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Do current regulations prevent unethical AI practices?

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Abstract

The rapid growth of artificial intelligence (AI) to ensure the competitiveness of corporations, driven by "data-hungry" companies, is raising ethical concerns about privacy governance and cybersecurity of datasets. It is key to avoid the abuse of users not aware of the economic value of their data, as well as their manipulation through advertising in digital markets, and by predicting their behavior, also to avoid the abuse of consumers' ignorance about the ethics of the products/services they consume. The European Union, through the Artificial Intelligence Act, developed a set of rules to safeguard the impact of AI on society and mitigate the adverse consequences of unethical behaviors, but these unethical AI practices are still occurring. This study uses an event model to calculate cumulative abnormal returns (CARs) with registered data on fines from AI ethical violations to measure the impact on financial markets of news about the unethical behavior of offending firms and to determine whether shareholders are rewarding these activities. Results help explain how some firms and their shareholders become immune to financial economic sanctions and turn into multi-violators who are not affected by the amount of the fines imposed on them, developing a "fine is a price" attitude. In summary, the findings of this study advise companies against engaging in this type of malpractice and make a great contribution in helping governments prevent the misuse of AI and its potentially disastrous consequences at both the individual and societal levels.

Keywords: *Artificial intelligence; unethical behavior, AI European regulation, GDPR, event analysis*

JEL Classification: G14, M10, M15

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1 INTRODUCTION

Data is nowadays the new oil, and Artificial Intelligence (AI) the new electricity, which creates value from this oil (Grover et al., 2022). AI is defined as systems that, given a complex goal, act by collecting and interpreting data to decide the best action(s) to take to achieve the given goal (Milossi et al., 2021). Combined with large amounts of data, AI has an enormous economic potential due to the numerous benefits that these systems can generate, such as reduction of costs and human errors or productivity improvements, competitiveness and competitive advantages (Montero Guerra et al., 2023; Otoiu et al., 2022). Given these positive expectations, AI is a booming industry. In fact, according to recent market forecasts, the size of the global AI market is expected to reach nearly USD 1.4 trillion in 2029, with a CAGR of 20.1% over the forecast period, 2022–2029 (Fortune Business Insights, 2022).

The rapid growth of AI is driven by "data-hungry" companies (Mazzini, 2020), and is raising ethical concerns about the interpretation of AI decisions, privacy governance and cybersecurity of datasets (Dwivedi et al., 2021; John-Mathews, 2022). These ethical concerns coexist in two distinct spaces: i) hard ethics, or right and wrong actions based on regulations and compliance

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(Ashok et al., 2022), and ii) soft ethics or do's and don'ts over and above existing regulation (Floridi, 2018). Among the concerns of soft ethics are the ethical use of AI in social, economic, environmental, educational, and beyond these, moral and philosophical domains (Reinares-Lara et al., 2018). To avoid these concerns about ethics, literature has demonstrated the need for AI ethical commitments (Méndez-Suárez et al., 2023) and ethical process standardization (Chromjakova et al., 2021).

Companies' conduct in the soft ethics space is key to avoiding the abuse of users not aware of the economic value of their data, as well as their manipulation through advertising in digital markets, and by predicting their behavior (Saura et al., 2021); also, to avoid the abuse of consumers' ignorance about the ethics of the products/services they consume, because their attention is focused on tangible features such as price (Kraus et al., 2022). Other undesirable ethical practices on users that give rise to excessive digital consumption can lead to digital harm because of overdependence (Kanungo et al., 2022), even with the undesirable effects of digital transformation on customers (Méndez-Suárez & Danvila-del-Valle, 2023), and which in some cases turn users into partners in algorithmic ethical crimes (Krügel et al., 2023). These affect both adults and adolescents (Reuters, 2023), as well as having an impact in the workplace (Venkatesh et al., 2023). These companies' unethical behaviors can be related to the strong effect of market pressure, linked to the desire of the managers of some publicly listed companies to satisfy the unrealistic expectations of investors (Soltani, 2014) as well as their own remuneration, by overlooking the intrinsic values of companies in favor of expectations of increased value created by investor demand (Gerbert & Spira, 2019).

