissal and legal action across these samples are statistically reliable.

In addition, we report probabilities of dismissal for countries with low and high corruption ratings to assess how country factors influence punishments, given that previous estimates are derived primarily from the U.S. context. The probability of dismissal in the U.S., 94%, is almost identical to that reported in Karpoff et al. (2008), and materially higher than the 77% dismissal rate in other countries. Surprisingly, for crimes committed in low and high corrupt countries we find no significant difference in the rate of dismissal (77% and 80% respectively), or the probability of legal action (43% versus 38%). One plausible explanation is that the sample respondents from corrupt countries are not random; they have selected a Big 4 auditor despite the accompanying risk of being held to higher control standards.

To conduct our empirical tests, we construct a measure of the severity of the punishment of the perpetrator (*Punishment*). *Punishment* takes the value zero if the organization does nothing, 1 if it dismisses or pursues legal action and 2 if it dismisses and pursues legal action. This is our main dependent variable of interest. In subsequent analysis we separately model dismissal and legal action.

Perpetrator Variables

Table 5 presents summary statistics on perpetrator variables. Eighteen percent of the perpetrators are senior executives of the company, 41 percent are middle managers and 40 percent are junior staff members. To measure the seniority of the perpetrator in our tests, we construct the variable *Seniority* that takes the value one for junior staff, 2 for middle managers, and 3 for senior executives. Mean (median) *Seniority* of perpetrators is 1.78 (2.00).

Transaction Variables

We construct two variables to reflect variation in the transactions in question. Summary data are also reported in Table 5. To control for the severity of a crime, we use survey responses to construct the variable *CMagnitude*, which measures its direct financial impact (i.e. regulatory fines, lawyer costs etc.) on the firm.[11] The variable takes the value of 1 for crimes with a direct financial impact less than $100K, 2 for crimes with impact between $100K and $5 million, 3 for crimes between $5 and $100 million and 4 for crimes with an impact of more than $100 million.[12] Mean (median) C*Magnitude* is 1.56 (1.00), suggesting that the typical direct cost of the crime for the organization ranged from $100,000 to as much as $5 million.

The survey reports information on the nature of all crimes detected by the sample firm during the prior year. In an effort to control for the nature of the sample crime committed, we include indicator variables to capture the incidence of *Accounting Fraud*, *Asset Misappropriation*, *Money Laundering*, *Insider Trading*, *Bribery*, *IP Infringement*, *Tax Fraud*, *Anti-Competitive Behavior*, or *Industrial Espionage* at the sample firms during the past year. However, since these indicator variables reflect the nature of all company crimes detected, and not just the crimes committed by the focal perpetrator, the variable is measured with error.[13] As reported in Table 5, the most frequent type of crime is asset misappropriation (79%), followed by accounting fraud and bribery (both 27%). There is a much lower incidence of the remaining crimes (anti-competitive behavior, money laundering, insider trading, intellectual property infringement, tax fraud, and espionage).

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[11] This variable does not include costs such as decreased employee morale and loss of business.

[12] All subsequent classifications of independent variables are also based on the survey responses, and therefore depend on the classifications used in the survey design.

[13] Measurement error will be zero if there is only one type of crime detected during the prior year. Unfortunately, less than ten percent of the observations are associated with occurrence of a single crime, limiting our ability to conduct a robust analysis of this sample.

Firm Variables

Table 5 also reports descriptive statistics for independent firm-related variables. *NCrimes* measures the frequency of economic crimes detected at the organization during the year prior to completion of the survey. It is constructed to take the value 0 for survey responses that indicate 1 to 10 crime events detected, 1 for 11 to 100, and 2 for more than 100 incidences. The mean (median) value of 0.28 (0.00) indicates that the typical sample firm detected between 1 and 10 incidents of white-collar crime in the year prior to the survey.

Firm Size captures the number of employees at the sample firm. It takes the value 1 for firms with up to 200 employees, 2 for firms between 200 and 1,000 employees, 3 for firms with between 1,000 and 5,000 employees, and 4 for firms with more than 5,000 employees. Median firm size is 2.0, indicating that the median firm employed between 200 and 1,000 employees. Thirteen percent of the sample firms have fewer than 200 employees, while the rest of the firms are almost equally distributed across the remaining three firm size classifications.

We construct an indicator variable (*Listed*) to capture whether a sample firm is publicly listed. Mean *Listed* is 0.41, implying that 41% of the sample firms are listed on public exchanges.

Finally, we use the World Bank corruption index as an indicator of the incidence of white-collar crime in a firm’s home country. Because the PwC survey was conducted in 2011 and examines crimes detected in the prior twelve months, we use the World Bank corruption index for 2010. The variable, *Country Corruption*, ranges from -2.5 to 2.5, with larger values assigned to countries with lower corruption rates. For the sample firms, the average country rating is 0.64.

Table 6 presents a univariate correlation matrix for the dependent and independent variables, and suggests that there are a number of significant correlations. *Punishment* is positively correlated with *Tenure*, *Crime Size*, *NCrimes*, *Firm Size*, *Asset Misappropriation* and *Listed* and has a modest negative correlation with *Seniority*. *Seniority* is strongly positively correlated with *Tenure*, *Crime Size*, *Accounting Fraud*, and *Bribery* and negatively correlated with *Firm Size*.

4. Findings

Given the dependent variable (*Punishment*) is ordinal and the distance between the adjacent categories is unknown, we use Ordered Logit Models to estimate the drivers of firm punishment decisions. To control for industry and geographic region of operation, we include fixed effects for these factors. Because we have limited numbers of observations for various countries, we divide the sample into seven geographic regions (North America, South America, West Europe, Southeast Europe, Africa, Asia, Australia and New Zealand).[14]

Estimates for the various models are reported in table 7. Perpetrators who are more senior face less severe punishment. The *Seniority* estimate of -0.272 in Model 1 is significant at the 5% level. It is unclear, however, whether this effect arises as a result of stiffer penalties for junior staff, or lower penalties for senior executives. To distinguish these effects, we include separate variables for *Senior Executives* and *Middle Managers*.

