CHARACTERISTICS OF FIRM MISCONDUCT AND EFFECTS ON CAPITAL MARKET REACTIONS

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Abstract

This article replicates earlier literature on capital market reactions to firm misconduct with rarely used Continental European data, after the financial crisis, and combines characteristics that previous literature has analyzed separately. We hand-collect press articles on 96 illegal misconducts of German firms between 2010 and 2019 and use the content of those articles to determine the misconduct type, misconduct characteristics, and information characteristics. Short-term cumulative abnormal returns (CARs) proxy for market reactions. We hypothesize and find negative market reactions that are stronger when the misconduct harms connected (vs. third) parties and when it primarily benefits the firm (vs. the offending individual). For information characteristics, we only find support for the prediction that markets react more negatively to confirmed misconduct (vs. suspicions). Some results are sensitive to including both misconduct and information characteristics or excluding financial statement fraud. Earlier research rarely tests for such sensitivity. Our research shows that market reactions to illegal misconduct are robust overall, but robust common determinants of effect strength are difficult to establish. These insights are of relevance for researchers when using capital market reactions to study misconduct implications and when referencing earlier research in this area.

Keywords: Corporate Crime, Corporate Governance, Event Study, Fraud Characteristics, Misconduct, Occupational Crime

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1. INTRODUCTION

We study capital market reactions to different types of criminal firm misconduct and what characteristics affect the reactions' magnitude. Negative effects of illegal corporate or occupational behaviour have attracted long-time and ongoing research interest (Amiram et al., 2018) and are of high practical relevance. Surveys from KPMG (2018) and PricewaterhouseCoopers (PwC, 2018) estimate that up to half of German firms were subject to criminal misconduct within two years. In many cases, markets will punish the offending firm (declining stock prices) or individual (layoffs) (Karpoff et al., 2008a, 2008b), potentially deterring misconduct (Friedrich & Quick, 2019). They might be a more meaningful element of corporate crime prevention than regulatory punishment or (corporate) criminal law, which is heavily debated in Germany (Bundesministerium der Justiz [BMJ], 2020).

Most existing research on market reactions to firm misconduct uses Anglo-Saxon data and focuses on single characteristics of misconduct (see subection 2.2). Changes in economic circumstances could reduce the generalizability of research using data from before or during the financial crisis (Armour et al., 2017; Kirat & Rezaee, 2019). Therefore, we ask the following research question:

RQ1: Are previous research findings on capital market reactions to firm misconduct sensitive to sample choices (Continental Europe, economic cycle) and to controlling for several misconduct characteristics simultaneously?

We hand-collected press reports on firm misconduct and identified 96 cases of listed German firms between 2010 and 2019. Also, we manually coded the types and characteristics of misconduct from these reports. Using stock return data and a market model to calculate short-term cumulative abnormal returns (CARs), we significantly negative reactions for our overall sample (mean CAR from one day before and after the event date = -3.20%), even when excluding financial statement fraud (-1.94%). Analysis of variance (ANOVA) results indicate that CARs significantly differ among misconduct types (see Table 1 for an overview of types). *Post hoc* analyses suggest that univariate differences exist only between financial statement fraud and any other misconduct category. Misconduct types remain an important driver of CARs even when we control for misconduct characteristics, information characteristics, and firm characteristics, use robust regression, or exclude financial statement fraud. We find consistently more negative market reactions for money laundering and tax evasion compared to competition fraud (our baseline).

For misconduct characteristics, we find some evidence that reactions are significantly less negative when the misconduct is an occupational crime (i.e., perpetrators act primarily in their personal interest) versus corporate crime (i.e., perpetrators act primarily in the firm's interest) and when it harms third parties (e.g., the general public vs. connected parties (contract partners)). For information characteristics, we find robust evidence that reactions are less negative when there is a suspicion (versus a confirmation). We found no significant effect of information quality (see Appendix for a definition) and self-disclosure (versus third-party disclosure). The effect of suspicion only partially holds in robust regression or when excluding the financial statement fraud cases. The effects of occupational crime are robust. Finally, the effects of harming third versus connected parties become more robust when excluding fraud observations. This indicates that including extreme observations in cross-sectional analyses may potentially mask the effect of other event characteristics.

Our research contributes to accounting and finance research concerned with the negative effects of firm misconduct on share prices. Our replication with data from a capital market setting that has fundamental differences compared to earlier-studied settings is relevant as it responds to calls for more replications (Salterio, 2014; Radhakrishnan, 2021). In addition, we use several empirical designs to illustrate the sensitivity of cross-sectional results, reconciling some of the results dispersed across multiple earlier studies. Our findings indicate that the explanatory power of some cross-sectional characteristics is sensitive to including other characteristics from the literature, supporting the relevance of merging different empirical approaches. Finally, our replication specifically accounts for the influential nature of rare and extreme financial statement fraud. Revisiting accounting research with influential observations contributes to understanding the robustness of earlier findings (Leone et al., 2019).

Our replication could also be relevant to practitioners who are concerned with misconduct control mechanisms. They could focus control and corporate governance activities more on the misconduct types and misconduct and information characteristics which show the most robust effects on capital market reactions. Our results could also help misconduct firms to re-evaluate their communication or image restoration strategies when facing a corresponding crisis. They need to understand which misconduct characteristics are most critical, which then determines the focus of communication and mitigation (Chakravarthy et al., 2014).

Finally, our study is relevant to the regulatory debate. Regulators could complement market punishments at the firm level by focusing on punishment at the individual level. Both elements eventually contribute to preventing fraud (Farber, 2005; Ugrin & Odom, 2010; Campa, 2018). Moreover, future discussions on corporate criminal law could consider the existing interplay of reputational and regulatory consequences. Capital markets already punish misconduct, but regulatory consequences may be more salient to decision-makers (Friedrich & Quick, 2019).

The remainder of the paper is structured as follows. In Section 2, we identify the characteristics of misconduct and information of interest, review the prior literature, and then derive our hypothesis. Subsequently, we describe our data collection and research design in Section 3. Section 4 summarizes and Section 5 discusses our results. Finally, in Section 6, we conclude.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Misconduct and information characteristics

There is no single definition for *criminal firm misconduct*, and what is considered criminal varies between jurisdictions and historically (Schell-Busey et al., 2016; Morales et al., 2014). However, to study events of firm misconduct, it is necessary to distinguish different types of it, and many researchers have proposed different types. Others focus on a description of misconduct characteristics instead of a classification of misconduct (see Table 2). We follow both approaches and include types of criminal misconduct as well as misconduct characteristics in our analysis.

The German Federal Criminal Police Office (*Bundeskriminalamt, BKA*) defines economic crime as "committing a trust-violating crime as part of an actual or feigned for-profit business which abuses the course of business life and causes large-scale threats or damages to the wealth of a large number of persons or the general public" (BKA, 2018, p. 2).

The first part of this definition emphasizes that the offender acts in a professional role. The offender has also been the focus of early definitions of economic crime (Sutherland, 1949). Hence, the first misconduct characteristic we analyse is *offender type*. While there is no one consensus differentiation of offender types (Friedrichs, 2002), we chose the popular dichotomous distinction into corporate and occupational crime — offender acts at least partially in the interest of the firm versus exclusively serving the interests of the offending individual (Agnew et al., 2009). The second part of the above definition focuses on the *victim type*, our second misconduct characteristic. We follow the literature and distinguish victims into connected and third parties (parties with a direct, e.g., contractual, relationship versus those without a direct relationship, e.g., the general public). Misconduct characteristics are summarized in Panel A of Table 1.

Table 1. Misconduct and information characteristics

<table>
<tr><th colspan="2">Characteristic</th><th>Forms</th></tr>
<tr><td colspan="3">Panel A: Misconduct characteristics</td></tr>
<tr><td colspan="2">Offender type</td><td>Corporate vs. Occupational crime</td></tr>
<tr><td colspan="2">Victim type</td><td>Connected vs. Third party</td></tr>
<tr><td colspan="3">Panel B: Information characteristics</td></tr>
<tr><td colspan="2">Information quality</td><td>High vs. Low</td></tr>
<tr><td colspan="2">Type of allegation</td><td>Suspicion vs. Confirmation</td></tr>
<tr><td colspan="2">Type of revelation</td><td>Self- vs. External disclosure</td></tr>
<tr><td colspan="3">Panel C: Types of firm misconduct</td></tr>
<tr><td>Category used in the present study[a]</td><td>Category used in Ewelt-Knauer et al. (2015)</td><td>Definition</td></tr>
<tr><td>Deception</td><td>Not included</td><td>Misrepresenting facts and damaging another person’s property to unlawfully gain a financial advantage, e.g., the falsification of product information</td></tr>
<tr><td>Financial statement fraud</td><td>Accounting fraud</td><td>Intentional misstatement (including omission) of amounts or disclosures in financial statements to deceive financial statement users</td></tr>
<tr><td>Capital markets fraud/violations</td><td>Insider trading
(less comprehensive)</td><td>Illegally distorting capital market conditions, e.g., abusing insider information or revealing wrong information</td></tr>
<tr><td>Competition fraud</td><td>Cartel agreements</td><td>Illegally distorting real market conditions on goods markets, e.g., through cartel agreements or the abuse of monopolistic conditions</td></tr>
<tr><td>Money laundering</td><td>Not included</td><td>Processing of criminal proceeds to disguise their illegal origin</td></tr>
<tr><td>Corruption</td><td>Corruption</td><td>Misusing a professional function and causing disadvantages for others in order to gain advantages for oneself or a third party, e.g., by receiving bribery payments</td></tr>
<tr><td>Tax evasion</td><td>Not included</td><td>Obtaining tax advantages through incorrect or inaccurate statements about tax-relevant facts</td></tr>
</table>

Note: [a] For all analyses, we group events with more than one category of misconduct happening concurrently in a group labelled ‘Several’, and group two events that could not be allocated to any of the misconduct types in a group labelled ‘Other’.