In this regard, the European Union, through the Artificial Intelligence Act (European Commission, 2021), developed a set of rules to safeguard the impact of AI on society and mitigate the adverse consequences of unethical behaviors of some companies (Duan et al., 2019). Among these rules is Title II, which addresses unethical AI practices that are sanctionable as prohibited by the European General Data Protection Regulation or GDPR (European Parliament and Council, 2016). But, after almost five years of operation and 2.4 billion euros in fines for prohibited AI practices under the GDPR (CMS.Law, 2023), these unethical AI practices are still occurring. Considering this, it is necessary to address the research gap called for by previous literature (Duan et al., 2019) by asking whether this government regulation is actually working, forcing companies to internalize the regulations on ethical externalities (Romero-Castro et al., 2022) and financial markets are punishing offending publicly listed companies (Cline et al., 2018), or whether these unethical AI behaviors are rewarded by shareholders because the misplaced incentives are simply too powerful (Desai, 2012; Foecking et al., 2021).

To address this research gap, the current study uses an event model to calculate cumulative abnormal returns (CARs) and thus the impact on financial markets of news about the unethical behavior of offending firms (Almaqableh et al., 2022). This is complemented by a dependence model to analyze the relationships between the CARs and selected characteristics. To conduct the analysis, the study uses 31 annotated observations of publicly traded companies that were fined for severe violations (i.e., more than €450,000) of AI ethical principles under the GDPR (CMS.Law, 2023).

This study provides key insights on shareholders' reactions to severe violations of the AI ethical principles. The results of this study contribute greatly to the understanding of the impact of the current GDPR regulation on AI practices in the European Union. It helps explain how some firms and their shareholders become immune to financial economic sanctions and turn into multi-violators who are not affected by the amount of the fines imposed on them, developing a

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"fine is a price" (Gneezy & Rustichini, 2000) attitude, that is especially punished on subsidiaries of parent companies. In summary, this study's findings make a great contribution in helping governments to prevent the misuse of AI and its potentially disastrous consequences at both the individual and societal levels (Duan et al., 2019).

Next, we present an overview of the literature in the field of shareholders' reactions to unethical behaviors. We then formulate three hypotheses on shareholders' reactions to AI violations. Next, we present the data and use event analysis and dependence modeling to determine the drivers that lead to unethical behaviors. We close with a discussion of the findings we encountered and add conclusions, theoretical and practical implications, and limitations.

2 THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

No legal framework truly regulates companies' ethics of AI. Rather, companies try to convince legislators that there is no need for it, and that self-management is sufficient (Hagendorff, 2020). However, self-regulation often fails because the drive to monetize AI leads to economics taking precedence over ethics (Campolo et al., 2017; Rosenberg, 2017). Indeed, previous literature has found that managerial opportunism is not eradicated due to the apparent lack of consequences in the securities markets for the beneficiaries, including executives, shareholders and investment managers with high-powered incentives (Desai, 2012; Wesley & Ndofor, 2013). In this sense, some authors claim that this is the case with AI at the moment, which is experiencing a situation similar to a "bubble", especially in digital environments (Gerbert & Spira, 2019).

Corporate malpractices become a scandal when they are made public and generate public outrage (Borelli-Kjaer et al., 2021). But, corporate AI scandals are yet to occur, as happened with other cases of misconduct, such as that which started the #MeToo movement against sexual harassment (Borelli-Kjaer et al., 2021) or the #StopHateforProfit campaign against violent or racist content on Facebook (Villagra et al., 2021).

