Essays on stakeholder relations and firm value

Barkó, Tamás

Publication date:
2018

Document Version
Publisher's PDF, also known as Version of record

Essays on Stakeholder Relations and Firm Value

Essays on Stakeholder Relations and Firm Value

Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. E.H.L. Aarts, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Ruth First zaal van de Universiteit op maandag 26 februari 2018 om 10.00 uur door

Tamás Barkó

geboren te Debrecen, Hongarije.

Promotores:

prof. dr. L.D.R. Renneboog

prof. dr. J.J.A.G. Driessen

Overige commissieleden:

dr. L.T.M. Baele

dr. P. Cziraki

dr. F. Braggion

dr. P.C. de Goeij

Acknowledgments

The cover page of this dissertation has only my name on it, but there are many people who supported me along the way, professionally or otherwise. This section is dedicated to them.

First and foremost, my utmost gratitude goes to my advisors, Luc and Joost. I am both privileged and honored that you have taken me as your doctoral student. Your guidance shaped the way I think, how I approach problems, and how I navigate my career. Thank you, Luc, for your support from day one. Thank you for arranging scholarships, research projects and visits. Thank you for teaching me about not only corporate finance but also art, diamonds and music. Thank you for introducing me to Servaes van der Meulen. Thank you for your wisdom and precious advice on personal matters. Thank you, Luc, for guiding me through my doctoral studies. And thank you, Joost, for keeping a watchful eye on me despite your duties as Head of Department, and always stepping in at the right time. Thank you both for... everything!

I would like to thank Fabio, Lieven, Peter and Péter for accepting to be on my dissertation committee. I truly appreciate the time and effort you put into reading my thesis and providing feedback. Your suggestions are invaluable and greatly improved all papers. I would also like to thank my co-author, Martijn. I learned a lot from our collaboration about approaching empirical work, structuring and writing academic papers, and accepting and incorporating feedback.

It has been an honor to work at the Department of Finance. The faculty is a collection of great minds who are also fun people. I thank David, Jean, Juan Carlos, Michel, Olivier, Paul, and the late Jos for their collaboration and support in teaching. The brown bag seminar series has always been a great opportunity to "test drive" my presentations. I am particularly grateful to Alberto, Frank and Rik for their constructive criticism. I thank Oliver for our numerous discussions, especially around the job market. Last but not least, I would like to thank Helma, Loes and Marie-Cecile for always arranging everything, even on the shortest notice.

I thank the faculty at the International Center for Finance at the Yale School of Management for hosting me for a research visit in the second year of my studies. I am thankful to William Goetzmann and Leigh Ann Clark for arranging my stay and mentoring me. My research visit would not have been possible without financial support from CentER Graduate School.

My appreciation also goes to my fellow Ph.D. students and friends. I am thankful to Ferenc, Gábor and Mánuel for always being there for me. I thank João for our midnight talks while overlooking the sleeping city, and for always showing a different perspective on life. Andreas always provided level-headed advice on coding and personal matters as well. I thank my favorite Russian couple, Elena and Dima, for nice city trips around the Netherlands and the crazy fun at Kermis. I am happy to have shared offices with Yaping, Ran, and Matjaž, who also agreed not to increase the temperature over 24°C. I am grateful to Bálint, Camille, Diana, Emanuele, Hao, Katya, Maaike, Marshall, Ricardo, and many others for making everyday life more fun.

I would like to thank Ernst for hiring me at the University of Mannheim and providing a nourishing environment to finish the final chapter of this dissertation.

My special thanks go to Péter. He encouraged me to pursue my doctoral studies and also provided tremendous help throughout the process. Thank you for explaining how academia works, for giving advice on my projects, for training me for the job market, but especially for supporting me with your friendship.

If I want to be honest with myself, I have to admit that this dissertation would not exist without Zorka. Thank you, Zorka, for loving me and being there for me through thick and thin. Thank you for always being there for me when I felt down. Thank you for understanding me. Thank you for making sense of things. Even thank you for micromanaging and supervising me. Thank you for YOU!

Last but not least, I would like to thank my family who understood and supported my decision to pursue a career abroad.

Tamas Barko

Mannheim, January 2018

Contents

Introduction

This doctoral dissertation consists of three chapters on stakeholder relationships and firm value. Extending on the grounds of neoclassical economics, stakeholder theory posits that it is not only the interest of shareholders that matters but that of all entities who deal with the corporation, directly or indirectly. The aim of this dissertation is to examine the interaction between the corporation and its various stakeholders.

Corporate scandals, like Enron, have shown the world that it is not enough to produce a positive bottom line on the income statement. Volkswagen is the poster child of firms that cover up their tracks to beat (or try beating) their competition. Apple is guilty of fixing prices for eBooks. The way corporations interact with their customers and investors is of first order. This dissertation examines how good practices lead to better valuation, how shenanigans lead to value dips, and how "bad guys" can be turned into model corporations.

In Chapter 1, I analyze credit default swaps of 658 obligors over the period 2002-2011 and along the dimensions of corporate social responsibility (CSR). I find that companies with good CSR levels have lower credit risk. Calculating credit default swap (CDS) spreads using a Merton-type structural model, I show that high CSR firms have lower implied CDS spreads and pricing errors. I exploit the variations in equity returns and credit spreads to construct capital structure arbitrage positions. I find that average returns are close to zero, albeit with large upside potential. Analyzing arbitrage returns along CSR, I document that trades on high CSR firms' assets are less risky and risk-adjusted returns are significantly higher than trades in the low CSR segment. My results suggest that incorporating CSR measures into the arbitrage strategy mitigates risk, especially for more aggressive strategies.

In Chapter 2, we use a detailed, proprietary dataset to shed light on the mechanisms and outcomes of investor activism promoting better environmental, social and governance (ESG) practices.[1] Our panel covers the years 2005-2014 and includes 660 targeted

[1]This chapter is based on joint work with Martijn Cremers and Luc Renneboog.

companies globally. Companies with higher market share, more analyst coverage, higher stock returns and greater liquidity are more likely to be engaged. Engagements reveal information, as ESG ratings are significantly adjusted for engaged firms. Activism is more likely to succeed for companies with a good ESG track record and following previous successful cases. Higher ownership concentration and short-term growth lower the likelihood of a favorable outcome. Successful engagements are followed by substantial increases in sales growth, though no significant changes in profitability. Buy-and-hold returns are small but significantly positive for engaged firms over the period up to about 12 months after the completion of the engagement and the stocks of successful engagements outperform those of unsuccessfully engaged firms. Excess cumulative abnormal returns (with four-factor risk-adjustment and relative to a matched sample) show that targeted firms do better than non-engaged firms by 2.7% over the over the 6-month period after the engagement file is closed. Targeting firms in the lowest (ex ante) ESG quartile pays off in the sense that these firms outperform their matched peers by 7.5% in the year after the activist ends the engagement.

In Chapter 3, I use information on class action lawsuits in the period 1996-2016 covering 1,249 cases and 888 individual firms to analyze the determinants of allegations and economic outcomes. Firms are more likely to be indicted if they are smaller, have a high level of investment, and have a bad stock market performance. Markets react negatively to lawsuits: firms may lose up to $1.3 billion or 23% of their market value around the start of the litigation procedure. This effect is more pronounced for firms that end up paying a settlement. I find no reversal in returns in the period after the filing, at significant court events or throughout the entire court procedure. Cross-sectional results indicate that firms with more resources to spend on litigation experience a smaller market reaction. Indicted firms significantly readjust their operations and their investor base changes as well. Finally, I find that a trading strategy based on fraud allegations yields a significant four-factor alpha of 3.7% per year.

Chapter 1

The Arbitrage Benefits of Corporate Social Responsibility

1.1. Introduction

The idea of corporate social responsibility (CSR) has become an important aspect of business since the 1990s. Social responsibility, also called social or ethical consciousness and sustainability, involves business practices and operations that promote environmental consciousness, product safety, labor relations and human rights. Social responsibility attracted the attention of firm managers and investors alike (for example, Renneboog, Ter Horst, and C. Zhang (2008a) or Soyka and Bateman (2012)).

Socially responsible investments drew considerable academic interest over the past decade. Most of the recent studies focus on the returns of socially responsible mutual funds (for a thorough review on the socially responsible fund literature see Barko and Renneboog (2016)). A common finding of studies conducted at the fund level is that, in general, socially responsible funds do not outperform their conventional counterparts but yield similar alphas over long holding periods. Looking at the individual firm level, Edmans (2011), and El Ghoul et al. (2011) find that companies with good employee relations earned positive alphas compared to matched pairs, and experienced more positive earnings surprises and announcement returns. Along a different dimension, Hong and Kacperczyk (2009) discover that sin stocks, companies that participate in the production

I would like to thank Luc Renneboog for his guidance and encouragement. I also thank Lieven Baele, Fabio Braggion, Archie Carroll, Peter Cziraki, Joost Driessen, Peter de Goeij, and Zorka Simon, as well as participants at the "Future of CSR" doctoral workshop of Humboldt University for helpful comments. I would like to thank Björn Imbierowicz for providing me with their CDS identifiers so that I have the broadest coverage possible.

and distribution of tobacco, alcohol, firearms and gambling, face higher ex ante expected returns, consequently their cost of capital is larger. Recent evidence by Lins, Servaes, and Tamayo (2017) shows that high CSR firms have higher returns and lower volatility in periods of economic downturn. Investigating the credit market, Goss and Roberts (2011), and H. Chen, Kacperczyk, and Ortiz-Molina (2012) report that firms with a good CSR track record have cheaper access to debt financing be it bank loans or publicly traded debt. Amiraslani et al. (2017) report that in the recent financial crisis high CSR firms could refinance their debt at lower rates and had better credit ratings than their lower rated counterparts.

In this paper, I try to answer the question whether the integration of a firm's equity and credit risk is stronger if the firm has a good environmental, social and governance (ESG) track record. As Kapadia and Pu (2012) show, short-horizon discrepancies in the pricing between a firm's equity and debt are common. However, in light of the theoretical predictions of Hong, Kubik, and Scheinkman (2012), and the empirical findings of Lins et al. (2017) and Amiraslani et al. (2017), I expect that these idiosyncratic divergences are less common for high CSR firms since they are more transparent. Consequently, I predict that firms with high levels of CSR have lower credit spreads, and their credit and equity risks are more integrated. I indeed find that firms with higher CSR have significantly lower credit risk, measured by their credit default swap (CDS) spreads. Furthermore, calculating the implied spread from a structural model is significantly closer to its market counterpart if a firm has high ESG scores.

If credit and equity markets are perfectly integrated, any distortions to the debt-equity relationship could be traded away by sophisticated arbitrageurs, such as hedge funds. However, as Kapadia and Pu (2012) show, short-horizon discrepancies in the credit-equity risk space are common and anomalous, and can be related to idiosyncratic risk. Additionally, market frictions, for instance margins, haircuts and other constraints, might prevent investment professionals from trading on these discrepancies, as the limits of arbitrage literature describes (Ashcraft, Gârleanu, and Pedersen, 2011; Gorton and Metrick, 2009; Gromb and Vayanos, 2002; J. Liu, Longstaff, and Mandell, 2006; Shleifer and Vishny, 1997). Arbitrage capital might also move too slowly to put an end to such opportunities, due to capital constraints or agency problems of delegated asset management, as in Mitchell, Pedersen, and Pulvino (2007); and Duffie (2010). While I cannot rule out that the observed differences in market and implied CDS spreads are related to the limits of arbitrage or slow moving capital, I expect that firms with higher transparency exhibit fewer discrepancies.[1]

To address the question, whether CSR affects the mispricing of equity and credit risk, I

[1]An implicit assumption here is that the pricing model that I employ is the correct one.

construct arbitrage portfolios combining equity and credit protection (see Byström (2006), Yu (2006) or Duarte, Longstaff, and Yu (2007) on this arbitrage strategy). I implement the techniques of capital structure arbitrage to extract information about the mispricing of debt and equity. To account for mispricing stemming from the limits of arbitrage, I implement trading rules that allow a base level of mispricing and only initiate a position once mispricing is unusually high. Establishing a hurdle for entering an arbitrage position also ensures that transaction costs are implicitly accounted for, as the profit potential has to be high enough to counter transaction costs. I expect that divergence from the baseline relationship between equity and credit risk represents a fundamental change for high CSR firms, which is not captured by my structural model. On the other hand, low CSR firms that have a low level of transparency are expected to have temporary discrepancies that revert back to their normal level. I do find that trades initiated on the assets of low CSR firms achieve convergence, i.e. the abnormal pricing error disappears, significantly more often than in case of high CSR firms. I also find that trading on episodes of idiosyncratic divergence is significantly less risky for high CSR firms.

1.2. Capital structure arbitrage

Capital structure arbitrage (CSA) is a relatively new concept that received attention from investment practitioners as the CDS market expanded in the early 2000s (Currie and Morris, 2002; Duarte et al., 2007). The essence of CSA is to hedge a position in equity risk with credit risk or vice versa. The arbitrageur uses common stocks and CDSs to create an arbitrage position. The idea of hedging equity and credit risk is in line with the concept outlined in the seminal paper of Merton (1974), that equity constitutes a call option on company assets. The theory of contingent claims states that since equity and debt have cash flow rights over the same set of cash flows, their risk should be related.

The extant empirical evidence on capital structure arbitrage indicates that the strategy is not a straightforward zero cost arbitrage. A general finding is that CSA is quite risky at the individual stock level, for example, in Duarte et al. (2007), and Bajlum and Larsen (2008), but a portfolio approach yields significant positive returns, see for example Yu (2006) or Svec and Reeves (2011). Cserna and Imbierowicz (2008), and Yu (2006) document that positions taken on speculative grade obligors yield higher returns than those taken on investment grade firms.

The advantage of an analysis based on capital structure arbitrage lies in the nature of the traded assets. While the stock market is very nimble in incorporating new information into equity prices, the same does not hold for the fixed income market. In fact, bonds often trade at a discount due to liquidity issues and tax considerations and thus reflect factors other than credit risk (Berndt and Obreja, 2010; Longstaff, Mithal, and Neis, 2005). In contrast, in the past 20 years the CDS market has grown exponentially, and has become liquid and efficient in the last 15 years (Cserna and Imbierowicz, 2008; Yu, 2006), single-name corporate credit default swaps constituting the most liquid segment of the market. According to IHS Markit (formerly Markit Group), the 1,000 most liquid CDS contracts account for over $1 trillion in notional amount and these obligors have, on average, 2,300 CDS contracts written on them. The market performed well following the turmoil caused by the subprime mortgage and during the subsequent financial and economic crises, as market participants correctly priced changing default probabilities (Stulz, 2010). The liquidity, efficiency and maturity of the CDS market implies that it is ahead of the corporate bond market in the information discovery process (Blanco, Brennan, and Marsh, 2005; Byström, 2006). Hilscher, Pollet, and Wilson (2015) test where most informed trades are executed and find that the equity market leads the CDS market. Taken together, these imply that capital structure arbitrage is indeed based on trading the underlying risk of the company.

The process of taking an arbitrage position evolves as follows. The agent determines the CDS spread using a certain pricing model. If the implied spread (c') differs significantly from the market spread (c), the agent sees an arbitrage opportunity and enters the market. Several possibilities arise here. Considering the pricing equation of CDS contracts in a general form, we have that $c' = f(S, \sigma_S, \theta)$, where θ is a vector of parameters other than equity price and volatility. Since volatility cannot be observed, the market spread implies that $c = f(S, \sigma_S^{imp}, \theta)$ has to hold for some implied volatility σ_S^{imp}. If $c > c'$, it might be that implied volatility is too high and will return to a lower level, resulting in a declining spread, in which case the agent should sell credit derivatives and sell equity to delta hedge the position. Alternatively, it might be that the CDS is priced correctly and equity volatility will increase to its implied level, leading the arbitrageur to sell equity and use CDS contracts to hedge the position. As shown by Hilscher et al. (2015) the equity market leads in the information discovery process, so in the subsequent analysis I always assume that CDS spreads should adjust to their model-implied levels. Consequently, I construct long and short positions in CDS contracts and delta hedge them by taking a similar position in equity.

In order to summarize the mechanics and risk profiles of the strategy, consider a position that goes long in the CDS contract and long in equity to hedge the position with respect to changes in equity prices. The following outcomes are possible

1. If both the spread and the equity price increase, convergence occurs and the arbitrageur makes a profit.

2. If the spread increases but the equity price declines, the gain from the CDS position is offset by the loss from the equity position.
3. If the spread decreases and the equity price increases, then returns offset each other.
4. If both the spread and the equity price decrease, the arbitrageur makes a loss.

To determine the implied CDS spread, I use the CreditGrades model by Finger et al. (2002).[2] This model has two main advantages. First, its closed-form solution is computationally convenient, second, it relies on observable parameters for the most part. The inputs are equity price and volatility, debt-per-share, and the risk-free rate. The CreditGrades Technical Document provides several suggestions for the calibration of the model with respect to its other parameters. Specifically, I assume a global ($\bar{L}$) recovery rate of 50% and a corresponding uncertainty (λ) of 30%. These figures rely on credit risk studies conducted by the RiskMetrics group, and are also used in the academic literature, for example, Yu (2006) or Duarte et al. (2007). For the asset-specific recovery rate (R), I use three different measures in my estimations, 25%, 50% and 75%. I calculate debt-per-share as a ratio of total liabilities and outstanding common stocks. Total liabilities are lagged one month in order to avoid any look-ahead bias.

The final input of the CreditGrades model is stock return volatility. In the original calibration of the model, Finger et al. (2002) approximate volatility by a 1000-day rolling window standard deviation. This parameter is the most widely disputed part of the model, several authors propose alternatives to the original volatility estimation. The literature has two main approaches to arrive at a superior volatility estimate. One branch suggests models that provide a better fit between stylized facts and estimated volatilities. For example, Ozeki et al. (2011), B. Y. Zhang, H. Zhou, and Zhu (2009), and C. Zhou (2001) introduce jumps into the volatility process. The other strand of the literature suggests the use of forward looking measures. Among others, Cao, Yu, and Zhong (2011), and Cremers, Driessen, and Maenhout (2008a) substitute historical volatility with its option-implied counterpart. Finally, Cremers et al. (2008b) show that combining forward-looking volatility with jumps has a superior performance in explaining credit spreads. Nevertheless, no volatility specification to date has been able to perfectly explain either levels or changes in credit spreads. Due to data availability, in this paper, I use exponentially weighted moving average (EWMA) estimates of volatility with a decay parameter of 0.95, as in Ericsson, Jacobs, and Oviedo (2009). EWMA allows considerably better volatility estimates than the 1000-day rolling window that result in improved pricing performance.[3]

[2] For a detailed overview of the CreditGrades model, see Appedix 1.A.

[3] I also estimate volatility using a GARCH(1,1) specification and a 60-day rolling window standard deviation that yield qualitatively similar results to EWMA. I discuss the various volatility specifications in Appendix 1.B.

While the CreditGrades model is appealing due to its simplicity and relative widespread use in the literature, there are several alternatives. These include the multifactor model of R.-R. Chen et al. (2008), the no-arbitrage pricing approach of Doshi et al. (2013) and the endogenous default specification of Leland and Toft (1996). However, as Yu (2006) points out, the actual choice of one structural model over the other is not of first order importance, as no model produces consistently better implied spreads on a day-to-day basis.

Structural models of credit risk are easy to implement, however, as pointed out by Collin-Dufresne, Goldstein, and J. S. Martin (2001), they perform poorly in pricing corporate debt. Schaefer and Strebulaev (2008) obtain similar results, but they also show that hedging positions on corporate bonds derived from a structural model are accurate. This suggests that structural models price credit risk correctly, and the poor performance in pricing bonds is due to other factors' effect on debt price. Studies on credit spread and CDS pricing confirm this latter result: Cremers et al. (2008a), Ericsson et al. (2009), Ericsson, Reneby, and H. Wang (2015), and Houweling and Vorst (2005) all come to the conclusion that structural models are appropriate for CDS or credit risk pricing.

In practice, the magnitude of mispricing is an important factor in the arbitrageur's decision to engage in an arbitrage position. A position is taken if one of the following relations holds: $c_t \leq (1+\alpha)c'_t$ or $c_t \geq (1+\alpha)c'_t$, where α is the trigger level, a non-trivial parameter. In my trading strategies, I use different levels for α. Specifically, I set up three different triggers based on the average pricing error and its standard deviation. I identify a selling trigger, if the error, defined as $c' - c$, is 1, 1.5 and 2 standard deviations below its mean level, where the mean is defined over a preceding period of 125 or 250 trading days. Similarly, I define a buying trigger if the error is significantly above its mean. The equity position, δ is determined by differentiating the pricing equation, $\frac{\partial c}{\partial S} = \delta$, which I obtain by higher order numerical differentiation, using the five point method for the first derivative.

I assume that an arbitrageur can invest \$1 that is on a margin account and I neglect transaction costs. Even though I do not incorporate transaction costs explicitly, the trading trigger can be considered an implicit transaction cost condition. That is, in expectation, profits should be large enough to initiate an arbitrage position. Once taken, a position is held until convergence occurs or a pre-specified holding period ends. The holding period is defined in trading days, either 20, 60 or 125 or 1, 3 and 6 months, respectively. I define convergence as either reaching a pricing error of zero, or returning to the initial level of the error. In addition, I also introduce a set of stop-loss trade out rules. A position is liquidated if returns drop below 5%, 10% or 100%.

1.3. Data and descriptive statistics

I collect senior debt and single-name CDS spreads for all non-financial companies around the globe covering the period 2002-2011. I restrict my attention to 5-year maturity CDS contracts as these constitute the most liquid segment of the market (Ericsson et al., 2009). I download bid, ask and closing spreads from Bloomberg for more than 1,800 obligors. I merge the spread data with quarterly balance sheet information from Compustat, and with share price and adjusted return information from Datastream. This yields a total of 658 obligors from 25 countries operating in 9 different industries.

I download 3-month government bill rates from Datastream as a proxy for the short-term risk-free rate. I also access the website of the Federal Reserve Bank of St. Louis to download 5- and 10-year constant maturity treasury indices; and yields on BofA Merrill Lynch BBB US; European, Middle Eastern and African (EMEA); Asian; and Latin American corporate bonds. I obtain the Fama-French (Fama and French, 2015) factor data from the website of Kenneth French.

I use credit rating information from Standard & Poor's, accessed through Datastream. I collect CSR scores from the Asset4 (Datastream) database. Asset4 constructs CSR scores by identifying best practices, and benchmark firms to country or industry standards. The agency rates companies in terms of corporate governance practices, social and environmental consciousness, and economic considerations, constituting the four pillars of corporate social responsibility. Environmental and corporate governance measures are intuitively defined. Social consciousness, among others, include employee relations, charitable giving and the respect of human rights. Economic considerations encompass product safety, customer relations and the production of sin products.[4]

Table 1.1 provides a summary of the main variables. Panel A reports equity and credit characteristics broken down by environmental, social and governance (ESG) quartiles. The mean daily stock return is about 0.04% and it does not differ across ESG quartiles. Stock return volatility on the other hand is significantly lower for high CSR firms, and the overall mean is 2% per day. The sample mean of CDS spreads is 130 bps. There is a negative correlation between the level of CSR and credit risk. Firms in the top ESG quartile have, on average, 44% lower spreads than firms in the bottom quartile. Interestingly, credit ratings do not differ across ESG quartiles, with the average firm having a BBB rating, however, this could be an artifact of relatively limited availability

[4]Sin products are defined as controversial products that are constant targets of social and political debate, such as gambling, pornography or tobacco.

of credit ratings.[5]

Stock returns are straightforward to compute, however, calculating CDS returns is a bit more involved, as one has to account for accrued premium payments. In computing CDS returns, I follow Bongaerts, De Jong, and Driessen (2011) who derive excess returns for CDS contracts, accounting for transaction costs. CDS returns can be expressed as

$$R_{k,t} - c_{k,t} = -\frac{1}{4}\left(\Delta CDS_{k,t} + \frac{1}{2}s_{k,t-\Delta t} + \frac{1}{2}s_{k,t}\right)\sum_{j=1}^{T-t} B_t(t+j)\mathbb{Q}_{k,t}^{SV}(t+j)$$
$$+ \frac{\Delta t}{4}\left(CDS_{k,t-\Delta t} - \frac{1}{2}s_{k,t-\Delta t}\right), \tag{1.1}$$

where $CDS_{k,t}$ is the market spread at time t for obligor k and $\Delta CDS_{k,t} = CDS_{k,t} - CDS_{k,t-\Delta t}$. $s_{k,t}$ denotes the bid-ask spread, $\mathbb{Q}$ is the risk-neutral survival probability up to time $t+j$, and $B_t(t+j)$ is the price of a risk-free zero-coupon bond maturing at $(t+j)$.[6] Equation 1.1 assumes an investor who sells credit protection at time $t - \Delta t$ at a spread of $CDS_{k,t-\Delta t} - \frac{1}{2}s_{k,t-\Delta t}$, paid in quarterly periods. The next day, at time t, the investor buys an offsetting contract at $CDS_{k,t} + \frac{1}{2}s_{k,t}$. The value of the resulting cash flows is the value of a portfolio of defaultable zero-coupon bonds.

Panel A of Table 1.1 reports that CDS returns are, on average, negative in the sample. However, this is not surprising as my sample includes the recent financial crisis, where the price of credit protection was increasing. Looking at the breakdown by ESG quartiles, the table reveals that while CDS returns are negative for all subsamples, the return in the highest quartile is only a half of that in the lowest quartile. Not all firms have credit protection traded on their debt throughout the entire sample. Figure 1.1 shows the number of firms with CDS contract over time. The sample starts with about 50 obligors in 2002, which number quickly rises, and by 2003 there are over 200 firms in the sample.

Panel B of the same table provides a breakdown by credit ratings. As with ESG ratings, stock returns are not different between various credit quality groups. The same holds for volatility that shows a statistically significant difference, however, the economic magnitude is negligible. CDS spreads are also only marginally different between the highest and lowest rated firms, and the relationship is non-monotonic, with the second quartile exhibiting the highest spreads. CDS returns tell a similar story across credit rating quartiles. Naturally, credit ratings themselves are different between quartiles, the worst average ratings being BB and the highest A+.

[5] The table reports numeric values for credit rating notches. Appendix 1.C provides the link between numeric and categorical ratings.

[6] I estimate risk-neutral probabilities using the CreditGrades model.

Panel C of Table 1.1 provides an overview of CSR scores. As Asset4 rates firms in terms of corporate social responsibility on a scale 0-100, the average firm is about in the middle. The panel also provides a breakdown in terms of total CSR score quartiles. Firms appear to have a balanced CSR profile as the scores for the 4 pillars of Asset4 line up with the overall score.

1.4. Results

1.4.1. CDS pricing

I estimate the CreditGrades model using three different recovery rates. I use 50% as in the original specification of the model, as well as a pessimistic (25%) and an optimistic (75%) recovery rate. Table 1.2 reports implied spreads. Panel A shows that the spreads differ across the three recovery rates. As expected, the pessimistic scenario yields the highest spread with 240 bps on average, while the middle and optimistic rates are 160 and 80 bps, respectively. Panel A of the table also gives a breakdown of implied spreads by ESG quartiles. Spreads are monotonically decreasing across ESG quartiles, irrespective of the recovery rate. The difference in mean spreads between the highest and lowest ESG quartile is 130 bps for the 25% recovery rate, and 40 bps for the optimistic scenario. Panel B reveals a different picture for credit ratings. While there is a statistically significant difference between the spreads of BB and A+ obligors, it is at most 10 bps. Additionally, implied spreads are the highest for the second quartile of credit ratings across all recovery rate levels.

Turning to pricing errors, Table 1.3 reports that the recovery rate with the best fit relative to market spreads is 50%. The mean pricing error for the middle recovery rate is 30 bps, while for the pessimistic and optimistic measures, erros are 110 bps and -50bps, respectively. Panel A shows that pricing errors are significantly smaller for firms with the best ESG practices, compared to the lowest quartile. Panel B provides a similar breakdown for credit ratings, however, there is no discernible difference in pricing errors across credit quality buckets at the 50% recovery rate. The lowest and highest credit rating groups exhibit a weak statistical significance between highest and lowest rated firms, however, the actual difference is less than 5 bps.

Figure 1.2 shows the evolution of the mean implied spread over time. The top panel of the figure shows that the implied spread is influenced strongly by spikes in volatility. The stock market downturn of 2002 and the financial crisis following the subprime mortgage crisis are both high volatility periods and corresponding implied spreads are higher than their market counterparts. This is in line with Alexander and Kaeck (2008) who show that CDS spread levels are sensitive to volatility regimes. The middle panel of the figure shows that this pattern holds for all recovery rates, with the pessimistic recovery rate consistently producing the highest implied spreads. Turning to the bottom part of the figure, the pricing errors also underscore the model's reliance on stock return volatility. Pricing errors are mostly positive for the conservative and middle recovery rates, the mean being 30 bps and 110 bps, respectively. The errors implied by the optimistic recovery rate fluctuate around 0, while the mean is -40 bps.

1.4.2. Arbitrage

After obtaining implied CDS spreads from the CreditGrades model, I turn to identifying capital structure arbitrage opportunities. Determining the trading trigger is a non-trivial part of the strategy and may differ between arbitrageurs. I examine a number of strategies. Since the pricing error is never exactly zero, I set up thresholds for significant errors. Each trading day, I compare the daily pricing error of an asset with its mean pricing error. I calculate the mean pricing error for each day as a rolling window average over the preceding 125 or 250 trading days (6 months or 1 year). I compare the daily pricing error with its mean and mark a trading trigger when the difference is large enough. I use a hurdle of either 1, 1.5 or 2 standard deviations relative to the mean. If there is a trading trigger, I use the average pricing error on that day as a reference point. If the daily pricing error returns to this reference point over the holding period of the arbitrage position, convergence occurs and I close the position. I calculate arbitrage returns for 20, 60 and 125-day holding periods. I also introduce a stop-loss rule to liquidate portfolios that generate unsustainable losses. I liquidate positions whenever their loss reaches 5%, 10% or 100%. As implied spreads are sensitive to the recovery rate, I calculate arbitrage returns for all three rates. Taken together, I calculate arbitrage returns for 3 trigger levels, 2 reference periods, 3 holding periods, 3 recovery rates, and 3 stop-loss rules, resulting in a total of 162 strategies.

Table 1.4 reports arbitrage returns for all strategies described. The table has three panels, with Panel A reporting returns for the 5% stop-loss rule, and Panel B and C for 10% and 100%, respectively. Each panel has three groups of columns corresponding to the pessimistic, middle and optimistic recovery rates. For each recovery rate, the table reports the three holding periods (columns) and withing holding periods the three hurdle rates for the two reference points. Mean returns are rather small in magnitude, never exceeding 1%. The largest mean return is 0.25% for the pessimistic recovery rate, where the position is initiated according to the 2-σ hurdle relative to the preceding 250 days, and held over 125 days. There is a clear pattern emerging from the table. Irrespective of the recovery rate and the stop-loss rule, returns are higher (or less negative) if the trading trigger is more conservative. That is, across all trades, the 2-σ hurdle with a reference of 250 days yields the highest returns on average.

In what follows, I focus on strategies with a 50% recovery rate, a 10% stop-loss rule, and with a reference period of 250 days.[7] I first calculate risk-adjusted returns at the trade level. I regress daily arbitrage returns on common equity and credit risk factors. Specifically, following Duarte et al. (2007), I run regressions of the following form

$$\begin{aligned} r_{t,i} =& \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} CMA_t + \beta_{5,i} RMW_t + \beta_{6,i} GOV(5)_t \\ &+ \beta_{7,i} GOV(10)_t + \beta_{8,i}\, US\text{-}BBB_t + \beta_{9,i} EMEA_t + \beta_{10,i} Asia_t + \beta_{11,i} Lat.Am._t + \epsilon_{t,i}, \end{aligned} \tag{1.2}$$

where MKT, SMB, HML, CMA and RMW are the Fama-French 5-factor portfolio returns (Fama and French, 2015). $GOV(5)$ and $GOV(10)$ are the constant maturity US treasury yields for 5 and 10 years, respectively. *US-BBB*, $EMEA$, *Asia* and *Lat.Am.* are long-term corporate bond yields for US BBB rated; European, Middle Eastern and African; Asian; and Latin American firms, respectively.

The regression results are summarized in Figure 1.3. The figure reveals that arbitrage returns have little to no exposure to the Fama-French 5 factors with average betas in the range of -0.006 and 0.001. While betas of fixed-income portfolios are also relatively small, they are a magnitude larger than Fama-French betas. Arbitrage returns, on average, load positively on 10-year US treasury yields and Latin American corporate bonds, and negatively on 5-year treasuries, and other domiciled corporate bonds. The mean of arbitrage alphas is positive and significant at 40 bps.

Next, I turn to the detailed analysis of arbitrage trades. Table 1.5 shows arbitrage returns by ESG quartiles. The table shows a mixed picture in terms of returns over ESG quartiles. There is no clear pattern moving from the lowest ESG quartile to the highest. However, two observations arise from the table. First, returns are the highest (least negative) across all triggers and trading periods for the lowest ESG quartile. Second, returns have the lowest variance in the highest ESG quartile. In unreported results I find that there are somewhat fewer trades initiated in the top ESG quartile (48,696 vs. 49,216 for the 1-σ trading trigger).The table also reveals that more conservative strategies are have higher (less negative) returns on average, however, their upside potential is also lower. As an example, the trading strategy with a 1-σ trigger and a holding period of 125 days has a

[7] I find qualitatively similar results for all other strategies.

mean return of -0.39% and maximum return of 60.65%, while its 2-σ counterpart exhibits -0.08% and 52.21%, respectively.

Table 1.6 extends the analysis of arbitrage returns by showing details on trade characteristics. The table shows that in shorter holding periods the proportion of converging trades is relatively low at 12.4-17.9%. Extending the holding period to 3 or 6 months results in a surge of convergence, up to about 45% and 60%, respectively. Moving towards more conservative trading triggers increases the proportion of long positions. The stop-loss rule of 10% is not binding for most trades, with the highest amount of stop-loss trade-outs being 0.9% across all strategies. The table exposes that trades in the highest ESG quartiles are held until the end of the predefined holding period in significantly more instances than lower quartiles across all strategies. The fact that the pricing error is, on average, significantly lower for high CSR firms, but convergence occurs for significantly fewer trades, suggests that shifts in the daily pricing error are permanent even if these shifts are 1 or 2-σ away from the previous mean.

Finally, I turn to the portfolio analysis of arbitrage returns. I construct equally weighted portfolios of daily arbitrage returns for all trades and by ESG quartiles. Figure 1.4 shows portfolio returns over time for the full sample, as well as the top and bottom ESG quartiles. The figure breaks down returns for the three trading triggers and holding periods. The figure shows that returns are indiscernible between the top and bottom ESG quartile for the largest part of the sample. However, the top quartile portfolio exhibits considerably lower variation during the recent financial crisis. I also regress these portfolio returns on the Fama-French 5-factor and fixed-income portfolios. I estimate Equation 1.2 for a single portfolio. The results are displayed in Table 1.7. To conserve space, I suppress all coefficients and focus only on alphas. The table reveals that risk-adjusted alphas are negative, ranging from -1 bps to -6 bps. The table also reports alphas for the lowest and highest ESG quartiles and the corresponding test for their equality. The results indicate that trades on higher CSR firms have significantly less negative alphas for the 1 and 1.5-σ trading triggers. However, the difference diminishes for more conservative strategies. Taken together, the results indicate that incorporating CSR into the arbitrage strategy and focusing on high ESG firms produces less risky and volatile portfolio returns.

1.5. Conclusion

This study investigates whether the observed link between corporate social responsibility and equity or credit markets can be translated into simultaneously trading on the two markets by applying the techniques of capital structure arbitrage. Capital structure arbitrage is a unifying framework, where I exploit variations in stock returns and credit spreads to identify profitable trades. I employ a Merton-type credit risk model to arrive at implied CDS spreads and subsequently initiate trades.

I find that observable and model implied spreads of high CSR firms are significantly lower than their lower rated counterparts. Additionally, I find that the pricing error, the difference between the model-implied and the market spread, is significantly lower for firms with a good ESG track record.

My results on capital structure arbitrage show that there are fewer trades initiated on high CSR firms. These arbitrage positions are considerably less risky than their low CSR counterparts, and their downside risk is limited. When I look at risk-adjusted returns, I find that high CSR trades have 2-3 times higher alphas than the low ones. This effect is particularly strong for less conservative trading strategies. Taken together, my results indicate that incorporating CSR into capital structure arbitrage has a limiting effect on the risk involved.

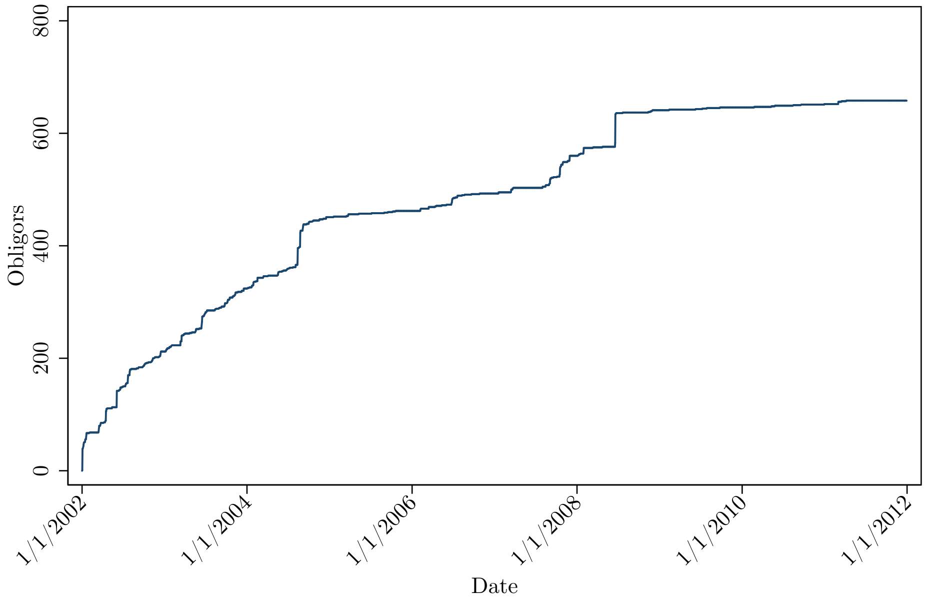


Figure 1.1 Number of CDS contracts

This figure shows the cumulative number of obligors in the sample over the period 2002-2011.