[14] Including country fixed effects instead decreases our sample but leaves our results unchanged.

The findings (reported in Model 2) show that the seniority effect is primarily driven by lower punishments for the most senior perpetrators. The estimate of -0.602 (odds ratio of 0.548) implies that for senior perpetrators the likelihood of severe punishment decreases by 45%.

The firm-level variables indicate that firms with more employees adopt tougher punishments of white-collar criminals. The estimate of 0.284 implies that for a one unit increase in firm size the probability of punishment increases by 33%. The tougher penalties for larger firms are consistent with larger firms assessing that the economic benefit from sending a strong message to employees about the company's commitment to compliance outweigh any regulatory, legal or reputational costs should news of the crime become public.[15]

Finally, estimates for several of the variables representing the nature of crimes detected by the sample firm during the prior year are significant. The estimate for *Asset Misappropriation* is 0.535, with an odds ratio of 1.707, and implies that the severity of punishment increases by 71% if the firm detects asset misappropriations. The *Insider Trading* estimate is positive and marginally significant (at the 10% level). Follow-up analysis indicates that this is peculiar to the sample U.S. and U.K. firms. Finally, the estimated coefficient on *Espionage* is -0.785 with an odds ratio of 0.456, implying that the likelihood of more severe punishment decreases by 54% for companies that have experienced industrial espionage. None of the other coefficients on types of crimes are significant. These results are broadly consistent with firms enacting tougher punishments for crimes where the perpetrator is stealing directly from the company and less severe

[15] The size effect could also be driven by small firms' reluctance to dismiss key employees. In unreported tests we find that the size effect is not driven exclusively by either small or large firms.

punishments for crimes that can be justified as being for the benefit of the company (e.g. espionage).

The estimated coefficients on *NCrime, Listed Firm, CMagnitude, and Country Corruption* are insignificant.[16] Models 3 and 4 control for whether the regulator has been informed. As noted above in our univariate tests, there is a significantly higher frequency of dismissal and legal action for crimes reported to the regulator. Consistent with these findings, the estimated coefficient on *Regulator Informed* is positive and highly significant. However, including this variable does not change the magnitude of the effect or statistical significance of the other coefficients.

Disentangling the Economic and Agency Models

It is difficult to interpret the finding that senior perpetrators suffer weaker punishments. Senior perpetrators may be treated more leniently because they are perceived to be costlier to replace. Alternatively, their lower punishment could reflect self-interest on the part of executives who mete out punishments, either from concern about any impact that publicizing the crime will have on their own reputations or from bias generated through having a close relationship with the senior perpetrator.

The challenge in interpreting the findings is exacerbated because executives responsible for setting punishments are likely to rationalize their decisions using economic analysis. Even those who consciously factored self-interest into their calculus will frame their decision based on its implications for firm performance. Further, many executives

[16] The region fixed effects could reduce significantly variation in corruption within a region and across countries compared to across regions and countries therefore forcing the coefficient on country corruption towards zero. However, removing the region fixed effects leaves the coefficient on country corruption unchanged.

may not be consciously aware of the impact of self-interest on their decisions given the high overlap between the predictions of the economic and agency models.

To distinguish the economic cost/benefit analysis and managerial self-interest explanations for the seniority findings, we require an instrument that is correlated with managerial self-interest, but uncorrelated with the economic explanation. Prior research suggests one plausible candidate: the gender of senior perpetrators. This research shows that male domination of senior ranks in most business organizations is accompanied by inherent biases favoring other male over women (see Schein 1996; Greenwald and Banaji, 1995; Greenwald, McGhee and Schwatrz, 1998; Berreby, 2005; Turco 2010). For example, Gorman and Kmec (2009), theorize on the conditions leading to why women's upward mobility might decline as they climb organizational hierarchies and find confirming evidence studying corporate law firms. More generally, a long line of research suggests that women executives are often seen as outsiders in informal male social networks (Brass 1985; Blair-Loy 2001). Kanter (1977) was the first to systematically document this phenomenon in the corporate setting. Social categorization processes and ingroup favoritism lead members of dominant groups to prefer and interact more often with fellow dominant group members (Pratto et al. 1994; Tajfel and Turner 2004), increasing the likelihood that subordinate group members, especially those in the numerical minority, will experience social isolation (Kanter 1977). Ibarra (1992; 1995) found that women and people of color tended to build functionally-differentiated networks, developing instrumental ties to members of dominant groups (men and whites, respectively) and friendship ties with members of their own groups. In contrast, dominant groups' networks tended to be homophilous (i.e., men's networks were composed of mostly men; whites networks were composed of mostly whites), and these relationships served instrumental and friendship functions simultaneously. If this network dynamics effect also holds for punishments meted out to perpetrators of white-collar crime, senior male executives who are members of the dominant social network will face lower rates of dismissal and/or legal action than senior female executives. No such bias is expected if punishments are based strictly on economic grounds.[17]

We therefore use an indicator variable (*Female*), that takes the value one if the perpetrator is female and zero otherwise, as an instrument that is interacted with *Seniority*. A significant positive interaction indicates that senior women receive stronger punishments than male peers, consistent with the agency explanation. An insignificant estimate indicates that there is no difference in more lenient punishments of senior men and women, consistent with the economic model. For our sample cases, 21% of the sample perpetrators are women. Not surprisingly, this frequency is lower for senior positions, where women make up only 16% of the population of perpetrators.