Next to misconduct characteristics, we consider systematic variation in the information about the misconduct and summarize related types in Panel B of Table 1. Our focus on misconduct revealed by the press motivates this choice. Moreover, stock price reactions require information that is new to the market and changes expectations about future risks or profitability of the offender (Dee et al., 2011; Murphy et al., 2009). Information is more likely to change market expectations when it is conveyed to a large audience by a credible source and when its content is precise enough to be considered novel and relevant by the audience (Epstein & Schneider, 2008; Dyck & Zingales, 2003). Therefore, we develop a dichotomous score that captures these information quality characteristics. Theory (discussion follows in subsection 2.3) predicts that the effects of information quality work through the precision and accessibility of information. Therefore, we analyze whether at least five newspaper articles are available and whether they report at least two of three pieces of information that increase the precision of the event description (monetary consequences, suspect/offenders, detailed misconduct description). As we consider allegations of misconduct, our second information characteristic is *allegation type*, distinguishing suspected from confirmed misconduct. Finally, *disclosure type*, whether new misconduct information is self-disclosed by the offender or disclosed by another party, is a signal about offender characteristics, such as trustworthiness (Fennis & Stroebe, 2014).

Our misconduct types follow the German police’s classification, which derives economic crime from § 74c of the Courts Constitution Act (*Gerichtsverfassungsgesetz, GVG*) and provides classifications in its yearly crime statistics (BKA, 2018, 2019). We consider all crimes labeled as economic or asset crimes. The major types are: 1) deception (classes 893100, 511000, and 515000–518900), 2) financial statement fraud (class 893200), 3) violation of capital markets regulation and capital markets fraud (classes 893300, 893600, 513000, and 514000), 4) competition fraud (class 893400), 5) employment fraud (class 893500), 6) embezzlement (classes 520000 and 530000), 7) falsification of documents (classes 540000 and 550000), and 8) criminal insolvency (class 560000). We add two types of “*Other*” crimes that are commonly used in prior literature: money laundering (class 633000) and corruption (class 650000). We also add tax evasion, which is not included in the police crime statistics because the police are not responsible for tax violations in Germany (BKA, 2019). We collapse types with less than five observations in our sample into “*Other*” to ensure meaningful frequencies for our analyses. Moreover, when the press consistently references more than one offense, we use the category “*Several*”. Panel C of Table 1 summarizes our remaining classification. It is similar to the classes used in Ewelt-Knauer et al. (2015) and covers a broader range of misconduct.

2.2. Prior literature

A large literature has shown that (alleged) criminal firm misconduct has negative effects on stock prices (Gatzert, 2015; Amiram et al., 2018). Table 2 gives an overview of some of the papers that focus (part of) their analysis on stock market reactions, including information about the sample, types of misconduct, considered misconduct or information characteristics, and average stock market reaction.

Table 2. Summary of results from prior event studies measuring stock market reactions on criminal firm misconduct (Part 1)

Reference	*Analysed population*	*Misconduct types*	*Misconduct/information characteristics*	*Event type*	*Event window*	*Ø CAR (%), (full sample)*	*Sample size*
Panel A: US studies							
Davidson and Worrel (1988)	Illegal firm misconduct (USA, 1970–1980)	No distinction	None	Newspaper articles	(-1, -1)	-0.9	131
Karpoff and Lott (1993)	Illegal firm misconduct (USA, 1978–1987)	Stakeholder fraud; government fraud; financial statement fraud; regulatory violations	Allegation type	Newspaper articles	(-1, 0)	-1.6	132
Davidson et al. (1994)	Illegal firm misconduct (USA, 1965–1990)	Among others: corruption, financial statement fraud, tax evasion, competition fraud	Allegation type; repeat vs. first-time offenders	Newspaper articles	(-1, 1)	< 0.1 (n.s.)	535
Cox and Weirich (2002)	Financial statement fraud (USA, 1992–1999)	Population covers only one category	None	Newspaper articles	(0, 0)	-23.2	27
Miller (2006)	Financial statement fraud (USA, 1987–2002)	Population covers only one category	Information quality (source; publication type; article recurrence)	Newspaper articles related to AAERs	(-1, 1)	-8.2	60
Fich and Shivdasani (2007)	Financial statement fraud (USA, 1998–2002)	Population covers only one category	None	Security class action lawsuits	(-1, 0)	-6.0	200
Karpoff et al. (2008b)	Financial statement fraud (USA, 1978–2002)	Population covers only one category	Reason for a federal investigation	Enforcement announcements	(0, 0)	-25.2	371
Gande and Lewis (2009)	Illegal firm misconduct (USA, 1996–2003)	Distinction not used in the analysis	None	Security class action lawsuits	(-1, 1)	-4.7	605
Murphy et al. (2009)	Illegal firm misconduct (USA, 1982–1996)	No distinction	Victim type	Newspaper articles	(-1, 0)	-1.4	394
Karpoff et al. (2017)	Foreign bribery (USA, 1978–2013)	Population covers only one category	With vs. without additional fraud allegation	Enforcement announcements	(0, 0)	-3.1	140
Sampath et al. (2018)	Foreign bribery (USA, 1978–2010)	Population covers only one category	With vs. without additional fraud allegations; top management involvement	Allegation (different data sources)	(0, 1)	-2.9	134
Abdulmanova et al. (2021)	Illegal firm misconduct (2004–2019)	No distinction	Investor attention	Security class action lawsuits	(-1, 1)	-1.9	295
Panel B: Non-US studies							
Europe (multiple countries): Carberry et al. (2018)	Firm misconduct, mostly illegal (UK, France, Germany, Netherlands, Belgium, 1995–2005)	Among others: corruption, financial statement fraud, tax evasion, competition fraud, capital markets fraud	Offender type; repeat vs. first-time offenders; location of misconduct; board independence allegation type; Information quality (media coverage; impact estimation)	Newspaper articles	(-2, 2)	-1.4	345
Mariuzzo et al. (2020)	Cartels (European Union, 1992–2015)	Population covers only one category	Regulatory fine; Information quality (media coverage); sentiment	Cartel raids of the European Commission	(-1, 1)	-1.2	194
France: Kirat and Rezaee (2019)	Violations of financial regulations (France, 2004–2017)	No distinction	Regulatory fine	Newspaper coverage of *Autorité des Marchés Financiers'* sanctions	(0, 0)	-0.8	54
Germany: Ewelt-Knauer et al. (2015)	Illegal firm misconduct (Germany, 1998–2014)	See Table 1	Top management involvement; multiple offenders; offender rejection; board member resignation; cooperation with authorities	Newspaper articles	(-1, 1)	-5.8	126

Table 2. Summary of results from prior event studies measuring stock market reactions on criminal firm misconduct (Part 2)

Reference	*Analysed population*	*Misconduct types*	*Misconduct/information characteristics*	*Event type*	*Event window*	*Ø CAR (%), (full sample)*	*Sample size*
Panel B: Non-US studies (continued)							
UK: Armour et al. (2017)	Illegal firm misconduct (UK, 2001–2011)	Distinction not used in the analysis	Victim type	Final notices of enforcement activity	(-1, 1)	-1.7	40
Global: Akhtar et al. (2019)	Tax evasion (FT 500, 2000–2014)	Population covers only one category	Allegation type; information quality (major vs. non-major newspaper)	Newspaper articles	(-1, 1)	< 0.1 (n.s.)	113
China: Wang et al. (2019)	Financial statement Fraud (China, 2007–2016)	Recognition fraud, disclosure fraud	Punishment type	Announcements of regulatory actions	(-2, 2)	-0.5	433
Japan: Tanimura and Okamoto (2013)	Illegal firm misconduct (Japan, 2000–2008)	Stakeholder fraud, government fraud, financial statement fraud, regulatory violations, individual fraud	Allegation type	Newspaper articles	(-1, 0)	-5.1	160

Notes: The column 'Event window' presents the time interval for which CARs were summed up, with the first (second) number being the start (end) of the event window in trading days relative to the event date — 0 represents the event date, and negative (positive) number denote the number of trading days before (after) that date. Ø CAR represents the mean cumulated abnormal return for the full sample of each paper in the cited event window. Results may be derived from different market models. All reported Ø CARs that are not labelled (n.s.) are statistically significant at the 5% level or better and are rounded to one decimal as some papers do not provide more than one decimal. Most of the papers contain more examinations than presented in the table, such as subsample analyses, analyses of multiple events of one misconduct case, or analyses covering different event windows. Because subsamples or different event windows are only available for some papers, we only report full sample analyses and the focal event window (if there is none, we present the (-1, 1) window), which are the most comparable results across all papers. As our study does not consider multiple events for one misconduct case, we restrict the reported results to initial announcements of misconduct cases. We also do not report multivariate analyses which do not control for misconduct or information characteristics but for other characteristics such as firm characteristics only.