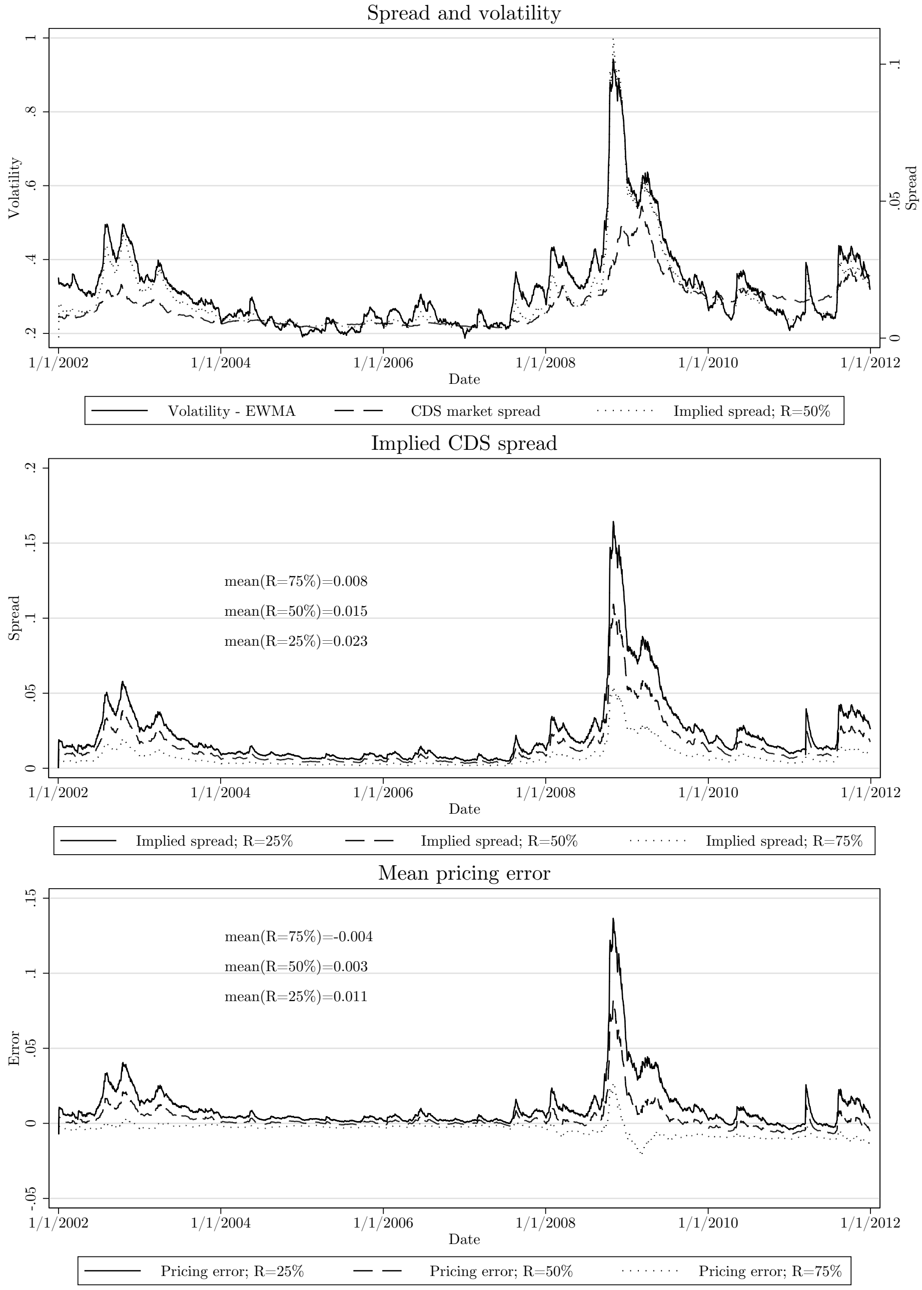


Figure 1.2 Market and implied CDS spreads

This figure shows the distribution of mean market and implied CDS spreads over time for all obligors. The top panel reports the mean market spread relative to the implied spread assuming a 50% recovery rate, as well as the average stock return volatility. The middle panel plots the implied spread for various recovery levels. The bottom panel displays the evolution of average pricing errors for various recovery rates over time. The implied spread is estimated using the CreditGrades model, assuming either a 25%, 50% or 75% recovery rate and using EWMA ($\lambda = 0.95$) volatility estimates. The pricing error is calculated by subtracting the market spread from the implied spread.

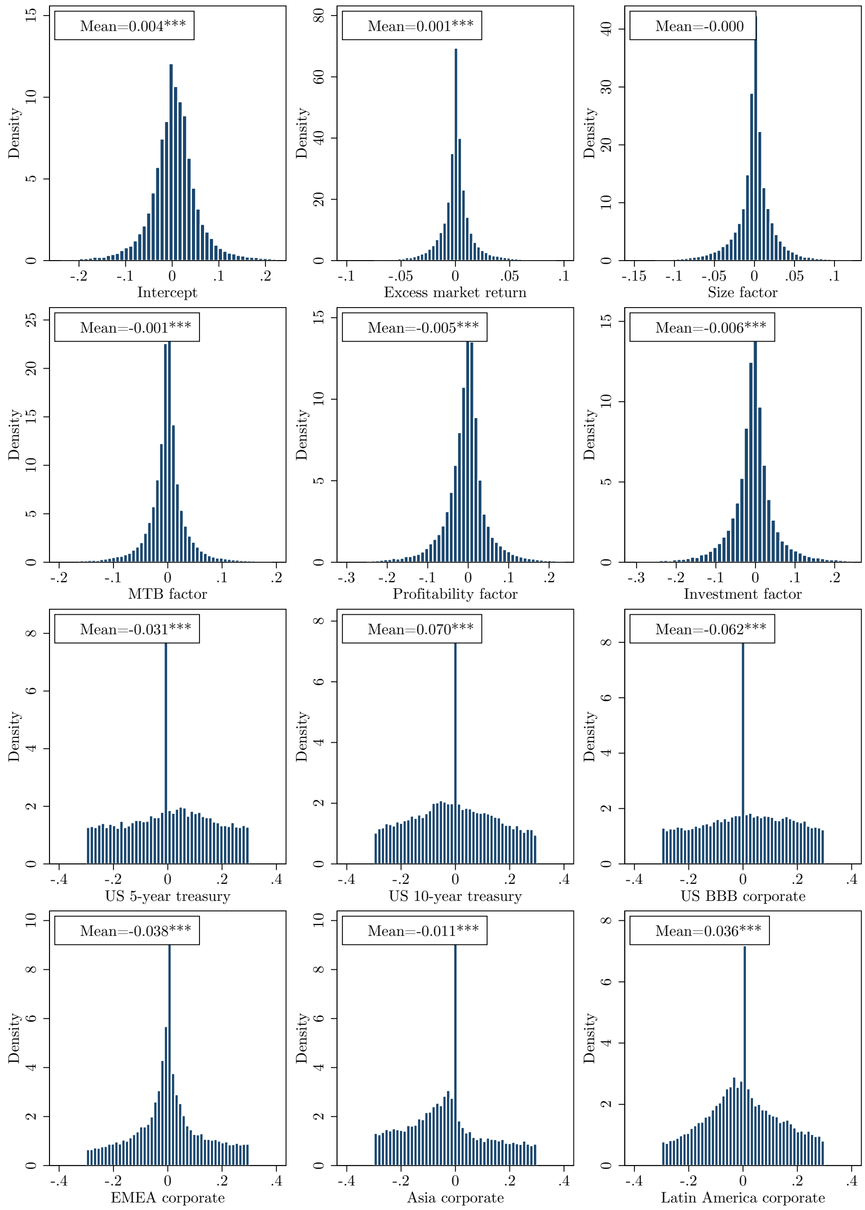


Figure 1.3 Risk factor exposures

This figure shows the distributions beta parameters from regressions of trade excess returns on excess returns of Fama-French 5-factor (Fama and French, 2015) and bond market portfolios. Beta parameters are based on 79,564 regressions, and are trimmed at 1% on both tails. Each panel reports the mean exposure in the upper-left corner. Trades are initiated when the difference between the observed and implied CDS spread is 2 standard deviations away from the mean pricing error in the preceding 250 trading days. The implied spread is calculated using the CreditGrades model, assuming a 50% recovery rate and using EWMA ($\lambda = 0.95$) volatility estimates. The predefined holding period is 60 days for all trades. Positions are liquidated if negative returns exceed 10% or mispricing returns to its preceding average. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

$$r_{t_i} = \alpha + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} CMA_t + \beta_{5,i} RMW_t + \beta_{6,i} GOV(5)_t + \beta_{7,i} GOV(10)_t + \beta_{8,i}\, US\text{-}BBB_t + \beta_{9,i} EMEA_t + \beta_{10,i} Asia_t + \beta_{11,i} LatAm_t + \epsilon_{t,i}.$$

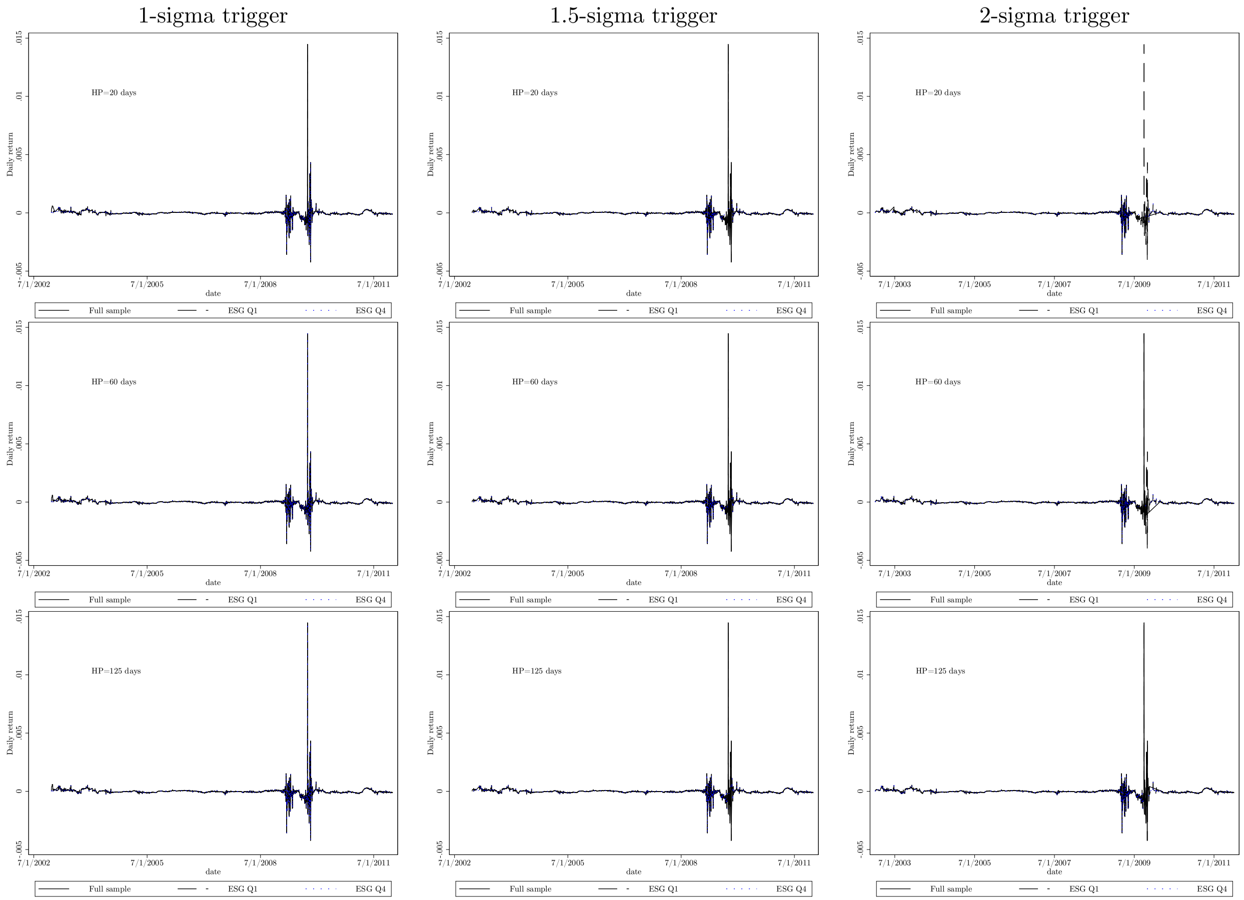


Figure 1.4 Portfolio returns

This figure displays capital structure arbitrage portfolio returns over time for various trading rules. Portfolios are formed daily taking the equal-weighted average of all trades. The figure show returns for the entire sample, and by top and bottom ESG quartiles. The top, middle and bottom rows show returns for 20, 60 and 125 days, respectively. The left column is based on a 1-σ trading trigger, while the middle and right refer to 1.5 and 2-σ triggers, respectively. A trade may be initiated if the difference between the observed and implied CDS spread is 1, 1.5 or 2 standard deviations away from the mean pricing error in the preceding 250 trading days. The implied spread is estimated using the CreditGrades model using EWMA ($\lambda = 0.95$) volatility estimates and assuming a 50% recovery rate. The pricing error is calculated by subtracting the market spread from the implied spread.

Table 1.1 Descriptive statistics

This table provides descriptive statistics for all obligors. The sample period is 2002-2011. The table reports statistics for the entire sample, and by ESG and credit rating quartiles. Panels A and B displays capital structure characteristics, while Panel C shows ESG figures. The table reports the mean, and the standard deviation in parentheses. The table also shows the test for the difference in means by the lowest and highest ESG or credit rating quartiles for each variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Capital structure characteristics by ESG

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
Stock ret. (%)	0.039	0.039	0.039	0.033	0.035	0.004	1,674,213	658
	(2.382)	(2.530)	(2.458)	(2.310)	(2.059)			
Volatility (EWMA)	0.020	0.022	0.021	0.020	0.018	0.004***	1,674,213	658
	(0.013)	(0.013)	(0.013)	(0.011)	(0.010)			
CDS spread	0.013	0.016	0.013	0.012	0.009	0.007***	1,252,181	658
	(0.026)	(0.026)	(0.025)	(0.021)	(0.018)			
CDS ret. (%)	-0.020	-0.024	-0.022	-0.017	-0.012	-0.012***	1,236,544	658
	(0.038)	(0.037)	(0.053)	(0.031)	(0.015)			
S&P credit rating	14.380	14.396	14.117	14.501	14.382	0.014	741,217	291
	(2.912)	(2.673)	(3.050)	(2.895)	(3.104)			

Panel B: Capital structure characteristics by credit quality

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
Stock ret. (%)	0.039	0.035	0.048	0.038	0.034	0.002	1,674,213	658
	(2.382)	(2.530)	(2.402)	(2.350)	(2.396)			
Volatility (EWMA)	0.020	0.021	0.021	0.020	0.020	0.000***	1,674,213	658
	(0.013)	(0.015)	(0.012)	(0.013)	(0.013)			
CDS market spread	0.013	0.014	0.016	0.013	0.013	0.001***	1,252,181	658
	(0.026)	(0.031)	(0.033)	(0.027)	(0.023)			
CDS ret. (%)	-0.020	-0.020	-0.023	-0.023	-0.017	-0.003***	1,236,544	658
	(0.038)	(0.036)	(0.043)	(0.059)	(0.023)			
S&P credit rating	14.380	11.126	13.888	15.681	18.156	-7.030***	741,217	291
	(2.912)	(1.977)	(0.507)	(0.671)	(1.468)			

Panel C: ESG characteristics

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
Asset4 score	52.139	44.280	50.410	54.272	59.627	-15.347***	1,393,586	613
	(6.451)	(3.403)	(2.672)	(3.061)	(3.601)			
Environmental	53.661	41.168	51.025	57.158	65.343	-24.174***	1,393,586	613
	(12.309)	(8.271)	(9.369)	(8.459)	(8.154)			
Social	52.915	43.907	51.179	55.675	60.934	-17.027***	1,393,586	613
	(7.759)	(4.655)	(4.496)	(4.464)	(4.777)			
Governance	51.687	45.097	50.001	53.366	58.313	-13.216***	1,393,586	613
	(9.026)	(9.637)	(7.511)	(6.832)	(6.066)			
Economic	50.322	46.991	49.500	50.907	53.906	-6.914***	1,393,586	613
	(3.677)	(2.628)	(2.405)	(2.622)	(3.091)			

Table 1.2 Implied CDS spreads

This table provides descriptive statistics for implied CDS spreads. The implied spread is estimated using the CreditGrades model, assuming either a 25%, 50% or 75% recovery rate and using EWMA ($\lambda = 0.95$) volatility estimates. Panel A provides a breakdown by ESG rating, while Panel B for credit ratings. The table reports the mean, and the standard deviation in parentheses. The table also shows the test for the difference in means by the lowest and highest ESG, and credit rating quartiles for each variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Implied spread by ESG

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
CDS spread R=0.25	0.024	0.029	0.025	0.023	0.016	0.013***	1,235,702	658
	(0.049)	(0.052)	(0.050)	(0.043)	(0.037)			
CDS spread R=0.50	0.016	0.019	0.017	0.015	0.010	0.009***	1,235,702	658
	(0.033)	(0.035)	(0.033)	(0.029)	(0.024)			
CDS spread R=0.75	0.008	0.010	0.008	0.008	0.005	0.004***	1,235,702	658
	(0.016)	(0.017)	(0.017)	(0.014)	(0.012)			

Panel B: Implied spread by credit rating

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
CDS spread R=0.25	0.024	0.025	0.027	0.022	0.024	0.001***	1,235,702	658
	(0.049)	(0.058)	(0.049)	(0.048)	(0.049)			
CDS spread R=0.50	0.016	0.017	0.018	0.015	0.016	0.001***	1,235,702	658
	(0.033)	(0.038)	(0.033)	(0.032)	(0.033)			
CDS spread R=0.75	0.008	0.008	0.009	0.007	0.008	0.000***	1,235,702	658
	(0.016)	(0.019)	(0.016)	(0.016)	(0.016)			

Table 1.3 CDS pricing errors

This table provides descriptive statistics for implied CDS spreads. The implied spread is estimated using the CreditGrades model, assuming either a 25%, 50% or 75% recovery rate and using EWMA ($\lambda = 0.95$) volatility estimates. The pricing error is calculated by subtracting the market spread from the implied spread. Panel A provides a breakdown by ESG rating, while Panel B for credit ratings. The table reports the mean, and the standard deviation in parentheses. The table also shows the test for the difference in means by the lowest and highest ESG, and credit rating quartiles for each variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Pricing error by ESG

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
CDS spread R=0.25	0.011	0.014	0.012	0.010	0.007	0.007***	1,235,702	658
	(0.038)	(0.040)	(0.040)	(0.034)	(0.030)			
CDS spread R=0.50	0.003	0.004	0.003	0.003	0.002	0.002***	1,235,702	658
	(0.025)	(0.027)	(0.026)	(0.022)	(0.020)			
CDS spread R=0.75	-0.005	-0.006	-0.005	-0.005	-0.004	-0.002***	1,235,702	658
	(0.019)	(0.020)	(0.019)	(0.016)	(0.014)			

Panel B: Pricing error by credit rating

	Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	T	N
CDS spread R=0.25	0.011	0.012	0.011	0.009	0.011	0.000**	1,235,702	658
	(0.038)	(0.043)	(0.036)	(0.036)	(0.037)			
CDS spread R=0.50	0.003	0.003	0.002	0.002	0.003	0.000	1,235,702	658
	(0.025)	(0.028)	(0.027)	(0.025)	(0.023)			
CDS spread R=0.75	-0.005	-0.005	-0.007	-0.005	-0.005	-0.000**	1,235,702	658
	(0.019)	(0.023)	(0.025)	(0.020)	(0.016)			

Table 1.4 Capital structure arbitrage returns

This table displays mean capital structure arbitrage returns and their standard deviations (in parentheses) for various pricing specifications and trading rules. Panel A shows statistics for a 5% stop-loss rule where the position is liquidated if losses reach or exceed 5%. Panel B and C display statistics for 10% and 100% stop-loss rules, respectively. In each panel, there are 3 column blocks corresponding to implied spreads based recovery rates at 25%, 50% and 75%, respectively. The table reports 3 predefined trading periods for each recovery rate at 20, 60 and 125 days, respectively. The table cross-sectionally differentiates various trading triggers. A trade may be initiated if the difference between the observed and implied CDS spread is 1, 1.5 or 2 standard deviations away from the mean pricing error in the preceding 125 or 250 trading days. The implied spread is estimated using the CreditGrades model using EWMA ($\lambda = 0.95$) volatility estimates. The pricing error is calculated by subtracting the market spread from the implied spread. All figures in percentages.

Panel A: 5% stop-loss rule

			Recovery rate=0.25			Recovery rate=0.50			Recovery rate=0.75		
			HP=20	HP=60	HP=125	HP=20	HP=60	HP=125	HP=20	HP=60	HP=125
125	1-σ	Mean	-0.030	-0.086	-0.130	-0.103	-0.249	-0.374	-0.220	-0.519	-0.772
		S. dev.	(0.626)	(1.125)	(1.647)	(0.558)	(1.063)	(1.578)	(0.544)	(1.019)	(1.467)
	1.5-σ	Mean	0.014	0.016	0.024	-0.062	-0.161	-0.247	-0.195	-0.481	-0.728
		S. dev.	(0.625)	(1.134)	(1.677)	(0.546)	(1.059)	(1.608)	(0.524)	(1.025)	(1.501)
	2-σ	Mean	0.041	0.088	0.145	-0.029	-0.084	-0.125	-0.164	-0.423	-0.656
		S. dev.	(0.566)	(1.094)	(1.666)	(0.505)	(1.042)	(1.617)	(0.493)	(1.024)	(1.562)
250	1-σ	Mean	-0.010	-0.032	-0.053	-0.090	-0.217	-0.337	-0.211	-0.517	-0.801
		S. dev.	(0.634)	(1.140)	(1.647)	(0.567)	(1.065)	(1.639)	(0.540)	(1.028)	(1.500)
	1.5-σ	Mean	0.033	0.077	0.121	-0.048	-0.120	-0.190	-0.183	-0.467	-0.740
		S. dev.	(0.636)	(1.132)	(1.655)	(0.540)	(1.063)	(1.637)	(0.508)	(1.024)	(1.515)
	2-σ	Mean	0.055	0.145	0.249	-0.015	-0.035	-0.048	-0.167	-0.427	-0.678
		S. dev.	(0.630)	(1.124)	(1.650)	(0.505)	(1.028)	(1.582)	(0.529)	(1.051)	(1.550)

Panel B: 10% stop-loss rule

			Recovery rate=0.25			Recovery rate=0.50			Recovery rate=0.75		
			HP=20	HP=60	HP=125	HP=20	HP=60	HP=125	HP=20	HP=60	HP=125
125	1-σ	Mean	-0.038	-0.104	-0.166	-0.112	-0.275	-0.424	-0.231	-0.553	-0.842
		S. dev.	(0.727)	(1.263)	(1.808)	(0.678)	(1.234)	(1.792)	(0.669)	(1.219)	(1.741)
	1.5-σ	Mean	0.012	0.006	-0.002	-0.067	-0.181	-0.289	-0.202	-0.511	-0.793
		S. dev.	(0.673)	(1.226)	(1.801)	(0.617)	(1.196)	(1.790)	(0.621)	(1.205)	(1.754)
	2-σ	Mean	0.040	0.080	0.123	-0.032	-0.097	-0.156	-0.168	-0.446	-0.712
		S. dev.	(0.584)	(1.154)	(1.759)	(0.553)	(1.137)	(1.747)	(0.550)	(1.161)	(1.776)
250	1-σ	Mean	-0.015	-0.046	-0.082	-0.098	-0.245	-0.388	-0.221	-0.554	-0.878
		S. dev.	(0.707)	(1.262)	(1.792)	(0.679)	(1.253)	(1.854)	(0.662)	(1.242)	(1.793)
	1.5-σ	Mean	0.032	0.070	0.102	-0.051	-0.141	-0.231	-0.189	-0.496	-0.805
		S. dev.	(0.673)	(1.222)	(1.769)	(0.602)	(1.220)	(1.825)	(0.584)	(1.199)	(1.767)
	2-σ	Mean	0.054	0.138	0.231	-0.018	-0.050	-0.078	-0.174	-0.458	-0.746
		S. dev.	(0.652)	(1.185)	(1.736)	(0.541)	(1.136)	(1.714)	(0.612)	(1.234)	(1.809)

Panel C: 100% stop-loss rule

			Recovery rate=0.25			Recovery rate=0.50			Recovery rate=0.75		
			HP=20	HP=60	HP=125	HP=20	HP=60	HP=125	HP=20	HP=60	HP=125
125	1-σ	Mean	-0.043	-0.138	-0.242	-0.117	-0.309	-0.499	-0.235	-0.599	-0.950
		S. dev.	(0.826)	(1.726)	(2.653)	(0.759)	(1.669)	(2.588)	(0.743)	(1.783)	(2.881)
	1.5-σ	Mean	0.010	-0.005	-0.038	-0.071	-0.199	-0.332	-0.206	-0.545	-0.873
		S. dev.	(0.719)	(1.395)	(2.163)	(0.685)	(1.433)	(2.215)	(0.687)	(1.645)	(2.616)
	2-σ	Mean	0.039	0.075	0.106	-0.035	-0.108	-0.183	-0.170	-0.465	-0.763
		S. dev.	(0.605)	(1.224)	(1.928)	(0.605)	(1.281)	(2.011)	(0.595)	(1.423)	(2.323)
250	1-σ	Mean	-0.018	-0.069	-0.134	-0.101	-0.279	-0.471	-0.225	-0.602	-1.001
		S. dev.	(0.790)	(1.595)	(2.402)	(0.733)	(1.682)	(2.735)	(0.726)	(1.799)	(2.986)
	1.5-σ	Mean	0.029	0.061	0.080	-0.053	-0.150	-0.259	-0.191	-0.522	-0.879
		S. dev.	(0.750)	(1.384)	(2.016)	(0.633)	(1.326)	(2.045)	(0.630)	(1.531)	(2.538)
	2-σ	Mean	0.052	0.133	0.219	-0.018	-0.057	-0.095	-0.177	-0.486	-0.827
		S. dev.	(0.690)	(1.269)	(1.859)	(0.557)	(1.230)	(1.847)	(0.661)	(1.602)	(2.624)

Table 1.5 Arbitrage returns by ESG

This table displays mean capital structure arbitrage returns for various trading rules. The table reports statistics for the entire sample, and by ESG quartiles. Each part shows statistics for 20, 60 and 125 days. The top part is based on a 1-σ trading trigger, while the middle and bottom refer to 1.5 and 2-σ triggers, respectively. A trade may be initiated if the difference between the observed and implied CDS spread is 1, 1.5 or 2 standard deviations away from the mean pricing error in the preceding 250 trading days. Positions are liquidated whenever losses exceed 10%. The implied spread is estimated using the CreditGrades model using EWMA ($\lambda = 0.95$) volatility estimates and assuming a 50% recovery rate. The pricing error is calculated by subtracting the market spread from the implied spread. All figures in percentages. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

			Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	N
1-σ	20	Mean	-0.098	-0.069	-0.126	-0.093	-0.082	0.013***	210,810
		S. dev.	(0.679)	(0.606)	(0.877)	(0.429)	(0.245)		
		Min.	-20.487	-11.654	-13.210	-11.314	-5.716		
		Max.	13.976	8.207	8.193	5.118	6.061		
	60	Mean	-0.245	-0.196	-0.244	-0.258	-0.224	0.028***	210,810
		S. dev.	(1.253)	(1.271)	(1.339)	(1.012)	(0.578)		
		Min.	-20.487	-16.011	-13.210	-11.338	-5.398		
		Max.	19.480	9.537	18.421	19.480	5.823		
	125	Mean	-0.388	-0.316	-0.387	-0.426	-0.379	0.063***	210,810
		S. dev.	(1.854)	(1.876)	(2.084)	(1.477)	(0.962)		
		Min.	-22.068	-16.011	-13.210	-11.338	-6.158		
		Max.	60.652	12.564	60.652	23.582	6.503		
1.5-σ	20	Mean	-0.051	-0.001	-0.061	-0.073	-0.068	0.067***	126,084
		S. dev.	(0.602)	(0.526)	(0.624)	(0.489)	(0.268)		
		Min.	-20.487	-11.654	-13.210	-11.314	-5.716		
		Max.	13.976	6.131	8.193	5.118	6.061		
	60	Mean	-0.141	-0.022	-0.173	-0.176	-0.179	0.157***	126,084
		S. dev.	(1.220)	(1.186)	(1.296)	(1.056)	(0.626)		
		Min.	-20.487	-12.769	-13.210	-11.338	-5.398		
		Max.	19.480	9.537	18.421	19.480	5.823		
	125	Mean	-0.231	-0.062	-0.241	-0.331	-0.305	0.243***	126,084
		S. dev.	(1.825)	(1.770)	(2.002)	(1.597)	(1.026)		
		Min.	-22.068	-12.874	-13.210	-11.338	-6.158		
		Max.	54.974	10.998	54.974	23.582	6.503		
2-σ	20	Mean	-0.018	0.031	-0.026	-0.054	-0.056	0.087***	79,564
		S. dev.	(0.541)	(0.515)	(0.579)	(0.495)	(0.291)		
		Min.	-14.292	-11.654	-13.210	-11.314	-5.716		
		Max.	13.976	3.267	5.982	5.118	6.061		
	60	Mean	-0.050	0.074	-0.079	-0.120	-0.143	0.217***	79,564
		S. dev.	(1.136)	(1.148)	(1.251)	(1.111)	(0.663)		
		Min.	-14.292	-12.769	-13.210	-11.338	-5.398		
		Max.	19.480	8.173	12.800	19.480	5.823		
	125	Mean	-0.078	0.124	-0.135	-0.200	-0.219	0.343***	79,564
		S. dev.	(1.714)	(1.692)	(1.967)	(1.582)	(1.052)		
		Min.	-14.292	-12.769	-13.210	-11.338	-6.158		
		Max.	52.211	10.290	52.211	23.582	6.503		

Table 1.6 Arbitrage characteristics by ESG

This table displays mean capital structure arbitrage characteristics for various trading rules. The table reports statistics for the entire sample, and by ESG quartiles. Each part shows statistics for 20, 60 and 125 days. The top part is based on a 1-σ trading trigger, while the middle and bottom refer to 1.5 and 2-σ triggers, respectively. A trade may be initiated if the difference between the observed and implied CDS spread is 1, 1.5 or 2 standard deviations away from the mean pricing error in the preceding 250 trading days. Positions are liquidated whenever losses exceed 10%. The implied spread is estimated using the CreditGrades model using EWMA (λ = 0.95) volatility estimates and assuming a 50% recovery rate. The pricing error is calculated by subtracting the market spread from the implied spread. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

			Full sample	Q1	Q2	Q3	Q4	Diff. (Q1-Q4)	N
1-σ	20	Convergence	17.9%	19.7%	18.1%	17.6%	16.0%	0.037***	210,810
		Stop-loss	0.1%	0.0%	0.5%	0.0%	0.0%	0.000***	210,810
		Cash-in	81.9%	80.3%	81.4%	82.4%	84.0%	-0.037***	210,810
		Holding	18	18	18	18	19	-0.205***	210,810
		Long	44.8%	52.4%	48.0%	40.1%	36.6%	0.158***	210,810
	60	Convergence	46.4%	50.8%	47.3%	46.9%	40.7%	0.101***	210,810
		Stop-loss	0.5%	0.3%	0.6%	0.2%	0.0%	0.003***	210,810
		Cash-in	53.1%	48.9%	52.1%	52.9%	59.3%	-0.104***	210,810
		Holding	44	43	44	43	45	-2.705***	210,810
		Long	45.8%	52.7%	48.6%	42.2%	37.8%	0.150***	210,810
	125	Convergence	64.0%	69.3%	65.9%	62.9%	57.7%	0.116***	210,810
		Stop-loss	0.7%	0.5%	0.9%	0.5%	0.0%	0.005***	210,810
		Cash-in	35.3%	30.2%	33.2%	36.6%	42.3%	-0.121***	210,810
		Holding	68	65	67	68	72	-6.883***	210,810
		Long	46.4%	53.6%	49.0%	42.5%	38.5%	0.151***	210,810
1.5-σ	20	Convergence	14.6%	16.4%	14.5%	14.5%	12.9%	0.035***	126,084
		Stop-loss	0.1%	0.0%	0.1%	0.0%	0.0%	0.000***	126,084
		Cash-in	85.3%	83.6%	85.4%	85.5%	87.1%	-0.035***	126,084
		Holding	19	19	19	19	19	-0.188***	126,084
		Long	51.9%	61.3%	53.8%	48.2%	42.2%	0.192***	126,084
	60	Convergence	43.5%	48.9%	44.4%	43.9%	36.8%	0.120***	126,084
		Stop-loss	0.3%	0.2%	0.2%	0.3%	0.0%	0.002***	126,084
		Cash-in	56.2%	50.9%	55.4%	55.8%	63.2%	-0.122***	126,084
		Holding	46	44	46	45	47	-3.131***	126,084
		Long	52.6%	61.1%	54.5%	49.4%	43.5%	0.176***	126,084
	125	Convergence	61.1%	67.7%	63.3%	60.1%	53.4%	0.143***	126,084
		Stop-loss	0.6%	0.3%	0.7%	0.7%	0.0%	0.003***	126,084
		Cash-in	38.3%	31.9%	36.0%	39.2%	46.6%	-0.147***	126,084
		Holding	71	68	71	70	76	-8.528***	126,084
		Long	52.9%	61.3%	55.0%	49.7%	43.9%	0.174***	126,084
2-σ	20	Convergence	12.4%	13.7%	12.8%	12.2%	10.8%	0.028***	79,564
		Stop-loss	0.0%	0.0%	0.1%	0.0%	0.0%	0.000***	79,564
		Cash-in	87.5%	86.3%	87.2%	87.8%	89.2%	-0.029***	79,564
		Holding	19	19	19	19	19	-0.128***	79,564
		Long	57.9%	69.7%	59.3%	54.2%	45.9%	0.238***	79,564
	60	Convergence	42.4%	48.1%	44.0%	42.1%	34.8%	0.132***	79,564
		Stop-loss	0.2%	0.3%	0.2%	0.4%	0.0%	0.003***	79,564
		Cash-in	57.3%	51.7%	55.9%	57.5%	65.2%	-0.135***	79,564
		Holding	47	45	46	47	49	-3.615***	79,564
		Long	58.5%	68.4%	60.1%	55.6%	47.4%	0.210***	79,564
	125	Convergence	60.2%	66.4%	63.5%	58.6%	51.9%	0.145***	79,564
		Stop-loss	0.5%	0.3%	0.8%	0.6%	0.0%	0.003***	79,564
		Cash-in	39.3%	33.3%	35.8%	40.8%	48.1%	-0.148***	79,564
		Holding	73	70	72	73	79	-9.198***	79,564
		Long	58.7%	68.4%	60.6%	55.1%	48.6%	0.199***	79,564

Table 1.7 Arbitrage portfolio returns

This table displays regression results of capital structure arbitrage portfolio returns on common risk factors for various trading rules. Portfolios are formed daily taking the equal-weighted average of all trades. The table reports statistics for the entire sample, and by top and bottom ESG quartiles. The table also shows the Hausman test for the difference in alphas between the highest and lowest ESG quartiles. Each part shows statistics for 20, 60 and 125 days. The top part is based on a 1-σ trading trigger, while the middle and bottom refer to 1.5 and 2-σ triggers, respectively. A trade may be initiated if the difference between the observed and implied CDS spread is 1, 1.5 or 2 standard deviations away from the mean pricing error in the preceding 250 trading days. The implied spread is estimated using the CreditGrades model using EWMA ($\lambda = 0.95$) volatility estimates and assuming a 50% recovery rate. The pricing error is calculated by subtracting the market spread from the implied spread. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

$$r_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 CMA_t + \beta_5 RMW_t + \beta_6 GOV(5)_t + \beta_7 GOV(10)_t + \beta_8 US\text{-}BBB_t + \beta_9 EMEA_t + \beta_{10} Asia_t + \beta_{11} LatAm_t + \epsilon_t.$$

			N	alpha	Q1-Q4 (χ^2)	Controls	Adj. R^2
1-σ	HP=20	Full sample	2,276	-0.0002***		Y	0.11
		Q4	2,243	-0.0002***	5.1673**	Y	0.24
		Q1	2,266	-0.0004***		Y	0.06
	HP=60	Full sample	2,276	-0.0002***		Y	0.22
		Q4	2,262	-0.0002***	6.7613***	Y	0.30
		Q1	2,276	-0.0003***		Y	0.08
	HP=125	Full sample	2,276	-0.0002***		Y	0.33
		Q4	2,275	-0.0001***	4.8558**	Y	0.34
		Q1	2,276	-0.0003***		Y	0.13
1.5-σ	HP=20	Full sample	2,275	-0.0002***		Y	0.05
		Q4	2,155	-0.0002***	9.2684***	Y	0.14
		Q1	2,267	-0.0006***		Y	0.03
	HP=60	Full sample	2,275	-0.0001***		Y	0.11
		Q4	2,185	-0.0001***	5.6629**	Y	0.15
		Q1	2,275	-0.0003***		Y	0.02
	HP=125	Full sample	2,275	-0.0001***		Y	0.24
		Q4	2,212	-0.0001***	1.8788	Y	0.15
		Q1	2,275	-0.0002***		Y	0.03
2-σ	HP=20	Full sample	2,249	0.0000		Y	0.02
		Q4	2,030	-0.0002***	0.9057	Y	0.10
		Q1	2,166	0.0000		Y	0.02
	HP=60	Full sample	2,266	0.0001		Y	0.05
		Q4	2,106	-0.0001**	1.3618	Y	0.08
		Q1	2,249	0.0000		Y	0.01
	HP=125	Full sample	2,266	0.0000		Y	0.17
		Q4	2,167	-0.0001***	0.0722	Y	0.10
		Q1	2,264	-0.0001		Y	0.01

Appendix 1.A CreditGrades

The CreditGrades model of Finger et al. (2002) was developed at the RiskMetrics group. This model provides a convenient closed-form solution for default probabilities and the swap spread, furthermore it is used by investment practitioners (Yu, 2006).