To ensure that any gender effects are not driven by differences in tenure between men and women perpetrators, we include the interaction between *Seniority* and tenure at the organization. Tenure might be negatively related to the severity of punishment both because individuals with longer tenure might have developed valuable firm-specific skills that the firm is hesitant to lose and/or strong personal relations with the senior management of the firm. Absence of control for tenure might lead to spurious results if tenure is

[17] Under the economic model, executives charged with punishing perpetrators might rationalize harsher penalties for senior women as reflecting systematic weaker performance for senior women executives than for their male peers. Yet prior research suggests that such perceptions are not borne out in reality, suggesting that this more a rationalization of the agency explanation (Eagly, Karau and Makhijani 1995; Dezso and Ross 2012).

correlated both with gender and seniority. *Tenure* takes the value of 1 if the employee had up to 2 years of service with the organization, 2 for 3 to 5 years of service, 3 for 6 to ten years, and 4 for more than 10 years of service. Mean (median) *Tenure* is 2.54 (2.00), indicating that the typical perpetrator had been employed at the firm for 3-5 years. The correlation between *Tenure* and *Seniority* is 0.303, both economically and statistically reliable.

We also use a second moderating variable, the number of other economic crimes detected at the sample firm, to help distinguish the competing explanations for lower punishments observed for senior perpetrators. Under the economic model, we argue that firms detecting multiple crimes in a given year face greater pressure to push for tough punishments of senior perpetrators than firms with only a single crime. All firms face the risk of one "bad apple" committing a crime. If regulators, customers and the public are expected to overreact to such incidents, particularly those committed by a senior executive, host firm executives are likely to push for more lenient punishments to reduce the risk of the crime becoming public. But the existence of multiple crimes increases pressure for them to send a strong message to other employees that economic crime is not tolerated and to promote tough punishments of senior perpetrators. In contrast, under the agency model, executives concerned about heightened risk of personal reputation and job security risks if multiple crimes are detected in a given year are likely to opt for lenient punishments of senior colleagues given a high frequency of white-collar crime in the organization.

We therefore interact *Seniority* with the frequency of white-collar crime at the firm during the prior year (*NCrimes*). If the estimate on this interaction is positive, senior perpetrators at firms with more economic crime are punished more than peers at firms with only one crime, consistent with the economic model. Alternatively, if the estimate is negative, senior perpetrators at multi-crime firms are punished even less than peers at firms with single crimes.

The results from including the interaction effects with *Seniority* are reported in Table 8. Consistent with results reported in Table 7, punishments are lower for senior executives, and in firms with cases of industrial espionage, and higher in larger firms and for companies where asset misappropriation is detected. However, as reported in Model 5, the significant positive *Female* interaction estimate indicates that senior women receive significantly higher punishments that senior men. Given that interaction terms do not have a straightforward interpretation in nonlinear models, versus linear models, we follow Ai and Norton (2003) and estimate predicted probabilities for different cells and for different levels of the outcome variable. Figure 1a shows the expected probability of no punishment for men versus women at different levels of seniority. Figure 1b shows the expected probability of dismissal and legal action for men versus women at different levels of seniority. The expected probability of no punishment for women decreases monotonically with seniority, whereas exactly the opposite is observed for men. For women the expected probability of no punishment monotonically decreases from 0.104 to 0.073 whereas for men it increases monotonically from 0.071 to 0.175. The expected probability of dismissal and legal action for women increase monotonically with seniority, whereas exactly the opposite is observed for men. For women the expected probability of dismissal and legal action monotonically increases from 0.297 to 0.384 whereas for men it decreases monotonically from 0.389 to 0.188. We also calculate marginal probabilities for each level of the outcome variable and each seniority-gender cell. We find that female senior executives have a 10% lower probability of receiving no punishment compared to male senior executives and a 19.5% higher probability of being dismissed and part of a legal action against them. All the effects documented above are significant at the 1% level. This effect is not explained by differences in the tenure of senior men and women; the estimate for the interaction between *Seniority* and *Tenure* is insignificant. Plots also indicate that the effect of tenure does not differ with seniority.

Model 6 reports estimates including the interaction between *Seniority* and *NCrimes*. The interaction estimate is -0.642, and highly significant. Figure 2a shows a plot of the predicted probabilities for different levels of crime frequency for perpetrators with different level of seniority. It demonstrates that the effect of seniority on punishment is more pronounced for organizations with widespread crime. While the expected probability of punishment is very similar across organizations with different level of crime frequency for junior staff and middle level managers, the results are strikingly different for senior executives. The expected probability of senior executives in organizations with widespread crime not being punished increases sharply. Moreover, junior staff are more likely to be punished if their organization experiences more crime, but this relation is reversed for senior executives. In organizations with a low frequency of economic crime, the predicted probability monotonically decreases modestly from 0.319 for junior staff to 0.262 for senior executives, whereas in organizations with a high frequency, it decreases sharply from 0.595 to 0.078. Again we corroborate these evidence by calculating marginal probabilities. We find that in organizations with high frequency of crime senior executives are 9.3% more likely to receive no punishment compared to other organizations. Similarly, in organizations with high frequency of crime senior executives are 12.4% less likely to be dismissed and be taken against legal action compared to other organizations. These effects are all significant at the 5% level. These findings are consistent with the lower punishments for senior executives at least in part being explained by host firm executives' concerns about their own reputation and job security should the crimes become public.

Finally, Model 7 includes both the *Female/Tenure* and *NCrimes* interaction variables. The findings are very similar to those reported above. Plotting the predicted probabilities leads to very similar inferences.

Additional Analysis

To further investigate the interaction between perpetrator seniority, gender, and the frequency of white-collar crime at sample firms, we re-estimate Model 5 for firms that do not report the crime to regulators. Focusing on this subsample is likely to increase the power of our tests of the economic and self-interest models of punishment for two reasons. First, management is likely to have more discretion over punishments for unreported crimes than when regulators are involved. Second, it excludes firms that pursue a zero tolerance policy for white-collar crime and report all crimes to regulators and consistently punish perpetrators.

The findings, in Table 9, confirm our main results. For crimes that are unreported to regulators, punishments are lighter for senior males and for senior executives at firms with multiple crime cases. In addition, punishments are lighter for perpetrators that do not steal directly from the company, and at smaller firms. In contrast, the findings for crimes reported to regulators show that punishments for senior men and women are comparable, and that independent variables are largely insignificant, suggesting that either managers of these firms have less discretion in punishing crimes, or have a adopted a zero tolerance policy towards white-collar crime.