We use it to derive the following four goals of our replication analysis.

First, only Carberry et al. (2018), Ewelt-Knauer et al. (2015), and Tanimura and Okamoto (2013) use multivariate analysis to study the effect of misconduct type on market reactions. Existing univariate results are inconsistent: Tanimura and Okamoto (2013, Table 4) do not find any effect of misconduct type. Carberry et al. (2018) and Ewelt-Knauer et al. (2015) only find that financial statement fraud has a stronger effect than "miscellaneous" misconduct and each other misconduct type has a significantly lesser effect than financial statement fraud, respectively. However, they do not compare all misconduct types to each other. Next to replicating the dominating effect of financial statement fraud, we combine univariate and multivariate analysis of how other misconduct types differentially affect the strength of the market reaction.

Second, despite the dominant nature of fraudulent financial reporting in pooled samples, earlier research studying misconduct and information characteristics does not consider cross-sectional differences by misconduct type. Only Karpoff and Lott (1993) account for the influential nature of financial statement fraud but find no consistent results with respect to the allegation type for misconduct other than financial statement fraud. We aim to replicate results regarding misconduct and information characteristics when controlling for misconduct type, influential observations, and when removing financial statement fraud observations.

Third, misconduct type and misconduct and information characteristics are arguably correlated. For instance, companies may be more likely to self-disclose for occupational crime, where it is easier to blame individuals. Few earlier studies combine those variables. Only Carberry et al. (2018) combine misconduct and information characteristics in one model. However, they do not include offender and victim types, which we argue form the core of the economic crime definition. Hence, our goal is to replicate earlier findings when controlling for possible correlations among a larger set of conceptually distinct characteristics.

Finally, coverage of US data and turbulent times at the turn of the century and during the 2008 financial crisis is more extensive than coverage of non-US jurisdictions and data after these crises. Some papers present evidence that investor reactions changed after the 2008 financial crisis (Armour et al., 2017; Kirat & Rezaee, 2019) and substantially differ between US and non-US settings (Wang et al., 2019). We add to studying the robustness of earlier results in a non-US, non-crisis setting.

Comparing prior literature to our approach, one previous analysis uses a large German misconduct sample[2]. Ewelt-Knauer et al. (2015) generally support the findings of prior Anglo-Saxon studies. Our paper differs in three important aspects. First, we focus on post-financial crisis data, attempting to replicate findings after capital markets have arguably undergone a major disruption with possibly lasting effects, e.g., considering the required soundness of business models and proper conduct. Second, we focus on

[2] Additionally, there is one multi-country study including Germany by Carberry et al. (2018). It is unclear to what extent their data includes legal but unethical conduct. Their sample (data collection stops at 2005) is outdated compared to Ewelt-Knauer et al. (2015). They find an overall mean CAR of -1.4%, which is much smaller than the overall mean CAR of -5.8% in Ewelt-Knauer et al. (2015) and -3.2% in our analysis.

misconduct and information characteristics vs. crisis communication and governance characteristics in Ewelt-Knauer et al. (2015). Third, as financial statement fraud is rare and unique, we use robust regressions[3] and exclude financial statement fraud cases to reduce the impact of these influential observations on average effects picked up in any analysis.

2.3. Hypothesis development

The theory supports the strong empirical evidence from above that, on average, corporate misconduct leads to declining stock prices of the perpetrator firm. Following Karpoff (2012), three effects combine for this decline, and we use these effects to guide our hypothesis development. First, prices adjust to the true value of the stock without the crime (*readjustment effect*) because the criminal operations and related returns will cease. Second, the firm is likely to bear monetary penalties due to legal fines or litigation. Third, reputational penalties result from a modification of contract terms between the firm and its stakeholders. Accordingly, we hypothesize as follows:

H1: Pooling all misconduct types together, on average, stock prices decline when a misconduct event is initially announced.

As earlier literature finds the highest CARs for financial statement fraud and US data, we expect to observe reactions at the lower end of the range of CARs (second-to-last column of Table 2). However, there are arguments that misconduct may be viewed relatively more or less severe after multiple crises in the 2000s and regulatory reactions. On the one hand, misconduct leads to larger reputation losses for financially distressed firms (Karpoff et al., 2008b). Moreover, people hold others to higher moral standards in times with high economic risks (Pitesa & Thau, 2014). Hence, reactions may be less severe in economically stable times. On the other hand, stricter regulations can raise awareness for the regulated issues and hence for misconduct (Gadenne et al., 2009), which may have increased reputational risks after the crises and ensuing regulations. Hence, replicating the overall negative stock price effect is not automatic. In addition, as discussed, results from earlier literature suggest the strongest results for financial statement fraud, leading to the following additional hypothesis:

H1a: Stock prices decline most for financial statement fraud.

Moreover, the clear conceptual differences between the remaining misconduct types suggest that differentiating those types could explain differences in stock market reactions. However, we are not aware of clear theoretical predictions as to how the remaining misconduct types differ regarding the readjustment effect, monetary penalties, and reputational penalties. Hence, we state the following hypothesis with a more exploratory character:

H1b: Stock price declines differ across misconduct types other than financial statement fraud.

Turning to the misconduct characteristics (Table 1, Panel A), we first distinguish corporate and occupational crime and discuss how they differ with respect to the readjustment effect, monetary penalties, and reputational penalties. Corporate crime means that perpetrators act primarily in the firm's interest. In comparison, occupational crime means that perpetrators act primarily in their personal interest. When the crime's beneficiary is the firm (*corporate crime*), the readjustment effect is negative because benefits for the firm disappear when the crime ends. When individuals benefit (*occupational crime*), firms often are victims, possibly leading to a positive readjustment effect when crime and the accompanying harm ends. Considering monetary penalties, firm sanctions are more likely for corporate crime, resulting in more negative future cash flows compared to occupational crime. For reputational penalties, corporate crime is more likely to involve multiple offenders and top management and send a signal of a weak firm culture, all of which yield more negative market reactions (Ewelt-Knauer et al., 2015; Sampath et al., 2018; Soltani, 2014). Together, these arguments lead to the following hypothesis:

H2: Stock prices decline more for corporate crime compared to occupational crime.

For different victim types, there is no obvious systematic difference in the readjustment effect and monetary penalties. Reputational penalties are expected to be substantially higher for connected compared to third-party victims because impaired contract terms are more likely to occur if contractors are directly harmed (Murphy et al., 2009; Armour et al., 2017). Hence, we hypothesize:

H3: Stock prices decline more when the misconduct directly affects connected parties compared to third parties.

However, whether this hypothesis holds in the German versus the Anglo-Saxon setting is empirically unclear due to cultural differences. Hofstede (1994) introduces the judgment of individual versus collective interests of society as one of five cultural dimensions. It conceptually parallels the argument that connected-party misconduct leads to more reputational damage than third-party misconduct. The degree of individualism is much larger in the US and the UK compared to Germany (Chui et al., 2010).

The last set of hypotheses covers different information characteristics (Table 1, Panel B). As we study events that represent the very first allegation of each misconduct, the level of confirmation of these allegations (*allegation type*) differs. While some contain mere suspicions or rumors, others report completed investigations and confirmed misconduct. Higher uncertainty when confirmation levels are low may lead to less severe stock market reactions, which we express in the next hypothesis:

H4: Stock prices decline more when the allegation is based on confirmed misconduct compared to unconfirmed misconduct.

For bad news, lower precision leads to less adverse perceptions (Epstein & Schneider, 2008; Hautsch & Hess, 2007; Kim & Verrecchia, 1991). Low

[3] OLS models are sensitive to influential observations (Greene, 2012). However, just removing fraud events is problematic because the data is correct and meaningful for the population of interest (Leone et al., 2019). The intuition behind robust regressions is to perform weighted ordinary least squares (OLS) regressions, reducing the weights of observations the more influential they become. See subsectoin 3.2 for further discussion.

coverage may exacerbate this effect, as it reduces information credibility (Dyck & Zingales, 2003). Finally, low coverage reduces attention, which may attenuate negative stock price reactions (Peress, 2008). Following these arguments, we formulate the next hypothesis:

H5: Stock prices decline more when information quality of the bad news is high.

Finally, we use discretionary disclosure theory to develop expectations about the influence of the disclosure type on stock market reactions. It suggests that managing negative disclosure aims to reduce damages (Verrecchia, 1983). Consequently, self-disclosures present bad information in the best possible way and before events become most negative (Graham et al., 2005). Hence, there is no (or less) suspicion of withholding (further) bad information, which reduces adverse effects (Fennis & Stroebe, 2014). Finally, in the case of self-disclosure, the firm acted on the misconduct before it became publicly known. While no misconduct firm prevented misconduct, self-disclosing firms at least show that they have the ability and willingness to end misconduct without outside pressure from press disclosures. These arguments indicate that a self-disclosure event signals less severe misconduct than disclosure by another party, leading to our last hypothesis:

H6: Stock prices decline less for self-disclosure compared to third-party disclosure of misconduct.