Next, we analyze previous research on the effects of corporate scandals on the market value of companies reported in the literature using the standard event study methodology. Some articles study the stock market reaction to firm's legal prosecution (Frooman, 1997; Gunthorpe, 1997). Others focus on scandals related to CEO misconduct and managerial indiscretions (Cline et al., 2018; Soltani, 2014). Several articles analyze corporate misconduct, including events related to financial misrepresentation and accounting irregularities or "cooking the books," and other types of misconduct such as fraud, tax fraud, corruption, market abuse or even environmental, as well as not protecting users against racist or hate content (Carberry et al., 2018; Villagra et al., 2021; Wesley & Ndofor, 2013). This category of firm misconduct includes the study of the impact on CARs as well as for multi-violator companies (Liu et al., 2022). CARs, defined as "the deviation between its [a firm] realized return at day *t* and the expected return" (Singh & Montgomery, 1987, p. 381), have been traditionally studied from the management perspective regarding some firms' strategic movements such as mergers and acquisitions (Barney, 1988). With respect to negative performance, authors studied sexual harassment scandals by analyzing many cases, including the well-known #MeToo movement (Borelli-Kjaer et al., 2021; King & Soule, 2007) or cases of environmental polluters. Researchers also studied the impact on the market values of environmental polluters (Bouzzine, 2021; Carpentier & Suret, 2022). And, some articles study miscellaneous categories such as data breaches on Facebook (Foecking et al., 2021) or the impact of drug busts on the market values of cryptocurrencies (Almaqableh et al., 2022). In general, the results of this analysis show a short-term negative effect of about 1–

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2% on the CARs around the event. The exception is reformulation events, indicating a serious financial misrepresentation, against which the market reacts more strongly (Cline et al., 2018).

3 RESEARCH OBJECTIVE, METHODOLOGY AND DATA

After reviewing the literature, we believe that the impact on the market value of practices prohibited by AI ethics laws is understudied, as we have not found research measuring the CARs of ethical AI failures of firms whose governance is not based on ethical behaviors (Dwivedi et al., 2021). Neither have we found literature that highlights the role of governments in the reinforcement, adaptation and improvement of regulations such as GDPR, analyzing whether the effect of sanctions on large companies is really effective, studying its impact on market values and reactions of shareholders (Duan et al., 2019).

3.1 Fine amount

Although unethical behaviors of listed companies may involve substantial fines, there are other intangible but relevant costs for companies, such as reputational costs or those of replacing employees or implementing new control measures (Cialdini et al., 2004). However, when there is no market reaction, investors expect that the fine will not affect future cash flows and that the misconduct will only have that consequence (Carberry et al., 2018). In this sense, why would any business choose to be socially responsible, assuming that social responsibility costs a firm more than irresponsibility (Frooman, 1997)?

This could be the case for some companies. For example, bank giant HSBC paid USD 4.8 billion in penalties, yet its illegal and unethical acts continued (Verschoor, 2018). In this regard, similar companies may have the perception that unethical behaviors come at a price, i.e., “a fine is a price,” and that these services can be purchased as many times as needed (Gneezy & Rustichini, 2000). Conversely, research has found in different experiments that both a larger size and a higher probability of a fine decrease the probability of engaging in unethical behavior (Bahník & Vranka, 2022; Laske et al., 2018), and that if lawsuits result in significant fines, the profitability of illegal behaviors is reduced, creating a necessary condition for lawsuits to generate deterrence (Muoghalu et al., 1990). Reviews of these contradictory findings have suggested the following hypothesis:

Hypothesis 1 (H1): The amount of the fine imposed for unethical AI violations has a significantly negative effect on cumulative abnormal returns.

3.2 Multi-violators

Previous research on irresponsibility argues that some companies become multi-violators of regulations, which conveys a reputation of corporate social irresponsibility (CSI), and which reduces stakeholder sanctions by creating groups of violators that reduce stakeholder attributions to each violating company by weakening the degree to which investors attribute the CSI of each violating company, consequently decreasing negative market reactions to the violating company (Liu et al., 2022). That could be the case for companies like Facebook, which turned out to be immune to data breaches, as investors did not react to the news, i.e., Facebook data breaches do not have a significant impact on Facebook’s stock price (Foecking et al., 2021). In addition, some organizations may be considered unethical because of a greater group loyalty than loyalty to stakeholders, which may be an explanation of why unethical behaviors are reiterated (Kundro & Nurmohamed, 2021). As a result, we consider the following:

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Hypothesis 2 (H2): Multi-violator firms have a significantly negative effect on cumulative abnormal returns.