Finally, we estimate our full model (Model 7) using *Dismissal*, an indicator that takes the value one if a perpetrator is dismissed and zero otherwise, as the dependent variable. *Dismissal* is similar to the variable of interest in Karpoff et al. (2008). The results, shown in Table 9, are very similar to those estimated using *Punishment* as the dependent variable. Plotting predicted odds for women versus men across seniority levels or for incidences of crime across seniority levels reveals very similar results.

Caveats

While the data allow us to study a phenomenon that is otherwise only partially visible to researchers, it nonetheless has its drawbacks. As we have discussed before, the sample is not a random one, limiting the potential generalizability of the results. It comprises clients of a Big 4 audit firm that responded to a survey and that were subject to economic crime that was detected. The results therefore may not be generalizable to clients of smaller audit firms, to responding clients unwilling to report detecting economic crime (even anonymously), or to firms that did not detect crimes.

Aside from generalizability concerns, our results are potentially affected by selection bias. For example, we report that 78% of the firms dismiss the perpetrator. But if companies that downplay economic crime and punish perpetrators less severely are less likely to respond to the survey used for our analysis, this reported dismissal rate is an overestimate of the rate for the population.

Perhaps more importantly, we worry about how selection bias could affect the cross-sectional relations we have documented. For example, we suspect that senior executives who opt for light punishments for senior perpetrators are less likely to respond to the survey used in our study. If such is the case, the underlying negative relation between seniority and punishment will be even stronger than that reported. Of course, the reverse would be true if such cases are more likely to be reported.

Selection bias could also potentially affect the interaction effects we document. Such would be the case if companies choosing light punishments for senior female perpetrators are less likely to respond to the survey, whereas companies punishing senior male perpetrators lightly are more likely to respond. Similarly, the interaction between seniority and crime frequency could arise if companies with a high frequency of crimes that punish senior perpetrators lightly have a high response rate to the survey whereas companies with few crimes that punish senior perpetrators severely have a low response rate. A priori, we see no good reason to expect that either of these selection effects is the case.

Finally, we recognize that there are measurement errors in some of our independent variables that could affect our reported estimates. This is particularly likely for variables representing crimes committed, since our data on these variables covers the frequency of crimes at the firm level, and not for the focal crime studied. In addition, the financial magnitude of the crime is measured crudely and could give rise to measurement error. If these measurement errors are correlated with other included variables, then our estimates are biased. However, we have no way to assess any such bias, or even its direction.

5. Conclusion

We document that there is considerable variation in punishments meted out to perpetrators of white-collar crime. This variation is consistent with executives determining appropriate punishments by an economic analysis of costs and benefits. For example, punishments are lighter for perpetrators of crimes that do not directly steal from the company, and at larger companies where it is more likely to be important to send a strong message that crime does not pay. In addition, some companies appear to report crimes to regulators and make decisions on punishments that are uncorrelated with factors reflecting economic costs and benefits, consistent with following a zero tolerance policy for white-collar crime.

But the findings suggest that executives who mete out punishments are also influenced by self-interest. They issue lighter punishments to senior executives, particularly senior males who are likely to belong to the dominant social network, and for senior executives of companies where multiple crimes have been detected during the past year, when it is more difficult to argue that the problem is "one bad apple" and not a more systemic problem that affects the reputation and job security of senior managers.

The findings also suggest that punishment decisions do not differ materially for companies located in countries where corruption is common and those operating in low corruption regimes. This is surprising; one might have anticipated that crimes in corrupt countries are more likely to be overlooked. Our findings, however, suggest that companies take economic crime equally seriously in these countries. Of course, given prior evidence that corrupt countries have weak legal institutions and enforcement, legal punishments for perpetrators of white-collar crime may be lighter than for peers in low corruption countries. A plausible alternative explanation is that the survey respondents from more corrupt countries are not a random sample. These firms chose a well-known Big Four audit firm, which probably increases the risk of detection of economic crime and the likelihood that crimes that are detected cannot be covered up. Such firms may respond very differently to detection of economic crimes than a random sample of firms from the same countries.

Our tests rely on survey data of the clients of a large audit firm. This database has several advantages. First, because the respondent was able to answer anonymously, there was little incentive not to report truthfully. Second, restricting the sample to respondents that acknowledged that they had experienced economic crime avoids concerns that the results are affected by including firms that detected but did not acknowledge economic crime, or from firms that experienced economic crime but did not detect it. However, as noted above, the sample is a not random one. It is therefore unclear whether the findings are generalizable to clients of smaller audit firms, to responding clients unwilling to report detecting economic crime (even anonymously), or to firms that did not detect crimes. Further, because the survey protects the identity of the companies in the sample, we are unable to carry out additional tests of interest using company data not covered in the survey questions.

Our findings raise numerous questions for future research. How representative are the findings reported in this study? What are the consequences for firms that punish white-collar crimes more aggressively? Are their actions effective in deterring would-be perpetrators? What are the consequences of reducing punishments for senior male executives? Do such decisions affect employee morale and corporate culture? Finally, what role do corporate boards play in overseeing punishment decisions, particularly for senior perpetrators?