3. RESEARCH METHODOLOGY

3.1. Data collection

We search the databases of the three major German business journals *Handelsblatt*, *Wirtschaftswoche* and *Börsenzeitung*, and of the two national daily newspapers *Süddeutsche Zeitung* and *Frankfurter Allgemeine Zeitung* to identify events that contain new and relevant public information (Cox & Weirich, 2002). Study period: after the financial crisis in January 2010 until the start of the COVID-19 pandemic in December 2019. We search for the German translations for 'fraud' and 'economic crime' in general and for our single misconduct types. We excluded hits that clearly involved no listed company. For each identified event, we used *LexisNexis* to find the first announcement of the event. This procedure yielded an initial sample of 147 events. We removed 13 events due to confounding events during the event window (e.g., the release of annual reports), 18 cases due to missing return data (in Refinitiv EIKON), and 20 cases where there was no clear event date or no consensus in press articles whether allegations were a reasonable suspicion of illegal misconduct. Our final sample includes 96 initial misconduct announcements (see Table 3). For our cross-sectional analyses, we drop another two observations because of missing control variables (in Refinitiv EIKON). We create all misconduct and information characteristics (see details in subsection 2.1 and Appendix) by content analysis of the collected newspaper articles. Two of the authors independently coded the variables and could resolve all cases with initial discrepancies.

Table 3. Sample selection

Selection step	***Number of firms***
Misconduct cases of listed German firms 2010–2019	147
Less	
Confounding events	13
Missing return data	18
Obscure misconduct information	20
Final sample size	***96***
Less firms with missing control variables	2
Sample size for cross-sectional analyses	**94**

Note: Confounding events include the release of annual reports, forecasted changes in earnings and sales, major executive changes, acquisition activities and dividend announcements. Return data is missing when firms went public only shortly before the event (insufficient data for the estimation period), were insolvent, or were listed in the unregulated stock market. Obscure misconduct information means that there was no clear event date or no consensus in press articles on whether allegations were a reasonable suspicion of illegal misconduct.

3.2. Research design

We calculate short-term abnormal stock returns using the market model of Markowitz (1959) and Sharpe (1963). It assumes a linear relationship between individual stock returns and the market portfolio return. In an empirical analysis, a corresponding market index proxies for the market portfolio, which is not directly observable. Consequently, the return $R_{i,t}$ of the stock of a certain firm *i* on day *t* is (MacKinlay, 1997):

$$R_{i,t} = \alpha_i + \beta_i R_{HDAX,t} + e_{i,t} \tag{1}$$

where, α_i and β_i are coefficients from an OLS regression; $R_{HDAX,t}$ is the return of the HDAX Index of the 100 largest listed firms (most highly capitalized stocks) in Frankfurt Stock Exchange on day *t* (Ewelt-Knauer et al., 2015); and $e_{i,t}$ is the residual. We estimate regression coefficients in an estimation period from 249 to 6 trading days prior to each event, which is an established estimation window in the literature (Corrado, 2011).

We obtain abnormal returns $AR_{i,t}$ for firm *i* on day *t* with the estimates from the results of OLS regressions of Eq. (1) as follows:

$$AR_{i,t} = e_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{HDAX,t}) \tag{2}$$

For all days in the event window *t* = [τ, *T*], cumulative abnormal returns CAR_i for firm *i* are the sum of the abnormal returns for each day *t* in the event window:

$$CAR_i = \sum_{t=\tau}^{T} AR_{i,t} \tag{3}$$

We test whether the mean (median) CARs of our full sample and several subsamples are significantly different from 0 with t-tests (Wilcoxon signed-rank tests). We run a one-way ANOVA with CAR from one day before and after the event date as our dependent variable, and misconduct category as our single factor to determine whether stock market reactions differ significantly across misconduct types. We use *post hoc* tests to identify pairwise differences between the different misconduct types. Finally, to the incremental effect of misconduct characteristics and information on capital market reactions after controlling for misconduct category, we estimate the following cross-sectional OLS model with robust standard errors adjusted for firm-level clustering:

$$CAR_{i,t} = \alpha + \sum \beta_j MISCAT_{j,i,t} + \gamma_1 CORP_{i,t} + \gamma_2 REL_{i,t} + \gamma_3 SUSP_{i,t} + \gamma_4 INFQ_{i,t} + \gamma_5 SDIS_{i,t} + \sum \delta_k CONTROLS_{k,i,t} + \varepsilon_{i,t} \tag{4}$$

Table 4. Sample characteristics

Misconduct category	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*Total*
Panel A: Misconduct types over time											
Full sample	9	17	8	12	9	8	8	12	5	8	96
Deception	1	5	0	0	1	0	1	0	1	1	10
Financial statement fraud	0	0	1	1	1	1	0	0	0	2	6
Capital markets fraud/violations	2	3	0	3	0	0	1	2	0	0	11
Competition fraud	3	4	2	3	3	1	5	5		1	27
Money laundering	1	0	0	0	0	1	0	0	2	1	5
Corruption	1	4	0	1	2	0	0	5	0	2	15
Tax evasion	0	0	1	1	1	1	0	0	1	0	5
Several	0	0	3	3	1	4	0	0	1	0	12
Other	1	1	1	0	0	0	1	0	0	1	5
Panel B: Misconduct and information characteristics over time											
OCC	2	6	1	3	0	1	1	3	4	2	23
REL	5	15	3	8	6	6	7	8	1	3	62
SUSP	9	14	7	8	6	3	8	6	3	6	70
INFQ	5	9	4	7	4	3	7	3	3	3	48
SDIS	8	13	7	10	8	6	8	11	4	7	82

Note: In both Panels, the column titles denote the calendar year for which the descriptive information is presented. The numbers represent the number of misconducts belonging to each misconduct category in the respective year in Panel A, and the number of misconducts with a score of one for each of the presented binary variables in the respective year in Panel B, respectively. Variable definitions can be found in Table 1 for the variables used in Panel A, and in Table A.1 (in Appendix) for the variables used in Panel B, respectively.

Events pertain to firm i at date t and we have multiple observations for some firms. *MISCAT* includes indicator variables for each misconduct category listed in Panel C of Table 1. We use the most frequent category *competition fraud* as our benchmark. *CONTROLS* include firm *SIZE*, *AGE*, and *PROFIT*. Appendix defines all variables. We sequentially add misconduct characteristics, information characteristics, and both sets of characteristics to our model in Eq. (4) to investigate the sensitivity of results when including (failing to include) other, potentially correlated, characteristics. Model 1 includes only the misconduct types *MISCAT* and the *CONTROLS*. In Model 2 we add the misconduct characteristics (*CORP* and *REL)* to base Model 1; and in Model 3, respectively, we add the information characteristics (*SUSP*, *INFQ*, and *SDIS)* to base Model 1. Model 4 contains all variables included in Eq. (4).

However, it is generally problematic to use standard OLS estimation on misconduct samples because they contain rare and extreme events, and OLS is sensitive to extreme observations (Greene, 2012). Treating these events as outliers, however, is debatable because the data is correct, and these extreme events conceptually do belong to the population of interest (Ewelt-Knauer et al., 2015). Still, these influential observations might be overweighed in a pooled analysis, which might distort some relationships of the less extreme subsample. For instance, Ewelt-Knauer et al. (2015) find some evidence that at least part of the results are sensitive to excluding extreme cases. Robust regression can help to create a balance between accounting for statistical issues of influential observations in OLS and for conceptual issues in defining the population of misconduct cases with meaningful information (Leone et al., 2019).

We use the M-estimator as a modification of OLS which is much less sensitive to influential observation while largely retaining desired statistical properties (Heij et al., 2004; Sorokina et al., 2013). As an alternative, we also re-estimate our OLS models after winsorizing our CARs at 1% and 99%. This approach also retains all cases and reduces the extent of influential observations but generally performs worse than robust regressions (Leone et al., 2019). However, it is quite common in cross-sectional event study analyses (Armour et al., 2017), serving as an additional benchmark to compare our M-estimator results. Finally, we remove financial statement fraud observations from our sample and rerun all estimations described above. This subsample reveals whether some associations (do not) exist only for fraud cases but not (do exist) for other misconduct types. The M-estimator is robust to influential observations by conducting a weighted OLS where residuals with absolute values of more than c ($c = 1.345 \times \hat{\sigma}$) are weighted less ($w_i \approx 0.4405/|\hat{\varepsilon}_i|$) than residuals with absolute values below c ($w_k = 1$) (Huber, 1981).

4. RESEARCH RESULTS

4.1. Description and analysis of misconduct type

In Table 4 (above), our sample was broken down by year and by misconduct category (Panel A), and by misconduct and information characteristics (Panel B).

The distribution of overall misconduct and misconduct types is relatively even across years. Only for deception, half of the events concentrate in 2011. Financial statement fraud, money laundering, and tax evasion are particularly rare. Considering misconduct characteristics, corporate crime (76.0% of all cases), and misconduct harming connected parties (64.6%) are more frequent than their counterparts. For information characteristics, exactly half of the observations have high and low information quality, while confirmations are comparably rare (27.1%), and external parties reveal most misconduct (85.4%). For all years, there is variation in at least four of these five variables and there is no obvious time variance in any of these variables. Turning to the control variables (untabulated, sample reduced to $n = 94$), the mean (standard deviation of) *SIZE* is 9.22 (1.74), *PROFIT* is 5.50% (5.81%), and *AGE* is 90.26 years (59.28).

Mean and median CARs are shown in Table 5. Panel A includes different event windows for the full sample.