3.3 Subsidiary

Literature considers that multinational enterprises (MNEs) contribute to the sustainable development of the local economies in which they operate, since greater institutional distance may entail a greater risk of facing mistrust from local markets. In this sense, MNEs, in an attempt to gain legitimacy, contribute abroad with CSR activities improving the perception of positive impact on stakeholders (Lee et al., 2021). But home country stakeholders react with different logics in home or host markets, leading investors to react more negatively to acts of corporate misconduct occurring in the home country than to those occurring outside the country in which a company is headquartered (Carberry et al., 2018). Unethical behavior abroad is also supposed to have consequences for the company's reputation at home (Nardella et al., 2023), however, in some cases, the opposite is true, and subsidiaries carry out CSI activities that, although unethical according to national laws, do not have a direct impact on their stakeholders in the country because they are located abroad. (Giuliani et al., 2014). In this sense we hypothesize the following:

Hypothesis 3 (H3): Violations at the parent or subsidiary companies have a significantly negative influence on the accumulated abnormal returns.

3.4 Data

To examine the three hypotheses, we collected data on violating companies from the CMS.Law (2023) database. To be included in the study, corporations had to (a) have committed violations under the GDPR corresponding to the Dutch Data Protection Authority top violation category, with fines starting at €450,000, in line with previous research (Méndez-Suárez et al., 2023), and (b) be listed on one of the world's stock exchanges at the time the fine was announced. If a corporation was listed on more than one market, data were collected only for the index reflecting the company headquarters. Data were collected from 2020 to 2022, and in the end 31 companies were found to meet the inclusion criteria. Stock market data for selected stocks and indexes were downloaded from Yahoo Finance and returns calculated using the R quantmod package (Ryan & Ulrich, 2022). Tab. 1 summarizes the information obtained, including the amount of the fine in millions of euros, the number of violations during the period from 2020 to 2022, and a binary variable indicating whether the company was a subsidiary (1) or not (0). The Tab. 1, also includes the descriptive statistics of the companies' returns during the 250-day observation period.

Tab. 1 – Event dates, corporation information and descriptive statistics of the 250-day observation window describing returns.

Date	Corporation/Subsidiary	Fine	Violations	Subsidiary	Market	min	max	mean	s.d.
2020-01-15	TIM Group	27.8	1	0	Milan	-0.0720	0.064	0.0001	0.017
2020-03-11	Google LLC	5.0	2	1	Nasdaq	-0.0770	0.104	0.0002	0.017
2020-07-14	Google Belgium SA	0.6	2	1	Nasdaq	-0.1110	0.104	0.0014	0.023
2020-10-01	H&M Hennes & Mauritz	35.2	1	0	Stockholm	-0.1207	0.132	-0.0004	0.030
2020-10-16	British Airways	22.0	1	0	London	-0.3082	0.225	-0.0052	0.054
2020-11-12	Vodafone Italia S.p.A.	12.2	2	1	London	-0.1153	0.099	-0.0008	0.024
2020-11-13	Ticketmaster UK Limited	1.4	1	1	NY S&P 500	-0.1658	0.183	0.0011	0.046
2020-11-18	Carrefour Banque	0.8	2	0	Paris	-0.1274	0.115	0.0000	0.021
2020-11-18	Carrefour France	2.2	2	0	Paris	-0.1274	0.115	0.0000	0.021
2020-12-11	BBVA	5.0	1	0	Madrid	-0.1508	0.166	-0.0003	0.037
2020-12-15	Twitter International Co	0.45	1	1	NY S&P 500	-0.2111	0.150	0.0029	0.039
2021-01-13	Caixabank Pay & Consum	3.0	2	0	Madrid	-0.1552	0.149	0.0000	0.033
2021-03-25	Fastweb S.p.A	4.5	1	0	Zurich	-0.0494	0.046	0.0000	0.011
2021-04-23	Equifax Iberica S.L.	1.0	1	1	NY Nasdaq	-0.0537	0.149	0.0024	0.021