First, let the present value of the periodic premium payments be

$$\mathbb{E}\left(c\int_0^T \exp\left(-\int_0^s r_u du\right) I_{\{\tau>s\}} ds\right), \tag{A.1}$$

where c, T and r are the CDS spread, the contract maturity and the risk-free rate respectively, while τ is the time of default and $I_{\{.\}}$ is the indicator function of default. If the default time and the risk-free rate are independent, this can be rewritten as

$$c\int_0^T P(0,s)q_0(s)ds, \tag{A.2}$$

where $P(\cdot)$ is the price of a risk-free zero-coupon bond and $q(\cdot)$ is the risk-neutral survival probability of the obligor. Second, the present value of the credit protection is

$$\mathbb{E}\left((1-R)\exp\left(-\int_0^s r_u du\right) 1_{\{\tau>s\}}\right), \tag{A.3}$$

where R is the asset specific recovery rate expressed as a percentage of face-value immediately after default. Again, assuming independence and a constant R, this can be rewritten as

$$-(1-R)\int_0^T P(0,s)q_0'(s)ds, \tag{A.4}$$

where q' is the density function of survival. The initial value of the contract is zero, because default cannot happen at $t = 0$ and no premium payments were made. Consequently, we obtain the spread by setting the initial value to zero. Thus

$$c = -\frac{(1-R)\int_0^T P(0,s)q_0'(s)ds}{\int_0^T P(0,s)q_0(s)ds}. \tag{A.5}$$

In the CreditGrades model, the asset value V_0 is assumed to follow a geometric Brownian motion with no drift, $dV_t/V_t = \sigma W_t$ with asset volatility σ, but is accurately approximated by the affine expression $V_0 = S_0 + \bar{L}D$, where S is the stock price, $\bar{L}$ is the average global recovery rate of a firm's assets and D is the dollar value of debt-per-share. L is assumed to follow a log-normal distribution with mean $\bar{L}$ and standard deviation λ. This latter parameter accounts for the uncertainty in recovery rates, in other words, it incorporates the cheapest-to-deliver option. Using the above linear approximation, survival probabilities have a closed-form expression. Specifically, we have

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t}\right) - d\Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right), \tag{A.6}$$

where

$$d = \frac{(S_0 + \bar{L}D)e^{\lambda}}{\bar{L}D},\ A_t^2 = \sigma^2 t + \lambda^2 \text{ and } \sigma = \sigma_S \frac{S_0}{S_0 + \bar{L}D}.$$

Here, σ_S is the equity volatility and $\Phi(\cdot)$ denotes the standard normal distribution. From the linearization we have that the underlying asset's volatility is approximated by equity volatility corrected for the capital structure and the global recovery rate of the company. Finally, the model arrives at Equation A.7 by introducing the asset-specific recovery rate (R) and the risk-free rate (r) into the framework yielding

$$c^* = r(1-R)\frac{1 - q(0) + H(t)}{q(0) - q(t)e^{-rt} - H(t)}. \tag{A.7}$$

In the preceding we have that

$$\begin{aligned}
H(t) &= e^{r\xi}(G(t+\xi) - G(\xi)), \text{with} \\
G(t) &= d^{z+1/2}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + d^{-z+1/2}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right), \text{using} \\
z &= \sqrt{1/4 + 2r/\sigma^2} \text{ and} \\
\xi &= \frac{\lambda^2}{\sigma^2}.
\end{aligned}$$

Appendix 1.B Volatility models

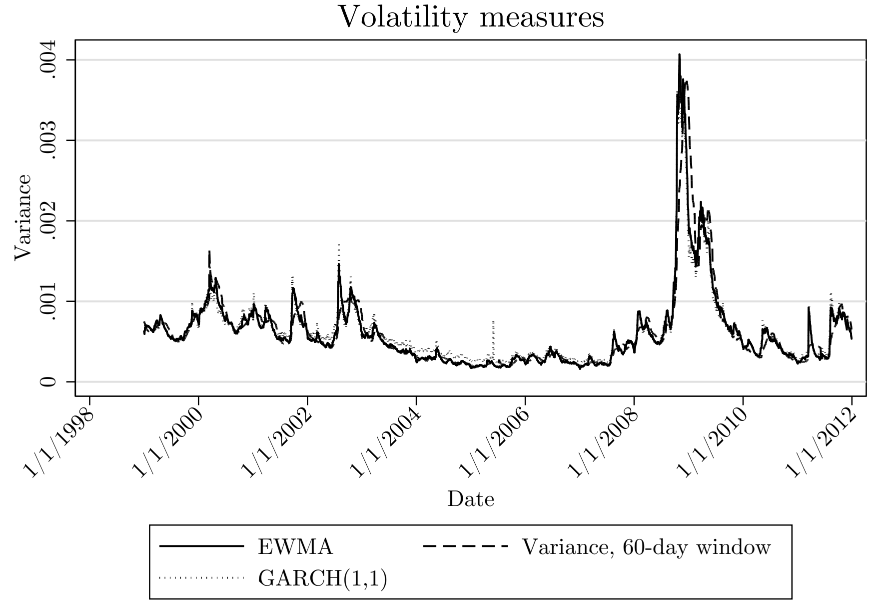


Figure B.1 Volatility measures

This figure shows various volatility measures over time for the mean stock return volatility in the sample. Exponentially weighted moving average (EWMA) smoothing is calculated with $\lambda = 0.95$ and a calibration window of 750 days. For GARCH(1,1), the estimation window is 750 days and the forecast period is 5 days. Finally, variance figures come from a 60-day equal-weighted rolling-window estimation. The calibration period is 1999-2001 for all models.

Table B.1 Volatility correlation table

This table reports Pearson correlation coefficients for various volatility measures. The first row [1] corresponds to variance calculated by exponentially weighted moving average smoothing with $\lambda = 0.95$ and a calibration window of 750 days. The second row [2] reports on variance predicted by a GARCH(1,1) model where the estimation window is 750 days and the forecast period is 5 days. The third row [3] reports on variance estimates from a 60-day equal-weighted rolling-window estimation. The calibration period is 1999-2001, while the reporting period is 2002-2011 for all models. P-values are reported in parentheses.

Variables	[1]	[2]	[3]
[1] EWMA	1.000		
[2] GARCH(1,1)	0.994	1.000	
	(0.000)		
[3] Variance, 60-day window	0.926	0.903	1.000
	(0.000)	(0.000)	

Appendix 1.C Credit ratings

Table C.1 S&P crdit ratings

This table shows the breakdown of long-term credit ratings by Standard & Poor's. The first column shows letter designations, while the second column displays notches numerically. The final 2 columns give qualitative rating descriptions.

S&P long term rating	Rating score	Quality	
AAA	22	Prime	Investment grade
AA+	21	High grade	
AA	20		
AA-	19		
A+	18	Upper medium grade	
A	17		
A-	16		
BBB+	15	Lower medium grade	
BBB	14		
BBB-	13		
BB+	12	Non-investment grade speculative	Non-investment grade
BB	11		
BB-	10		
B+	9	Highly speculative	
B	8		
B-	7		
CCC+	6	Substantial risks	
CCC	5	Extremely speculative	
CCC-	4	Default imminent with little prospect for recovery	
CC	3		
C	2		
SD	1	In default	
D	1		

Chapter 2

Shareholder Engagement on Environmental, Social, and Governance Performance

2.1. Introduction

Increasingly prominent, activist investors such as hedge funds, pension funds, and influential individual shareholders and families set out to reshape corporate policies and strategy (e.g., Becht et al. (2017) and Becht et al. (2009). In this paper, we focus on activism from a different perspective: given that socially responsible investments (SRI) have become increasingly important, we examine whether investor activism is able to promote corporate social responsibility (CSR) as reflected in environmental, social, and governance (ESG) practices, and whether such activism affects ESG practices, corporate performance and investment results.

In the past two decades, socially responsible investing has grown from a niche segment to become mainstream. The UN Principles for Responsible Investing (2015), which establishes principles of responsible investing and guidelines for companies, reports that a large number of institutions (managing about $59 trillion) has endorsed these investing

This chapter is based on joint work with Martijn Cremers and Luc Renneboog.
We would like thank the data provider for providing us with detailed, proprietary information on their shareholder activism procedures. We are grateful for comments from Lieven Baele, Fabio Braggion, Peter Cziraki, Peter de Goeij, Frank de Jong, Bart Dierynck, Elroy Dimson, Joost Driessen, Alex Edmans, Caroline Flammer, Julian Franks, William Goetzmann, Marc Goergen, Camille Hebert, Hao Liang, Alberto Manconi, Ernst Maug, Zorka Simon, Oliver Spalt, Michael Ungehauer, Servaes van der Meulen, Cara Vansteenkiste, Chendi Zhang, Yang Zhao, and seminar participants at the HAS Summer Workshop in Economics, University of Mannheim, Cardiff Business School, Ghent University, Tilburg University, and University Paris-Dauphine. An earlier version of this paper was titled "Activism on Corporate Social Responsibility."

principles, thereby declaring that corporate social responsibility is an essential part of their due diligence process and matters for investment decisions. Further, the Global Sustainable Investment Alliance, (2015) estimates that over $21 trillion of professionally managed assets are explicitly allocated in accordance with ESG standards, driven by pension funds but increasingly also by mutual funds, hedge funds, venture capital and real estate funds. A subset of these investors actively engages with the companies in their portfolios, requesting that companies improve their environmental, social, and governance (ESG) practices (see, e.g., Dimson, Karakaş, and Li (2015) or Doidge et al. (2015)).[1]

In our paper, we study investor activism on corporate social responsibility using a large, detailed, and proprietary dataset on CSR activist engagements by a leading European investment management firm that is managing SRI funds both for its own account and for its clients. To the best of our knowledge, this is the first paper to investigate such ESG engagements in an international context. In particular, this paper addresses the following questions: (i) how does the activist investor choose target companies aiming at improving their ESG practices?; (ii) how are such engagements carried out?; (iii) are such engagements successful in improving the targets' ESG performance?; (iv) what drives success or failure in ESG activism?; and (v) is the activism visible in the targets' operations (e.g., accounting returns, profit margin, sales growth, etc.) and (vi) in terms of investment value creation (i.e., stock returns).

Our panel spans a decade (2005-2014), 660 engaged companies from around the globe, and 847 separate engagements. The engagements in our sample primarily concern social matters (43.3%) and environmental issues (42.3%), while only relatively few concern governance issues (14.4%). As a result, these CSR engagements are quite different from the activities by other activist investors such as hedge funds, that generally focus on financial value through advocating for asset restructuring and governance improvement (e.g., Becht et al. (2017)), but do not consider social and environmental practices as independent objectives.

We find that engaged companies typically have a higher market share and are followed by more analysts than their peers. Accordingly, in order to avoid selection bias and to account for unobserved heterogeneity, in subsequent analyses we match the engaged firms to control firms from the same industry that are similar ex ante in terms of size, market-to-book ratio, ESG rating, and ROA. In the case of environmental and social activism, the most common channel for engagement is either a letter or email addressed to the top management or the board of directors. In cases that relate to governance, the activist typically participates in shareholder meetings or meets in person with firm

[1] Throughout the paper, we use the terms "engagement" and "activism", as well as "engager" and "activist", interchangeably.

representatives (managers or non-executive directors).

In our sample, firms with lower ex ante ESG ratings are more likely to be engaged by the activist. Our evidence suggests that these engagements reveal information about the ESG practices at the engaged companies, which information is subsequently reflected in commercially-available, independent ESG ratings. On the one hand, targets with ex ante low ESG ratings see their ratings improve during the activism period. On the other hand, for targets with high ex ante ESG ratings, the engagement process seems to induce a negative correction during the activism period, suggesting that some of the concerns of the activist investor were not previously incorporated in these ratings and are publicly disclosed due to the activism.

The activist considers the engagement as successful depending on whether or not the target sufficiently adjusts its policy on one of more ex ante determined ESG dimensions. Most of the engagement files in our sample (59%) are considered successfully closed by the activist, which is more likely for targets with a larger market share, a good ESG track record, and earlier successful engagements. The presence of a large controlling shareholder, high short-term growth and a larger cash reserve are associated with a lower likelihood of success. The activist's request for a material change from the engaged company (which we call a reorganization) reduces the likelihood of a successful outcome, relative to an engagement that, e.g., stimulates the target to be more transparent in its ESG policies.

Examining the changes in operating performance following engagement, we find no relation with accounting performance or any of its components. However, sales growth increases on average substantially following a successful engagement, which could indicate that the implemented changes appeal to a broader customer clientele. Finally, we find positive buy-and-hold stock returns in the month of the completion of the engagement and over subsequent time windows of 6 and 12 months. After the completion of an engagement, excess stock returns (with four-factor adjustment and relative to a matched sample) are higher after successful outcomes, where the difference between successful and unsuccessful engagements is mainly significant within a period of 6 to 12 months, and disappears subsequently. For example, the excess returns of targeted firms are higher than those of non-targeted peer firms by 2.7% over the 6-month period following the engagement. Results are especially strong for firms with low ex ante ESG scores. Specifically, targeted firms in the lowest ex ante ESG quartile outperform their matched peers by 7.5% in the year after the end of the engagement. Our results thus suggest that the activism regarding corporate social responsibility generally improves ESG practices and corporate sales and is profitable to the activist.

2.2. Literature review

This paper links up with several related but confined strands of the literature: shareholder activism in general, SRI fund management and the impact of ESG screening devices, and the impact of unobservable activism (i.e., taking place behind the scenes). Shareholder activism in general can be loosely partitioned into three categories (Dimson et al., 2015): traditional activism, hedge fund activism, and corporate social responsibility activism. Traditional activism is typically exercised by mutual funds or pension funds and generally concerns topics related to corporate governance or restructuring. Hedge fund activists seek to create financial value by influencing corporate strategy and structure. Activism on CSR aims to improve corporate citizenship, mainly focusing on issues related to environmental and social topics.

Social responsibility and ethical investments have religious roots (e.g., in the 17th century Quaker movement; Renneboog et al. (2008a)). Still, it was not until the 1960's that socially responsible investing (SRI) gained momentum and the general public's interest. Growing concerns about human rights, pacifism, and environmental issues paved the way of today's SRI. The first modern investment vehicle catering to socially responsible investors was Pax World Fund, a mutual fund founded in 1971. Since then, SRI has been expanding from a niche market strategy to a mainstream investment style. According to SRI reports, total assets under management (AUM) surpassed the $21 trillion mark globally (Global Sustainable Investment Alliance, 2015), with $6.20 trillion in the United States (US SIF, 2014) and $6.72 trillion in Europe (Eurosif, 2014).

Fund managers apply various techniques and screens to form socially responsible portfolios. Bollen (2007), and Renneboog, Ter Horst, and C. Zhang (2008b) and Renneboog, Ter Horst, and C. Zhang (2011) differentiate among distinct types of SRI screens. First, negative screening is the most basic type that avoids investing in firms that sell products such as alcohol, tobacco, weaponry, abortion-related drugs, and pornography. Second, positive screens select companies that meet above average standards in areas such as the protection of the environment, the promotion of human rights, or the sustainability of investments. Third, negative and positive screens are often combined, yielding the so-called "transversal" (Capelle-Blancard and Monjon, 2014), "sustainable" or "triple bottom line" ("people, planet and profit") screens. Finally, the fourth generation of SRI funds combines the sustainable investing approach (third generation) with shareholder activism. In this approach, portfolio managers attempt to influence their portfolio companies' policies through direct engagement with the management/board of directors or through using voting rights at annual shareholder meetings.

The existing literature offers conflicting evidence in terms of the financial returns of activism. English II, Smythe, and McNeil (2004) argue that the effect of activism is only cursory, finding an effect in the first six months following the announcement of activism and diminishing afterwards. Nelson (2006) concludes that abnormal returns are insignificant for any time window, once confounding effects are controlled for. Greenwood and Schor (2009) report that returns to activism are positive only for the cases where targeted companies are acquired as a result of activism. In a survey paper, Gillan and Starks (2007) find no positive effect of activism in the long run, and no convincing evidence of a causal relation between activism and performance. In contrast, some studies show evidence of beneficial activism. One of the first on institutional investor activism was Smith (1996) who studied the California Public Employees' Retirement System (CalPERS) that was able to use activism as a way to generate shareholder wealth (the "CalPERS effect"), but had no effect on operating performance. Using information from 13-D filings, Brav et al. (2008) document that firms targeted by activist hedge funds in the US have abnormal returns of 7% around the announcement of activism, and that there is no reversal in returns in the subsequent year. Bebchuk, Brav, and W. Jiang (2015) find no evidence of reversals in the five-year period subsequent to the 13-D filings, and lasting improvements in operating performance. [2]

Investor activism is not always conducted publicly: influential and major shareholders (institutional investors, families and individuals, corporations) may be active behind the scenes. In a case study of the Hermes UK Focus Fund, Becht et al. (2009) find evidence that activism through private channels creates significant returns and increases operating performance in periods before the market is aware of what is actually going on behind the scenes. Doidge et al. (2015) confirm, for a sample of Canadian institutional investors, that engaging companies through private channels increases shareholder value.

Another body of literature evaluating the performance of SRI funds (see, e.g., Margolis, Elfenbein, and Walsh (2011) and Barko and Renneboog (2016) for comprehensive overviews), which indicates that SRI funds at best perform on par with their market benchmarks or their conventionally managed counterparts. Krueger (2013) shows that stock prices react to the release of CSR news, especially when it is negative. A few papers show that some SRI funds are able to outperform: Gil-Bazo, Ruiz-Verdu, and Santos (2010) demonstrate that specialized management firms, that perform active portfolio

[2] However, Cremers et al. (2015) find that firms targeted by activist hedge funds have similar stock returns and lower increases in Tobin's Q compared to ex ante similar firms that were not targeted by activist hedge funds, suggesting that while activist hedge funds may have stock-picking ability, it is less clear whether their activism, on average, causes improvements in firm performance.

selection, are able to outperform conventional mutual funds.[3] Gibson and Krueger (2017) show that funds' investment strategies based on sustainability are related to the chosen investment horizon and yield positive risk-adjusted returns. The pressure on individual firms to address ESG issues has been highlighted in the US SIF (2014) and Eurosif (2014) reports, which state that about 28% and 40% of institutional investors filed ESG-related requests to their portfolio companies in the US and Europe, respectively. Among these institutions, it is predominantly mutual funds and pension funds that contact companies regarding environmental and social issues Dyck et al. (2015).

Using a proprietary sample of U.S. activist files, Dimson et al. (2015) uncover that successful engagements in social and environmental topics induce positive returns and improvements in operating performance and corporate governance. Hoepner et al. (2016) find that ESG activism reduces left tail firm risk, especially when target firms respond with material actions to the activist's requests. Looking at shareholder proxy proposals, Flammer (2015) documents that proposals that pass only by a small margin, generate significant returns and superior long-term accounting performance. It is not ex ante clear that specific activist tactics are effective across countries. One reason is that legal rules and corporate orientations toward shareholders or stakeholders (and the resulting regulation regarding ESG issues) as well as the voluntary adoption of CSR policies (e.g., reflecting social preferences or institutional development) differ across countries, inducing varying levels of CSR performance (Liang and Renneboog, 2017).

2.3. Data

2.3.1. Engagement data

We have obtained a proprietary database on investor activism from a large European asset manager with more than $250 billion in total net assets under management. The activist has offices and manages funds across Europe, North America and Asia, and has long had a focus on ESG-specific investments. The activist mainly manages mutual funds and pension funds, has a specialized team of analysts that combines both in-house and independent third-party research to identify companies that have room for improvement in their ESG policies. Our database covers the universe of their completed engagement cases over the period starting in the third quarter of 2005 through the end of 2014. This enables us to test differences in engagement techniques and corresponding

[3] This is in line with the findings of Cremers and Petajisto (2009), who show that mutual funds' outperformance of their benchmark is positively correlated with the portion of actively managed stocks in their portfolio.

outcomes. As Liang and Renneboog (2017) show, there is an important difference in the perception and implementation of CSR across countries with different legal, political and historical origins, such that the findings for one region do not necessarily apply to another. Therefore, we split the sample into three distinct regions based on the corporate domiciles: North America, Europe, and Other (mostly Asia-Pacific) companies. Engaged companies are all either part of the MSCI All-Cap World Index or a major regional or country index. In total, our database has 847 completed engagement sequences involving 660 different companies.

The asset manager employs a specialized ESG-team that screens companies around the world. An activist case starts with the identification of a concern where the target company can improve upon its ESG practices. The engagement team relies on its own research, as well as reports published by specialized research companies and institutes (e.g., the environmental report of the World Bank or the UN Global Compact Monitor). An engagement case can also be triggered by some unforeseen event or crisis, where the engager screens a firm's ESG policies and concludes that they are insufficient to deal with the crisis and hence requests changes to address it. A prominent example is the 2010 Deepwater Horizon oil spill in the Gulf of Mexico, which BP arguably could have avoided or mitigated if they had had clearly formulated environmental and disaster contingency plans in place (Watkins, 2010), and that has triggered policy adjustments in the energy sector and enhanced scrutiny by the providers of CSR performance scores and activists.

At the initiation of an engagement, the activist formulates a clearly defined objective. We first partition the engagement cases into two groups based on the engagement's objectives, distinguishing those aimed at (i) changing the operations of the firm, e.g. implementing new environmental technology for better water management, or board-restructuring ("reorganization"-oriented engagements), versus at (ii) providing more information on specific ESG dimensions, e.g. these typically involve requests for better reporting standards, such as the publication of a detailed sustainability report ("transparency"-oriented engagements). Each of these engagement categories can be further partitioned according to which of the E, S, and G dimensions was the main dimension of interest.

At the start of an engagement, the activist also decides whether to carry out the engagement alone or in a coalition with one or more other activists, and whom to contact at the company. Typical contact persons in the engaged firm include executive and non-executive management (such as the CEO, investor relations personnel, and ESG representatives). The activist in this study has a self-imposed deadline of three years to achieve the desired outcome. If a successful outcome is reached, it usually occurs within 20 months.

The ESG-team gives advice to its own in-house fund managers (of both SRI and conventional funds) but also works on commissioned cases on behalf of consulting clients' portfolios (as the asset manager also manages external investment funds). The activist typically does not own a major block surpassing the 5% reporting threshold, such that the activist is generally not required to file 13-D reports in the US.

In an environmentally-related example, the engager contacted a large French cosmetics and beauty company regarding their use of palm oil, after a major UK retailer announced a ban on palm oil products coming from unsustainable sources. The engager was concerned that this ban and the skeptical attitude towards the use palm oil would affect the competitive position of the company in its industry, and requested clarification regarding the use of palm oil in its products. The company provided the requested information, demonstrating that it was only a minor user of palm oil and that it was purchasing its supplies from sustainably managed sources. The activist asked the company to provide this information on its website. After the company complied and published a detailed sustainability report with a special focus on environmental reporting (demonstrating that its potential liability in relation to palm-olive concerns was very limited), this transparency case was successfully closed. This example shows two elements typical for the engagement cases in our sample: first, there is always a trigger for engagements that can be either a significant event, the surfacing of new information, or changes in the regulatory or competitive environment. Second, the engager formulates a specific request and the engagement team follows through with that request and makes sure that all requirements are fulfilled by the engaged company before the file can be successfully closed. In Appendix 2.A, we provide some more illustrations for each main ESG dimension.

For each engagement sequence, we verify that the "successful" closure of the engagement case is indeed determined by the ESG criteria set initially by the activist. Furthermore, we cross-reference outcomes with Factiva records and company websites to check the validity of registered outcomes. We find no evidence that the data include erroneous reporting.

2.3.2. Company-level data

We obtain our firm-level data from a variety of sources: accounting and stock return data are from Datastream, ESG performance indicators from Asset4 (available through Datastream), analyst coverage data from I/B/E/S, and ownership data from Morningstar and Orbis. We merge the data from different sources using ISINs, Datastream Codes, and I/B/E/S identifiers, and cross-check, by means of company names, that all available data are properly matched. We use the international industry return data from Kenneth French's website to calculate abnormal returns. We define industries in various ways, following the classification on French's website for 10, 17 and 49 major industry groups, depending on the availability of a suitable control firm (see below). All variable definitions and their respective sources are provided in Appendix 2.C.

2.4. Engagement characteristics

The engagement cases are categorized into three themes based on the underlying goal, environmental, social, or governance. Within each theme, the engager distinguishes among a variety of topics and subtopics, of which we show the frequency of occurrence in Table 2.1. This table also exhibits the percentage of successfully closed engagement files, the number of contacts between engager and target firm, the length of engagement sequence, and the main contact type.[4] The table shows that the engager focuses mostly on environmental and social topics, making up 42.3% and 43.3% of the 847 cases, respectively. About 60 percent of the cases are closed successfully, varying by topic: firms are most responsive to engagements regarding public health issues, labor standards, climate change, reporting standards, and corporate governance issues.[5] The average number of contacts with targeted firms and the average length of the engagement process are, respectively, higher and lower for successful cases than for unsuccessful ones. The most frequently used means of contact is a formal letter or email; in case of public health issues, the engager and the firm often meet and, in case of corporate governance engagements, the activist takes the issue to the annual or extraordinary shareholder meeting about half the time.

In Table 2.2, we further break down the engagements by ESG theme by distinguishing between: (i) the aim of the engagement triggering reorganization (board or asset restructuring, or operational changes), versus enhancing transparency (see section 3.1), and (ii) whether the engaged firm is initially open to the activist's demand (in this case, "receptiveness" equals one) versus whether the firm initially resists the demand (in which case "receptiveness" equals zero). Initial receptiveness of the activist's demands by management does not necessarily imply success at the end of the engagement period;

[4]A more detailed overview for the subtopics is presented in Appendix 2.B. In order to keep things tractable and to avoid working with very small subsamples, in the multivariate analysis we will focus on the three main ESG topics (for which we also distinguish between reorganization and transparency cases).

[5]A success rate of 60% is higher than the one reported in Dimson et al. (2015); our sample covers a different time period. A high success rate in activist cases is not unprecedented as, for example, Klein and Zur (2009) report a success rate of 60% and 65% for hedge fund and private equity activists, respectively.

this variable just measures the willingness of companies to start a conversation with the activist.

Overall, about 51.5% of engagements aim at inducing a material change in company policy (reorganization), and two thirds of the engaged companies are initially receptive to the engager's request and participate in an initial discussion. When we study the percentage of successful cases over time (by year of engagement initiation), we observe that success rates by year vary between 61% and 78% (with exception of 2009 when the highest number of cases were initiated and the subsequent success dropped to 33%, for which the financial crisis may be responsible).

We also examine the frequency of the various forms of communication between engager and target. Out of the nearly 3,000 activities recorded in the case files, public channels (such as annual or extraordinary general meetings and press releases) account for only 170 (or 5.6%) of the instances, and these are mainly corporate governance cases. One third of the contacts occurred via email, 18.5% by means of a letter, 11.4% via a conference call, and in 10.9% of the cases, a personal meeting took place (in 2.8% of the cases at the firm's premises, and in 8.1% of the cases firm representatives came to one of the engager's offices). Over the whole sample period, the number of contacts between targets and the engager across all activist cases has stayed steady. Out of the 17 Fama-French industries, oil and petroleum firms, as well as financials are engaged the most (93 and 86 cases, respectively), followed by pharmaceuticals, utilities, and retail companies. In terms of geographical focus, 54% of the targets are from Europe, 24% from North-America, 16% from the Asia-Pacific region, and the remainder from Latin-America or Africa.

2.5. Engaging target firms

2.5.1. Matching methodology

To examine the determinants of the activist's decision, we first consider the characteristics of target companies in the year preceding the engagement relative to a matched sample, in order to mitigate the possibility that any observed ESG changes would have happened without the engagements. Our matching pool is the entire universe of companies included in the Thomson Reuters Asset4 ESG database, which contains firms that are included in major indices such as MSCI World, MSCI Europe, DJ Stoxx600, NASDAQ100, Russell 1000, FTSE250, and ASX 300, and which comprises more than 4,200 stocks. The Asset4 ESG database has several advantages. First, it is an international index with broad coverage of large international companies, and contains virtually all our sample firms. Second, this database provides dynamic ESG performance scores that are given by a rating agency that is independent from the engager, and that thus allows us to examine whether the engagements lead to ESG changes that are captured by outsiders. Third, Thomson Reuters is a for-profit organization that is paid by the (SRI) investors for access to its ESG ratings rather than by the rated companies, which implies that rating shopping is unlikely to be an issue (as opposed to, for example, credit ratings where issuers pay for the ratings, see Benmelech and Dlugosz (2009)).

To construct the matched sample, we take several steps. First, we exclude all engaged companies that are also part of the Asset4 database. Second, we restrict the pool to industries based on the 49 Fama-French industry group classification. Third, we calculate the Mahalanobis distance score for each possible engaged and matching company combination based on size, market-to-book ratio, ESG score, and ROA in the year prior to the engagement. The advantage of this matching method is that we do not impose a hierarchy on the matching variables by sequentially sorting companies into portfolios. Furthermore, the Mahalanobis distance score is not sensitive to the scaling of the data and performs well with a small number of matching covariates (Stuart, 2010). The outcome of the matching procedure, the Mahalanobis score, is an intuitive measure that takes the covariance of matching variables into account (and that reduces to the Euclidean distance if the covariances are equal to zero). We cannot find a match based on 49 industries for 14 engaged firms, for which we relax the set of possible matches based on 17 (rather than 49) industries. After calculating the score for each company in our universe, we pick the three companies with the lowest distance metric from the engaged company as the controls. For companies that have multiple engagement cases, we keep the same set of matching companies for subsequent engagements. As a robustness test, we re-estimate all our multivariate analyses with (i) a single best match, and (ii) other matching methods based on propensity scores (Leuven and Sianesi, 2003), but do not report these results as they lead to similar conclusions.

2.5.2. Univariate results

We present summary statistics for target and matching firm characteristics in Table 2.3, testing the difference in means and medians between the engaged and matching sample using a paired t-test and a Wilcoxon signed-rank test, respectively. To test the difference between the means of the engaged and the control sample, we create a "pseudo-company" for each engaged company using the equally-weighted mean of three matched companies, as in Brav et al. (2008) or Dimson et al. (2015). The pseudo-company characteristic is calculated as

$$\tilde{X}_i = \frac{1}{3}\sum_{j=1}^{3} X_{j,i}, \tag{2.1}$$

where $\tilde{X}_i$ represents a characteristic variable for a pseudo-company for each engaged company i and $X_{j,i}$ is the characteristic variable for each matched company $j = 1, \ldots, 3$. All variables definitions and their respective sources are provided in Appendix 2.C.

ESG performance. As explained above, we use ratings provided by Thomson Reuters Asset4 that capture the ESG attributes of target and matching companies. The "aggregate" ESG rating is the equally-weighted average of the following four underlying sub-ratings or pillars: environmental, social, governance, and economic outlook issues. The first three refer to the usual topics of ESG, while the economic pillar addresses the financial performance and economic outlook. We document in Table 2.3 that, both at the aggregate ESG level and the individual pillar level, engaged companies have significantly higher ESG scores than non-engaged firms. This observation is similar to Dimson et al. (2015), who also find that engaged companies already have a higher standards of corporate governance in place prior to investor activism. We also use a modified version of the Entrenchment index (E-index) of Bebchuk, A. Cohen, and Allen Ferrell (2009); out of their six proposed governance provisions, we include poison pills, golden parachutes, staggered boards, and supermajority for bylaws and mergers, as Asset4 only records these variables for all companies. We find, that on average, engaged firms do not have a different aggregate level of these governance provisions than non-engaged firms.

Risk and performance. The annual stock returns of engaged companies are not statistically different from the matched, non-engaged firms, while the engaged firms exhibit lower stock return volatility and greater liquidity. They also have somewhat higher accounting returns, sales growth, Tobin's Q, and interest coverage. Economically, however, these differences are modest. Engaged companies have somewhat higher market share in their respective industries. Other variables (profit margin, sales growth, asset turnover) do not differ.

Cash and expenses. Free cash flow and cash holding figures are comparable across the two samples (Table 2.3). Engaged companies have slightly lower capital expenditures as a fraction of total assets (0.4%), spend more on advertising, and pay out more in the form of dividends both in absolute terms and as a percentage of their net income. Cash holdings, free cash flows, and operating expenses do not differ from those of matched firms.

Size and capital structure. Engaged companies are significantly larger, in terms of assets, sales and market value of equity, although they have significantly fewer tangible assets. Their book leverage is similar to that of their matched peers.

Ownership. Table 2.3 also reveals that the average holding of our activist engager is small but still significantly higher in engaged firms than in its matched counterparts. Engaged companies have fewer blockholders (owning a stake of 5% or larger), but when considering the different types of owners (e.g. financial institutions, industrial companies, the government, hedge funds and private equity, individuals and families), we find no meaningful differences. The number of blockholders might seem large (Edmans and Holderness, 2017), however, this is driven by firms outside of North America. When we partition the sample into North American, European and other domiciled firms, we see that North American firms, on average, have 3 blockholders, European firms have 4, and other, mainly Asian, companies have more than 4. The majority of engaged firms are independent companies, with no shareholder controlling 25% or more of the shares through direct or indirect holdings.

2.5.3. Multivariate results

In Table 2.4, we show the results of probit regressions estimating the likelihood of being engaged by the activist. We first analyze whether firm size, performance, market share, leverage, stock liquidity, cash holdings, dividend yield, capital expenditure, and analyst coverage is related to the choice of the targets, while controlling for year, industry, and geographic fixed effects. The marginal effects exhibited in column (1) of Table 2.4 indicate that our matching procedure was effective, as none of the above variables help predict which firms are targeted, with the exception of a smaller size, a higher stock market performance, higher product market share, and more analyst coverage. The results also show that the asset manager does not generally target companies multiple times, which suggests that engagements are evaluated and started on a per-case basis and that the activist does not have "favorite" targets.

Second, in column 2 we add the percentage of shares owned by the activist prior to the engagement, whether the firm is independent (does not have a major blockholder controlling at least 25% of the equity), the corporate governance index, and the aggregate ESG score. For the sample of all engagement cases, we find that firms with lower ESG scores are more likely to be targeted. Economically, the marginal likelihood of -0.103 (z-statistic of -1.79) implies that a standard deviation decrease in the ESG score (of 23.8) is associated with an increase in the likelihood to be targeted of 2.45%, which is a 10% increase over the unconditional probability. This shows that the activist tends to target companies with more room for improvement in their ESG practice. Ex-ante, it seems reasonable to expect greater scope for ESG improvements at firms with low ESG scores.

In the subsequent columns of Table 2.4, we separately estimate the likelihood to be engaged in the environmental (columns 3-4), social (columns 5-6) and governance (columns 7-8) areas. We find that the results from columns 1-2 largely hold, although, in case of the governance dimension, companies that have lower potential growth opportunities but are profitable (in terms of share price performance) and in which the engager has a higher ex ante equity holding are significantly more likely to be contacted by the activist.[6] Overall, the results indicate that the activist chooses targets that are visible firms with large market shares and in which the activist holds a larger share stake. The tests on the whole sample indicate that the activist does concentrate on firms in the poorest ESG performance category.[7]

2.6. Engagement success

In this section, we consider the drivers of "successful" engagements. As we noted above, success is not determined by the realization of value that could be triggered by the adoption of the activist's requirements nor does it depend on whether the activist demands can be met with little or much effort, but only depends on whether the target complies with whatever the activist set as the ex ante demand. Table 2.5 explores possible drivers of successful engagements, which include (in addition to the variables in Table 2.4) indicator variables for whether or not the activist requests a reorganization effort rather than just more transparency (captured by the variable "Reorganization"), whether or not the engagement was conducted jointly with other activists (captured by the variable "Joint targeting"), whether top executives in the target were contacted by the activist versus lower-level managers or non-executive directors (captured by the variable "Contacted executives"), the number of contacts over the course of engagements (captured by the variable "Number of contacts") and finally whether any previous engagement was successfully concluded (captured by the variable "Success streak").[8]

[6]As a robustness test, we repeat the analysis in the first panels of Table 2.4 for varying levels of engagement whereby the ordering refers to differences in the effort level in engagement. Specifically, we estimate ordered probit models, where the dependent variable is one for engagements triggered for reasons of transparency ("light engagements"), two for reorganization reasons ("strong engagements"), and zero in case of no engagement. In unreported results, we find that previous findings are robust to ordering and, for the strong engagements, the coefficients are larger (in absolute terms).

[7]We repeat the analysis of Table 2.4 with geographical segmentation between North American, European and other domiciled companies. The analysis is presented in Table D.1. We find that the results are qualitatively similar.

[8]We repeat the analysis of Table 2.5 with geographical segmentation between North American, European and other domiciled companies. The analysis is presented in Table D.2.

The results in column 1 reveal that, on average, cases where the activist requests the target to make significant changes in terms of board or asset restructuring or a change in ESG-related operations is significantly less likely to lead to a successful closure of the case by the activist. For example, the coefficient of "Reorganization" equals -0.170, which suggests that such far-reaching requests have a 17% lower likelihood to be successfully closed, compared to an overall success rate of 60%. This is not surprising, as the required effort level in reorganization engagements is much higher for the firm than in the cases where there is only a demand for more transparency and information provision. In general, it is easier to achieve "success" in transparency cases but it is questionable whether these cases are likely to generate significant value that is subsequently reflected in the stock price or the accounting performance. In contrast, reorganization cases may be more likely to lead to value enhancement but may also be harder to achieve as they require more substantial or far-reaching corporate decisions, which the management may be more reluctant to make.

Returning to column 1 of Table 2.5, we find that eventual success of the engagement is not higher if the activist jointly targets a company with other activists, if executives rather than non-executives are the main contact at the target, when the number of contacts between the activist and the firm is higher, or when a firm is more visible (a larger number of analysts following the firm). Companies that previously implemented changes requested by the activists are more likely to do so again. Targets are also more likely to meet the activist's request when their sales growth is lower. In particular, the coefficient on "Sales Growth" of -0.244 indicates that a standard deviation decrease in sales growth (of 0.290) is associated with an increase in the likelihood of success of 7.1%.

Next, column 2 examines additional variables capturing governance and ESG aspects. We find no persistent relation between engagement success and the proportion of the shares owned by the activist and the increases in this equity stake (Holding increase) during the engagement process, and the target's corporate governance (as proxied by the aggregate index of shareholder rights provisions the entrenchment index). However, firms with a higher ESG score prior to engagement are more likely to comply with the requests of the activists. The marginal likelihood of 0.448 means that a standard deviation increase in ESG ratings is associated with a 10.7% increase in the probability of success. This is consistent with the ex ante ESG score indicating how much firms care about ESG issues, or that firms with a stronger ESG track record have the necessary ESG resources and know-how largely in place already, such that compliance does not require a large departure from existing practices.

As it is possible that the activist is more likely to select firms to target where they anticipate that a successful engagement is more easily achieved, we estimate as a robustness analysis a two-stage Heckman model to control for potential selection issues. For the selection equation, we use model (2) of Table 2.4. We find that the above results exhibited in Table 2.5 carry through, and that selection does not appear to be an issue (as the inverse Mills ratio is insignificant in all our specifications).

When we analyze the outcome of engagement by ESG theme in columns 3-8, we find that reorganization requests are less likely to be successful and that previous successful engagements only matter for the subset of engagements related to environmental issues, but not for social or governance engagements. For environmental engagements, large cash holdings are associated with a reduced probability that the case is closed successfully, perhaps because large cash holdings occur at corporations that are less dependent on external capital markets and that accordingly are less interested in good investor relationships. For the subset of social engagements, those at firms with a larger market share are more likely to be successful, which suggests that market-leaders in their industry are more open to investor engagement or are more worried about potential negative media stories. The sensitivity to the engagement is also larger for firms who seem under pressure because of lower sales growth. Finally, governance engagements are more likely to be successful at firms with low buy-and-hold returns over the past year, which is strongly statistically significant once we control for the entrenchment index and the ESG rating in column (8). However, lower stock market performance is not related to a higher likelihood of success for environmental or social engagements. This suggests that corporations deem investor concerns more relevant when they have performed relatively poorly in the stock market, but primarily when faced with governance activism, perhaps to forestall more significant shareholder activism.

2.7. Analysis of performance after engagement

There are several ways through which implementing or increasing CSR can increase firm value. Pro-social behavior can be rewarding for various stakeholders, shareholders, as well as the management (Baron (2008); Bénabou and Tirole (2006)): first, higher ESG standards can increase consumer loyalty through product quality signaling, and consequently lead to higher market share, as well as higher and less volatile profits (Albuquerque, Durnev, and C. Zhang, 2017). Second, employee satisfaction fosters productivity and efficiency, also leading to higher profits (Edmans, 2011; Edmans, 2012). Third, corporate social responsibility can attract a specific shareholder base with long-term investment goals, thereby reducing pressure on management to generate short-term profits and allowing them to undertake investments that yield returns over a longer time horizon (Gaspar et al., 2013). Fourth, improved governance standards also indicate better management practices and result in higher future performance (Alan Ferrell, Liang, and Renneboog, 2016). Finally, investments in CSR could be similar to paying an insurance premium to avoid rare events that could harm a firm and which are not priced yet (Hong and Liskovich, 2015; Lins et al., 2017).