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Appendix

Variable	Definition
Punishment	Punishment takes the value zero if the organization does nothing, 1 if it dismisses or pursues legal action and 2 if it dismisses and pursues legal action.
Dismiss perpetrator	Dismiss perpetrator takes the value of one if the perpetrator is fired or otherwise it is zero
Legal action	Legal action takes the value of one if the firm takes legal action against the perpetrator or otherwise it is zero
Seniority	Seniority takes the value one for junior staff, 2 for middle managers, and 3 for senior executives.
Senior executives	One if the perpetrator is a senior executive or zero otherwise
Middle managers	One if the perpetrator is a middle manager or zero otherwise
Junior staff	One if the perpetrator is a junior staff or zero otherwise
Female	Female takes the value of one if the perpetrator is female and zero otherwise.
Tenure	Tenure takes the value of 1 if the employee had up to 2 years of service with the organization, 2 for 3 to 5 years of service, 3 for 6 to ten years, and 4 for more than 10 years of service.
CMagnitude	CMagnitude takes the value of 1 for crimes with a direct financial impact less than $100K, 2 for crimes with impact between $100K and $5 million, 3 for crimes between $5 and $100 million and 4 for crimes with an impact of more than $100 million.
NCrimes	NCrimes takes the value of 0 for survey responses that indicate 1 to 10 crime events detected, 1 for 11 to 100, and 2 for more than 100 incidences.
Firm Size	Firm Size takes the value of 1 for firms with up to 200 employees, 2 for firms between 200 and 1,000 employees, 3 for firms with between 1,000 and 5,000 employees, and 4 for firms with more than 5,000 employees.
Listed	Takes the value of one if the firm is listed on a stock exchange
Country Corruption	A measure of the absence of corruption in a country from the World Bank
White-collar Crimes	
Accounting Fraud	Accounting Fraud takes the value of 1 for an instance of accounting fraud and zero otherwise.
Asset Misappropriation	Asset Misappropriation takes the value of 1 for an instance of asset misappropriation and zero otherwise.
Money Laundering	Money Laundering takes the value of 1 for an instance of money laundering and zero otherwise.
Insider Trading	Insider Trading takes the value of 1 for an instance of insider trading and zero otherwise.
Bribery	Bribery takes the value of 1 for an instance of bribery and zero otherwise.
IP Infringement	IP Infringement takes the value of 1 for an instance of IP infringement and zero otherwise.
Tax Fraud	Tax Fraud takes the value of 1 for an instance of tax fraud and zero otherwise.
Anti-competitive Behavior	Anti-competitive Behavior takes the value of 1 for an instance of anti-competitive behavior and zero otherwise.
Industrial Espionage	Industrial Espionage takes the value of 1 for an instance of industrial espionage and zero otherwise.
Regulator Informed	One if the firm informed the regulators about the crime or else zero

Figure 1a

Expected probabilities of no punishment for men and women perpetrators at various levels of seniority

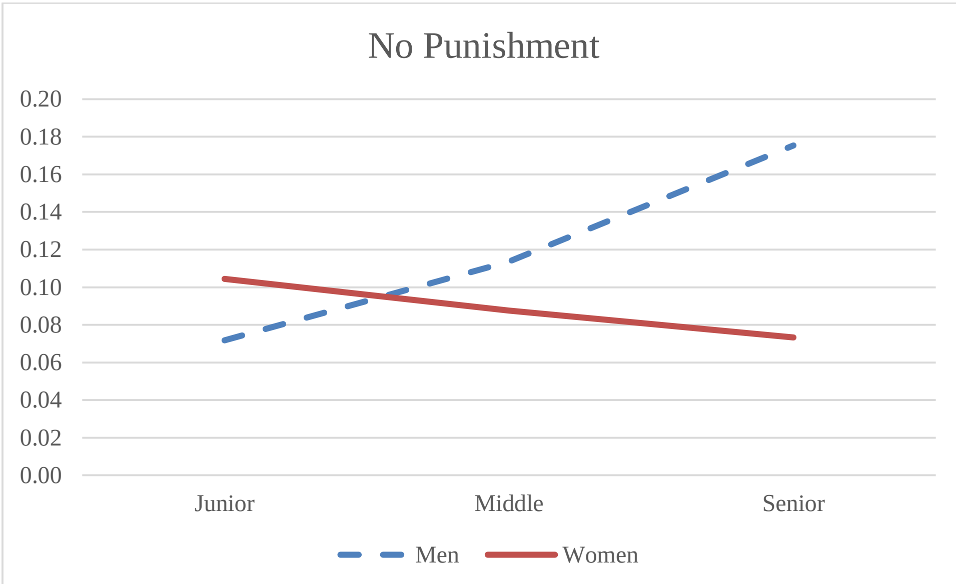

Figure 1b

Expected probabilities of dismissal and legal action for men and women perpetrators at various levels of seniority

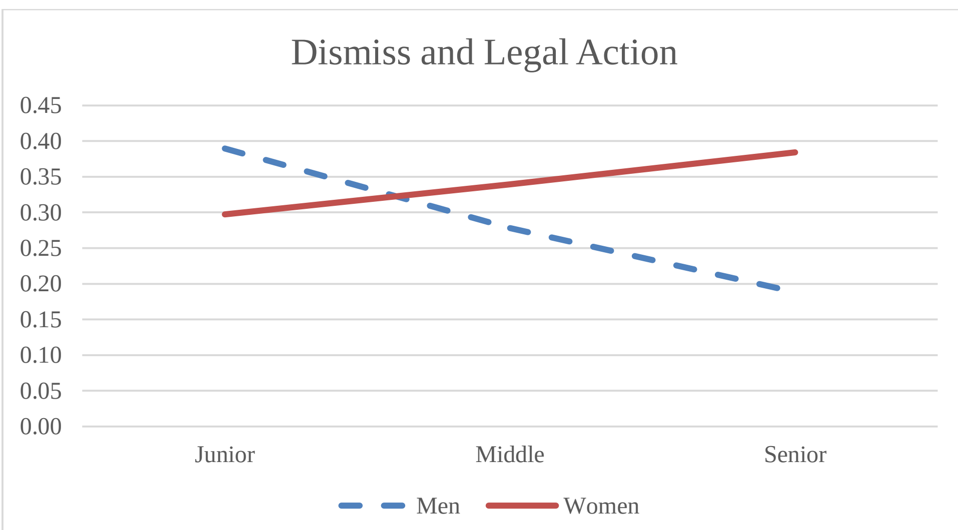

Figure 2a

Expected probabilities of no punishment for perpetrators at organizations with different frequency of incidents of white-collar crime (low, medium or high) at various levels of seniority