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2021-05-13	Iren Mercato S.p.A.	2.8	1	0	Milan	-0.0362	0.048	0.0007	0.013
2021-07-16	Amazon Road Transp. Spain	2.0	2	1	NY S&P 500	-0.0545	0.079	0.0009	0.018
2021-09-02	FB Meta Platforms Ireland	17.0	4	1	NY Nasdaq	-0.0631	0.083	0.0012	0.020
2021-10-21	Caixabank S.A.	6.0	2	0	Madrid	-0.0480	0.149	0.0022	0.022
2021-12-16	Enel Energia S.p.A	26.5	1	0	Milan	-0.0551	0.063	-0.0007	0.013
2022-01-27	Cosmote Mobile	6.0	1	0	Athens	-0.0487	0.041	0.0014	0.013
2022-02-01	Vodafone España, S.A.U.	3.94	1	1	London	-0.0891	0.048	-0.0001	0.014
2022-02-01	Telefónica Móviles España.	0.90	1	0	Madrid	-0.0437	0.063	0.0005	0.015
2022-02-01	Orange Espagne S.A.U.	0.70	2	1	Paris	-0.0326	0.028	0.0003	0.009
2022-02-11	Amazon Europe Core.	746.0	2	1	NY S&P 500	-0.0781	0.135	-0.0001	0.018
2022-03-15	WhatsApp Ireland Ltd.	225.0	4	1	NY Nasdaq	-0.2639	0.073	-0.0012	0.026
2022-04-05	Copenague Danske Bank	1.3	1	0	Stockholm	-0.0755	0.051	0.0002	0.018
2022-06-23	Total Energies	1.0	1	0	Paris	-0.0593	0.081	0.0010	0.017
2022-07-26	Volkswagen	1.10	1	1	Frankfurt	-0.0762	0.106	-0.0015	0.023
2022-08-19	ACCOR SA	0.60	1	0	Paris	-0.1351	0.152	-0.0015	0.032
2022-09-05	Meta Platforms, Inc.	405.0	4	1	NY Nasdaq	-0.2639	0.175	-0.0028	0.034
2022-11-25	Meta Platforms, Inc.	265.0	4	1	NY Nasdaq	-0.2639	0.175	-0.0035	0.039

Note: Data from (CMS.Law, 2023). Date is date of decision; Fine is the amount of the fine imposed on the company – to better interpret the results of the regression analysis, the amount is translated into million euros (1 ≙ 1,000,000); Violations are the number of AI ethical violations in the period analyzed; Subsidiary is a binary variable representing whether the fine was imposed on a subsidiary (1), or on the parent company (0); Market refers to the stock market on which the parent company is listed.

The corporations provide a reasonable representation of the full range of industries of developed economies, coming from eight different sectors; regarding the sample size, similar sizes have been used in previous event analysis (i.e., Monfort et al., 2021; Villagra et al., 2021).

3.5 Model specification

To carry out the empirical analysis, first, we used the event study method, a powerful tool that can help researchers assess the financial impact of news that may affect listed companies, since this metric does not use accounting profits, which are often criticized as not being good indicators of companies' true results; although there are also theoretical concerns with the use of this methodology, as it may not be the most appropriate method for testing the impact of corporate social responsibility (Mcwilliams & Siegel, 1997). We performed the analysis in two phases. First, to obtain the CARs for each case in the dataset, an event model was calculated. Second, a dependence model was constructed to understand the relationships between CARs and the three hypothesis-driven factors. To ensure the reliability of the results, two complementary modelling approaches were adopted: robust multiple regression analysis, and another based on a Bayesian regression model. CARs were analyzed using the classical financial event analysis, which has proven successful in previous studies (Foecking et al., 2021; Monfort et al., 2021). Under this method, the researcher determines whether an "abnormal" return (AR) exists, if the returns are different from what they would have been in the absence of the event. From this determination, the investigator can also infer the significance of the event with a standard t-test to determine the significance of CARs (Foecking et al., 2021).