We first test the impact of engagements on the operations and characteristics of target firms. We estimate differences-in-differences (DD) specifications (Equations 2.2 and 2.3) whereby the dependent variables are market-based measures of performance (Tobin's Q), accounting-based measures (ROA, operating expenses, sales growth, profit margin, asset turnover), sales market share, investments (CapEx), ownership (long-term holdings, toehold stake of the activist), ESG performance (ESG ratings; environmental, social, governance scores), corporate governance (entrenchment index), and visibility (analysts following), for two treatments, the successful completion of the engagement case (Equation 2.2) and the engagement treatment irrespective of subsequent success (Equation 2.3):

$$y_{i,t} = \alpha + \beta \cdot post_t + \gamma \cdot success_i + \delta \cdot post_t \times success_i + \nu \cdot controls_{i,t} + \epsilon_{i,t}, \quad (2.2)$$

$$y_{i,t} = \alpha + \beta \cdot post_t + \gamma \cdot engaged_i + \delta \cdot post_t \times engaged_i + \nu \cdot controls_{i,t} + \epsilon_{i,t}, \quad (2.3)$$

where *Post* is an indicator variable that equals 1 for the 1-year period following the successful closure of a case, and zero otherwise (Equation 2.2), or for the 2-year period after the engagement and 0 otherwise (Equation 2.3). The latter case captures the typical period that the engagements last. Equation 2.2 is estimated for the sample comprising engaged companies (both successful and unsuccessful ones), whereas Equation 2.3 is estimated on the sample comprising both engaged companies and non-engaged matched firms.

We apply the same methodology on various subsamples: the reorganization-oriented engagements, the quartiles of firms with the lowest and highest ESG scores (measured prior to engagement), and the environmental-, social-, and governance-oriented cases. In all these specifications, the vector Controls includes leverage, size, tangibility of assets, and time and industry fixed effects.[9] We cluster standard errors at the firm level.

For the sake of brevity, we only report the δ coefficients in Table 2.6, where each coefficient comes from a separate regression. In Panel A, we report the δ coefficients for the evaluation of success for all engagement cases (column 1) and for six subsamples. The results indicate that, on average, accounting performance does not significantly change following a successful engagement. This is in line with Klein and Zur (2011) results that hedge fund activism does not improve accounting performance. Sales growth, in

[9] In the analysis of Tobins Q, we also include ROA, CapEx and sales growth.

contrast, improves on average after successful engagements by 3-22% across virtually all subsamples (with the only exception the subsample of social engagements). Given the typical sales growth of 10.1% in the year preceding engagement, the overall jump of 7.6% is not only statistically, but also economically quite meaningful.

The coefficients on the ESG performance ratings confirm that successful engagements lead to higher ESG scores for targets with the ex ante weakest ESG ratings (the lowest quartile). The results suggest that if a case is closed successfully with an ex ante poorly rated company, the ESG rating on average increases by 10.6, which is a significant boost of 13.7% compared to the mean. This growth is most pronounced for environmental ratings, where we observe an 18.6% gain relative to the initial rating.

It is possible that the mere fact that an activist targets a firm generates an effect even if the activist does not attain its specific goal over the course of engagement. To investigate this issue, we turn to panel B of Table 2.6, where we also report the DD coefficients of an analysis where the treatment effect is engagement (and the non-treated sample consists of matched non-engaged firms). As before, we also study the changes in corporate and ESG performance as well as some other firm characteristics for the full sample and a set of subsamples. We find that the engagement in itself has little impact on the ex post accounting performance (column 1) or any other firm characteristic (with exception of the market share, which is a little lower). For example, the increases in sales growth that we document for successful cases is not occurring for unsuccessful cases.

The subsamples of firms within the lowest versus highest (ex ante) ESG quartiles yield some interesting results: the mere fact of engaging poor ESG targets triggers significant increases in their ESG scores (the overall and the sub-scores on E, S, and G aspects all augment as well as the economic outlook sub-score which proxies for shareholder and customer loyalty). So, the mere engagement, independent of the ultimate success of the engagement case, triggers changes in the ESG profile of the target, which is picked up by the independent ESG evaluation providers. For the firms in the highest ex ante ESG quartile, we observe the inverse: here, all the ESG scores go down after the engagement. This could be the result of an information revelation process: the activist conducts research to identify companies with a potential for improvement in one of the ESG dimensions. If the activist correctly identifies those companies, then subsequent ESG ratings should reflect this new information and the adjusted ESG scores then incorporate the potential ESG problem which drives the scores down. This implies that research and engagement activity brings new information to market actors and better reveals the ESG practices of companies. Previously low-rated companies are not “lost cases” and late best-performers might still have room for improvement. As the activist engages companies, the rating agency generally seems to realize over the course of that engagement that previous scores did not incorporate all of the activist's concerns, i.e., that engaged companies still had key ESG points to improve on.[10]

2.8. Returns to engagement

In this section, we measure buy-and-hold returns (BHRs, which are raw, unadjusted cumulative returns) and cumulative abnormal returns (CARs, corrected for exposure to the global market, size, book-to-market and momentum Fama-French-Carhart return factors) of the target's stock during and after the engagement. We use stock return data from Datastream and download our factor data from the website of Kenneth French.

In Table 2.7, we report BHRs for various event windows, i.e., in the month around the completion of the engagement (distinguishing between successful versus unsuccessful completion), and over time windows of 6 and 12 months following the end of the engagement. We find that, on average, BHRs are small but positive and statistically significant in the month following the closure of a case (at 0.8%). These positive returns stem from the successfully closed cases that generated BHRs of 1.2%, while cases where the target firm does not comply do not generate any significant return. Over the period of six months after the completion, successful cases generate returns of 4.3%, whereas unsuccessful ones incur stock price decreases by 3.1%. Over a one-year time period, we still find significant return differences between the successful and non-successful cases.

We re-estimate these BHRs over the same time windows for different subsamples and also report them in Table 2.7. The target subsamples based on the ex ante ESG scores the highest or lowest quartiles do not yield any significant post-engagement financial returns, a finding that does not depend on the engagements being (un)successful.

Successful reorganizations yield BHRs of 2.3% in the month of the completion of the engagement and over a longer time window of 6 months; the BHRs of unsuccessful reorganization attempts are negative by 3.5%. When we partition the engagement files by ESG dimension, we also find significant differences: over the short run of one month, successful engagements of the environmental and governance type trigger statistically significant BHRs of 1.8% and 2.9%, respectively, although only the former are different from unsuccessful cases. Over the time window of 6 months after the end of the engagement, successful environmental, social, and governance engagements outperform their unsuccessful counterparts by 10.1%, 4.0%, and 1.6%, respectively. Turning to BHRs

[10] In unreported results, we define the pre- and post-periods of Equations 2.2 and 2.3 in various ways. Specifically, we move the cutoff 1-3 years after the start of engagements, and 1-3 years after completion. The results are qualitatively similar to the ones presented here.

over one year, governance engagements yield a return of 8.4% on average (but there is no statistical difference between successful and unsuccessful ones), and successful social engagements are 8.3% higher than the unsuccessful cases (5.8% minus -2.5%).

In Figure 2.1, we depict the mean BHR of equally-weighted portfolios of engaged companies, where the portfolios were created one month prior to the event month and the returns are calculated over the subsequent 18 months. The return difference between successful and unsuccessful cases is highest for the period 6 to 12 months following the completion. Figures depicting the mean BHR over 18 months after the completion of the engagement for the subsamples of engaged North-American, European, and Other (mainly Asia-Pacific) firms, respectively, exhibit a similar picture (not shown). For North-American and European firms, the BHRs gradually increase and level off after about 8-9 months, and the difference in BHRs between (un)successful engagement firms is at the maximum between 6 and 12 months. For the Other subsample, the average BHR across all firms gradually declines over 5 months, but the returns of the unsuccessful cases decline faster than the successful ones.

We calculate cumulative abnormal returns (CARs) for the three different time windows following the completion of engagements (as in Table 2.7) using the four-factor global Fama-French-Carhart model. We do so for all engaged firms and for the subsamples with successful and unsuccessful ones, and by subtracting the CARs from those of their matched firms, we obtain excess CARs (ECARs) that we report in Table 2.8.[11] The top panel shows that the average ECARs are positive, close to zero (0.5%) but still significantly different from zero in the month after the completion of the engagement (be it successful or unsuccessful). This means that the engaged firms slightly outperform the non-engaged ones. This difference increases to 2.7% in the 6-month period after the engagement file is closed (but there is no difference between successful or unsuccessful completion of the cases). The firms of which the activist demands a reorganization outperform the matched firms by 4.4% in the six months after the closure of the activist's case (but the difference between successfully or unsuccessfully closed files is not statistically significant).

Turning to the firms in the lowest (ex ante) ESG quartile, we find that these firms outperform the matched firms by 7.1% (7.5%) in the 6 months (1 year) after the activist ends the engagement. These successfully engaged low-ESG firms outperform the firms of which the activist closed the file unsuccessfully: successful firms have an average ECAR of 8.4% over the 6-month period (and outperform the unsuccessful ones by 2.4%) and of 11.3% over the year (and outperform the unsuccessful firms by 6.8%). This implies

[11] As a robustness check, we also use Fama-French-Carhart factors, 17 Fama-French industry portfolios, as well as size and book-to-market matched portfolios. We find that the results are qualitatively similar.

that it is important to target low ESG firms as they then significantly outperform their not-engaged peers. This pattern is not visible for engaged firms with an (ex ante) high ESG classification; they do not obtain significant ECARs. Firms targeted for environmental or governance deficiencies exhibit significant and positive ECARs of 3% (over a 6-month period) and 14.1% (over a one-year period), respectively.[12]

Figure 2.2 corroborates the findings in Table 2.8: the CARs for the successful engagements remain flat for about 6-7 months, where after the CARs decline. The decrease in CARs for unsuccessful cases sets in after about one month since completion. The gap in the CARs between successful and unsuccessful cases reaches a maximum after about 8-12 months. For North-American successfully engaged targets, the CARs remain positive until about 9 months and then rapidly decline whereas the CARs of the unsuccessful cases goes down after 2 months, showing a big gap in CARs after about 8-9 months. For European targets, there is hardly a difference in CARs between (un)successful targets; their CARs gradually decrease after about 9 months.[13]

Taken together, the results in Table 2.7 and 2.8 imply that the activist can make a modest return provided he sells his share stake in the successfully target 6 to 12 months after closing the case and within 3 months in unsuccessfully engaged firms.

2.9. Conclusion

By means of a large detailed, global dataset comprising the aspects the activism on corporate social responsibility that takes place behind the scenes by a major investment fund, we analyze the reasons and success of corporate engagement. We match each engaged firm with three firms that were not engaged and are most similar to the engaged firms in terms of size, market-to-book ratio, ROA, and ESG score in the year prior to the engagement and belong to the same industry.

The activist generally targets large firms with large market shares. Targeted firms are more likely to be in the highest ex ante ESG quartile, which is somewhat surprising as one would expect the activist to concentrate on firms with poor ESG performance

[12]Given that the activist focuses mostly on the E and S factors and less on governance, the subsample of (un)successful cases is rather small which may explain the reason why the unsuccessfully closed cases yield higher ECARs than the successful ones).

[13]A natural extension of this work is to look into the portfolio holdings of the activist in more detail. Since the activists primary objective is to generate financial returns through their stock holdings and engagements, it is important to further investigate their holdings and check if there is a different point in time when they realize returns, not when they actually close the file. The available data on fund holding changes are not sufficiently precise we would need daily data to enable us to a return calculation at the fund level. On the same note, the definition of a successful engagement is determined by the activist.

if ESG improvements are expected to be related to the generation of value. Relative to the matched sample, target firms have a higher stock market performance, a higher product market share, and are more visible (have more analyst coverage). The firms that are engaged on corporate governance issues are somewhat smaller, have a dispersed ownership structure, have lower potential growth opportunities (Tobin's Q) but are otherwise profitable (both in terms of previous year buy-and-hold returns and accounting performance).

Next, we study whether the engagement is successfully completed or not. The definition of success is the activist's and reflects whether the target firm has complied with the activist's demands. One could question the relevance of this definition, considering that in some cases compliance may require little effort from the firm. In other cases, the target is asked to make substantial changes in terms of board or asset restructuring or in ESG-related operations, which is less likely to lead to a successful closure of the case. It is hence not surprising that when a "hard" engagement occurs, the likelihood of successful engagement is lower than in cases just requiring more ESG transparency and information provision. Eventual success of the engagement does not depend on joint targeting nor on who is the main contact in the target firm (management or non-executive directors). More intensive contact between the activist and the target does yield success more frequently, though only for European targets. Also, companies that were targeted in the past and complied with the activist's requests are also more likely to do so again. European firms under pressure - with declines in sales and negative buy-and-hold returns - more frequency adopt the activist's suggestions. Our results also reveal that firms with a good ESG track record prior to engagement (e.g. the firms in the highest ESG performance quartile in North-America and Europe) are more likely to comply with the requests of the activists. Firms that did not care much about ESG issues continue to do so as they seem reluctant to adopt the suggestions by the CSR activist.

The real effects of engagement of the target firm are rather modest. Our differences-in-differences analyses reveal that, on average, accounting performance measures and its components do not significantly improve after engagement. The only exception are sales, which significantly grow after the engagement, both statistically and economically.

Interestingly, the mere engagement independent of the ultimate success of the engagement case triggers changes in the ESG profile of the target, which is picked up by the independent ESG evaluation providers. Firms with poor ex ante ESG performance scores obtain higher ESG score, whereas for the firms in the highest ex ante ESG quartile we observe the inverse change: here, all the ESG scores go down after the engagement. If the activist correctly identifies companies with an ESG problem, then subsequent ESG ratings may reflect this new information and the adjusted ESG scores then incorporate the potential ESG problem, which drives the scores down. Previously low-rated companies are not “lost cases” and late best-performers might still have room for improvement. As the activist engages companies, the rating agency seems to realize that previous scores did not incorporate all of the activist's concerns in that engaged companies still had key ESG points to improve on.

From the activist's perspective, the activism seems to come with, at best, modest financial returns the period immediately following the successful closing of the cases, though we find no evidence that targets are negatively affected by the activism. On average, the buy-and-hold returns for completed engagement are small, but still positive and statistically significant in the month following the closure of a case (at 0.8%). These returns can be dissected into positive returns that stem from the successfully closed cases (generating BHRs of 1.2%) and zero BHRs for unsuccessful engagements. Over longer time windows (e.g. six months), successful cases generate returns of 4.3% whereas unsuccessful ones incur stock price decreases by 3.1%. Further extending the time period to one year, reveals strong return differences between the successful and non-successful cases. Successful reorganizations, which require most compliance effort from the target, yield BHRs of 2.3% in the month the completion of the engagement, and over a longer time window of 6 months, the BHRs of unsuccessful reorganization attempts are negative by 3.5%.

When we partition the engagement files by ESG dimension, we find significant differences: the largest BHRs are generated by successfully engaging targets on environmental and governance issues (the one-month BHRs amount to 1.8% and 2.9%, respectively). Over the time window of 6 months after the end of the engagement, successful environmental, social, and governance engagements outperform their unsuccessful counterparts by 10.1%, 4.0%, and 1.6%, respectively. When we turn to BHRs over one year, we report that governance engagement yield a return of 8.4%, and that successful social engagements are 8.3% higher than the unsuccessful cases.

The BHRs calculated over the 18 months starting one month prior to the engagement diverge most for successful and unsuccessful engagement for the period 6 to 12 months following the completion of the case. An analysis of excess cumulative abnormal returns, controlling for exposure to global market, size, book-to-market and momentum factors, and measured relative to the CARs of matched peer firms, shows that that the engaged firms slightly outperform the non-engaged ones: the average ECARs are positive (0.5%) and significantly different from zero in the month after the completion of the engagement, and augment to 2.7% over the 6-month period after the engagement file is closed. Reorganization demands by the activist make a targeted firm outperform its non-targeted (but otherwise similar) peer-company by 4.4% in the six months after the completion of the activist's case. Targeting firms in the lowest (ex ante) ESG quartile pays off in the sense that these firms outperform their matched peers by 7.1% (7.5%) in the 6 months (1 year) after the activist ends the engagement. Furthermore, successfully engaged low-ESG firms outperform the unsuccessfully engaged low-ESG firms; the former have average ECAR of 8.4% over the 6-month period (and outperform the unsuccessful ones by 2.4%) and of 11.3% over the year (and outperform the unsuccessful firms by 6.8%).

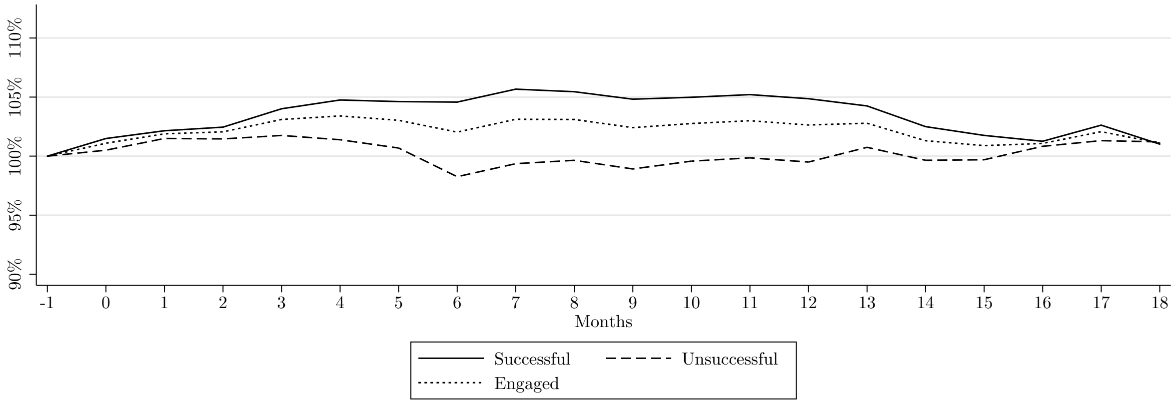


Figure 2.1 Buy-and-hold returns after completion

The figure shows buy-and-hold returns for an equally weighted portfolio of engaged companies. The portfolios are formed at the completion of engagements.

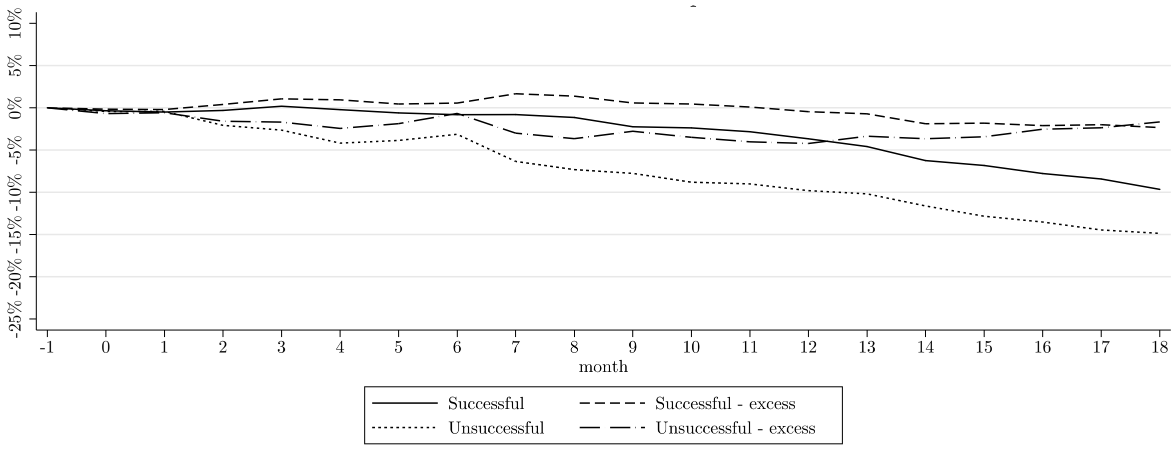


Figure 2.2 Cumulative abnormal returns after completion

The figure shows cumulative abnormal returns for equally weighted portfolio of engaged companies and above a matched sample. The portfolios are formed at the completion of engagements. Returns are adjusted for Fama-French-Carhart global factors.

Table 2.1 Engagement characteristics by outcome

This table shows the breakdown of completed engagements by ESG themes and topics. A further breakdown of engagement topics is provided in Appendix B. In the first part, the number and percentage of all and successful engagements are reported. The second and third part report statistics for the number of contacts, the length of the engagement and the typical contact type, for successful and unsuccessful cases, respectively. The length of engagement sequences is defined in calendar days. The contact type is the most frequently applied contact channel per topic. Percentages are calculated over all cases.

	Whole Sample (1)				Successful (2)						Unsuccessful (3)					
	All engagements		Successful		Contact number		Length of sequence		Contact type		Contact number		Length of sequence		Contact type	
	N	%	N	%	Mean	Median	Mean	Median		%	Mean	Median	Mean	Median		%
Theme: Environmenta																
Climate Change	21	5.9%	17	81.0%	5.2	5	584.4	491	Email	41.2%	4.8	4.5	383.8	500	Email	75.0%
Ecosystem Services	113	31.6%	64	56.6%	5.2	4	857.8	909	Email	50.0%	3.9	4	700.9	895	Letter	65.3%
Environmental Mgmt.	224	62.6%	109	48.7%	3.1	2	379.6	328	Letter	37.6%	2.5	2	583.0	730	Letter	62.6%
Total	358	42.3%	190	53.1%	4.0	3	559.0	451	Letter	42.1%	2.9	2	612.6	730	Letter	63.7%
Theme: Social																
Public Health	30	8.4%	27	90.0%	3.0	2	395.5	341	Meeting	37.0%	1.7	2	329	357	Email	66.7%
Human Rights and Ethics	238	66.5%	116	48.7%	3.3	3	424.1	374.5	Letter	37.1%	2.7	3	479.6	491	Letter	47.5%
Labor Standards	99	27.7%	80	80.8%	4.6	4	647.4	716	Email	63.7%	6.3	5	938.9	1,064	Email	68.4%
Total	367	43.3%	223	60.8%	3.7	3	500.7	391	Letter	46.6%	3.1	3	537.1	491	Letter	50.7%
Theme: Governance																
Corporate Governance	86	70.5%	66	76.7%	3.4	2	448.6	270.5	A/EGM	39.4%	2.3	2.5	234.4	98	A/EGM	50.0%
Mgmt. and Reporting	36	29.5%	30	83.3%	4.3	3.5	402.5	388	Meeting	36.7%	3	2.5	600.2	681.5	Meeting	33.3%
Total	122	14.4%	96	78.7%	3.7	3	434.2	355.5	Letter	38.5%	2.4	2.5	318.8	196.5	Email	46.2%
Total	847		509	60.1%												

Table 2.2 Number of engagements by reorganization and target firm receptiveness

This table shows the breakdown of completed engagements by ESG themes and topics. A further breakdown of topics is provided in Appendix B. An engagement case is defined as reorganization if the engager requests a change in the strategy or governance of the firm. A company is deemed as receptive if it responds to the request of the engager. The first part of the table reports the breakdown of reorganization cases, and receptiveness by firms for all cases. The second and third part of the table give a breakdown of reorganization and receptiveness by successful and unsuccessful cases, respectively. Percentages are calculated over all cases for each topic.

	Full sample (1)					Successful (2)				Unsuccessful (3)			
	All	Reorganization		Receptiveness		Reorganization		Receptiveness		Reorganization		Receptiveness	
	N	N	%	N	%	N	%	N	%	N	%	N	%
Theme: Environmental													
Climate Change	21	0	0.0%	17	81.0%	0	0.0%	16	76.2%	0	0.0%	1	4.8%
Ecosystem Services	113	74	65.5%	82	72.6%	31	27.4%	56	49.6%	43	38.1%	26	23.0%
Environmental Mgmt.	224	178	79.5%	116	51.8%	69	30.8%	107	47.8%	109	48.7%	9	4.0%
Total	358	252	70.4%	215	60.1%	100	27.9%	179	50.0%	152	42.5%	36	10.1%
Theme: Social													
Public Health	30	0	0.0%	24	80.0%	0	0.0%	21	70.0%	0	0.0%	3	10.0%
Human Rights and Ethics	238	124	52.1%	143	60.1%	47	19.7%	115	48.3%	77	32.4%	28	11.8%
Labor Standards	99	2	2.0%	90	90.9%	1	1.0%	78	78.8%	1	1.0%	12	12.1%
Total	367	126	34.3%	257	70.0%	48	13.1%	214	58.3%	78	21.3%	43	11.7%
Theme: Governance													
Corporate Governance	86	49	57.0%	67	77.9%	34	39.5%	64	74.4%	15	17.4%	3	3.5%
Mgmt. and Reporting	36	9	25.0%	33	91.7%	8	22.2%	30	83.3%	1	2.8%	3	8.3%
Total	122	58	47.5%	100	82.0%	42	34.4%	94	77.0%	16	13.1%	6	4.9%
Total	847	436	51.5%	572	67.5%	190	22.4%	487	57.5%	246	29.0%	85	10.0%

Table 2.3 Descriptive statistics

This table reports summary statistics for all variables. For each case, we keep the first firm-year observation and use a lag of one year. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, we draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, ESG score, size, market-to-book ratio and ROA. The t-statics stand for the difference in means between the engaged and the control group. The Z-score is calculated for the Wilcoxon signed rank test, for which we use the median difference between the engaged firm and the control group. For the t-statistics and Z-scores we report p-values in brackets. Variables are winsorized at 2.5% on both tails of the distribution. All variable definitions are in the Appendix.

	All cases						Control		Difference	
Variable	Obs.	Mean	Sdev.	25%	Median	75%	Obs.	Mean	t-test	Rank
ESG ratings										
ESG score	705	77.315	23.821	70	88.520	94.010	2,337	67.861	[0.000]	[0.000]
Environmental score	705	74.627	25.317	63.900	86.990	93.030	2,336	67.412	[0.000]	[0.000]
Social score	705	76.913	23.534	67.860	86.770	94.010	2,336	67.194	[0.000]	[0.000]
Governance score	705	64.412	26.324	45.940	73.910	85.530	2,336	57.244	[0.000]	[0.000]
Economic score	705	71.345	26.151	54.780	81.480	92.660	2,336	63.508	[0.000]	[0.000]
E-index	641	0.376	0.252	0.250	0.250	0.500	1,988	0.360	[0.136]	[0.151]
Risk and performance										
Buy-and-hold return	833	0.075	0.459	-0.209	0.067	0.290	2,544	0.052	[0.224]	[0.835]
Volatility	826	0.324	0.183	0.185	0.280	0.409	2,530	0.327	[0.609]	[0.001]
Amihud ILLIQ	827	0.176	0.851	0	0	0.002	2,452	0.164	[0.703]	[0.000]
Asset turnover	846	0.848	0.566	0.460	0.760	1.130	2,544	0.827	[0.375]	[0.371]
Profit margin	841	0.080	0.147	0.035	0.071	0.123	2,537	0.083	[0.637]	[0.177]
ROA	846	0.059	0.064	0.020	0.052	0.090	2,544	0.053	[0.009]	[0.000]
ROE	846	0.157	0.166	0.086	0.152	0.235	2,544	0.133	[0.000]	[0.000]
Sales growth	835	0.101	0.290	-0.061	0.079	0.219	2,534	0.109	[0.445]	[0.020]
Market share	847	0.028	0.030	0.004	0.015	0.048	2,544	0.017	[0.000]	[0.000]
Market-to-book	843	2.578	1.986	1.338	1.982	3.202	2,544	2.361	[0.001]	[0.255]
Tobin's Q	843	1.977	1.284	1.124	1.604	2.392	2,544	1.891	[0.073]	[0.033]
Cash and expenses										
Cash holding	846	0.066	0.073	0.019	0.041	0.084	2,544	0.067	[0.771]	[0.000]
CapEX	846	0.053	0.046	0.021	0.041	0.075	2,544	0.057	[0.060]	[0.000]
Operating expenses	817	0.862	0.128	0.806	0.881	0.938	2,532	0.862	[0.933]	[0.779]
Size and capital structure										
Log total assets	846	9.623	1.858	8.461	9.862	11.060	2,544	9.293	[0.000]	[0.000]
Log sales	841	9.146	1.719	8.177	9.549	10.617	2,537	8.798	[0.000]	[0.000]
Log market equity	843	9.164	1.752	8.095	9.486	10.802	2,544	8.907	[0.000]	[0.000]
Book leverage	846	0.327	0.220	0.161	0.302	0.461	2,544	0.320	[0.381]	[0.408]
Tangibility ratio	845	0.313	0.234	0.119	0.271	0.479	2,538	0.338	[0.010]	[0.000]
Other										
Dividend yield	843	0.029	0.027	0.011	0.024	0.040	2,544	0.026	[0.012]	[0.138]
Dividend payout	846	0.389	0.508	0.121	0.325	0.525	2,544	0.353	[0.070]	[0.756]
Company age	845	51.850	52.544	14	37	81	2,544	52.573	[0.681]	[0.000]
Analysts	810	19.076	10.621	11	19	27	2,502	14.169	[0.000]	[0.000]

Continued on next page

Continued from previous page

	All cases						Control		Difference	
Variable	Obs.	Mean	Sdev.	25%	Median	75%	Obs.	Mean	t-test	Rank
Ownership										
Holding of engager	847	0.002	0.002	0	0.001	0.002	2,544	0.001	[0.051]	[0.580]
Average ownership	847	0.048	0.077	0.011	0.019	0.048	2,544	0.046	[0.314]	[0.000]
Blockholders	847	3.851	1.813	3	4	5	2,544	4.092	[0.001]	[0.000]
Funds	847	0.018	0.068	0	0	0	2,544	0.015	[0.196]	[0.000]
Hedge fund & PE	847	0.009	0.020	0	0.003	0.007	2,544	0.010	[0.172]	[0.000]
Individuals	847	0.018	0.068	0	0	0	2,544	0.015	[0.196]	[0.000]
Independent firm	829	0.840	0.367	1	1	1	2,498	0.848	[0.547]	[0.000]

Table 2.4 Analysis of targeting

This table reports the marginal effects obtained from probit regressions on the probability of targeting relative to a matched sample, where the dependent variable is 1 if a company if targeted and 0 otherwise. The first two columns report regression results for the whole sample of engagements (1-2), while the second, third and fourth set of columns refer to Environmental (3-4), Social (5-6) and Governance (7-8) cases, respectively. Marginal effects are evaluated at the mean of the respective independent variable. The variable "ESG score" is the equal ESG rating for the full sample and the corresponding score for each specific engagement theme, expressed as a percentage. Standard errors are clustered at the firm level. The matching sample is determined by Mahalanobis score matching on industry, size, market-to-book, ESG and ROA. Variable definitions are provided in the Appendix. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Full sample		Environmental		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log total assets	-0.033***	-0.009	-0.001	0.012	-0.015**	0.005	-0.017***	-0.028***
Tobin's Q	-0.008	-0.001	0.001	0.008	0.002	0.006	-0.015***	-0.025***
Sales growth	0.001	-0.045	0.002	-0.014	-0.034	-0.053	0.025	0.014
BHR over 12 months	0.084***	0.114***	0.014	0.020	0.044***	0.060***	0.029***	0.050***
ROA	0.146	0.034	0.045	-0.028	0.094	0.058	0.001	-0.001
Sales market share	3.838***	3.453***	1.114***	0.915**	1.783***	1.403***	0.798***	1.040***
Cash holding	-0.005	0.050	0.066	0.032	-0.017	0.043	0.017	0.076
Book leverage	0.018	0.036	0.052	0.046	-0.053	-0.029	0.005	0.008
Dividend yield	0.600	1.451**	0.233	0.633**	0.214	0.564	0.252	0.528***
CapEX	0.014	-0.020	0.190	0.197	-0.177	-0.322	-0.127	-0.095
Amihud ILLIQ	0.001	-0.354*	-0.027	-0.185**	0.009	-0.097	-0.011	-0.512
Analysts	0.013***	0.016***	0.005***	0.005***	0.005***	0.006***	0.003***	0.004***
Previous engagement	-0.014	-0.019**	-0.025***	-0.030***	-0.004	-0.004	0.008***	0.009***
Holding of engager		4.276		1.327		0.936		1.898***
Independent company		0.032		0.008		0.018		0.018
Entrenchment index		-0.023		-0.011		-0.028		0.012
ESG score		-0.103*						
E score				-0.046				
S score						-0.057*		
G score								-0.001
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Geographic FE	yes	yes	yes	yes	yes	yes	yes	yes
Pseudo R2	0.10	0.18	0.12	0.15	0.11	0.16	0.27	0.33
N	3,174	2,478	3,174	2,478	3,174	2,478	3,174	2,478

Table 2.5 Analysis of success

This table reports the marginal effects obtained from linear probability regressions on the probability of success. The dependent variable equals 1 if the engagement is successful and 0 otherwise. The first two columns report regression results for the whole sample of engagements (1-2), while the second, third and fourth set of columns refer to environmental (3-4), social (5-6) and governance (7-8) cases, respectively. Standard errors are clustered at the firm level. The dummy "Reorganization" takes the value 1 for reorganization cases and 0 otherwise. The dummy variable "Joint targeting" equals one for cases where the engager contacts the company with a group of other activists. The variable "Contacted executives" is 1 if executive management is contacted and 0 otherwise. "Number of activities" and "Success streak" refer to the number of contacts per case and the number of previous successful cases with the company. Other variable definitions are provided in the Appendix. *, ** and *** indicate statistical significance at the 10%, 5% and 1%, respectively.