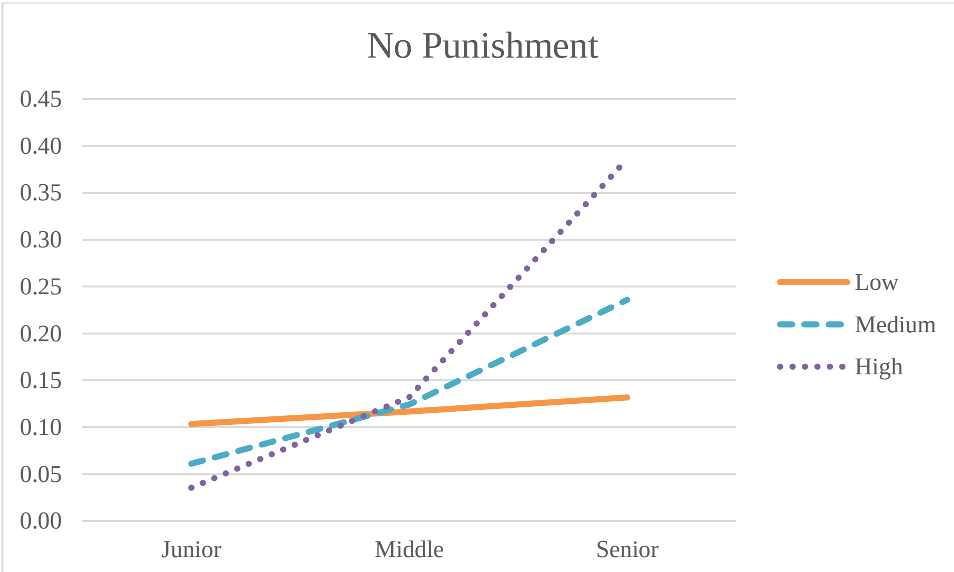

Figure 2b

Expected probabilities of dismissal and legal action for perpetrators at organizations with different frequency of incidents of white-collar crime (low, medium or high) at various levels of seniority

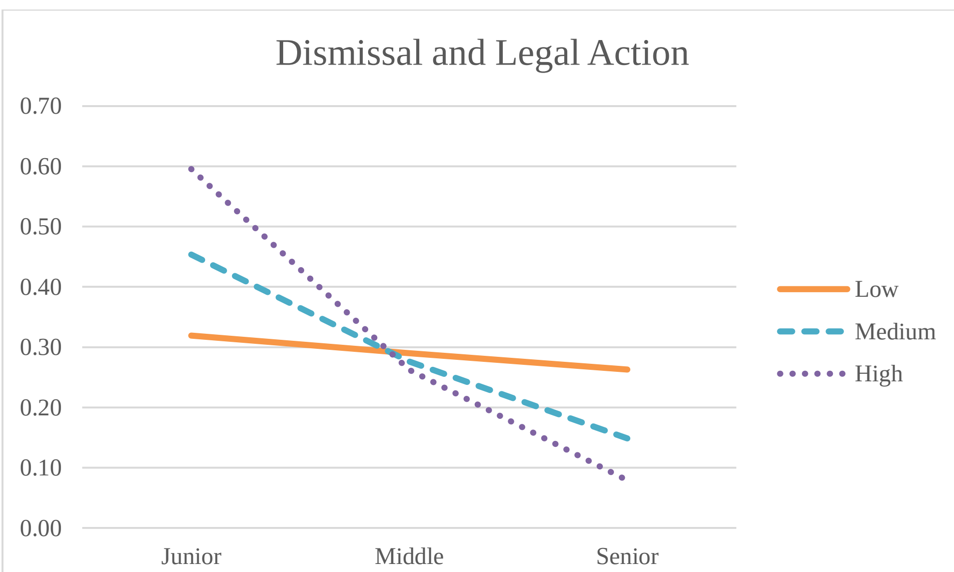

Table 1
Sample selection

All survey respondents	3,877
Minus: no reported economic crime	2,574
Economic crime sample	1,303
Minus: economic crime by non-employees of the firm	573
Economic crime from firm employees	730
Minus: Missing seniority data	14
Minus: Missing other company data	49
Final Sample	**667**

Table 2
Frequency of sample white-collar crime companies by country

Country	Number of Firms	%	Country	Number of Firms	%
Argentina	21	3.1	Middle East	22	3.3
Australia	19	2.8	Namibia	1	0.1
Belgium	13	1.9	Netherlands	3	0.4
Brazil	27	4.0	New Zealand	24	3.6
Bulgaria	7	1.0	Nigeria	1	0.1
Canada	8	1.2	Norway	3	0.4
Cyprus	2	0.3	Papua New Guinea	1	0.1
Czech Republic	14	2.1	Peru	6	0.9
Denmark	24	3.6	Poland	12	1.8
Ecuador	3	0.4	Romania	11	1.6
Finland	11	1.6	Russia	25	3.7
France	25	3.7	Singapore	1	0.1
Germany	2	0.3	Slovakia	10	1.5
Ghana	6	0.9	South Africa	33	4.9
Greece	10	1.5	Spain	32	4.8
Hong Kong	2	0.3	Sweden	8	1.2
Hungary	8	1.2	Switzerland	9	1.3
India	13	1.9	Thailand	20	3.0
Indonesia	7	1.0	Turkey	6	0.9
Ireland	7	1.0	UK	28	4.2
Italy	10	1.5	USA	35	5.2
Kenya	41	6.1	Ukraine	14	2.1
Lithuania	3	0.4	Venezuela	11	1.6
Malaysia	23	3.4	Vietnam	3	0.4
Mexico	42	6.3	Total	667	100.0

Table 3
Frequency of sample white-collar crime companies by industry

Industry	Number of Firms	%
Aerospace and defense	3	0.4
Automotive	23	3.4
Chemicals	11	1.6
Communication	25	3.7
Education	6	0.9
Energy, utilities and mining	49	7.3
Engineering and construction	42	6.3
Entertainment and media	21	3.1
Financial services	107	16.0
Food related	9	1.3
Government/state-owned enterprises	51	7.6
Health and care	12	1.8
Hospitality and leisure	19	2.8
Insurance	33	4.9
Manufacturing	70	10.5
Pharmaceuticals and life sciences	30	4.5
Professional services	29	4.3
Property	3	0.4
Retail and consumer	76	11.4
Technology	13	1.9
Transportation and logistics	35	5.2
Total	667	100.0