The estimation window for calculating normal returns spans from 250 days before the fine announcement to 50 days before (Campbell et al., 1997, Chapter 4). Our event window, the period in which the event is observed and abnormal returns calculated, is that of T = – 5 to T = 5 (i.e., Mcwilliams & Siegel, 1997; Villagra et al., 2021). The T ± 5 day window was selected because it allowed consideration that the announcement of the fine could have been preceded by leaks to the media, as well as the fact that shareholders could have made late decisions after learning of the company's violation of AI ethical principles. To check for robustness, the modeling was repeated using different event windows, and the results did not change significantly. We calculate AR as the difference between realized returns and the estimated normal returns using the Market Model:

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$$AR_{it} = R_{it} - \left(\alpha_i + \beta_i R_{mt}\right) \tag{1}$$

for stock i at time t, where R_m is the market return and α_i and β_i are the ordinary least squares parameters estimated obtained from the regression of R_{it} on R_{mt} over the estimation period preceding the event, 250 to 50 days prior to the event (Mcwilliams & Siegel, 1997).

4 RESULTS AND DISCUSSION

4.1 Results

The estimated CARs for each company are shown in Tab. 2. Surprisingly, the values are only significant in 9% of the cases (3 out of 31), even though the total amount of fines for AI ethical violations in the sample amounts to 1.83 billion euros. This result differs greatly from those previously reported in the literature, where in most cases events related to corporate unethical behavior are accompanied by a 1–2% shareholder penalty. It is noteworthy that the three significant CARs are in line with the worst penalties in the market, ranging from 8% to 13% loss in shareholder value, well above the 4.1% loss reported in the literature.

Tab. 2 – CARs and associated *t* values for the estimation window (−250, −50) and the event window T ± 5-day.

	T ± 5-day window	
Corporation/Subsidiary	CAR	T-Stats
TIM Group	0.1076	1.87
Google LLC	**-0.0885**	-2.34**
Google Belgium SA	0.0489	0.66
H&M Hennes & Mauritz	-0.0686	-0.71
British Airways	-0.0109	-0.08
Vodafone Italia S.p.A.	-0.1153	-1.67
Ticketmaster UK Limited	-0.2015	-1.18
Carrefour Banque	0.0307	0.52
Carrefour France	0.0307	0.51
BBVA	-0.0012	-0.01
Twitter International Co	-0.1830	-1.74
Caixabank Pay & Consum	0.0098	0.11
Fastweb S.p.A	-0.0021	-0.07
Equifax Iberica S.L.	**-0.1084**	-2.23**
Iren Mercato S.p.A.	-0.0074	-0.19
Amazon Road Transp. Spain.	0.0593	0.83
FB Meta Platforms Ireland	0.0043	0.08
Caixabank S.A.	0.0238	0.28
Enel Energia S.p.A	-0.0029	-0.08
Cosmote Mobile	-0.0474	-1.04
Vodafone España, S.A.U.	-0.0470	-0.75
Telefónica Móviles España.	-0.0152	-0.46
Orange Espagne S.A.U.	0.0099	0.40
Amazon Europe Core.	**-0.1338**	-3.01***
WhatsApp Ireland Ltd.	-0.0292	-0.70
Copenhagen Danske Bank	-0.0136	-0.32
Total Energies	0.0102	0.25
Volkswagen	-0.0060	-0.08
ACCOR SA	0.0106	0.10
Meta Platforms, Inc.	0.1026	0.85
Meta Platforms, Inc.	-0.0288	-0.21