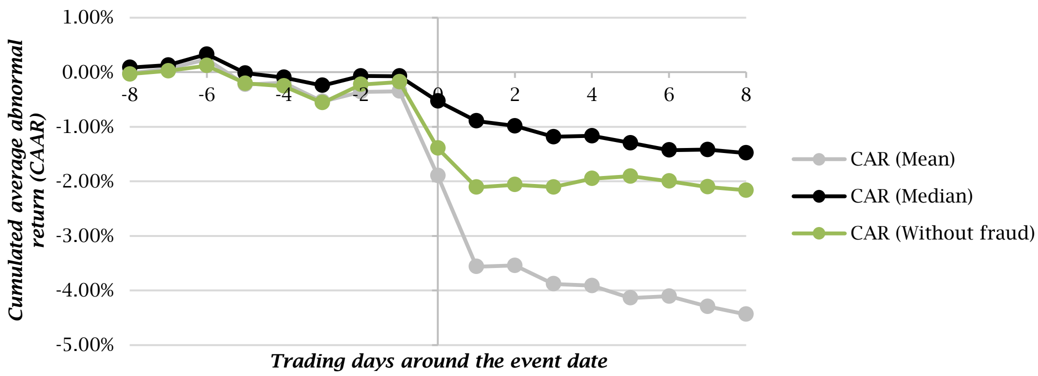
Table 5. Univariate results

Sample parameters	*N*	*Mean (%)*	*Std. dev. (%)*	*Median (%)*	*Negative*	*T-statistic*	*Z-statistic*
Event window	*Panel A: Mean CARs for full sample in different event windows*						
(-1, -1)	96	-2.76	8.21	-0.98	70%	-3.296***	-5.217***
(0, 0)	96	-3.17	8.98	-0.87	68%	-3.462***	-4.519***
(-1, 0)	96	-3.50	10.74	-0.98	70%	-3.190***	-4.456***
(0, 1)	96	-3.54	11.12	-1.12	69%	-3.120***	-4.270***
(-1, 1)	96	-3.20	8.47	-1.25	72%	-3.705***	-5.008***
Misconduct type	*Panel B: Mean CARs by misconduct type in the (-1, 1)-window*						
Full sample without fraud	96	-1.94	4.28	-1.17	71%	-4.296***	-4.676***
Deception	10	-3.49	6.95	-1.43	90%	-1.588	-2.085**
Financial statement fraud	6	-22.19	24.01	-15.47	83%	-2.264*	-1.676
Capital markets fraud/violations	11	0.66	1.71	0.52	36%	1.290	-0.994
Competition fraud	27	-1.15	2.16	-0.79	63%	-2.582**	-2.249**
Money laundering	5	-6.32	9.10	-1.80	100%	-1.036	-1.863*
Corruption	15	-1.05	1.83	-0.64	67%	-1.884*	-1.493
Tax evasion	5	-1.18	0.73	-1.58	100%	-3.593**	-1.863*
Several	12	-3.36	5.13	-2.21	75%	-2.271**	-2.308**
Other	5	-4.41	3.75	-2.29	100%	-2.630*	-1.863**

*Note: This table presents descriptives and test results of cumulative abnormal returns, which were estimated for each event separately with the procedure outlined in subsection 3.2 and Eq. (1), (2), and (3). The estimation window is from 249 trading days to 6 trading days before the event date. In Panel A, the column event window presents the time interval for which CARs were summed up, with the first (second) number being the start (end) of the event window in trading days relative to the event date. 0 represents the event date, and the negative (positive) number denotes the number of trading days before (after) that date. In Panel B, the misconduct type describes the subsample used in each row. The event window is (-1, 1) for all data reported in Panel B. For both Panels, the column negative is the percentage of negative CARs based on all observations in each event window or subsample, respectively. T-statistic contains the t-statistic of a one-sample t-test that mean CARs are 0. Z-statistic contains the statistic corresponding to a non-parametric Wilcoxon signed rank test that the true location of the median is 0. *, **, and *** denote statistical significance at the 10%, 5% and 1%level of a two-tailed test, respectively.*

There is a significantly negative market reaction in short-term windows around the event date. Figure 1 shows that these reactions are not anticipated in the days before the event, and the negative reaction persists for at least eight days.

Figure 1. Mean and median CARs from eight days before to eight days after the event



Note: This figure presents mean and median CARs (see note to Table 5 for details) in the (-8, x)-window where x is the trading day indicated on the x-axis. The light grey graph represents mean CARs of our full sample (n = 96), the black graph median CARs of our full sample, and the dark grey graph mean CARs of our sample without financial statement fraud (n = 90).

These results clearly support *H1*. To ensure comparability with Ewelt-Knauer et al. (2015), we conduct all further analyses with CARs in the window (-1, 1). Panel B of Table 5 shows CARs for our subsample without financial statement fraud and for all misconduct types separately. The large reduction of the mean CAR for the sample without financial statement fraud despite only removing six observations is a first indicator that our fraud observations are indeed influential, and the reduced sample is a reasonable sample for further analyses. All misconduct types except for capital markets fraud/violations have negative mean CARs that are significant in a t-test, Wilcoxon signed rank test, or both.

Finally, our results of one-factorial ANOVA confirm that misconduct type is a significant factor in explaining variation in CARs in the (-1, 1)-window (F = 6.654; $p < 0.001$; untabulated). *Post hoc* Tukey's Honestly Significant Difference (HSD) tests (untabulated) indicate that financial statement fraud yields significantly more negative CARs compared to all other misconduct types ($p < 0.009$) and that CARs of all other types of misconduct do not significantly differ from each other ($p > 0.645$). Hence, we find initial support for *H1a* but not for *H1b*.

4.2. Cross-sectional results

The results of our cross-sectional model from Eq. (4) with our full sample are shown in Panel A of Table 6. The first column contains Model 1, which includes only the misconduct types and the controls. Columns two and three contain Models 2 and 3, which additionally cover the misconduct and information characteristics, respectively. The last column contains the full Model 4.

Table 6. Cross-sectional results (Part 1)

Variable	***Model 1***		***Model 2***		***Model 3***		***Model 4***	
	Estimate	***T-value***	***Estimate***	***T-value***	***Estimate***	***T-value***	***Estimate***	***T-value***
Panel A: Full sample (n = 94) with regular OLS regression								
Intercept	-10.69%	-1.89*	-7.99%	-1.34	-15.99%	-2.11**	-16.77%	-2.02**
Misconduct type								
Deception	-1.14%	-0.58	-1.94%	-0.91	-1.36%	-0.66	-1.93%	-0.98
Financial statement fraud	-14.12%	-1.81*	-13.98%	-1.78*	-14.95%	-2.15**	-14.13%	-2.09**
Capital markets fraud/violations	1.99%	1.35	0.35%	0.31	0.36%	0.23	-2.87%	-1.55
Money laundering	-5.42%	-2.15**	-8.18%	-3.11***	-5.94%	-2.49**	-7.80%	-3.12***
Corruption	0.82%	1.01	-1.65%	-1.52	0.01%	0.01	-1.99%	-1.57
Tax evasion	-0.63%	-0.52	-3.61%	-2.00**	-1.73%	-1.72*	-5.16%	-2.89***
Several	-1.37%	-0.87	-3.10%	-1.67*	-0.74%	-0.52	-2.30%	-1.28
Other	-1.41%	-1.32	-3.77%	-2.91***	-1.50%	-0.82	-3.22%	-1.65
Misconduct characteristics								
OCC			2.86%	3.20***			4.73%	3.08***
REL			-2.34%	-2.01**			-1.20%	-0.85
Information characteristics								
SUSP					4.27%	2.00**	4.42%	1.91*
INFQ					0.57%	0.55	0.80%	0.73
SDIS					-1.21%	-0.69	1.07%	0.50
Control variables								
SIZE	0.81%	1.50	0.78%	1.45	1.14%	2.01**	1.12%	2.08**
PROFIT	-10.52%	-1.03	-12.89%	-1.22	-4.95%	-0.45	-9.48%	-0.95
AGE	0.02%	3.07***	0.02%	2.76***	0.02%	2.80**	0.02%	2.58**
Adjusted R^2		0.31		0.32		0.35		0.38
Panel B: Full sample (n = 94) with robust regression using the M-estimator								
Intercept	-4.51%	-2.43**	-2.51%	-1.26	-6.30%	-2.61***	-6.34%	-2.50**
Misconduct type								
Deception	-0.44%	-0.41	-1.33%	-1.25	-0.81%	-0.71	-1.28%	-1.15
Financial statement fraud	-10.74%	-8.05***	-10.58%	-8.13***	-11.08%	-7.71***	-10.95%	-7.73***
Capital markets fraud/violations	1.86%	1.91*	0.70%	0.66	1.24%	1.19	-0.48%	-0.40
Money laundering	-3.11%	-2.34**	-5.12%	-3.33***	-3.31%	-2.36**	-4.93%	-3.10***
Corruption	0.55%	0.62	-1.19%	-1.06	0.23%	0.25	-1.34%	-1.16
Tax evasion	-0.70%	-0.51	-2.84%	-1.85*	-1.11%	-0.78	-3.44%	-2.12**
Several	-0.80%	-0.83	-2.12%	-1.99**	-0.41%	-0.41	-1.68%	-1.48
Other	-2.29%	-1.71	-3.99%	-2.76***	-2.57%	-1.83*	-3.84%	-2.59***
Misconduct characteristics								
OCC			2.12%	2.66***			2.70%	3.93***
REL			-1.62%	-1.88**			-1.27%	-1.37
Information characteristics								
SUSP					1.61%	1.94*	1.56%	1.82*
INFQ					0.67%	0.99	0.84%	1.27
SDIS					-1.31%	-1.24	0.15%	0.13
Control variables								
SIZE	0.28%	1.57	0.24%	1.41	0.44%	2.25**	0.44%	2.90**
PROFIT	-10.17%	-1.89*	-12.10%	-2.26**	-8.27%	-1.47	-8.97%	-1.89*
AGE	0.01%	2.38**	0.01%	2.28**	0.01%	2.13**	0.01%	2.18**