	Full sample		Environmental		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reorganization	-0.170***	-0.159***	-0.376***	-0.275**	0.018	-0.019	-0.044	0.039
Joint targeting	0.043	0.030	0.083	0.074	0.049	0.055	-0.165	-0.221
Contacted executives	-0.05	-0.040	0.012	-0.126	-0.193**	-0.085	-0.049	0.027
Number of contacts	0.005	0.005	0.006	0.012	-0.025**	-0.02	0.014	0.012
Success streak	0.031**	0.021*	0.056**	0.045*	0.007	0.016	0.017	-0.017
Log total assets	0.021	-0.053**	0.021	-0.089**	0.048*	-0.039	0.053	0.152**
Tobin's Q	-0.005	-0.019	-0.01	-0.074	-0.021	-0.019	-0.002	0.074
Sales growth	-0.244***	-0.353***	-0.209*	-0.304*	-0.215*	-0.314**	-0.632***	-1.123***
BHR over 12 months	-0.007	-0.048	-0.018	0.012	0.015	0.058	-0.259	-0.433**
ROA	-0.16	-0.314	-0.569	0.145	0.846	-0.363	1.113	1.968*
Sales market share	1.134	1.906**	-0.363	0.358	1.993*	2.796**	-0.997	-0.91
Cash holding	-0.225	-0.723**	-0.959**	-1.327***	0.184	-0.568	0.473	0.304
Book leverage	0.054	-0.089	-0.176	-0.087	0.280**	-0.097	0.363	-0.024
Dividend yield	-0.53	0.295	-0.508	0.941	-0.54	-0.08	-1.995	-0.831
CapEX	-0.213	0.322	-0.739	-0.483	0.984	2.173*	-0.149	1.117
Amihud ILLIQ	0.007	0.389	0.119**	-0.178	0.015	1.192**	0.331**	-6.162
Analysts	0.001	-0.001	-0.003	-0.006	0.004	0.007*	-0.005	-0.018*
Toehold		0.007		-0.007		0.005		-0.019
Toehold increase		-0.014		-0.1		0.047		0.104
Independent company		0.076		-0.007		0.099		-0.264
Entrenchment index		0.020		0.121		-0.163		-0.411
ESG rating		0.448***						
E rating				0.575***				
S rating						0.398**		
G rating								0.075
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Geographic FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R2	0.20	0.22	0.22	0.24	0.27	0.30	0.08	0.18
N	784	577	336	255	332	227	116	95

Table 2.6 Financial and ESG performance, and ownership after engagement

This table reports the results of differences-in-differences estimations of the effect of engagement and success on financial and ESG performance, as well as changes in ownership. The table reports the coefficient of the differencing term. The pre-treatment period is defined one year before the start of an engagement sequence. In panel A, post-treatment is defined one year after completion. In Panel B, post-treatment is defined two years after the first contact with the company. The period variable is 1 for post-treatment and 0 otherwise in both panels. In Panel A, the treatment is success versus no success, where the treatment variable is 1 for success and 0 otherwise. In Panel B, the treatment is engaged versus matched companies, where the treatment variable is 1 for engaged companies and 0 for the control sample. The matching sample is determined by Mahalanobis score matching on industry, size, market-to-book, ESG and ROA. Leverage, size, tangibility, and industry and time fixed effects are included in all specifications. Additionally, for Tobin's Q ROA, CapEx and sales growth are also included. Standard errors are clustered at the firm level. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Success vs. no success

	All cases	Reorg.	Lowest ESG quartile	Highest ESG quartile	E cases	S cases	G cases
Tobin's Q	-0.043	-0.008	-0.167	0.110	0.036	-0.124	0.266*
ROA	-0.003	-0.003	0.006	0.002	0.008	-0.006	-0.019
Operating expenses	0.002	-0.006	0.014	-0.012	-0.008	0.008	-0.019
CapEX	0.004	0.002	0.001	0.003	0.005	0.001	-0.001
Sales growth	0.076***	0.053*	0.093*	0.103*	0.097***	0.032	0.229**
Sales market share	0.000	0.001	-0.002	0.003	0.002	0.000	0.000
Profit margin	-0.018	-0.005	0.004	0.001	0.022	-0.039**	-0.093
Asset turnover	0.010	-0.023	0.032	0.004	0.003	0.023	-0.043
Long-term holdings	0.304	-0.217	0.527	-1.708	2.098**	-0.778	-4.161
Holding of engager	0.012	0.012	0.007	-0.028*	-0.019	0.043**	-0.010
ESG rating	-0.654	1.605	10.635***	-0.231	1.844	-3.849	-0.953
Environmental score	0.129	2.780	13.917***	-0.491	1.552	-2.122	-3.103
Social score	-0.491	1.557	4.394	-1.016	0.143	-2.374	-0.553
Governance score	-1.855	-0.905	-2.513	0.900	1.157	-4.603*	-2.629
Economic score	-1.129	1.612	6.429	6.070	2.604	-4.368	0.265
Entrenchment index	0.026	0.037	0.003	0.031	0.002	0.040	0.016
Analysts	-0.336	-0.147	-0.468	-1.567	-1.037	0.470	0.522

Panel B: Engaged vs. matched

	All cases	Reorg.	Lowest ESG quartile	Highest ESG quartile	E cases	S cases	G cases
Tobin's Q	0.013	0.039	-0.060	0.019	0.058	-0.062	0.093
ROA	-0.000	-0.003	0.008	-0.005	0.001	0.001	-0.005
Operating expenses	0.003	0.004	0.010	0.000	-0.007	0.010	0.009
CapEX	0.002	0.000	-0.002	0.003	0.002	0.000	0.007**
Sales growth	-0.011	-0.018	0.031	-0.015	0.005	-0.008	-0.064
Sales market share	-0.001***	-0.001	0.000	-0.004**	-0.001	-0.002**	-0.002
Profit margin	0.002	-0.004	0.026	-0.008	0.000	0.003	0.004
Asset turnover	-0.016	-0.028**	-0.014	-0.050**	-0.004	-0.022	-0.030
Long-term holdings	0.520	0.380	-0.155	1.178	0.379	0.282	1.659*
Holding of engager	0.009	-0.004	-0.025	0.017	-0.004	0.006	0.048
ESG rating	0.522	0.957	9.284***	-4.134***	0.677	0.385	-0.214
Asset4 environmental	0.281	1.376	10.425***	-4.901***	0.135	0.119	0.720
Asset4 social	-0.996	-0.982	4.167	-6.406***	-1.114	-0.858	-1.367
Asset4 governance	-0.475	0.322	8.822***	-8.681***	0.208	-1.113	-1.611
Asset4 economic	2.229	3.469*	21.680***	-9.294***	2.852	2.299	-0.467
Entrenchment index	0.006	0.009	0.006	0.021	-0.001	0.012	0.018
Analysts	0.258	0.351	0.705	0.788	0.688*	0.108	-0.640

Table 2.7 Buy-and-hold portfolio returns after completion

The table presents mean buy-and-hold returns for different event windows after the completion of engagements and various subsamples by regions. For each subsample and event window, returns are calculated for the entire subsample, successful and unsuccessful engagements, respectively. The table reports whether the mean is equal to zero and the difference between successful and unsuccessful cases. For differences, one-sided statistics are reported. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	[0]			[0,6]			[0,12]		
	All	Success	No success	All	Success	No success	All	Success	No success
All cases									
Mean	0.008**	0.012**	0.002	0.013	0.043***	-0.031**	0.018	0.044**	-0.019
Obs	847	509	338	841	503	338	804	471	333
Diff. (t-stat)		1.338*			3.976***			2.346***	
Lowest ESG quartile									
Mean	0.000	-0.002	0.003	-0.010	0.031	-0.043	0.010	0.023	0.000
Obs	176	78	98	176	78	98	170	74	96
Diff. (t-stat)		-0.344			1.829**			0.412	
Highest ESG quartile									
Mean	0.010	0.009	0.016	0.022	0.033	-0.020	0.028	0.036	0.001
Obs	165	131	34	165	131	34	155	122	33
Diff. (t-stat)		-0.462			1.121			0.484	
Reorganization cases									
Mean	0.011**	0.023***	0.002	-0.004	0.036	-0.035**	-0.010	0.011	-0.026
Obs	436	190	246	436	190	246	425	182	243
Diff. (t-stat)		2.191**			2.623***			0.997	
Environmental									
Mean	0.010**	0.018***	0.000	-0.016	0.032	-0.069***	-0.013	0.010	-0.036
Obs	358	190	168	353	185	168	330	167	163
Diff. (t-stat)		1.867**			3.806***			1.240	
Social									
Mean	0.001	0.000	0.002	0.023*	0.040**	-0.003	0.024	0.058**	-0.025
Obs	367	223	144	366	222	144	352	208	144
Diff. (t-stat)		-0.200			1.621*			2.074**	
Governance									
Mean	0.026**	0.029*	0.019	0.069**	0.072**	0.056	0.084*	0.074	0.123
Obs	122	96	26	122	96	26	122	96	26
Diff. (t-stat)		0.319			0.214			-0.474	

Table 2.8 Excess cumulative abnormal returns at case closure

This table reports cumulative abnormal return statistics for various event windows and subsamples in excess of a matched sample. For each subsample, cumulative abnormal return statistics are reported for three event windows. The beginning of an event window is defined as the month when an engagement case is completed, the end of the window is either the month, when the engagement is completed or 6 or 12 months following completion. The estimation period is 36 months prior to engagement. We use the Fama-French-Carhart model for the estimation of normal returns. Excess abnormal returns are calculated monthly subtracting the returns of an equally weighted portfolio of matched companies. The matching sample is based on Mahalanobis score matching on industry, size, market-to-book, ESG and ROA. For each event window and subsample combination we test whether the mean cumulative abnormal return is 0 and the difference between successful and unsuccessful cases. For differences, we calculate one-sided statistics where the alternative hypothesis is that successful engagements earn larger returns. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	[0]			[0,6]			[0,12]		
	All	Success	No success	All	Success	No success	All	Success	No success
					Full sample				
Mean	0.005*	0.006	0.007	0.027***	0.022*	0.036**	0.019	0.024	0.012
Obs	846	509	337	841	504	337	810	477	333
Difference		0.228			-0.737			0.400	
					Reorganization cases				
Mean	0.006	0.011	0.002	0.044***	0.035	0.051***	0.022	0.046	0.005
Obs	435	190	245	435	190	245	424	182	242
Difference		0.912			-0.549			0.914	
					Lowest ESG quartile				
Mean	0.006	0.025**	-0.001	0.071***	0.084**	0.060*	0.075**	0.113**	0.045
Obs	176	78	98	176	78	98	172	75	97
Difference		2.488***			0.462			0.921	
					Highest ESG quartile				
Mean	0.007	0.002	0.024	0.003	0.004	0.003	-0.006	-0.004	-0.012
Obs	165	131	34	165	131	34	155	122	33
Difference		-1.524			0.022			0.102	
					Environmental				
Mean	0.009**	0.005	0.014	0.030**	0.008	0.055**	-0.004	0.001	-0.010
Obs	358	190	168	354	186	168	335	171	164
Difference		-0.887			-1.711			0.237	
					Social				
Mean	0	0.007	-0.006	0.015	0.022	0.004	-0.002	0.004	-0.011
Obs	366	223	143	365	222	143	353	210	143
Difference		1.913**			0.654			0.330	
					Governance				
Mean	0.011	0.004	0.041	0.057	0.047	0.094	0.144***	0.109**	0.272***
Obs	122	96	26	122	96	26	122	96	26
Difference		-1.098			-0.547			-1.425	

Appendix 2.A Engagement case examples

Environmental

Amid a changing regulatory environment, the activist hired a third party analyst firm to evaluate the effects of new legislation on utility companies. The activist was specifically interested in the risks associated with the CO2 emissions of energy companies. After assessing the report, the activist reached out to company XXX on March 12, 2009. In a phone call, the activist requested information on two specific issues related to CO2 emissions. First, they were interested in the company's strategy to reach statutory CO2 targets; and second, the strategy regarding the acquisition and construction of new power plants. Following up on the phone call, the activist paid a visit to XXX's headquarters on April 24, 2009, meeting an investor relations officer of the company. At this meeting, the activist elaborated on the requests in more detail, stressing that their ultimate goal was that the company published a sustainability report in response to these requests. The company representative assured the activist that the company was aware of the changing regulatory environment and that they were already working on a sustainability report to appease investors. Following the publication of the report, the activist got back to the company in email on September 18, 2009 requesting more details on future prower plants. This was followed by a further email on December 8. Finally, the company fulfilled all request of the activist publishing all information online. After the activist verified the published information, the case was closed as successful on February 25, 2010.

Social

The activist engaged financial institution YYY on March 10, 2006 to acquire more information on human rights policies, following the publication of a BankTrack report in January that indicated that YYY reported less information on the topic than its peers. Specifically, the activist was concerned about the ethical standards of the bank corresponding to investments in Russia and third world countries. The first meeting took place at the activist's offices with an investor relations officer of YYY. This meeting was followed by a conference call on April 6, 2006 during which a YYY executive assured the activist that the bank had nothing to hide. Furthermore, the executive explained that they do take human rights issues into account for project financing and investments, although, as this was part of their internal scoring processes, they did not want to disclose details to maintain their competitive position. In response to the request for more transparency, the YYY executive promised that they would publish a sustainability report for 2006. Following the publication of the report, engagers had a last meeting on October 26, 2006 with the investor relations officer to go over the details of the report. As the report covered all concerns that the engager previously raised, the case was closed as successful.

Governance

The activist engaged company ZZZ in 2007 concerning the size and composition of the supervisory board of the company. The activist was concerned that the size of the board was not large enough to fully oversee the company's operations. A further concern was that the CEO of the company was also the chairman of the supervisory board. The activist voiced these concerns in collaboration with other investors at the AGM in mid-2007. ZZZ showed willingness to revise its governance practices, however, the CEO remained the chairman of the board. The activist revisited the case in 2008 and 2009 at the AGMs to no avail. Since they could not reach their goal of improving ZZZs corporate governance, they closed the cases as unsuccessful on May 12, 2009.

Appendix 2.B Engagement topics – detailed

Environmental

Climate Change: Carbon Disclosure Project, Climate Change

Ecosystem Services: Alternative Energy, Biodiversity, Eco-Efficiency; Emissions, Effluents and Waste; Nuclear Power, PVC and Phthalates, Tropical Hardwood, Water

Environmental Management: Environmental Management, Environmental Policy & Performance, Environmental Reporting, Environmental Supply Chain Standards

Social

Human Rights and Ethics: Animal Testing, Anti-Corruption, Customer Satisfaction, Ethics, Fur, Gambling, Human Rights, Military Production and Sales, Pornography and Adult Entertainment Services, Social Supply Chain Standards, Stakeholder Management & Reporting, Sustainability Reporting

Labor Standards: Attraction & Retention, Controversial Regimes, Forced and Compulsory Labor, Human Capital, Labor Standards, Privacy & Freedom of Speech, Third World, Training & Education, UN Global Compact

Public Health: Access to Medication, Alcohol, Genetic Engineering, Healthy Nutrition, Integration in Products, Intensive Farming & Meat Sale, Product Safety, Tobacco

Governance

Corporate Governance: Board Practices, Governance Structure, Remuneration, Shareholder Rights, Supervisory Board

Management and Reporting: Accountability & Transparency, Anti-Corruption, Corporate Strategy, Risk & Crisis-Management, Stakeholder Management & Reporting

Appendix 2.C Variable definitions

Table C.1 Variable definitions

This table provides variable definitions. All variables based in $ terms, if applicable.

Variable	Definition	Source
ESG scores		
ESG score	Equally weighted Asset4 score: based on the Environmental, Social, Governance and Economic pillars (0-100)	Datastream - Asset4
Environmental score	Environmental pillar score: a companys impact on living and non-living natural systems, as well as complete ecosystems (0-100)	
Social score	Social pillar score: a companys ability to generate trust and loyalty with its workforce, customers and society (0-100)	
Governance score	Governance pillar score: a companys systems and practices that ensure that its executives and board act in the interest of (long-term) shareholders (0-100)	
Economic score	Economic pillar score: a companys capacity to generate sustainable growth and returns through the efficient use of its assets and resources (0-100)	
Entrenchment index	Index of entrenchment measures (E-index): poison pill, golden parachute, staggered board, bylaws and lock-ins (0-1)	
Risk and performance		
BHR	Buy-and-hold stock return over 12 months	Datastream
Volatility	Stock return volatility	
Amihud ILLIQ	Amihud illiquidity measure multiplied by $1 million	
Asset turnover	(Total sales)/(Total assets)	
Profit margin	(Net income)/(Total sales)	
ROA	(Net income)/(Total assets)	
ROE	(Net income)/(Book value of equity)	
Sales growth	Year-over-year sales growth	
Sales market share	Percentage of total industry sales	
Market-to-book	(Market value of equity)/(Book value of equity)	
Tobin's Q	(Market value of equity + Total book liabilities)/(Book value of equity + Total book liabilities)	
Cash and expenses		
Cash holding	(Total cash)/(Total assets)	Datastream
CapEX	(Capital Expenditures)/(Total assets)	
Operating expenses	(Operating expenses)/(Sales)	
Size and capital structure		
Log total assets	Natural log of total assets	Datastream
Log sales	Natural log of total sales	
Log market equity	Natural log of total market capitalization	
Book leverage	(Total book liabilities)/(Total book liabilities + Book value of equity)	
Tangibility ratio	(Plant, property and equipment)/(Total assets)	

Continued on next page

Continued from previous page

Variable	Definition	Source
Other		
Dividend yield	(Total dividends paid)/(Market value of equity + Market value of preferred shares)	Datastream
Dividend payout	(Total dividends paid)/(Net income)	
Company age	Years since incorporation or IPO date	
Analysts	Mean number of analysts issuing earnings (EPS) forecasts annually	I/B/E/S
Ownership		
Holding of engager	Portfolio holdings of engager (total)	Morningstar
Toehold	Indicator variable; 1 if the engager increases its holdings prior to targeting	
Toehold increase	Indicator variable; 1 if the engager increases its holdings over the course of targeting	
Average ownership	Mean of ownership stakes	Orbis
Number of blockholders	Number of owners with a +5% stake	
Long-term investors	Holdings by pension and mutual funds	
Hedge funds and PE	Holdings by edge funds, venture capitalists and private equity firms	
Individuals and family	Holdings by individuals and families	
Independent company	Indicator if a company has no majority shareholder with a stake larger than 25%	
Miscellaneous		
Contact number	Number of contacts with the target company	Activist
Contact type	The dominant channel of communication	
Contacted executives	Role of contact person at target company; 1 for executive officers, 0 otherwise	
Geographic FE	Fixed effects for Asia, Europe, North America and Other regions	
Industry FE	Fixed effects for 17 Fama-French industries	
Joint targeting	Targeting in collaboration with other activists; 1 if jointly targeted, 0 otherwise	
Length of sequence	Time span of targeting in days	
Previous engagements	Number of previous cases with the same company	
Success	The originally defined goal is achieved; 1 for success, 0 otherwise	
Success streak	Number of previous successful cases with the same company	
Receptiveness	1 if the target firm is initially willing to collaborate with the activist; 0 otherwise	
Reorganization	1 for material request aimed at changing the company's operations; 0 for an engagement aimed at enhancing transparency	

Appendix 2.D Geographical breakdown

Table D.1 Analysis of targeting by regions

This table reports the marginal effects obtained from probit regressions on the probability of targeting relative to a matched sample. The first two columns report regression results for the whole sample of engagements (1-2), while the second, third and fourth set of columns refer to North American (3-4), European (5-6) and Other domiciled (7-8) companies, respectively.The dependent variable equals 1 if the company is targeted and 0 otherwise. Marginal effects are evaluated at the mean of the respective independent variable. Standard errors are clustered at the firm level. The matching sample is determined by Mahalanobis score matching on industry, size, market-to-book, ESG and ROA. Variable definitions are provided in the Appendix. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Full sample		North America		Europe		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log total assets	-0.033***	-0.009	0.024	0.027	-0.082***	-0.058***	0.033**	0.071***
Tobin's Q	-0.008	-0.001	0.016	0.010	-0.027*	-0.009	0.019	-0.005
Sales growth	0	-0.045	-0.196**	-0.153*	0.034	0.045	0.101	-0.035
BHR over 12 months	0.084***	0.114***	-0.034	-0.036	0.088***	0.143***	0.092**	0.068
ROA	0.146	0.034	1.027**	0.928**	-0.034	-0.245	0.092	-0.017
Sales market share	3.838***	3.453***	3.015***	2.386**	4.318***	3.953***	1.228	0.099
Cash holding	-0.005	0.050	0.285	0.194	-0.074	-0.080	-0.426*	-0.349
Book leverage	0.018	0.036	0.184*	0.150	-0.039	-0.002	-0.087	-0.310**
Dividend yield	0.600	1.451**	-0.345	0.261	0.901	1.725**	0.637	1.617*
CapEX	0.014	-0.020	-0.325	-0.390	-0.449	-0.468	0.842**	0.844*
Amihud ILLIQ	0	-0.354*	-0.035	-136.388***	0.001	-0.140	0	-0.906
Analysts	0.013***	0.016***	0.003	0	0.022***	0.023***	-0.008***	-0.001
Previous engments	-0.014	-0.019**	-0.016	-0.026	-0.015	-0.017*	-0.005	-0.020
Holding of engager		4.276		8.161**		5.428**		18.180
Independent company yes=1		0.032		0.068		0.037		0.050
Entrenchment index		-0.023		0.158*		-0.096		-0.297***
ESG score		-0.103*		0.025		-0.083		-0.079
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Geographic FE	yes	yes	no	no	no	no	no	no
Pseudo R2	0.10	0.18	0.09	0.25	0.22	0.28	0.06	0.24
N	3,174	2,478	776	641	1,722	1,501	676	319

Table D.2 Analysis of success by regions

This table reports the marginal effects obtained from linear probability regressions on the probability of success. The dependent variable equals 1 if the engagement is successful and 0 otherwise. The first two columns report regression results for the whole sample of engagements (1-2), while the second, third and fourth set of columns refer to North American (3-4), European (5-6) and Other domiciled (7-8) companies, respectively. Standard errors are clustered at the firm level. The dummy "Reorganization" takes the value 1 for reorganization cases and 0 otherwise. The dummy variable "Collaboration" equals one for cases where the engager contacts the company with other activists. The variable "Contacted executives" is 1 if executive management is contacted and 0 otherwise. "Number of activities" and "Success streak" refer to the number of contacts per case and the number of previous successful cases with the company. Other variable definitions are provided in the Appendix. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Full sample		North America		Europe		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reorganization	-0.170***	-0.159***	-0.284*	-0.231	-0.162***	-0.138**	0.222	-0.067
Joint targeting	0.043	0.030	0.275**	0.218	-0.023	-0.025	-0.107	-0.245
Contacted executives	-0.05	-0.040	-0.174	-0.216	0.053	0.038	-0.235*	0.292
Number of activities	0.005	0.005	-0.001	-0.003	0.012*	0.011	0.017	0.074
Success streak	0.031**	0.021*	0.080	0.021	0.017	0.013	0.092	0.117
Log total assets	0.021	-0.053**	-0.029	-0.120***	0.019	-0.012	0.085***	0.047
Tobin's Q	-0.005	-0.019	0.026	-0.001	-0.011	-0.013	-0.019	-0.215**
Sales growth	-0.244***	-0.353***	-0.083	0.016	-0.410***	-0.442***	0.033	0.255
BHR over 12 months	-0.007	-0.048	0.187*	0.236**	-0.124*	-0.219***	0.008	-0.135
ROA	-0.16	-0.314	-0.776	-1.713*	0.307	0.321	1.157	-1.175
Sales market share	1.134	1.906**	2.026	1.954	0.772	0.65	-0.309	-4.341
Cash holding	-0.225	-0.723**	-0.676	-1.010**	-0.349	-0.731*	0.436	1.889
Book leverage	0.054	-0.089	-0.283	-0.455**	0.13	0.065	0.213	-0.255
Dividend yield	-0.53	0.295	0.576	4.387**	-1.177	-1.317	-1.118	-0.515
CapEX	-0.213	0.322	1.236	2.217**	-0.804	-0.645	0.666	0.523
Amihud ILLIQ	0.007	0.389	0.093***	-152.027***	0.067*	0.258	-0.021	0.541
Analysts	0.001	-0.001	-0.001	0	0.003	-0.001	-0.004	-0.028
Initial holding jump		0.007		0.008		-0.003		0.084
Holding increase		-0.014		-0.033		0.045		0.148
Independent company		0.076		0.087		0.004		-0.076
Entrenchment index		0.020		-0.044		0.152		-0.163
ESG rating		0.448***		0.586**		0.237		1.031*
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Geographic FE	yes	yes	no	no	no	no	no	no
Industry FE	yes	yes	no	no	no	no	no	no
Adjusted R2	0.2	0.22	0.16	0.23	0.23	0.22	0.17	0.11
N	784	577	192	166	433	360	159	51

Chapter 3

Tangible and Intangible Fraud Outcomes

3.1. Introduction

The extant literature on corporate fraud is predominantly concerned with the effects of prosecuted fraud, be it stock market reaction, firm outcomes or executive turnover. However, conventional wisdom suggests that if a large group of investors becomes concerned with the firm's operations and management, and they take legal steps to assert their claims, it may have an effect on firm value and outlook. In this paper, I examine how the market reacts when a firm is indicted by a large group (i.e. class) of shareholders, and whether this market value reaction can be attributed to tangible changes in the firm's operations, or to a loss of reputation and hence a change in the value of intangible assets. I also investigate whether litigation conveys valuable information to the market.

Large corporate scandals, like Enron, WorldCom, and more recently Volkswagen are widely publicized in the media, but represent only the tip of the iceberg. The Association of Certified Fraud Examiners estimates that, in 2015 alone, 5% of revenues were lost due to fraud adding up to $6.3 billion. The report also states there is an irregularity at every fourth public firm. The findings of Dyck, Morse, and Zingales (2013) are equally alarming. They estimate that in any given year, up to 6% of S&P 1500 firms engage in fraud that is eventually prosecuted by the Department of Justice. Fraud not only causes directly measurable capital market losses, but has other, far-reaching effects on society.

I would like to thank Luc Renneboog for his guidance and encouragement. I also thank Lieven Baele, Fabio Braggion, Peter Cziraki, Joost Driessen, Peter de Goeij, Ernst Maug, Gabor Neszveda, Stefan Ruenzi and Zorka Simon, as well as seminar participants at the HAS Summer Workshop in Economics and University of Mannheim for helpful comments.

In my paper, I study the effect of fraud revelation on stock market performance and analyze the cross-section of returns to identify company characteristics that act as a "red flag" and also the ones that mitigate market reaction. Additionally, I look at the factors that make a firm suspicious to investors. My sample covers over 1,200 firms in the period 1996-2016. To the best of my knowledge, this is the first paper that looks at all indictments and not only settled fraud cases allowing me to measure the direct effect of litigation. I use data on class action filings to identify fraudulent firms.[1] Class actions are civil lawsuits initiated by investors and thus represent cases where corporate actions and management decisions exceed the "tolerance" threshold of shareholders, and are not considered bad luck or an honest mistake.

I focus on class actions for two reasons. First, it is the enforcement channel with the lowest attrition rate (Karpoff et al., 2017a). Second, it provides a sample where indicted firms surpass shareholders' threshold of tolerance for errors and thus these firms are considered by their own shareholders to conduct business in an unruly way that erodes trust and is potentially value destroying. Analyzing the characteristics of firms whose shareholders file a lawsuit, I find that these firms tend to have relatively high market-to-book ratios and exceptionally high growth in terms of sales. When I look at the determinants of lawsuit filings, I document that large firms that have a bad year in terms of stock market performance are more likely to be indicted.

My results show that fraud is indeed widespread. In my sample, covering the S&P 1500, I find that about 60 cases are filed each year, the propensity of fraud being the highest in the financial, healtchare, services and tech industries. This is an overall 4% of the index constituents, but I also find a higher propensity of fraud around bubbles, for example, the number of filings was 95 in 2008, or almost 60% higher than the average.

My findings indicate that even the announcement that a company is taken to court has a non-trivial effect on the stock market. In the 1-day window around the day of filing a lawsuit, the average firm experiences an abnormal stock market drop of 2.7% and an abnormal market value dip of about $375 million. However, it appears that investors are –to some extent– able to assess if a lawsuit is meritorious, as firms that end up paying damages to their investors exhibit a 5% negative return at the initial announcement, while this figure is -1% for companies that are eventually cleared of all charges. While the difference between the returns of ex post settling and acquitted firms is large, even the latter group experiences a sizable value drop of $218 million. The fact that the value drop for prosecuted firms is significantly larger than the eventual penalty suggests that a

[1] Throughout the paper, I use the term "fraudulent" for companies that end up in court. Within fraudulent companies, I distinguish firms that are acquitted and firms that eventually pay a settlement. Settlement is often reached without a court order, and the establishment of intent. I assume that the claim was meritorious if the company agrees to pay a settlement.

lawsuit significantly reduces reputation. To asses whether the value drop of falsely accused firms is a selection issue, I construct a matching sample of similar, non-fraudulent firms. I determine the control sample within the same industry, and by size, market-to-book ratio and past returns. Estimating the abnormal returns for the control group reveals that there is indeed a litigation effect, as the abnormal return of the control sample is zero around the filing date at all reasonable critical levels. I also look at returns around the closure of court proceedings in order to identify if there is a reversal effect once a case nears its end. I find no significant price movements on the day the final order is issued by the court or in the overall period of the lawsuit. Strikingly, this is also true for acquitted firms. This result suggests that the drop in reputation is factored in into prices at the initiation of the lawsuit. Looking at tangible measures of firm performance, I find that litigation does not have an effect on sales or the return on equity, albeit sales growth and margins decrease. Overall, this suggests that fraudulent firms experience a value loss in intangible assets. This loss can be quantified as the market value drop for firms that are acquitted, or about $900 million. For firms that end up paying a settlement, the loss is the difference between the settlement amount and the market value drop. In monetary terms, it is $2,010 million and $1,632 million for voluntary and ordered settlements, respectively.

I also analyze what drives the market value drop for indicted firms to assess whether the market sees fraud as need or greed (Wells, 2001). First, in cross-sectional regressions on observable risk characteristics, I find that fraudulent firms indeed experience significantly lower returns than their matched peers around lawsuit filings. On average, firms with high past volatility experience more negative returns. However, fraudulent firms that are large and that hold large amounts of cash are less affected. This could be due to investors' perception that these firms can weather the litigation process. Subsequent analyses support this argument, as indicted firms reduce their investments and hold more cash compared to the matched sample. Fraudulent firms that have large past volatility and that experienced a profitability shock experience a more measured price drop. Second, turning to governance characteristics, I find that firms with high institutional ownership also have lower returns, for which the potential channel is that some institutions might fire-sale fraudulent firms. Looking at the investor base of fraudulent firms, I confirm that institutions hold -2.6% less shares of these firms in the quarters following the filing of the lawsuit. Third, considering the investment activities of firms, I find no significant link between past acquisitions and the market reaction to fraud.

Finally, I test whether litigation conveys valuable information to the stock market. Constructing a long-short portfolio, I find that an investor can earn significant returns trading around litigation events. A portfolio that goes short in stocks of indicted firms and long in stocks of similar firms that do not face a court procedure earns a risk-adjusted alpha of 3.7% annually.

This paper contributes to several strands of the literature on corporate fraud. First, I advance the literature on the pervasiveness of corporate fraud. Corporate fraud is considerably more prevalent than the aforementioned mega cases. Naturally, managers try to conceal fraudulent behavior, to evade legal consequences that could harm their personal wealth and reputation (Karpoff, Lee, and G. S. Martin, 2008a). As a result, the literature only has estimates on the extent of corporate fraud. Karpoff, Lee, and G. S. Martin (2008b) look at accounting restatements and follow-up enforcements by the Securities Exchange Commission (SEC) and find that in the period 1978-2002 less than 1% of CRSP firms restated their earnings and the apprehension rate of ill-intentioned restatements is about 80%. This suggests that fraud is relatively scarce, however, Dyck et al. (2013) arrive at a different conclusion. Using the demise of Arthur Andersen after the Enron scandal as a natural experiment, they estimate the pervasiveness of fraud by looking at irregularities uncovered by new auditors. Their results indicate that the likelihood that an S&P 500 company engages in fraud in any given year is as high as 15%. Additionally, in boom periods, such as the dot-com bubble, when investor scrutiny is more lax, as many as 6% or 30 of the largest US firms commit fraud. I add to this literature by showing in a large and comprehensive sample that if we consider a broad definition, the incidence of fraud is 4%, with considerable industry and time-series variation.

Second, my paper adds to the literature that looks at various types of fraud. Prior research typically focuses on a particular type of fraud. The fraud category receiving the highest attention in the literature is financial misrepresentation and earnings manipulation (for example, Dechow, Sloan, and Sweeney (1996), Desai, Hogan, and Wilkins (2006), Karpoff et al. (2008b), and Palmrose, Richardson, and Scholz (2004)). Other fraud types examined include product recalls and product market reputation (e.g., Johnson, Xie, and Yi (2014)), environmental violations (c.f. Karpoff, Lott Jr., and Wehrly (2005) and Konar and M. A. Cohen (2001)), and bribery (e.g., Hong and Liskovich (2015) and Karpoff, Lee, and G. S. Martin (2017b)). Studies on corporate fraud typically focus on one area due to data availability (Karpoff et al., 2017a), as there is no single database that includes all types of fraud. Academics use 4 datasets in most studies, the Stanford Class Action Clearinghouse (SCAC) for class actions, the Government Accountability Office (GAO) and Audit Analytics (AA) for restatements, and the Accounting and Auditing Enforcement Releases (AAER) for corporate wrongdoing prosecuted by the SEC. While these databases have considerable overlap, there are cases of fraud that are omitted in one or several of them. Looking at financial misrepresentation prosecuted by the Department of Justice due to the violation of Section 13(b) of the Securities Exchange Act of 1934, Karpoff et al. (2017a) find that the attrition rate can be as high as 61% (GAO) and it is the SCAC database that performs best, leaving out 13% of the cases. My contribution to this literature is to focus on class actions irrespective of the reason shareholders file them. This enables me to show the effects of litigation cases that arise when shareholders are displeased with the current operations of the firm.

Third, I contribute to the literature on the cost of fraud to shareholders. Regardless of the specific type of fraud, corporate misconduct is costly to society. The 2016 report of the Association of Certified Fraud Examiners (ACFE) claims that firms lose 5% of their revenues due to fraud. The report estimates that in 2015 alone \$6.3 billion was lost because of corporate misconduct. As Zahra, Priem, and Rasheed (2005) put it, *"Where top management fraud exists, we all lose."* Dechow et al. (1996) find that the initial announcement that a firm is under investigation results in a 9% drop in stock prices, aggravated by a widened bid-ask spread, suggesting that stocks of these firms become less liquid. Looking at SEC imposed penalties, Karpoff et al. (2008b) find that markets impose a penalty on firms that is 7.5 times larger than the actual fine they have to pay. Looking at the entire investigation period, they find that firms lose, on average, 38% of their market value, or \$4.08 for every dollar of inflated value. This effect is even more pronounced for firms that remain listed during and after the SEC investigation process at \$5.17 for each inflated dollar. Based on class actions in the SCAC database, Dyck et al. (2013) report a loss of 21.8% for fraudulent firms. Looking at firms investment opportunities, Yuan and Y. Zhang (2014) find that fraudulent firms experience an increase in cost of capital and invest less in long term assets. My findings indicate that even the fact that a company is taken to court has a non-trivial effect on the stock market. I also find that indicted companies hold on to more cash and spend less on capital expenditures.

Shareholder losses, however, are not the only negative outcome attributable to fraud. The reputation of managers involved in fraud is ruined, and they may also face financial penalties and possible imprisonment (Karpoff et al., 2008a). Managers who are not directly involved or prosecuted could also suffer a reputation loss, as potential employers might see them as passive bystanders. Additionally, if fraud puts a firm out of business then employees are also adversely affected as they lose their jobs and potentially their savings, if their retirement plan was strongly tied to the company' s stock. Related businesses also have to deal with a loss of revenues. These costs are hard to quantify, but the overall effect on society can be substantial (Zahra et al., 2005).

Finally, this study links up with the strand of literature that examines the motives to commit fraud. If the adverse effects of corporate fraud are so large, the question naturally arises: why would managers decide to engage in fraudulent behavior? Wells (2001) identifies two incentives to commit fraud: need or greed. The motives for "need" to commit fraud can be the need for external financing, to cover up financial distress or to acquire business. First, when a firm wants to expand rapidly, but its cost of capital is too high managers might try to make the numbers look better than they actually are. For example, Dechow et al. (1996), and Burns and Kedia (2006) both find that firms with large accounting restatements that were penalized by the SEC had ex ante considerably higher external capital needs than similar, non-fraudulent firms. Second, firms that are in distress might want to hide their fragile status. Looking at leverage as a proxy for distress, Burns and Kedia (2006) find that firms with high leverage that is costly are more likely to cook the books. However, in a related study, Bergstresser and Philippon (2006) do not find such an effect. Third, managers might engage in fraudulent behavior if they see it as the only way to conduct business. Karpoff et al. (2017b) argue that in certain situations, e.g., dealing with officials in highly corrupt countries, fraud might be a necessity. They also show that in the majority of bribery cases, the present value of the business prospect outweighs penalties, and even if bribery is caught by authorities, the market reaction is non-negative, as long as no financial fraud is involved. However, if a firm engages in bribery and misrepresentation, the market reaction is even more severe than described above. I add to the extant literature by showing that firms having a bad performance streak are more likely to be indicted.

The "greed" motivation to commit fraud comes from how compensation schemes are set up. The exposure of CEO wealth to company stock has increased 6-fold in the 1980-2000 period (Bergstresser and Philippon, 2006) and base salary also tripled between 1993-2011 (Kaplan and Rauh, 2013). While Kaplan and Rauh (2013) and Gabaix, Landier, and Sauvagnat (2014) argue that CEO pay is determined by the market and thus wage is simply the price of talent, recent evidence by Antón et al. (2016) point out that managers' pay is strongly related to the performance of their rivals. In the latter setting, managers might be more incentivized to cook the books so that their performance and ultimately their pay is more in line with that of their rivals. The fraud literature shows that the amount of equity pay, specifically, stock option grants is positively related to the likelihood of committing fraud. For example, Bergstresser and Philippon (2006) and J. Jiang, Petroni, and I. Y. Wang (2010) find that larger option plans induce executives to manage accruals, and this effect is even more pronounced for CFOs than CEOs. This paper confirms that CEO compensation is only weakly related to fraud detection and the market reaction.

Since there is a lot at stake if a firm commits fraud, legislative bodies have been trying to devise a regulatory environment that deters fraud, encourages the revelation of fraud, and generally increases the oversight and controlling power of shareholders. The Sarbanes-Oxley Act of 2002 was enacted as essentially a response to the Enron and WorldCom accounting scandals. The act calls for stricter reporting and auditing standards. Following the outbreak of the recent financial crisis, the Dodd-Frank Act of 2010 was drafted to increase prudency in financial markets, but it also had passages that increased incentives for whistleblowing. As shown by Dyck, Morse, and Zingales (2010), whistleblowing entails large costs. Employees may lose their jobs if they try to uncover fraud, while it can be very costly for external monitors to investigate a firm. To alleviate these problems, the Dodd-Frank Act protects whistleblowing employees, and also provides a bounty for whistleblowers who highlight fraud which violates federal rules. Dodd-Frank also introduced mandatory say-on-pay. Kronlund and Sandy (2015) show that firms do react to shareholder proposals, even though these proposals are only advisory. Their results indicate that as a response to shareholder votes, firm decrease base salaries and increase equity grants, with a positive net effect on compensation. While further evidence is missing, this revised wage structure could increase incentives to commit fraud in the long run. I contribute to this discussion by showing that while institutional investors are not necessarily better at detecting fraudulent behavior, they do react significantly and rebalance their portfolios towards companies that do not engage in fraud.

3.2. Class action lawsuits

A class action lawsuit is a legal case where a group of plaintiffs, the *class*, claims the same damages from the defendant, typically from companies or organizations. Class actions belong to the jurisdiction of civil courts and are treated under civil law. Classes may be formed on any base that the plaintiffs have in common, such as consumer rights, minority issues, antitrust allegations, or securities fraud.

At the federal level, class actions are regulated under Rule 23 of the Civil Procedure, but states may have specific statutes. In order to harmonize court procedures and prevent frivolous cases, Congress passed the Private Securities Litigation Reform Act of 1995 (PSLRA) and subsequently the Class Action Fairness Act of 2005 (CAFA). Through the enactment of these two acts and the several amendments of Rule 23, class action lawsuits appear to be well codified, however, they are still subject to considerable debate (Coffee, 2015). The underlying concern is that litigation is not the optimal tool to address corporate wrongdoing. As Spamann (2016) argues, in a frictionless world, contracting should provide the right incentives and deterrents such that executives do not engage in fraudulent behavior. However, as perfect contracts are impossible to draw up, the need for legislation prevails. One possibility to monitor companies is to set up a supervisory agency, the other is to let individual stakeholders claim damages. Currently, the former role is filled by the SEC, while the latter by civil courts, and ultimately by class actions. In everyday practice, investigations by the SEC and class action filings are not coordinated.

Prosecutions by the SEC can lead to class action filings and vice versa, but there is no automatic link.

Proponents of class actions argue that this procedure allows marginal stakeholders to have their voice heard, while opponents claim that it is only a tool for attorneys to line their pockets (Rakoff, 2015). Criticism stems from the fact the plaintiff law firms typically charge a considerable fraction of the settlement amount in fees and expenses. In this setting, attorneys may be incentivized to seek out potential class actions and also go to courts that tend to lean towards plaintiffs. This often leads to frivolous cases, where the allegation is not even established and supported by firm evidence. For example, in the wake of the internet boom, the number of securities class actions skyrocketed (Perino, 2002). As a response, Congress passed PSLRA that aimed to reduce the number of non-meritorious filings. The Act was successful in the sense that pleading rates increased afterwards, suggesting that more substantiated cases reached courts. Another issue arising from misaligned incentives is forum shopping. Prior to the passing of the CAFA in 2005, there were class action hotspots across the US. As an example, Madison County (Illinois) had a class action filing rate of 20 times the national average (Brickman, 2002).[2] In a response, the CAFA states that class actions with diversity jurisdiction, where the number of plaintiffs is at least 100 and where the total amount in controversy is minimum $5 million should fall under federal jurisdiction. These conditions lead virtually all securities class actions to federal courts.

In addition to misaligned incentives, critics of class actions also argue that the settlement process is inefficient in that the settlement costs are borne by innocent parties, as compensatory damages are paid by corporations and not executives. This results in a wealth transfer between past and present shareholders that reduces social welfare. Ironically, long-term shareholders may suffer a loss twice, first when a fraud is revealed and stock prices drop (Dyck et al., 2013) and second when the company is prosecuted (although these shareholders could recover some of their losses from the settlement fund). Nevertheless, as Webber (2015) argues, a world without class actions further aggravates the wealth transfer between investors because, in such an environment, only large shareholders would recuperate their losses at the expense of their small counterparts who cannot afford legal representation.

It appears that class actions are necessary to safeguard all stakeholders' interests, although improvements to the current system are suggested by, for example, Spamann (2016) who theorizes that the limited liability of executives should be altered to the

[2] Madison County was a hot spot mainly for consumer product-related complaints. Securities litigation class actions have a higher hurdle rate to enter court as the identification of economic wrongdoing is more complex than that of a poorly performing product.

extent that the prospect of legal actions is a deterrent against fraudulent behavior. The approach of Coffee (2006) calls for better coordination between supervisory bodies and plaintiff firms. He argues that plaintiff firms should be employed by or work closely with the SEC. This setup would allow the SEC to have oversight of the quality of cases taken to court. Furthermore, collaboration would reduce or eliminate the duplication of efforts and enlarge the information pool.

3.2.1. Class action procedure

In the US, class actions are regulated under Rule 23 of the Federal Rules of Civil Procedure (Cooper Alexander, 2000). The rule ensures that class action procedures are standard across the United States. Figure 3.1 shows a schematic representation of the class action procedure.

The *class period* is the time period over which plaintiffs claim to be defrauded by the defendant. The class period is well defined with an exact *start* and *end* date, or potentially further defined e.g., in case of intraday price manipulation allegations. While the class period is the first element on the timeline, it is only defined once the class action is formally filed. The time between the class period end and the *first filing* (or first complaint) varies from case to case. Furthermore, it is possible that fraudulent behavior is revealed by a whistleblower other than the plaintiff (firm). The exact date of this *discovery* is hard to pinpoint (Dyck et al., 2010). In many cases, discovery can be associated with the case filing, especially in cases where law firms investigate potentially fraudulent companies. In general, the time gap between the class period end and the first filing date has been decreasing over time, suggesting that either information dissemination has become more efficient after fraud discovery, or law firms have become more proficient in uncovering fraudulent companies.