Note: Bold indicates significant coefficients; ***p<0.01; **p<0.05

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To answer the questions, which are the research hypotheses of the present study, the following two modeling approaches were used. Firstly, a robust multiple linear regression was used (Foecking et al., 2021) that is appropriate for event analysis because it is robust to outliers, since we cannot eliminate them, as they provide valuable information about the effect of the event (Sorokina et al., 2021). Secondly, a Bayesian estimation was used that assumes that the only information available is that which has already been collected and provides complete information about the distribution of the estimated parameters rather than a local approximation (Gelman et al., 2013). The Bayesian model was specified using non-informative a priori probabilities (flat priors) to avoid introducing additional subjective criteria. Posterior probabilities were estimated using the MCMC algorithm with five chains and 100,000 iterations, where the first 50,000 were initially excluded, giving a final total of 250,000 iterations. The two models calculations were performed in R (R Core Team, 2022), the robust regression using the lmtest library (Zeileis & Hothorn, 2002) and the Bayesian regression analysis using the rstanarm library (Goodrich et al., 2022); the results of both models are shown in Tab. 3.

Tab. 3 – Results for the Robust Multiple Linear and Bayesian regressions.

	Dependent variable CAR						
	Robust Multiple Linear Regression			Bayesian Regression			
	Coefficient	Robust Std. Error	T-Stats	Coefficient	Std. Error	CI Low	CI High
Intercept	-0.04541	0.01918	-2.36**	-0.04579	0.02300	-0.09247	0.00014
Fine Amount	-0.00007	0.00005	-1.40	-0.00008	0.00008	-0.00025	0.00008
Number of Violations	**0.03961**	0.01256	3.15***	**0.03910**	0.01375	0.01211	0.06746
Subsidiary	**-0.08057**	0.02816	-2.86***	**-0.07913**	0.02639	-0.13369	-0.03096
Number of observations	31						
R^2	0.3393						

Note: Bold indicates significant coefficients; ***p<0.01; **p<0.05 (in robust multiple linear regression). CI refers to 95% Confidence Intervals of Bayesian coefficients, significant values are those not including 0.

A possible explanation as to why Fine Amount (H1) is not significant may be because there are large fines compared to lower fines, although both are serious offenses, despite our efforts to limit this problem by using robust multiple regression, which is less sensitive to outliers. As for the number of violations (H2), in light of the the results of the CARs analysis (Tab. 2), only 3 of the 31 companies had negative and significant CARs, meaning that the markets are not punishing these behaviors, and even more may be investing in this kind of multiviolation companies for their overall goal of making money, see, e.g., Foecking et al. (2021), who found no CARs in Meta data breaches. Finally, subsidiary (H3) had the expected negative impact.

4.2 Discussion

We reject hypothesis H1, that the fine amount has a significant impact on CARs, which shows that the current GDPR sanctions are not having a deterrent effect against unethical behavior in AI. For some companies “a fine is a price,” and they are willing to pay the fines as many times as necessary to achieve their goals, because this social irresponsibility may cost a firm less than responsibility, i.e., shareholders can expect that the amount paid will not be sufficient to have a financial impact on future cash flows, neither economically nor reputationally. We accept the hypothesis H2, that multiple breaches of the GDPR regulation in relation to ethical AI have an impact on CARs. The impact is positive, meaning that the higher the number of violations, the lower the impact on CARs; in this sense, we corroborate previous literature, as in a multiple violators framework there are lower negative stakeholder reactions against a company’s CSI behaviors compared to a single violator framework (Liu et al., 2022). Hypothesis H3, that illegal AI behaviors at subsidiaries have a significant impact on CARs, is also accepted; the negative

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sign means that as a company is a subsidiary, unethical behaviors have more impact on parent companies' stock prices, i.e., shareholders penalize defaults abroad more severely.

Our study yields several significant results. First, the role of GDPR legislation is important to understand shareholders' behavior regarding violating companies of different types of AI prohibited practices. This finding is important to define new measures in line with the suggestion of previous research (Duan et al., 2019) about the critical role that government plays in safeguarding the impact of AI on society by developing adequate policies, regulations, ethical guidance and legal frameworks to prevent misuses of AI and their potential disastrous consequences at both individual and societal levels. Second, the study identified the multi-violator framework, in which some companies have a reiterative unethical behavior, that perhaps should be prosecuted more severely. Third, our research reinforces the idea that if investors learn that boycotts do not actually threaten revenue, then they would not react negatively to protests associated with boycotts (King & Soule, 2007).