Table 6. Cross-sectional results (Part 2)

Panel C: Model 4 results for sample without fraud cases (n = 89) and different estimations						
Variable	*Regular OLS*		*OLS with winsorization*		*M-estimator*	
	Estimate	*T-value*	*Estimate*	*T-value*	*Estimate*	*T-value*
Intercept	-6.79%	-2.57**	-6.95%	-2.43**	-5.26%	-2.04**
Misconduct type						
Deception	-2.68%	-1.46	-2.54%	-1.38	-1.41%	-1.34
Capital markets fraud/violations	-0.84%	-0.97	-1.01%	-1.14	-0.29%	-0.25
Money laundering	-7.76%	-2.69***	-8.09%	-2.83***	-4.69%	-3.10***
Corruption	-2.11%	-1.98*	-2.25%	-2.19**	-1.55%	-1.41
Tax evasion	-4.68%	-2.83***	-5.06%	-3.01***	-3.24%	-2.10**
Several	-2.89%	-1.75*	-2.98%	-1.83*	-1.91%	-1.76*
Other	-4.46%	-5.15***	-4.75%	-5.18***	-4.41%	-2.92***
Misconduct characteristics						
OCC	3.43%	3.59***	3.51%	3.62***	2.53%	2.84***
REL	-2.31%	-2.20**	-2.50%	-2.44**	-1.47%	-1.66*
Information characteristics						
SUSP	1.20%	1.57	1.25%	1.67*	1.09%	1.29
INFQ	1.70%	1.99**	1.69%	1.97*	0.91%	1.44
SDIS	0.15%	0.19	0.34%	0.43	0.30%	0.27
Control variables						
SIZE	0.58%	2.31**	0.57%	2.09**	0.40%	2.07**
PROFIT	-13.78%	-2.09**	-14.23%	-2.16**	-8.26%	-1.51
AGE	0.01%	1.97*	0.02%	2.42**	0.01%	1.44
Adjusted R²		0.31		0.32		

*Note: This table presents the results of regressions of Eq. (4) with subsets (Models 1, 2, and 3) and the entire set (Model 4) of the right-hand side of the equation. In all Panels and columns, the dependent variable is the CAR of the (-1, 1)-window (see note to Table 5 for details). Model 1 only contains the misconduct category and control variables. Model 2 additionally contains misconduct characteristics, Model 3 adds information characteristics, and Model 4 adds both. In Panel C, all columns report the results of different estimations of Model 4. Panels A and B contain our full sample (n = 94, because data on controls is missing for 2 observations) and Panel C contains a sample without observations of the misconduct category financial statement fraud (n = 89). In Panel A, all Models are estimated with regular OLS regression and robust standard errors clustered by firm, as some firms have multiple instances of misconduct in our sample. In Panel B, all Models are estimated with the robust M-estimator as described in subection 3.2. In Panel C, the first column contains regular OLS estimations with robust standard errors clustered by firm (as in Panel A) and the third column contains the robust M-estimation (as in Panel C). The second column contains regular OLS estimation with robust standard errors clustered by firm, but the continuous variables are winsorized at 1% and 99%. In all Panels and columns, the estimate represents the coefficient estimate from the respective regression and t-value represents the t-statistic of a test that the coefficient equals 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level of a two-tailed test, respectively. Variable definitions can be found in Table 1 and Appendix.*

Panel B of Table 6 contains the same models, also based on the full sample, but uses the robust M-estimator instead of regular OLS regression. Panel C of Table 6 contains regressions with a sample excluding financial statement fraud cases. It only covers Model 4. The first column reports results of the regular OLS estimation, the second column those of OLS estimation with the continuous variables winsorized at 1% and 99%[4], and the last column reports the M-estimator results.

Consistent with our ANOVA and *post hoc* tests, our cross-sectional models confirm that the misconduct type has explanatory power for variations in CARs beyond other misconduct, information, or firm characteristics. Controlling for such characteristics and comparing all other misconduct types to competition fraud as the most common misconduct type, several misconduct types yield significantly more negative reactions. This is even more pronounced in Panel C of Table 6 when we remove financial statement fraud as the most extreme category. Besides the consistent negative effect of financial statement fraud (abnormal returns are between 10.58% and 14.95% more negative than those of competition fraud), we find the most consistently more negative market reactions to instances of money laundering (between 3.11% and 8.18% more negative) and tax evasion (between 0.63% and 5.16% more negative). These results are consistent with *H1a* and *H1b*[5].

Turning to *H2*, *OCC* is consistently significantly positive. All else equal, CARs for occupational crime are between 2.12 and 4.73 percentage points higher (less negative or more positive) than for corporate crime, which is economically meaningful[6]. Hence, we find support for *H2* that corporate crime leads to significantly more negative market reactions than occupational crime. As the second misconduct characteristic, *REL* is consistently negative and is consistently significant in the sample excluding fraud. Coefficients between -1.20% and -2.50% are economically meaningful. Therefore, consistent with *H3*, harming connected parties leads to significantly more negative market reactions than harming third parties, at least when excluding financial statement fraud.

[4] For brevity, we do not present results with winsorized data for the full sample. Replicating the analysis in Table 6 Panels A and B after winsorizing continuous variables at 1% and 99% does not change our inferences.

[5] As we have few observations for some misconduct types, we did not include industry or year fixed effects because this would greatly reduce the power of our tests. In untabulated tests, we repeat our analysis in Table 6 after including industry and year fixed effects. To have sufficiently many observations per industry, we simply distinguish automobile ($n = 24$), financial industry ($n = 21$), other industrial products ($n = 31$), and other ($n = 20$). As expected, the results for our misconduct type indicators become weaker in Panels A and B, with most coefficients of money laundering and tax evasion not reaching significance. In Panel C, money laundering and tax evasion remain significant. The other results remain robust, except for *REL* becoming insignificant in Panel A Model 2 and *SUSP* becoming insignificant in Panel B and Panel C. Adjusted R^2s are between 0.41 and 0.44 in Panel A and 0.28 and 0.30 in Panel C.

[6] With the mean CAR in our full sample (sample without fraud) of -3.20% (-1.94%, see Table 5), we consider effects with a single-digit absolute percentage as economically meaningful, also because each 1% change of the mean market value in our sample (mean *SIZE* of 9.22 equals a market value of about EUR10,100 million) corresponds to an absolute market value change of EUR101 million.

Regarding information characteristics and hypotheses *H4, H5,* and *H6*, we find some support for *H4* that suspicions lead to less negative market reactions than confirmations (*SUSP* coefficients between 1.09% and 4.42%). This effect is sensitive to excluding financial statement fraud observations. We find no consistent evidence for *H5* and *H6*, as *INFQ* and *SDIS* are insignificant in most specifications.

5. DISCUSSION

Our results replicate the broad finding from previous literature that firm misconduct leads to significant negative market reactions. The average magnitude of a 3.2% reduction in stock prices over a three-day window is similar to many earlier findings. Ewelt-Knauer et al. (2015) find a substantially larger reaction and there are several studies finding reductions of less than 2%. Hence, the direction of effects seems to be well established, but magnitudes differ, and research cannot fully explain or predict these differences. As these events are rare and idiosyncratic, many determinants of reaction magnitude are likely unobservable.

Our results with respect to misconduct types suggest that financial statement fraud, money laundering, and tax evasion are most heavily punished by capital markets. However, our ANOVAs and tighter empirical designs (see footnote 4) do not yield significant results and some magnitudes for tax evasion are below 1 percentage point. Therefore, it might be possible that some misconduct types largely represent underlying characteristics that cause the differences in capital market reactions. Those characteristics might be difficult to observe, which is why we believe that distinguishing misconduct types can still be helpful in studying and governing misconduct. Another issue with misconduct types is that they represent broad categories of misconduct. Single events within the same category may still be heterogeneous. Hence, scrutinizing categorizations and developing them further is important to interpret and generate useful findings when it comes to misconduct types.

We make two observations regarding our replication of earlier research findings. First, including misconduct and information characteristics together (Model 4 of Table 6) versus separately (Models 2 and 3) changes the results regarding victim type (*REL*). Hence, we find some support for our expectation that it is critical to control for correlations among those characteristics. Second, results in Panels A and B of Table 6 are inferentially identical, suggesting that the influential nature of financial statement fraud observations does not affect inferences in our sample. However, when excluding financial statement fraud in Panel C, we find different results regarding victim type (*REL*) and information characteristics (*SUSP* and *INFQ*). It is possible that there are systematic differences in the determinants of capital market reactions for financial statement fraud and other types of illegal firm misconduct. Care is necessary when interpreting results from pooled cross-sectional analyses.