After the first complaint is filed, the court procedure begins, however, it is possible that several cases are filed at the same court, or there are filings in multiple districts, all claiming the same or similar damages. In this case, the filings are *consolidated* by the court, appointing a single judge to preside over the case and a lead plaintiff to head the process. It is possible that, through the consolidation process, the class period is revised to accommodate all claims. The consolidated case is referred to as the *reference filing*. Once a case is filed or consolidated, the court has to determine if the filing can be maintained as a class action and certify it. After the class is certified, the lead plaintiff is obliged to give notice to absent members of the class. This notice is typically disseminated through a website where class members can register to be able to track all court proceedings and file for claims from the settlement fund.[3] There are no restrictions in terms of holding amounts or legal status, the class can be joined by any investor who held any number of shares during the certified class period.

The court procedure has 3 potential outcomes. First, it is possible that the two sides engage in conversation and reach a *voluntary settlement* without any court order. In this case, the parties file a *stipulation of settlement* and all further court proceedings are canceled, conditional on the court finding the settlement fair to all class members.[4] Settlement typically entails that the defendant does not admit any degree of wrongdoing, but is willing to settle with the plaintiffs to maintain good faith. This outcome can be regarded essentially as an out-of-court resolution, where the parties come to an agreement themselves and the court only supervises the process. Second, the parties can decide to proceed with the trial, but then the court might find that the case is unsubstantiated and *dismiss* it. Third, if the case is meritorious, but the parties cannot reach an agreement, the court evaluates the assertions of both parties, orders the establishment of a settlement fund (*ordered settlement*) and closes the case (*final ruling*). If the parties disagree with the final ruling of the court or the dismissal of a case, they can take the case to the Court of Appeals or ultimately the Supreme Court. Once a case is closed, either through one form of settlement or dismissal, and all appeal procedures are exhausted, no investor can bring the same case to court again. It is important to note that civil courts never pronounce defendants guilty. A settlement order only states that plaintiffs' claim is meritorious and the defendant is obliged to compensate plaintiffs.

3.2.2. Case study: Investors versus General Motors

The Illinois-based law firm, Cafferty Clobes Meriwether & Sprengel LLP filed a complaint against General Motors (GM) at the Eastern District Court of Michigan on March 21, 2014. The complaint stated that GM engaged in a scheme to hide from consumers and investors that their cars, produced between late 2010 and March 2014, were plagued with a number dangerous defects, resulting in multiple adverse events, even fatal car crashes. In the period of February 7 to March 11, 2014 the company started a recall program for the affected vehicles, which resulted in a share price drop from \$36.11 to \$34.09, or a market value drop of about \$82.8 million dollars. On March 17, GM extended the recall program to include over 1.5 million additional vehicles, resulting in a total of 3.1 million recalled cars. In the month leading up to the filing of the lawsuit, GM's shares exhibited a cumulative abnormal return of -6.8%.

[3] Figure B.1 provides an illustration of such a website.

[4] The judge or a settlement judge is most often actively involved in establishing the settlement fund, especially for large classes (Cooper Alexander, 2000).

Independently from the original filing, but related to it, Bernstein Litowitz Berger & Grossmann LLP of New York also filed a complaint against GM . The cases were consolidated under one docket and the New York Teachers' Retirement System was appointed lead plaintiff, represented by Bernstein Litowitz Berger & Grossmann LLP. Additionally, the class action period was revised to cover the period from November 17, 2010 up to and including July 24, 2014.

The parties filed a stipulation of settlement on November 13, 2015, which was preliminary approved by the court on November 20. On March 9 of the following year, the court approved the settlement fund as fair to all class members, and granted attorneys' fees and expenses.[5] Overall, GM's investors recovered $300 million in damages.[6]

3.3. Data

The data in this paper come from multiple sources. I obtain fraud data from the Stanford Securities Class Action Clearinghouse (SCAC) website. This website contains all securities class action filings since the enactment of the PSLRA. I collect all available information from this website using a webcrawler and then hand collect company identifiers to merge with other financial databases. Since that SCAC database does not contain settlement amounts for all cases, I conduct web searches for class action websites to gather this information. Accounting and stock market information is retrieved from the CRSP-Compustat merged database (CCM). Board characteristics and compensation data are downloaded from BoardEx and ExecuComp, respectively. I source data on analysts from I/B/E/S and data on accounting restatements from Audit Analytics. Information on mergers and acquisitions is from SDC Platinum.

3.3.1. Sample construction

The fraud database originally consists of 4,179 individual cases and covers the period 1996-2016. After dropping cases initiated against private companies (e.g. mutual fund management firms, brokerage firms or pension funds) there are 3,828 cases remaining in the sample. For inclusion in the final sample, I require that a firm has available information in CCM, as well as in ExecuComp and BoardEx, for executive compensation and board characteristics data, respectively. By construction of the latter two databases,

[5] Closed cases, either dismissed or settled, cannot be taken back to court in the future, e.g., by shareholders who forgot to join the class. In legal terms, the case is *dismissed with prejudice.*

[6] See Figure B.1 for details on the settlement.

this restricts my sample –to a large extent– to S&P 1500 firms. After merging the fraud data with the other databases, I obtain a sample of 1,249 fraud cases for 888 individual companies. Out of these cases, 117 are still ongoing at the time of my data acquisition.

3.3.2. Control sample and matching

In subsequent analyses, I contrast the fraud sample with similar, non-fraudulent companies. I define a company as non-fraudulent if it does not appear in the SCAC database. To arrive at the control sample, I apply a matching algorithm. My starting point is again the S&P 1500 universe over the sample period, or about 3,400 companies.[7] I match fraudulent firms to similar companies within the same Fama-French 49 industries based on market capitalization, market-to-book ratio and past stock return, and with replacement. For each potential fraudulent-control company pair, I calculate the Mahalanobis distance metric and keep the 3 closest matches.[8] If I cannot find a match within 49 industries (14 instances), I relax the classification to 17 industries. If a firm appears multiple times in the fraud sample, I determine the control group for the first appearance and keep it for subsequent cases. The Mahalanobis score is a convenient measure of similarity as it does not require any modeling assumptions, as for example with sorting or regression-based propensity score matching. Furthermore, the Mahalanobis metric takes into account the covariance between matching covariates, and if covariances are zero, the measure reduces to the Euclidean distance.

The topmost section of Table 3.3 contains the main matching variables. The test statistics show that the matching procedure worked well in case of the market-to-book ratio and past returns, as the test for the equality of means cannot be rejected. However, indicted firms appear to be, on average, significantly larger than their matched counterparts. This result is not unexpected as the matching universe is restricted to the S&P 1500, which means that the average Fama-French 49 industry is populated by about 30 firms. Therefore, the number of potential matches is relatively low, especially for an industry with multiple indicted firms, and hence even matched firms can be statistically different along the matching dimensions. The Fama-French industry classification can be somewhat restrictive. For example, my fraud sample contains Northrop Grumman which is classified as a "defense" company within the 49 industries. In this classification, the only match in the S&P 1500 is Raytheon. However, relaxing the classification to 17 industries, Northrop Grumman falls into the "aviation" category and has more than 3 matches within the S&P 1500 universe.

[7]BoardEx and ExecuComp track companies after their exclusion from the S&P 1500, similarly they retroactively collect data prior to inclusion for new S&P 1500 constituents.

[8]My results are robust to keeping only the closest match for each indicted firm.

3.3.3. Fraud characteristics

The final fraud sample consists of 1,249 cases for 888 individual companies, meaning that about every second company had, on average, 2 lawsuits during my sample period. Figure 3.2 shows the number of new class action filings per year, as well as the number of ongoing frauds in any given year that are brought to court at a later time. Ongoing fraud is defined as the class action period given in the case filing. The figure shows that there were two peak periods in which fraud was more prevalent: the dot-com bubble and the financial crisis. This observation is corroborated by Table 3.1 that shows that filings in the technology and financial sectors reached their all-time high in 2001 and 2008, respectively.

Turning to the spatial distribution of class action filings, I find that cases are far from evenly distributed across the United States, and there is also variation within states.[9] As Figure 3.4 illustrates, there are 4 states in my sample where cases are concentrated, New York, California, Texas and Illinois, in descending order of frequencies. Among these states, the number of cases per industries also shows considerable variation. The financial sector takes first place in New York (90 out of 242), technology in California (111 out of 238), and services in Texas and Illinois, respectively, with about 20 out of 70 cases each.

While New York and California appear to top other states in terms of class action filings, the question arises whether class actions are in fact overrepresented in these two states in my sample. In order to answer this question, I contrast the overall litigation intensity in each state with the number of listed firms headquartered in the area.[10] Figure 3.4 shows that my sample is in line with the overall intensity of class actions for New York and California, however, Texas and Illinois have lower intensities, behind Arizona, Florida and New Hampshire. A possible explanation for this is that there might be large, specialized law firms filing cases at courts in their vicinity. For example, Milberg LLP, a New York-based law firm that focuses on counseling plaintiffs, was involved in about a quarter of all class actions in the SCAC database.[11]

Investors' ultimate goal when filing class actions is the recovery of their losses through damages. Table 3.2 gives a breakdown of mean settlement amounts by industries and years. The overall mean of settlement is about $78 million, with the largest amounts

[9]There are 89 districts across the 50 states, and a total of 94 districts including territories.

[10]I look at headquarter locations as an overwhelming majority of firms is incorporated in Delaware, for example, 69% of Fortune 500 companies, but most of them are headquartered elsewhere. As an example, Facebook was incorporated in Delaware, but has its headquarters and largest employee base in Menlo Park, California.

[11]In unreported results, I find that the top law firms in my sample are the same as in the full SCAC database, albeit in a slightly different order.

awarded in utilities, financials, and conglomerates, respectively. This ordering is driven by the inclusion of the largest ever settlements like Enron and Tyco International, with $7.2 and $3.2 billion, respectively. However, my sample mean is still lower than the $198 million reported by Dyck et al. (2010), but their sample is more restrictive, heavily tilted towards mega cases. When I restrict settlement amounts in the range between $3 million and $1 billion to represent typical class actions, in unreported results, I find that the mean settlement is about $67 million. In this latter setting, largest settlements are paid by financials, conglomerates and consumer cyclical product manufacturers, respectively. It is important to note that most cases in my sample where the parties reach a settlement are in fact out-of-court settlements and guilt is not established by the court nor pleaded by the defendants. However, for the purpose of my study, I do differentiate cases that are settled voluntarily and ones that are settled through a court order.

Considering the operational aspects of class actions, Table 3.3 indicates that, on average, the length of the class action period is 466 days or about 5 quarters. The time to filing, or the gap between the end of the class action period and the first case filing date is, on average, 107 days. However, in more than 50% of cases the lag is less than a month. The filing speed has been improving lately, with the median case being filed no later than 21 days after the class period in the years 2011-2015. Recent cases are filed considerably faster than cases in the earlier part of the sample. As an example, Volkswagen' s diesel fraud was uncovered by the California office of the Environmental Protection Agency on September 18, 2015 (Friday) and a lawsuit followed within one week, on September 25.[12] On the other hand, in periods of financial distress (e.g., the dot-com bubble and the financial crisis), when companies are expected to be under more serious scrutiny, I observe that some cases are brought to court where the filing date and the class period end can be up to 6 months apart. There are typically 4 law firms involved in prosecuting a case, but with mega cases I find this number multiple times higher, for example, there were a total of 33 law firms representing plaintiffs against Enron. Finally, I note that there are 41 cases filed in a given industry (as defined by SCAC) in any given year.

[12]This lawsuit concerns securities class action litigation and should not be confused with the consumer class action that settled the "dieselgate" scandal, even though the underlying reason is the same.

3.4. Engaging in fraud

3.4.1. Univariate results

Table 3.3 provides descriptive statistics for the fraud and the control sample. Each fraudulent firm is matched with 3 similar companies in the same industry using the Mahalanobis distance metric calculated from size and market-to-book. For each fraudulent firm, I create a pseudo-firm based on the average characteristics of the 3 matched companies.[13]

Compensation. It is a well established fact in the literature that a higher level of executive compensation, especially variable and equity based compensation induces managers to manipulate earnings or provide misleading information to investors (e.g., Bergstresser and Philippon (2006) or Burns and Kedia (2006)). Table 3.3 reveals that executives of indicted firms are paid more both in terms of base salary and equity based compensation (options and stocks combined). While the difference in means is statistically significant in for salary, in economic terms, the difference of $50,000 is probably not enough to outweigh the potential loss of reputation and hampered career outlooks that could result from the discovery of fraud (Aharony, C. Liu, and Yawson, 2015). However, the $800,000 difference in the value of equity based compensation is significant both statistically and economically.

Board structure. Table 3.3 shows that there are no significant differences between fraudulent and control firms with respect to having an independent chairman or CEO duality. Overall, the statistics suggest in 60% of the cases the CEO is the chairman of the board, in 10% of the sample the board is chaired by an executive other than the CEO, and in 30% of the sample there is an independent chairman. Fraudulent firms have more directors, of whom more are independent (i.e. non-executive), who held more positions in the past and who typically sit on more different boards at the same time. It appears that fraudulent firms work with directors who are better connected and have a considerably larger professional network size, compared to their counterparts in matched firms. Fraudulent firms appear to have a more diverse board structure, with more women and foreign nationals involved. Finally, fraudulent firms have somewhat younger CEOs, proxied by the time to retirement, who also have a shorter tenure in the position.

It is ex ante unclear what to expect with respect to the relationship of board characteristics and the likelihood to engage in fraudulent behavior. Ferris, Jagannathan,

[13]Table A.1 provides a description for all variables, as well as their respective sources.

and Pritchard (2003) argue busier directors perform just as well as directors that sit on a single board. However, Falato, Kadyrzhanova, and Lel (2014) find that an attention shock at one firm can have an adverse effect on director-interlocked firms, suggesting that the effort a director can devote to monitoring is limited.

Outside monitors. External monitors can be important in uncovering corporate misconduct (Dyck et al., 2010). I find that indicted companies are followed by more equity analysts and have a larger institutional shareholder base. Breaking down institutional ownership even further, the holdings of advisory firms, banks, insurance companies and investment managers do not differ significantly, but there is substantial variation in the holdings of institutions that do not fit any of the previous four categories.

Risk and profitability. In the context of securities class action litigation, one can expect that firms are indicted either because they go through a period of turmoil, their performance is overinflated, or they deceive shareholders with false claims about the future prospects of their business. I address the first two possibilities by looking at measures of past performance, and the third one by inspecting what outlook the market has on the firm. Fraudulent companies exhibit a somewhat lower, though statistically insignificant, buy-and-hold return in the year preceding the filing of a lawsuit, but with large volatility. Both fraudulent and control stocks appear to be highly liquid, captured by Amihud's illiquidity measure (Amihud, 2002), although it is not a surprise as the sample contains large firms where price impact is expected to be relatively small. Fraudulent companies operate less efficiently as their profitability measures are lower than those of non-fraudulent firms. However, their market share and annual sales growth is considerably larger, both statistically and economically. Finally, fraudulent firms have appreciably higher market-to-book and Tobin's Q ratios.

Taken together, measures of risk and profitability indicate that fraudulent firms are riskier and managed less efficiently than their matched peers. Furthermore, it appears that indicted firms can somehow deceive the market, because despite their lower level of efficiency they have markedly higher market-to-book ratios.

Size and capital structure. Fraudulent firms are larger in terms of size, including total assets, sales and the market value of equity. They also have higher leverage, indicating that in addition to external monitors associated with equity, they are also possibly screened by debtholders to a larger extent. Indicted firms have a lower level of tangibility which ties in with the observed high replacement ratios.

Cash, investments and payout. Firms that are taken to court hold slightly more cash, yet, their external financing need is considerably higher as estimated by the SA-index of external financing need Hadlock and Pierce (2010). The dividend policies of fraudulent and control firms are not markedly different. Turning to expenses, I find that operating expenses are not distinguishable between the two groups, however, fraudulent firms invest considerably more in long term assets. This expense and investment pattern can explain why fraudulent firms have a weaker bottom line.

Acquisitions. T. Y. Wang (2013) shows that fraudulent firms have a higher level of M&A activity. My sample shows the same pattern across fraudulent and control firms. While the majority of firms do not conduct deals during their respective class action period, 25% of my sample firms complete 1 or more deals. These deals are significantly larger for fraudulent acquirers, almost double over their non-fraudulent counterparts. I proceed to break down acquisitions into 2 categories: diversifying and expansion. I label an acquisition as diversifying if the acquirer and the target are in different 2-digit SIC industries. An acquisition is labeled as expansion if the deal takes place within a particular 2-digit SIC industry. I find that both fraudulent and control firms perform more expansion acquisitions than diversifying deals, although for indicted firms the figures are much closer in relative terms. Furthermore, irrespective of the acquisition type I find that fraudulent companies close bigger deals. This suggests that these acquisitions are value destroying acts of empire building.

Restatements. Since class action litigations might be only one of several channels through which corporate wrongdoing is revealed, I examine accounting restatements in the sample. The results show that almost 18% of fraudulent companies issued restatements compared to 5% in the control group. Restatements in the fraud sample are not only more numerous, but also have larger effects on the value of equity. Furthermore, in 70% of the cases the board was involved in forging the numbers at fraudulent firms, while this metric is 55% for the control group. The SEC followed up on these restatements with an investigation in 31% and 13% of the time for fraudulent and control firms, respectively. Restatements were labeled as financial fraud in 3 times as many cases when issued by a fraudulent firm compared to the control group.

3.4.2. Multivariate results

I estimate the probability of fraud detection and court outcomes using observable firm characteristics in the S&P 1500. I estimate a probit model for the probability of fraud detection, where the dependent variable is 1 if a firm is indicted and 0 otherwise. I also estimate the determinants of court outcomes using probit and ordered probit models. I run a probit model where the dependent variable is 1 if a firm pays a settlement and 0 otherwise. In order to distinguish between voluntary and ordered settlements, I also estimate an ordered probit model where the dependent variable is 1 for voluntary settlements, 2 for ordered settlements and 0 for dismissed cases. In order to account for selection bias in modeling the court outcome, I also estimate the probit and ordered probit models of the court outcome using Heckman's 2-stage method.

I follow T. Y. Wang (2013) and Dyck et al. (2013) in the specification of the selection equation. They argue that there are ex ante and ex post detection factors, as well as fraud commission factors that come into play at different stages around the engagement in fraud and its subsequent detection.

Ex ante detection factors. Ex ante detection factors can be interpreted as "red flags" that draw heightened attention to the firm. A high level of real investments (CapEx) might induce managers to commit fraud through manipulating cash flow figures to reduce the cost of capital T. Y. Wang (2005). Similarly, higher M&A activity can lead to the need to doctor the numbers (e.g., Erickson and S.-W. Wang (1999) or Louis (2004)). Sophisticated players, such as institutional investors and equity analysts can be more effective at uncovering fraud. Additionally, larger firms might be under stricter monitoring, but at the same time, managers of such corporations might feel that they can hide fraud easier.

Ex post detection factors. Ex post detection factors are the ones that potentially increase the probability of detection, but their influence can be hard to assess before or at the time of the commission of fraud. These factors serve as the basis of my identification. I use industry litigation intensity to proxy for increased scrutiny from investors. Additionally, I include measures of performance shocks to control for unexpected changes in profitability and stock returns. I take the residual from an AR(1) regression of ROA, where a positive residual translates into a positive shock. To account for return shocks, I create an indicator variable that is 1 if the firm had a stock return in the lowest quartile of its industry in the year preceding the court filing. I also control for the 1-year buy-and-hold return of firms, and their stock return volatility in the same period. Finally, I control for the 4 industries that experience the most litigations: financials, healtcare, services and technology.

Fraud commission factors. I also include variables beyond the ex ante detection factors that might have an influence on the propensity to commit fraud. In order to deal with "need or greed" I include leverage, external financing need and profitability. I calculate external financing need using the SA-index of Hadlock and Pierce (2010). If managers engage in fraud out of need, I can expect that leverage and external financing need will have a positive effect on the propensity of fraud commission. However, if fraud is induced by greed, it is profitability that should have a more pronounced effect.

Table 3.4 shows the results of the probit estimations. In the first column of the table, I include the univariate probit estimation of fraud detection with all controls, except for variables describing the court process. Companies that invest large amounts in long-term assets, firms with external financing need are indicted more. Additionally, the performance metrics indicate that a stock return shock and high volatility increase the likelihood of being cited to court. Surprisingly, companies that are more profitable, are also more likely to face a lawsuit, and abnormal litigation intensity in a certain industry also reduces the likelihood that the marginal firm is indicted.

Turning to the univariate probit model on the propensity of paying a settlement, I observe that smaller firms, firms dependent on external financing, as well as firms closing a larger number of acquisition deals are more likely to settle. Additionally, firms that experience a return shock and those with high volatility are prone to paying a settlement. To disentangle the differences between the two settlement types, I estimate an ordered probit model. Overall, the estimates for the various outcomes show a similar pattern as those of the probit. There is no difference between the outcomes in terms of size and external financing need. However, return shocks, volatility, litigation intensity and acquisition activity all drive firms to settle voluntarily relative to settling through a court order. This suggests that firms are more likely to reach an agreement with plaintiffs when there is high pressure from investors in the industry, and when they want to end a bad performance streak.

In Section 3 of Table 3.4, I estimate probit models that account for the fact that case outcomes are a result of a first stage selection, i.e. the indictment. The 2-stage estimation also allows me to introduce lawsuit-specific variables. The results indicate that firms are more likely to settle voluntarily when industry litigation is high, and the number of plaintiff law firms is large. However, firms that are taken to court repeatedly are less likely to settle either voluntarily or through a court order.

3.5. The effects of fraud revelation

Reading the news on class action lawsuits, it is apparent that the stock market always reacts if a firm is indicted. For example, when news broke about the "defeat device" in Volkswagen cars, the stock of VW fell by a total of 35% over 1 week, until the first lawsuit was filed. Therefore, I estimate the market reaction to lawsuit filings in my sample.

3.5.1. Short-term returns

In order to gauge the market reaction to the revelation of fraud, I estimate abnormal returns around the filing of securities litigation class actions. I estimate the Fama-French-Carhart 4-factor model (Carhart, 1997; Fama and French, 1993), and use factor return data from the website of Kenneth French.[14] I estimate betas in the [-250,-31] window. For IPO fraud allegations, I require at least 3 months' worth of data for estimation (no less than 60 trading days). I define the event window up to 1 month before and after the court filing as [-20,20]. The motivation for such a long event window around the filing is twofold. First, as discussed before, it is hard to pinpoint the exact date of discovery in many cases, but it is reasonable to assume that discovery happens in the interval between the end of the class action period and the filing date. On the other end, I allow a long window post-filing to be able to observe any reversal pattern following the filing.

My results show that being indicted is bad news. The upper section of Figure 3.5 shows that abnormal returns are particularly low in the [-5,0] window around filing and the effect is more pronounced for fraudulent companies. The week prior to the filing day has the overall lowest returns. This suggests that it is not necessarily the news about discovery, but the news about litigation that has the larger effect. Returning to the Volkswagen example, the stock fell by the largest amount on the day the company was indicted, not on the day the report was published by Environmental Protection Agency. Turning to the lower section of the figure, I note that cumulative abnormal returns (CAR) decline in the period leading up to the filing, even more so the week before the filing and then level off in the subsequent month. While (cumulative) abnormal returns are about 6% higher for eventually dismissed cases, there is still no reversal. The figure also shows that the control sample does not experience any unusual price movements.

Table 3.5 shows summary statistics for CARs. Panel A reports the results for CARs around case filings. The numbers in Panel A fully support the results from Figure 3.5. CARs are significantly negative across all event windows. Furthermore, the difference between settled and dismissed cases is also markedly different, but there is no difference between CARs of voluntary and ordered settlements.

In order to assess whether the market reacts to a significant event in the court process or to the final court order, I also calculate CARs around the approval of the settlement fund and the final court order. Panel B of Table 3.5 displays CARs around settlement events, while Panel C reports CARs around the final court order. I find no reversal either

[14] My results are robust to using alternative models, such as the Fama-French 5-factor model (Fama and French, 2015).

at intermediate or final dates, but there is a small but statistically significant drop when a voluntary settlement is filed.

To assess the economic magnitudes of abnormal returns around lawsuit filings, I calculate value losses and contrast them with the eventual penalty amount. Table 3.6 displays my findings. I calculate value losses on a rolling basis. Specifically, I have $\Delta MV_t = MV_{t-1} \cdot AR_t$. I find that indicted firms lose about \$1.3 billion or about 23% of their market value. Firms that end up paying a settlement lose significantly more. Voluntary settlements can be attributed with a loss of \$2.1 billion, while ordered settlements with \$1.7 billion, though the difference is not significant. This loss can be attributed more to a loss of reputation than the forecast of the eventual settlement amount, as the latter is about 20 times lower. Losses are non-trivial for dismissed cases either, as over the [-20,20] window these firms also lose almost \$900 million of their market value. The differences in market value losses between settled and dismissed cases are significant across all windows.

3.5.2. Long-term returns

The question naturally arises given these large losses, whether indicted firms experience a reversal. To investigate this, I estimate a long-run event study around the lawsuit filing and throughout the court process. I estimate a 4-factor model based on monthly data in the [-48,-2] window relative to the lawsuit filing. I require at least 24 months of data for IPO fraud allegations. I define the event window over the [-1,36] months around the lawsuit filing, as the average length of the court procedure is about 3 years.

Figure 3.6 graphically shows the return pattern over the [-1,36] horizon. Following an initial dip in the filing month, CARs stay negative. The return pattern of ordered settlements shows a reversal, however, initial losses are not recovered. Table 3.7 corroborates the figure. The returns of indicted firms are significantly lower than those of control firms. Additionally, irrespective of the case outcome, cumulative abnormal returns never revert back to zero. Cases that are settled through a court order show a slight reversal, but the 36-month CAR is still about -11%.

3.5.3. The cross-section of returns

Next, I turn to the cross-sectional analysis of abnormal returns. In what follows, I regress CARs on observable firm characteristics, governance measures and metrics of M&A activity. In all specifications, I compute heteroskedasticity robust standard errors that are clustered at the firm level. I run regressions of the form

$$CAR[-20, 20] = \alpha + \beta controls + \epsilon. \tag{3.1}$$

Table 3.8 shows the results of regressing CARs on observable stock market and accounting characteristics. On the one hand, I find that larger firms that hold more cash and had a better-than-expected year in terms of profitability have significantly higher abnormal returns, keeping other things constant. On the other hand, indicted firms that are more dependent of external financing earn a significantly lower return. This result indicates that the market considers these firms to be able to weather the litigation process. The stocks of firms in the healthcare industry are also hit harder. Furthermore, I observe a weakly significant negative effect in terms of litigation intensity. Surprisingly, if an indicted company experienced a profitability shock or high volatility in the year prior to the filing date, its CAR is less negative than that of a firm with relatively stable performance and stock return. I interpret this as a liberation effect, in that the market considers the lawsuit as a tool that puts and end to a bad streak. Columns 6-7 indicate that the market is able –to some extent– to forecast the eventual court outcome. Firms that end up settling the case earn a significantly lower CAR around the start of the litigation process. Firms that pay a larger settlement also have a more negative CAR.

In Table 3.9, I extend Equation 3.1 with measures of governance and monitoring. My results in the table are largely in line with previous studies on corporate fraud. I find that base salary is positively, while equity incentives are negatively related to CARs, however only base salary is statistically significant. Reporting quality, measured by the number of restatements and their effect on equity does not have an effect on CARs around court filings. The majority of board characteristics do not affect CARs. However, gender ratio and nationality mix are significant determinants of CARs. Finally, turning to outside monitors, I find that the number of equity analysts following a firm does not have an effect on CARs. It is unsurprising, as analysts themselves cannot put a price pressure on firms. Institutional investors can, and I indeed find the a larger institutional shareholder base is associated with significantly lower abnormal returns, especially for investment companies and other institutions, like pension funds. This can potentially indicate that some institutions start offloading fraudulent companies from their portfolios, either due to regulation or pressure from their clientele.

In Table 3.10, I focus my attention on the M&A activity of indicted firms. Again, I enrich specification 1 from Table 3.8 with additional controls on acquisitions. Looking at the number and value of completed deals in the class action period, I do not find that M&A has a significant effect on stock returns around class action filings.

Partitioning acquisitions into expansion and diversification acquisitions does not change the conclusion.

3.5.4. Long-term effects

Next, I turn to the analysis of long-term firm performance and changes in the investor base. I estimate differences-in-differences (DD) models around the filing of the lawsuit. In the DD, the treatment effect is 1 for fraudulent firms and 0 for the control group. For operational measures, I look at the [-3,3] years around the lawsuit. The time indicator variable is 1 starting in the year of the lawsuit and for the 3 subsequent years, and 0 prior to the lawsuit. For holding information, I examine the [-12,12] quarter around the filing. The time indicator variable is 1 in the quarter of the lawsuit filing and in the 12 subsequent quarters and 0 otherwise. The DD specification is of the following form (with ROA as an example):

$$ROA_{i,t} = \alpha + \beta Post_t \gamma + Treated_i + \delta Post_t \times Treated_i + Controls_{i,t} + \epsilon_{i,t}. \tag{3.2}$$

Table 3.11 shows the results of the DD estimation. To conserve space, the table only reports the differencing term (δ) for the full sample and various case outcome breakdowns. Therefore, each cell in the table refers to a different specification. Panel A shows the results for operational measures. In each regression, I control for market-to-book and size, as well as year and industry fixed effects, and cluster standard errors at the firm level. The results indicate that sales and the return on equity do not change. However, overall profitability and sales growth are negatively affected by the lawsuit. Indicted firms reduce long-term investments and hold more cash. Their dependence on external financing also increases around the lawsuit filing.

Panel B reports changes in institutional holdings around lawsuit filings. I control for log market capitalization and market-to-book, and quarter and industry fixed effects in each specification. The results indicate that institutions lower their holding in indicted firms by 2.6% in total. Furthermore, all types of institutions offload a significant amount of shares from their portfolio.

3.5.5. Trading around fraud

Litigation has a significant effect on the returns of indicted firms. The question then naturally arises, whether an investor can profit from trading on the information that a lawsuit brings to the market. To asses this question, I devise a simple trading strategy. I construct a long-short portfolio of indicted and control firms. The trading strategy is the following. In the month following the lawsuit filing I create an equally weighted portfolio that is long in the control firms and short in the indicted companies. I hold each position until the court process is finished.

Table 3.12 shows the characteristics of this trading strategy. In Panel A, the table reports the portfolio's mean return and average size. In a typical month, there is about 591 stocks in the portfolio. The portfolio has positive returns through the entire sample period, even in the dotcom bubble and the housing crisis. The mean return is 14% over the entire period.

Panel B of the table shows the risk-adjusted returns of the trading strategy. I estimate the CAPM, the Fama-French 3-factor, the Fama-French-Carhart and the Fama-French 5-factor alphas. The alphas are significant and positive irrespective of the risk adjustment. The annualized alpha is 2.6%-4.2% depending on the model applied.

3.6. Conclusion

Using a detailed dataset on class action lawsuits, I analyze what drives the market reaction to lawsuit filings and what makes a company suspicious to investors. To mitigate selection issues, I match indicted firms to firms that do not experience any lawsuits.

Firms that are taken to court are typically large with large market share, are followed by more analysts, and have a large institutional shareholder base. This indicates that visible firms with more outside monitors are suspected more often. My multivariate results indicate that a disastrous stock market performance in the year preceding the lawsuit filing is also associated with an increased probability of being sued.

Firms that are taken to court experience a significant negative return in the period leading up to the lawsuit filing, and there is no reversal effect in the month after the filing date or throughout the court process. Negative returns are more pronounced for firms that end up settling the lawsuit, suggesting that markets can forecast the outcome of lawsuits to some degree. Looking at dollar values, I observe that the value losses are sizable, up to

$2 billion for settling and about $900 million for acquitted firms. The settlement amount is about 1 twentieth of the value drop for fraudulent firms meaning that $1.8 billion is loss in reputation. Furthermore, there are no abnormal stock price movements around the final order of the court, nor at the approval of the settlement amount or at any point during the course procedure. This suggests that it is the filing of the lawsuit that conveys more information to the market. Taken together, these indicate that litigation imposes a great penalty on firm reputation, especially since the long-term value drop for eventually acquitted firms is as high as 50% of the value drop of firms that end up paying a settlement.

Examining the cross section of announcement returns, I find that firms with large cash holdings and firms that are bigger experience a more modest market reaction. This suggests that the market considers these firms to be able to weather the litigation process. This is confirmed by operational changes, as indicted firms tend to increase their cash holdings and reduce investments. Among governance measures, I find that the presence of large institutional investors leads to a considerable value drop. Institutions also reduce their holdings in fraudulent firms considerably compared to similar firms not facing a court procedure.

I find that indicted firms change their operations, by holding more cash and investing less in long-term assets. They do not experience a sales drop, but their profitability and sales growth decreases. This indicates that their customer relations also suffer from the lawsuit.

Finally, I show that a trading strategy based on available information on class action filings yields positive returns. A long-short portfolio of non-fraudulent and fraudulent firms earns a four-factor alpha of 3.7% annually.

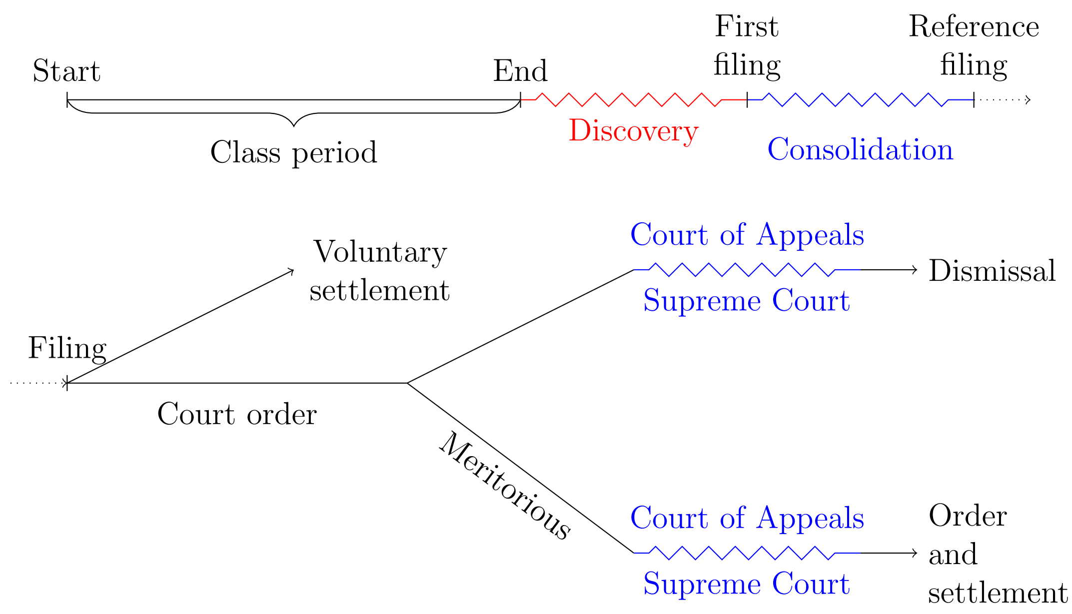


Figure 3.1 Class action timeline

This figure provides a schematic overview of the timeline of class actions and the following court process.

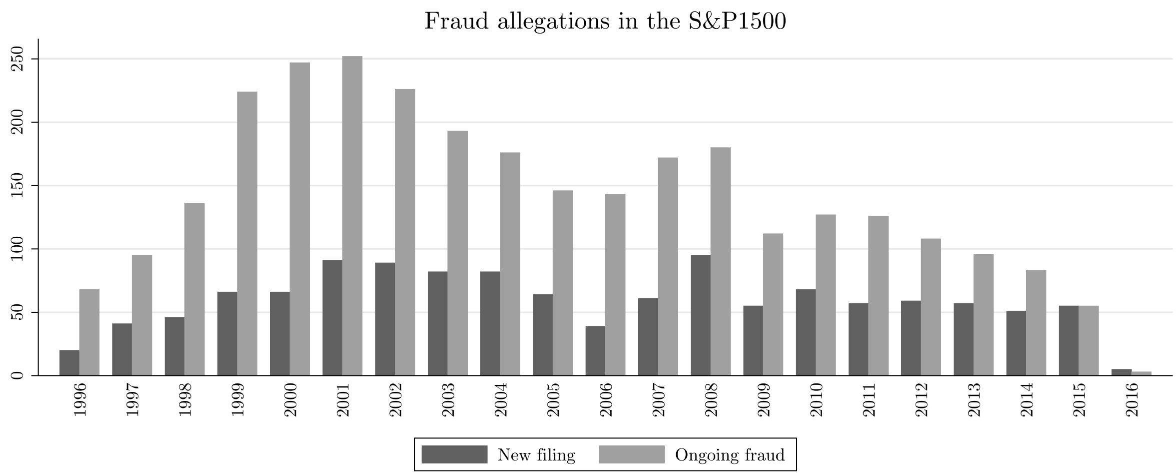
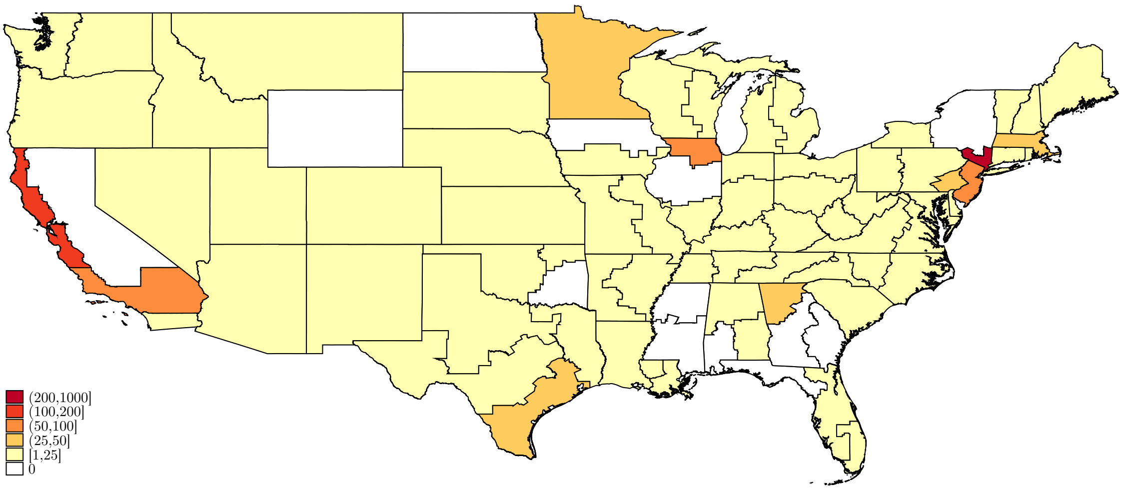


Figure 3.2 Fraud occurrence and class action filing intensity

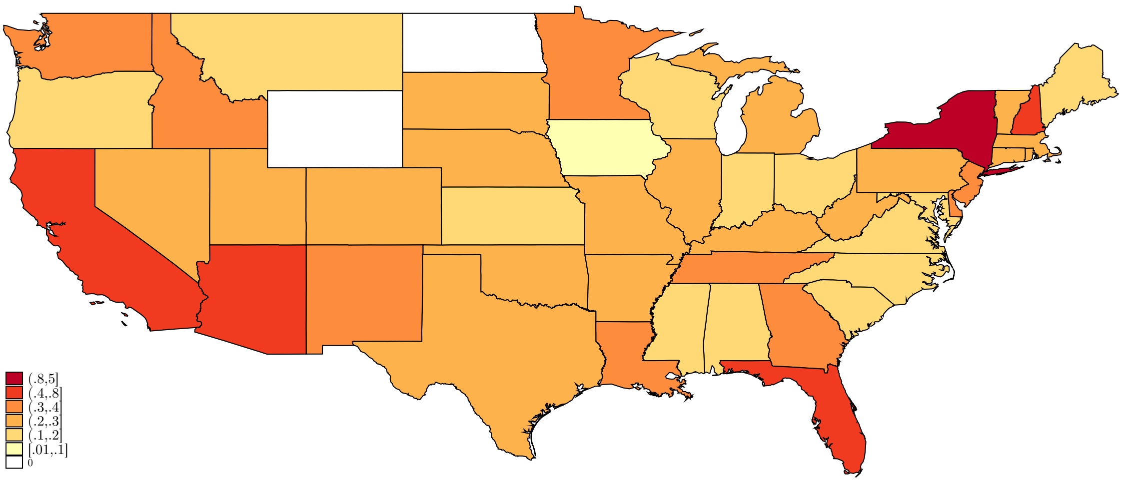
The figure shows the number of fraudulent and indicted firms in the S&P 1500 universe over time. Frequencies are calculated based on first identified complaint filings. Ongoing fraud is defined by the span of the class action period once a case is brought to court.