Table 4
Probability of various punishments for sample of white-collar crimes

	Nature of punishment	
	Dismissal	Legal action
Full sample (N=667)	78%	40%
Reporting crime to regulator:		
Report (N=111)	87%	56%
Do not report (N=556)	76%***	37%***
U.S. firm:		
Yes (N=35)	94%	34%
No (N=632)	77%***	41%
Firms from:		
Low corruption countries (N=363)	77%	43%
High corruption countries (N=304)	80%	38%

*** notes statistically significant differences based on a Likelihood Ratio Chi-Square test at the 1% level.

Table 5
Summary statistics on variables for white-collar crime sample

Variable	N	Median	Mean	Std	Minimum	Maximum
Punishment	667	2.00	1.19	0.65	0.00	2.00
Dismiss perpetrator	667	1.00	0.78	0.41	0.00	1.00
Legal action	667	0.00	0.40	0.49	0.00	1.00
Seniority	667	2.00	1.78	0.73	1.00	3.00
Senior executives	667	0.00	0.18	0.39	0.00	1.00
Middle managers	667	0.00	0.41	0.49	0.00	1.00
Junior staff	667	0.00	0.40	0.49	0.00	1.00
Female	608	0.00	0.21	0.41	0.00	1.00
Tenure	608	2.00	2.54	1.01	1.00	4.00
CMagnitude	667	1.00	1.56	0.65	1.00	4.00
NCrimes	667	0.00	0.28	0.54	0.00	2.00
Firm Size	667	2.00	2.70	1.02	1.00	4.00
Listed	667	0.00	0.41	0.49	0.00	1.00
Country Corruption	667	0.47	0.64	1.11	-1.08	2.39
White-collar Crimes						
Accounting Fraud	667	0.00	0.27	0.44	0.00	1.00
Asset Misappropriation	667	1.00	0.79	0.40	0.00	1.00
Money Laundering	667	0.00	0.05	0.22	0.00	1.00
Insider Trading	667	0.00	0.05	0.22	0.00	1.00
Bribery	667	0.00	0.27	0.45	0.00	1.00
IP Infringement	667	0.00	0.04	0.21	0.00	1.00
Tax Fraud	667	0.00	0.04	0.20	0.00	1.00
Anti-competitive Behavior	667	0.00	0.08	0.28	0.00	1.00
Industrial Espionage	667	0.00	0.01	0.12	0.00	1.00
Regulator Informed	667	0.00	0.17	0.37	0.00	1.00

Table 6
Correlation matrix for white-collar crime sample

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Punishment	1.00																	
2	Seniority	-0.06	1.00																
3	Female	0.01	-0.17	1.00															
4	Tenure	0.08	0.30	-0.04	1.00														
5	NCrimes	0.11	-0.01	0.02	-0.03	1.00													
6	Firm Size	0.16	-0.11	0.07	0.16	0.31	1.00												
7	Listed	0.09	-0.03	-0.02	0.01	0.10	0.27	1.00											
8	CMagnitude	0.10	0.33	-0.06	0.19	0.36	0.24	0.14	1.00										
9	Country Corruption	0.01	0.01	0.13	0.06	0.02	0.12	0.02	0.03	1.00									
10	Accounting Fraud	0.00	0.28	0.00	0.14	0.11	-0.02	-0.04	0.18	0.02	1.00								
11	Asset Misappropriation	0.11	-0.08	-0.01	0.03	0.11	0.17	0.07	0.03	0.06	-0.17	1.00							
12	Money Laundering	0.06	0.05	0.00	0.04	0.18	0.05	0.07	0.15	-0.04	0.01	-0.03	1.00						
13	Insider Trading	0.07	0.11	0.03	0.02	0.06	-0.05	0.04	0.12	-0.05	0.04	-0.08	0.07	1.00					
14	Bribery	0.02	0.23	-0.11	0.07	0.23	0.09	0.11	0.27	-0.13	0.10	-0.09	0.06	0.04	1.00				
15	IP Infringement	-0.01	0.07	0.03	-0.01	0.14	0.06	-0.05	0.14	0.04	0.06	0.00	0.11	0.08	0.08	1.00			
16	Tax Fraud	-0.03	0.19	-0.02	0.07	0.06	-0.09	-0.05	0.16	0.01	0.19	-0.06	0.05	0.05	0.12	0.03	1.00		
17	Anti-competitive Behavior	-0.02	0.15	-0.03	0.03	0.04	0.00	0.03	0.09	-0.10	0.01	-0.06	-0.05	0.00	0.15	0.09	0.02	1.00	
18	Industrial Espionage	-0.04	0.00	0.09	-0.02	0.03	-0.05	0.00	0.05	0.05	-0.02	0.00	0.03	0.08	-0.02	0.09	0.04	0.05	1.00
19	Regulator Informed	0.17	0.07	0.05	0.05	0.09	0.05	0.03	0.15	0.11	0.11	0.00	0.10	0.02	0.12	0.08	0.13	-0.02	0.04

Table 7
Ordered logit models of the relation between punishments for perpetrators of white-collar crime and perpetrator, transaction and company variables.