The reiteration of violations and the huge amount in fines paid by companies (Tab. 1) reinforces the idea that the application of legal sanctions as punishment for organizational misconduct is not deterring wrongdoing, as was expected to happen (McDonnell & Nurmohamed, 2021). Research also demonstrated that firms involved in AI unethical behavior are preserving firm value for shareholders, as equity markets may insufficiently penalize firms for their strategies (Wesley & Ndofor, 2013).

5 CONCLUSION

Our study aims to understand shareholder reactions to fines for unethical AI behavior under the European GDPR. Despite growing interest in AI, the role of ethics in AI behavior receives less attention, and there is little empirical knowledge. Our study examines the impact on markets of government sanctions for serious violations of AI ethical principles by listed companies to find out whether these behaviors are punished by financial markets or instead rewarded because the misplaced incentives are too powerful. Our study investigates the causes influencing the CARs caused by reports of fines given for unethical behavior. It provides new insights into the effect of government regulation of AI ethics in relation to the fine amounts, multi-violator behaviors and responses toward infringement due to subsidiaries.

In conclusion, there are no market reactions to AI misconduct against AI practices prohibited by GDPR. In fact, investors expect that the fines will not affect future cash flows, and that the misconduct will not have more consequences than the fine. On the other hand, the AI Bubble and the poor reaction of the market and stakeholders to unethical behaviors of companies calls for further government regulation because listed companies assumed that "a fine is a price" (Gneezy & Rustichini, 2000), and they are quite willing to pay the "price" for continuing unethical behaviors (i.e., Meta with four fines in 14 months, paying for them almost 1 billion euros). In this sense, the insights serve as a platform to extend the study to unlisted companies that have also made severe AI violations.

The CARs methodology has proven to be valid to serve as a dependent variable to further explore the behavior of companies regarding AI ethical misconduct. The results of this study contribute greatly to the understanding of the impact of current GDPR regulation on AI practices in the European Union. In fact, our study underlines the importance of further improvements to E.U. regulation on AI after analyzing the lessons learned; it also contributes to the field of AI ethics in the European Union.

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The present study helps explain how some firms and their shareholders become immune to financial economic sanctions and turn into multi-violators who are not affected by the amount of the fines imposed on them, developing “a fine is a price” (Gneezy & Rustichini, 2000) behavior, especially for subsidiaries of parent companies.

Our study underlines the importance of further developing the E.U. regulatiosn on AI after analyzing the lessons learned. This study contributes to the field of AI ethics in the European Union.

However, there are some limitations that might lead to new avenues for research: first, although the data has at least 10 observations per independent variable, the sample is smaller than datasets used in other studies (Borelli-Kjaer et al., 2021); in addition, this limitation of the data set did not allow for the inclusion of additional hypotheses in the study, so further research on the topic should be conducted that would include a larger sample, which would allow for a more in-depth analysis. In addition, the sample is mixed, it covers multiple industries, and it would be interesting to make a sectorial analysis of the different sectors in terms of aspects of ethical behavior. Also, this article has focused on large listed companies, but non-listed SMEs are in the same digital transformation process (Skare et al., 2023) and are having the same kind of ethical issues (CMS.Law, 2023). Finally, future studies should compare the analysis with other well-developed AI regulation apart from Europe, such as the United States or China, to look to see if the results are similar or if they differ.

The findings of this study make a great contribution in helping governments prevent the misuses of AI and its potentially disastrous consequences at both the individual and societal levels (Duan et al., 2019) by understanding both the stakeholder and the company’s behavior. We are at a turning point in history where governments can head towards a more ethical and efficient global legislated environment.

As a closing remark, the results of this study support the voices claiming that the “SolarWinds Moment” of AI, which will burst the bubble, is about to occur due to the potential scandals of unethical behavior in which companies and managers may be involved (Barlow, 2022). They also make it clear that it is necessary to study why such scandals have not yet occurred, due to the damage that certain companies do to society with this type of unethical behavior with AI because, to answer the question in the title of our article, regulation is insufficient.

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