Other territories: AK: 0; HI: 0; PR: 3; VI: 0.

Figure 3.3 Spatial distribution of securities litigation class action filings

The figure shows the geographical dispersion of securities class action filings across the contiguous US area and federal court districts. Frequencies are calculated based on first identified complaint filings. The sample period is 1996-2016.



Other territories: AK: 0; HI: 0; PR: 0.34; VI: 0.75.

Figure 3.4 Spatial distribution of securities litigation class action filing intensity

The figure shows the geographical dispersion of securities class action filing intensity across the contiguous US area and states. Filing intensity is the ratio of class action filings and the number of firms headquartered in a given state. Class action filing frequencies are calculated based on first identified complaint filings in the entire SCAC universe. The sample period is 1996-2016.

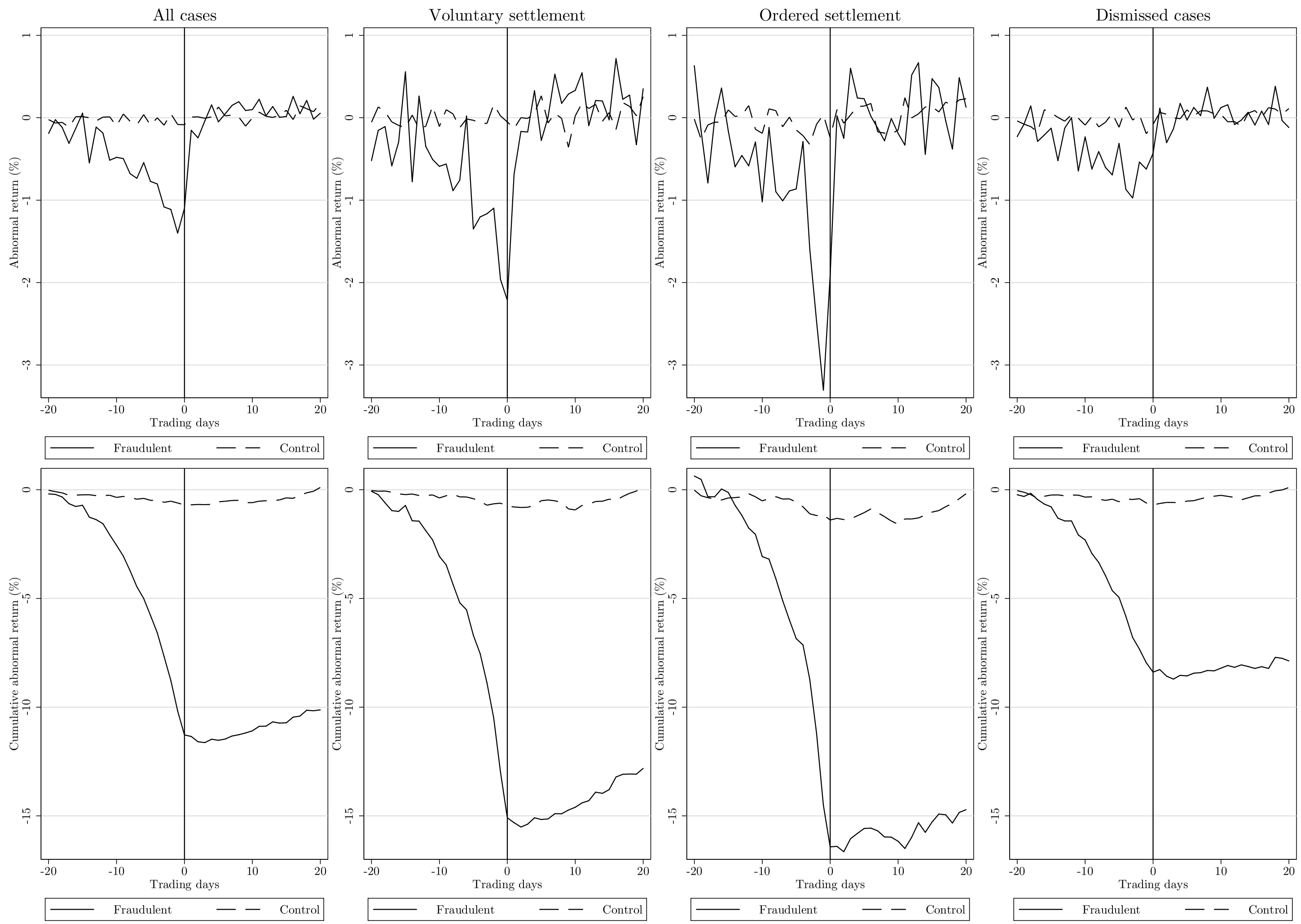


Figure 3.5 Abnormal and cumulative abnormal returns around securities litigation class action filings

The figure shows abnormal returns and cumulative abnormal returns in the [-20,20] day window around securities class action filings for all cases, voluntarily settled cases, cases settled by order and dismissed cases, respectively. Settled cases are either settled through an agreement between the parties or through a final judgment and order by the court. Dismissed cases are dismissed by the court as non-meritorious. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date.

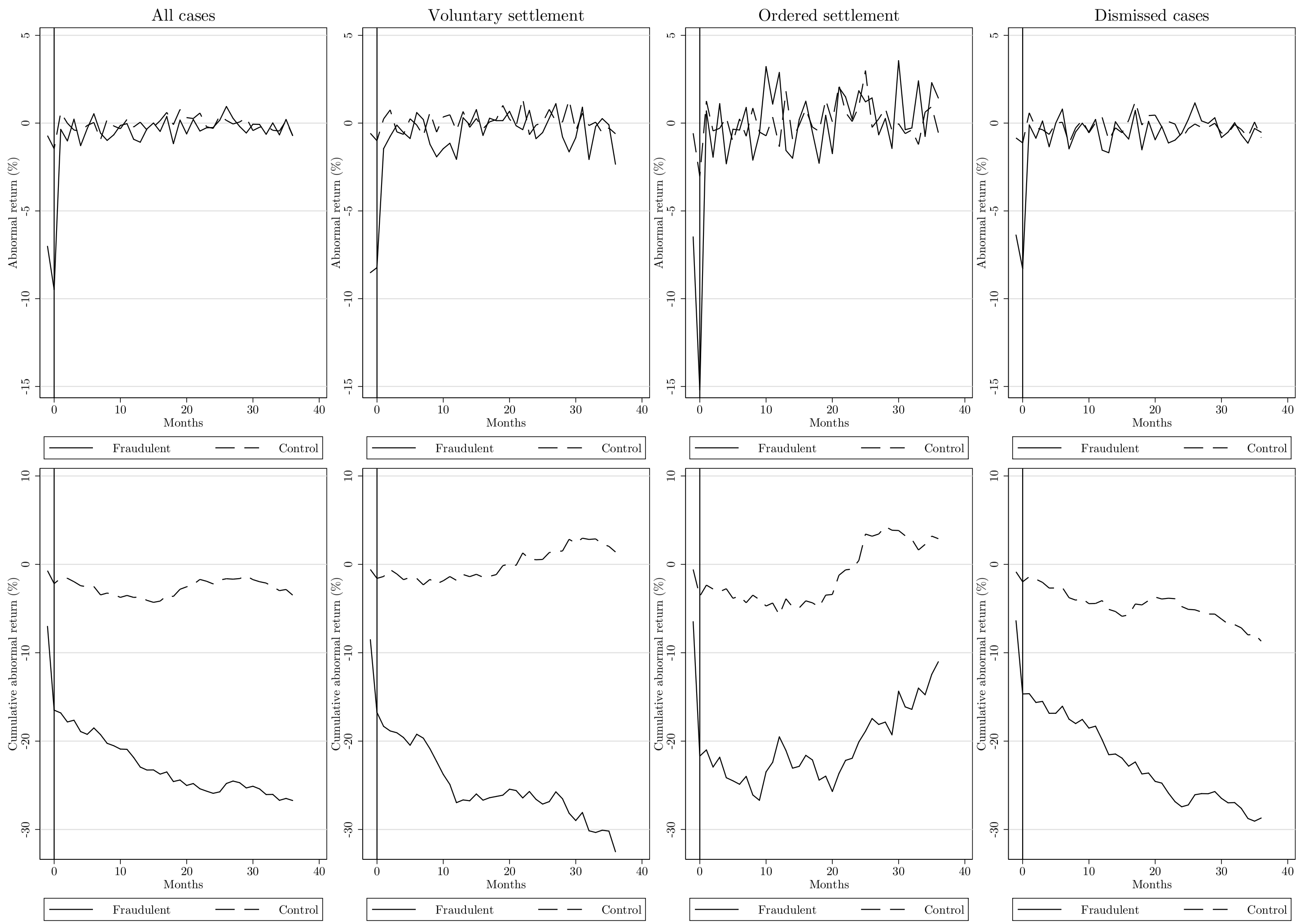


Figure 3.6 Long-term abnormal and cumulative abnormal returns around securities litigation class action filings

The figure shows abnormal returns and cumulative abnormal returns in the [-1,36] month window around securities class action filings for all cases, voluntarily settled cases, cases settled by order and dismissed cases, respectively. Settled cases are either settled through an agreement between the parties or through a final judgment and order by the court. Dismissed cases are dismissed by the court as non-meritorious. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-48,-2] months relative to the filing date.

Table 3.1 Filings by industries and years

This table shows the yearly distribution of new securities litigation class action filings by industries. Industry definitions are provided by SCAC.

	Basic Materials	Capital Goods	Conglomerates	Consumer Cyclical	Consumer Non-Cyclical	Energy	Financial	Healthcare	Other	Services	Technology	Transportation	Utilities	Total
1996	0	1	0	0	1	0	4	3	0	7	3	1	0	20
1997	3	3	0	0	0	0	4	4	0	10	14	2	1	41
1998	0	2	0	4	1	0	4	13	0	4	17	1	0	46
1999	0	4	3	5	4	2	7	10	1	12	18	0	0	66
2000	2	0	2	5	6	0	7	6	0	12	22	0	4	66
2001	0	1	0	4	6	0	9	8	0	19	42	0	2	91
2002	2	0	2	2	0	3	19	13	0	15	16	1	16	89
2003	4	2	1	1	2	0	24	16	0	12	15	0	5	82
2004	2	5	1	3	0	1	20	9	0	21	17	0	3	82
2005	3	0	1	6	6	1	9	13	0	7	17	1	0	64
2006	0	0	0	2	3	0	5	5	0	10	14	0	0	39
2007	0	4	0	2	2	0	15	9	0	16	12	1	0	61
2008	0	0	2	2	3	2	50	10	0	12	12	0	2	95
2009	4	2	2	3	0	1	21	5	0	12	5	0	0	55
2010	2	2	0	1	2	6	14	16	0	14	10	0	1	68
2011	2	1	0	2	3	3	7	5	0	11	18	2	3	57
2012	2	1	0	5	3	5	4	13	0	10	11	1	4	59
2013	0	0	0	5	1	1	5	5	15	12	13	0	0	57
2014	2	1	0	3	2	1	8	11	0	13	7	2	1	51
2015	3	1	0	3	3	2	8	6	0	7	17	2	3	55
2016	0	0	0	0	1	0	0	1	0	2	1	0	0	5
Total	31	30	14	58	49	28	244	181	16	238	301	14	45	1,249

Table 3.2 Settlements by industries and years

This table shows the yearly distribution of mean settlement amounts of securities litigation class action cases by industries. The year of settlement is the year when a settlement gets final approval from the court. Industry definitions are provided by SCAC. Settlement figures are in nominal $ million.

	Basic Materials	Capital Goods	Conglomerates	Consumer Cyclical	Consumer Non-Cyclical	Energy	Financial	Healthcare	Other	Services	Technology	Transportation	Utilities	Overall
1996														
1997					2.5									2.5
1998	10						30			140	4.8			46.2
1999		14.8						4.3		176.6	7	5		58.2
2000	2.9	22.5		3.7			20.2	13	0.8	3.3	56	34		23
2001				0.5	38.5		64	3.8		37.6	60.7			45.2
2002		92.5			2.5		116.9	17.3		44.4	25.4			50.5
2003				8.9	35		203.8	55		79	75.9	15	145.5	92.4
2004	4		255	7.9	6.1		26.2	82.3		29.7	50.6		38.5	49.9
2005	92.4	18		4.8	21.5		30.3	16.8		33.1	45.7		32.8	31.6
2006		10	7	11.7		9	82.3	103.6		53.5	37.6		8	51.9
2007		14.6			6.6		36.3	90		39.5	332.8		164.6	142.5
2008		1.2		42	57.3		11.5	6.5		14.9	20.6		7,227.4	261.8
2009	10.6	17.3	6.5	750			116.9	50.2		37.6	12.9	1.5		52.3
2010	15	55		3.9		10.5	96.3	84.6		19.6	82			67.6
2011	20	25				5	72.1	81.2		10.8	30.2			45.1
2012				186.2	13	238.1	206.1			45.4	40.7			112.3
2013			70.5	104.3	241.4		140.8	48.8		10.1	35		4	84.9
2014		19.5	40		5	82.5	366	82.9		74.8	10.5			110.8
2015	9.5				8.1	27.6	164.7	59.7	5	19.6	14		73.1	44.4
2016	42			77.3	31		171.7	68.7	37.7	18.9	5.3			75.5
Overall	22.5	21.5	105.7	58.2	53.7	68.2	133.7	61.3	16.7	37.7	52.6	6.9	393.8	77.8

Table 3.3 Summary statistics

This table reports summary statistics for all variables. For each case, I keep the first firm-year observation and use a lag of one year. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. The t-statics stand for the difference in means between the fraud and the control group. The Z-score is calculated for the Wilcoxon signed rank test, for which I use the median difference between the fraudulent firm and the control group. For the t-statistics and rank tests I report p-values in brackets. Dollar amounts are in millions. All variable definitions are in the Appendix.

	Indicted						Control		Difference	
Variable	Obs.	Mean	Sdev.	25%	Median	75%	Obs.	Mean	t-test	Rank
Matching variables										
Size	1,248	8.275	2.268	6.614	7.931	9.751	3,505	7.815	[0.000]	[0.000]
Buy-and-hold return,	1,143	0.142	0.960	-0.300	0.005	0.340	3,456	0.118	[0.339]	[0.000]
Market-to-book	1,248	3.572	20.607	1.357	2.357	4.141	3,503	3.107	[0.198]	[0.109]
Fraud characteristics										
Class period length	1,246	466	509	146	286	610				
Time to filing	1,246	107	157	6	27	113				
Law firms	1,249	4	4	2	3	5				
Voluntary settlement	1,249	0.265	0.442	0.000	0.000	1.000				
Settlement amount $	664	77.751	351.845	2.325	10.000	40.150				
Industry litigation	1,249	41.399	49.845	18.000	31.000	46.000	3,747	41.399	[1.000]	[1.000]
Compensation										
Salary ($)	1,248	0.780	0.481	0.458	0.742	1.000	3,505	0.715	[0.000]	[0.081]
Equity incentives	1,249	2.087	4.927	0.000	0.000	2.111	3,747	1.210	[0.000]	[0.001]
Board structure										
Indep. chairman	839	0.328	0.470	0.000	0.000	1.000	2,489	0.347	[0.317]	[0.000]
CEO duality	839	0.597	0.491	0.000	1.000	1.000	2,489	0.575	[0.268]	[0.007]
Number of directors	839	10.081	3.139	8.000	10.000	12.000	2,489	9.765	[0.007]	[0.033]
Independent director	839	8.460	2.945	6.000	8.000	10.000	2,489	8.189	[0.018]	[0.662]
Previous board seats	839	1.502	1.651	0.000	1.143	2.250	2,489	1.211	[0.000]	[0.153]
Other board seats	839	0.261	0.525	0.000	0.000	0.375	2,489	0.186	[0.000]	[0.008]
Time on board	839	7.435	3.589	4.829	7.125	9.422	2,489	8.805	[0.000]	[0.000]
CEO tenure	831	4.236	4.321	1.300	2.900	5.500	2,463	5.142	[0.000]	[0.000]
CEO retirement	839	9.963	4.123	7.400	9.680	12.000	2,489	9.021	[0.000]	[0.000]
Network size	839	1390.	878	820	1172	1705	2,489	1070	[0.000]	[0.000]
Gender ratio	839	0.879	0.102	0.818	0.889	1.000	2,489	0.886	[0.055]	[0.234]
Nationality mix	832	0.092	0.155	0	0	0.200	2,470	0.063	[0.000]	[0.086]
Outside monitors										
Analyst	937	13.401	8.343	6.917	11.833	18.167	2,887	11.310	[0.000]	[0.000]
Institutional holding	942	0.735	0.241	0.591	0.746	0.879	2,924	0.717	[0.021]	[0.016]
Mutual fund holding	943	0.287	0.120	0.205	0.283	0.368	2,928	0.290	[0.598]	[0.791]
Advisory firm holding	942	0.145	0.101	0.060	0.125	0.211	2,922	0.143	[0.531]	[0.447]
Bank holding	942	0.083	0.047	0.053	0.081	0.106	2,922	0.083	[0.908]	[0.574]
Insurance holding	932	0.021	0.027	0.005	0.010	0.027	2,903	0.021	[0.630]	[0.000]
Investment holding	897	0.024	0.049	0.007	0.010	0.017	2,793	0.024	[0.697]	[0.000]
Other holding	942	0.464	0.222	0.332	0.462	0.609	2,923	0.447	[0.027]	[0.155]

Continued on next page

Continued from previous page

	Indicted						Control		Difference	
Variable	Obs.	Mean	Sdev.	25%	Median	75%	Obs.	Mean	t-test	Rank
Risk and profitability										
Volatility	1,143	0.486	0.324	0.283	0.396	0.592	3,456	0.403	[0.000]	[0.000]
Buy-and-hold return	1,143	0.142	0.960	-0.300	0.005	0.340	3,456	0.118	[0.339]	[0.000]
Amihud ILLIQ	1,143	0.008	0.066	0.000	0.001	0.003	3,456	0.009	[0.886]	[0.000]
ROA	1,028	0.013	0.422	-0.008	0.038	0.087	2,858	0.040	[0.002]	[0.000]
ROE	1,028	0.101	2.765	0.005	0.101	0.187	2,858	0.072	[0.585]	[0.824]
Asset turnover	1,248	0.899	0.886	0.341	0.717	1.201	3,504	0.905	[0.784]	[0.000]
Sales growth	1,185	0.184	0.854	0.000	0.003	0.181	3,423	0.027	[0.000]	[0.000]
Market share	1,245	0.009	0.020	0.001	0.003	0.011	3,504	0.006	[0.000]	[0.003]
Profit margin	1,028	0.013	0.422	-0.008	0.038	0.087	2,858	0.040	[0.002]	[0.000]
Market-to-book	1,248	3.572	20.607	1.357	2.357	4.141	3,503	3.107	[0.198]	[0.109]
Tobin's Q	1,237	3.205	4.574	1.236	1.895	3.420	3,500	2.589	[0.000]	[0.343]
Size and capital structure										
Size	1,248	8.275	2.268	6.614	7.931	9.751	3,505	7.815	[0.000]	[0.000]
Log of sales	1,244	7.718	1.956	6.370	7.657	9.174	3,504	7.324	[0.000]	[0.000]
Log of market equity	1,248	8.069	1.894	6.731	7.944	9.358	3,502	7.690	[0.000]	[0.000]
Book leverage	1,249	0.354	0.592	0.046	0.289	0.527	3,747	0.257	[0.000]	[0.001]
Tangibility	1,223	0.197	0.198	0.049	0.130	0.281	3,419	0.219	[0.002]	[0.000]
Cash, investments and payout										
Cash holdings	1,237	0.110	0.126	0.021	0.063	0.158	3,469	0.100	[0.013]	[0.004]
CapEx	1,023	0.057	0.060	0.022	0.041	0.072	2,840	0.054	[0.035]	[0.036]
Operating expenditures	1,028	0.906	0.752	0.417	0.700	1.136	2,858	0.918	[0.647]	[0.000]
Dividend yield	1,241	0.016	0.049	0.000	0.000	0.019	3,495	0.016	[0.701]	[0.000]
Dividend payout	1,026	0.726	15.691	0.000	0.000	0.153	2,851	0.309	[0.229]	[0.000]
SA-index	1,248	14.269	14.099	5.135	11.513	19.917	3,505	9.837	[0.000]	[0.000]
Acquisitions										
Acquisitions	1,249	0.717	1.642	0.000	0.000	1.000	3,747	0.608	[0.051]	[0.004]
Acquisitions/assets	1,249	0.075	0.369	0.000	0.000	0.014	3,747	0.044	[0.000]	[0.000]
Diversifying acq.	1,249	0.320	1.113	0.000	0.000	0.000	3,747	0.233	[0.005]	[0.012]
Div. acq./assets	1,249	0.032	0.308	0.000	0.000	0.000	3,747	0.013	[0.001]	[0.000]
Expansion acq	1,249	0.396	0.950	0.000	0.000	0.000	3,747	0.375	[0.587]	[0.000]
Exp. acq./assets	1,249	0.043	0.205	0.000	0.000	0.000	3,747	0.031	[0.014]	[0.000]
Restatements										
Restatement	1,249	0.177	0.382	0.000	0.000	0.000	3,747	0.054	[0.000]	[0.000]
Effect on income	1,249	-19.824	191.193	0.000	0.000	0.000	3,747	-21.002	[0.972]	[0.001]
Effect of equity	1,249	-7.809	86.831	0.000	0.000	0.000	3,747	-0.123	[0.000]	[0.001]
Board involvment	1,249	0.123	0.329	0.000	0.000	0.000	3,747	0.029	[0.000]	[0.000]
SEC investigation	1,249	0.054	0.227	0.000	0.000	0.000	3,747	0.006	[0.000]	[0.000]
Financial fraud	1,249	0.021	0.143	0.000	0.000	0.000	3,747	0.003	[0.000]	[0.020]
Auditor same	1,249	0.732	0.443	0.000	1.000	1.000	3,747	0.753	[0.128]	[0.000]

Table 3.4 Fraud detection and case outcome

This table shows the results of probit regressions on fraud detection (indictment) and court case outcome (settlement). For ordered probit models, the baseline is case dismissal. The table reports regression coefficients and their corresponding average marginal effects in brackets. Fraudulent firms are compared with the universe of S&P 1500 companies. Standard errors are robust to heteroskedasticity and clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)			(3)		
	Probit	Probit	Ordered probit		Heckman probit	Heckman ordered probit	
Dependent var. (D)	Indicted (D=1)	Settled (D=1)	Voluntary settlement (D=1)	Ordered settlement (D=2)	Settled (D=1)	Voluntary settlement (D=1)	Ordered settlement (D=2)
Size	-0.044***	-0.027*	-0.028*	-0.028*	-0.009	-0.043	-0.043
	[-0.006]	[-0.002]	[-0.001]	[-0.001]	[-0.003]	[-0.005]	[-0.002]
CapEx	0.892***	0.809*	0.710	0.710	0.033	0.951	0.951
	[0.117]	[0.053]	[0.026]	[0.021]	[0.011]	[0.105]	[0.054]
Acquisition value	0.034	0.086**	0.083**	0.083**	0.087	0.099	0.099
	[0.004]	[0.006]	[0.003]	[0.002]	[0.030]	[0.011]	[0.006]
SA-index	0.008***	0.007***	0.007**	0.007**	0.004	0.007	0.007
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
Book leverage	0.011	0.019	0.021	0.021	0.061	0.089	0.089
	[0.001]	[0.001]	[0.001]	[0.001]	[0.021]	[0.010]	[0.005]
ROA	0.209**	0.120	0.109	0.109	0.010	-0.192**	-0.192**
	[0.027]	[0.008]	[0.004]	[0.003]	[0.004]	[-0.021]	[-0.011]
Profitability shock	-0.001	-0.037	-0.041	-0.041			
	[-0.000]	[-0.002]	[-0.002]	[-0.001]			
Return shock	0.268***	0.229***	0.228***	0.228***			
	[0.035]	[0.015]	[0.008]	[0.007]			
Buy-and-hold ret.	-0.001	-0.018	-0.023	-0.023			
	[-0.000]	[-0.001]	[-0.001]	[-0.001]			
Volatility	0.250***	0.178**	0.195***	0.195***			
	[0.033]	[0.012]	[0.007]	[0.006]			
Institutional hold.	-0.051	-0.095	-0.121	-0.121	0.056	-0.286	-0.286
	[-0.007]	[-0.006]	[-0.004]	[-0.004]	[0.019]	[-0.032]	[-0.016]
Analyst coverage	-0.001	-0.004	-0.004	-0.004	-0.007	-0.003	-0.003
	[-0.000]	[-0.000]	[-0.000]	[-0.000]	[-0.003]	[-0.000]	[-0.000]
Litigation intensity	-0.043**	0.056	0.072*	0.072*	-0.046	0.327***	0.327***
	[-0.006]	[0.004]	[0.003]	[0.002]	[-0.016]	[0.036]	[0.019]
SEC investigation					0.232	0.141	0.141
					[0.080]	[0.016]	[0.008]
Serial offender					-0.109	-0.208*	-0.208*
					[-0.037]	[-0.023]	[-0.012]
Number of law firms					0.010	0.041***	0.041***
					[0.003]	[0.005]	[0.002]
N	16,300	16,226	16,300	16,300	16,300	16,300	16,300
N-Uncensored					1,144	1,144	1,144
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y
rho					0.015	0.615	0.615
p-value					0.967	0.335	0.335

Table 3.5 Cumulative abnormal returns around court filings

This table shows cumulative abnormal returns for various event windows around securities litigation class action filings. The table also provides a breakdown for settled and dismissed cases. Settled cases are either settled voluntarily through an agreement between the parties or through a final judgment and order by the court. Dismissed cases are dismissed by the court as non-meritorious. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: CARs around court filing

	Full sample		Control group		Voluntary settlement		Ordered settlement		Dismissed		Differences			
	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	t-stat			
	(1)		(2)		(3)		(4)		(5)		1 vs. 2	3 vs. 5	4 vs. 5	3 vs. 4
CAR[-1,1]	-0.027***	(0.139)	-0.002**	(0.047)	-0.049***	(0.168)	-0.052***	(0.159)	-0.009*	(0.119)	9.112***	3.937***	3.884***	-0.223
CAR[-1,3]	-0.029***	(0.150)	-0.002	0.062	-0.052***	(0.176)	-0.048***	(0.175)	-0.014**	(0.133)	8.877***	3.554***	2.857***	0.214
CAR[-5,5]	-0.066***	(0.214)	-0.001	(0.090)	-0.100***	(0.255)	-0.096***	(0.240)	-0.039***	(0.183)	14.303***	3.968***	3.391***	0.156
CAR[-10,10]	-0.090***	(0.259)	-0.003	(0.126)	-0.114***	(0.297)	-0.141***	(0.307)	-0.058***	(0.225)	14.938***	3.061***	3.956***	-0.972
CAR[-20,20]	-0.101***	(0.308)	0.001	(0.176)	-0.118***	(0.333)	-0.147***	(0.359)	-0.077***	(0.287)	13.786***	1.904*	2.736***	-0.911
Obs	1,149		3,451		300		192		548					

Panel B: CARs around settlement filing

	(1)		(2)		(3)		(4)		(5)		1 vs. 2	3 vs. 5	4 vs. 5	3 vs. 4
CAR[-1,1]	0.001	-0.048	0.000	-0.044	-0.006*	-0.050	0.002	-0.047	0.004	-0.048	-0.285	2.411**	0.438	1.432
CAR[-1,3]	-0.003	-0.065	0.002	0.053	-0.010**	-0.063	0.002	-0.064	0.000	-0.065	1.943*	1.931*	-0.384	1.835*
CAR[-5,5]	-0.001	-0.094	0.004***	-0.077	-0.004	-0.081	0.002	-0.094	0.000	-0.099	1.484	0.569	-0.172	0.638
CAR[-10,10]	-0.001	-0.145	0.004*	-0.110	0.006	-0.127	-0.012	-0.155	-0.002	-0.149	1.110	-0.736	0.682	-1.236
CAR[-20,20]	-0.002	-0.220	0.005	-0.164	0.007	-0.195	0.003	-0.245	-0.007	-0.223	0.889	-0.838	-0.497	-0.159
Obs	851		2,695		229		144		478					

Panel C: CARs around final order

	(1)		(2)		(3)		(4)		(5)		1 vs. 2	3 vs. 5	4 vs. 5	3 vs. 4
CAR[-1,1]	0.003*	-0.050	0.000	-0.042	0.004	-0.052	0.000	-0.056	0.003	-0.047	-1.905*	-0.222	0.662	-0.698
CAR[-1,3]	0.002	-0.068	0.001	0.053	0.004	-0.069	0.008	-0.074	-0.001	-0.066	-0.156	-0.804	-1.291	0.531
CAR[-5,5]	0.001	-0.103	0.004**	-0.081	0.002	-0.118	0.005	-0.090	0.000	-0.099	0.731	-0.243	-0.490	0.215
CAR[-10,10]	0.000	-0.148	0.003	-0.111	0.005	-0.144	-0.003	-0.149	-0.002	-0.150	0.685	-0.595	0.034	-0.487
CAR[-20,20]	-0.006	-0.206	0.003	-0.164	-0.009	-0.181	0.008	-0.186	-0.008	-0.224	1.297	0.013	-0.791	0.847
Obs	850		2,689		230		143		477					

Table 3.6 Market value change around lawsuit filings

This table the shows the market value change of indicted firms around the filings of securities litigation class actions. The table also provides a breakdown for settled and dismissed cases. Settled cases are either settled voluntarily through an agreement between the parties or through a final judgment and order by the court. Dismissed cases are dismissed by the court as non-meritorious. The table shows the change in market value over the event window relative to the market value of the firm 2 months prior to the filing datet. Market value change is calculated using abnormal returns. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Full sample		Voluntary settlement		Ordered settlement		Dismissed		Differences		
	Mean	Sd. dev.	Mean	Sd. dev.	Mean	Sd. dev.	Mean	Sd. dev.	t-stat.		
	(1)		(2)		(3)		(4)		2 vs. 4	3 vs. 4	2 vs. 3
Loss[-1,1]	-375.2***	(3035.5)	-695.2***	(3132.7)	-625.0*	(5067.5)	-218.1**	(2103.4)	2.362**	1.081	0.172
Loss[-1,3]	-373.1***	(2940.7)	-694.5***	(3143.5)	-603.1*	(4924.0)	-186.4**	(1827.4)	2.572**	1.145	0.229
Loss[-5,5]	-755.2***	(4087.2)	-1433.1***	(4809.8)	-920.8**	(5680.6)	-462.7***	(3142.1)	3.146***	1.062	1.035
Loss[-10,10]	-992.6***	(4952.9)	-1638.9***	(5410.8)	-1422.2**	(7593.9)	-602.4***	(3701.2)	2.960***	1.437	0.344
Loss[-20,20]	-1319.5***	(6476.0)	-2149.3***	(6753.9)	-1686.8**	(10000.6)	-894.9***	(5037.5)	2.817***	1.051	0.564
Settlement			139.1	(535.1)	54.8	(109.3)					-2.645***
Loss proportion	-0.232	(0.702)	-0.324	(1.077)	-0.337	(0.732)	-0.154	(0.398)	2.637***	3.291***	-0.155
Obs.	1,149		300		192		548				

Table 3.7 Long-term cumulative abnormal returns around lawsuit filings

This table shows cumulative abnormal returns for various event windows around securities litigation class action filings. The table also provides a breakdown for settled and dismissed cases. Settled cases are either settled voluntarily through an agreement between the parties or through a final judgment and order by the court. Dismissed cases are dismissed by the court as non-meritorious. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-48,-2] trading days relative to the filing date. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: CARs around court filing

	Full sample		Control group		Voluntary settlement		Ordered settlement		Dismissed		Differences			
	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	t-stat			
	(1)		(2)		(3)		(4)		(5)		1 vs. 2	3 vs. 5	4 vs. 5	3 vs. 4
CAR[-1,1]	-0.170***	-0.309	-0.016***	-0.223	-0.182***	-0.321	-0.210***	-0.339	-0.148***	-0.296	15.618***	1.343	2.026**	-0.776
CAR[-1,6]	-0.186***	-0.495	-0.025***	-0.370	-0.199***	-0.469	-0.249***	-0.615	-0.161***	-0.476	9.953***	0.963	1.717*	-0.863
CAR[-1,12]	-0.224***	-0.688	-0.036***	-0.542	-0.274***	-0.662	-0.195***	-0.804	-0.199***	-0.671	8.070***	1.354	-0.048	0.999
CAR[-1,18]	-0.253***	-0.854	-0.035***	-0.700	-0.267***	-0.804	-0.244***	-0.996	-0.236***	-0.844	7.334***	0.446	0.089	0.239
CAR[-1,36]	-0.269***	-1.258	-0.035*	-1.021	-0.325***	-1.234	-0.110	-1.463	-0.295***	-1.222	5.386***	0.298	-1.433	1.475
Obs	800		2,701		220		132		406					

Table 3.8 Determinants of market reaction: Risk characteristics

The table shows cross-sectional differences of securities class action filings' abnormal returns with respect to observable firm risk characteristics. The dependent variable is CAR[-20,20] in all specifications. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Standard errors are robust to heteroskedasticity, and clustered at the firm and the year-month level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

CAR[-20,20]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraud	-0.566***	-0.558***	-0.574***				
Size	-0.010	-0.010	-0.010	0.030***	0.030***	0.029***	0.031**
Market-to-book	-0.003	-0.002	-0.003	-0.001**	-0.001**	-0.001**	-0.003**
Book leverage	0.001	0.001	0.001	0.021*	0.020*	0.023*	0.029**
CapEx	-0.083	-0.054	-0.083	0.110	0.123	0.101	0.134
Cash holding	-0.084	-0.085	-0.084	0.313***	0.307***	0.295***	0.465***
Dividend payout	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.004
Sales growth	0.033	0.033	0.032	-0.010	-0.011	-0.009	-0.015
Volatility	-0.048**	-0.049**	-0.049**	0.056	0.056	0.053	0.014
Return shock	0.043**	0.043**	0.043**	0.064***	0.064***	0.065***	0.104***
Profitability shock	-0.008	-0.007	-0.008	0.028	0.028	0.029	0.035
SA-index	0.001	0.001	0.001	-0.000	-0.000	-0.000	0.001
Amihud ILLIQ	-0.001	-0.001	-0.001	-0.141**	-0.133*	-0.142**	-0.168
Industry litigation			0.000	-0.001	-0.001	-0.001	-0.001
Serial offender				-0.002	-0.002	-0.003	0.001
Voluntary settlement					-0.023		
Settled						-0.040*	
Settlement							-0.044***
Fraud×							
Size	0.042***	0.042***	0.043***				
Market-to-book	0.002	0.001	0.002				
Leverage	0.025*	0.023*	0.024*				
CapEx	0.294	0.293	0.301				
Cash	0.457***	0.457***	0.457***				
Dividend payout	-0.001	-0.000	-0.001				
Sales growth	-0.041	-0.041	-0.038				
Volatility	0.111***	0.110**	0.121**				
Return shock	0.020	0.019	0.021				
Profitability shock	0.047**	0.048**	0.047**				
SA-index	-0.003***	-0.003**	-0.003**				
Amihud ILLIQ	-0.103	-0.104	-0.108				
Industry litigation			-0.000				
Financial		-0.039					
Healthcare		-0.056**					
Services		-0.029					
Technology		-0.025					
Constant	0.142	0.180**	0.142	-0.510***	-0.509***	-0.478***	-0.524***
Observations	4,153	4,153	4,153	1,022	1,022	1,022	483
Adjusted R-squared	0.04	0.04	0.04	0.08	0.08	0.08	0.13
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	Y	Y	Y	Y	Y

Table 3.9 Determinants of market reaction: Governance characteristics

The table shows cross-sectional differences of securities class action filings' abnormal returns with respect to observable governance characteristics. The dependent variable is CAR[-20,20] in all specifications. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Standard errors are robust to heteroskedasticity, and clustered at the firm and the year-month level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

CAR[-20,20]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraud	-0.201***	-0.205***	-0.261***	-0.087	0.120	-0.186**	-0.157*
Salary	-0.041**						
Equity incentives	0.002						
Restatements		-0.037					
Market val. change		-0.048					
SEC investigation		0.017					
Auditor same			0.001				
Directors				0.002	0.002		
Independent chair				0.027**			
CEO duality				0.032**			
Gender ratio					-0.023		
Nationality mix					-0.006		
Analyst coverage						-0.000	-0.000
Institutional hdg.						-0.111***	
Advisory firm hdg.							-0.185
Bank hdg.							-0.693***
Insurance hdg.							0.112
Investment hdg.							0.108
Other hdg.							-0.051
Fraud×							
Salary	0.047*						
Equity incentives	-0.000						
Restatements		-0.010					
Market val. change		-0.138					
SEC investigation		0.006					
Auditor same			0.007				
Directors				-0.003	-0.004		
Independent chair				-0.006			
CEO duality				-0.006			
Gender ratio					-0.213*		
Nationality mix					0.159*		
Analyst coverage						0.002	0.002
Institutional hdg.						-0.036	
Advisory hdg.							0.194
Bank hdg.							0.402
Insurance hdg.							-0.487
Investment hdg.							-0.792**
Other hdg.							-0.104*
Constant	0.057	0.064	0.066	0.018	0.072	0.130	0.123
Observations	4,185	4,185	3,751	2,865	2,846	4,185	3,293
Adjusted R-squared	0.04	0.03	0.04	0.03	0.03	0.04	0.04
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Table 3.10 Determinants of market reaction: Investment characteristics

The table shows cross-sectional differences of securities class action filings' abnormal returns with respect to observable investment characteristics. The dependent variable is CAR[-20,20] in all specifications. Abnormal returns are estimated using the Fama-French-Carhart 4-factor model. The estimation window is [-250,-31] trading days relative to the filing date. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Standard errors are robust and clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

CAR[-20,20]	(1)	(2)	(3)	(4)	(5)	(6)
Fraud	-0.566***	-0.564***	-0.567***	-0.572***	-0.564***	-0.565***
Acquisitions	0.001					
Acquisition value		-0.052				
Expansion acq.			0.006			
Exp. acq. value				-0.039		
Diversifying acq.					-0.008	
Div. acq. value						-0.116
Fraud×						
Acquisitions	0.006					
Acquisition value		0.019				
Expansion acq.			0.014			
Exp. acq. value				0.082		
Diversifying acq.					0.010	
Div. acq. value						0.057
Constant	0.143	0.144	0.146	0.143	0.140	0.144
Observations	4,153	4,153	4,153	4,153	4,153	4,153
Adjusted R-squared	0.04	0.04	0.04	0.04	0.04	0.04
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 3.11 Differences-in-differences analysis around court filings

The table shows the results of differences-in-differences estimations for various samples. Each line represents a different independent variable. The table reports the difference (interaction term) for each specification (δ). Panel A displays results for operational performance measures, while Panel B reports those for holdings. The post variable is determined around the first court filing date. In Panel A, post is 1 in the year of the filing and afterwards, and 0 otherwise. In Panel B, the post variable is 1 in the quarter of the filing and afterwards, and 0 otherwise. The estimation period is [-3,3] years in Panel A. In Panel B, the estimation period is [-12,12] quarters. The treatment variable is 1 for the fraudulent sample and 0 for the control sample. In Panel A, I control for year and industry fixed effects, as well as size and market-to-book in all specifications. In Panel B, I control for quarter and industry fixed effect, as well as log market capitalization and market-to-book in each specification. The control sample is determined by Mahalonobis distance metric matching. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Standard errors are robust to heteroskedasticity, and clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Operational measures

δ	Full sample	Voluntary	Ordered	Dismissed
Log of sales	0.012	0.040	0.124**	-0.020
ROA	-0.031***	-0.059***	-0.028	-0.013
ROE	0.206	-0.192*	-0.718	0.902
Tobin's Q	-1.182***	-1.503	-1.826***	-0.816***
Volatility 1 year	0.060***	0.073***	0.072***	0.048***
Profit margin	-0.031***	-0.059***	-0.028	-0.013
Sales growth	-0.129***	-0.104***	-0.305***	-0.071***
Cash holdings	0.008**	0.011**	0.005	0.012***
CapEx	-0.004**	-0.002	-0.006	-0.004*
OpEx	0.015	0.054*	0.047	-0.018
SA-Index	0.322**	0.423*	0.055	0.267
Book leverage	0.021	0.035	0.101*	-0.008

Panel B: Holdings

δ	Full sample	Voluntary	Ordered	Dismissed
Institutional holding	-0.026***	-0.038***	-0.023	-0.021**
Advisory firm holding	-0.006***	-0.009**	-0.005	-0.004
Bank holding	-0.003***	-0.002	-0.004	-0.004**
Insurance holding	-0.003***	-0.004**	-0.001	-0.003**
Investment holding	-0.003***	0.002	-0.008*	-0.004**
Other holding	-0.011**	-0.024***	-0.003	-0.007

Table 3.12 Portfolio analysis

The table shows portfolio characteristics for an investment in fraudulent and non-fraudulent firms. The portfolio is an equal weighted investment of short positions in fraudulent companies and long positions in control firms. Stocks enter the portfolio 1 month after a firm is indicted and are held until the closure of the court procedure. Panel A reports descriptive portfolio characteristics. Panel B shows risk adjusted returns. For all engaged companies, I draw 3 matching pairs with replacement. The Mahalanobis distance is determined based on industry, size, past return and market-to-book ratio. Standard errors are heteroskedasticity robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Portfolio statistics

	Full sample	1996-2005	2006-2016	Dotcom bubble	Housing crisis
Annualized return	0.140	0.172	0.110	0.128	0.165
	(0.389)	(0.410)	(0.368)	(0.457)	(0.619)
Portfolio size	590.711	567.193	612.748	616.972	782.417
	(270.170)	(336.225)	(187.208)	(103.295)	(35.698)
Obs.	246	119	127	36	24

Panel B: Risk-adjusted returns

	(1)	(2)	(3)	(4)
Market$-r_f$	0.518***	0.514***	0.492***	0.539***
	(0.028)	(0.021)	(0.022)	(0.027)
SMB		0.188***	0.195***	0.197***
		(0.037)	(0.036)	(0.040)
HML		0.206***	0.184***	0.144***
		(0.032)	(0.031)	(0.051)
RMW				0.047
				(0.051)
CMA				0.107
				(0.072)
Momentum			-0.001***	
			(0.000)	
Constant	0.003***	0.003***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	246	246	246	246
Adjusted R-squared	0.63	0.71	0.72	0.71
Annualized alpha	0.042	0.033	0.037	0.026

Appendix 3.A Variable definitions

Table A.1 Variable definitions

This table reports variable descriptions and their respective sources.