	Model 1		Model 2		Model 3		Model 4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Seniority	**-0.272**	**0.036**			**-0.283**	**0.029**		
Senior Executive			**-0.602**	**0.026**			**-0.633**	**0.019**
Middle Manager			-0.141	0.458			-0.130	0.499
NCrimes	0.113	0.520	0.109	0.534	0.116	0.512	0.111	0.527
Firm Size	**0.284**	**0.003**	**0.277**	**0.005**	**0.278**	**0.004**	**0.270**	**0.006**
Listed	0.029	0.869	0.021	0.904	0.020	0.909	0.012	0.946
CMagnitude	0.200	0.179	0.201	0.177	0.164	0.268	0.164	0.269
Country Corruption	-0.135	0.257	-0.129	0.283	-0.174	0.152	-0.166	0.171
Accounting Fraud	-0.059	0.770	-0.057	0.778	-0.087	0.671	-0.084	0.682
Asset Misappropriation	**0.535**	**0.011**	**0.549**	**0.009**	**0.558**	**0.008**	**0.574**	**0.007**
Money Laundering	0.135	0.753	0.153	0.722	0.156	0.708	0.177	0.671
Insider Trading	0.636	0.091	0.653	0.083	0.642	0.090	0.660	0.080
Bribery	0.159	0.413	0.149	0.445	0.056	0.780	0.044	0.828
IP Infringement	-0.223	0.588	-0.219	0.595	-0.319	0.442	-0.315	0.451
Tax Fraud	-0.122	0.774	-0.081	0.848	-0.256	0.558	-0.207	0.635
Anti-competitive Behavior	0.021	0.941	0.004	0.990	0.065	0.812	0.046	0.868
Industrial Espionage	-0.785	0.075	-0.760	0.080	**-0.920**	**0.027**	**-0.891**	**0.029**
Regulator Informed					**0.953**	**<.0001**	**0.962**	**<.0001**
Industry effects	Yes		Yes		Yes		Yes	
Geography effects	Yes		Yes		Yes		Yes	
Pseudo R-squared	10.8%		10.9%		13.2%		13.4%	
N	667		667		667		667	

Table 8
Ordered logit models of the relation between punishments for perpetrators of white-collar crime and perpetrator, transaction and company variables, including interactive effects with perpetrator seniority.

	Model 5		Model 6		Model 7	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value
Seniority	-0.815	0.012	-0.137	0.315	-0.692	0.034
Seniority*Female	**0.700**	**0.029**			**0.738**	**0.022**
Seniority*Tenure	0.122	0.287			0.123	0.280
Seniority*NCrimes			**-0.642**	**0.006**	**-0.684**	**0.004**
Female	**-1.110**	**0.048**			**-1.150**	**0.043**
Tenure	-0.077	0.739			-0.060	0.796
NCrimes	0.017	0.927	**1.214**	**0.007**	**1.195**	**0.010**
Firm Size	**0.285**	**0.006**	**0.296**	**0.002**	**0.293**	**0.005**
Listed	0.060	0.749	0.067	0.706	0.100	0.597
CMagnitude	0.198	0.215	0.226	0.130	0.239	0.134
Country Corruption	-0.095	0.460	-0.135	0.262	-0.096	0.459
Accounting Fraud	-0.049	0.819	-0.002	0.992	0.011	0.961
Asset Misappropriation	**0.675**	**0.003**	**0.555**	**0.009**	**0.694**	**0.003**
Money Laundering	-0.001	0.999	0.321	0.470	0.174	0.705
Insider Trading	**0.633**	**0.113**	**0.723**	**0.056**	**0.718**	**0.074**
Bribery	0.231	0.260	0.150	0.440	0.230	0.262
IP Infringement	-0.393	0.369	-0.044	0.912	-0.173	0.690
Tax Fraud	-0.183	0.666	-0.110	0.799	-0.179	0.679
Anti-competitive Behavior	0.069	0.828	0.074	0.792	0.123	0.694
Industrial Espionage	**-0.895**	**0.042**	**-0.797**	**0.105**	**-0.900**	**0.060**
Industry effects	Yes		Yes		Yes	
Geography effects	Yes		Yes		Yes	
Pseudo R-squared	14.0%		11.9%		15.2%	
N	608		667		608	

Table 9
Ordered logit models of the relation between punishments for perpetrators of white-collar crime and perpetrator, transaction and company variables, including interactive effects with perpetrator seniority. Estimates are reported separately for crimes reported/not reported to the regulator, and using dismissal as a measure of punishment.

Sample	Regulator Informed= No		Regulator Informed= Yes		All Firms	
Dependent Variable	Punishment				Dismissal	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value
Seniority	-0.808	0.029	-1.533	0.266	-0.742	0.070
Seniority*Female	**0.965**	**0.021**	-1.484	0.240	**0.704**	**0.077**
Seniority*Tenure	0.154	0.239	0.489	0.327	0.121	0.405
Seniority*NCrimes	**-0.607**	**0.025**	0.048	0.964	**-0.731**	**0.037**
Female	-1.510	0.028	2.589	0.331	-1.055	0.147
Tenure	-0.123	0.638	-0.614	0.591	-0.242	0.442
NCrimes	1.145	0.032	-0.762	0.638	1.732	0.018
Firm Size	**0.224**	**0.049**	**1.170**	**0.018**	**0.300**	**0.037**
Listed	0.236	0.270	-0.003	0.998	0.098	0.715
CMagnitude	0.129	0.500	0.750	0.208	-0.299	0.167
Country Absence of Corruption	-0.118	0.408	-0.099	0.907	-0.039	0.822
Accounting Fraud	0.001	0.996	-0.550	0.594	0.041	0.888
Asset Misappropriation	**0.675**	**0.010**	0.815	0.396	**0.538**	**0.064**
Money Laundering	**-0.415**	**0.443**	**3.175**	**0.035**	-0.228	0.675
Insider Trading	**0.782**	**0.081**	0.091	0.960	**1.155**	**0.080**
Bribery	0.161	0.493	0.972	0.374	0.500	0.092
IP Infringement	-0.166	0.753	-1.290	0.374	-0.104	0.848
Tax Fraud	-0.440	0.444	-1.643	0.317	**-1.015**	**0.044**
Anti-competitive Behavior	-0.186	0.572	2.248	0.273	0.683	0.164
Industrial Espionage	**-1.195**	**0.035**	-2.315	0.375	-0.663	0.380
Industry effects	Yes		Yes		Yes	
Geography effects	Yes		Yes		Yes	
Pseudo R-squared	16.5%		41.9%		12.9%	
N	504		104		608	