Our consistent and largely robust results for misconduct characteristics give us confidence that the differentiation of corporate versus occupational crime and distinguishing victim types are meaningful. Moreover, definitions developed in the literature seem sufficiently clear and measurable to observe consistent results in empirical data. We find a different picture for information characteristics. The only well-observable information characteristic we could identify is the nature of suspicion versus confirmation of the misconduct. This characteristic clearly changes the uncertainty of the information, which might be the single most important factor for capital markets when acting on new information. However, we cannot confidently rule out that other information characteristics that we were unable to observe additionally contribute to market reactions.

Lastly, when we consider our control variables, results indicate that larger firms suffer significantly less negative abnormal returns. We also find evidence suggesting stronger reactions for more profitable firms. Finally, markets react less negatively to misconduct of older firms. These observations are consistent with earlier literature (Ewelt-Knauer et al., 2015).

6. CONCLUSION

We attempt to add to the literature which analyzes capital market reactions to illegal misconduct in a business context reported by the press. We collect a sample of 96 misconduct cases by German firms uncovered between 2010 and 2019. Our goal was to replicate earlier analyses of misconduct and information characteristics considering the following features. First, we use a non-US, post-financial crisis and pre-COVID sample. Second, we account for possible correlations between previously separately analyzed characteristics. Third and last, we analyze the influential nature of extreme and rare financial statement fraud observations.

We replicate earlier findings on overall capital market reactions to illegal firm misconduct and corroborate that financial statement fraud yields the strongest reactions. We further provide some evidence that other misconduct types are useful in explaining systematic differences in the strength of capital market reactions. For misconduct characteristics, we replicate that corporate crime yields stronger reactions than occupational crime. We find stronger reactions to misconduct harming connected versus third parties consistently only when we exclude financial statement fraud. We are unable to provide a strong replication of the effects of different information characteristics.

Our approach has several limitations. Although our approach to collecting data was comprehensive, our sample is comparably small due to the rare nature of the events we cover. Hence, our insignificant results do not necessarily suggest that the effects do not exist. Instead, it is possible that the power of our tests was too low to detect those effects. The small sample size also limits the number of variables we can include in our models. Hence, future research with larger samples may include additional variables to detect more results and potentially more interdependencies. However, our sampling choice has the advantage that it enabled us to focus on a period of relative economic stability, restrict our sample to instances that were clearly identifiable as suspicions of illegal behavior, and to keep a homogeneous context by restricting the sample to one country. Another limitation is that our replication in the German context does not allow conclusions of whether results generalize to contexts outside of our scope and the scope of the literature we cover (see Table 2), e.g., developing economies. We cannot analyze whether some of our findings are specific to Germany. Therefore, we encourage more work in this area, especially in settings that have received little attention. In addition, we only found two multi-country studies in earlier literature, and we are not aware of an analysis of potential similarities or differences between countries. To fill this gap future research with data from multiple countries could carry out such comparisons.

Despite these limitations, we argue that our replication contributes to the earlier literature by showing which results are robust and sensitive to our unique sample, the inclusion of misconduct and information characteristics, and different treatments of influential observations. We respond to calls for replication in accounting and finance (Salterio, 2014; Radhakrishnan, 2021). Practitioners could also benefit from our replication study. Corporate governance and crisis response activities could focus on misconduct which is most likely to cause the greatest damage. Finally, regulatory discussions on corporate criminal law could benefit from understanding existing reputational consequences of misconduct when debating whether and where regulatory action could complement such market reactions.

REFERENCES

1. Abdulmanova, A., Ferris, S. P., Jayaraman, N., & Kothari, P. (2021). The effect of investor attention on fraud discovery and value loss in securities class action litigation. *Journal of Financial Research, 44*(3), 513–552. https://doi.org/10.1111/jfir.12249
2. Agnew, R., Piquero, N. L., & Cullen, F. T. (2009). General strain theory and white–collar crime. In S. Simpson & D. Weisburd (Eds.), *The criminology of white-collar crime* (pp. 35–60). Springer. https://doi.org/10.1007/978-0-387-09502-8_3
3. Akhtar, S., Akhtar, F., John, K., & Wong, S. W. (2019). Multinationals' tax evasion: A financial and governance perspective. *Journal of Corporate Finance, 57*, 35–62. https://doi.org/10.1016/j.jcorpfin.2017.11.009
4. Amiram, D., Bozanic, Z., Cox, J. D., Dupont, Q., Karpoff, J. M., & Sloan, R. G. (2018). Financial reporting fraud and other forms of misconduct: A multidisciplinary review of the literature. *Review of Accounting Studies, 23*(2), 732–783. https://doi.org/10.1007/s11142-017-9435-x
5. Armour, J., Mayer, C., & Polo, A. (2017). Regulatory sanctions and reputational damage in financial markets. *Journal of Financial and Quantitative Analysis, 52*(4), 1429–1448. https://doi.org/10.1017/S0022109017000461
6. Bundeskriminalamt (BKA). (2018). *Bundeslagebild Wirtschaftskriminalität 2017* [Federal situation report on white-collar crime 2017]. https://www.bka.de/SharedDocs/Downloads/DE/Publikationen/JahresberichteUndLagebilder/Wirtschaftskriminalitaet/wirtschaftskriminalitaetBundeslagebild2017.html?nn=28030
7. Bundeskriminalamt (BKA). (2019, April 02). *Polizeiliche Kriminalstatistik (PKS)* [Police crime statistics]. https://www.bka.de/DE/AktuelleInformationen/StatistikenLagebilder/PolizeilicheKriminalstatistik/PKS2018/pks2018_node.html
8. Bundesministerium der Justiz (BMJ) (2020, June 22). *Gesetz zur Stärkung der Integrität in der Wirtschaft* [Business Integrity Strengthening Act]. https://www.bmj.de/SharedDocs/Gesetzgebungsverfahren/DE/Staerkung_Integritaet_Wirtschaft.html
9. Campa, D. (2018). Regulatory enforcement and the effectiveness of fraud training: A European investigation into earnings manipulation. *Comptabilité Contrôle Audit, 24*(1), 81–111. https://doi.org/10.3917/cca.241.0081
10. Carberry, E. J., Engelen, P.-J., & Van Essen, M. (2018). Which firms get punished for unethical behavior? Explaining variation in stock market reactions to corporate misconduct. *Business Ethics Quarterly, 28*(2), 119–151. https://doi.org/10.1017/beq.2017.46
11. Chakravarthy, J., deHaan, E., & Rajgopal, S. (2014). Reputation repair after a serious restatement. *The Accounting Review, 89*(4), 1329–1363. https://doi.org/10.2308/accr-50716
12. Chui, A. C. W., Titman, S., & Wei, K. C. J. (2010). Individualism and momentum around the world. *The Journal of Finance, 65*(1), 361–392. https://doi.org/10.1111/j.1540-6261.2009.01532.x
13. Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance, 51*(1), 207–234. https://doi.org/10.1111/j.1467-629X.2010.00375.x
14. Cox, R. A. K., & Weirich, T. R. (2002). The stock market reaction to fraudulent financial reporting. *Managerial Auditing Journal, 17*(7), 374–382. https://doi.org/10.1108/02686900210437471
15. Davidson, W. N., & Worrel, D. L. (1988). The impact of announcements of corporate illegalities on shareholder returns. *Academy of Management Journal, 31*(1), 195–200. https://journals.aom.org/doi/abs/10.5465/256506
16. Davidson, W. N., Worrell, D. L., & Lee, C. I. (1994). Stock market reactions to announced corporate illegalities. *Journal of Business Ethics, 13*(12), 979–987. https://doi.org/10.1007/BF00881667
17. Dee, C. C., Lulseged, A., & Zhang, T. (2011). Client stock market reaction to PCAOB sanctions against a Big 4 auditor. *Contemporary Accounting Research, 28*(1), 263–291. https://doi.org/10.1111/j.1911-3846.2010.01044.x
18. Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance, 46*(4), 1325–1359. https://doi.org/10.1111/j.1540-6261.1991.tb04620.x
19. Dyck, A., & Zingales, L. (2003). *The media and asset prices* (Working Paper). UCLA Anderson School of Management. https://www.anderson.ucla.edu/faculty_pages/romain.wacziarg/mediapapers/DyckZingales.pdf
20. Epstein, L. G., & Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *The Journal of Finance, 63*(1), 197–228. https://doi.org/10.1111/j.1540-6261.2008.01314.x
21. Ewelt-Knauer, C., Knauer, T., & Lachmann, M. (2015). Fraud characteristics and their effects on shareholder wealth. *Journal of Business Economics, 85*(9), 1011–1047. https://doi.org/10.1007/s11573-015-0773-5
22. Farber, D. B. (2005). Restoring trust after fraud: Does corporate governance matter? *The Accounting Review, 80*(2), 539–561. https://doi.org/10.2308/accr.2005.80.2.539