Variable	Description	Source
Fraud characteristics		
Class period length	Span of time period (days) over which plaintiffs claim to be defrauded as defined in the case filing.	Stanford Securities Class Action Clearinghouse (SCAC)
Time to filing	Time between class period end and first case filing date (days).	
Law firms	Number of law firms involved as plaintiffs.	
Voluntary settlement	The defendant and plaintiffs enter a stipulation of agreement. Indicator variable (1 if voluntary)	
Settlement amount	Settlement amount ($ million).	
Industry litigation	Number of litigations in industry per year, based on entire SCAC universe.	
Compensation		
Salary	Base salary ($ million).	ExecuComp
Total equity incentives	Equity and option compensation ($ million).	
Board structure		
Independent Chairman	Chairman has no executive status, indicator variable (1 if independent)	BoardEx
CEO/Chair	CEO duality: the CEO is the chairman of the board, indicator variable (1 if duality)	
Directors	Number of directors on board	
Independent director	Non-executive directors on the board	
Previous board seats	Number of previous board positions held	
Other board seats	Number of currently held other board positions	
Time on board	Tenure in current board position	
CEO tenure	CEO tenure as CEO (years).	
CEO retirement	CEO time to retirement (years).	
Network size	Network size of a director defined as known connections to other directors.	
Gender ratio	Ratio of female and male directors, 1 all male.	
Nationality mix	Ratio of US nationals to internationals on the board, 0 all US national.	
Outside monitors		
Analysts	Number of analysts issuing EPS estimates	I/B/E/S
Institutional holding	Percentage of market value held by institutions	Thomson Reuters (s12 and 13f)
Mutual fund holding	Percentage of market value held by mutual funds	
Advisory firm holding	Percentage of market value held by independent investment advisory firms	
Bank holding	Percentage of market value held by banks	
Insurance holding	Percentage of market value held by insurance companies	
Investment holding	Percentage of market value held by investment companies	
Other holding	Percentage of market value held other, miscellaneous institutions	

Continued on next page

Continued from previous page

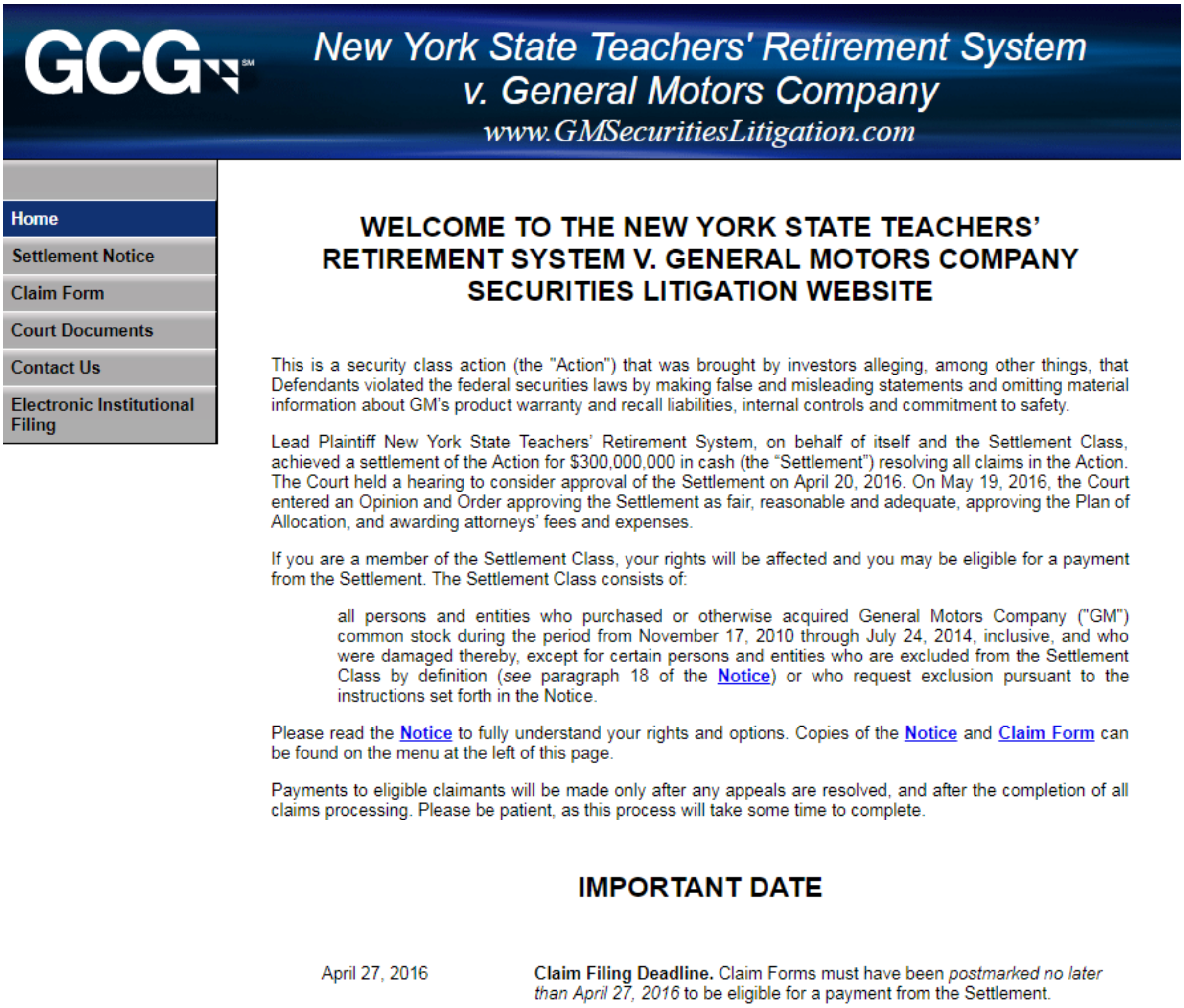
Variable	Description	Source
Risk and profitability		
Volatility	Average daily stock return volatility over the year, annualized.	CRSP
Buy-and-hold return	1-year buy-and-hold return	
Amihud ILLIQ	1-year mean Amihud illiquidity measure	
ROA	$\frac{\text{Net income}}{\text{Total assets}}$	Compustat
ROE	$\frac{\text{Net income}}{\text{Book equity}}$	
Asset turnover	$\frac{\text{Revenues}}{\text{Total assets}}$	
Sales growth (annual)	$\frac{\text{Revenues}_t}{\text{Revenues}_{t-1}} - 1$	
Market share	$\frac{\text{Revenues}}{\text{Total industry revenues}}$	Compustat
Profit margin	$\frac{\text{Net income}}{\text{Total assets}}$	
Market-to-book	$\frac{\text{Market equity}}{\text{Book equity}}$	
Tobin's Q	$\frac{\text{Market equity+Long term book debt}}{\text{Book equity+Long term book debt}}$	
Size and capital structure		
Size	natural log of Total assets	Compustat
Log of sales	natural log of revenues	
Log of market equity	natural log of market equity	
Book leverage	$\frac{\text{Long term book debt}}{\text{Long term book debt+Book equity}}$	
Tangibility	$\frac{\text{Plant, property and equipment}}{\text{Total assets}}$	
Cash, investments and payout		
Cash	$\frac{\text{Cash}}{\text{Total assets}}$	Compustat
CapEx	$\frac{\text{Capital expenditures}}{\text{Total assets}}$	
OpEx	$\frac{\text{Operating expenses}}{\text{Total assets}}$	
Dividend yield	$\frac{\text{Total dividends}}{\text{Market equity+Preferred equity}}$	
Dividend payout	$\frac{\text{Total dividends}}{\text{Net income}}$	
External financing	SA-index; Hadlock-Pierce measure of external financing need $-.737\ln(\text{assets}_t) + .043\ln(\text{assets}_t)^2 - .04\text{age}_t$	
Acquisitions		
Acquisitions	Number of acquisitions in class action period, globally, worth at least \$50 million	SDC Platinum
Acquisition/assets	Value of all acquisitions over total assets	
Div. acquisitions	Number of acquisitions in other 2-digit SIC industries; diversifying.	
Div. acq./assets	Value of diversifying acquisitions over total assets	
Exp. acquisitions	Number of acquisitions in same 2-digit SIC industries; expansion	
Exp. acq./assets	Value of expansion acquisitions over total assets	
Restatements		
Restatements	Number of accounting restatements in class period	Audit Analytics
Effect on income	Cumulative effect of restatements on net income (\$ million).	
Effect on equity	Cumulative effect of restatements on market equity (\$ million).	
Board involvment	Board was involved in restatement, indicator variable (1 if yes).	
SEC investigation	SEC investigated restatement, indicator variable (1 if yes).	
Financial fraud	Restatement is prosecuted as financial fraud, indicator variable (1 if yes).	
Auditor same	Auditor was the same (incumbent auditor) over class action period, indicator variable (1 if yes).	

Continued on next page

Continued from previous page

Variable	Description	Source
Miscellaneous		
Profitability shock	The residual from an AR(1) regression of ROA. A positive residual means a positive shock.	
Return shock	The 1-year buy-and-hold return is in the lowest quartile in the industry. Indicator variable, 1 if there is a shock.	
Age	Company age measured as the years since IPO or since the first appearance in Compustat	

Appendix 3.B Class action example



GCG

New York State Teachers' Retirement System
v. General Motors Company
www.GMSecuritiesLitigation.com

Home
Settlement Notice
Claim Form
Court Documents
Contact Us
Electronic Institutional Filing

WELCOME TO THE NEW YORK STATE TEACHERS' RETIREMENT SYSTEM V. GENERAL MOTORS COMPANY SECURITIES LITIGATION WEBSITE

This is a security class action (the "Action") that was brought by investors alleging, among other things, that Defendants violated the federal securities laws by making false and misleading statements and omitting material information about GM's product warranty and recall liabilities, internal controls and commitment to safety.

Lead Plaintiff New York State Teachers' Retirement System, on behalf of itself and the Settlement Class, achieved a settlement of the Action for $300,000,000 in cash (the "Settlement") resolving all claims in the Action. The Court held a hearing to consider approval of the Settlement on April 20, 2016. On May 19, 2016, the Court entered an Opinion and Order approving the Settlement as fair, reasonable and adequate, approving the Plan of Allocation, and awarding attorneys' fees and expenses.

If you are a member of the Settlement Class, your rights will be affected and you may be eligible for a payment from the Settlement. The Settlement Class consists of:

> all persons and entities who purchased or otherwise acquired General Motors Company ("GM") common stock during the period from November 17, 2010 through July 24, 2014, inclusive, and who were damaged thereby, except for certain persons and entities who are excluded from the Settlement Class by definition (*see* paragraph 18 of the Notice) or who request exclusion pursuant to the instructions set forth in the Notice.

Please read the Notice to fully understand your rights and options. Copies of the Notice and Claim Form can be found on the menu at the left of this page.

Payments to eligible claimants will be made only after any appeals are resolved, and after the completion of all claims processing. Please be patient, as this process will take some time to complete.

IMPORTANT DATE

April 27, 2016	**Claim Filing Deadline.** Claim Forms must have been *postmarked no later than April 27, 2016* to be eligible for a payment from the Settlement.

Figure B.1 Class action website example

The figure shows the home page of a typical class action case. Retrieved on August 7, 2017 from http://www.gmsecuritieslitigation.com/.

Bibliography

Aharony, Joseph, Chelsea Liu, and Alfred Yawson (2015). "Corporate Litigation and Executive Turnover". *Journal of Corporate Finance* 34, pp. 268–292.

Albuquerque, Rui, Art Durnev, and Chendi Zhang (2017). *Corporate Social Responsibility and Firm Risk: Theory and Evidence*. Working paper 359/2013. ECGI.

Alexander, Carol and Andreas Kaeck (2008). "Regime Dependent Determinants of Credit Default Swap Spreads". *Journal of Banking & Finance* 32 (6), pp. 1008–1021.

Amihud, Yakov (2002). "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects". *Journal of Financial Markets* 5 (1), pp. 31–56.

Amiraslani, Hami, Karl V. Lins, Henri Servaes, and Ane Tamayo (2017). *The Bond Market Benefits of Corporate Social Capital*. Working paper 535/2017. ECGI.

Antón, Miguel, Florian Ederer, Mireia Giné, and Martin C. Schmalz (2016). *Common Ownership, Competition, and Top Management Incentives*. Working paper 511/2017. ECGI.

Ashcraft, Adam, Nicolae Gârleanu, and Lasse Heje Pedersen (2011). "Two Monetary Tools: Interest Rates and Haircuts". *NBER Macroeconomics Annual* 25 (1), pp. 143–180.

Bajlum, Claus and Peter Tind Larsen (2008). *Capital Structure Arbitrage: Model Choice and Volatility Calibration*. Working paper.

Barko, Tamas and Luc Renneboog (2016). "Mutual Funds: Management Styles, Social Responsibility, Performance, and Efficiency". *Mutual Funds and Exchange-Traded Funds*. Ed. by H. Kent Baker, Greg Filbeck, and Halil Kaymaz. New York, New York: Oxford University Press, pp. 268–290.

Baron, David P. (2008). "Managerial Contracting and Corporate Social Responsibility". *Journal of Public Economics* 92 (1–2), pp. 268–288.

Bebchuk, Lucian A., Alon Brav, and Wei Jiang (2015). "The Long-Term Effects of Hedge Fund Activism". *Columbia Law Review* 115 (5), pp. 1085–1155.

Bebchuk, Lucian A., Alma Cohen, and Allen Ferrell (2009). "What Matters in Corporate Governance?" *The Review of Financial Studies* 22 (2), pp. 783–827.

Becht, Marco, Julian Franks, Jeremy Grant, and Hannes Wagner (2017). "Returns to Hedge Fund Activism: An International Study". *The Review of Financial Studies* 30 (9), pp. 2933–2971.

Becht, Marco, Julian Franks, Colin Mayer, and Stefano Rossi (2009). "Returns to Shareholder Activism: Evidence from a Clinical Study of the Hermes UK Focus Fund". *The Review of Financial Studies* 22 (8), pp. 3093–3129.

Bénabou, Roland and Jean Tirole (2006). "Incentives and Prosocial Behavior". *American Economic Review* 96 (5), pp. 1652–1678.

Benmelech, Efraim and Jennifer Dlugosz (2009). "The Credit Rating Crisis". *NBER Macro Annual* 24 (1), pp. 161–207.

Bergstresser, Daniel and Thomas Philippon (2006). "CEO Incentives and Earnings Management". *Journal of Financial Economics* 80 (3), pp. 511–529.

Berndt, Antje and Iulian Obreja (2010). "Decomposing European CDS Returns*". *Review of Finance* 14 (2), pp. 189–233.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh (2005). "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps". *The Journal of Finance* 60 (5), pp. 2255–2281.

Bollen, Nicolas (2007). "Mutual Fund Attributes and Investor Behavior". *Journal of Financial and Quantitative Analysis* 42 (3), pp. 683–708.

Bongaerts, Dion, Frank De Jong, and Joost Driessen (2011). "Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market". *The Journal of Finance* 66 (1), pp. 203–240.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas (2008). "Hedge Fund Activism, Corporate Governance, and Firm Performance". *The Journal of Finance* 63 (4), pp. 1729–1775.

Brickman, Lester (2002). "Anatomy of a Madison County (Illinois) Class Action: A Study of Pathology". *Civil Justice Report* 6.

Burns, Natasha and Simi Kedia (2006). "The Impact of Performance-Based Compensation on Misreporting". *Journal of Financial Economics* 79 (1), pp. 35–67.

Byström, Hans (2006). "Creditgrades and the iTraxx CDS Index Market". *Financial Analysts Journal* 62 (6), pp. 65–76.

Cao, Charles, Fan Yu, and Zhaodong Zhong (2011). "Pricing Credit Default Swaps with Option-Implied Volatility". *Financial Analysts Journal* 67 (4), pp. 67–76.

Capelle-Blancard, Gunther and Stéphanie Monjon (2014). "The Performance of Socially Responsible Funds: Does the Screening Process Matter?" *European Financial Management* 20 (3), pp. 494–520.

Carhart, Mark M. (1997). "On Persistence in Mutual Fund Performance". *The Journal of Finance* 52 (1), pp. 57–82.

Chen, Huafeng, Marcin Kacperczyk, and Hernán Ortiz-Molina (2012). "Do Nonfinancial Stakeholders Affect the Pricing of Risky Debt? Evidence from Unionized Workers". *Review of Finance* 16 (2), pp. 347–383.

Chen, Ren-Raw, Xiaolin Cheng, Frank J. Fabozzi, and Bo Liu (2008). "An Explicit, Multi-Factor Credit Default Swap Pricing Model with Correlated Factors". *Journal of Financial and Quantitative Analysis* 43 (1), pp. 123–160.

Coffee John C., Jr. (2006). "Reforming the Securities Class Action: An Essay on Deterrence and Its Implementation". *Columbia Law Review* 106 (7), pp. 1534–1586.

Coffee John C., Jr. (2015). *Entrepreneurial Litigation*. Harvard University Press.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin (2001). "The Determinants of Credit Spread Changes". *The Journal of Finance* 56 (6), pp. 2177–2207.

Cooper Alexander, Janet (2000). *An Introduction to Class Action Procedure in the United States*. Working paper.

Cremers, Martijn, Joost Driessen, and Pascal Maenhout (2008a). "Explaining the Level of Credit Spreads: Option-Implied Jump Risk Premia in a Firm Value Model". *The Review of Financial Studies* 21 (5), pp. 2209–2242.

Cremers, Martijn, Joost Driessen, Pascal Maenhout, and David Weinbaum (2008b). "Individual Stock-Option Prices and Credit Spreads". *Journal of Banking & Finance* 32 (12), pp. 2706–2715.

Cremers, Martijn, Erasmo Giambona, Simone M. Sepe, and Ye Wang (2015). *Hedge Fund Activism and Long-Term Firm Value*. Working paper.

Cremers, Martijn and Antti Petajisto (2009). "How Active Is Your Fund Manager? A New Measure That Predicts Performance". *The Review of Financial Studies* 22 (9), pp. 3329–3365.

Cserna, Balázs and Björn Imbierowicz (2008). *How Efficient are Credit Default Swap Markets? An Empirical Study of Capital Structure Arbitrage Based on Structural Pricing Models*. Working paper.

Currie, Anthony and Jennifer Morris (2002). "And Now for Capital Structure Arbitrage". *Euromoney*.

Dechow, Patricia M., Richard G. Sloan, and Amy P. Sweeney (1996). "Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC*". *Contemporary Accounting Research* 13 (1), pp. 1–36.

Desai, Hemang, Chris E. Hogan, and Michael S. Wilkins (2006). "The Reputational Penalty for Aggressive Accounting: Earnings Restatements and Management Turnover". *The Accounting Review* 81 (1), pp. 83–112.

Dimson, Elroy, Oğuzhan Karakaş, and Xi Li (2015). "Active Ownership". *The Review of Financial Studies* 28 (12), pp. 3225–3268.

Doidge, Craig, Alexander Dyck, Hamed Mahmudi, and Aazam Virani (2015). *Can Institutional Investors Improve Corporate Governance Through Collective Action*. Working paper.

Doshi, Hitesh, Jan Ericsson, Kris Jacobs, and Stuart M. Turnbull (2013). "Pricing Credit Default Swaps with Observable Covariates". *The Review of Financial Studies* 26 (8), pp. 2049–2094.

Duarte, Jefferson, Francis A. Longstaff, and Fan Yu (2007). "Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller?" *The Review of Financial Studies* 20 (3), pp. 769–811.

Duffie, Darrell (2010). "Presidential Address: Asset Price Dynamics with Slow-Moving Capital". *The Journal of Finance* 65 (4), pp. 1237–1267.

Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes Wagner (2015). *Do Institutional Investors Drive Corporate Social Responsibility? International Evidence*. Working paper.

Dyck, Alexander, Adair Morse, and Luigi Zingales (2010). "Who Blows the Whistle on Corporate Fraud?" *The Journal of Finance* 65 (6), pp. 2213–2253.

Dyck, Alexander, Adair Morse, and Luigi Zingales (2013). *How Pervasive is Corporate Fraud?* Working paper.

Edmans, Alex (2011). "Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices". *Journal of Financial Economics* 101 (3), pp. 621–640.

Edmans, Alex (2012). "The Link Between Job Satisfaction and Firm Value, With Implications for Corporate Social Responsibility". *The Academy of Management Perspectives* 26 (4), pp. 1–19.

Edmans, Alex and Clifford G. Holderness (2017). "Blockholders: A Survey of Theory and Evidence". *The Handbook of the Economics of Corporate Governance*. Ed. by Benjamin Hermalin and Michael Weisbach. North Holland: Elsevier, pp. 541–636.

El Ghoul, Sadok, Omrane Guedhami, Chuck C. Y. Kwok, and Dev R. Mishra (2011). "Does Corporate Social Responsibility Affect the Cost of Capital?" *Journal of Banking & Finance* 35 (9), pp. 2388–2406.

English II, Philip C., Thomas I. Smythe, and Chris R. McNeil (2004). "The "CalPERS Effect" Revisited". *Journal of Corporate Finance* 10 (1), pp. 157–174.

Erickson, Merle and Shiing-Wu Wang (1999). "Earnings Management by Acquiring Firms in Stock for Stock Mergers". *Journal of Accounting and Economics* 27 (2), pp. 149–176.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo (2009). "The Determinants of Credit Default Swap Premia". *The Journal of Financial and Quantitative Analysis* 44 (1), pp. 109–132.

Ericsson, Jan, Joel Reneby, and Hao Wang (2015). "Can Structural Models Price Default Risk? Evidence from Bond and Credit Derivative Markets". *Quarterly Journal of Finance* 05 (03), pp. 1–32.

Eurosif (2014). *European SRI Study*. Report. Eurosif.

Falato, Antonio, Dalida Kadyrzhanova, and Ugur Lel (2014). "Distracted Directors: Does Board Busyness Hurt Shareholder Value?" *Journal of Financial Economics* 113 (3), pp. 404–426.

Fama, Eugene F. and Kenneth R. French (1993). "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics* 33 (1), pp. 3–56.

Fama, Eugene F. and Kenneth R. French (2015). "A Five-Factor Asset Pricing Model". *Journal of Financial Economics* 116 (1), pp. 1–22.

Ferrell, Alan, Hao Liang, and Luc Renneboog (2016). "Socially Responsible Firms". *Journal of Financial Economics* 122 (3), pp. 585–606.

Ferris, Stephen P., Murali Jagannathan, and A. C. Pritchard (2003). "Too Busy to Mind the Business? Monitoring by Directors with Multiple Board Appointments". *The Journal of Finance* 58 (3), pp. 1087–1111.

Finger, Christopher C., Vladimir Finkelstein, Jean-Pierre Lardy, George Pan, Thomas Ta, and John Tierney (2002). *CreditGrades Technical Document*. Working paper.

Flammer, Caroline (2015). "Does Corporate Social Responsibility Lead to Superior Financial Performance? A Regression Discontinuity Approach". *Management Science* 61 (11), pp. 2549–2568.

Gabaix, Xavier, Augustin Landier, and Julien Sauvagnat (2014). "CEO Pay and Firm Size: An Update after the Crisis". *The Economic Journal* 124 (574).

Gaspar, José-Miguel, Massimo Massa, Pedro Matos, Rajdeep Patgiri, and Zahid Rehman (2013). "Payout Policy Choices and Shareholder Investment Horizons". *Review of Finance* 17 (1), pp. 261–320.

Gibson, Rajna and Philipp Krueger (2017). *The Sustainability Footprint of Institutional Investors*. Working paper 17-05. Swiss Finance Institute.

Gil-Bazo, Javier, Pablo Ruiz-Verdu, and Andre A. P. Santos (2010). "The Performance of Socially Responsible Mutual Funds: The Role of Fees and Management Companies". *Journal of Business Ethics* 94 (2), pp. 243–263.

Gillan, Stuart L. and Laura T. Starks (2007). "The Evolution of Shareholder Activism in the United States". *Journal of Applied Corporate Finance* 19 (1), pp. 55–73.

Global Sustainable Investment Alliance, (2015). "Global Sustainable Investment Review 2014". *Global Sustainable Investment Alliance*.

Gorton, Gary B. and Andrew Metrick (2009). *Haircuts*. Working paper 15273. NBER.

Goss, Allen and Gordon S. Roberts (2011). "The Impact of Corporate Social Responsibility on the Cost of Bank Loans". *Journal of Banking & Finance* 35 (7), pp. 1794–1810.

Greenwood, Robin and Michael Schor (2009). "Investor Activism and Takeovers". *Journal of Financial Economics* 92 (3), pp. 362–375.

Gromb, Denis and Dimitri Vayanos (2002). "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs". *Journal of Financial Economics* 66 (2), pp. 361–407.

Hadlock, Charles J. and Joshua R. Pierce (2010). "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index". *The Review of Financial Studies* 23 (5), pp. 1909–1940.

Hilscher, Jens, Joshua M. Pollet, and Mungo Wilson (2015). "Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets". *Journal of Financial and Quantitative Analysis* 50 (3), pp. 543–567.

Hoepner, Andreas, Ioannis Oikonomou, Zacharias Sautner, Laura T. Starks, and Xiaoyan Zhou (2016). *ESG Stakeholder Engagement and Downside Risk*. Tech. rep.

Hong, Harrison and Marcin Kacperczyk (2009). "The Price of Sin: The Effects of Social Norms on Markets". *Journal of Financial Economics* 93 (1), pp. 15–36.

Hong, Harrison, Jeffrey D. Kubik, and Jose A. Scheinkman (2012). *Financial Constraints on Corporate Goodness*. Working paper.

Hong, Harrison and Inessa Liskovich (2015). *Crime, Punishment and the Halo Effect of Corporate Social Responsibility*. Working paper.

Houweling, Patrick and Ton Vorst (2005). "Pricing Default Swaps: Empirical Evidence". *Journal of International Money and Finance* 24 (8), pp. 1200–1225.

Jiang, John, Kathy R. Petroni, and Isabel Yanyan Wang (2010). "CFOs and CEOs: Who Have the Most Influence on Earnings Management?" *Journal of Financial Economics* 96 (3), pp. 513–526.

Johnson, William C., Wenjuan Xie, and Sangho Yi (2014). "Corporate Fraud and the Value of Reputation in the Product Market". *Journal of Corporate Finance* 25, pp. 16–39.

Kapadia, Nikunj and Xiaoling Pu (2012). "Limited Arbitrage between Equity and Credit Markets". *Journal of Financial Economics* 105 (3), pp. 542–564.

Kaplan, Steven N and Joshua Rauh (2013). "It's the Market: The Broad-Based Rise in the Return to Top Talent". *The Journal of Economic Perspectives* 27 (3), pp. 35–55.

Karpoff, Jonathan M., Allison Koester, D. Scott Lee, and Gerald S. Martin (2017a). "Proxies and Databases in Financial Misconduct Research". *The Accounting Review* 92 (6), pp. 129–163.

Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin (2008a). "The Consequences to Managers for Financial Misrepresentation". *Journal of Financial Economics* 88 (2), pp. 193–215.

Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin (2008b). "The Cost to Firms of Cooking the Books". *Journal of Financial and Quantitative Analysis* 43 (03), pp. 581–611.

Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin (2017b). *Foreign Bribery: Incentives and Enforcement*. Working paper.

Karpoff, Jonathan M., John R. Lott Jr., and Eric W. Wehrly (2005). "The Reputational Penalties for Environmental Violations: Empirical Evidence". *The Journal of Law and Economics* 48 (2), pp. 653–675.

Klein, April and Emanuel Zur (2009). “Entrepreneurial Shareholder Activism: Hedge Funds and Other Private Investors”. *The Journal of Finance* 64 (1), pp. 187–229.

Klein, April and Emanuel Zur (2011). “The Impact of Hedge Fund Activism on the Target Firm’s Existing Bondholders”. *The Review of Financial Studies* 24 (5), pp. 1735–1771.

Konar, Shameek and Mark A. Cohen (2001). “Does the Market Value Environmental Performance?” *The Review of Economics and Statistics* 83 (2), pp. 281–289.

Kronlund, Mathias and Shastri Sandy (2015). *Does Shareholder Scrutiny Affect Executive Compensation?* Working paper.

Krueger, Philipp (2013). “Corporate Goodness and Shareholder Wealth”. *Journal of Financial Economics* 115 (2), pp. 304–329.

Leland, Hayne E. and Klaus Bjerre Toft (1996). “Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads”. *The Journal of Finance* 51 (3), pp. 987–1019.

Leuven, Edwin and Barbara Sianesi (2003). “PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing”. *Statistical Software Components*.

Liang, Hao and Luc Renneboog (2017). “On the Foundations of Corporate Social Responsibility”. *The Journal of Finance* 115 (2), pp. 304–329.

Lins, Karl V., Henri Servaes, and Ane Tamayo (2017). “Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis”. *The Journal of Finance* 72 (4), pp. 1785–1824.

Liu, Jun, Francis A. Longstaff, and Ravit E. Mandell (2006). “The Market Price of Risk in Interest Rate Swaps: The Roles of Default and Liquidity Risks”. *The Journal of Business* 79 (5), pp. 2337–2359.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis (2005). “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market”. *The Journal of Finance* 60 (5), pp. 2213–2253.

Louis, Henock (2004). “Earnings Management and the Market Performance of Acquiring Firms”. *Journal of Financial Economics* 74 (1), pp. 121–148.

Margolis, Joshua D., Hillary Anger Elfenbein, and James P. Walsh (2011). *Does it Pay to Be Good... And Does it Matter? A Meta-Analysis of the Relationship between Corporate Social and Financial Performance*. Working paper.

Merton, Robert C. (1974). “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates”. *The Journal of Finance* 29 (2), pp. 449–470.

Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino (2007). “Slow Moving Capital”. *American Economic Review* 97 (2), pp. 215–220.

Nelson, James M. (2006). “The “CalPERS Effect” Revisited Again”. *Journal of Corporate Finance* 12 (2), pp. 187–213.

Ozeki, Takaaki, Yuji Umezawa, Akira Yamazaki, and Daisuke Yoshikawa (2011). “An Extension of CreditGrades Model Approach with Lévy Processes”. *Quantitative Finance* 11 (12), pp. 1825–1836.

Palmrose, Zoe-Vonna, Vernon J. Richardson, and Susan Scholz (2004). “Determinants of Market Reactions to Restatement Announcements”. *Journal of Accounting and Economics* 37 (1), pp. 59–89.

Perino, Michael A. (2002). “Did the Private Securities Litigation Reform Act Work?” *University of Illinois Law Review* 2003 (4), pp. 913–977.

Rakoff, Jed S. (2015). “The Cure for Corporate Wrongdoing: Class Actions vs. Individual Prosecutions”. *The New York Reveiw of Books* 62 (18).

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang (2008a). “Socially Responsible Investments: Institutional Aspects, Performance, and Investor Behavior”. *Journal of Banking & Finance* 32 (9), pp. 1723–1742.

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang (2008b). “The Price of Ethics and Stakeholder Governance: The Performance of Socially Responsible Mutual Funds”. *Journal of Corporate Finance* 14 (3), pp. 302–322.

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang (2011). “Is Ethical Money Financially Smart? Nonfinancial Attributes and Money Flows of Socially Responsible Investment Funds”. *Journal of Fianancial Intermediation* 20 (4), pp. 562–588.

Schaefer, Stephen M. and Ilya A. Strebulaev (2008). “Structural Models of Credit Risk are Useful: Evidence from Hedge Ratios on Corporate Bonds”. *Journal of Financial Economics* 90 (1), pp. 1–19.

Shleifer, Andrei and Robert W. Vishny (1997). “The Limits of Arbitrage”. *The Journal of Finance* 52 (1), pp. 35–55.

Smith, Michael P. (1996). “Shareholder Activism by Institutional Investors: Evidence from CalPERS”. *The Journal of Finance* 51 (1), pp. 227–252.

Soyka, Peter A. and Mark E. Bateman (2012). *Finding Common Ground on the Metrics that Matter*. Working paper.

Spamann, Holger (2016). “Monetary Liability for Breach of the Duty of Care?” *Journal of Legal Analysis* 8 (2), pp. 337–373.

Stuart, Elizabeth A. (2010). “Matching Methods for Causal Inference: A Review and a Look Forward”. *Statistical Science* 25 (1), pp. 1–21.

Stulz, René M (2010). “Credit Default Swaps and the Credit Crisis”. *The Journal of Economic Perspectives* 24 (1), pp. 73–92.

Svec, Jiri and Nick Reeves (2011). *Capital Structure Arbitrage: An Analysis of the Australian CDS Market*. Working paper.

UN Principles for Responsible Investing (2015). “Report on Progress 2015”. *UN Principles for Responsible Investing.*

US SIF (2014). “Annual Report: US SIF and US SIF Foundation”. *US SIF.*

Wang, Tracy Yue (2005). *Securities Fraud: An Economic Analysis*. Working paper.

Wang, Tracy Yue (2013). “Corporate Securities Fraud: Insights from a New Empirical Framework”. *Journal of Law, Economics, and Organization* 29 (3), pp. 535–568.

Watkins, Michael (2010). “How BP Could Have Avoided Disaster”. *Harvard Business Review* 88 (6).

Webber, David H. (2015). “Shareholder Litigation Without Class Actions”. *Arizona Law Review* 57 (1), pp. 201–267.

Wells, Joseph T. (2001). “Why Employees Commit Fraud: It’s either Greed or Need”. *Journal of Accountancy* 5 (2).

Yu, Fan (2006). “How Profitable is Capital Structure Arbitrage?” *Financial Analysts Journal* 62 (5), pp. 47–62.

Yuan, Qingbo and Yunyan Zhang (2014). “The Real Effects of Corporate Fraud: Evidence from Class Action Lawsuits”. *Accounting & Finance*, pp. 1–33.

Zahra, Shaker A., Richard L. Priem, and Abdul A. Rasheed (2005). “The Antecedents and Consequences of Top Management Fraud”. *Journal of Management* 31 (6), pp. 803–828.

Zhang, Benjamin Yibin, Hao Zhou, and Haibin Zhu (2009). “Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms”. *The Review of Financial Studies* 22 (12), pp. 5099–5131.

Zhou, Chunsheng (2001). “The Term Structure of Credit Spreads with Jump Risk”. *Journal of Banking & Finance* 25 (11), pp. 2015–2040.