23. Fennis, B. M., & Stroebe, W. (2014). Softening the blow: Company self-disclosure of negative information lessens damaging effects on consumer judgment and decision making. *Journal of Business Ethics, 120*(1), 109–120. https://doi.org/10.1007/s10551-013-1647-9
24. Fich, E. M., & Shivdasani, A. (2007). Financial fraud, director reputation, and shareholder wealth. *Journal of Financial Economics, 86*(2), 306–336. https://doi.org/10.1016/j.jfineco.2006.05.012
25. Friedrich, C., & Quick, R. (2019). Der Abschreckungseffekt von Konsequenzen von Bilanzbetrug für Individuen und Unternehmen — Wahrnehmung von Vorständen [The deterrent effect of consequences of accounting fraud for individuals and companies — Board perceptions]. *Betriebswirtschaftliche Forschung und Praxis, 71*, 19–52. https://tubiblio.ulb.tu-darmstadt.de/118719/
26. Friedrichs, D. O. (2002). Occupational crime, occupational deviance, and workplace crime: Sorting out the difference. *Criminal Justice, 2*(3), 243–256. https://doi.org/10.1177/17488958020020030101
27. Gadenne, D. L., Kennedy, J., & McKeiver, C. (2009). An empirical study of environmental awareness and practices in SMEs. *Journal of Business Ethics, 84*(1), 45–63. https://doi.org/10.1007/s10551-008-9672-9
28. Gande, A., & Lewis, C. M. (2009). Shareholder-initiated class action lawsuits: Shareholder wealth effects and industry spillovers. *Journal of Financial and Quantitative Analysis, 44*(4), 823–850. https://doi.org/10.1017/S0022109009990202
29. Gatzert, N. (2015). The impact of corporate reputation and reputation damaging events on financial performance: Empirical evidence from the literature. *European Management Journal, 33*(6), 485–499. https://doi.org/10.1016/j.emj.2015.10.001
30. Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics, 40*(1), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002
31. Greene, W. H. (2012). *Econometric analysis* (7th ed.). Pearson.
32. Hautsch, N., & Hess, D. (2007). Bayesian learning in financial markets: Testing for the relevance of information precision in price discovery. *Journal of Financial and Quantitative Analysis, 42*(1), 189–208. https://doi.org/10.1017/S0022109000002246
33. Heij, C., De Boer, P., Franses, P. H., Kloek, T., & van Dijk, H. K. (2004). *Econometric methods with applications in business and economics.* Oxford University Press. http://dl.rasabourse.com/Econometrics_Erasmus/Christiaan_Heij_Paul_de_Boer.pdf
34. Hofstede, G. (1994). The business of international business is culture. *International Business Review, 3*(1), 1–14. https://doi.org/10.1016/0969-5931(94)90011-6
35. Huber, P. J. (1981). *Robust statistics.* John Wiley & Sons. https://doi.org/10.1002/0471725250
36. Karpoff, J. M. (2012). Does reputation work to discipline corporate misconduct? In T. G. Pollock & M. L. Barnett (Eds.), *The Oxford University handbook of corporate reputation* (pp. 361–382). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199596706.013.0018
37. Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008a). The consequences to managers for financial misrepresentation. *Journal of Financial Economics, 88*(2), 193–215. https://doi.org/10.1016/j.jfineco.2007.06.003
38. Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008b). The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis, 43*(3), 581–611. https://doi.org/10.1017/S0022109000004221
39. Karpoff, J. M., Lee, D. S., & Martin, G. S. (2017). *Foreign bribery: Incentives and enforcement.* https://ssrn.com/abstract=1573222
40. Karpoff, J. M., & Lott, J. R., Jr. (1993). The reputational penalty firms bear from committing criminal fraud. *The Journal of Law and Economics, 36*(2), 757–802. https://doi.org/10.1086/467297
41. Kim, O., & Verrecchia, R. E. (1991). Trading volume and price reactions to public announcements. *Journal of Accounting Research, 29*(2), 302–321. https://doi.org/10.2307/2491051
42. Kirat, T., & Rezaee, A. (2019). How stock markets react to regulatory sanctions? Evidence from France. *Applied Economics, 51*(60), 6558–6566. https://doi.org/10.1080/00036846.2019.1644443
43. Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research, 47*(1), 241–276. https://doi.org/10.1111/j.1475-679X.2008.00318.x
44. KPMG. (2018, July 5). *Wirtschaftskriminalität in Deutschland 2018* [Press-release].
45. Leone, A. J., Minutti-Meza, M., & Wasley, C. E. (2019). Influential observations and inference in accounting research. *The Accounting Review, 94*(6), 337–364. https://doi.org/10.2308/accr-52396
46. MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13–39. https://www.jstor.org/stable/2729691
47. Mariuzzo, F., Ormosi, P. L., & Majied, Z. (2020). Fines and reputational sanctions: The case of cartels. *International Journal of Industrial Organization, 69*, Article 102584. https://doi.org/10.1016/j.ijindorg.2020.102584
48. Markowitz, H. M. (1959). *Portfolio selection: Efficient diversification of investments.* Yale University Press.
49. Miller, G. S. (2006). The press as a watchdog for accounting fraud. *Journal of Accounting Research, 44*(5), 1001–1033. https://doi.org/10.1111/j.1475-679X.2006.00224.x
50. Morales, J., Gendron, Y., & Guénin-Paracini, H. (2014). The construction of the risky individual and vigilant organization: A genealogy of the fraud triangle. *Accounting, Organizations and Society, 39*(3), 170–194. https://doi.org/10.1016/j.aos.2014.01.006
51. Murphy, D. L., Shrieves, R. E., & Tibbs, S. L. (2009). Understanding the penalties associated with corporate misconduct: An empirical examination of earnings and risk. *Journal of Financial and Quantitative Analysis, 44*(1), 55–83. https://doi.org/10.1017/S0022109009090036
52. Peress, J. (2008). *Media coverage and investors' attention to earnings announcements* (Working Paper). https://doi.org/10.2139/ssrn.1106475
53. Pitesa, M., & Thau, S. (2014). A lack of material resources causes harsher moral judgments. *Psychological Science, 25*(3), 702–710. https://doi.org/10.1177/0956797613514092
54. PricewaterhouseCoopers (PwC). (2018). *Wirtschaftskriminalität 2018. Mehrwert von Compliance — Forensische Erfahrungen.* https://www.pwc.de/de/risk/pwc-wikri-2018.pdf
55. Radhakrishnan, S. (2021). TIJA forum on replication: An overview. *The International Journal of Accounting, 56*(03), Article 2150011. https://doi.org/10.1142/S1094406021500116

56. Salterio, S. E. (2014). We don't replicate accounting research — Or do we? *Contemporary Accounting Research, 31*(4), 1134–1142. https://doi.org/10.1111/1911-3846.12102
57. Sampath, V. S., Gardberg, N. A., & Rahman, N. (2018). Corporate reputation's invisible hand: Bribery, rational choice, and market penalties. *Journal of Business Ethics, 151*(3), 743–760. https://doi.org/10.1007/s10551-016-3242-3
58. Schell-Busey, N., Simpson, S. S., Rorie, M., & Alper, M. (2016). What works? A systematic review of corporate crime deterrence. *Criminology & Public Policy, 15*(2), 387–416. https://doi.org/10.1111/1745-9133.12195
59. Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management Science, 9*(2), 277–293. https://doi.org/10.1287/mnsc.9.2.277
60. Soltani, B. (2014). The anatomy of corporate fraud: A comparative analysis of high profile American and European corporate scandals. *Journal of Business Ethics, 120*(2), 251–274. https://doi.org/10.1007/s10551-013-1660-z
61. Sorokina, N., Booth, D. E., & Thornton, J. H. (2013). Robust methods in event studies: Empirical evidence and theoretical implications. *Journal of Data Science, 11*(3), 575–606. https://doi.org/10.6339/JDS.2013.11(3).1166
62. Sutherland, E. H. (1949). *White-collar crime*. The Dyden Press.
63. Tanimura, J. K., & Okamoto, M. G. (2013). Reputational penalties in Japan: Evidence from corporate scandals. *Asian Economic Journal, 27*(1), 39–57. https://doi.org/10.1111/asej.12004
64. Ugrin, J. C., & Odom, M. D. (2010). Exploring Sarbanes-Oxley's effect on attitudes, perceptions of norms, and intentions to commit financial statement fraud from a general deterrence perspective. *Journal of Accounting and Public Policy, 29*(5), 439–458. https://doi.org/10.1016/j.jaccpubpol.2010.06.006
65. Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of Accounting and Economics, 5*, 179–194. https://doi.org/10.1016/0165-4101(83)90011-3
66. Wang, Y., Ashton, J. K., & Jaafar, A. (2019). Money shouts! How effective are punishments for accounting fraud? *The British Accounting Review, 51*(5), Article 100824. https://doi.org/10.1016/j.bar.2019.02.006

APPENDIX

Table A.1. Variable definitions

Variable	***Definition***
Misconduct characteristics	
REL	Dummy variable with a value of 1 if the primary damaged party is a connected party, 0 otherwise.
OCC	Dummy variable with a value of 1 if the misconduct is an occupational crime, 0 otherwise.
Information characteristics	
SUSP	Dummy variable with a value of 1 if the crime is suspected, but not confirmed, 0 otherwise.
INFQ	Dummy variable with a value of 1 if there are less than five newspaper articles available on *NexisLexis* on the event day or the day after OR if there are less than two of the following three pieces of information available: monetary consequences, suspect/offenders, detailed misconduct description.
SDIS	Dummy variable with a value of 1 if the crime is disclosed by a third party, 0 when it is self-disclosed.
Control variables	
SIZE	Natural logarithm of the last year-end market value (Datastream item MV) before the event.
AGE	Year of the event minus year the firm was founded.
PROFIT	Last year-end operating cash flow (Worldscope item #04860) before the event scaled by last year-end total assets (Worldscope item #02999) before the event.